Department of Spatial Sciences

Spatio-Temporal Modelling of Bluetongue Virus Distribution in Northern Australia Based on Remotely Sensed Bioclimatic Variables

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This thesis is presented for the Degree of Doctor of Philosophy of Curtin University of Technology

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Declaration

To the best of my knowledge and belief this thesis contains no material previously published by any other person except where due acknowledgement has been made.

This thesis contains no material which has been accepted for the award of any other degree or diploma in any university.

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ABSTRACT

The presence of Bluetongue virus (BTV) in Northern Australia poses an ongoing threat for animal health and although clinical disease has not been detected in livestock, it limits export of livestock from the infected areas. BTV presence is governed by variable environmental conditions, which influence vector and host habitats. The National Arbovirus Monitoring Program (NAMP) was established to determine the extent of virus activity and control the risk of infection spread. Groups of young cattle, previously unexposed to infection, are regularly tested to detect evidence of transmission. This approach is labour and cost intensive and difficult to operate in the remote areas of Northern Australia. The resulting data are therefore characterised by spatial and temporal gaps. The aim of this research is to assess the use of remotely sensed environmental and climatic data as a means of predicting the distribution of BTV seroprevalence throughout Northern Australia to complement conventional surveillance.

Environmental factors relating to the viruses' host and vector habitats and the transmission cycle of BTV have been identified based on the extensive review of virus ecology. Different data sources have been assessed to provide sufficient spatial and temporal coverage for the definition of spatio-temporal environmental variables that can be used to explain and predict the distribution of BTV. Following this assessment, satellite data products from the Moderate Resolution Imaging Spectroradiometer (MODIS) and the Tropical Rainfall Measuring Mission (TRMM) were acquired for the Pilbara in Western Australia, and the Northern Territory. These were reprojected and processed into spatio-temporal variables for the period between the years 2000 and 2009. Due to uncertainty in the precision of the geographic location and timing of animals tested for seropositivity, summary statistics of bioclimatic variables were generated at the station (i.e. property) level for each year. Different combinations of these variables, including vegetation greenness and phenology, land surface temperature and precipitation were screened for correlation with BTV presence using a Generalised Additive Model approach. A final model was developed to predict the presence or absence of BTV seropositivity on the basis

of statistical significance of the remotely sensed predictor variables, and informed by knowledge of virus ecological principles.

The model, based on the maximum seasonal Normalised Difference Vegetation Index (NDVI), and mean and maximum land surface temperature variables provided excellent discriminatory ability and the basis for the generation of prediction maps of BTV seropositivity for the first eight years. Besides internal assessment, the model's predictive capabilities were validated using monitoring data from the season 2008/09.

It has been demonstrated that the predictions are useful in complementing complement NAMP surveillance by identifying areas at higher risk for seropositivity in cattle, which aids planning of livestock movement and further monitoring activities. Uncertainty in the model was attributed to the spatio-temporal inconsistency in the precision of the available serosurveillance data. The discriminatory ability of models of this type could be further improved by ensuring that exact location details and date of NAMP BTV test events are consistently recorded.

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This research has been made possible through a number of institutions and individual persons who not only motivated me to move to Australia but also provided assistance throughout the more than three years I have worked on this project. For those I forgot to mention here, please accept my gratitude for the role that you have played.

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TERMS AND ACRONYMS

Below is a list of terms and acronyms used in the thesis:

AB-CRC	Australian Biosecurity Cooperative Research Centre for Emerging Infectious Disease
AMSR	Advanced Microwave Scanning Radiometer
AMSU	Advanced Microwave Sounding Unit
ASRIS	Australian Soil Resource Information System
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
AVHRR	Advanced Very High Resolution Radiometer
AIC	Akaike Information Criterion
ANN	Artificial Neural Network
AUC	Area under the ROC curve (see ROC)
BoM	Australian Bureau of Meteorology
BRDF	Bidirectional Reflectance Distribution Function
CSIRO	Commonwealth Scientific and Industrial Research Organisation
CMORPH	NOAA Climate Prediction Center Morphing Technique
CU	Cattle Unit
DAFWA	Department of Agriculture and Food Western Australia
DEM	Digital Elevation Model
DSE	Dry Sheep Equivalent
ENFA	Ecological Niche Factor Analysis
ENSO	El Niño – Southern Oscilllation
ETM	Enhanced Thematic Mapper
EVI	Enhanced Vegetation Index
FAO	Food and Agriculture Organisation of the United Nations
GAM	Generalised Additive Model
GDD	Growing Degree Days
GIS	Geographic Information System or Science
GLM	Generalised Linear Model
GLW	Gridded Livestock of the World dataset
GPW	Gridded Population of the World dataset
GMS	Geostationary Meteorological Satellite

GOES	Geostationary Operational Environmental Satellites
GWR	Geographically Weighted Regression
HDF	Hierarchical Data Format
IPWG	International Precipitation Working Group
IR	Infrared
JAXA	Japan Aerospace Exploration Agency
LST	Land Surface Temperature
MIR	Mid Infrared
MODIS	Moderate Resolution Imaging Spectroradiometer
NASA	National Aeronautics and Space Administration
NAMP	National Arbovirus Monitoring Program
NBAR	Nadir BRDF-Adjusted Reflectance (also see BRDF)
NDVI	Normalised Difference Vegetation Index
NIR	Near Infrared
NOAA	National Oceanic and Atmospheric Administration
NSW	New South Wales
NT	Northern Territory
NVIS	National Vegetation Information System
OIE	Office international des epizooties (World Organisation for Animal Health)
PCA	Principal Component Analysis
PMW	Passive Microwave
PR	TRMM Precipitation Radar (also see TRMM)
ROC	Receiver Operating Characteristic
QLD	Queensland
SAR	Synthetic Aperture Radar
SDS	Scientific Dataset
SG	Savitzky-Golay Filter
SiNDVI	Small integrated NDVI (also see NDVI)
SPOT	Satellite Pour l'Observation de la Terre
SZA	Solar Zenith Angle
TAIR	Air Temperature
TIR	Thermal Infrared
TM	Thematic Mapper

TMI	TRMM Microwave Imager (also see TRMM)
TMPA	TRMM Multi-satellite Precipitation Analysis (also see TRMM)
TRMM	Tropical Rainfall Measuring Mission
VI	Vegetation Index
VPD	Vapour Pressure Deficit
WA	Western Australia
WHO	World Health Organisation
WMO	World Meteorological Organisation

List of Viruses and Diseases:

AKA	Akabane Virus
BEF	Bovine Ephemeral Fever Virus
BSE	Bovine Spongiform Encephalopathy
BT/BTV	Bluetongue / Bluetongue Virus
DEN/DENV	Dengue Fever/ Dengue Virus
EHD	Epizootic Haemorrhagic Disease Virus
JE/JEV	Japanese Encephalitis Virus
KUN/KUNV	Kunjin Virus
MVE/MVEV	Murray Valley Encephalitis Virus
RR	Ross River Virus

CHAPTER 1

INTRODUCTION

1. 1 Problem Formulation

Arthropod transmitted viruses (arboviruses) such as Bluetongue virus (BTV) are enzootic in the northern parts of Australia, where they pose a threat to human and animal health. The ecology of arboviruses involves a transmission cycle between competent insect vectors (e.g. mosquitoes or biting midges), who blood-feed on vertebrate hosts (e.g. humans, livestock, feral animals) and thereby may transmit the virus. Each component of the transmission cycle is influenced by the interplay of underpinning environmental variables such as climatic conditions, vegetation, terrain and soil properties, which characterise the vector and host habitat structure.

Current virus surveillance in Australia is based on antibody testing of sentinel animals at regular time intervals, complemented by strategic serological surveys. This approach is time consuming, expensive, and the resulting data are characterised by an incomplete spatial coverage and a coarse temporal resolution. As a consequence, it is impracticable to predict disease spread over space and time within the timeframe necessary for early warning systems. As an alternative, epidemiologists have used environmental data from earth observation satellites combined with serological data to map vector habitats and hence estimate the potential virus distribution over large areas (e.g. malaria in Africa). Such epidemiological studies rely on low cost data available at wide areal coverage and high temporal resolution over longer periods.

This research addresses the current lack of an efficient and cost-effective methodology for the area-wide prediction of arbovirus occurrence in the North of Australia, using BTV as the target virus. Different remote sensing instruments and ancillary datasets are assessed for their capability to provide environmental and climatic data to be used within a spatial distribution model that can predict BTV presence accurately and hence complement traditional surveillance methods in areas, where these are impractical.

1. 2 Background

1.2.1 Bluetongue Virus

Bluetongue virus is an Orbivirus transmitted by biting midges that causes a non-contagious, infectious disease of wild and domestic ruminants. The virus is spread almost worldwide in the tropics and subtropics approximately between the latitudes 35°S and 40°N (Mellor 2001). In recent years, the effects of climate change have contributed to an extension of its distribution area into higher latitudes and facilitated major outbreaks in Europe (Mellor et al. 2009; Saegerman, Berkvens, and Mellor 2008). In the Mediterranean region, over one million sheep have died from both the disease itself and elective culling since 1998 (Purse et al. 2005).

The virus is transmitted between its ruminant hosts almost exclusively via the bites of *Culicoides* midges, which act as the predominant vectors. Hence, the global distribution is limited to the areas where the biting midges can survive. In Australia, currently five species of *Culicoides* have been identified by entomologists as competent vectors for BTV, namely *C. fulvus*, *C. wadai*, *C. actoni*, *C. dumdumi* and *C. brevitarsis*. Amongst them, *C. brevitarsis* is the most widely distributed species, while other midges species are less expansively distributed and are confined to areas within the limits of *C. brevitarsis* distribution (Kirkland 2004). In general, *Culicoides* habitats are determined by environmental and climatic factors, including temperature, moisture, geographic barriers, vegetation cover and health, the presence of ruminants as blood reservoirs for feeding, as well as the availability of breeding sites. Dispersal of *Culicoides* is not limited to their flight range of a few kilometres, but can extend to hundreds of kilometres if midges are blown by prevailing winds as aerial plankton (Mellor 2001).

1.2.2 Distribution and Control of BTV in Australia

Although BTV is endemic in Australia, no signs of clinical disease have been observed in the major sheep herds. The major reason is that from the presently 70 million sheep (Curtis 2009), only a few hundred graze in areas where the virus is permanently present (Kirkland 2004). Nevertheless, BTV has a major impact on the Australian livestock industry by restricting trade of sheep, cattle or goats. Even if trade is not prevented, it becomes very expensive due to serological tests and other measures necessary to reduce the perceived BTV risk (Oliver 2004). After the first isolation of BTV in Australia near Darwin in the late 1970s, a sentinel herd system for arbovirus surveillance was installed. The system was gradually expanded from Northern Australia to the Eastern States and resulted in the establishment of the National Arbovirus Monitoring Program (NAMP) in 1993. The locations of sentinel herds are confined to the areas of commercial cattle operations (Melville 2004) and are selected representatively to allow mapping of the distribution of infections. Hence most herds are positioned along the border between expected infected and uninfected areas, or where infection occurs irregularly. Herds within the affected areas are also tested to assess the seasonal intensity of infection. Supplementary, expected BTV-free areas are monitored to verify their free status (Animal Health Australia 2006). Sentinel herds usually consist of 10 to 25 young cattle, which have initially returned negative tests for Bluetongue antibodies. Cattle are replaced annually or after seroconversion is determined. The herds are bled at regular intervals, with the frequency being approximately proportional to the probability of arbovirus activity. Opportunistic serological surveys complement the testing of sentinel herds. The second corner post of surveillance is vector trapping and quantification of *Culicoides* species at the sentinel herd sites and a number of other strategic locations (Cameron 2004). The data sampled at the monitoring sites are collected in a central database, which defines the main input for the definition of three zones according to regulations of the World Organisation for Animal Health (OIE): ‘free of BTV’, ‘infected’, an a “surveillance” buffer zone between those two. The zone boundaries are defined and adjusted on the basis of monitoring results and expert knowledge.

1.2.3 The Role of Remote Sensing and Geographic Information Science in Epidemiology

The field of spatial epidemiology aims to investigate and map the spatial distribution of emerging diseases over time, based on the distribution of vectors, hosts and incidences (Ostfeld, Glass, and Keesing 2005). The basic underlying concept comprises three components as observed by Pavlovsky (1966). First, diseases tend to be limited geographically; second, the spatial variation of diseases is influenced by biological and physical variations that support the distribution of the pathogen, its vectors and hosts; and third, if these biotic and abiotic environmental conditions can be delineated on a map, then spatial and temporal patterns of disease risk should be predictable.

With the evolution of Geographic Information Science and associated tools, and the availability of data collected by remote sensing satellites, there has been a revival of interest in these early concepts, which are still widely accepted. The distribution of arthropod virus vectors is closely coupled with environmental factors that can now be mapped on a broad scale by the aid of spatial technologies. As computer power increases, ever larger datasets can be handled in Geographic Information Systems (GIS), analysed, used as input for statistical and biological models and eventually visualised and communicated to the user community. It is not surprising that epidemiologists have adopted these technologies in many countries to predict the distribution of vectors like mosquitoes, ticks or biting midges to assess and monitor the risk for disease dispersal and outbreaks over time (Cameron 2000a; Chalke 2006; De La Rocque et al. 2004; Graham, Atkinson, and Danson 2004; Guis et al. 2007; Tatem et al. 2003).

The basic requirement for arbovirus modelling over large areas is the reliable availability of historic, contemporary and future data on environmental conditions, collected at regular intervals with consistent high quality. Furthermore, the necessary frequent update rate of data requires a cost efficient solution, especially with a view to implementing BTV early warning systems. Two sensors that meet these requirements and deliver publicly available data at no cost have gained importance particularly for environmental monitoring applications: the Advanced Very High Resolution Radiometer (AVHRR) and the MODerate Resolution Imaging Spectroradiometer (MODIS). The series of AVHRR sensors have collected environmental data since 1978 at a rather low resolution between 1.1 km and 8 km (Hay et al. 2006), but they are invaluable for monitoring environmental changes due to the historical data coverage. MODIS on board the Terra and Aqua satellites, which were launched in 1998 and 2002, respectively, has advantage over AVHRR by collecting data at a higher spatial resolution between 250 and 1000 m, depending on the channel (Chalke 2006; Tatem, Goetz, and Hay 2004). With 36 spectral bands a variety of meteorological and other ecological variables can be derived. The low revisit time of 1-2 days increases the chance of recording cloudless images over an area and hence facilitates the monitoring of dynamic spatial environmental processes. With a scheduled operation period of 18 years, the MODIS data archive will facilitate global long-term observations of disease related factors.

In the case of BTV, spatial epidemiologists successfully modelled its distribution in Europe using remote sensing and GIS and so could predict the outbreak in the 1990's. Besides meteorological parameters like temperature and rainfall, which are most relevant for estimating vector survival rates (Purse et al. 2005), environmental variables derived from satellites were used in modelling the occurrence of vector-borne diseases. These included dynamic factors like vegetation indices, soil moisture and surface water (e.g. Baylis and Rawlings 1998; Chalke 2006; Purse, Tatem, et al. 2004). By incorporating such remotely sensed variables, vector distribution could be more accurately predicted on an area-wide basis.

1. 3 Research Objectives

1.3.1 Aims of the Research

The overall aim of this research, which forms part of an Australian Biosecurity CRC funded project on arboviral diseases, is to provide a better understanding of the relationship between the spatio-temporal variability of climatic and environmental conditions and the occurrence of Bluetongue virus. This understanding will eventually facilitate the prediction of the future distribution and potential diffusion scenarios of the virus. To achieve this ambitious goal, the primary objective of the project is:

- To test the application of remotely sensed environmental variables for the development of predictive models of BTV presence and absence in Northern Australia across space and through time.

To address this primary objective encompasses the following secondary objectives:

- To identify relevant spatial data suitable for the definition of environmental factors that relate to the distribution of BTV as the target virus. The availability, spatial and temporal resolution of remote sensing imagery, topographic, climatic, vegetation and other ancillary data will play a crucial role in the capability to accurately model and predict BTV host and vector dynamics; and

- To develop algorithms for timely delivery of multi-temporal spatial data to model bioclimatic landscapes relating to BTV host and vector dynamics. The reliability of these spatio-temporal data for estimating and mapping the distribution of infected hosts in the study areas will be assessed using arbovirus surveillance data from within and beyond the period under investigation.

1.3.2 Expected Outcomes

The expected outcomes of this research include:

- A summary of environmental biotic and abiotic factors and available data sources, relevant to model habitats, dispersal and abundance of the main BTV vectors *Culicoides spp.;*
- An effective, cost efficient and rapid methodology to derive those environmental factors from satellite images, meteorological and ancillary datasets of sufficient quality, and of appropriate spatial and temporal resolution;
- A spatio-temporal model of virus distribution based on bioclimatic variables; as well as
- A better understanding of Bluetongue host and vector dynamics in the spatio-temporal domain.

1. 4 Significance and Benefits of the Research

Vector-borne diseases are an emerging threat for humans and livestock worldwide. BTV is an arbovirus, which has killed a large number of sheep during major outbreaks of the Bluetongue disease in Europe, Asia and Africa. Although no evidence for severe clinical disease has been found in Australia, it has halted export of cattle and even cattle products since then. International trade of livestock according to OIE guidelines is restricted to cattle that were held in BTV-free zones prior to export (Oliver 2004). The current zone definition within NAMP delivers important information for planning live stock exports. However, this process is solely based on ground based surveillance and expert knowledge, while neglecting important environmental factors. There is currently no national capability to predict disease spread consistently over space and time necessary for early warning systems. The limitations of the approach were highlighted in 2000, when the diffusion of BTV into the Pilbara region in Western Australia could not be predicted.

Rational control of the virus activity requires an understanding of the transmission cycle of BTV, which is governed by complex spatial interactions between the vectors (biting midges) and hosts (predominantly domestic and wild ruminants). Dynamic environmental, biological, agricultural and socio-economic factors and their spatio-temporal variations affect the habitats of hosts and vectors, and as such determine the activity and movement patterns of the virus. Despite the ongoing intensive monitoring in Australia, these factors and the ecology and epidemiology of BTV are still poorly understood, as pointed out by Melville (2004) during an international Bluetongue Symposium. While localised studies in the Eastern States of Australia were quite successful in modelling the distribution of only one vector species, the situation is different for Northern Australia. The presence of a variety of *Culicoides* species as potential BTV vectors as well as the large observation area with complex climatic and geographic interactions make the development of distribution models difficult. Furthermore, the proximity to South East Asia bears the risk of further virus incursions. Hence, there is a high research demand for investigations in this area to get a better understanding of BTV activities on a regional scale and in case of new incursions, to predict the possible distribution of the pathogen well ahead in time.

The advance of spatial epidemiology is very closely tied to the availability of data on environmental and climate factors to describe to the occurrence of vector and host species. Despite the ongoing development and the successful application of spatio-temporal models to predict BTV outbreaks in the Mediterranean region, the lack of suitable data has long been a limiting factor in research (Herbreteau et al. 2007). However, with the increasing availability of remote sensing data, particularly from the MODIS instrument, monitoring of environmental factors has become more efficient on a regional to global scale with appropriate temporal and spatial resolution. This research aims to investigate the potential of MODIS and other satellite-borne sensors for epidemiological studies particularly for the Australian conditions, by delivering area-wide environmental and climatic data at low cost.

Another issue discussed by Ostfeld, Glass & Keesing (2005) is the prediction of disease risk or incidence only by distribution of host and vector species. While the generation of presence/absence maps is relatively simple using existing GIS methods, more dynamic models are necessary. To facilitate timely prediction of arbovirus spread, varying environmental conditions affecting ecological processes have to be incorporated, including plant and animal life cycles, soil moisture, as well as vegetation type and condition. Although arboviruses are enzootic in some areas, under certain environmental conditions, viruses migrate to distant areas, when linkages between suitable habitats and breeding places are established. These spatial processes have yet to be fully investigated and formalized. Eventually the research aims to contribute to a better understanding of the relationship between dynamic landscape, environmental and climate factors and the risk for vector-borne diseases.

1. 5 Research Methodology

The study area covers parts of Northern Australia, where BTV is endemic and extends to areas where BTV is not endemic, but which might be subject to further spread of the virus. The regions investigated are the Pilbara-Gascoyne in Western Australia (WA) as well as the entire Northern Territory (NT), both of which are characterised by varying levels of virus activity and a great environmental diversity.

The study comprises two major stages which are carried out sequentially as outlined below:

i) Timely delivery of multi-temporal spatial data relating to virus vector and host dynamics, through:
   a. Review of relevant literature on BTV transmission, host and vector ecology, and the utilisation of Geographic Information Technology, remotely sensed data, as well as ecological and statistical modelling techniques to predict virus distribution;
   b. Inventory of sources for environmental and climatic data relevant to the ecology of BTV vectors and hosts. Data from remote sensing

satellites, weather stations, and government agencies are assessed for their quality, spatial and temporal resolution required for mapping at a regional scale; and

c. Development of algorithms for the generation and timely delivery of spatio-temporal variables that relate to arbovirus host and vector dynamics.

ii) Predicting the distribution of BTV using spatio-temporal modelling techniques, incorporating the following steps:

a. Identifying the crucial bioclimatic variables associated with virus dynamics in the study area;

b. Developing models for spatio-temporal mapping of BTV presence and absence, based on the underpinning bioclimatic variables; and

b. Performing an evaluation process to assess the predictive capabilities of the resulting distribution model.

The next section provides a brief overview of the chapters in this thesis. The main stages of the study in relation to the thesis chapters are outlined in Figure 1.1 below.

1. 6 Overview of Thesis

This thesis comprises eight chapters. Chapter 1 introduces the problem and provides relevant background information on Bluetongue in Australia and its significance for animal health and the livestock industry. Based on the stated objectives and the proposed outcomes, a simplified structure of this research is outlined.

Chapter 2 reviews the historic and present distribution of BTV, its hosts and vectors and investigates possible causal environmental and climatic factors that influence the transmission cycle. An overview of the current surveillance system is provided, and its limitations are discussed.

Chapter 3 introduces the field of spatial epidemiology and explains the basic concept of disease presence being dependent on suitable habitat conditions for host and vectors. Based on these ecological principles, modelling techniques used in ecological and epidemiological applications are explored. Advantages and disadvantages are highlighted in order to find the most appropriate and robust technique for this study on landscape, environmental and climatic factors. The chapter concludes with methods for model validation.

Chapter 4 provides a brief overview of the principles of remote sensing and its role for mapping the distribution of vector-borne diseases. Current and future satellite sensors delivering environmental data at low, medium and high spatial resolution are reviewed. The applicability of the available environmental data from these sensors to this study is discussed, considering factors like spatial and temporal resolution, cost of data acquisition and processing. Also a variety of bioclimatic variables that can be derived from remotely sensed data and have been previously used in comparable studies are reviewed.

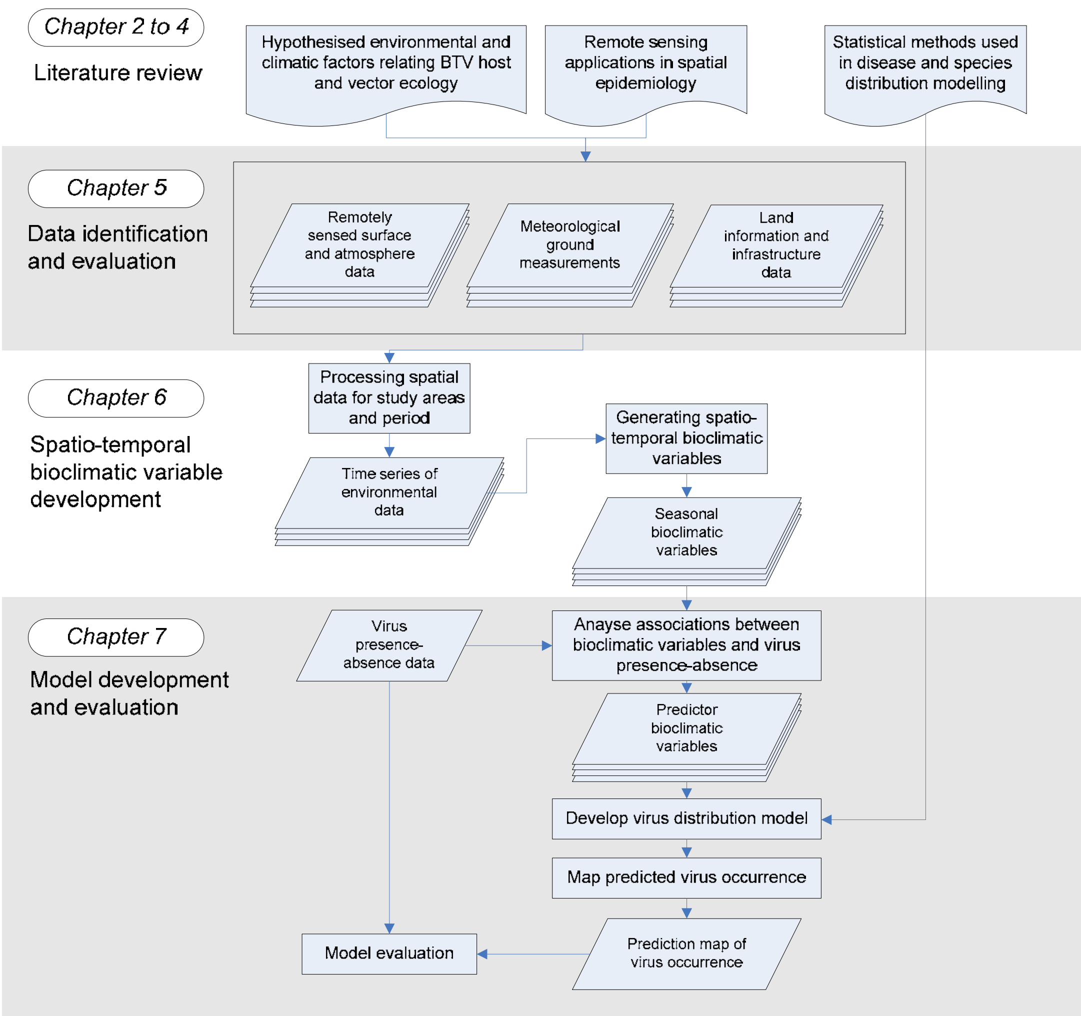


Figure 1.1 Research structure and relationship to the chapters of this thesis

Chapter 5 introduces the study areas in the Pilbara-Gascoyne region and the Northern Territory in terms of climate, weather patterns, topography, pastoral potential and virus activity. All data sources used in subsequent chapters are presented. The software packages used to analyse, present and derive the various outputs of this study are documented.

In Chapter 6, the methodology is described to transform the satellite data into a set of meaningful bioclimatic variables. Processing of data from MODIS and the Tropical Rainfall Measuring Mission (TRMM) is detailed, followed by a discussion of issues with cloud cover and missing data in the tropical North of the country. Governed by the underlying spatial and temporal resolution of the virus presence/absence data, the variables were aggregated into seasonal variables on a pastoral property level, utilising station average conditions and a novel weighting approach.

Chapter 7 continues with the spatial analyses of relationships between the seasonal bioclimatic variables and BTV occurrence, upon which a spatial distribution model is developed. Annual prediction maps derived from the best fitting model are presented and the model results are validated and discussed.

The thesis is concluded in Chapter 8, with a summary of the outcomes in relation to the stated objectives and recommendations for future research.

CHAPTER 2

REVIEW OF BLUETONGUE VIRUS, ITS HOSTS AND VECTORS IN AUSTRALIA

In order to model the distribution of an arbovirus like Bluetongue it is important to understand the ecology of the virus, identify relevant vector and host species and their preferred habitat, and understand the role of the surrounding environment in each stage of the transmission cycle. The following chapter reviews the epidemiology and ecology of Bluetongue virus, with a focus on the Australian continent, from the first discovery of the virus to current surveillance and control mechanisms.

2. 1 Arboviruses in Australia

Arboviruses, or arthropod-borne viruses, are generally defined by the World Health Organisation (WHO) (1967) as a group of "viruses maintained in nature by a biological transmission cycle between susceptible vertebrate hosts and haematophagous (bloodsucking) arthropod vectors". Vectors include mosquitoes, ticks, sand flies and biting midges. For an arbovirus to be sustained and pose a risk for human and animal health in an area, both hosts and vectors have to be present at that location in sufficient numbers (Chalke 2006; Hanley and Weaver 2008). Suitable environmental conditions particularly for the vectors, are therefore crucial for the abundance and distribution of an arbovirus.

In Australia, more than 75 arboviruses have been reported, of which 12 are of concern for human health, including Dengue (DEN), Kunjin (KUN), Japanese Encephalitis (JE), Murray Valley Encephalitis (MVE) and Ross River (RR) (Russell and Dwyer 2000). Arboviruses affecting animal health and causing economical impact for the livestock industry include the Bovine Ephemeral Fever (BEF), Epizootic Haemorrhagic Disease (EHD), Akabane (AKA) and Bluetongue (BT) (Gard et al. 1988; St. George 1989). The latter is the subject of the following sections in this chapter.

2. 2 Bluetongue Virus

2.2.1 Epidemiology

Bluetongue virus is of the genus Orbivirus and includes 24 known serotypes (Attoui et al. 2009). It was first found in sheep in South Africa in the 19th century and first described clinically as Malarial Catarrhal Fever by Hutcheon (1902). From an African origin, which BTV is traditionally regarded as having, the virus spread out almost worldwide in the tropics and subtropics approximately between the latitudes 35°S and 40°N (Mellor 2001). Major outbreaks in sheep occurred in Cyprus (1943), Portugal and Spain (1956), Pakistan (1959) and India (1969) and raised concerns in countries with large sheep populations, such as Australia (Erasmus and Potgieter 2009; Gibbs and Greiner 1994).

The first evidence of BTV in Australia was provided by the isolation of serotype 20 from *Culicoides* collected at Beatrice Hill, NT, in March 1975. Serotype 21 was isolated, followed by serotypes 3, 9, 15, 16, 20 and 23 (St. George 1995; Ward 1994a). More recently, BT 7 was found for the first time in mid 2007 near Humpty Doo (NT) (Animal Health Australia 2008; Melville et al. 2009; Murray 2008) and BT 2 was isolated from sentinel cattle in the Northern NT in December 2008 (Animal Health Australia 2009a; Murray 2009). Except for serotypes 1 and 21, which are widely distributed across northern and eastern coastal regions of Australia, serotypes 2, 3, 7, 9, 15, 16, 20 and 23 occur in the northern region of Australia but do not spread beyond (Kirkland 2004).

In recent years, the effects of global climate change have resulted in an extension of the BTV distribution area into higher latitudes and facilitated major outbreaks in Europe. In the Mediterranean region, over 1 million sheep died from both the disease itself and elective culling between 1998 and 2004 (Purse et al. 2005). During 2006 and 2007, a major outbreak of Bluetongue 8, which reached parts of Northern Europe, including France, Germany, Denmark and Great Britain halted livestock movement from that region and caused still unknown costs (Mellor et al. 2009; Saegerman, Berkvens, and Mellor 2008).

In Australia, BTV has been found in the northern parts of WA, the NT and Queensland (QLD) as well as eastern Queensland and north eastern New South Wales (NSW). Fluctuation of the viruses' expansion have been observed over the past years, which are mainly explained by weather patterns, extreme temperature ranges, droughts or intensive wet seasons (Animal Health Australia 2001). In the Pilbara region in WA, where BTV was present between 2000 and 2007, the virus was not found the following two years but appeared again in August 2010. The annual and quarterly reports of Animal Health Australia provide a general overview of the current situation for Bluetongue and other livestock diseases in Australia (e.g. Animal Health Australia 2009b). Figure 2.1 shows an overview of BTV zone boundaries between 2003 and 2010.

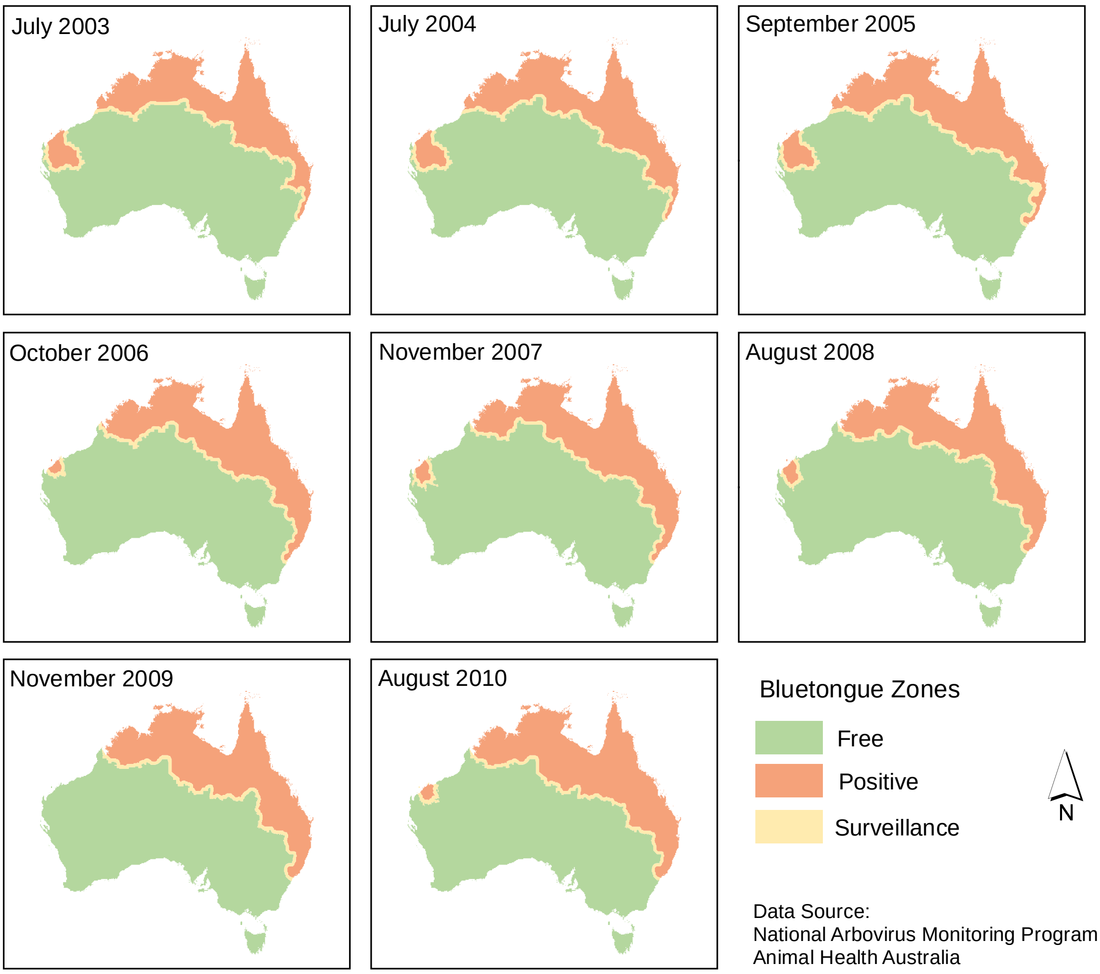


Figure 2.1 Selected Bluetongue zone maps published by Animal Health Australia between 2003 and 2010

For areas that are declared free from disease, no viral activity must have been detected for at least the past two years. These BTV free areas are separated from the BTV positive zones by a 50 km wide surveillance buffer. The surveillance system underlying the definition of these zones is described in Section 2.4 below. Although these maps do not give an accurate representation of the actual occurrence of the virus, as they include additional safety buffers, they do provide a general overview of BTV susceptible regions.

2.2.2 Bluetongue Disease

BTV can cause Bluetongue, a non-contagious, infectious disease of wild and domestic ruminants, particularly sheep. Clinical signs in sheep depend on the breed, the virus type or strain and environmental conditions (Mellor 2001). The severity of the infection ranges from subclinical infection through fever to severe clinical disease and even death. In cattle, goats and wild ruminants, the disease is usually asymptotic or subclinical. However, some serotypes, e.g. BT 8 exhibit greater virulence in cattle with serious socio-economic consequences (Saegerman, Berkvens, and Mellor 2008). The name Bluetongue originates from the swollen and sometimes cyanotic tongue, which is one of the symptoms of severely affected sheep (Maclachlan et al. 2009; Maclachlan and Gard 2009). Besides supportive treatment there is no specific therapy for Bluetongue. However, once the serotype for an outbreak has been determined, a suitable vaccine can be developed and administered to the livestock to prevent further infections. In Australia, where BTV is endemic in the northern parts, no signs of clinical disease under natural conditions have been observed in the major sheep herds (Kirkland 2004). This is at least in part because sheep are rarely raised in regions where the virus is permanently present and the viruses that are present in regions adjacent to sheep-rearing areas are considered to be non-pathogenic. However, disease has been observed in small groups of sheep when they were moved to the tropical part of the NT (Kirkland 2004).

2.2.3 Implications of Bluetongue for the Livestock Industry in Australia

Arboviruses, including BTV can cause serious production losses in the livestock industry throughout the world. Major costs are related to limitations in trade, and control mechanisms like vaccination and housing of animals to minimise contact with the vectors. In the Netherlands alone, the net costs associated with the recent

BTV outbreak in 2006 and 2007 were estimated at € 200 million, particularly affecting cattle farmers (Velthuis et al. 2010). In an earlier paper Tabachnick (1996) estimated the annual loss in the US due to BTV induced export limitations at USD 125 million.

While currently in Australia pathogenic serotypes are confined to the far North of the Northern Territory, far removed from susceptible commercial sheep populations, BTV has been an important restriction to the export of livestock since its first isolation (Doyle 1989; Kirkland 2004). Trade of livestock, semen and embryos, but not animal products such as meat and milk from a declared BTV zone is subject to strict regulations by the OIE. Even if trade is not prevented, it becomes very expensive due to serological tests and other measures necessary to reduce the perceived BTV risk (Oliver 2004). Australia has developed an internationally recognised National Arbovirus Monitoring Program (NAMP) based on scientific methods and international guidelines that helps to reduce the risk of undetected virus incursions and movements and declare areas free from disease (see Section 2.4).

The introduction of rigorous monitoring and the accompanied definition of zones, amongst other economic factors, lead to a significant change in livestock production. Producers in regions where Bluetongue is endemic or the only economic export route leads through the declared Bluetongue zone are now producing cattle for markets in Southeast Asia, traditionally for Indonesia (Van Vreeswyk and Thomas 2008). These countries host the same BTV serotypes as Australia and are therefore less sensitive to the risk of importing infected livestock (Daniels et al. 2004). Cattle producers in regions where BTV is rarely found, such as some areas in the Pilbara, are often targeting high price export markets for livestock in the Near East, including Israel (Department of Agriculture and Food Western Australia 2006). Although some BTV serotypes are present in this part of the world (Mellor et al. 2008), fears of importing new strains require strong evidence of disease freedom from trade partners. Therefore, identifying BTV on a cattle station previously free from disease and hence changing the status of that station and many others in the declared risk zone has not only significant economic, but also socio-economic implications. This challenges the management and operation of a monitoring system that relies heavily on the collaboration of pastoralists who are willing to have their cattle tested for BTV.

However, following international guidelines as outlined in Section 2.4.1 is crucial to facilitate safe trade, provide confidence in Australian Biosecurity measures and hence maintain a thriving livestock industry. More than 850,000 head of cattle and 4 million head of sheep were exported in 2008/09 from Australia to the world, with a gross value of AUD 339 million and AUD 560 million, respectively (Australian Bureau of Statistics 2010).

2. 3 Bluetongue Transmission Cycle

BTV is transmitted between susceptible ruminant hosts exclusively via bites of certain species of the *Culicoides* biting midge (Diptera: Ceratopogonidae). The distribution of the virus is consequently limited to areas where these midges occur and even within these areas transmission might be limited to periods of highest vector abundance. While the timing of activity differs between species, it is generally limited to the periods before and after sunset and sunrise, respectively. Peaks have been observed within one hour before dusk and up to three hours thereafter, and around one hour before dawn (Bellis et al. 2004). During this period adult female midges blood-feed on ruminants and may thereby transmit the virus. Once infected, the vector remains infected for its lifetime and transmits the virus with every blood meal. The hosts become viraemic 2-6 days after infection (Mellor 2001; Purse et al. 2005) and can remain infectious for up to 60 days (OIE 2009). However, generally

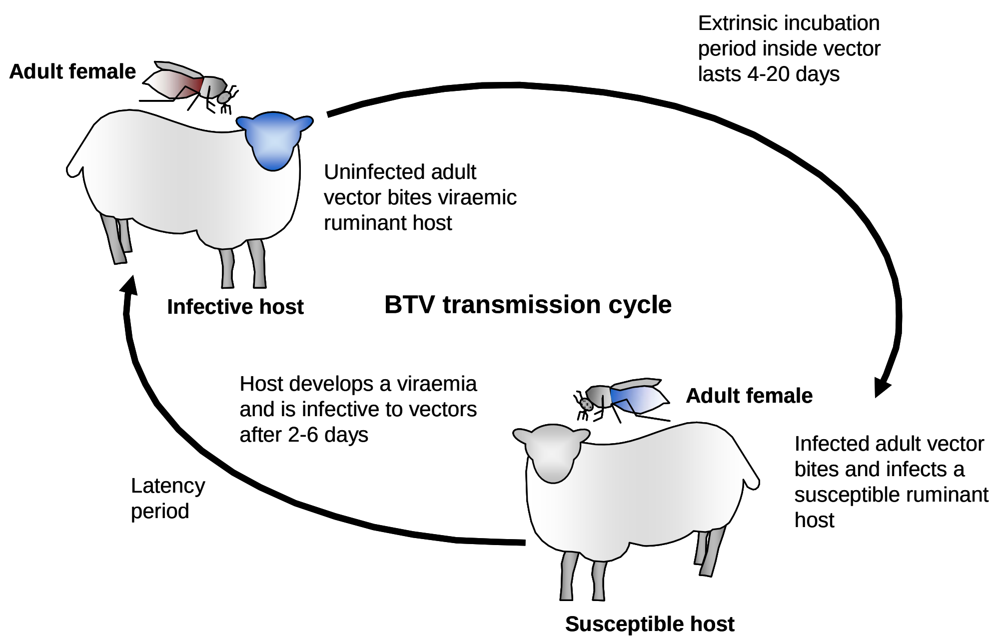


Figure 2.2 Transmission cycle of Bluetongue virus, after Purse et al. (2005)

infections last for 7-28 days in cattle and less then two weeks in sheep (Animal Health Australia 2009a; Ward 1994a). Each stage is influenced by the surrounding environment, with temperature and moisture levels determining activity, survival and development rates of the vectors (Purse et al. 2005). Figure 2.2 summarises the stages of the transmission cycle.

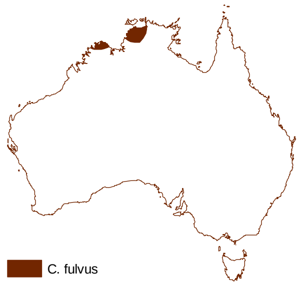
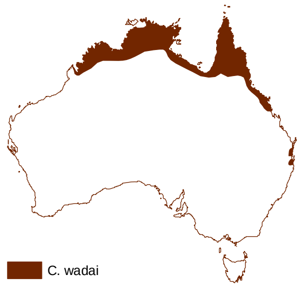
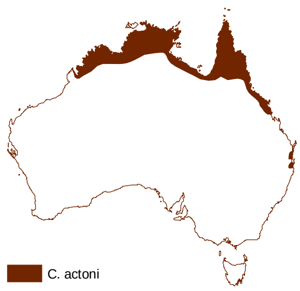
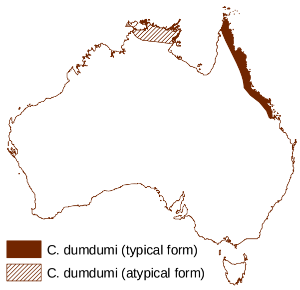
2.3.1 Culicoides Biting Midges

Worldwide, more than 1400 species of *Culicoides* have been named and they have been found on all large inhabited land masses, excluding Hawaii, Iceland and New Zealand. Their habitats range from sea level to an elevation of 4000 m (Mellor, Boorman, and Baylis 2000). *Culicoides* are amongst the smallest blood feeding insects and range in size from 1-3 mm. Different species are distinguishable mainly by their unique wing pattern. The development stage requires some form of humidity and eggs are accordingly laid in habitats that meet this criterion. The midges also seek the proximity of hosts, so they tend to breed in sites like irrigation channels, dams or even cattle dung. *Culicoides* have been found to transmit a wide range of bacteria, protozoal and helminth parasites, but they are best known as virus vectors. To date, more than 50 viruses have been isolated worldwide (Mellor, Carpenter, and White 2009).

2.3.2 Culicoides Vectors of Bluetongue in Australia

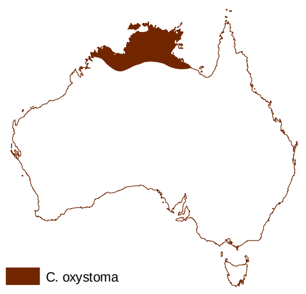
In Southeast Asia, 168 different species of *Culicoides* are recorded (Wirth and Hubert 1989), of which some occur on the Australian continent that are capable of transmitting BTV. Out of the 16 species tested, seven supported virus growth, but only *C. fulvus*, *C. wadai*, *C. actoni* and *C. brevitarsis* are considered competent vectors (Standfast, Dyce, and Muller 1985). Amongst them, *C. brevitarsis* is the most widely distributed species, while the others remain within the extent of *C. brevitarsis* and are confined to the far North of Australia (Kirkland 2004). More recently, it has been recognized that some of the insects previously identified in Northern Australia as *C. fulvus* are in fact *C. dumdumi*, which has therefore been confirmed as another competent vector (Bellis and Dyce 2005). The typical form of *C. dumdumi* has only been found in North Queensland, while an atypical form was also identified in the Northern Territory. Table 2.1 provides details on main vectors, their distribution, preferred hosts and relevance for BTV.

Table 2.1 Competent Bluetongue vectors in Australia, compiled from Animal Health Australia (2001), Bellis and Dyce (2005), Dyce (1982), Standfast, Dyce, and Muller (1985), Standfast, Muller, and Dyce (1992), Ward (1994a), Wirth and Hubert (1989)

Species	**Characteristics**	**Distribution Map**
C. fulvus	Distribution: Sub-estuarine areas in northern NT and the Kimberley Hosts: cattle, ox, buffalo Breeding sites: tropical, sub-coastal areas (larval habitat unknown) Vector competence: infection rate very high (lab) for BT 1 (43%), 20 (64%), 21 3.6%); BT 1 isolated from wild caught insect	
C. wadai	Distribution: North WA, NT, areas with rainfall > 800 mm Hosts: cattle, ox, buffalo Breeding sites: discrete patches of cattle and buffalo dung on pastures Vector competence: infection rate moderate (lab) for BT 1 (10.8%) and 20 (4.2%); no sheep to sheep infection	
C. actoni	Distribution: Northern NT, Kimberley, areas with rainfall > 800 mm Hosts: cattle, sheep, horses Breeding sites: rotting native fruit Vector competence: 1-2% infection rate (lab), sheep to sheep transmission shown	
C. dumdumi	Distribution: Coastal and sub-coastal regions along the East Coast of QLD (typical form) and the NT (atypical form); possible occurrence in north WA Hosts: cattle, ox, buffalo Breeding sites: rotting seaweed or other rotting vegetation Vector competence: infection rate moderate (lab) for BT 15 (8%) and 21 (3.6%)	
C. brevitarsis	Distribution: North and East Australia Hosts: cattle, sheep, horses Breeding sites: discrete patches of cattle and buffalo dung Vector competence: 0.2 – 0.3% infection rate (lab) for BT 1, 20, 21; BT 1 isolated from field caught insect; despite the low infection rate, wide distribution makes it the most important BTV vector in Australia	

Since *C. brevipalpis*, *C. peregrinus* and *C. oxystoma* have been infected with BTV in the laboratory they are considered potential vectors, but no natural infection has been recorded. Although they are not considered as functional BTV vectors, they are listed here as potential vectors and their expansion has to be monitored (see Table 2.2).

Table 2.2 Incompetent Bluetongue vectors in Australia, from Animal Health Australia (2001), Bellis and Dyce (2005), Dyce (1982), Standfast, Dyce, and Muller (1985), Standfast, Muller, and Dyce (1992), Ward (1994a), Wirth and Hubert (1989)

Species	Characteristics	Distribution Map
C. brevipalpis	Distribution: North NT, recently caught in the Western Kimberley (WA) around Broome Hosts: cattle, sheep, horses Breeding sites: discrete patches of cattle and buffalo dung Vector competence: 0.9% infection rate for BT 1 (Lab), but population levels are never high and the species is facultatively autogenous for the first egg mass (autogenous mosquitoes do not require blood to mature an initial egg batch and, instead, acquire nutrients for egg provisioning as larvae) > no pressure for a first blood meal > very low vector capability	
C. peregrinus	Distribution: Coastal floodplains of Northern NT Hosts: cattle (preferred), ox, buffalo, horses Breeding sites: shaded and sunlit ground waters Vector competence: Infection rate very low (no virus isolated from insects that fed on viraemic sheep), but 2 sheep (of 4) developed antibodies after treated with midges suspension	
C. oxystoma	Distribution: North of NT and WA with rainfall > 800 mm Hosts: bovids, like buffalo (preferred) or ox Breeding sites: variety of ground waters (most exposed to direct sunlight and contaminated with bovid faeces and supporting algae growth) Vector competence: Infection rate very low (no virus isolated from insects that fed on viraemic sheep), but 1 sheep developed antibodies after treated with midges suspension	

Tables 2.1 and 2.2 were compiled from various publications that provide comprehensive overviews of vector ecology (Animal Health Australia 2001; Bellis and Dyce 2005; Dyce 1982; Standfast, Dyce, and Muller 1985; Standfast, Muller, and Dyce 1992; Ward 1994a; Wirth and Hubert 1989). Although a number of *Culicoides* have been tested for their vector potential, the studies are by no means complete. Limited resources, and the difficulty of infecting vectors with the virus, are only some of the obstacles to overcome (Mellor, Boorman, and Baylis 2000).

2.3.3 Hosts

Bluetongue virus has a wide variety of ruminant hosts. In Australia, the life cycle of BTV is based on vectors and hosts species introduced with European settlement, as originally no ruminant species were present on the continent. While sera from cattle, buffaloes, deer, goats and sheep have been found to react with BTV, no reactions have been found in sera collected from pigs, horses, camels, marsupials (kangaroos and wallabies) or humans (St. George 1985).

The preference for any of the possible hosts depends much on the vector species, but generally *Culicoides* orient towards the strongest olfactory and visual stimulus. If a mixed herd of cattle and sheep is present, the midges tend to bite the cattle, which have a more accessible skin for biting insects (Animal Health Australia 2001). Also some of the *Culicoides* species emerge from cattle dung and will therefore encounter cattle before sheep.

2.3.4 Interepidemic Survival and Overwintering

In the endemic regions of BTV in the far North of Australia, where temperature, moisture, habitat and feeding conditions are consistently suitable for the survival, growth and reproduction of vectors, virus activity has been determined year round. Further south in endemic regions, suitable habitat conditions (e.g. temperature range, humidity levels) are found only seasonally. Especially in the cooler regions of inland NSW, *Culicoides* cannot survive during the winter months but reintroduction occurs in years in which conditions become favourable. Virus distribution in those areas can sometimes be accidental (e.g. through movement of infected hosts) but often occurs as a result of the vectors’ independent or mechanical movement (e.g. through wind or weather patterns, or transport) (Bishop et al. 2000).

The possibility of vertical transmission as a means for overwintering has been subject of many studies. In the case of vectors, several barriers to infection and transmission of arboviruses exist in *Culicodes* and no evidence has been found for transovarian transmission to date (Mellor, Carpenter, and White 2009). However, recent evidence was found in Europe for the possibility of vertical transmission of BTV in dairy cattle (Menzies et al. 2008; Santman-Berends et al. 2010). Calves had become infected with serotype 8 through transplacental and contact transmission. This path of transmission might be less important in periods where vectors are abundant, but in areas and/or times of low vector activity it may play a significant role by the lack of other routes of transmission. No evidence has yet been found for vertical transmission of other serotypes such as those present in Australia.

2.3.5 Environmental Factors Influencing Vectors and Hosts

Several climatic and environmental factors have a profound influence on vector and host habitats and populations and similarly on the epidemiologies of related arboviruses. Each of the factors and combinations thereof influence both a range of lifecycle stages of *Culicoides* (activity or biting rate, dispersal, larval development, adult survival, seasonality and abundance) and also livestock and, as a consequence, virus transmission.

2.3.5.1 Climate and Weather

Three climatic factors particularly related to *Culicoides* abundance and spread, are air temperature, humidity, wind speed and direction. *Culicoides* midges are crepuscular and most active in dawn, when humidity levels rise and the risk of desiccation decreases. With suitable light intensity, temperature and wind are the influencing factors for vector activity. Increasing wind is negatively correlated to vector activity for a wide variety of *Culicoides* (Mellor 2001) and at wind speeds of greater than 2.2 m/s activity of *C. brevitarsis* is fully suppressed (Murray 1987). Temperature on the other hand shows a positive correlation with activity rates. Below 18°C, activity of *C. brevitarsis* is suppressed (Murray 1987), but upper limits also exist at 35°C (Sellers 1992). In arid environments such as Australia, where moisture levels are particularly important for *Culicoides* survival, activity occurs at dawn, when the saturation deficit of the air is minimised, and higher humidity lowers the risk of desiccation. However, direct precipitation, even light rainfall, inhibits activity of some if not all species (Murray 1975). After rainfall, survival rates of *C. brevitarsis* appear to increase (Murray 1991) as does the number of blood meals taken by individuals. Temperature has less strong effects on survival and needs to be considered in conjunction with the variations in relative humidity. The climatic variables temperature range and rainfall exhibit seasonal variations in Australia. In the South with cold winters, *C. brevitarsis* almost disappear in the winter months and the peaks in population are found in summer and autumn. In the North, with higher minimum temperatures, peak activity is related to the end of the wet season (Muller et al. 1982; Murray 1975). Long range dispersal of *Culicoides* is part of their biology and it is suggested that they can be blown as far as 700 km on prevailing winds (Sellers 1992). Favourable temperatures within these winds are between 12°C and 35°C, which are found at heights up to 1.5 km. Wind speeds at which flights have been found range from 10 – 40 km/h.

2.3.5.2 Vector Habitats

C. brevitarsis, one of Australia's most important vectors of BTV, maintains a close relationship with cattle. Adult females need to blood-feed on the cattle in late afternoon and at night, but also require sufficient humidity levels for survival. Bishop et al. (1995; 1994) identified the margins of dams and (green) open grassland as the preferred habitats in a farm environment, where cattle are present during parts of the day and the midges find protection from desiccation during their resting phase. These studies were conducted on a small property in the temperate climate of Eastern Australia under conditions that rarely exist in the Northern Australian tropical, arid and semi-arid regions. Nevertheless, the importance of grassy vegetation in these areas as a means of maintaining humidity levels during the day has been recognised. Consequently, as the entomologist Glen Bellis explained (personal communication, September 23, 2009), during regular trapping of vectors at feedlots, where there is little vegetation but cattle numbers are high, few insects are caught.

2.3.5.3 Vector Oviposition

The main BTV vectors in Australia, *C. brevitarsis* and *C. wadai*, are exclusive ruminant dung breeders, relying more than the other *Culicoides* species on the availability of cattle, buffalo or goats. Other species that are confined to the tropical North of Australia, breed in ground waters or rotten fruit (see Tables 2.1 and 2.2).

Adult female *C. brevitarsis* lay a batch of eggs in fresh dung pads, not older than 7 days, from where they hatch about one day after deposition. After the larvae have gone through three stages, they pupate and emerge as adults in 7-10 days under optimal conditions (Campbell and Kettle 1976).

2.3.5.4 Density, Fecundity, and Longevity of the Vector

Abundance is a function of several factors: high rates of activity, low rates of dispersal, rapid larval development, low adult mortality, and year-round breeding (Mellor, Boorman, and Baylis 2000). The influence of environmental factors varies from place to place. The latitudinal limits are often determined by temperature, while abundance is related to summer rainfall, as has been shown for *C. brevitarsis* in NSW (Murray and Kirkland 1995). In regions further north, where temperature is more suitable, both temperature and rainfall have been positively related to the risk of BTV seroconversion of cattle during the wet season (Ward 1996). A major response to adequate rain is good pasture growth that may well change the quantity and quality of cow pads, increasing their availability for oviposition and suitability for the immature stages of *C. brevitarsis* (Murray 1991). While vectors are active year-round in the tropical North, the major period of activity is between November and May, when temperatures are favourable on the East Coast of QLD and the Northeast of NSW and tropical and monsoonal rainfall creates suitable breeding sites in the otherwise arid regions of the North (Pilbara, Kimberley). Adult female *Culicoides* start mating on the day of hatching and after having the first blood meal they lay their eggs. Midges may then be ready for another blood meal within 1-2 days, but it takes 1-2 weeks after an infective blood meal (depending on the temperature) before the midge becomes infected with the virus which may be excreted through the saliva during subsequent blood meals (Animal Health Australia 2001). Once infected, *Culicoides* may transmit the virus for their lifetime of several weeks.

2.3.5.5 Movement and Migration of Vectors and Hosts

Dispersal of *Culicoides* is not limited to their flight range of a few kilometres, but can extend to 700 km if midges are blown by prevailing winds as aerial plankton (Mellor, Boorman, and Baylis 2000). Movement of infected hosts (particularly livestock) plays an important role in the spread of BTV and is discussed below.

2.3.5.6 Anthropogenic Influence

The most relevant anthropogenic influence on BTV abundance is the movement of livestock around the pastoral regions of Australia. As most of the susceptible vectors preferentially feed on cattle and some rely on cattle dung to breed, midges numbers might rise and fall with the availability of suitable livestock. Moving cattle from areas where BTV is endemic to epidemic areas could lead to outbreaks, if the environmental conditions are favourable. As an example, the Pilbara region experienced an outbreak of BTV in 2001, more than 20 years after the last recording of BTV. According to the former NAMP coordinator for WA, R. Norris (personal communication, March 14, 2008), it is assumed that infected cattle had been moved from the Kimberley into an environment that supported BTV at least for several years, before the virus temporarily disappeared in 2007. Another possible factor supporting BTV emergence might be the significant rise in cattle numbers, changing from a sheep industry almost solely to cattle stations (Animal Health Australia 2001). Although no direct relationship can be proven between the first isolation of BTV and the increase in cattle numbers since the late 1990’s, it is certainly an effect that needs to be taken into consideration, when estimating vector numbers and BTV infections. Figure 2.3 shows the historical development of total numbers of cattle and sheep held in the Pilbara between 1909 and 2006, based on data from the Australian Bureau of Statistics.

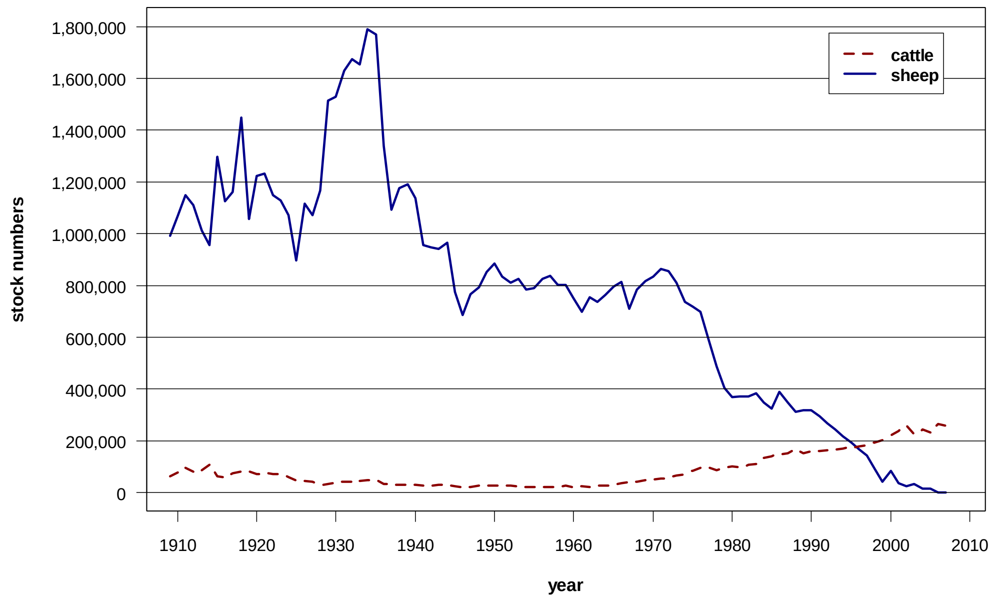


Figure 2.3 Sheep and cattle numbers in the Pilbara from 1909 to 2006. Source: Australian Bureau of Statistics and the Pastoral Lease Information System

Other anthropogenic influences to BTV host and vector ecology include the creation of dams and water points as well as changes to native vegetation (introduction of new species, burning) to improve livestock welfare and hence provide potential focal points of virus activity.

2. 4 Current Surveillance and Control

2.4.1 International Legislation

The OIE as the major legal body controlling animal health has established protocols for surveillance and trade to protect Bluetongue-free countries from incursions of the virus (Papadopoulos, Mellor, and Mertens 2009). Details on the requirements for surveillance and other control mechanisms are published annually in the Terrestrial Animal Health Code (OIE 2009). In this document a BTV infected country or zone is a clearly defined area with evidence of BTV during the past two years. A country or zone is considered BTV-free, if the area is north of the latitude 53°N and south of 34°S and is not adjacent to a BTV infected zone, or a surveillance program has demonstrated no evidence of BTV during the past two years, or no competent vectors are present. The code also sets out recommendations for the import of ruminants from BTV-free, seasonally free and infected zones or countries. Veterinary authorities need to certify that livestock were born or kept at least for 60 days before shipping in a BTV-free country or zone, or must have been kept in a BTV-free zone or country for at least 28 days and then tested negative for BTV antibodies. It is a further requirement that cattle must be protected from *Culicoides* attacks and not be transferred through a BTV infected zone prior to export.

2.4.2 The National Arbovirus Monitoring Program

After the first isolation of BTV near Darwin (NT), a sentinel herd system for BTV monitoring was installed. The system was gradually expanded from Northern Australia to the Eastern States and resulted in the establishment of the NAMP in 1993. The NAMP operates on the basis of monitoring cattle in sentinel herds, strategic serological surveys and trapping of vectors throughout the country.

2.4.2.1 Sentinel Cattle and Serological Surveys

The locations of sentinel herds are confined to the areas of commercial cattle operations (Melville 2004) and are selected representatively to allow mapping of the distribution of infections. Hence most herds are positioned along the border between expected infected and uninfected areas, or where infection occurs irregularly. Herds within the affected areas are also tested to assess the seasonal intensity of infection. Supplementary, areas which are expected to be BTV-free are monitored to verify their free status (Animal Health Australia 2006). Figure 2.4 shows an overview of NAMP sites in northwest Australia that were tested between November 2000 and October 2009.

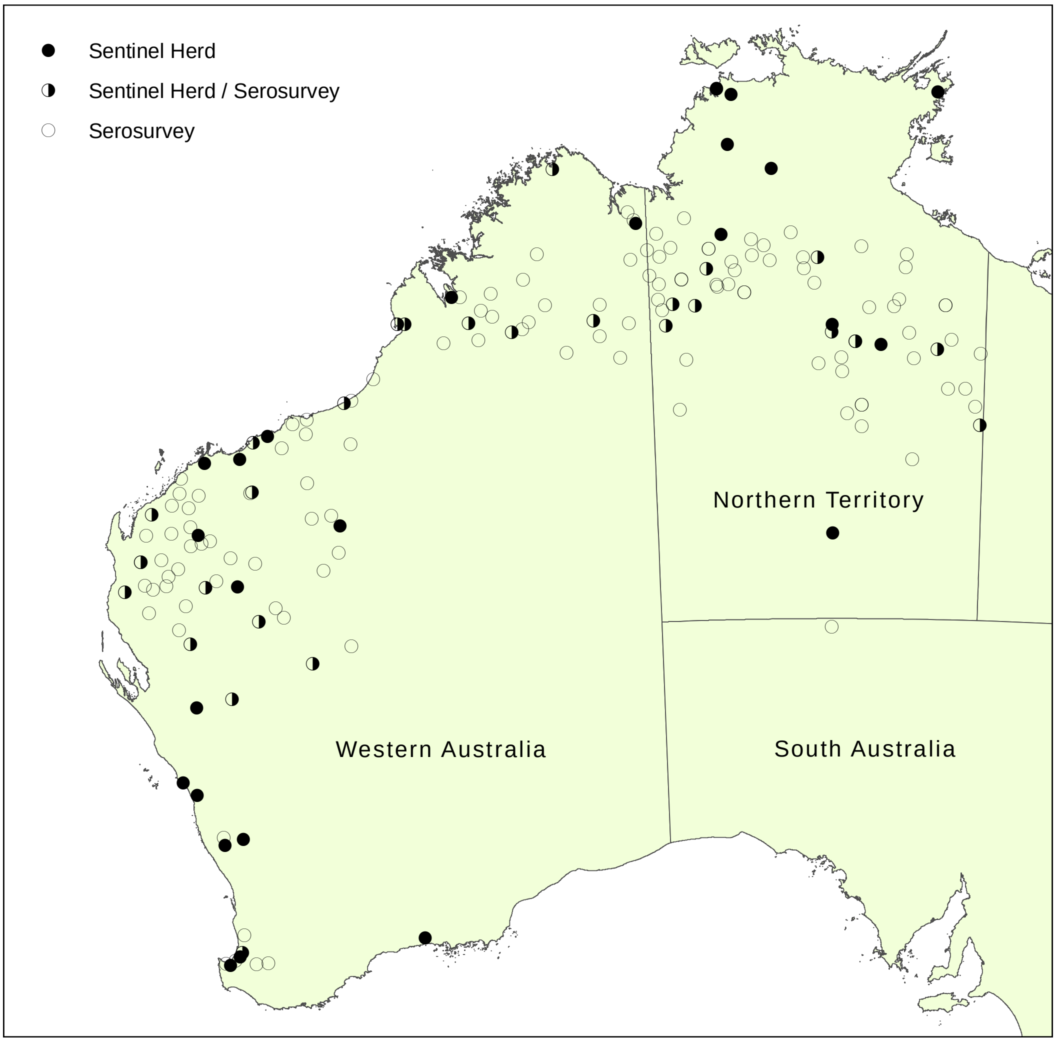


Figure 2.4 Location of NAMP sites (sentinel herds and serological surveys) tested between November 2000 and October 2009 in WA and the NT. Note: not all sites are tested regularly. For a more detailed annual overviews see Figures 5.4 and 5.8 in Chapter 5

Sentinel herds usually consist of 10 to 25 young cattle, which have initially tested negative for BTV antibodies. The animals are bled in intervals ranging from monthly to at least twice a year (pre and post summer) and samples are tested for BTV antibodies to determine seroconversion during the BTV activity season. Cattle are replaced annually or after seroconversion has been determined. In addition to the sentinel herd system, opportunistic serological surveys are conducted during the mustering season. Random blood samples are taken from cattle not older than 12 months and born on the property, and tested for BTV. In contrast to sentinel animals, the same animal is not necessarily sampled twice. The campaign usually starts at the end of the wet season in May and may last until October, with most samples taken in August and September.

2.4.2.2 Vector Trapping

The second corner stone of surveillance is vector trapping and quantification of *Culicoides* species at the sentinel herd sites and numerous other strategic locations (Cameron 2004). Light traps are usually positioned in trees near cattle during new moon, up to ten times a year. After two consecutive nights, the specimens - caught in a preserving solution - are sent an entomologist for identification.

2.4.2.3 Virus Isolation

In addition to serological tests, NAMP conducts virus isolation studies at two sites on Cape York (QLD) and one site at Beatrice Hill Farm (BHF) Research Station, 60 km north of Darwin. At BHF incursions of new BTV strains from overseas have been detected for the first time in Australia. At BHF, sentinel animals are bled weekly for virus isolation and monthly for serology (Melville 2004).

2.4.3 Resulting Data and Information

The data sampled at monitoring sites are entered into the NAMP database via a secure web based interface, which has been in operation since 1998 (Cameron 2000b). This database defines the main input for the definition of three zones according to OIE guidelines as mentioned earlier. The zones ‘free of BTV’, ‘infected’ and a ‘surveillance zone’ as buffer between those two are defined and adjusted on the basis of monitoring results, property boundaries and expert knowledge (Cameron 2004). Although a spatio-temporal distribution model of BTV host and vectors has been developed by Cameron (2000a) using geographical and environmental factors in addition to monitoring results, the model has never been operationally used in the zone definition process (Angus Cameron, AusVet Animal

Health Services, personal communication, February 28, 2008). The current zoning maps, automatically generated reports on BT status and vector numbers can be access through the *NAMPinfo* web interface (Animal Health Australia 2010).

2.4.4 Limitations

The traditional monitoring described here is very time consuming and also expensive. With limited resources available and large remote areas to observe, data on arbovirus activity exhibit strong spatial and temporal limitations. Numbers and locations of cattle herds and vector trapping sites vary from year to year, as sentinel animals are moved within properties or operation is ceased. Hence, presence and absence information for vectors and virus is often available for a certain period and only at property level, which can include areas of some tens of thousands of hectares. Even where the geographic location of sample sites is known, e.g. for trapped vectors, and detection of vector activity is possible, this detection is limited to specific locations, which are sparsely and unevenly distributed over Australia. Furthermore, the time intervals between serological tests and vector trapping are often irregular, due to varying accessibility of sites and size of the surveyed region. Extending the surveillance program is costly and difficult to achieve under the current policy that providing cattle for sentinel herds and serological surveys is voluntary for pastoralists. Finding BTV on a property often means significant losses not only on the positively tested station, but also on neighbouring properties in a radius of 100 km. As a consequence of the limitations of traditional monitoring, the spatio-temporal variations of virus ecology are still incompletely understood.

2. 5 Summary

Australia hosts a wide range of arthropod transmitted viruses, some of which pose a serious threat for human and animal health. Bluetongue virus is an Orbivirus transmitted by *Culicoides* biting midges that can cause Bluetongue, a non-contagious, infectious disease of wild and domestic ruminants, particularly sheep. While there is no immediate risk of a BTV outbreak in the large sheep populations in the South of Australia, the presence of the virus the North causes limitations to the trade of livestock.

The distribution of BTV is limited to the tropic and sub-tropic regions in the North of Australia and along the East Coast, where the environmental conditions are suitable to sustain the transmission cycle of the virus. Currently, five *Culicodes* species are known to be capable of transmitting the virus in Australia. Importantly, the presence, emergence and survival of these vector species is closely related to environmental factors, such as temperature, humidity, vegetation, as well as the availability of ruminant hosts.

Current surveillance of BTV activity includes testing of sentinel animals for antibodies, complemented by serological surveys and trapping of vectors. While this system has been recognised for its ability to reliably monitor and report the disease status to international trade partners, it is not the most efficient approach. Resulting data from the remote pastoral areas in North Australia are sparse and characterised by large spatial and temporal gaps.

CHAPTER 3

DISEASE DISTRIBUTION MODELLING IN SPATIAL EPIDEMIOLOGY

The ecology of Bluetongue virus has been explored in the previous chapter, with a review of environmental factors relevant to the transmission cycle of the pathogen.

This chapter first introduces the field of spatial epidemiology, which is concerned with the analysis of disease patterns and spatio-temporal linkages between disease occurrence and environmental factors. The following section continues with a description and comparison of potential modelling techniques that are frequently applied in epidemiology to predict the spatial distribution of disease from a set of explanatory variables. The strengths and weaknesses of each method are highlighted. Recommendations are then given for the most appropriate method for vector-borne disease modelling within the context of this research. The chapter concludes with an overview of measures for model evaluation.

3. 1 Spatial Epidemiology

The field of spatial epidemiology studies the distribution of diseases, as well as the causes and consequences of spatial variation in disease risk (Clements and Pfeiffer 2009; Ostfeld, Glass, and Keesing 2005). When the location, and ideally also the time of disease occurrence is known, e.g. through human cases or serological surveys, spatial analytical methods can be used to address the following sequence of questions: What is the distribution of the disease? Can any spatial or spatio-temporal patterns be detected? What are the causal factors underpinning these patterns? Can those factors be mapped to identify risk areas and ideally change the factors to improve human and animal health? (Robinson 2000). A number of books provide comprehensive overviews on the use of spatial statistical methods, GIS and remotely sensed environmental risk factors in the field of epidemiology to answer these questions (Durr and Gattrell 2004; Hay, Graham, and Rogers 2006; Hay, Randolph, and Rogers 2000; Pfeiffer et al. 2008). The fundamental concepts and most relevant methods and data for distribution modelling will be highlighted in Chapter 3 and 4.

3.1.1 History and Future of Spatial Epidemiology

The cholera outbreak map by Dr. John Snow (see Figure 3.1) is probably the best known and earliest example of a spatial epidemiological application. The locations of cholera incidents were plotted on a street map of London together with the locations of public water pumps as the possible risk factors. This approach supposedly lead to the identification of a contaminated pump in Broad Street as the cause of the outbreak. Following the removal of the handle from the pump no further incidences were reported. While today it is acknowledged that this well might not be the only cause for the outbreak (McLeod 2000), the map published by Snow has made him a hero in medical geography, spatial epidemiology and related disciplines. Snow not only demonstrated the importance of maps for spatial reasoning, but also promoted the benefits of maps for decision making and risk communication.

Figure 3.1 Dr. John Snow’s map of deaths from cholera in the area around Broad Street in London. Source: Gilbert (1958)

More than 150 years later, spatial epidemiology has developed into an innovative field that is driven by advances in digital data processing, spatial statistical analysis and modelling (Clements and Pfeiffer 2009). Environmental variables derived from remote sensing satellites have become widely available to be used as risk factors in epidemiological models (Hay et al. 2006). Geographic Information Science and Systems and statistical analysis software provide means for efficient processing and analysis of environmental and disease data to identify spatial and temporal patterns and predict future occurrences (see Chapter 4).

3.1.2 The Concept of Landscape Epidemiology

In the 1930s the pioneering Russian parasitologist Pavlowsky (1966) first discovered the importance of the landscape and the environment for the transmission of infectious diseases, and coined the term Landscape Epidemiology. Pavlovsky made three basic observations, which are still fundamental to epidemiology and underpin the work presented in this thesis. Firstly, diseases tend to be limited geographically to an area, which is also known as the focus or nidus of the disease. According to the third edition of Webster's New World Medical Dictionary, nidus is the latin word for nest and is used in medicine to refer to any structure that resembles a nest in appearance. In the context of this research, nidus refers to a breeding place where bacteria, parasites and other agents of a disease lodge and develop. Secondly, the spatial variation of the disease is influenced by biological and physical variations that support the distribution of the pathogen, its vectors and hosts.

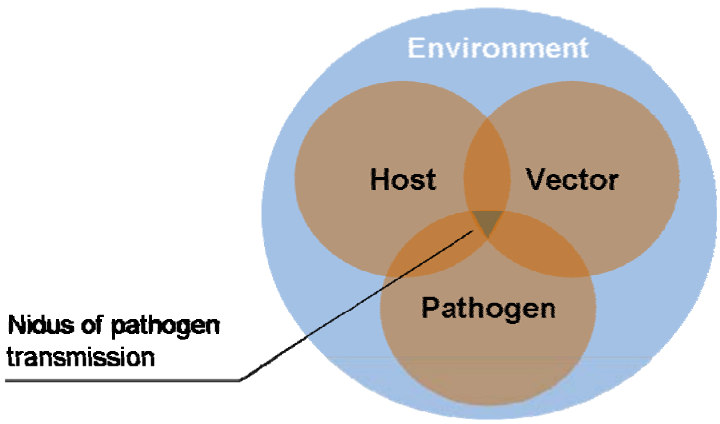


Figure 3.2 Conceptual nidus showing how competent vector, host and pathogen populations intersect within a permissible environment to enable pathogen transmission. Adapted from Reisen (2010)

A natural nidus of disease exists under certain conditions of climate, vegetation, soil, and microclimate at locations, where vectors, infected and uninfected hosts cluster (see Figure 3.2). Thirdly, if these biotic and abiotic conditions can be delineated on a map, then spatial and temporal patterns of disease risk should be predictable.

3.1.3 Scale and Scope of Variations in Environmental Conditions

The environmental conditions defining the nidus or focus of a disease are spatially and temporally dynamic and variations are important at different spatial and temporal scales. Changes in climate often occur on a regional to global scale, in contrast to the local to regional scale variations in landscape.

Temporal variations in climate can be divided into seasonal (intraannual), annual (interannual), and long-term (decadal or longer) change (Reisen 2010). Seasonal changes in temperature, precipitation and day length are closely related to primary productivity and food availability and therefore determine the favourable and hence reproductive periods of vectors and hosts. Long term climate cycles such as the El Niño - Southern Oscillation (ENSO) can influence the duration and intensity of these favourable periods. The El Niño phase of the three to eight year ENSO cycle may lead to drought in Australia and reduced risk for BTV infections (Ward and Johnson 1996), while increasing rainfall and hence the risk for Rift Valley Fever in East Africa (Linthicum et al. 1999). Above these long term climate patterns, a trend of global warming has been observed in the last century with an increase in mean annual surface air temperature in Australia by about 0.9°C (CSIRO and Bureau of Meteorology 2007). One of the associated risks is the dispersal of vector-borne diseases from their known distribution into areas that have previously been outside the habitable range of the vectors, mainly due to low temperatures. There is evidence that climate change was one of the main factors to allow the spread of BTV into Northern Europe (Purse et al. 2005; Purse and Rogers 2009), but this relationship is less obvious for other arboviruses and it is advisable to investigate alternative causal factors (Gould and Higgs 2009; Rogers and Randolph 2006).

On a spatial scale, favourable climatic conditions may persist over large areas, such as the tropics, where many pathogens are endemic, including Bluetongue, Dengue or parasites such as Malaria. In times of adverse conditions, such as drought or low temperatures, arbovirus vectors may survive only in small refugia with favourable conditions on a very local scale. In an arid landscape, these can be permanent water holes or riparian landscapes where hosts and vectors congregate. The concentration of host and vector populations in these small areas may even enhance transmission. Subsequent changes in regional climate may then expand the permissive habitats, thereby creating opportunities for pathogen dispersal into new or existing foci across heterogeneous landscapes. This phenomenon has been studied for the annual reintroduction of BTV in the Hunter Valley in Australia after winter (Bishop, Barchia, and Spohr 2000; Bishop, Spohr, and Barchia 2004b). At the other extreme, diseases can spread over several countries and act on a continental scale, such as the 2006/2007 outbreak of BTV in Europe, or even globally. Examples for the latter include the distribution of Avian Influenza (Yee, Carpenter, and Cardona 2009), as well as Yellow Fever and Dengue, both of which are found in many tropical countries around the globe (Rogers et al. 2006). Expanding transport networks, mainly aviation and ship-borne transport, facilitate and accelerate the spread of many pathogens, including arboviruses (Tatem, Rogers, and Hay 2006).

From these examples it becomes clear that neither spatial nor temporal scale can be neglected when studying the patterns of disease distribution. When deciding on the spatial and temporal scope of a study, the spatial and temporal resolution of environmental data need to be considered, as well as the modelling approach.

3.1.4 Epidemiological Data

Epidemiological studies that investigate the frequency and distribution of disease, involve the collection and analysis of health data, and for this study in particular, animal health data. These data may relate to clinical signs, therapy, post-mortem or laboratory examinations (Thrusfield 2007). If a study is undertaken prospectively, the epidemiologist has to decide on the data to be collected. Retrospective studies, such as the one presented here, rely on existing data, collected by veterinarians, abattoirs, animal health organisation, or as part of surveillance activities, such as Australia’s NAMP (Section 2.4.2).

For epidemiological data to be used in spatial analyses, the locations of the observations or measurements need to be recorded. This includes the coordinates of a specific point location associated with a spatial reference system, such as latitude and longitude. Mobile GPS-enabled devices are able to record location information at accuracies in the range of 10 m horizontally (Hay 2000) and usually allow for capture of associated attributes. Another form of registering point locations includes the physical address of e.g. a farm or veterinary practice, although this approach may introduce inaccuracies due to geocoding errors (Zinszer et al. 2010). Point based information may be useful for some studies, especially at a local scale, when clusters of disease shall be detected. However, point locations may be only representative, when the target population is immobile, such as livestock held in enclosures. Often the true location of an incidence is unknown, and the support, regarded as the effective size of each sample (Isaaks and Srivastava 1989), is much wider. On large farms, cattle could have been able to roam over a large area before a survey could be conducted. In this case the support would expand over the whole property and areal representation of the farm would be more appropriate (Pfeiffer et al. 2008). Due to cost-efficiency considerations and complexity of analyses, point representations of either the farm house or the farm centroid are still predominantly used, even though this introduces spatial error (Durr and Froggatt 2002).

While it would be desirable to preserve the original location information, this may often be against confidentiality policies, particularly when dealing with public health data. Epidemiological data are therefore often provided in aggregated form as summary statistics at a defined administrative level, such as a shire, state or country. The most common form of aggregation is to count the total number of disease cases in an area. These counts can then be expressed as prevalence or incidence rate (Pfeiffer et al. 2008). In brief, prevalence is the number of instances of a disease (or associated attributes, e.g. infection or presence of antibodies), divided by the number of animals in the population at risk at a certain point in time. Incidence rate measures the rapidity with which new cases of disease develop over time. The full definition of these and other measures of disease occurrence is provided by Thrusfield (2007).

It is important that the choice of administrative unit matches with the spatial resolution at which the epidemiological conclusions are drawn. If assessing the occurrence of BTV on a continental level, district or shire data should be appropriate, but if the relationship with local environmental conditions is to be investigated, data on single farm locations are necessary. Also the influence of changing zone boundaries on the observed spatial patterns, the so called Modifiable Areal Unit Problem (MAUP) (Openshaw 1984) needs to be recognised. This is related to ecological fallacy, which is a widely recognized error that occurs in data interpretation, when conclusions for individuals are drawn from aggregate statistics for a group, to which the individuals belong (Cressie 1993). Consequently, if a farm has been declared BTV positive, this does not necessarily mean that all cattle are infected.

Epidemiological data can be, and often are, replete with errors and uncertainty that compromise location and attribute accuracy. These errors can include incorrect georeferencing; confusion about the correct choice of spatial reference unit, e.g. administrative unit; incorrect diagnosis of a disease, which may lead to false presence or absence records; and confusion over the aggregation method, which may lead to the use of incorrect location and data values. If the investigator has control over data collection and analysis, much of the uncertainty can be controlled or at least accounted for. However, if the data come from another source, it is important to be aware of the quality and methods that have been used to produce the data (Atkinson and Graham 2006).

The following sections within this chapter will review distribution modelling approaches frequently used in ecology and epidemiology, as well as measures for model evaluation.

3. 2 A Framework for Disease and Species Distribution Models

The purpose of any model is to represent the complexity of a real world system. Models can improve the understanding of a system and be used to predict or describe an outcome within a system (O'Brien 2004). Distribution models used in ecology aim to predict the geographic range of species based on known occurrences and environmental factors. In epidemiology, and in particular when dealing with vector-borne diseases, the distribution of vector and host species is of major interest to predict the probability of pathogen transmission. In general, two major groups of models are used for vector-borne diseases, namely mathematical biological (or process based) models and statistical models.

Mathematical models have been developed, predominantly for Malaria, for over a century, following the pioneering work of Ross (1911). Ross modelled the spread of disease by dividing the human and mosquito populations into epidemiological classes and describing the flows from one class to another by the use of functional equations. Ross's models and subsequently improved versions (e.g. by Dietz, Molineaux, and Thomas 1974; MacDonald 1957; Molineaux and Gramiccia 1980) typically describe host and vector population dynamics using a set of empirically determined parameters, such as vector capacity, mortality rates, and length of the gonotrophic cycle (the egg production/laying cycle of the female mosquito). These models are well suited to extrapolation to novel situations, (e.g. to assess the effect of interventions), and for investigating the impacts of short-lived changes in driving environmental factors on vector and host populations (Maude et al. 2010). However, prior knowledge about these driving factors is required to produce meaningful models. Other disadvantages of mathematical biological models are their static nature and often oversimplified assumptions. Only recently, dynamic climatic and environmental changes have been incorporated (e.g. Hoshen and Morse 2004). In contrast, statistical models are mainly data driven. This makes them in the presence of sufficiently reliable data particularly useful to explain disease patterns, and investigate disease – environmental linkages without the need for prior knowledge of the detailed ecological relationships. Due to the fact that little is still known about the exact transmission cycle of BTV in Northwestern Australia, this research focuses on statistical modelling approaches, which are described hereafter.

The modelling process is iterative and can be separated into five major steps as outlined in Figure 3.3. Predictive modelling typically begins with a conceptual model of how the real world functions. Nature is too complex and heterogeneous to be predicted by a single model in every aspect. Distribution models are therefore often a necessary trade-off between precision (empirical, statistical models) and generality (causal, process based models) (Guisan and Zimmermann 2000). For arbovirus modelling, it would be desirable to increase generality by using all causal factors in the prediction, i.e. several environmental variables known to be related to the ecology of the virus, over a large area. However, this would at the same time compromise the precision, accuracy and robustness of the model, by introducing uncertainties with each additional variable and requiring the reduction of spatial and temporal resolution to be able to handle the model computationally. Also a model that very accurately describes the suitable habitat conditions for a species in one area, may not work for the same species in another area.

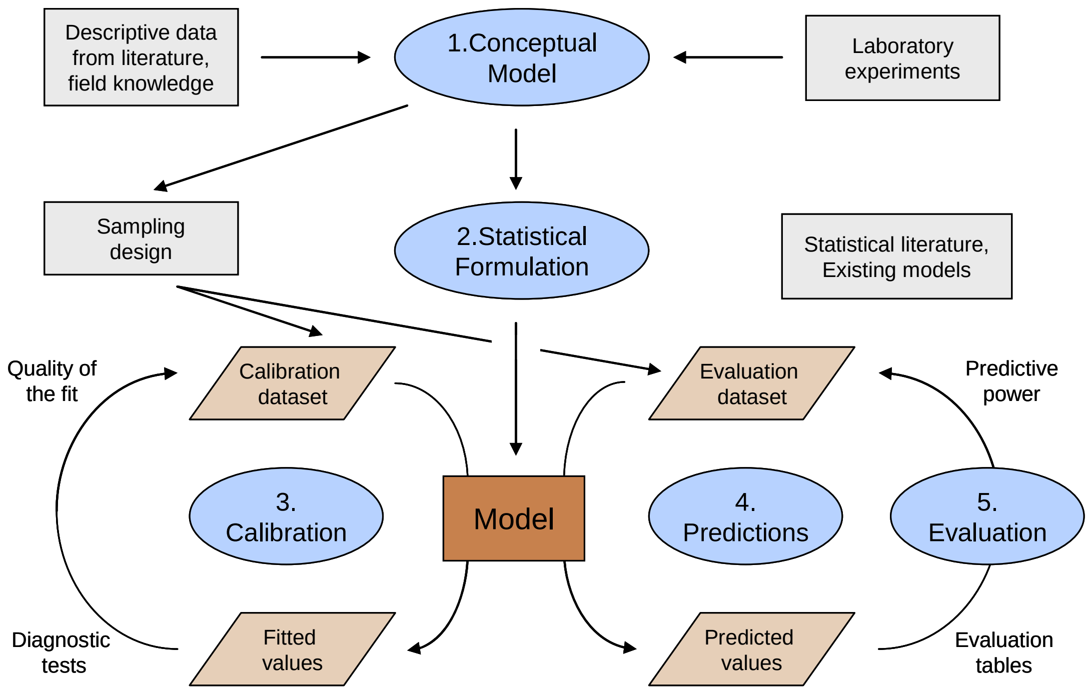


Figure 3.3 Overview of the successive steps (1-5) of the (generic) model building process, if two independent datasets are available – one for model calibration and one for model evaluation. Adapted from Guisan and Zimmermann (2000)

The first step, the formulation of a conceptual model based on knowledge from literature, field work and laboratory experiments will ideally lead to the choice of an appropriate spatial and temporal scale and a set of conceptually meaningful explanatory variables for the predictive model (see Chapter 5).

Also, an efficient sampling strategy needs to be developed, for the species or disease under investigation as well as the explanatory bioclimatic variables. A number of approaches have been reviewed in the literature (e.g. Thrusfield 2007) that can be separated into probabilistic (e.g. random, systematic, stratified) and non-probabilistic (e.g. convenience, purposive, haphazard) approaches. Surveillance programs, such as NAMP apply a stratified random sampling strategy, where from the population at risk (the strata), e.g. all cattle on a pastoral station, individuals are selected randomly for bleeding. Cattle age has been included in NAMP as an additional selection criteria within the population at risk, to ensure the tested animals are young enough that they could have been exposed to the virus only during a single season. Ideally, the choice of sampled cattle stations should be systematic rather than random to provide an even spatial coverage, at least of at-risk areas (Curran et al. 2000). Often, as in the case of NAMP, a convenience approach is followed due to practical and strategic considerations, and the spatial variation of observations will necessarily be biased. This needs to be considered when interpreting the model outcome. In many cases, particularly when working with surveillance data retrospectively, the modeller is not involved in sampling design.

Methods for the acquisition of environmental data for the entire study area at the desired resolution will be discussed in Chapter 4. For the purpose of model development and to establish a relationship between environment and disease, it is crucial to decide on a support of the response variable, i.e. the effective sample size, or space on which each observation is defined, that makes biological sense and is constant across the region of interest (Curran and Atkinson 1999; Curran et al. 2000). For example, when animals sampled at a specific location have been exposed to a much wider environment that might have led to infection with the virus, then the choice of support should reflect this.

The second step in model development comprises the choice of a suitable algorithm for predicting a particular response variable and estimating the model coefficients, as well as finding an optimal statistical approach with regards to the particular modelling context (Guisan and Zimmermann 2000). In epidemiology, the response variable may be a count of disease summarised by an area unit (e.g. county or state) or more simply, as in the present project, disease presence (‘positive’) or absence (‘negative’) at a given location (e.g. farm or household). Less frequently, compared to other disciplines (e.g. ecology), the outcomes may be measured on a continuous or ordinal scale (Pfeiffer et al. 2008). Hence, in Section 3.3, the focus will shift to statistical modelling approaches dealing with binary presence/absence data. Consideration will also be given to identifying a robust approach that may deal with a small sample size, is easy to implement and, in view of a future operational implementation, easy to operate and communicate. Section 3.4 will then discuss spatial effects that may induce variations between the response at different location, and present ways of expanding traditional models to deal with those effects.

The third step is model calibration, an iterative process that aims to enhance the accuracy and predictive power of the model. This task involves the selection of variables or combinations of variables to be included in the model. It can be either arbitrarily (which is not recommended), automatically (e.g. by stepwise inclusion or stepwise exclusion of variables used on regression models), by following physiological principles, or by following shrinkage rules (Harrell, Lee, and Mark 1996). The main decisions to be made by the modeller are the starting set of variables, the statistical or knowledge based criteria upon which to exclude or include a variable, and when to stop adding or subtracting a variable. In many instances, developing a parsimonious model that achieves a certain predictive capability with as few parameters as possible is the preferred strategy. This strategy is based on the principle known as Occam’s Razor, which suggests that the simplest explanation is more likely the correct one. In the case of epidemiological modelling, using fewer variables to explain virus distribution also limits the risk of propagating errors present in the environmental data. As a rule of thumb, Harrell, Lee, and Mark (1996) suggest that no more than *m/10* predictors should be included in the final model, where in the case of a binary response *m* is the number of observations in the least represented category.

Variable selection may be based on strict statistical measures or upon the improved fit of the model to the data with or without the variable. A number of measures that are available to assess model fit will be discussed in Section 3.5 and have previously been reviewed by Rogers (2006). There is some controversy, as to whether using as many predictor variables as possible (also termed data mining) improves the fit of the model, or leads to models that are neither parsimonious nor informative biologically. Overfitting a model with too many parameters may produce a model that performs well within the context of the data used for development, but may fail to be robust, when used elsewhere (Rushton, Ormerod, and Kerby 2004). A more recent trend to information theoretic approaches (Burnham and Anderson 2002) is based on the definition of a set of candidate models with prior knowledge and uses the Akaike Information Criterion (AIC) to select the best-performing one (Gibson et al. 2004). Rushton, Ormerod, and Kerby (2004) suggest that these approaches will lead to more ecologically sound and parsimonious models.

Once the response of a species or disease to multiple environmental variables has been derived with any of the described modelling techniques, the possible distribution within the modelled area can be predicted. GIS has often been used to implement predictive models (Aspinall and Veitch 1993; Chalke 2006; Guisan, Weiss, and Weiss 1999; O'Brien 2004) for a number of reasons. They have the advantage of providing capabilities for exploratory analysis of disease patterns, handling large predictive datasets that are spatial in nature very efficiently, and rapidly turning the model outcome into a communicable map (for reviews see Durr and Gattrell 2004; Kistemann, Dangendorf, and Schweikart 2002; Pfeiffer et al. 2008; Rinaldi et al. 2006). However, not all statistical models are easily implemented in a GIS environment and some of the modelling steps (statistical formulation and model calibration) may need to be conducted in a statistical package, such as R or SPSS or specific ecological modelling programs (Guisan and Zimmermann 2000).

The last and most important step in model selection and development is model validation or evaluation, as it is alternatively termed. Several methods have been developed that analyse the predictive success of models based on measuring the agreement between model predictions and field observations and those are further described in Section 3.5. Generally, two approaches can be distinguished that either use a single dataset to calibrate and then evaluate the model, or alternatively use two separate datasets, one for calibration (the training dataset) and one for evaluation (the evaluation dataset).

3. 3 Statistical Modelling Approaches for Vectors and Vector-Borne Diseases

3.3.1 Logistic Regression Models

Regression analysis has been widely used in ecology and epidemiology to establish relationships between a single (simple regression) or a combination (multiple regression) of predictor variables (independent variables) and the response (dependant) variable. In studies where the response variable is interval or ratio, linear regression may be appropriate (Baylis and Rawlings 1998; Hay, Snow, and Rogers 1998; McCann, Baylis, and Williams 2010). However, as Austin (2002) points out, environmental functions tend to be rarely linear and therefore multiple linear regression is not often used.

Logistic regression, however, is capable of predicting a binary response variable (e.g. presence/absence) from either continuous or categorical predictor variables, and is therefore very popular amongst epidemiologists. Logistic regression makes no assumption about the distribution of the independent variables. They do not have to be normally distributed, linearly related or of equal variance within each group.

The logistic regression function takes the form:

$$Logit(p) = \beta_0 + \beta_1 x_1 + ... + \beta_m x_m \tag{3.1}$$

where β_0 is the intercept, $\beta_1 \ldots \beta_m$ are the regression coefficients, and $x_1 \ldots x_m$ are the predictor variables. *Logit(p)* is the logarithm of the odds, written as:

$$Logit(p) = \log\left[\frac{p}{1-p}\right] \tag{3.2}$$

This transformation leads to the logistic model, where the probability of the outcome *p* can be expressed as a function of *m* explanatory variables:

$$p = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + ... + \beta_m x_m)}} \tag{3.3}$$

This equation has the convenient property, that *p* is bounded between the logical range of 0 and 1, where 1 represents the highest probability for the dependent variable, e.g. the presence of BTV based on vegetation greenness and mean day temperature.

As shown in the review by Rushton, Ormerod and Kerby (2004), logistic regression has been applied by ecologists to map the distribution of a large variety of plant and animal species and communities, including Rufous Bristlebird in Victoria (Gibson et al. 2004) and aquatic invertebrates in the Himalaya (Manel, Ceri Williams, and Ormerod 2001). In epidemiology, logistic regression has been applied to model the distribution of Murray Valley Encephalitis in Western Australia (Chalke 2006), Bluetongue in Corsica (Guis et al. 2007), the arbovirus vector *Culicoides Imicola* in Italy (Conte et al. 2003), and Foot and Mouth Disease in Northern Thailand (Cleland et al. 1996).

Some of the strengths of logistic regression, e.g. its statistical robustness, the fact that it is a well defined method and various statistical measures exist for validation (O'Brien 2004), have certainly contributed to its widespread application in species distribution mapping (Rushton, Ormerod, and Kerby 2004). Nevertheless, it is acknowledged that, despite the great accuracy of some logistic regression models, the assumptions that have to be made are often not realistic (Rogers 2006). Logistic regression only allows a single transition from 0 (absence) to 1 (presence) across the entire range of a predictor variable in the situation where the response is an increasing function of the predictor variable. However, in nature often more than one transition between species presence and species absence may be found. As an example, the increase of temperature from very low levels (species is absent) to intermediate levels (species is present) to very high levels (species is absent again) clearly shows two transitions on a single predictor variable. In such a case a logistic regression model would only capture parts of the species' distribution.

3.3.2 Generalised Linear Models and Generalised Additive Models

First developed in the 1960's, Generalised Linear Models (GLM) have found widespread application in ecology (Guisan, Edwards, and Hastie 2002). One of the reasons is their ability to handle a multitude of probability distributions that describe ecological data, including normal, binomial or Poisson distributions. GLMs are mathematical extensions of linear models that allow for non-linearity and non-constant variance structures in the data. Generalised Additive Models (GAM) (Hastie and Tibshirani 1990) are a further semi-parametric extension of GLMs, where the only assumption to be made is that the functions are additive and that the components are smooth (Guisan, Edwards, and Hastie 2002). The strength of these models is their ability to deal with highly non-linear and non-monotonic relationships between the response and the explanatory variables.

In a GLM, the predictor variables x_i are combined to produce a linear predictor *LP*, which is related to the expected value *E(Y)* of the response variable *Y* through a link function *g()* in the form:

$$g(E(Y)) = LP = \beta_0 + \sum_i \beta_i x_i \tag{3.4}$$

where β_0 is the intercept and βi are the regression coefficients. The distribution of Y may be any of the distributions of the exponential family, and the link function may be any monotonic differentiable function (e.g. logarithm or logit) (Guisan, Edwards, and Hastie 2002). GLM where a binomial distribution is used for the link function are equivalent to logistic regression.

GAMs are in contrast to GLMs data- rather than knowledge-driven. The relationship between the response and the explanatory variables is determined directly from the data rather that assuming some form of parametric relationship (Yee and Mitchell 1991). GAMs relate the expected response $E(Y)$ to the predictor variables x_i via:

$$g(E(Y)) = \beta_0 + \sum_i f_i(x_i) \tag{3.5}$$

where f_i are the various functions. In practice, GAMs can be parameterised just like GLM, with the exception that some predictors can be modelled non-parametrically using smoothing functions, in addition to linear and polynomial terms (Guisan, Edwards, and Hastie 2002).

GAMs have been increasingly used in ecological modelling (Austin 2007), and application examples include studies of ecological factors related to the distribution of vegetation in New Zealand (Yee and Mitchell 1991) and Switzerland (Lehmann 1998) or of breeding birds in Spain (Seoane, Bustamante, and Diaz-Delgado 2004). In Australia, McLeod and Pople (2010), used a GAM to map the habitats of feral camels in the NT. GAMs have also been applied to investigate the risk for cancer (Kelsall and Diggle 1998), and study the effect of air pollution on public health (Schwartz 1996). However, compared to logistic regression, fewer epidemiological studies seem to exploit the potential of GAMs.

The advantage of using GAMs instead of GLMs (or similarly logistic regression) for presence/absence modelling is the additional flexibility through the replacement of linear functions with unknown smooth functions. Any response shape is possible, which allows the estimate to follow the observations more closely (Austin and Meyers 1996). This makes GAMs particularly attractive for ecological modelling where linear relationships are seldomly found. A minor drawback is the lack of a conventional mathematical function, which makes it difficult to communicate the influence of each predictor variable on the response (Heegaard 2002).

3.3.3 Discriminant Analysis

An alternative to logistic regression is discriminant analysis, proposed by Rogers, Hay and Packer (1996). In contrast to the regression methods presented previously, which seek a least squares or error-minimizing description of epidemiological data, discriminant analysis seeks to maximise the between-sample variance relative to the within-sample variance or other measure of spread around the sample means (Pfeiffer et al. 2008). The samples are considered categorical, such as presence or absence of disease, and are defined by multivariate normal distributions of the same set of predictor variables, but with different multivariate means or centroids and (usually) different co-variances (Rogers 2006).

In classical linear discriminant analysis, the same co-variance matrix is used for presence and absence data. Linear discriminant analysis has been used with varying levels of accuracy for the prediction of tsetse flies in various regions of Africa (e.g. Rogers, Hay, and Packer 1996) and, using a stepwise approach, to predict Bluetongue infections in Queensland based on maximum temperature and rainfall (Ward 1994b). However, as Robinson (2000) notes, the assumption of a common covariance matrix for both presence and absence is unrealistic and violated by the data. Instead, using non-linear discriminant analysis, which is equivalent to the maximum likelihood classification known from remote sensing applications, a discriminating function that produces more accurate classification results can be defined (Robinson, Rogers, and Williams 1997a; Rogers 2000). Formulae for linear and non-linear discriminant analysis are found in Pfeiffer (2008 pp. 103-107) or Rogers, Hay and Packer (1996).

Essentially, discriminant analysis and logistic regression are very similar and often produce a similar outcome (Press and Wilson 1978). Nevertheless, the strict assumption of normally distributed explanatory variables can be seen as a major limitation compared to the more flexible regression statistics. However, if the predictors are normally distributed, discriminant analysis may be the more powerful and efficient strategy (Tabachnick and Fidell 2007).

3.3.4 Environmental Envelopes and Ecological Niche Factor Analysis

Environmental envelopes define an envelope in multidimensional attribute space, within which a species can be expected to be found and persist (O'Brien 2004). The response variable tends to be presence/absence and responses are classified as ‘present’ if they fall within a given percentile for all variables. Additionally, a ‘marginal’ class may be added for responses that fall within that percentile for some factors but outside for others (Figure 3.4).

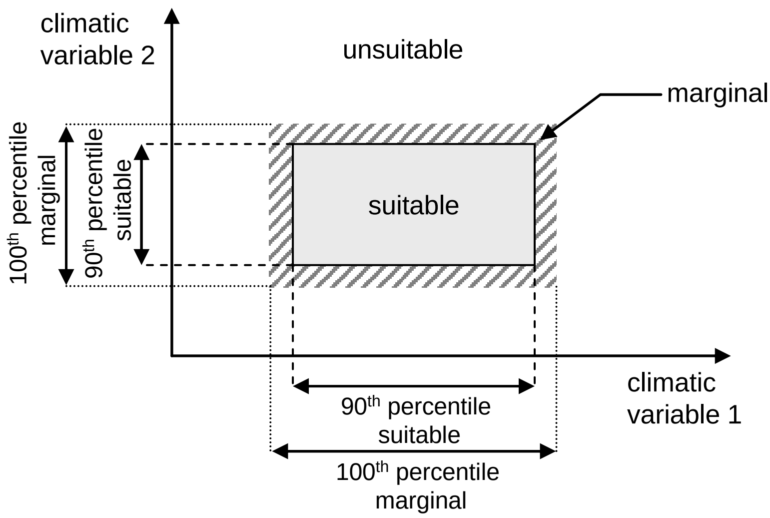


Figure 3.4 Rectilinear environmental envelope for two climatic variables, after Skidmore et al. (1996)

A number of different algorithms have been developed to define environmental envelopes and those are often formalised in specialised software packages with GIS functionality. The most basic environmental envelopes are rectilinear, such as the technique implemented in the BIOCLIM software (Busby 1991). The BIOCLIM model fits a species-specific minimal rectilinear envelope in a multidimensional climatic space, an approach equivalent to the parallepiped or boxcar image classification algorithms used in multispectral remote sensing applications. BIOCLIM models have been developed to map a number of species, particularly in Australia, for example the endangered snake *Hoplocephalus bungaroides* (Penman et al. 2010) or kangaroos (Skidmore, Gauld, and Walker 1996), and also to assess the effects of climate change (Hughes 2003).

More sophisticated approaches define environmental envelopes using bounding polygons or fuzzy clouds. HABITAT (Walker and Cocks 1991) is an expansion of the BIOCLIM concept that uses a convex polytope (multidimensional polygon) envelope rather than rectilinear envelopes and also works with an expanded range of environmental factors. Both models create continuous envelopes in multidimensional attribute space, including all data points, or those within a given percentile. Any new location will therefore be classified as ‘suitable’ if all its attribute values fall within the given range (O'Brien 2004).

A slightly different concept to environmental envelopes is followed by climatic mapping, which was designed to study the risk of introducing an invasive species into a new area under the influence of climate change (Sutherst 2004), rather than mapping natural distributions. As an example, the CLIMEX program (Sutherst and Maywald 1985) determines a climatic envelope of favourable conditions that is defined by growth (optimum climatic range) and stress indices (wet, dry, hot, cold) from a global climatic database. Model parameters are determined using occurrence and abundance of the target species from outside the area under risk of introduction. Besides a number of applications in invasive plant and animal species mapping, CLIMEX has been used to map the potential spread of the arbovirus vector *C. Wadai* in Australia under a changing climate, based on known occurrences in Asia (Standfast and Maywald 1992).

The Ecological Niche Factor Analysis (ENFA) method, developed by Hauser (1995) and implemented in the BIOMAPPER software (Hirzel et al. 2002) is similar to the environmental envelope approach in requiring presence-only data. ENFA is an extension of Principal Component Analysis (PCA) that reduces the predictor variables to a few uncorrelated factors, but retains their ecological meaning (Hirzel et al. 2002). Having the advantage of working with presence-only data, ENFA has also been used to generate pseudo absence data as a preparatory step for developing GLMs (Calvete et al. 2009).

The major strength of environmental envelopes is that they can be easily interpreted in biological terms. They also offer the opportunity to include expert knowledge, where data are lacking (O'Brien 2004). However, compared to GLMs and GAMs (Segurado and Araújo 2004), the predictive performance of environmental envelopes is rather poor.

3.3.5 Bayesian Methods

Bayesian methods have become increasingly popular in epidemiological applications over the past 20 years, in common with the development of fast computational algorithms needed to solve the often complex models (Lawson 2008). Bayesian models combine *a priori* probabilities of species or disease occurrence with the probability (or likelihood) of occurrence conditional to the value of each environmental predictor (Guisan and Zimmermann 2000).

The prior probability distribution is an initial assumption that may be based on previous results, literature, or expert opinion. Conditional probability, denoted as *P(X/Y)* is the probability of a response variable *Y* being in a given state, given that the predictor variable *X* is in a particular state, and is usually derived from the data. When the sample size is large, the conditional probabilities will dominate the outcome, in studies that are data poor, the prior distributions will dominate. For a comprehensive overview of Bayesian methods used in epidemiology, see Lawson (2008), Lawson, Browne, and Vidal Rodeiro (2003), or Lawson and Cressie (2000).

In a hierarchical Bayesian model (or alternatively termed Bayesian network), different parameters may be added to the model to improve the outcome. A Bayesian network is represented through a Directed Acyclic Graph (DAG) with directed (cause-effect) linkages between different nodes, each of which represents a predictor or response variables (Figure 3.5).

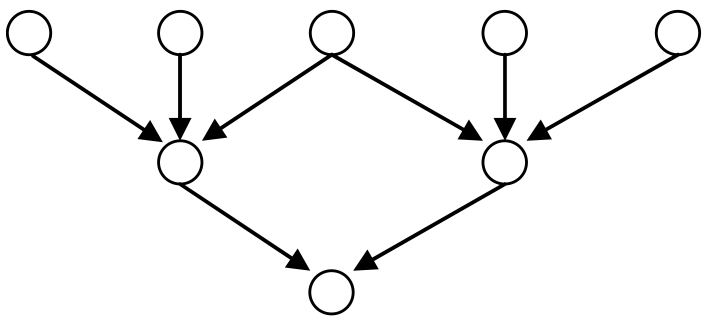


Figure 3.5 A simple Bayesian network, after Stassopoulou, Petrou, and Kittler (1998)

For each node, prior and conditional probability distributions are defined. Using combination rules, conditional probability distributions are propagated through the network. Realistic models in disease mapping often have two or more hierarchy levels and the resulting complexity of the posterior distribution makes it impossible to determine its exact form. Various posterior sampling algorithms have been developed (e.g. Gibbs Sampler, Markov Chain Monte Carlo) (see Lawson 2008). The implementation of these methods in dedicated software packages, such as BUGS (Bayesian inference Using Gibbs Sampling) and its Windows version WinBUGS (Lawson, Browne, and Vidal Rodeiro 2003; Lunn et al. 2000) have had a huge effect on the dissemination and acceptance of Bayesian modelling in epidemiology.

The study of Stevenson et al. (2005) exemplifies an approach, where a hierarchical model was used to investigate the factors influencing the distribution of Bovine Spongiform Encephalopathy (BSE) in Great Britain. Initially, a so called fixed effects model, e.g. using GLM, is developed under the assumption that the influence of the predictor variables on the response is independent of the location. However, the assumption that the predictor variables alone explain the distribution of BSE may be violated by the presence of spatial autocorrelation between sample sites (see Section 3.4 for further details) or other random effects. Therefore, the authors developed a Bayesian mixed effects model (or hierarchical model) that accounts for the structured (spatially correlated) and unstructured heterogeneity in the data. The prior probability was determined by the response from the fixed effects model.

Multilevel Bayesian models have been developed to investigate the distribution of a number of infectious diseases, including BTV in Spain (Allepuz et al. 2010), BSE in Great Britain (Stevenson et al. 2005), and Malaria in South Africa (Kleinschmidt et al. 2002).

One of the major strengths of probability based methods like Bayesian approaches is the flexibility to incorporate both data and expert knowledge. They are also able to deal with uncertainties that may be included in the probability distributions and propagated through the model. Dedicated software tools, such as WinBUGS are now widely available and provide efficient means to even develop more complex models.

3.3.6 Other Methods

In the previous sections a number of modelling techniques based on presence and absence data were reviewed, which help to increase the understanding of biological and other processes that determine the distribution of species in space and time. Alternative approaches have been applied to ecological and also disease modelling (see reviews by Austin 2007), but as Rogers (2006) argues, they often simply reproduce the distribution map or points drawn from the distribution map through a “pattern-matching” approach. While the resulting prediction maps might be highly statistically accurate, these approaches provide minimal biological insight (Rogers 2006). The use of artificial neural network models and k-nearest neighbour techniques is therefore discouraged , as is that of tree-based classification methods, and those hybrid systems such as the genetic algorithm for rule-set prediction (GARP) (Stockwell and Peters 1999), that use genetic algorithms to improve on initial approaches using more traditional methods.

3. 4 Dealing with Spatial Effects

In most classical statistical methods, independence of observations is a fundamental assumption. However, this assumption may be violated, if spatial dependence is found in a dataset. In this case, data from spatially close samples contribute less additional information than if they were further apart. As a consequence of ignoring this effect in modelling, errors may be underestimated and the significance of some predictor variables may be overestimated (Pfeiffer et al. 2008). It has therefore become common practice to analyse the residuals in the model results for spatial dependence (or spatial autocorrelation; see Section 3.4.2) and if present, to apply one of the various methods that have been developed to deal with the problem of spatial dependence and heterogeneity (see Section 3.4.3).

3.4.1 Spatial Heterogeneity and Dependence

The basic principle behind spatial dependence, following Tobler’s (1970) First Law of Geography, is that attribute values measured at locations that are close together are more similar than those taken from more distant locations (Pfeiffer et al. 2008). If this dependence does not vary regardless of the location in a geographic area, the underlying spatial process is called stationary. In contrast, if the dependence structure varies throughout the area, the process is termed unstationary or heterogeneous. If the dependence in a stationary process is the same in any direction, it is considered isotropic, whereas if dependence changes with direction then it is considered to be anisotropic.

First order effects describe large (macro-) scale variations in the mean of the outcome of interest due to location or other explanatory variables. This effect expresses itself as a trend across a geographical region. For example, the risk for infectious disease transmission may decrease from North to South in a region due to changes in temperature that affect the survival of an infectious vector. Second order effects are small-scale variations due to interactions between neighbours, also called spatial heterogeneity. These effects may be found, e.g. where disease cases cluster around a saleyard, or disease vectors show some local habitat preference.

3.4.2 Measuring Spatial Autocorrelation

The measure of the degree of similarity between the attributes of neighbouring samples is also termed spatial autocorrelation. Based on the fact that spatial autocorrelation is very common, a number of techniques have been developed to measure it. Moran's *I* and Geary's *C*, as well as a local Moran test are discussed here as examples for methods working with aggregated data, such as disease status on a farm or county level. Other autocorrelation measures can be found e.g. in Cliff and Ord (1973, 1981). Metrics that identify clusters amongst point locations are discussed elsewhere (e.g. Pfeiffer et al. 2008).

In order to derive any measurement of autocorrelation, the neighbourhood between locations needs to be determined. Neighbourhood may be defined based on adjacency or distance. Approaches using adjacency (also called contiguity), define neighbourhood between polygons, e.g. by sharing a border (rook contiguity), corner or border (queen contiguity), or through a second order neighbourhood (neighbours of neighbours) (Pfeiffer et al. 2008). Approaches based on distance consider polygons with their centroid located within a specific distance as being adjacent.

Moran's *I* coefficient of correlation (Moran 1950) quantifies the similarity of an outcome variable among areas that are defined as spatially related. It takes the form:

$$I = \frac{n\sum_i \sum_j w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{(\sum_i \sum_j w_{ij})\sum_i (y_i - \bar{y})^2} \tag{3.6}$$

where n is the number of spatial units, y_i is the attribute of an area (e.g. the residuals of a model), and $\bar{y}$ the mean of the attributes. w_{ij} defines the closeness between areas i and j through a weight matrix that assigns areas that are close in space a higher weight than those that are more distant. A Moran's I of 0 indicates no clustering, while a positive value indicates positive spatial autocorrelation (i.e. clustering of areas with similar attribute values) and a negative value indicates negative spatial autocorrelation (i.e. contiguous areas tending to have dissimilar attribute values). A disadvantage of Moran's I is that it is based on the assumption that the correlation is isotropic (i.e. the same in all directions) and that the attribute of interest is evenly distributed within the study area. The lack of anisotropy can be overcome by changes in the weight matrix to reflect directional indifferences. In epidemiology to account for population differences between spatial units, the use of proportional measures instead of e.g. disease counts is recommended (Pfeiffer et al. 2008).

Another weighted estimate of spatial autocorrelation is provided by Geary's contiguity ratio (abbreviated to Geary's C). In contrast to Moran's I it does not consider similarities between regions, but between pairs of regions. Geary's C ranges from 0 to 2, where zero is an indicator for perfect positive autocorrelation and 2 indicates perfect negative autocorrelation. It can be calculated with the following equation:

$$C = \frac{(n-1)\sum_i \sum_j w_{ij}(y_i - y_j)^2}{2\left(\sum_i (y_i - \bar{y})\right)\left(\sum_i \sum_j w_{ij}\right)} \tag{3.7}$$

where n is the number of spatial units in the study area, w_{ij} are the weights in the spatial proximity matrix, y_i are the attributes under investigation and $\bar{y}$ is the mean of all attributes.

3.4.3 Incorporating Spatial Dependence into Distribution Models

When the residuals of a model are plotted on a choropleth map as an initial step, they may show some spatial pattern. If spatial autocorrelation can be found using the tests discussed before, then the original models should be extended by including additional parameters. A number of techniques have been developed, including those that extend the regression models and the increasingly popular Bayesian mixed effects models (described in Section 3.3.5).

Using so called frequentist approaches, regression models are extended with a normally distributed random effect term with a covariance matrix. There are three types of spatial covariance structures that can be used: conditional autoregressive, simultaneous autoregressive and moving average models. For the mathematical equations see Pfeiffer et al. (2008) and for a comparison of these models refer to (Dormann et al. 2007). All these methods assume the same degree of autocorrelation across the study area and few methods exist that allow for non-stationarity. One such approach is Geographically Weighted Regression (GWR) by Brunsdon, Fotheringham and Charlton (1996). According to Dormann et al. (2007), however, this approach is not targeted at distribution modelling due to its limited use for hypothesis testing, as the coefficient estimates depend on spatial position.

The Bayesian approaches described in Section 3.3.5 provide additional flexibility to incorporate a mixture of terms for random effects that can be spatially structured (spatially correlated), or unstructured (spatially random). Compared to the methods described above, which provide a single (global) autocorrelation coefficient, spatially correlated random-effect terms are calculated for each spatial unit. For a theoretical background of Bayesian approaches see Lawson (2008), Lawson, Browne, and Vidal Rodeiro (2003), Lawson and Cressie (2000), and Pfeiffer et al. (2008). Bayesian methods can be used for area as well as point data, however when working with point data the contiguity matrix may become very large and complex. An alternative is to fit a logistic geostatistical model, implemented in the geoR and geoRglm packages (Diggle and Ribeiro 2007). The difference to area-based approaches can be found in the addition of a structured (spatially correlated) heterogeneity term that is allowed to vary continuously through space rather than discretely.

There has been a significant advance from considering spatial dependence as annoyance in distribution models (Horne and Schneider 1995) to the increasing development of spatially explicit distribution models, particularly using Bayesian approaches. However, as noted by Pfeiffer et al. (2008) and Pfeiffer (2004), incorporating spatial dependence in model building is only justified if significant autocorrelation is found. Otherwise a fixed effects model should provide a satisfactory description of the data. Also by choosing a resolution for the aggregation area that is lower than the scale at which spatial dependence occurs, the development of complex spatial models may be avoided.

3. 5 Evaluating the Accuracy of Distribution Models

Evaluating or validating a model is the last task in the modelling exercise. While it lies in the nature of a model that it cannot be tested for being true or false, it can be assessed for providing good testable hypotheses relevant to important problems (Levins 1966) and for the accurate prediction of biological patterns (Guisan and Zimmermann 2000). Furthermore, model evaluation includes a measure of adequacy, which depends on the purpose of the project and the domain to which the model is supposed to be applicable (Fielding and Bell 1997).

Depending on the available sample size there are two main approaches for evaluating the predictive power of a model. In the first approach, a single dataset is used to calibrate and evaluate a dataset. Different methods exist to select samples for testing, including leave-one-out or Jack-knife (n samples of 1 case are tested sequentially, the remaining n - 1 cases comprise the training set), bootstrap sampling (sampling with replacement) or cross validation (Fielding and Bell 1997; Guisan and Zimmermann 2000). In the second approach, if the data set is large enough to be split, two separate datasets are used for model calibration and model evaluation.

There are two types of prediction errors that may result from a presence/absence model: false negatives and false positives. To assess the performance of a presence/absence model the observed and predicted presence/absence patterns are usually cross tabulated in a confusion or error matrix that identifies true positive (a), false positive (b), false negative (c) and true negative (d) cases predicted by each model (Figure 3.6). A number of measures reviewed by Fielding and Bell (1997), Pearce and Ferrier (2000) and Rogers (2006) can be derived from the count values in the confusion matrix (a-d) and the total number of observations N (see Table 3.1).

		Actual	
		+	-
Predicted	+	a	b
	-	c	d

Figure 3.6 A confusion or error matrix that cross-tabulates observed (actual) presence/absence patterns against those predicted: (a) true positive values; (b) false positives; (c) false negatives; (d) true negatives

Out of these accuracy measures, Cohen's Kappa (κ) has been most widely used for assessing the accuracy of the prediction of a categorical variable. The values range from -1 (model entirely opposite to observation) through 0 (model fit no better than random) to 1 (perfect fit) (Rogers 2006). Despite its utility in summarising the entire information in the confusion matrix, there are some caveats. The major criticisms are that κ does not distinguish between the types or causes of disagreement, and its sensitivity to unequal class sizes, high or low prevalence (Fielding and Bell 1997).

As mentioned earlier in this chapter, if results from a model are on a continuous scale (e.g. probability), in order to build a confusion matrix, they need to be transformed to the scale of the observations. For binary data, the probabilities are truncated at a specific threshold. While an arbitrary threshold of 0.5 is commonly used, this often does not provide the best agreement between predicted and observed values (Pearce and Ferrier 2000). Freeman and Moisen (2008) suggest choosing a threshold that optimizes one of the accuracy measures listed in Table 3.1. For example, if false negative errors are considered more serious than false positive errors the threshold can be adjusted to decrease the false negative rate at the expense of an increased false positive error rate.

Alternatively, a threshold independent measure, such as the receiver operating characteristic (ROC) plot methodology may be used. A ROC plot is produced by plotting all sensitivity values (true positive fraction) on the y-axis against their equivalent (1 - specificity) values (false positive fraction) for all available thresholds between 0 and 1 on the x-axis (Fielding and Bell 1997). While the ROC curve itself can be used to find a suitable probability threshold for binary maps, the area under the ROC curve (AUC) has become an important index widely used in particular to assess logistic regression models. The AUC provides a single measure of accuracy, is independent of a specific threshold and less affected than κ by a high/low overall prevalence (Rogers 2006). The AUC can assume values between 0.5 and 1, where values of 0.5 – 0.7 indicate low accuracy, values of 0.7 – 0.9 indicate useful applications and values of > 0.9 indicate high accuracy (Swets 1988).

Table 3.1 Overview of accuracy measures applicable in distribution modelling, compiled from Fielding and Bell (1997) and Rogers (2006)

Measure	**Description**	**Calculation**
Correct classification rate	Total fraction of the sample that is correctly predicted	$\frac{a+d}{N}$
Sensitivity	Ability to identify positives correctly	$\frac{a}{a+c}$
Specificity	Ability to identify negatives correctly	$\frac{d}{b+d}$
False positive rate	Proportion of wrongly predicted positives	$\frac{b}{b+d}$
False negative rate	Proportion of wrongly predicted negatives	$\frac{c}{a+c}$
Positive predictive power (PPP)	Probability that a case is positive, if the algorithm classifies the case as positive	$\frac{a}{a+b}$
Negative predictive power (NPP)	Probability that a case is negative, if the algorithm classifies the case as negative	$\frac{d}{c+d}$
Cohen's Kappa (κ)	Index of agreement for positive and negative samples combined	$\frac{(a+d)-\frac{(a+c)(a+b)+(b+d)(c+d)}{N}}{N-\frac{(a+c)(a+b)+(b+d)(c+d)}{N}}$

3. 6 Selection of Modelling Approach

The main models considered for distribution mapping in this chapter were logistic regression, GLM, GAM, discriminant analysis, environmental envelopes and Bayesian methods. Most of these models are empirical, data driven, while some can be at least partly knowledge driven.

Currently, little is still known about the conditions related to the changing limits of BTV distribution in the Northwest of Australia. In order to identify the driving bioclimatic factors for Bluetongue occurrence from the presence and absence data in the NAMP database, an empiric model will be the most appropriate choice. In addition, some prior knowledge about the ecology of BTV vectors that is available for the East Coast of Australia, can be incorporated in the model building process, by developing and selecting the most appropriate bioclimatic variables. It is most likely, that pure statistical measures alone would not necessarily lead to an ecologically sound set of predictor variables.

It is therefore proposed to use a multiple regression model, such as a GLM or GAM with a binomial distribution to build an initial model based on both statistically and biologically significant environmental variables. GAMs and GLMs have been widely applied in ecology due to their robustness and support of a multitude of probability distributions that best describe ecological data. In particular the semi-parametric GAM offers a flexible tool for exploratory analysis of predictor variables that do not follow a standard response curve (see Section 7.3.1). This enables the modeller, during the variable selection process, to maximise the model predictive capabilities, while maintaining biological integrity. It can be expected that due to the small sample size, a stable model would only allow for a small set of predictor variables (see Harrell, Lee, and Mark 1996). However, this is in line with the plea for parsimony in distribution models found throughout the literature. If warranted by strong spatial autocorrelation, the initial non-spatial model may be extended by spatial heterogeneity terms using a hierarchical Bayesian approach similar to Stevenson et al. (2005).

3. 7 Summary

The field of spatial epidemiology aims to investigate the causal factors for the spatial variation of disease risk. Occurrence or focus of vector-borne disease is defined by climatic and environmental factors that govern the interaction between vectors, hosts and pathogens. Mapping these underlying factors enables epidemiologists to develop models of disease distribution and risk. However, in order to establish the relationship between environment and disease it is important to investigate the origin of the disease data. Epidemiological data, including the location of disease incidents, are often collected at different levels of aggregation, ranging from farms to shires or whole countries. Considering this aggregation is crucial for determining the support, i.e. the spatial and temporal range within which the environment influences each case, and consequently choosing the required spatial and temporal resolution of the environmental data which will de discussed in Chapter 4.

Following the introduction to spatial epidemiology, a typical workflow for the development of a species distribution model was presented. The major steps of the workflow are:

i) Development of a conceptual model;
ii) Statistical formulation;
iii) Model calibration;
iv) Prediction of species distribution; and
v) Model evaluation (validation).

The chapter continued with a review of modelling techniques that could deal with the binomial presence/absence data as collected by NAMP to develop ecologically meaningful models that are robust and easy to implement.

The brief discussion of spatial autocorrelation highlighted the importance of accounting for spatial dependency in model development. A summary of accuracy metrics was presented that can be used for internal and external model validation. Finally, a recommendation was made to use GLM and GAM to develop a data driven model, but still incorporate prior knowledge through the choice of ecologically meaningful predictor variables.

The following chapter will review current meteorological and environmental earth observation satellites and associated data products with applications in disease distribution modelling. A variety of environmental and climatic variables, also referred to as bioclimatic variables, will be presented as possible candidates for model development.

CHAPTER 4

APPLICATIONS OF REMOTE SENSING IN SPATIAL EPIDEMIOLOGY

This chapter provides a brief overview of the principles of remote sensing, before reviewing current and future remote sensing technology and data as well as derived environmental variables commonly used to investigate vector-borne diseases.

4. 1 Remote Sensing in Epidemiology

Remote sensing data have been widely adopted by epidemiologists to study a number of vector-borne diseases, which have been summarised by Kalluri (2007), including Malaria, Dengue fever, Rift Valley fever and Leishmaniasis. These studies dealt with the mapping of disease, host and vector distribution and abundance, modelling of disease risk, early prediction and also the forecasting of disease at a local (e.g. Brown et al. 2008; Clennon et al. 2006), to regional (e.g. Baylis et al. 1998; Martin et al. 2008; Rizzoli et al. 2007) and global scale (e.g. Rogers et al. 2006). The basic common principle behind these studies is the utilisation of relationships between environmental factors derived from remote sensing data and the presence or absence of the disease of interest (Curran et al. 2000; Schuster et al. 2009). Remote sensing technology is not able to identify disease vectors directly, but it can be used to characterise the landscape in which vectors thrive. Environmental parameters such as land and sea surface temperature, vegetation type, amount and health can be identified and measured from space. In contrast to other measurements, e.g. from weather stations, remotely sensed data provide spatially regular information with area-wide coverage, which makes them particularly useful in remote areas. They also have the distinctive advantage of being captured automatically, repeatedly (Kalluri et al. 2007) and unobstrusively when using passive sensors (Jensen 2007). Some derived high level data products are available at no cost to the user (Tatem, Goetz, and Hay 2004).

4.1.1 Principles of Remote Sensing

Remote sensing is defined by Lillesand et al. (2008) as the *"science and art of obtaining information about an object, area, or phenomenon through the analysis of data acquired by a device that is not in contact with the object, area or phenomenon under investigation"*. Many scientific fields, including Geology, Ecology, Meteorology and Epidemiology have adopted the technology for applications ranging from environmental monitoring, to weather observations, topographic and geological mapping, to name a few of the examples found in the literature (e.g. Campbell 2007; Jensen 2007).

The rationale behind remote sensing is the measurable electromagnetic energy that is reflected or emitted by features that are either on the earth surface, such as soil, water, vegetation, or buildings, or in the atmosphere, such as clouds and aerosols. Depending on the system used, the energy can be generated by the sensor itself (active systems, that transmit and receive microwave radiation, e.g. RADAR) or be ambient energy, which on the earth is typically radiated from the sun (passive systems operating in the visible to infrared range).

Electromagnetic energy covers a range of different wavelengths as shown in Figure 4.1, ranging from ≤ 0.03 nm (Gamma rays) to ≥ 30 cm (Radio waves). The part of the electromagnetic spectrum that is typically used for environmental remote sensing (e.g. vegetation monitoring) is the solar reflective range between 0.38 μm (blue light) and 3.00 μm (Mid-infrared radiance – MIR). In this range, the energy measured by a sensor depends upon properties such as the pigmentation, moisture content and cellular structure of vegetation, the mineral and moisture contents of soils and the level of sedimentation of water (Richards and Jia 2006). Also the human visible spectrum ranging from 0.38 μm to 0.72 μm is found here.

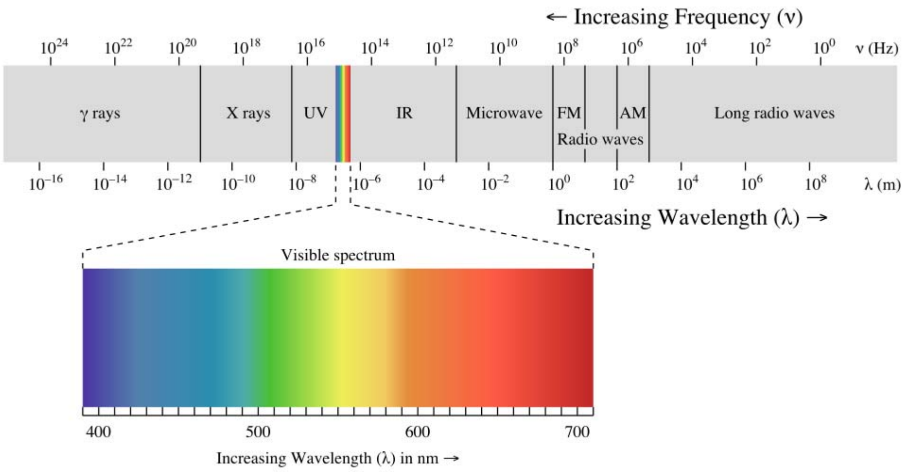


Figure 4.1 The Electromagnetic Spectrum, Courtesy of Philip Ronan

Thermal properties of a surface, (e.g. land surface temperature) are detected by sensors operating in the thermal infrared range (11-12 μm). In the microwave range from 20 to 60 GHz, atmospheric oxygen and water vapour have a strong effect on energy transmission and thus can be inferred by measurements in that range (Richards and Jia 2006)

By recording the proportion of energy reflected by an object or surface at different wavelengths we can make inferences about its properties. This specific response of an object to incident radiation that makes it distinguishable from other features is called the spectral response pattern or signature. Figure 4.2 shows the spectral response of water, vegetation and soil. The positions of spectral channels for common remote sensing instruments are indicated. These are discussed in the following sections.

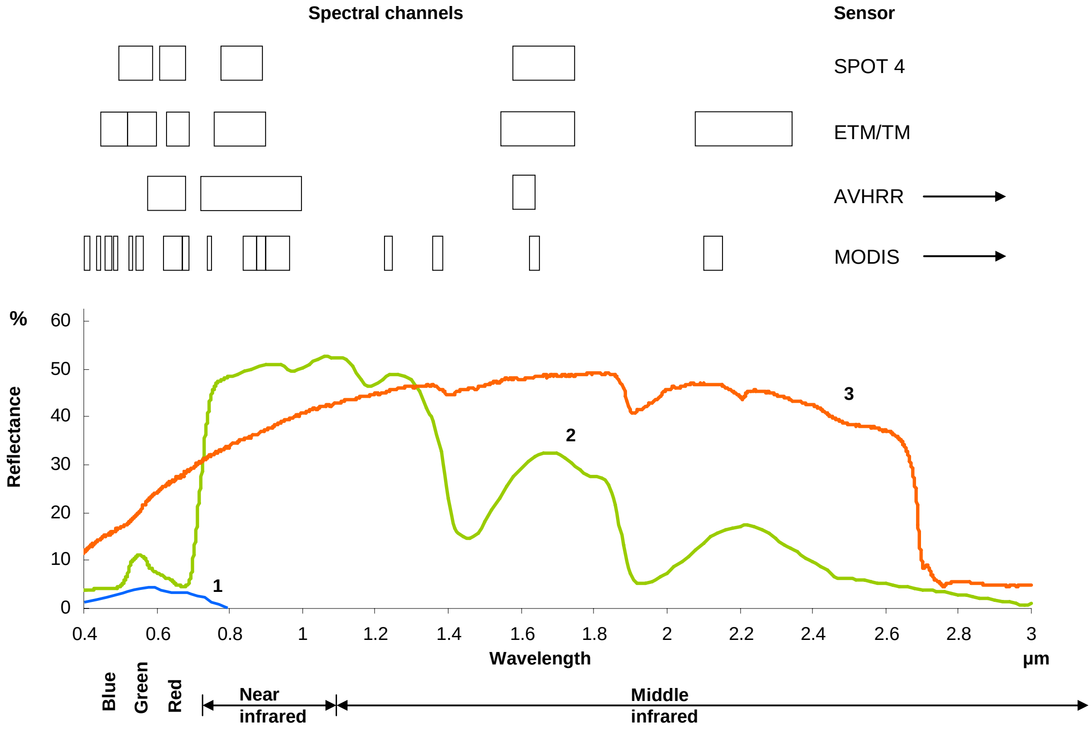


Figure 4.2 Spectral reflectance curves for clear water (1), green grass (2) and bare soil (3) in the visible and near-to-mid infrared range, and the position of spectral channels for common remote sensing instruments, after Richards and Jia (2006). Source of spectral reflectance data: ASTER Spectral Library (Baldridge et al. 2009)

Clear water reflects visible wavelengths and absorbs higher frequency wavelengths, Vegetation absorbs blue and red light energy used for photosynthesis, and leaves a small reflectance peak between that makes it appear green (Mather 2004). Vegetation is reflective in near infrared and mid infrared wavelengths. For soils, reflectivity generally increases with higher wavelength.

In some cases, the interaction between incident radiation and surface material varies from time to time, depending on factors like orientation of the sun (solar azimuth), height of the sun in the sky (solar elevation angle), the direction of the sensor in relation to nadir (the look angle) and the state and structure of the vegetation if this is the target (Mather 2004). The Bidirectional Reflectance Distribution Function (BRDF) (Nicodemus 1965; Nicodemus et al. 1977) describes the response of a surface at all possible view and illumination angles. It may be used to model the reflectance as if viewed from nadir and as such, correct for the spatial variance in directional remote sensing (Schaaf et al. 2002; Strahler 1997). Another factor to be considered is the Earth's atmosphere, which alters the radiation as it passes through, and can compromise the quality of the received data. The effects can be scattering, refraction and absorption of radiation. Only specific wavelengths, called atmospheric windows are relatively easily transmitted through the atmosphere and these are used in remote sensing.

Remote sensing instruments can be mounted on aircraft or satellite platforms. Sensors or radiometers record the incoming radiation digitally for a discrete area on the Earth surface. The size of the smallest recordable area determines the spatial resolution of the sensor and depends on the height of the flight path or orbit, and sensor characteristics. Most sensors operate in discreet wavelength bands or channels in the visible, near infrared (NIR), mid infrared (MIR) or thermal infrared (TIR) range of the spectrum. The bandwidth of each channel (spectral resolution) and the number of bands (spectral dimensionality) determine the ability of a sensor to record subtle differences in the spectral response of the sensed surface. The level of different brightness values that can be recorded for each band is known as the radiometric resolution. Another important characteristic is the temporal resolution or repeat time, which is the time taken between viewing the same part of the Earth. It is determined by orbital characteristics and may be constrained by the internal storage capacity of the sensor. Remote sensing data therefore tend to have either a high temporal, spectral or spatial resolution, but not all of them (Hay 2000).

Further details on the physical basics of remote sensing, the actual recording mechanisms, issues of atmospheric absorption, terrain and surface effects, sensor view angle, and specific sensor characteristics are discussed in numerous text books (e.g. Campbell 2007; Lillesand, Kiefer, and Chipman 2008; Mather 2004; Richards and Jia 2006), In the following sections space-borne sensors commonly used in epidemiology, and the bio- and geophysical information (i.e. earth surface or atmospheric properties, such as surface temperature, soil moisture, surface cover, air humidity, or air temperature) that can be derived from the measured surface reflectance are discussed.

4.1.2 Satellite Remote Sensing Platforms and Sensors

The selection of an appropriate sensor depends on the objectives of the study, the ecology of hosts, vectors and pathogens and the temporal and spatial scales at which transmission takes place (Kalluri et al. 2007). In most cases, it is a trade-off between spatial resolution (< 1 m to several kilometres) and temporal resolution (half-hourly to near-monthly). Figure 4.3 shows the requirements of epidemiology in relation to remote sensing in other disciplines.

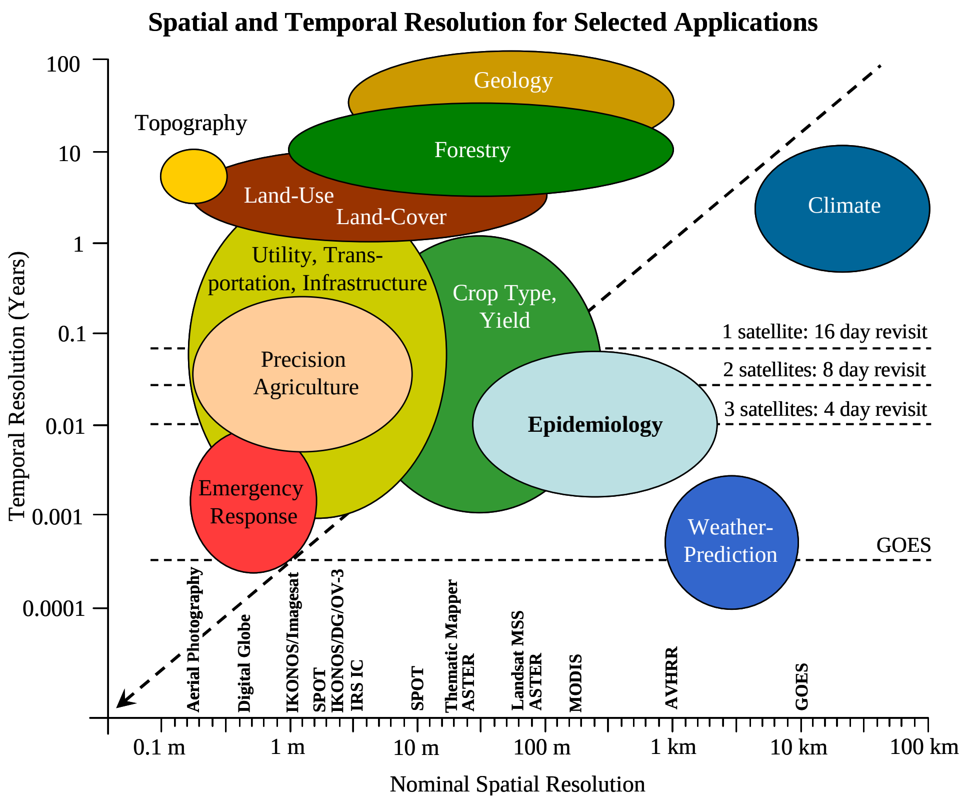


Figure 4.3 Spatial and temporal resolution considerations for different applications of remote sensing, after Jensen (2007)

Not all of the available sensors have proven useful for epidemiological studies and some are constrained by image costs and availability. Extensive reviews of data from past, present and future sensors applied in epidemiology are provided by Beck, Lobitz, and Wood (2000), Dale et al. (1998), Hay (2000), Hay et al. (2006), Huh and Malone (2001), Tran et al. (2010), and Washino and Wood (1994). The currently operating weather and environmental satellites that are particularly useful in arbovirus studies are discussed below and have been broadly categorised according to their spatial resolution into low (≥ 1000 m), moderate (250 m to 1000 m) and high resolution sensors (≤ 30 m).

4.1.2.1 Low Resolution Meteorological Satellites

Meteorological applications such as weather forecasts require near real-time weather observations over large areas. Dedicated sensors generally operate at a coarse spatial resolution and are capable of capturing surface and air temperature at different altitudes, monitoring cloud cover and movement, as well as water vapour and precipitation for an area at a high temporal frequency. The bands of major importance are in the visible, near infrared, and thermal infrared range, sensors measuring precipitation typically utilise the microwave spectrum.

Geostationary satellites operated by several countries under the umbrella of the World Meteorological Organization (WMO), are positioned in orbits about 36,000 km above the Earth's surface to constantly monitor a specific area on the ground. The Meteosat Mission, operated by the European Organisation for the Exploitation of Meteorological Satellites (Eumetsat), covers Europe and Africa, and the western Indian Ocean. The first of the Meteosat Second Generation (MSG) satellites was launched in 2002 and provides images every 15 minutes since going fully operational in 2004 (Hay et al. 2006). The spatial resolution ranges from 1.4 km in the visible bands to 3 km for all other bands (thermal infrared, water vapour) (Schmetz et al. 2002). Satellites with equivalent capabilities for the American and Pacific region are operated by the National Oceanic and Atmospheric Administration (NOAA). NOAA's Geostationary Operational Environmental Satellites (GOES), capture images at a spatial resolution of 1 km in the visible and 4-8 km in the thermal bands every 15 minutes for the continental United States and every 30 minutes for the hemisphere between the North Poles and 20°S latitude (Jensen 2007). The

Australasian region is currently observed by the Japanese Advanced Meteorological Imager (JAMI) aboard the geostationary Multi-functional Transport Satellite (MTSAT)-2, following the former Japanese Geostationary Meteorological Satellite (GMS) series (Kawamura et al. 2010). For Australia, hourly data are available at a spatial resolution of 1 km for the two visible and at 4 km for the 4 infrared bands. Half-hourly images are available for the northern half hemisphere, including Japan.These optical and thermal sensors may be used indirectly to infer ground precipitation based on measurements of cloud reflectivity or cloud top temperature, which are related to probability and intensity of rainfall (Prigent 2010). Less frequent but more direct measurements can be achieved with specifically designed microwave instruments, such as the passive Advanced Microwave Scanning Radiometer-E (AMSR-E) on board NASA’s Aqua satellite (Section 2.5.2.2) or the instruments on board the TRMM. Ongoing research by the International Precipitation Working Group (IPWG) (Turk and Bauer 2006) has shown that passive microwave measurements deliver more accurate instantaneous measurements, while Infrared (IR) techniques provide the best long term estimates (Ebert and Manton 1998) and it is suggested that a combination of both techniques would be advantageous.

TRMM was jointly launched by NASA and the Japan Aerospace Exploration Agency (JAXA) in 1997 to monitor and predict tropical cyclone tracks and intensity, estimate rainfall, and monitor climate variability (precipitation and sea surface temperature) between the latitudes 38°N and 38°S, at spatial resolutions from 2.1 to 45 km (*TRMM - Tropical Rainfall Measuring Mission* 2010). The satellite, positioned in a low non-sunsynchronous orbit, carries three instruments: TRMM Microwave Imager (TMI), the Visible/Infrared/Scanner (VIRS) and the first operational space-borne Precipitation Radar (PR) (Jensen 2007). A number of TRMM data products are readily available, such as the TRMM and other satellites rainfall product (3B42) that exploit the advantages of several sensors on board. Originally designed for an operation period of 3 years, TRMM is likely to remain operative until 2012. With the Global Precipitation Mission (GPM) a follow up project is currently in the implementation stage and anticipated to be launched in 2013 – 2014 (*Global Precipitation Measurement* 2010; Smith et al. 2007).

4.1.2.2 Moderate to Low Resolution Sensors

Two sensors delivering publicly available data at low cost that have gained importance particularly for environmental monitoring applications are the Advanced Very High Resolution Radiometer (AVHRR) and more recently the MODerate Resolution Imaging Spectroradiometer (MODIS). The series of AVHRR sensors carried on polar orbiting NOAA satellites have collected environmental data since 1978 at a low to moderate spatial resolution between 1.1 and 8 km. The very high resolution (VHR) in the acronym relates to the improved radiometric resolution compared to the earlier sensors. Daily coverage of the entire Earth and a large historical data archive have made AVHRR invaluable for monitoring environmental changes and for applications in large area epidemiology. Hay et al. (2006) provide ample details about the sensor, data processing and epidemiological applications.

The MODIS instruments are on board NASA's Earth Observation System (EOS) Terra and Aqua satellites, which were launched into a sunsynchronous orbit in 1999 and 2002 respectively. Their advantage over AVHRR is due to their higher spatial and spectral resolution. The MODIS sensors collect data every 12 to 24 hours (depending on the use of one or both sensors) over a wide spectral range at spatial resolutions of 250 m (Red, NIR), 500 m (MIR) and 1 km (TIR) (*MODIS Web* 2010). This low revisit time increases the chance of recording cloudless images over an area and hence facilitates the monitoring of dynamic spatial environmental processes. With 36 spectral channels (from 0.62 to 14.385 μm) and 12-bit radiometric resolution a large number of meteorological and other geophysical parameters and variables can be derived, such as the Normalised Difference Vegetation Index (NDVI), Land Surface Temperature (LST) and Landcover/Landcover change. Most of these data are readily available as quality controlled MODIS products (discussed in the following sections), which reduces the need for time consuming atmospheric correction, georegistration, image composition and processing.

With a scheduled operation period of 18 years, the MODIS data archive facilitates global long term observations of disease related factors (Tatem, Goetz, and Hay 2004). The timeline for planned follow up missions, the National Polar-orbiting Operational Environmental Satellite System (NPOESS) and its predecessor, the

NPOESS Preparatory Project (NPP), expected to be launched as early as 2011, are currently under review (*NPOESS* 2010). Once in operation, the Visible/Infrared Imager/Radiometer Suite (VIIRS) on board will provide data continuity for parameters currently recorded by AVHRR and MODIS. However, differences in data acquired by those sensors due to varying overpass times need to be considered (Townshend and Justice 2002).

4.1.2.3 High Resolution Sensors

Disease mapping projects conducted on a local scale generally aim to detect and monitor potential disease foci, or more specifically for vector-borne diseases, the vector habitats. This task includes monitoring of ground cover, permanent and ephemeral bodies of open water and wetlands. Very often, these features, such as narrow streams are to small to be detectable by moderate resolution sensors (Chalke 2006), and high resolution data are required instead.

Present polar orbiting satellites carrying high resolution sensors include Landsat 5 and 7 with the Thematic Mapper (TM) and Enhanced Thematic Mapper (ETM) instruments, the Satellite Pour l'Observation de la Terre (SPOT) - 5 with the High Resolution Geometric (HRG) camera on board and the EOS Terra platform with the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER). These have repeat cycles of 16, 26 and 16 days, and a spatial resolution of 15-30 m, 2.5-5 m and 15-90 m respectively, depending on the channel.

Various epidemiological studies have used high resolution satellite imagery, particularly from Landsat satellites (Bogh et al. 2007; Brown et al. 2008; Kitron et al. 1996), which have collected invaluable data on land cover change that are now freely available electronically (Cheng et al. 2009). Nevertheless, limited evidence for widespread adoption of data from the other named sensors is found in literature due to various limiting factors, including availability of cloud free images, temporal resolution and processing requirements (Herbreteau et al. 2007). Moreover, commercial very high resolution systems (sub-meter to 4 m horizontal resolution) launched in recent years, including Ikonos, Quickbird, Rapid Eye and GeoEye, are often operated to collect data ‘on demand’ rather than on a regular basis. This and associated high costs of the collected data are not advantageous for monitoring larger areas like Australia frequently under similar conditions (time of day, viewing angle, etc). However, high resolution radiometer sensors like ASTER on multi-sensor platforms may be used as a zoom-lens for the other (lower resolution) instruments on board for validation and calibration purposes (*ASTER Mission* 2010).

4. 2 Remotely Sensed Environmental Variables for Epidemiological Applications

A wide range of environmental and climatic variables with relevance to arboviral diseases can be derived from geostationary (GEO) and low Earth orbiting (LEO) remote sensing platforms. These include rainfall, air and land surface temperature, vegetation type and condition, or humidity. These variables often replicate ground based climatic, soil or vegetation datasets that have been used in epidemiological studies, e.g. by Conte et al. (2007), Dascălu, Ionescu, and Rizac (2007), Ward and Thurmond (1995) or Wittmann, Mellor, and Baylis (2001). However, remote sensing data are in many aspects advantageous as shown in the following sections, mainly due to wider areal coverage and shorter update cycles, while retaining the overall spatio-temporal patterns observed on the ground.

Which parameters can be extracted from remote sensing data primarily depends on the spatial resolution of the instrument as well as the available spectral bands. High resolution instruments are able to detect specific environmental attributes, including soil type and plant species, while low and moderate resolution sensors such as MODIS record average environmental conditions over the large areas covered by a pixel, and are used for regional studies of vegetation condition or precipitation.

Converting the radiation measured by a sensor into environmental variables for epidemiological applications involves a number of pre-processing steps. These are explained in detail by Mather (2004) and Richards (2006), and include radiometric, atmospheric and geometric corrections, image registration and reprojection to an appropriate spatial reference system. The corrected images are then transformed into either 1) climatic or geophysical parameters that are built on the relationship between emitted radiation and ground based measurements, using physical and/or empirical models (e.g. precipitation, land surface temperature), or 2) indices, which are defined by different mathematical band combinations (e.g. vegetation or water indices)

(Lillesand, Kiefer, and Chipman 2008). For many sensors, data products at different processing levels are provided to the scientific community, ranging from raw data to multi-band images and quality controlled scientific datasets. While these products offer scientists the opportunity to focus on the interpretation rather than the processing of the data, it is crucial to assess data quality and its fitness for a particular application. This is often neglected in epidemiological studies, either due to time and cost constraints, or limited access to ground truth data in the same spatial and temporal domain as the remotely sensed data (Goetz, Prince, and Small 2000). Therefore, the supplied metadata and quality information, e.g. for the MODIS Land datasets (Roy et al. 2002) or results from validation activities (Morisette, Privette, and Justice 2002) are frequently the only source to assess fitness for use.

4.2.1 Rainfall

Rainfall is often related to an increase in abundance of arbovirus vectors, particularly mosquitoes (Thomson et al. 1996). Also the short-term and long-term occurrence of BTV in Australia has been linked to rainfall (Ward 1994a; Ward and Thurmond 1995). The distribution of competent *Culicoides* vectors is generally confined to areas in excess of 800 mm annual precipitation (Standfast, Dyce, and Muller 1985). However, this relationship is not necessarily immediate, as all but very light rainfall initially suppresses vector activity and may even wipe out vector populations, particularly if extensive flooding occurs. The associated increase in humidity, soil moisture, availability of vegetation and the development of breeding grounds may lead to a lagged abundance of vector populations and increased risk of virus transmission (Ward and Thurmond 1995).

Before the launch of TRMM with the first precipitation radar in 1997, rainfall intensity retrieval has been mostly based on passive sensors using the visible, IR and passive microwave (PMW) wavelengths, which lack the ability to obtain a three dimensional structure of clouds and precipitation (Michaelides et al. 2009). Thus, combining data from active and passive sensors and ancillary data (e.g. wind and rain gauge data) is the only feasible strategy to improve the accuracy of cloud and precipitation retrievals from satellite imagery (Stephens and Kummerow 2007). Michaelides et al. (2009) categorised methods for multisatellite precipitation retrieval into 1) those that use ancillary products from sensors not in the PMW range to actively adjust the PMW derived rainfall intensities (e.g. Huffman et al. 2007), and 2) those which use the ancillary data to temporally interpolate the rain maps from one overpass of a PMW sensor to the next one (e.g. Joyce et al. 2004).

The TRMM Multisatellite Precipitation Analysis (TMPA), was developed by Huffman et al. (2007). It provides a calibration-based sequential scheme for combining precipitation estimates from multiple satellites, as well as gauge analyses where feasible, at fine scales (0.25° x 0.25° and 3 hourly) for a global band extending from 50 degrees South to 50 degrees North latitude. The estimates depend on the input from different sets of LEO PMW sensors and GEO IR (~10.7µm) instruments. TRMM combined instrument (TMI+PR) estimates as well as the Global Precipitation Climatology Project (GPCP) and Climate Assessment and Monitoring (CAMS) monthly rain gauge analysis are also incorporated in TMPA. The method performs reasonably on a monthly scale and detects large scale rain events, but shows less ability in correctly specifying moderate to light rain rates at short time intervals (Michaelides et al. 2009).

The Climate Prediction Center morphing method (CMORPH) uses motion vectors derived from half-hourly interval IR GEO satellite imagery to propagate the relatively high quality precipitation estimates derived from PMW data for a global product. Additionally, shape and intensity of the precipitation features are modified (morphed) during the time between microwave sensor scans using a time-weighted linear interpolation. A detailed description of the algorithm can be found in Joyce et al. (2004). The process yields spatially and temporally complete PMW derived precipitation estimates, with the performance depending on the used PMW retrieval method. CMORPH has been available since December 2002 with different temporal and spatial resolutions: 30 min/8 km, 3-hourly/~25 km, daily/~25 km. The higher spatial resolutions are produced through interpolation of the individual satellite estimates that have a coarser resolution of about 12 to 15 km.

Still, interpolated rainfall variables are often found in species distribution models (e.g. Baylis et al. 1998; Baylis, Meiswinkel, and Venter 1999). A few studies have used satellite derived cold cloud duration (CCD) as surrogate for precipitation probability (e.g. Hay, Snow, and Rogers 1998; Thomson et al. 1996), but there is little evidence for adoption of more advanced satellite based rainfall estimates like TMPA and CMORPH in epidemiology. The usability of these methods and associated data products for this study will be further explored in Chapter 5.

4.2.2 Temperature

Temperature regulates many land surface processes and is the single most important factor for survival and replication rates of arbovirus vectors. More specifically, higher temperatures are known to increase growth rates of vector populations, decrease the length of the gonotrophic cycle and hence the interval between blood meals, shorten the extrinsic incubation period of the virus in the vector and increase the rate of virus evolution (Ruiz et al. 2010). Minimum and maximum daily temperatures measured on or above ground, as well as temperature time series are frequently used as variables in predicting Bluetongue (e.g. by Purse, Baylis, et al. 2004; Purse et al. 2007; Wittmann, Mellor, and Baylis 2001), and other insect-borne diseases (Rizzoli et al. 2007; Rogers 2000).

4.2.2.1 Land Surface Temperature

Land Surface Temperature (LST) is here referred to as the radiometric (kinetic) temperature related to the TIR radiation emitted from the ground (Norman and Becker 1995). This can be top of canopy in vegetated areas or soil surface in bare areas. LST plays an important role for the development and survival of the larval stage of vectors, particular for the ground breeding species of *Culicoides* that transmit BTV in Australia. Although previously the spatial and temporal variability of LST has been used as an index of vector abundance (Malone et al. 1994; Rogers, Hay, and Packer 1996), absolute temperatures may be better suited for studies of vector survival and reproductive success (Goetz, Prince, and Small 2000).

Land surface temperature can be inferred from the thermal infrared bands of moderate to coarse resolution instruments like AVHRR, MODIS or higher resolution instruments like ASTER and ETM. Accurate determination of LST depends on the knowledge of the emissivity of the surface and the availability of clear sky images (Goetz, Prince, and Small 2000). The split-window approach is the most commonly applied technique to reduce the error from atmospheric effects, based on the differences in signal attenuation between two thermal bands (Hay and Lennon 1999).

There are two methods implemented for LST retrieval from MODIS. One is a generalised split-window approach based on calibrated radiance data of bands 31 and 32 data (Wan and Dozier 1996) and the second one is the physics based day/night algorithm (Wan and Li 1997) using a pair of day-time and night-time data in TIR bands 20, 22, 23, 29, and 31–33. Daily or 8-daily data products are available for both methods at 1 km and 5 km spatial resolutions, respectively. Validation attested the MODIS LST products accuracy to be in the order of ± 1 K (Wan 2008; Wan et al. 2002; Wan et al. 2004) for lakes, snow/ice, and dense vegetated areas. However, in arid and semi-arid regions, where surface emissivity may vary significantly with location and time, the split-window algorithm tends to underestimate LST (Hulley and Hook 2009; Wan et al. 2002). It remains unclear, though, if this is the case in the savannahs of Northern Australia.

4.2.2.2 Air Temperature

Air temperature (TAIR) measured about 2 m above ground is a primary descriptor of terrestrial environmental conditions (Prihodko and Goward 1997) and potentially more useful for many applications than ground temperature, which bears little relationship to the micro-environment in which an insect, animal, plant or human is living (Cresswell et al. 1999; Goetz, Prince, and Small 2000).

Two major techniques have been developed for TAIR retrieval, mainly utilising the LST derived from MODIS, AVHRR or meteorological satellites. One technique, known as the temperature–vegetation index, is based on the hypothesis that the LST over a thick vegetation canopy is close to ambient TAIR and utilizes the negative correlation between LST and NDVI (Prihodko and Goward 1997; Stisen et al. 2007). The achieved accuracies of TAIR estimates are in the range of 3 K (Stisen et al. 2007). The other approach, known as the statistical method, often combines LST/brightness temperature and other parameters, such as geographic location and altitude (Yan et al. 2009), solar zenith angle (SZA) (Cresswell et al. 1999), or combinations thereof (Jang, Viau, and Anctil 2004), to derive TAIR through regression analysis. Vancutsem et al. (2010) found generally good correlation between LST from the MODIS night overpass and the observed minimum air temperature, an important variable in epidemiology. However, estimates of maximum day temperature based on MODIS LST, NDVI and SZA, respectively, showed variable accuracy across ecosystems. Analyses of the effects of using LST from the earlier Terra or the later Aqua overpass, showed little difference in the correlation with the measured TAIR on the ground (Mostovoy et al. 2006).

4.2.2.3 Degree Days

Besides using minimum and maximum temperatures to define the habitat extent of a species, the number of days, for which temperatures are above a certain threshold, expressed in Growing Degree Days (GDD), is often used to predict phenological events. Development and establishment of insects (Baker et al. 1984; Kunkel et al. 2006) or plants depends on the accumulation of specific quantities of heat required to complete all live stages or for a crop to mature (Neteler 2010). Growing Degree Days are calculated as follows:

$$GDD = \begin{cases} T_{mean} - T_{base} \; if \; T_{mean} > T_{base} \\ 0 \qquad if \; T_{mean} \leq T_{base} \end{cases} \tag{4.1}$$

where *GDD* is the number of degree days for a particular day, T_{mean} is the mean temperature of the day, and T_{base} is the base temperature. The most appropriate values of T_{base} vary by species and represent the threshold below which all development is suppressed (McMaster and Wilhelm 1997). Some applications also used an upper threshold (e.g. Cesaraccio et al. 2001), since temperatures exceeding a critical value result in slower development of an organism or its development ceasing altogether.

Growing Degree Days are generally derived from air temperature at observation stations (Yang et al. 2006), but alternative definitions based on LST (Neteler 2010) and using weeks instead of days (Ruiz et al. 2010) have been found. Compared to GDD obtained from ground observations, those derived from 8-daily MODIS LST generally follow the same curve, but were systematically overestimated in a Canadian study (Hassan et al. 2007).

4.2.3 Atmospheric and Near-Surface Humidity

Atmospheric humidity is a factor of equal importance to arbovirus vector survival as temperature (Kalluri et al. 2007). It may be expressed in terms of specific, absolute or relative humidity, or Vapour Pressure Deficit (VPD) (Goetz, Prince, and Small

2000). The latter is a measure of the lack of moisture equilibrium between an object and the surrounding atmosphere and is a particularly useful index for the drying power of air and hence the desiccation rate of vectors and their eggs (Green and Hay 2002).

Prince and Goward (1995) developed a method to derive VPD from AVHRR that is based on the differences between the TIR channels 4 and 5, which has also been employed in air temperature estimation. More recently, Hashimoto et al. (2008) applied an empiric VPD model based on LST and long term air temperature (Granger 2000) to MODIS LST data. The VPD maps produced with those methods show spatial and temporal patterns that are in general agreement with known climatic patterns and interpolated meteorological observations (Goetz, Prince, and Small 2000). However, absolute errors in VPD tend to be large (Green and Hay 2002), and Granger's (2000) method performed poorly along the coast and over sparsely vegetated areas (Hashimoto et al. 2008). This is in line with the problems associated with LST derival over arid and semi-arid regions due to the large spatial and temporal variability of surface emissivity.

An operational algorithm to derive water vapour from ratios of several MODIS bands in the thermal range aims to remove the effects of the variation of surface reflectance with wavelength for most land surfaces (Gao and Kaufman 2003). A 1 km resolution NIR water vapour product is generated during the day, and daily, 8-daily, and monthly IR water vapour products are generated day and night at a spatial resolution of 1°. The products, aimed at the study of seasonal and annual variations of water vapour on regional and global scales, have typical errors in the derived water vapour values ranging between 5% and 10% (Gao and Kaufman 2003). However, an evaluation of the product by McAtee and Maier (2006) showed that these algorithms perform poorly over continental Australia with an RMS error of 44%.

Alternatively, microwave sensors capable of deriving atmospheric humidity parameters can be found on the Terra and Aqua platforms, most notably the Atmospheric Infrared Sounder (AIRS) and the Advanced Microwave Sounding Unit (AMSU) (Tatem, Goetz, and Hay 2004). However, in addition to the lack of validation studies, their low spatial resolution makes them less useful for epidemiological studies that operate at local or regional scales using near surface environmental conditions.

What is common to any of the higher level humidity estimators is that they are typically derivatives of a combination of satellite products and ancillary data and are as such prone to propagate errors and uncertainties from the input parameters. Understandably, the epidemiological community has hardly adopted any of the presented humidity variables in favour of more robust lower level variables, such as LST or vegetation indices (see next section).

4.2.4 Vegetation

Information about vegetation is integral to the study of vector-borne diseases, which are linked to the vegetated environment at least during some aspect of their transmission cycle (Beck, Lobitz, and Wood 2000). Vegetation not only provides shelter from desiccation during resting periods for some vector species (Bishop et al. 1995; Bishop et al. 1994), and nectar supply particularly for the male population of blood sucking insects, it also strongly influences the distribution of hosts (e.g. grazing livestock) and hence the focus of disease transmission. The spatial and temporal variability of vegetation type and condition is governed by the combined impact of rainfall, temperature, humidity, topographic effects, soil, water availability, and human activities. Therefore, vegetation indices and type, which are described hereafter, are also used as surrogates for many of these environmental variables.

4.2.4.1 Vegetation Type and Landscape Composition

Land cover maps that delineate vegetation type and landscape composition at varying hierarchy levels are generally derived from high resolution imagery e.g. from Landsat or SPOT. Image classification techniques are applied to automatically categorise all pixels in an image into land cover classes. The two main approaches are unsupervised and supervised classification, which differ in the definition of the pixel categories. The supervised classification involves a training step, where an image analyst defines the spectral characteristics of a class by selecting pixels representative for a category in the image, whereas in unsupervised classification, the image data are automatically aggregated into natural spectral groups or clusters.

General overviews of image classification methods are given e.g. by Lillesand, Kiefer, and Chipman (2008) or Mather (2004), while Curran et al. (2000) specifically addresses applications in disease mapping.

Global and regional land cover datasets are also available and useful for broad scale studies where detailed information on particular plant species is not required. Examples include the 300 m resolution GlobeCover product (Arino et al. 2008) and the global annual MODIS Landcover product, which is produced at 500 m spatial resolution (Friedl et al. 2010). For the Australian continent, a dedicated dynamic land cover classification derived from satellite remote sensing data has been proposed (Lymburner et al. 2008), but is currently not available. Instead, a number of regions have been mapped as part of traditional vegetation surveys, which used aerial photo mosaics to delineate vegetation communities at scales between 1:100,000 and 1:1 million (e.g. Beard 1975b). Other surveys have been conducted to assess the condition of rangeland land systems (see Chapter 5 for details). Data on native vegetation and soils on different aggregation levels have been homogenised across Australia and are now available through the National Vegetation Information System (NVIS) and Australian Soil Resource Information System (ASRIS), respectively. However, these data are all static in nature and remote sensing approaches are therefore increasingly used to monitor dynamic changes such as land cover, related e.g. to pastoral management (Hamilton, Chilcott, and Savage 2008) or mosquito vector habitats (Dale et al. 1998).

Specific vegetation type information offers opportunities to map species habitat and range. Several studies have used vegetation type and structure to study vector habitats (e.g. Hayes et al. 1985). More often than looking at specific plant species, homogenous landscape units, defined by environmental variables, such as vegetation or soil type, are used in health studies (e.g. Beck et al. 1994). Using a supervised classification of SPOT imagery to create a mosaic of major landscape units, De La Rocque (2004) found BT seroprevalence was highest in districts with a high percentage of meadows.

To be able to utilise landscape units for disease cause and effect analysis requires some method of quantification. So called Landscape Metrics have been developed by

McGarigal and Marks (1995) for this purpose to describe either the patch itself in terms of e.g. mean patch size and shape, or to characterize the spatial relationship between the patches, e.g. nearest neighbour, contagion and connectivity (McGarigal and McComb 1995). In epidemiology, Landscape Metrics have been applied to study the relationship between landscape composition and the presence of Bluetongue virus (Guis et al. 2007), Murray Valley Encephalitis virus (Chalke 2006) and West Nile virus in horses (Pradier, Leblond, and Durand 2008).

However, more frequently than plant species composition and landscape metrics, the amount and density of vegetation cover is associated with disease and vector abundance (Goetz, Prince, and Small 2000).

4.2.4.2 Vegetation Indices

A vegetation index (VI) is a dimensionless, radiometric measure that indicates relative abundance and activity of green vegetation (Jensen 2007). Summaries of the various vegetation indices that can be extracted from remotely sensed data are given e.g. by Jackson and Huete (1991), Jensen (2007), Lyon et al. (1998), Running et al. (1994), and Wiegand et al. (1991). VIs are generated using mathematical combinations of several bands of remote sensing data that utilise the significant differences in reflectance of vegetation in the blue, green, red and NIR bands (previously shown in Figure 4.2). The index is typically a sum, difference, ratio or other linear combination that reduces multi-band observations to a single numerical index (Wiegand et al. 1991). Vegetation indices are simple tools for exploring or quickly evaluating the state of vegetation over large areas. They enhance the spectral contrast of vegetation and minimise effects like viewing and sun angles, topography or soil variations to facilitate consistent spatial and temporal comparisons. The usefulness of any VI for a specific application depends upon the relationship that may be found between the index and the variable of interest, e.g. biomass, primary productivity (Warren 2007).

The Normalized Difference Vegetation Index (NDVI), originally envisaged by Rouse et al. (1973) is the most commonly used index in health studies. NDVI is calculated as a normalised ratio from the RED and NIR bands and hence is less affected by the absolute reflectance values:

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{4.2}$$

The values can theoretically range from -1 to 1, with highly vegetated land producing values close to 1, while NDVI over bare land will be close to zero and assume negative values over water (Holben 1986; Tucker 1979). NDVI has been associated with habitat suitability for disease vectors, such as ticks (Eisen, Eisen, and Lane 2006; Ogden et al. 2006), *Anopheles* spp. mosquitoes (Shililu et al. 2003) and *Culicoides* biting midges (Purse, Tatem, et al. 2004).

Despite its usefulness as a robust vegetation index, NDVI has some disadvantages, including saturation in high biomass areas, sensitivity to background soil brightness and differential atmospheric effects (Huete, Jackson, and Post 1985; Huete et al. 1997). The Enhanced Vegetation Index (EVI) was developed to optimise the vegetation signal with improved sensitivity in high biomass regions and improved vegetation monitoring through a de-coupling of the canopy background signal and a reduction in atmosphere influences (Huete et al. 2002). The equation takes the form,

$$EVI = G\frac{NIR - RED}{NIR + C_1 RED - C_2 BLUE + L}(1 + L) \tag{4.3}$$

where G is a gain factor set to 2.5 and L is a soil adjustment factor empirically determined as 1.0. C_1 and C_2 are coefficients that describe the use of the blue band in correction of the red band for atmospheric aerosol scattering and have been determined empirically as 6.0 and 7.5, respectively.

NDVI and EVI are produced as standard MODIS products at 500 m and 250 m using 8-day compositing periods.

4.2.4.3 Vegetation Phenology

In regions outside the endemic range of arboviruses, transmission may be suppressed during certain periods of the year, be it through low temperatures or periods of low precipitation or even drought. The underlying pattern can be attributed to seasonal climatic differences, or shifts in the spatial distribution of bioclimatic zones, which are also reflected in the growing periods of vegetation.

Vegetation phenology refers to the timing of different life-cycle events of the plants, such as greenup and senescence (i.e., the start and end of growing season) (Zhang et al. 2003). A number of methods have been developed to analyse long time series of NDVI and extract phenological parameters, some of which are shown in Figure 4.4.

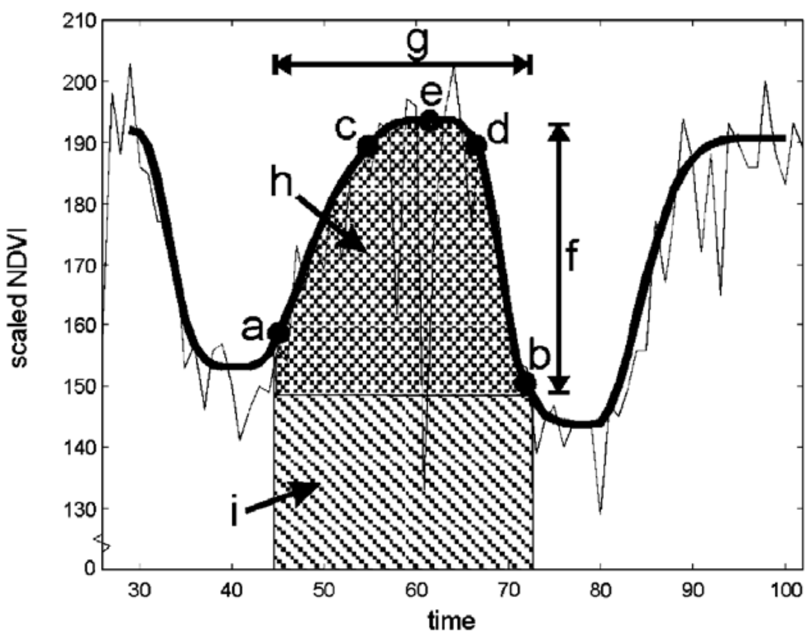


Figure 4.4 Examples of seasonality parameters that can be computed from NDVI time series: (a) beginning of season, (b) end of season, (c) left 90% level, (d) right 90% level, (e) peak, (f) amplitude, (g) length of season, (h) small integral over growing season giving area between fitted function and average of left and right minimum values, (i) large integral over growing season giving area between fitted function and zero level. Source: Jönsson and Eklundh (2004)

Phenology extraction from NDVI time series typically involves as a first step removal of noise that arises from varying atmospheric conditions and sun-sensor-surface viewing geometries (Hird and McDermid 2009). In a second step, phenological markers for the start and end point of one or more seasons is determined. Several methods are available that either work with a fixed NDVI threshold or a portion of the maximum seasonal greenup (Bradley et al. 2007; Jönsson and Eklundh 2002), or by analysing the rate of change in curvature and slope along the fitted curve (Zhang et al. 2003).

A number of smoothing techniques have been applied to NDVI time series, including Fourier transform (Stöckli and Vidale 2004), wavelet transform (Martínez and Gilabert 2009), function-fitting (Beck et al. 2006; Bradley et al. 2007; Jönsson and

Eklundh 2002; Zhang et al. 2003), and filtering methods (Chen et al. 2004). Hird and McDermid (2009) assessed several of these techniques for their ability to preserve the characteristics of the growing season and found that Asymmetric Gaussian (Jönsson and Eklundh 2002) and Double-logistic (Beck et al. 2006) function fitting techniques performed best. From the other tested filters, an adapted Savitzky-Golay (1964) filter gave the best results and is also superior to the fast Fourier transforms (e.g. Chen et al. 2004), which usually have problems to detect short seasons marked by rapid increases in NDVI.

4.2.5 Soil Moisture and Surface Wetness

Wet soils indicate a suitable habitat for species of snails, mosquito larvae, ticks, and worms (Beck, Lobitz, and Wood 2000). Consequently, sufficient moisture levels are also an important requirement for the presence of some ground breeding arbovirus vectors, such as some species of *Culicoides* (Foxi and Delrio 2010). However, none of the Australian BTV vector species is known to lay their eggs in wet soil (see Tables 2.1 and 2.2).

Several types of sensors that can detect near surface soil moisture are listed e.g. by Beck, Lobitz, and Wood (2000), and include passive microwave sensors, microwave Synthetic Aperture Radar (SAR), shortwave-infrared, and thermal-infrared sensors. Passive microwave systems such as AMSR-E (Njoku et al. 2003) have the advantage that they can penetrate cloud, have reduced sensitivity to land surface roughness and vegetation, and the signal has a direct relationship with soil moisture through the soil dielectric constant (Draper et al. 2009). Comparisons of different products have shown that the algorithm used for soil moisture retrieval plays an equally important role for the quality of a soil-moisture dataset as the technical specifications and performance of the satellite system (Draper et al. 2009; Wagner et al. 2007). In relation to this project the very low spatial resolution of most datasets, which depends on the bands used in the algorithm, and might be as low as 56 km for the standard AMSR-E product, is considered a major disadvantage. Alternatively, soil moisture can be estimated from data in the visible and IR spectrum based on the relationship between LST and NDVI, which is also utilised for air temperature and evapotranspiration rate estimates (Goetz, Prince, and Small 2000). Brooker and Michael (2000) also found that precipitation and vegetation amount may be useful indicators for soil moisture, since rainfall increases humidity and soil moisture and vegetation cover prevents evaporation and conserves soil moisture. In fact, NDVI has therefore often been used in arbovirus studies as a surrogate for soil moisture (e.g. by Calvete et al. 2009; Purse, Tatem, et al. 2004; Tatem et al. 2003).

4.2.6 Surface Water

Water is a requirement for many stages of disease cycles, particularly those involving arthropod vectors. Different forms of surface water, ranging from lakes, water holes, and streams to flooded grasslands and forests, salt lakes, wetlands and swamps provide a breeding habitat for larvae of a number of mosquito and midge species. While most Australian BTV vectors do not rely on surface water to breed, water that acts as drinking supply for livestock potentially increases the risk of virus transmission, by creating areas where high densities of virus amplifiers, hosts and vector may be found together.

In contrast to rainfall that has often been used as a predictive variable for occurrence of mosquito-borne viruses like Dengue, Japanese and Murray Valley Encephalitis, Ross River and Malaria, remote sensing of surface water offers the opportunity of mapping the direct link between water habitat and disease. As Chalke (2006) points out, the correlation between rainfall and habitat is highly variable in both space and time, and the area of resulting habitat, i.e. surface water that results from rainfall, is influenced by the local geology, soil type, vegetation, watershed characteristics and anthropogenic intervention. Local habitat development may also result from rainfall events far from the area of flooding.

Surface water mapping can be conducted on local to regional scales, depending on the purpose of the study and the size of the habitat to be mapped. The AVHRR and MODIS instruments are able to monitor surface water daily, at spatial resolutions of 1 km and 250 m, respectively, which limits their application to regional studies involving larger rivers, dams and lakes, and large scale flooding. However, the high temporal resolution may aid in capturing highly dynamic flood events that are frequent in the semi-arid and arid regions of Australia during the wet season. Higher resolution instruments, such as ASTER, SPOT and TM/ETM facilitate identification of smaller surface water features, such as small streams and tributaries, as well as small flooded areas in forests and flood plains.

A number of water classification methods have been developed, including change detection (e.g. Faruolo et al. 2009), spectral matching (e.g. Roshier and Rumbachs 2004), or simple threshold analysis (e.g. Lacaux et al. 2007) of the NIR, MIR or thermal bands, or of ratios such as visible/NIR visible/MIR, or NDVI. Common to these algorithms are difficulties in defining boundaries between land and turbid or highly saline water bodies (Campbell 2007) or detecting flooded areas with high vegetation cover (Townsend and Walsh 1998). Active systems such as SAR have been successfully applied to identify water beneath vegetation cover, either exclusively (Milne 1999) or in combination with optical sensors and Digital Elevation Models (e.g. Li and Chen 2005). What makes SAR less practicable for dynamic surface water monitoring over large areas is the relatively high cost, and limited accessibility of recent and historical data covering Australia (Dale et al. 1998).

4.2.7 Wind

Wind may affect the flight of arbovirus vectors like *Culicoides* in two ways. Unsupported flight for the purpose of finding hosts for blood meals, for mating and egg-laying, and for seeking shelter, is limited to times of low wind speed (Murray 1987). During times where wind velocity exceeds the unaided flight speed, midges may be transported from 5 to 700 km in heights of up to 1.5 km, where they can survive in temperatures between 12 and 35°C (Sellers 1980; Sellers 1992).

In areas, where arboviruses are not endemic, infected vectors carried by wind are one possible route of introduction of a pathogen, besides travel, trade and animal movements. Ritchie and Rochester (2001) showed for example that Japanese Encephalitis was introduced from New Guinea into Australia through wind blown *Culex spp.*. Other examples include local (Bishop, Barchia, and Spohr 2000) and long distance wind dispersal of *Culicodes* carrying Bluetongue or Akabane viruses, which has been demonstrated around the globe (Ducheyne et al. 2007; Hendrickx et al. 2008; Sellers 1992).

Data on wind speed and direction used for those studies are seldom directly sourced from satellite observations, but are mostly the results of meteorological models. Hendrickx (2008) used data from the European Centre for Medium-Range Weather Forecasts (ECMWF) to compute wind density maps, based on forward trajectories. Wind trajectory analysis has also been applied to model the long-range movement of spores of plant pathogens, e.g. across the Torres Strait, Australia (Daly and Tran-Nguyen 2008).

While wind dispersal of vectors is an important environmental factor not to be neglected, suitable habitat conditions at the point of arrival need to be present for the establishment and consequent spread of a viable vector population. A current study undertaken at the Commonwealth Scientific and Industrial Research Organisation (CSIRO) is investigating the risk of introducing exotic vectors of Bluetongue to Australia (Australian Biosecurity CRC for Emerging Infectious Disease 2010). However, such investigations of wind-induced vector dispersal would go beyond the scope of this research.

4.2.8 Density of Population at Risk

While many arbovirus studies focus on vector habitat mapping, information about the location and density of a host population (human or animal) is essential to estimate the risk for disease transmission, which can only occur where vectors and hosts can interact. If suitable hosts as major food sources for female arbovirus vectors are absent, a viable vector population cannot be established. An even stronger host-vector link exists in the transmission cycle of BTV, where vectors breed exclusively in the dung of ruminant hosts.

Mapping the human and/or animal host population, which is in most cases the population at risk for infection, is therefore a necessary task in many epidemiological studies (Balk et al. 2006). Ideally, detailed data from a census, wildlife inventory, or livestock identification system are available (Allepuz et al. 2010). However, in sparsely populated regions, such as the rangelands of Northern Australia, or areas like Africa, where census data are often not available, population density models are the only source of information. These models are generally built based on satellite imagery and ancillary data (see Wu, Qiu, and Wang 2005 for a review). Similar to the Gridded Population of the World (GPW) dataset for humans (see Balk et al. 2006 for details and alternative approaches) a livestock density map has been produced by the Food and Agriculture Organisation (FAO) for global applications. The freely available Gridded Livestock of the World (GLW) dataset (Robinson, Franceschini, and Wint 2007) has been produced to provide population density estimates for cattle, buffalo, sheep, goats, pigs and poultry/chickens at a resolution of about 5 km at the equator, using statistical data and environmental variables. Since the GLW dataset is built on a model that uses similar bioclimatic variables as intended for this research, it will not be further considered as an additional variable.

4.2.9 Topography

The last factor that is discussed in this chapter is static in nature, but influences many of the other dynamic environmental factors. Topographic characteristics of a landscape, including landforms, elevation, surface orientation and slope often determine the boundaries of local habitats. This can be either directly by creating a physical barrier to species movements (e.g. through steep slopes or cliffs), or by influencing wind and temperature patterns. An increase in elevation is generally coupled with a decrease in temperature and this relationship has been used for example to model the distribution limits of tick-borne diseases (e.g. Altobelli et al. 2008), or Malaria (e.g. Mushinzimana et al. 2006; Shililu et al. 2003).

In the absence of climatic data, topographic attributes computed from Digital Elevation Models (DEM) can be used to model long term climatological variables, such as topographic radiation and temperature, wind exposure and even precipitation (Böhner and Antonic 2009). Other topographic attributes that may be relevant to vector habitats include modelled surface runoff, soil wetness and landforms classified as low depressions that are subject to flooding (Hengl and Reuter 2009; Wilson and Gallant 2000). Freely available elevation data for Australia that are suitable for regional scale applications have been recently reviewed by Hirt, Filmer, and Featherstone (2010) and include the Shuttle Radar Topography Mission (SRTM) DEM with a horizontal resolution of 90 m and the ASTER-DEM with a nominal resolution of 30 m.

4. 3 Summary

As described in Chapter 3, mapping environmental factors that define the focus of a disease enables epidemiologists to develop disease distribution models. Data from environmental and meteorological remote sensing satellites have many characteristics that make them particularly useful for this task, the most important of which are the large spatial coverage, and the low cost of data acquisition. Choosing the appropriate remote sensing instrument, which will be further explored in Chapter 5, is a critical part in this study and in any application of remote sensing. Following Chalke (2006), consideration should hereby be given to five major criteria:

1. spectral dimensionality and resolution available from the sensor;
2. spatial resolution of the sensor;
3. temporal resolution of the sensor;
4. historic, current and future data availability from the sensor; and
5. costs involved in acquiring and processing data.

What variables can be derived from a sensor depends largely on its spectral characteristics. Vegetation indices, such as NDVI for example require images from sensors operating in the red and near infrared spectrum, while accurate rainfall estimates will only be possible using a combination of active and passive radar systems. The spatial resolution determines which features may be discerned from the images and is therefore an important factor for analysis. For regional or continental studies, low to moderate resolution sensors (e.g. AVHRR or MODIS) provide sufficient detail to monitor larger scale environmental changes and climatic conditions that govern epidemiological processes. The high temporal resolution generally associated with these sensors (Thomson and Connor 2000) make them particularly useful for studies of vector or disease processes that are influenced by daily, weekly or monthly climatic and environmental trends. Higher spatial resolution images are often utilised for local studies. They are less suited for regional studies of dynamic processes over tropical regions, where it is unlikely that sensors like SPOT, ASTER and Landsat will provide daily or monthly cloud-free images. Besides the technical criteria, considerations of data availability from a sensor are also necessary. Consistent historic data coverage is required to build distribution models, and if these models are to be used to predict future disease distribution, then a sensor with guaranteed data continuity should be selected. Finally, the availability of quality controlled higher level products as well as cost aspects are important considerations in health studies. The fact that often a multitude of potential causal factors need to be investigated leaves little time to process each of the factors from the raw images and conduct extensive validation.

The review of remotely sensed environmental variables used previously in arboviral studies suggests that Vegetation Indices and Phenology, Land Surface Temperature and Rainfall are also potentially useful for the development of spatio-temporal BTV distribution models. These variables are freely available as ready to use data products, e.g. from MODIS and TRMM, and are constantly being refined and validated by a relatively large user community (discussed in Chapter 5). Other climatic variables, such as air temperature, humidity or soil moisture are also relevant for the survival of BTV vectors. However, these measures are generally derived empirically from the other primary variables, a process which introduces an additional layer of uncertainty, but does not necessarily create unique information. This view is supported by the lack of literature found on widespread application in disease modelling. Wind has been identified as important factor for studying dispersal of arbovirus vectors, but this would go beyond the scope of this research. More static land surface features, including topography, vegetation type and the built environment (not discussed here) may be used to delineate the general habitat boundaries of vectors and hosts. A final selection and computation of candidate variables for this study will be presented in Chapter 5.

CHAPTER 5

SELECTION OF STUDY AREA AND DATA

The previous chapters provided background information on Bluetongue virus and reviewed statistical approaches and remotely sensed variables used in epidemiological studies to model the distribution of vector-borne diseases.

This chapter first introduces the study areas in the Pilbara-Gascoyne region and the Northern Territory. It then identifies the required spatial and temporal resolution for this study, based on an examination of the virus surveillance dataset. Thereafter, a conceptual model is developed that includes the main hypothesised drivers for BTV activity and forms the basis for the selection of suitable environmental and climatic datasets. A number of remote sensing data products are assessed for their fitness to identify regional variations in vegetation, land surface temperature and precipitation. The chapter concludes with an overview of other ancillary datasets and software employed in this research.

5. 1 Study Areas

The analysis focused on two distinct regions of Australia, the Pilbara and Gascoyne regions in the Northwest of WA (Figure 5.1), and the entire area of the Northern Territory (Figure 5.5). This choice is mainly based on the relatively dense surveillance network as previously shown in Section 2.4.2.1. Other factors that make these areas ideal test cases to study the linkages between environmental factors and the distribution of BTV include the varying levels of enzootic and epizootic virus activity (see Figures 5.4 and 5.8), the incorporation of different climate regimes (from tropical to semi-arid and arid), and the potential for a southwards expansion of the virus that would pose a risk to the more productive livestock holdings in those areas. While the latter aspect has been the focus of much of the research on BTV in the eastern parts of Australia (Bishop, Barchia, and Spohr 2000; Bishop, Spohr, and Barchia 2004a, 2004b), similar studies have not been undertaken in the North and Northwest of the continent. Also, very few studies (e.g. Chalke 2006) have been conducted in this part of the world or under similar conditions (in terms of environmental, climatic and sample site characteristics) that assess the potential of using remotely sensed bioclimatic variables to model the distribution of arboviruses.

5.1.1 Pilbara and Gascoyne

The study area comprising the Pilbara and Gascoyne regions, in the course of this thesis simply referred to as the Pilbara, lies between longitudes 112° 55' and 121° 41'E and latitudes 18° 41' and 29° 51'S and covers an area of about 510,000 km^2. The Pilbara is best known for the prosperous resource industry and the beautiful rugged landscape that is also home to the ecologically important Chichester-Millstream and Karijini National Parks, the latter of which is the largest of its kind in WA. An overview of the region showing major landscape elements, roads and regional centres is provided in Figure 5.1.

5.1.1.1 Topography and Hydrology

The study area (Figure 5.1) is bounded by the Indian Ocean to the North and East, the Murchison River Mouth to the South and the Great and Little Sandy Deserts to the East. Rising from this ancient landscape, the most prominent features are the mountainous plateaus of the Hamersley and Chichester Ranges, where relative relief between the plains and some crests can reach 600 m, but is usually about 200 m (Payne, Holman, and Mitchell 1988). Most water courses, including the large Fortescue, Ashburton, Gascoyne and Murchison rivers, are ephemeral and are fed principally by summer rain. After heavy rain events, the barren landscape is unable to hold the water, which runs off rapidly from the large catchment areas and results in extensive flooding of the vast and flat alluvial plains. While flooding is only temporary, some permanent pools in the dry river beds as well as flooded clay pans provide a source of water for livestock year-round. Along the northern coast, extensive sandy plains with some longitudinal dunes characterise the landscape as well as broad clay plains with numerous clay pans. In the eastern reaches of the region, comprising the Canarvon Basin, slightly sloping sand plains are the predominant landform (Payne, Curry, and Spencer 1987). The Great Sandy Desert to the East of the region provides a natural barrier between the Pilbara and the Kimberley, a region with higher levels of rainfall and arbovirus activity (Animal Health Australia 2001). Means of introduction other than natural flight of vectors (e.g. through livestock movement, or airborne dispersal of vectors) are therefore the more likely cause of the BTV outbreaks in the Pilbara.

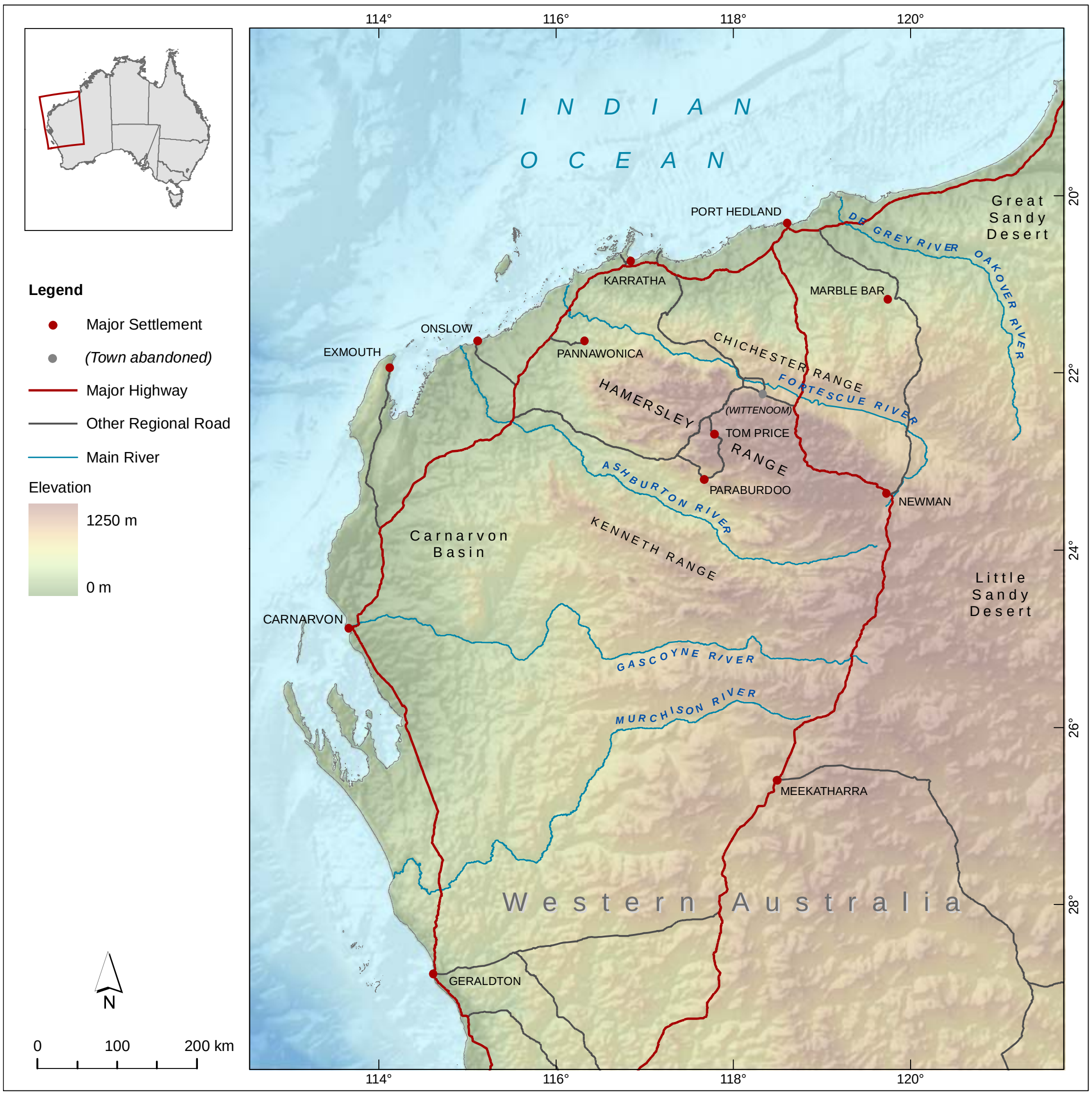


Figure 5.1 Topography of the Pilbara-Gascoyne region

5.1.1.2 Climate

The Pilbara and Gascoyne lie in Köppen-Geiger zones *Hot Arid Steppe* and *Hot Arid Desert* (Peel, Finlayson, and McMahon 2007). Most of the average 250–400 mm rain per year falls between December and June and originates from cyclonic activity and thunderstorms. Winter rain is infrequent and statistically only occurs every 3 out of 5 years. Average summer temperatures are very high with mean maxima often exceeding 40°C and minima of 25°C on average, while winters are mild (Suijdendorp 1980; Van Vreeswyk et al. 2004). Figure 5.2 shows the long-term averages of rainfall, minimum and maximum temperature for three locations in the study area.

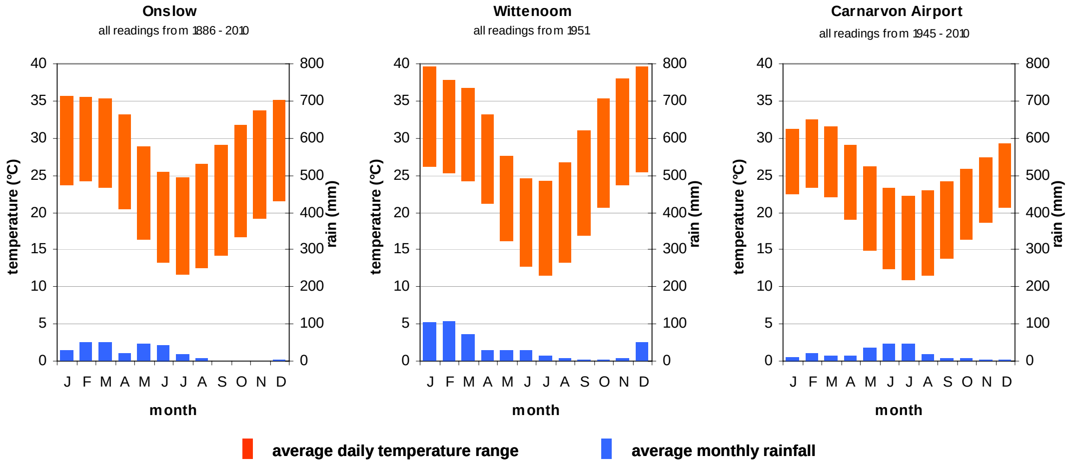


Figure 5.2 Average daily temperature range and monthly rainfall from long-term weather observations at Onslow, the now abandoned town of Wittenoom, and Carnarvon

5.1.1.3 Soils, Vegetation and Land Use

The area inland from present day Karratha was first assessed for its pastoral potential in 1861 by Frank T. Gregory (Van Vreeswyk et al. 2004), before state-wide vegetation surveys were conducted by Gardner (1928) and Beard (1975a, 1975b) at scales of 1:4,800,000, and 1:1,000,000, respectively. Later, a number of rangeland surveys were commissioned by the Department of Agriculture to map topography, soil and plant communities in different land systems (Tille 2006) at a scale of 1:250,000, e.g. for the Pilbara (Van Vreeswyk et al. 2004), the Ashburton (Payne, Holman, and Mitchell 1988) and Gascoyne River (Wilcox and McKinnon 1970) catchments, and the Carnarvon Basin (Payne, Curry, and Spencer 1987).

The type of vegetation predominating in an area depends on the landform and soil type. As summarised by Suijdendorp (1980) and Tille (2006), most of the hilly terrain and stony inland flats are dominated by hummock grasslands with different types of spinifex grass and low mulga woodlands. Of the various types of spinifex, some of the softer types are palatable to livestock. Denser perennial grasslands are found on the flood plains along the major creeks and water courses, with native grasses being increasingly replaced by Buffel and Birdwood grasses introduced from India. The coastal alluvial plains have soft spinifex grasslands on the loamy soils while clay soils support tussock grasslands. Hard and soft spinifex grasslands are found on the coastal sandy plains. While about 65% of the resource rich study area are pastoral properties, some areas, particularly in the Hamersley Ranges are too rugged and the vegetation unsuitable for pastoral purposes (Payne, Holman, and Mitchell 1988). Flood plains along the rivers as well as some of the coastal plains bear the highest carrying capacity for livestock. Figure 5.3 provides an overview of pastoral areas and other land uses in the study area.

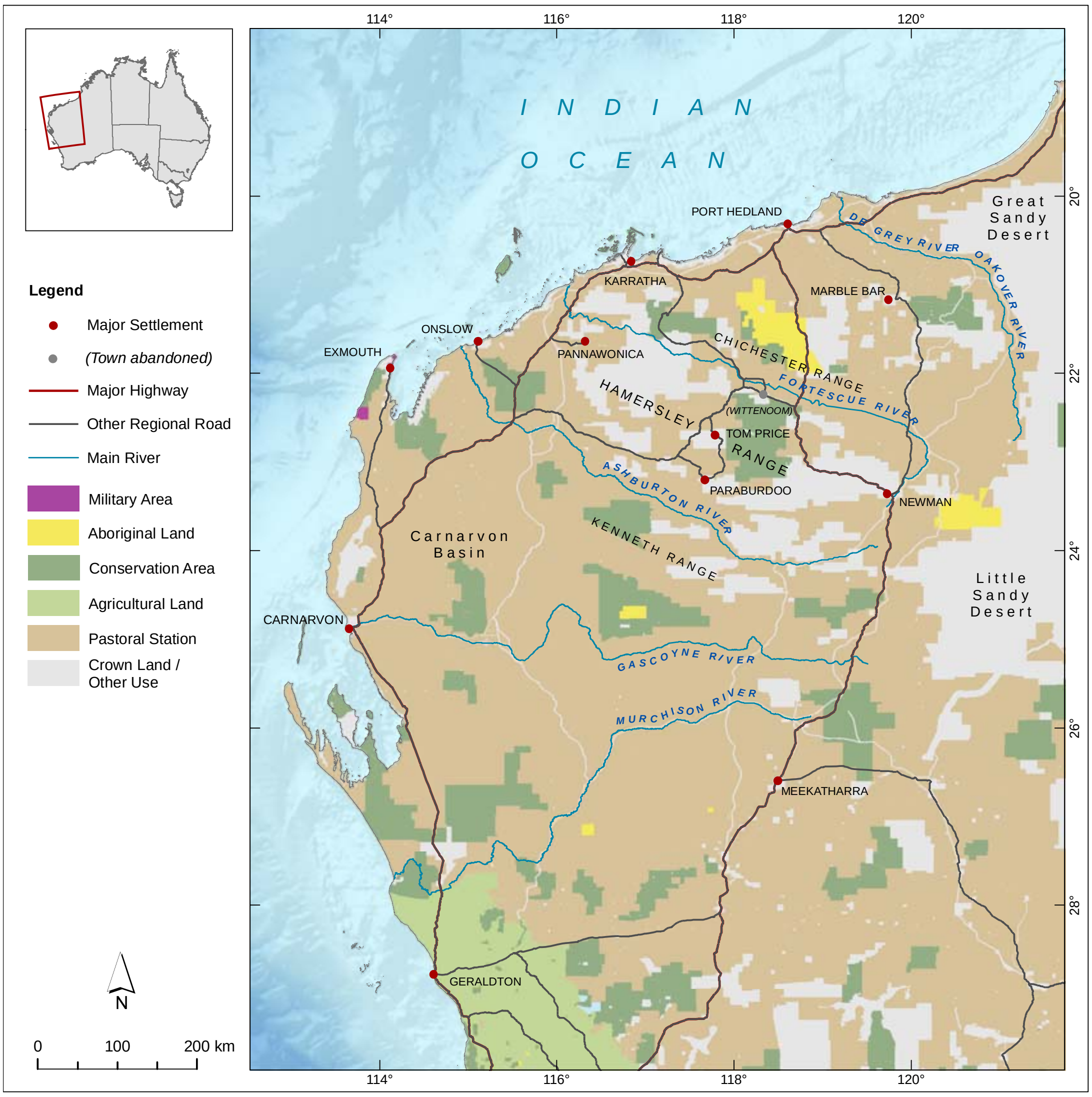


Figure 5.3 Extent of pastoral properties, conservation areas, aboriginal land and crown land in the Pilbara-Gascoyne region. Note that pastoral properties managed by aboriginal communities are mapped as pastoral stations

5.1.1.4 Host and Vector Activity

Bluetongue is epizootic in this area, and after an anecdotal outbreak in the late 1970’s no evidence of virus presence could be found for several years. However, the large increase in cattle numbers in the region since the 1990's (as earlier shown in Figure 2.3), which provide reservoirs for dung breeding BTV vectors like *C. brevitarsis*, has likely contributed to an outbreak in 2000. As shown in Figure 5.4, the number of infected properties increased initially, but this might partly be explained by an intensification of surveillance activities.

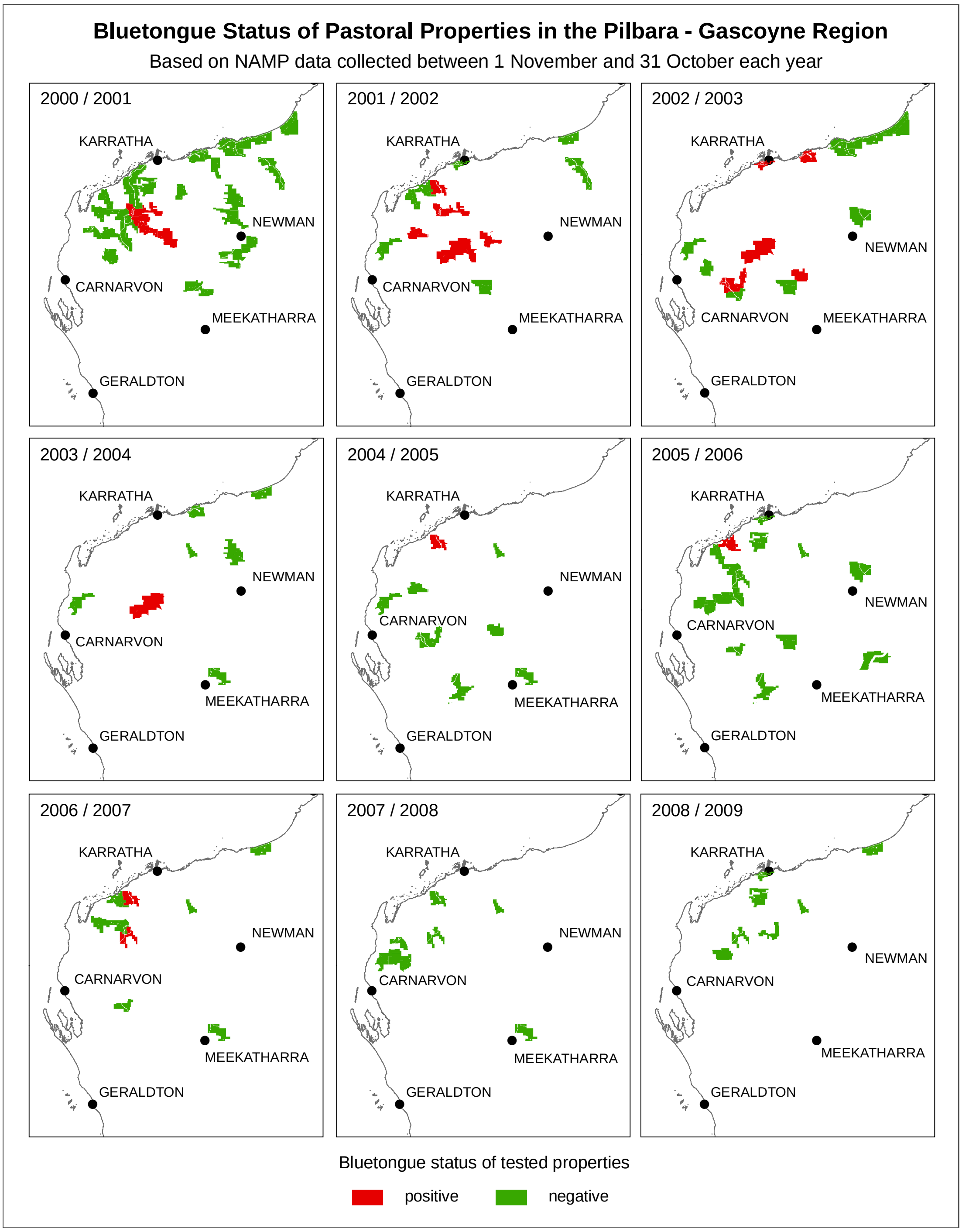


Figure 5.4 Overview of BTV activity on pastoral properties in the Pilbara - Gascoyne region tested between November 2000 and October 2009

A subsequent steady decline in virus antibody detections over the years from 2002 to 2006 resulted in the declaration of the Pilbara as BTV-free in 2009, two years after the last detection. However, in August 2010, the detection of BTV antibodies in cattle from a station near Onslow required the reintroduction of the BTV infected zone in parts of the Pilbara. This is outside the period considered in the present research and therefore not shown on the map in Figure 5.4. Also in 2010, a single specimen of the competent vector *C. wadai* has been trapped near Karratha for the first time. While this development is not as dramatic as the potential distribution of the vector modelled by Standfast and Maywald (1992) under a climate change scenario, it raised awareness for the risks that a southwards expansion of the species might pose on the more productive livestock holdings in the state. It has therefore become a major motivation for NAMP, besides fulfilling international OIE requirements, to provide early warning of any expansion of the vector's habitat range.

5.1.2 Northern Territory

The whole Northern Territory covers about one sixth of the Australian landmass, which equates to an area of 1.35 million km^2. Pastoralism is the major land use throughout much of the Northern Territory with beef cattle being the main enterprise. Aboriginal land use and conservation areas are also significant, including the Arnhem Land, Kata Tjuta, and the Kakadu and Litchfield National Parks.

5.1.2.1 Topography and Hydrology

As shown in Figure 5.5, the Northern Territory is a country of gentle to moderate relief, consisting mostly of plains that rise from sea level at the North Coast to about 590 m near Alice Springs, before falling again towards Lake Eyre (Perry 1960). Most of the more rugged hilly and mountainous landscape is found in the North. This includes the rugged dissected plateaus ranging from Arnhem Land southeast into QLD, as well as the area contiguous with the Kimberley region in WA. The large catchments of the Victoria, Daly and Roper Rivers are found in this region. In the South, the McDonnell Ranges, which extend in east-west direction over half of the width of the NT at the same latitude as Alice Springs, are the only large mountain mass. While the highest mountain of the Territory, Mt Zeil (1531 m above sea level) is found here, the relative relief, at less than 600 m, is generally low.

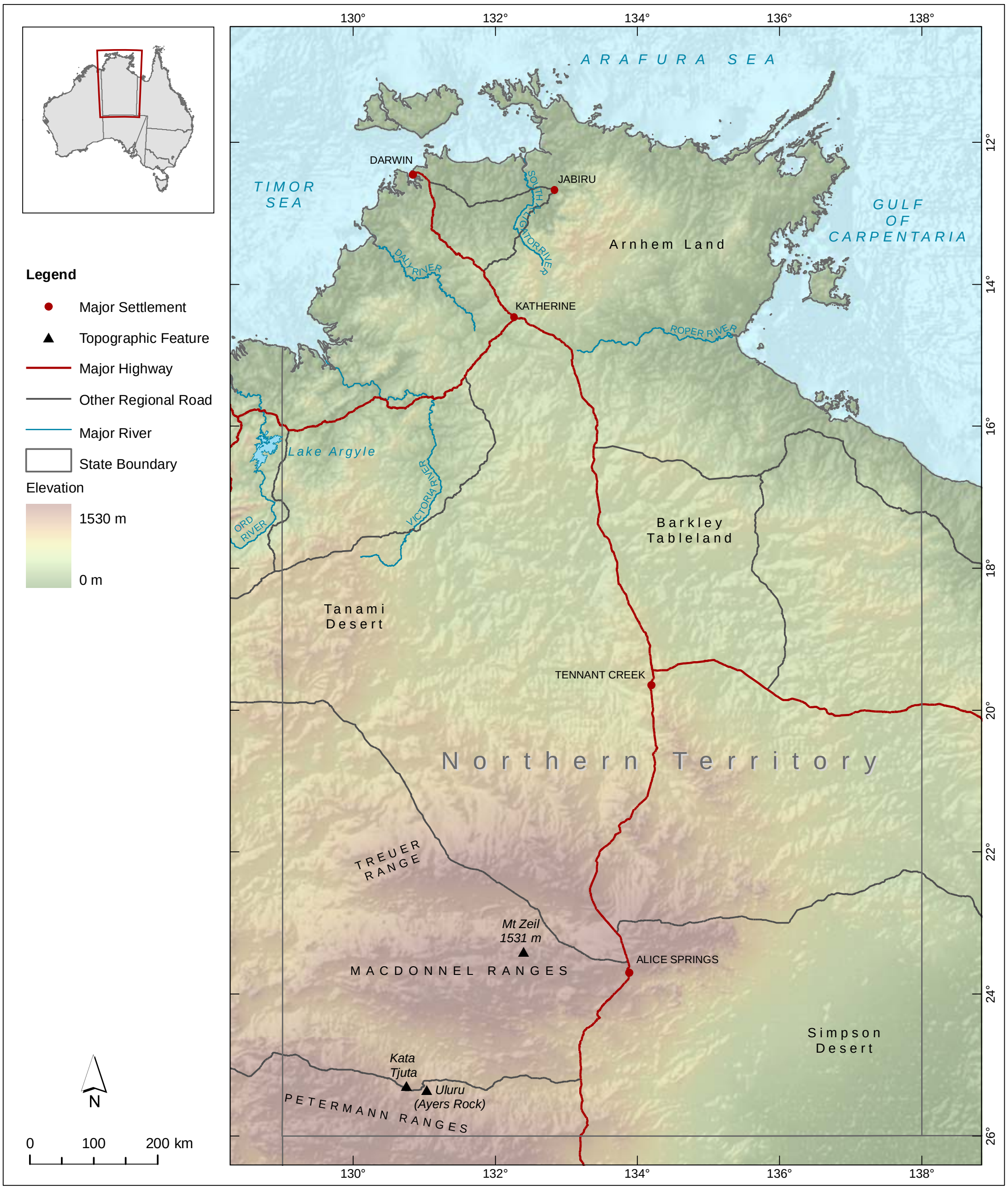


Figure 5.5 Topographic overview of the Northern Territory

5.1.2.2 Climate

The climate of the Northern Territory is under the influence of the north-west monsoon with a summer wet season and a winter dry-season. From north to south the climate changes from Köppen-Geiger zones *Tropical Savannah* to *Hot Arid Steppe* and *Hot Arid Desert* (Peel, Finlayson, and McMahon 2007), with annual rainfall ranging between 250-500 mm in the South and 1000-1700 mm in the North. Most rain falls between November and April.

While it is warm in the North throughout the year, frost can occur in the arid interior as far north as Alice Springs (Wilson et al. 1990). Long-term average conditions are shown in Figure 5.6.

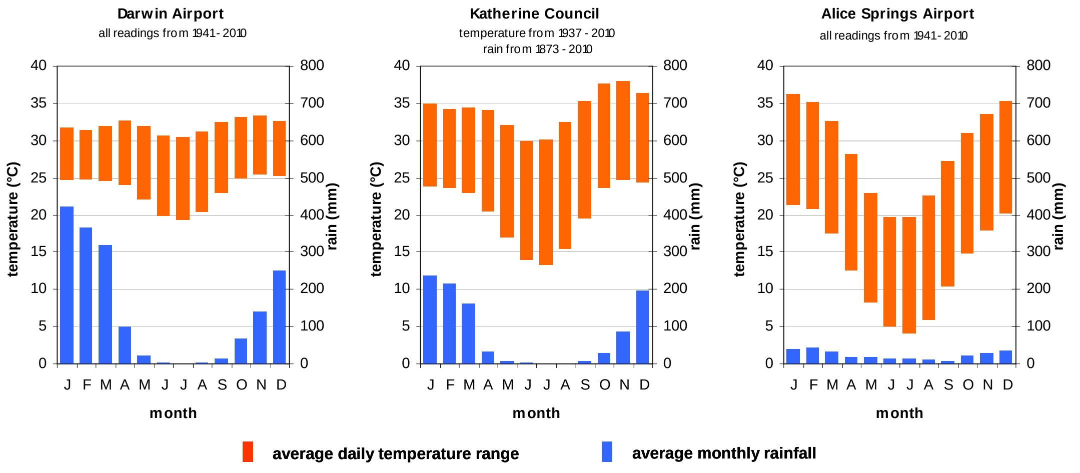


Figure 5.6 Average daily temperature range and monthly rainfall from long-term weather observations at Darwin, Katherine, and Alice Springs

5.1.2.3 Soils, Vegetation and Land Use

Vegetation in the Northern Territory ranges from tussock grasslands, shrublands and low open woodlands in the South to tall woodland with patches of monsoon rainforest in the North. A territory-wide vegetation map at a scale of 1:1 million has been compiled by Wilson et al. (1990). More detailed land system maps are available at a scale of 1:250,000 for the northern parts of the NT. A territory-wide vegetation map at nominal scale of 1:100,000 has been proposed during a workshop in 2008 (Brocklehurst et al. 2008), but has not yet been completed.

Perry (1960) divides the NT ‘vegetationally’ into two halves: The northern half, where rainfall exceeds 380 mm (15 inch) and Eucalyptus species are predominantly found, and the southern half with less that 380 mm annual rainfall, where Eucalypts are virtually absent. Treeless grasslands on heavy clay soils are found in both parts, but they are more extensive in the North. Particularly the Barkley Tableland and the Victoria River District are home to ephemeral grass species that provide nutritious stock fodder during and after the wet season. Later in the dry season, cattle are forced to feed on the less nutritious short perennial grasses. In the central and southern part, vast areas are characterised by spinifex grasslands with scattered shrubs and low trees that cover the sand plains, dune fields and stony hills. About 48% of the

Northern Territory is leased for pastoral purposes (Wilson et al. 1990), as also shown in Figure 5.7. Only the drier regions covering the Tanami and Gibson deserts in the South as well as the Arnhem Land and the National Parks in the North have been considered unsuitable for pastoralism and returned to their traditional owners or protected for conservation purposes. Some intensive horticulture occurs particularly in the North in the regions around Darwin and Katherine.

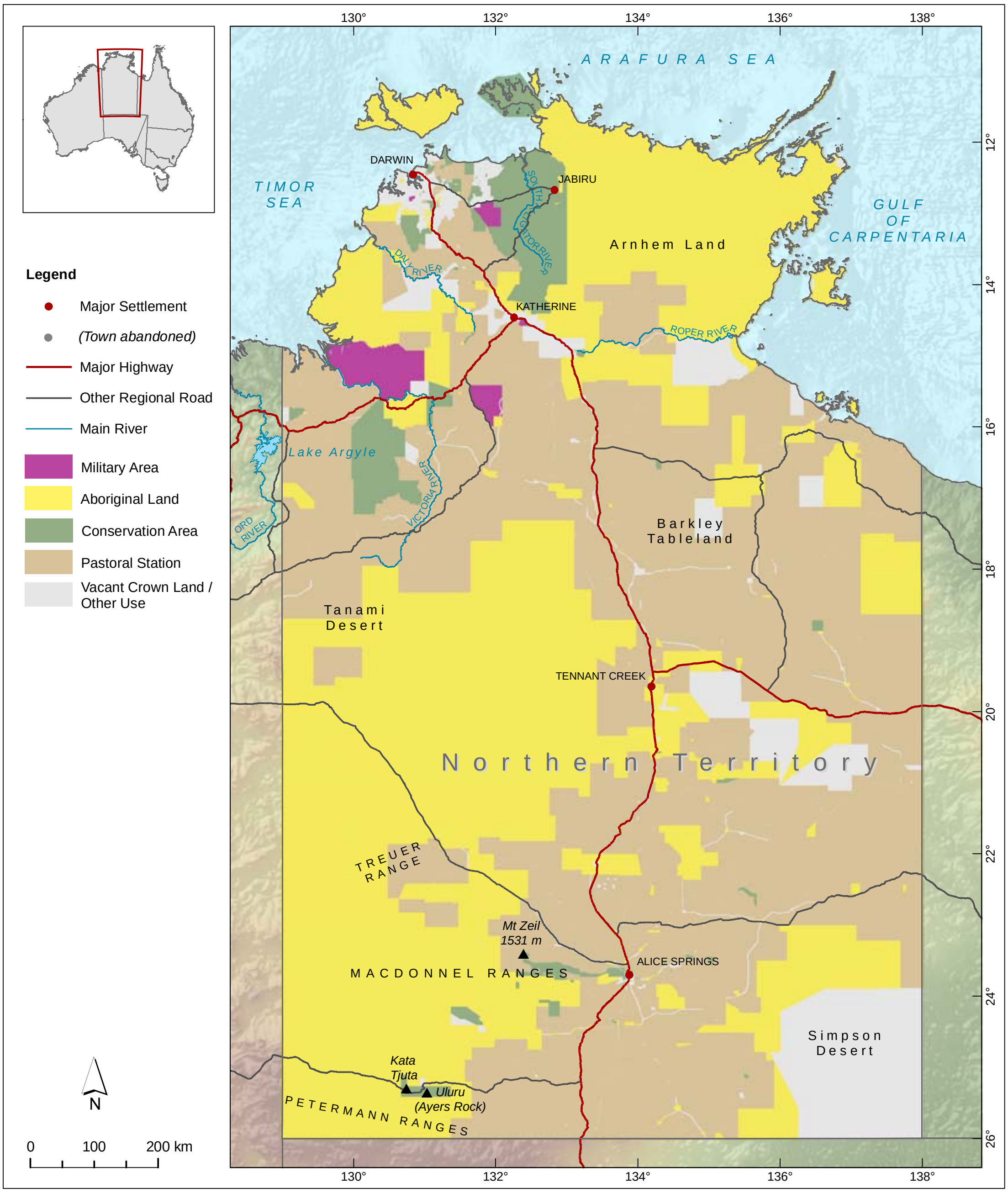


Figure 5.7 Extent of pastoral properties, conservation areas, aboriginal land and crown land in the Northern Territory. Note that pastoral properties managed by aboriginal communities are mapped as pastoral stations

5.1.2.4 Host and Vector Activity

Bluetongue is endemic north of 13° latitude, and epidemic south of that line with occurrences in Katherine and the Victoria River District in some years. The peak of activity is typically between January and May, but late seroconversions have occurred between August and September (Animal Health Australia 2001).

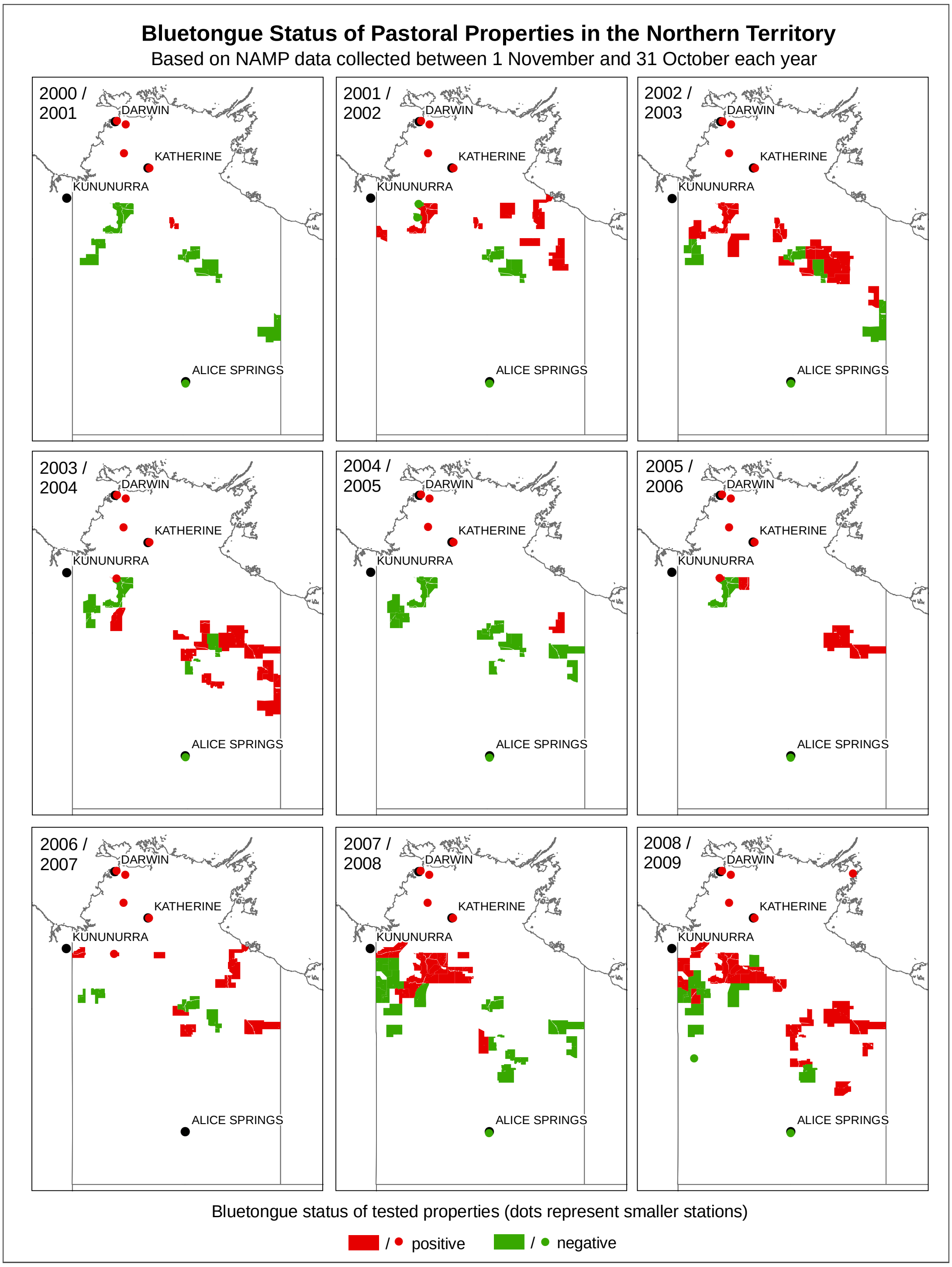


Figure 5.8 Overview of BTV activity on pastoral properties in the Northern Territory tested between November 2000 and October 2009

Surveillance activities focus on the detection of new strains of BTV and other viruses as well as vector incursions from South East Asia on the prevailing winds. Several BTV serotypes found in Australia have been isolated from sentinel cattle at the Beatrice Hill research station north of Darwin. Figure 5.8 shows the varying levels of BTV activity throughout the years 2000 to 2009.

5. 2 Conceptual Model and Spatio-temporal Data Requirements

A conceptual model is the first stage in the development of a predictive distribution model (Guisan and Zimmermann 2000). In this case the concept represents a simplified view of the natural complexity of virus ecology. After defining the characteristics of the response variable, i.e. answering the question *What shall be predicted?*, all environmental factors that hypothetically influence the outcome of the response (e.g. virus presence or absence) may be included in the concept. For parsimony, and because the aim of this research is not to develop a complex disease model, a set of the most promising environmental factors is being selected for the development of predictor variables. Based on this conceptual model, an assessment of suitable data products can then be conducted. Therefore, considerations need to be given to the required minimum spatial and temporal resolution, which is governed by the seasonality of virus activity and the characteristics of the virus dataset (sampling frequency, spatial reference unit), both of which are discussed below.

5.2.1 Defining the Response Variable

Data on the primary phenomenon of interest (i.e. the response variable), whether it be the vector or the disease, are required to build a statistical model of its relation to the secondary (or explanatory) variable (e.g. temperature or rainfall) (Curran et al. 2000). These data may come in a variety of formats. Epidemiological models have for example been developed based on disease prevalence (Kleinschmidt et al. 2000), intensity of infection (Clements, Moyeed, and Brooker 2006), vector abundance (Altobelli et al. 2008; Baylis et al. 1998), or presence and absence of a virus (e.g. Boyer, Ward, and Singer 2010; Calvete et al. 2009; Chalke 2006). As part of the surveillance activities under the NAMP, a series of data related to the presence of arboviruses are recorded, such as serological status of cattle or number of potential arbovirus vectors. These measures are potential response variables to be predicted for either a certain location or aggregated over an area. Hence a decision needs to be made based on the NAMP data on the type of response variable used in this study as well as the most appropriate spatial and temporal support that influences the outcome at each location similarly (Curran et al. 2000).

Vector trapping is conducted once every one to two months at selected sample sites, where the number of specimens for each species is recorded. However, while trapping methods are being constantly improved (Bishop et al. 2006), it has been acknowledged by entomologists that the number of caught insects is not necessarily representative for vector abundance, due to various factors reducing the efficiency of the utilised light traps (Bishop et al. 2000). This, together with the fact that vector sample sites are very widely dispersed over the study areas, excludes vector presence and absence or abundance as response variables.

Seroconversion data from sentinel herds are usually collected at regular intervals from once a month to twice annually. Complimentary serological surveys are conducted less frequently on an ad-hoc basis. Cattle are often only accessible once a year during mustering, when they are driven to the yards where they can be tested by veterinary officers. Often, this rare opportunity for testing is missed due to limited human resources and the inaccessibility of some properties. Both approaches deliver information about the presence of antibodies in the blood of tested cattle and hence about BT presence and absence. Only for particular sites, viruses are isolated to determine the serotype (Melville 2004). It was therefore decided on using the presence and absence of BTV as the response variable, regardless of the serotype and without differentiating between data from sentinel herd and serological surveys.

Knowledge about the timing of infection is vital for the identification of environmental risk factors, which may have contributed to the abundance of vectors and hence the increased risk for transmission. At sites with sentinel herds that are tested monthly, the range of possible infection dates is relatively narrow. However, for the majority of sites, where serological surveys are conducted once a year, the timing of infection can only be estimated with an accuracy of several months. BTV antibodies can still be detected for several months post infection or even for the host’s life time (Mertens et al. 2009), and as Figure 5.9 demonstrates, this may be well after the annual peak of virus activity. The timing of serological surveys at

Glenflorrie Station in the Pilbara has been related to a time series of NDVI, which is an indicator for vegetation growth, soil moisture and humidity and therefore likely to be related to the peak of vector abundance and activity. This follows from the observation that cattle were tested seropositive in August 2006 after a higher than usual NDVI curve during the preceding wet season.

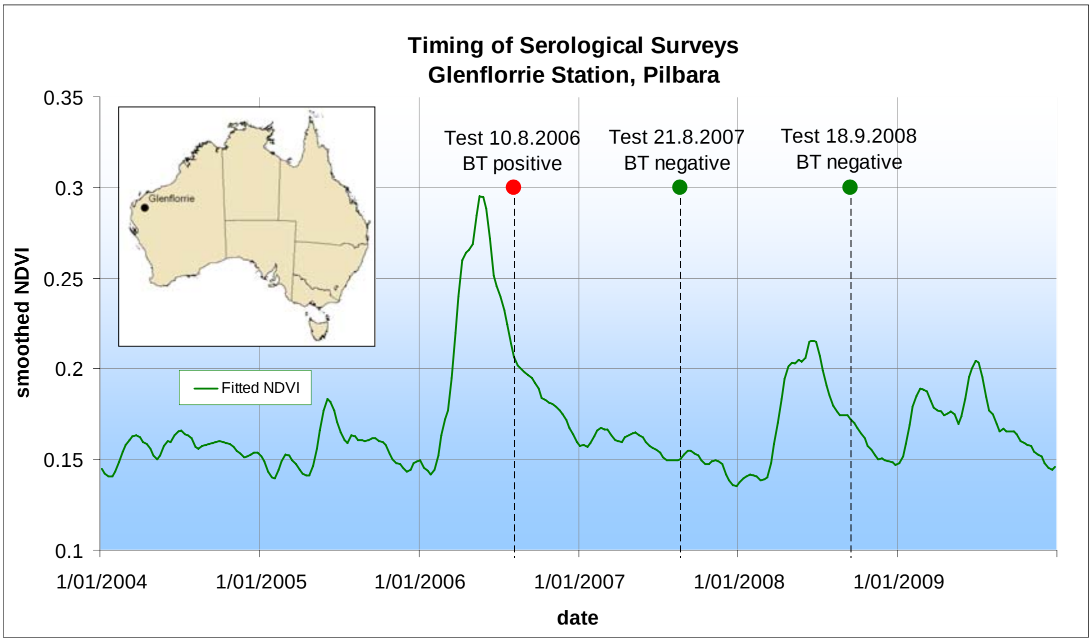


Figure 5.9 Relationship between timing of serological survey and the peak of seasonal vegetation greenup

The temporal support has therefore been chosen to be a full season, from the onset of virus activity at the beginning of the wet season in one year to the onset of the wet season in the following year. To be consistent across space and time, and after expert consultation with Lorna Melville, the NAMP coordinator for the NT (personal communication, September 29, 2008), as well as exploratory analysis of the NAMP data, a season was defined as lasting from the 1st of November to the 31st of October the following year. Analysis of three sentinel herds in the NT showed that seroprevalence (i.e. the number of cattle that tested positive based on serology) was lowest in September and October (Figure 5.10). New infections from November onwards are most likely related to the upcoming wet season with an increase in humidity. Consequently, seroconversion data are aggregated for each sample site over the specified period from November to October and summarised as presence and absence of BTV. Blood samples originating from the recruitment of sentinel cattle are excluded from the analysis. The rationale behind this is that cattle selected for the sentinel herd have not been previously exposed to high virus activity and would therefore induce bias towards BTV negative samples.

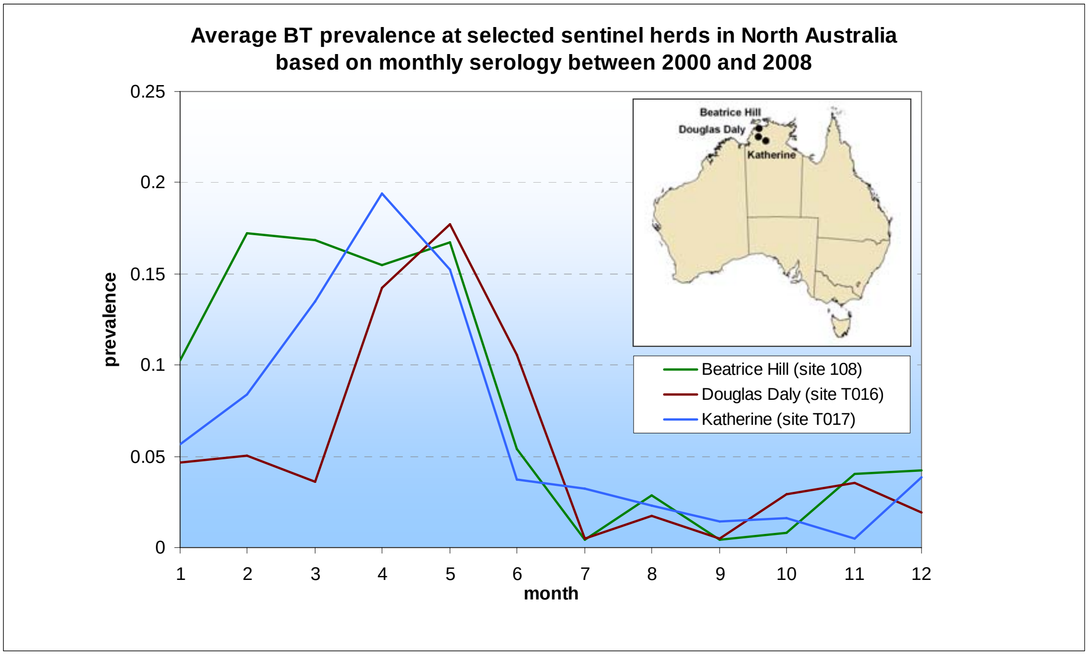


Figure 5.10 Average monthly BTV seroprevalence at three sentinel herds in the Northern Territory between November 2000 and October 2008

On a spatial scale the support has to be assumed to be as large as the whole pastoral property or research station, as no detailed location information is usually recorded by the NAMP operators. Seasonal environmental conditions need to be assessed for the whole station area in order to statistically analyse the relationship between presence and absence of BTV on a station and the environment. However, possible strategies for identifying areas on a station that are more likely to carry hosts and vectors are discussed in Chapter 6.

5.2.2 Environmental Factors Relevant to BTV

Based on the ecology of BTV, crucial environmental factors influencing vector and host populations and therefore the occurrence and abundance of the virus have been identified in Chapter 2. These factors have been extracted from literature and the hypothesis tested in this thesis is that they are related to BTV activity in Northern Australia. Of particular interest are the environmental conditions defining the habitats of the vector *C. brevitarsis*, due to it having the most widespread distribution of all known BTV vectors and its relatively well-known ecology (compared to other species). In Chapter 4, data from a variety of satellite remote sensing platforms were discussed, that are suitable for the development of spatio-temporal bioclimatic variables related to these environmental factors.

Based on the findings of the previous chapter, a conceptual model has been developed from a reduced set of bioclimatic variables (see Figure 5.11). Criteria for the selection included the known relevance to BTV occurrence, previous application within distribution models at regional to global scale, as well as the level of preprocessing involved to derive the variable. Priority was given to variables that are available as atmospherically corrected data products at low cost, to reduce the amount of data processing requirements, and to those that can act as surrogates for other important factors. For example, the use of land surface temperature has been preferred over air temperature, which is usually derived from a range of remotely sensed factors (see Section 4.2.2.2) and cannot be validated within this study due to the lack of suitable ground data. Similarly, although air humidity is vital for vector survival, its derivation from other factors like NDVI and land surface temperature does not add any additional information over these variables. Instead, errors in the input dataset may be propagated or even amplified. Also indicated in the conceptual model are the possible remote sensing platforms, based on the findings from the previous chapter.

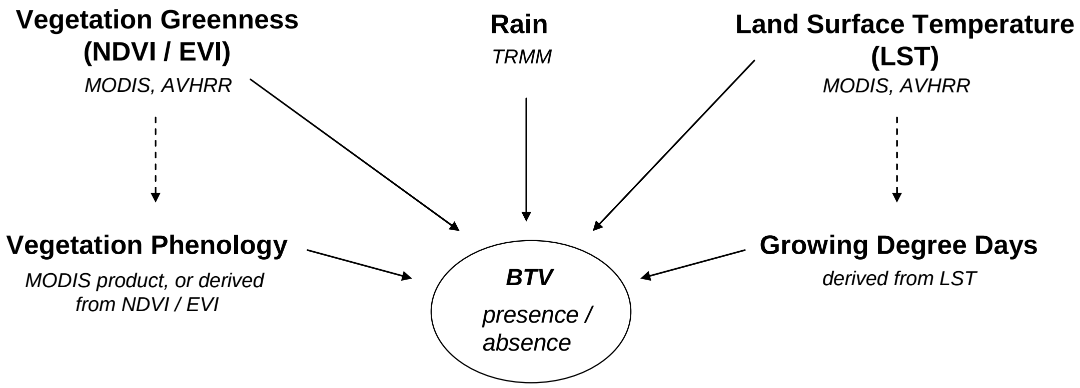


Figure 5.11 Simple conceptual model of factors related to BTV activity in Northern Australia

5.2.3 Spatial and Temporal Resolution Requirements for Environmental Data

The target spatial and temporal supports for the BTV occurrence data have been defined previously. Accordingly, the size of a pastoral property will define the minimum scale for the analysis and model building processes. The environmental variables will necessarily have to be aggregated on a cattle station level. It is however important to preserve regional features as well as the environmental variability, which both have an effect on virus transmission cycles. The rationale behind that is, once the model parameters have been determined, the aim is to predict the probability of BTV presence as a continuous surface over the entire study area. Annual prediction maps are to be produced, based on the environmental variables of a particular year. In order for the prediction maps to be useful for decision making, a pixel must be small enough to be associated with features on the ground, e.g. to identify paddocks that might be a higher risk, or to delineate areas that are best suited for vector trapping.

A regional scale is therefore considered adequate for this study, with resolutions ranging from 500 m to 1000 m for vegetation and land surface temperature variables. Remotely sensed area-wide rainfall measurements are generally available at lower resolutions, e.g. 25 km from TRMM. While this is not ideal for depicting small scale rainfall events, it provides information on regional rainfall patterns and a pixel would still be smaller than the average size of a pastoral property (about 1,850 km^2 in the Pilbara – Gascoyne region, and 2,800 km^2 in the Northern Territory.

Similar research that has been undertaken on a regional scale include the study by Tatem et al. (2003), where the low spatial resolution AVHRR sensor was utilised for monitoring of environmental variables which successfully predicted the distribution of the BTV vector *C. imicola*. Hay et al. (1998) also demonstrated the capacity of regional monitoring with AVHRR for predicting mosquito-borne malaria seasons. The LST and VI products from MODIS at resolutions of 1000 m and 500 m respectively, have been used by Altobelli et al. (2008) to predict the distribution of ticks in Northern Italy. Chalke (2006) has similarly demonstrated the application of MODIS derived NDVI variables for analysis of MVEV in Northwestern Australia.

As previously defined, the minimum temporal resolution of 12 months for exploratory data analysis and model development is governed by the virus dataset. Consequently, environmental conditions or changes to the environment over the same period need to be captured and distilled into seasonal variables, while preserving the characteristics of the season (see Chapter 6). Not all 12 months will be equally important, however the period during and after the wet season, when the highest levels of virus activity are recorded, is of particular interest, as are the winter months where temperature is the crucial factor for vector survival.

Bioclimatic parameters associated with habitat dynamics have diverse temporal characteristics. Some of them such as climatic factors or related changes of surface conditions (e.g. flooding, or surface temperature) are highly dynamic in time, while others such as vegetation might change more slowly. Different temporal resolutions are therefore needed for each of the factors in order to accumulate or average measurements accurately over time (see Table 5.1 below).

Table 5.1 Required temporal resolution for the remotely sensed climatic and environmental datasets

Factor	**Aggregation method**	**Required temporal resolution of source data**
Rainfall	Accumulation of rainfall	Hourly to daily
Land surface temperature	Average minimum, maximum and mean temperatures	Half-daily to capture day and night temperatures
Growing degree days	Accumulation of average daily temperature	Half-daily to capture day and night temperatures
NDVI/EVI	Maximum NDVI/EVI	Weekly to monthly
Vegetation phenology	Extraction of seasonal phenology measures from NDVI/EVI time series	Weekly

Particularly during the wet season, there is a reduced possibility of obtaining images over tropical areas that are not significantly affected by atmospheric conditions such as cloud cover. In order to gather high quality data at the required resolution for this project, images need to be obtained at a higher frequency. However, if the target variable is an average or accumulated value over a certain period, e.g. the mean monthly night temperature, it might not be necessary to acquire daily images and then determine the average temperature range. A number of data products exist, for example for MODIS, that provide quality controlled 8-daily or monthly environmental data, which reduce the resources required for data acquisition and processing significantly.

5. 3 Selection of Remote Sensing Instruments and Data Products

To facilitate the identification and analysis of spatio-temporal relationships between BTV dynamics and earth surface and atmospheric conditions the data reflecting these conditions need to meet specific requirements. Data must be continuously available for the whole study area. Their spatial and temporal resolution must be appropriate to this study as defined in the previous section.

5.3.1 Selection of Remote Sensing Platforms

Based upon the definition of the spatial and temporal resolution requirements of this project, the range of possible platforms is reduced to AVHRR, MODIS, and for rainfall variables, to TRMM and CMORPH precipitation estimates.

Before the availability of MODIS, many regional studies investigating correlations between environment and BTV or Malaria have utilised data from AVHRR. However, the big advantages of MODIS, such as the higher spatial resolution, enhanced stability of both spectral and geolocational accuracy (Huete et al. 2002; Wolfe et al. 2002), as well as the large variety of freely available atmospherically corrected data products, make it the preferred instrument for this project. Although the future supply of MODIS and MODIS-like data products through continuity missions is a major strength, a limitation of MODIS is the smaller archive of historical data. Imagery from the Terra platform only dates back to February 2000 and MODIS images from the Aqua satellite are available from August 2002 onwards. BTV surveillance data for this project extends from before 2000 till present so the availability of historic MODIS imagery limits the full use of available virus data for developing and testing models. Nevertheless, the MODIS sensor on board the Terra satellite meets all of the requirements for this project, and will therefore be utilised for monitoring of vegetation and land surface temperature in Northern Australia between 2000 and 2009.

A review of candidate data products from the MODIS sensor is provided in the following section, followed by a comparison of rainfall estimates using the TMPA and CMORPH methods, with rain gauge data.

5.3.2 MODIS Data Products

MODIS offers a range of daily, 8-daily, 16-daily and monthly standard data products at native spatial resolutions of 250 m, 500 m and 1000 m, and different processing levels (Justice et al. 2002). Level one (source data) and level two data (derived geophysical variables) are geolocated to latitude and longitude. Level three products deliver temporally and or spatially manipulated geophysical variables and level four products are either model output or results from analyses of lower level data products. Both are usually provided as integerised values in an equal-area Sinusoidal projection in tiles measuring about 1113 km by 1113 km (Wolfe, Roy, and Vermote 1998). All data products are delivered in a hierarchical data format (HDF) and can be obtained at no cost from the Land Processes Distributed Active Archive Centre (LP DAAC). The current generation of MODIS products is termed Collection 5, which, depending on the product, offers several advantages over previous collections (Ganguly et al. 2010; Wan 2008) and is therefore used throughout this project.

Datasets of major interest for this project are those from which the vegetation indices (NDVI and EVI) and subsequently, phenological parameters can be extracted, as well as data on land surface temperature. In view of the need for a continuous time series from which phenology and growing degree periods can be derived, 8 –16-daily images composited from cloud-free daily images are preferable.

5.3.3 Vegetation Indices and Vegetation Phenology from MODIS

Vegetation monitoring with MODIS can be carried out in two ways, either using the dedicated Vegetation Index and Vegetation Dynamics products or calculating these two parameters from surface reflectance data. The following sections explore both avenues in order to find the most appropriate solution for this project.

5.3.3.1 MODIS/Terra Vegetation Indices 16-Day L3 Global 250 m

The MODIS Vegetation Index product (MOD13Q1) provides 16-day composites of the NDVI and EVI indices (see section 4.2.4.2) at a spatial resolution of 250 m. It is produced from gridded level two daily surface reflectance data corrected for molecular scattering, ozone absorption, and aerosols (Vermote, El Saleous, and Justice 2002). While the red and NIR bands included in NDVI and EVI are natively available at a 250 m spatial resolution, the 500 m blue band that is included in EVI for aerosol resistance, needs to be resampled to the higher resolution (Huete et al. 2002). Prior to compositing the NDVI data, a filter selects higher quality, near-nadir observations that show the least distortions, and are free from clouds and cloud shadows, from the 16 days of observation. This overcomes the effect introduced by a whiskbroom scanner like MODIS that the pixel size on the ground increases with the viewing angle.

The goal of compositing methodologies is to select the best observation, on a per pixel basis, from all the retained filtered data, to represent each pixel over the 16-day compositing period. Depending on the number of good quality pixels after screening, the compositing algorithm chooses between two approaches. If valid pixels are available for at least two out of 16 days, the algorithm compares the two highest NDVI values after filtering and selects the observation closest to nadir with the highest observed NDVI value, using the constrained-view angle-maximum value composite (CV-MVC) approach. In all other cases, i.e. when one or more pixels over 16 days showed cloud cover, mixed clouds or were adjacent to clouds, the largest NDVI value over the 16-day period is selected, using an approach called maximum value composite (MVC) (Didan and Huete 2006).

The VI values in the MOD13Q1 product are accompanied by auxiliary information on different parameters, such as aerosol quantity and likelihood of snow cover, as well as an overall indication of the usefulness of each data point. MODIS NDVI was designed to be compatible with AVHRR NDVI products and therefore provides continuity for time series used in historical applications. Thus it was initially considered for this research. However, assessment of the data showed that the land/water mask used to clip the dataset and exclude ocean pixels, was shifted eastwards by up to 4 km. As a result, relatively large areas along north south oriented coast lines were missing (Figure 5.12). This error which was not previously known to the research community has been reported to the MODIS Land Science Team (K. Didan, personal communication, November 13, 2008), and is now documented on the MODIS Land Quality Assessment website (NASA Goodard Space Flight Centre 2009). However, it is not expected to be fixed before the next major update cycle of MODIS products due in late 2010. For this reason, although the product was initially the preferred option, an alternative dataset was chosen to derive the vegetation indices. Since it has been shown that viewing angles have a large impact on the reflectance from the vegetation canopy and hence the resulting vegetation indices, a dataset was investigated that would account for these bidirectional reflectance effects.

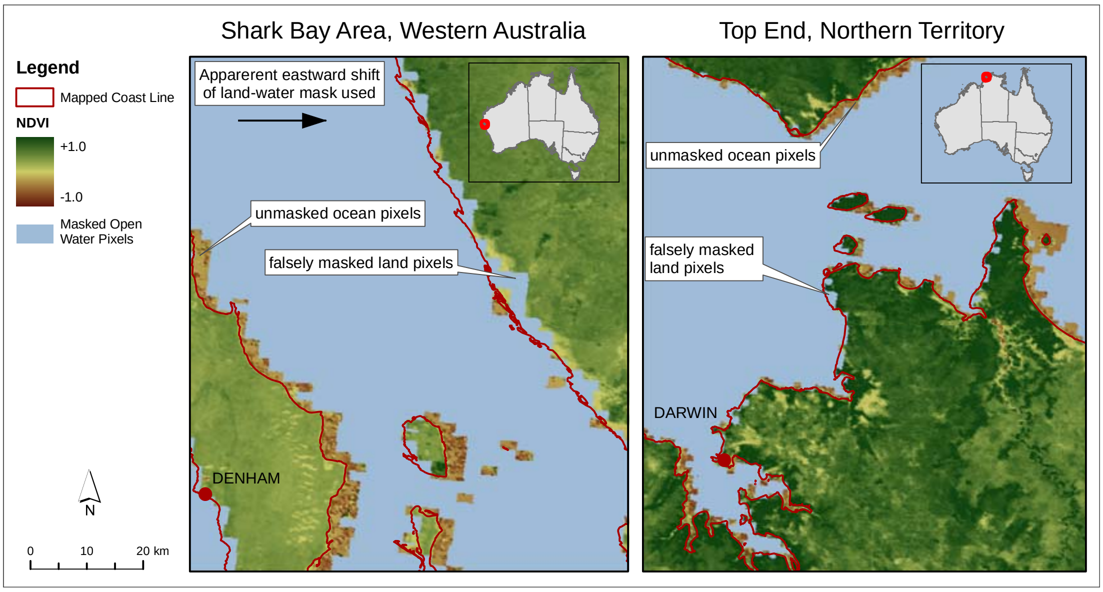


Figure 5.12 Missing pixels due to misplacement of the land water masked used in the generation of the MOD13Q1 product

5.3.3.2 MODIS Nadir BRDF-Adjusted Reflectance 16-Day L3 Global 500 m

The MODIS Nadir Bidirectional Reflectance Distribution Function (BRDF)-adjusted Reflectance (NBAR) product (MCD43B4) has been developed to minimise the effects of clouds, variable view angles, and atmospheric aerosols (Schaaf et al. 2002). The underlying BRDF function models the anisotropic scattering effects of surfaces under different illumination and observation conditions, i.e the BRDF describes mathematically the observed changes in reflectance, when an illuminated target is viewed from different angles. Consequently, it enables the prediction of surface reflectance as a function of solar and viewing geometry. The BRDF is wavelength dependent and is determined by the structural and optical properties of the surface. These properties include shadowing, multiple scattering, transmission, reflection, and absorption and emission by surface elements. Parameters from the BRDF model are used to predict what reflectance should be in a given sensor/solar geometry, which in case of the NBAR product is the nadir observation at a mean solar zenith angle over a 16-day period. The MODIS NBAR product is operationally produced in a rolling 8-day interval from 16 days of registered, multi-band, atmospherically corrected surface reflectance data from the MODIS instrument on both the Terra and Aqua platforms. In Collection 5, NBAR data are generated for bands 1-7 at 500-m spatial resolution and distributed with accompanying data on band quality.

Since view angle effects, as well as cloud and aerosol contamination, have been removed, NBAR is ideal for applications such as time series analysis of NDVI, which have traditionally had to depend on compositing methods to reduce these effects. The product has therefore been increasingly used to investigate vegetation dynamics from NBAR derived vegetation indices (see below), to map global land cover (Friedl et al. 2010) and also to provide global bioclimatic variables for use in epidemiology (Scharlemann et al. 2008).

5.3.3.3 MODIS Land Cover Dynamics Yearly L3 Global 1 km

The MODIS Land Cover Dynamics (MLCD) product (MCD12Q2) has been developed to support studies of seasonal phenology and interannual variation in land surface and ecosystem properties. MCD12Q2 is produced using the algorithm presented in Zhang et al. (2003), which fits series of piecewise logistic functions to vegetation index time series. The algorithm characterises vegetation growth cycles using four transition dates estimated from time series of MODIS enhanced vegetation index (EVI) data: (1) greenup: the date of onset of EVI increase; (2) maturity: the date of onset of EVI maximum; (3) senescence: the date of onset of EVI decrease; and (4) dormancy (Ganguly et al. 2010).

While the MCD12Q2 product could be potentially of interest for this project, at the time of writing it has only been made available for the years 2000 – 2006. Assessment of a test dataset further indicated that the amount of missing data in the study areas makes in less useful for this project.

5.3.3.4 Selection of MODIS Product for Vegetation Monitoring

The investigation into products capable of either providing vegetation indices or the bands to calculate those indices gave some clear indication on the most appropriate dataset. The BRDF-Adjusted MCD43B4 product has ideal characteristics to derive spatially coherent VI maps that are not biased by different viewing angles. Although the spatial resolution of 500 m is not as high as for the Vegetation Index product, it provides enough detail for regional studies. The MCD43B4 dataset has therefore been selected for this study to generate NDVI and EVI time series that can be analysed further for the extraction of phenological variables as described in Chapter 6.

5.3.4 Land Surface Temperature from MODIS

5.3.4.1 MODIS Land Surface Temperature & Emissivity 8-Day L3 Global 1km

The MODIS Land Surface Temperature and Emissivity products (MOD11A2 from Terra satellite and MYD11A2 from Aqua satellite) provide land surface temperature and emissivity values averaged over a period of 2-8 days at a spatial resolution of 1 km (Wan 2009). The products are the result of the generalised split-window LST algorithm (Wan and Dozier 1996), which is aimed at reaching an accuracy of better than 1°K (+/− 0.7°K stddev.) for areas with known emissivities in the range −10°K to 58°K (Wan 2008). Data are ideally generated under clear-sky conditions to avoid mixing with cloud top temperature. Low quality pixels resulting from clouds and other atmospheric disturbances, which constitute a significant obstacle for continuous LST monitoring, are marked in an accompanying quality assessment (QA) layer. LST is observed by the two MODIS sensors four times per day, at 10:30 and 22:30 local solar time by MODIS Terra, and at 01:30 and 13:30 by MODIS Aqua. Data for the morning and afternoon/evening overpasses are encoded in the dataset as LST night and LST day, respectively. The other layers included in the MOD11A2 product are quality assessment, observation times, view angles, a record of clear sky days and nights, and emissivities in Bands 31 and 32 estimated from land cover types (Wan 2009).

Ecologically, using night and day temperatures from the Aqua overpass might seem to be the preferred option, as they are captured closer to the daily temperature minimum and maximum, respectively. However, Mostovoy et al. (2006) showed that the strength of the correlation between observed and remotely sensed LST did not significantly change with the overpass time. Therefore, if we are not interested in the absolute minimum temperatures, but in the relative temperature patterns, the additional 2 years of coverage from the Terra platform outweighs that disadvantage.

In an epidemiological context, the MOD11A2 product has been used by Scharlemann et al. (2008) to generate a Fourier processed time series over 5 years. Neteler (2010) produced gap filled LST maps for the prediction of tick-borne encephalitis in Northern Italy, using the daily MOD11 LST dataset.

5.3.4.2 MODIS Land Surface Temperature & Emissivity 8-Day L3 Global 5km

An alternative product, MOD11B1, consists of 8-daily LST and emissivity data at 5 km spatial resolution. It is generated by the day/night LST algorithm (Wan & Li, 1997). However, this product has been disregarded due to the lower spatial resolution.

5.3.5 Satellite-based Precipitation Products

The TRMM 3B42 or ‘TRMM and Other Satellite Precipitation Product’ (Huffman et al. 2007) and CMORPH (Joyce et al. 2004) from NOAA’s Climate Prediction Center provide global satellite derived precipitation data sets. These products have been shortlisted for this project due to their quality, and their spatial and temporal properties. As reviewed in Chapter 4, the strength of these methods is the combination of high resolution optical and infrared sensors with the active and passive microwave sensors that are able to penetrate cloud cover and provide three-dimensional rainfall estimates. The two methods and related datasets are compared to rain gauge measurements hereafter.

5.3.5.1 TRMM and Other Satellite Precipitation Product

TRMM data are acquired as part of a joint mission by the Japan Aerospace Exploration Agency (JAXA, formerly NASDA) and the US National Aeronautics and Space Administration (NASA). The TRMM science team developed the algorithms for the processing of the rainfall data products, also known as TRMM Multisatellite Precipitation Analysis (TMPA) (Huffman et al. 2007), that is carried out by the TRMM Science Data and Information System (TSDIS) and the TRMM office. The data are archived and distributed by the Goddard Earth Sciences (GES) Data and Information Services Center (DISC) free of charge.

The TRMM and Other Satellites Rainfall Product (3B42) has been available since 1998. It provides 3-hourly rain rates (mm/hr) at a 0.25° by 0.25° spatial resolution, which approximates to a 25 km resolution for Northern Australia. Precipitation estimates are produced in four stages: 1) the microwave precipitation estimates from the TMI and PR sensors on the TRMM satellite are calibrated and combined, 2) infrared precipitation estimates are created using the calibrated microwave precipitation, 3) the microwave and IR estimates are combined, and 4) rain gauge data are incorporated (Huffman and Bolvin 2009; Huffman et al. 2007). In the current version 6 of the product, the estimates depend on the input from different PMW sensors from low earth orbit satellites (AMSR-E, AMSU-B) and infrared data from geosynchronos satellites (GMS, GOES-East, GOES-West, Meteosat-7, Meteosat-5, and NOAA-12.). The Global Precipitation Climatology Project (GPCP) and Climate Assessment and Monitoring (CAMS) monthly precipitation gauge analyses are used for calibration (Huffman et al. 2007). Depending on the availability of these analyses, the 3B42 product is currently available within two weeks after the end of each month (Huffman and Bolvin 2009).

5.3.5.2 Real-Time TRMM Product

The real-time TRMM product 3B42RT is computed in near real-time (i.e. within about 6 hours), and constitutes the timeliest source of TMPA estimates. The processing of the 3B42RT data set requires several simplifications compared to the 3B42 product, which is designed to maximise the quality of the estimates. In near real-time it is for example not possible to apply rain gauge data. Huffman and Bolvin (2009) therefore strongly recommend using the 3B42 instead of the 3B42RT data set for any research that is not specifically focusing on near real-time applications.

5.3.5.3 CMORPH

The CMORPH (Joyce et al. 2004) morphing scheme to temporally interpolate microwave patterns with IR-based motion vectors has been briefly described in Section 3.2.1. CMORPH data have been available since December 2002 with different spatial and temporal resolutions. Half-hourly precipitation estimates are available at pixel sizes of 8 km, while 3-hourly and daily precipitation estimates are provided at pixel sizes of 25 km. CMORPH estimates are processed and distributed by the NOAA Climate Prediction Center (CPC) about 18 hours past real-time. More timely estimates are provided by the QMORPH product, which is available within 3 hours of real-time (*NOAA CPC Morphing Technique ("CMORPH")* 2010).

5.3.5.4 Satellite Images Versus Weather Station Readings

When comparing satellite derived precipitation estimates to the rain gauge data available for WA, the first clearly outperforms the second in terms of its extensive and regular spatial coverage especially in the inland regions of WA where rain gauge stations are relatively sparse and irregularly distributed (Figure 5.13). Although interpolation of the ground measurements is operationally carried out by the Bureau of Meteorology (BoM), the error of these data increases as the station density decreases (Weymouth et al. 1999). Weather events such as heavy thunderstorms, which are characterised by a limited spatial extent might not even be recognised, due to moving through a gap between gauge stations without being recorded (or even due to disruption to the gauge stations) with no data for the event subsequently being available for interpolation.

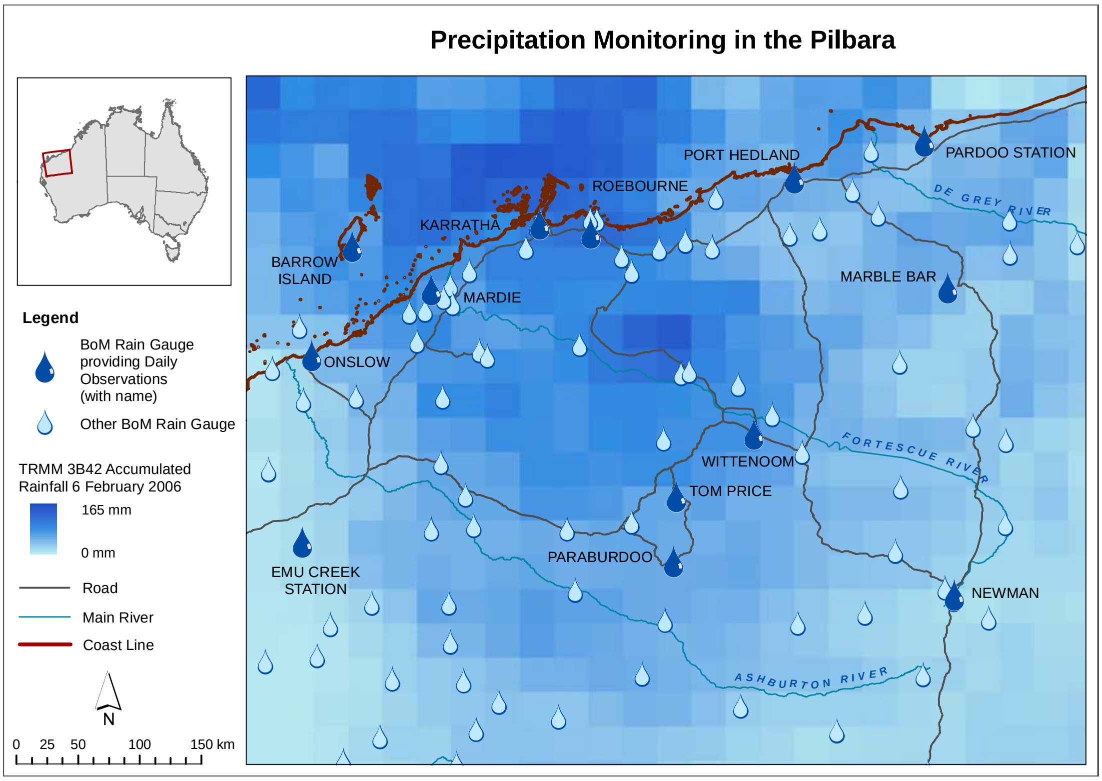


Figure 5.13 Plotting BoM rain gauge locations over a TRMM accumulated rainfall dataset (capturing tropical cyclone *Emma*) clearly shows the advantage of satellite imagery, where rainfall figures need to be obtained in sparsely populated areas

Further concerns about weather station data quality and also quality control as provided by the BoM are incompleteness and inaccuracy of data records due to e.g. instrument failure and irregular calibration or absence of the observer. However, the alternative satellite precipitation products provide not direct measurements but estimates depending on specific cloud properties (Yan et al. 2005). They are operationally or semi-operationally processed by a variety of algorithms that have been developed during the last few decades. Precipitation data products have different spatial, temporal and quality features and their performance also strongly depends on the observed precipitation regime. In general, satellite precipitation estimates show a greater accuracy for tropical, convective, and summertime rainfall than for mid-latitude, stratiform, and wintertime rainfall (Ebert 2004).

Before using satellite rainfall estimates it is necessary to understand their accuracy and limitations. Validation and intercomparison of different satellite precipitation products is done for several regions including Australia (Ebert, Janowiak, and Kidd 2007), Europe (Kidd 2004) and the US (Janowiak 2004) as a project of the International Precipitation Working Group (IPWG). The results for Australia are made available online (Ebert 2007). One of the key findings from ongoing research of the IWG is that satellite estimates usually detect heavy rainfall events too frequently while light rainfall is not estimated often enough (Ebert, Janowiak, and Kidd 2007). Consequently, satellite based precipitation data are biased low during winter by underestimating rainfall. Ebert, Janowiak, and Kidd (2007) further showed that the CMORPH algorithm is less accurate, compared to the TRMM 3B42 data, especially in the focus areas of this project. CMORPH data strongly overestimate heavy rainfall as produced by tropical systems, the dominant weather systems during the wet season in Northern Australia, which are hypothesised to be important drivers of arbovirus dynamics. In contrast, TRMM shows slight underestimates of these events.

5.3.5.5 Selection of Precipitation Product

Based on a comprehensive analysis and interpretation of the validation data provided by the BoM Research Centre (see Schuster et al. 2009) TRMM 3B42 was finally chosen as the basic rainfall data set for this study. Although these data do not deliver high precision rainfall rates, which are not required by this project, they provide the most accurate and coherent information for the entire study area. The verification results pointed out that 3B42 data performed well for stronger rainfall events which are associated with the dominant weather systems of the northern parts of WA during the wet season. CMORPH was not chosen as a main data source, because it showed pronounced overestimates e.g. in the Kimberley region and was not available before December 2002.

5. 4 Land Information and Infrastructure Datasets

Data on more static parameters such as topography, hydrology, geology, soils, land cover and infrastructure are produced by national (Geoscience Australia) and state mapping agencies (Landgate) as well as the Department of Agriculture and Food Western Australia (DAFWA) in scales ranging from 1:100,000 to 1:1 million. The main purpose of these datasets within the project is not to use them as additional predictor variables, but to inform the structuring of the bioclimatic data layers, i.e. to decide which area to weight higher in the modelling process, or which to exempt from the predictions. The key data sets considered for the project are described below.

5.4.1 Topographic Base Data

Regional topographic base maps have been produced nation-wide at a scale of 1:250,000 as part of the GEODATA TOPO 250K Series 3 (Geoscience Australia 2006). This dataset, published digitally in the latest version in 2006 provides much of the topographical base layers utilised in this project for reference mapping. Of major interest are hydrological features (including watercourses, lakes, canals, flats, bores, reservoirs etc.), transport infrastructure (roads railways), as well as reserves (natural and aboriginal) and military areas.

5.4.2 Pastoral Property and Infrastructure Datasets

Data on pastoral properties and related infrastructures (i.e. water points, dams, fences, yards and homesteads) are provided by the responsible state government Departments. Property boundaries are a crucial dataset for this project as they define the primary spatial reference unit for BTV presence/absence data. These data are available as cadastre data from DAFWA for the Pilbara region and from the Department of Planning and Infrastructure in the Northern Territory. Data on infrastructure are captured either from topographic maps (e.g. the Geoscience

Australia 1:250,000 dataset mentioned before) or through field inspections as part of the rangeland condition monitoring activities.

5.4.3 Digital Elevation Data

Terrain parameters such as slope and aspect derived from a DEM can be used to model surface water runoff, soil moisture, radiant fluxes, or extract landforms. Such information is of use in this project to exclude certain areas from the study, e.g. due to their steep slope and inaccessibility for hosts and vectors. Several datasets suitable for mapping at regional scale are available, of which data from the Shuttle Radar Topography Mission (SRTM) with a spatial resolution of 90 m (JPL2008b) provide the best spatial resolution for regional applications while providing higher accuracy compared to the higher resolution ASTER DEM (Hirt, Filmer, and Featherstone 2010). The latest version of a national DEM for Australia with a spatial resolution of 9 arc seconds (250 m) has been generated using spot heights and terrain break lines from the GEODATA TOPO 250K (Geoscience Australia 2006), trigonometric points from the National Geodetic Database and as well as additional elevation, streamline and sink point data digitised from 1:100,000 source material (Hutchinson et al. 2008). This dataset, provided by Geoscience Australia, is particularly useful for overview mapping on a continental scale (as in Figure 5.1). Digital elevation data with a very high spatial resolution only cover parts of coastal and metropolitan areas and are therefore of limited use for this project.

5.4.4 Rangeland Land Systems

As a result of several survey campaigns the pastoral areas of WA have been mapped and classified into land system units, comprising dominant geomorphology, soils, vegetation and climate (Van Vreeswyk et al. 2004). Most mapping is at scale of 1:250,000, except for the Kimberley Region (1:1 million) and Wiluna-Meekatharra (1:506,880). Similar maps have been produced for the Northern Territory, though only 30% of the area is mapped at the scale of 1:250,000, while the remainder of the Territory, particularly the South is only mapped at a 1:1 million scale. On a national level, land systems maps have been homogenised in the Australian Soil Resource Information System (ASRIS) (McKenzie et al. 2005). Although mapping is rather coarse at the land system level, and extraction of information on landforms, soils and vegetation groups within the units is impracticable, the data provide information on the carrying capacity of the land and hence facilitate estimating the distribution of livestock as arbovirus hosts.

5. 5 Software

5.5.1 GIS, Remote Sensing and Data Processing Software

The remote sensing package ERDAS Imagine (ERDAS Inc. 2008) was used initially for data assessment. Most of the resource intensive data management and data processing was implemented in ArcGIS 9.3 (ESRI Inc. 2008) using Python scripts specifically developed for this project to automate the generation of the bioclimatic variables. Other software used in this project includes the MODIS Reprojection Tool MRT (Dwyer and Schmidt 2006) as well as the TIMESAT package (Eklundh and Jönsson 2010), which will be discussed in the later sections where appropriate.

5.5.2 Statistical Software

The R programming language and environment for statistical computing and graphics (R Development Core Team 2010) was used throughout the project for exploratory analysis and development of the predictive models, described in Chapter 7, and the preparation of graphs.

5. 6 Summary

In this chapter, the study areas in the Pilbara-Gascoyne region and the Northern Territory have been introduced in terms of virus activity, hydrology and topography, climate as well as soils and vegetation. These regions span vast landscapes influenced by several climatic zones, and are characterised by varying levels of virus activity, all of which makes them an ideal test bed for the application of remote sensing to study the distribution of BTV.

An analysis of the virus dataset concluded with the definition of the minimum required spatial and temporal resolution for model building and prediction. The heterogeneity of the dataset requires the aggregation of presence/absence data for the period from November to October on a pastoral property level in order to build spatial relationships with the environment. To preserve the seasonal characteristics of the region, but limit the dependence on daily images that may be obscured by cloud cover, a weekly to fortnightly temporal resolution was selected. The spatial resolution for the environmental data has been chosen to detect host and vector habitats on the ground and capture regional rainfall patterns. A set of bioclimatic factors for predictor variable definition was chosen and included vegetation indices (NDVI and EVI), LST, rainfall, as well as the derived factors vegetation phenology and GDD. After the selection of MODIS and TRMM for the delivery of medium spatial resolution and high temporal resolution satellite data, various data products where assessed for their fitness. The final selection of satellite remote sensing data is listed below (Table 5.2) together with topographic and land information datasets employed for this study (Table 5.3).

Table 5.2 Remote sensing data products selected for this study

Remote sensing product	**Spatial resolution**	**Spatial coverage**	**Temporal resolution**	**Temporal coverage**	**Source**
MODIS Nadir BRDF-Adjusted Reflectance (MCD43B4)	500 m	global	16-day	2000 – current	LP DAAC [1]
MODIS Land Surface Temperature and Emissivity (MOD11A2)	1 km	global	8-day	2000 – current	LP DAAC [1]
TRMM and Other Satellite Precipitation Product (3B42)	25 km	global	3–hourly – monthly	1998 – current	GES DISC DAAC [2]

[1)] Land Processes Distributed Active Archive Center (LP DAAC); [2)] Goddard Earth Sciences Data and Information Service Center Distributed Active Archive Center (GES DISC DAAC)

Table 5.3 Land Information and Infrastructure datasets selected for this study

Data set	**Scale, spatial resolution (for DEM data)**	**Spatial coverage**	**Creation time**	**Source**
GEODATA TOPO 250K topographic base data	**1: 250,000**	**Australia**	**2006**	**Geoscience Australia**
Pastoral property and infrastructure data	**1: 250,000**	**WA, NT**		**DAFWA [1] NT DLP [2]**
Rangeland land systems	**1:250,000 – 1:1,000,000 [3]**	**WA, NT**	**2006 (WA)**	**DAFWA [1] NRETA[4]**
SRTM [5] DEM Version 4.1	**90 m**	**Global**	**2008**	**CGIAR-CSI [6]**
GEODATA 9 Second DEM Version 3	**250 m**	**Australia**	**2008**	**Geoscience Australia**

[1)] Department of Agriculture and Food WA (DAFWA); [2)] NT Department of Lands and Planning (DLP); [3)] depending on the region; [4)] NT Department of Natural Resources, Environment, The Arts and Sport (NRETA); [5)] Shuttle Radar Topography Mission (SRTM); [6)] Consultative Group for International Agriculture Research – Consortium for Spatial Information (CGIAR-CSI)

The chapter concluded with an overview of software products used in this research. In the following chapter, the process of generating bioclimatic variables from the remotely sensed data products is explained.

CHAPTER 6

GENERATION OF BIOCLIMATIC VARIABLES

The process of selecting the remote sensing and ancillary datasets used for this research has been described in Chapter 5. This chapter continues with the description of the process developed to transform the collection of remotely sensed data into mosaics of bio- and geophysical parameters. A set of seasonal bioclimatic variables is generated that characterise the most crucial periods for arboviral activity and can hence be related to the observed presence of BTV on the ground.

6. 1 General Workflow and Processing Environment

One of the aims of this research is to develop an efficient and cost-effective methodology to provide a timely source of data and bioclimatic variables to predict the distribution of BTV over large areas. The steps involved in this task are outlined in Figure 6.1 and will be described in detail in the following sections.

The Pilbara and the Northern Territory are two environmentally unique and diverse study areas which have been identified to implement and test the methodology, which relies on the input from MODIS and TRMM data products. The ecology of BTV differs between the two regions, and while the Northern Territory in part supports year-round virus activity, BTV in the Pilbara is generally epidemic. The range of vector species is also considerably larger in the Northern Territory. The presence of different climate zones means that availability of cloud-free remotely sensed data and hence specific variables will vary, depending on season and region. Extraction of bio- and geophysical parameters and variable development is therefore conducted separately for each study area with the additional advantage of increased processing efficiency. Consequently, it is intended that separate models will be developed for each region using different sets of environmental factors.

Data are acquired to cover nine consecutive seasons from 2000/2001 to 2008/2009. The first eight seasons are used for model building and internal validation, while data from the season 2008/2009, which are not available for model development initially, are used for external validation. This way, the model’s ability to predict the likely hood of virus transmission based on historic occurrences and recent climatic and environmental conditions can be assessed.

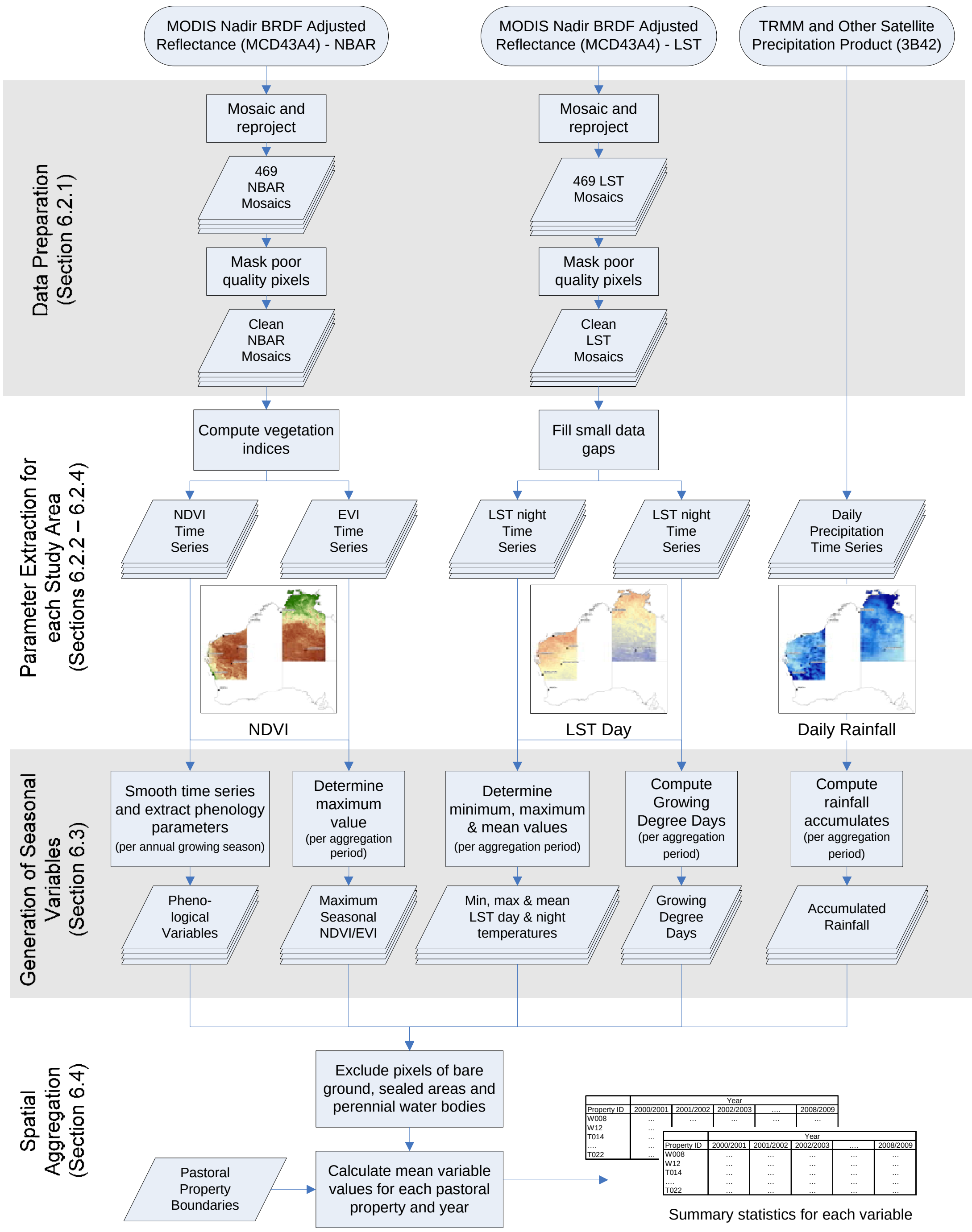


Figure 6.1 Simplified workflow for the generation of bioclimatic variables from remote sensing data products, and aggregation of annual statistics on pastoral property level

In contrast to other studies that compiled seasonality variables from remotely sensed data over several years using Temporal Fourier Analysis (TFA) (Hay et al. 2006;

Scharlemann et al. 2008), this study will generate annual seasonal variables. This approach facilitates the preservation of seasonal characteristics for individual years, the generation of annual prediction maps, and analysis of the drivers for the inter-annual variations in virus distribution. While TFA has been widely used in vector-borne disease studies (e.g. Rogers 2000; Tatem et al. 2003), the resulting data are best suited to identify factors related to general habitat suitability, as described by a typical seasonal signal of environmental variables, such as land surface temperature or NDVI over an annual, bi-annual or tri-annual cycle. This study however aims to investigate the inter-annual variability of environmental variables and the associated fluctuations in arbovirus activity.

The study uses a geographic coordinate system of latitude and longitude, due to the larger area covered and because this is the most widespread reference system for global climate and environmental datasets. For analyses involving area and distance measurements, the datasets are reprojected to a Lambert Conformal Conic projection, which shows the least distortions for Australia on a continental scale (Intergovernmental Committee on Surveying & Mapping 2009).

The processing environment, comprising the MODIS Reprojection Tool (described below), ArcGIS with the Spatial Analyst Extension, and the scripting language Python facilitated the development of an efficient automated processing chain. Data processing was performed on a standard PC (Intel Core 2, 3 GHz, 4 GB RAM) with the data held on two 1 TB external hard drives. The scripts are reusable for future processing as new data become available.

6. 2 Extraction of Bio- and Geophysical Parameters from Remote Sensing Data

6.2.1 MODIS Data Preparation

The MODIS data products Nadir BRDF-Adjusted Reflectance (MCD43A4), including the related quality information data (MCD43A2), as well as Land Surface Temperature and Emissivity (MOD11A2) were acquired from the Land Processes Distributed Active Archive Center (LP DAAC) through the NASA Warehouse Inventory Search Tool (WIST) for the period between February 2000 and May 2010. The data are provided on a Sinusoidal projection as 460 tiles for the entire Earth

(Figure 6.2). Each tile consists of 2400 x 2400 pixels, for the 500 m spatial resolution MCD43A2 data set and 1200 x 1200 pixels for the 1000 m spatial resolution MOD11A2 dataset. To cover the area of WA and the NT requires 11 of these tiles (H27V11, H27V12, H28V10, H28V11, H28V12, H29V10, H29V11, H29V12, H30V10, H30V11, H31V10), which equates to more than three quarters of the Australian landmass (see Figure 6.3). In total, satellite images were acquired for 469 8-day periods (also referred to as epochs), which amounts to 170 GB of raw data. The MRT software (Dwyer and Schmidt 2006) was used to reproject from the original Sinusoidal projection to a geographic coordinate system of latitude and longitude and create a seamless mosaic for each epoch.

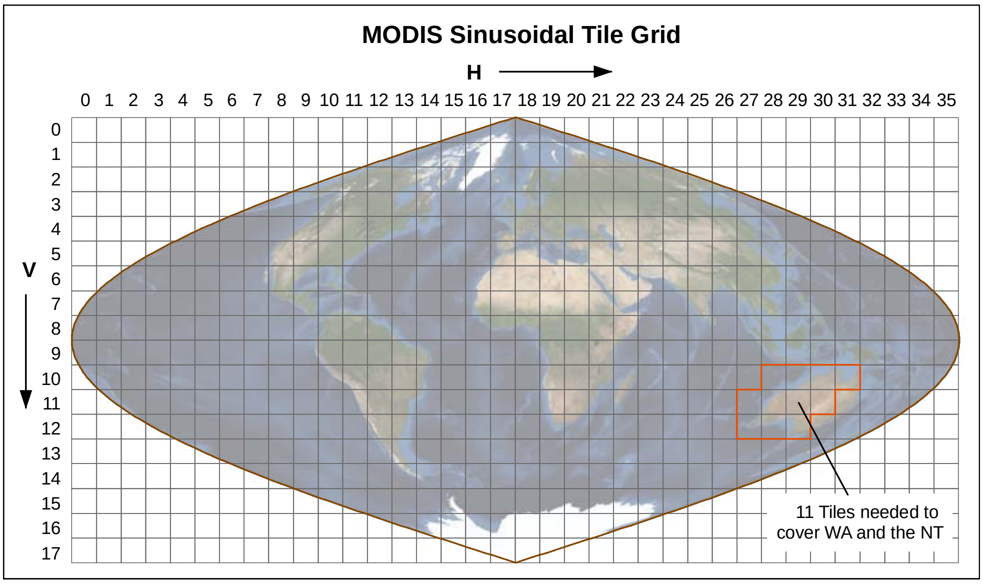


Figure 6.2 MODIS Sinusoidal GRID and tiles needed to cover WA and the NT. Image Source: Stöckli et al. (2006)

Amongst other formats, MRT offers export to GeoTiff, which is a standard format that can be read by most GIS packages and was therefore selected for this study. The geographic subsetting ability of MRT was utilised to extract the area between longitudes 112.0459° and 138.0901°E and latitudes 10.5012° and 35.5022°S as shown in Figure 6.3.

The MRT software supports nearest neighbour, bilinear, and cubic convolution resampling. For this work, nearest neighbour resampling was chosen as it is able to maintain the original values in each of the layers during resampling, particularly the bit-pattern encoded structure of the quality maps, as it does not interpolate between existing bit values. To provide a consistent spatial resolution across the MODIS datasets, the MOD11A2 data with a nominal resolution of 1000 m were resampled to 500 m resolution, which is equivalent to 0.0046° at the equator in the geographic reference system. Subsequently, several datasets were clipped with a coastline dataset to cover only the mainland of Australia.

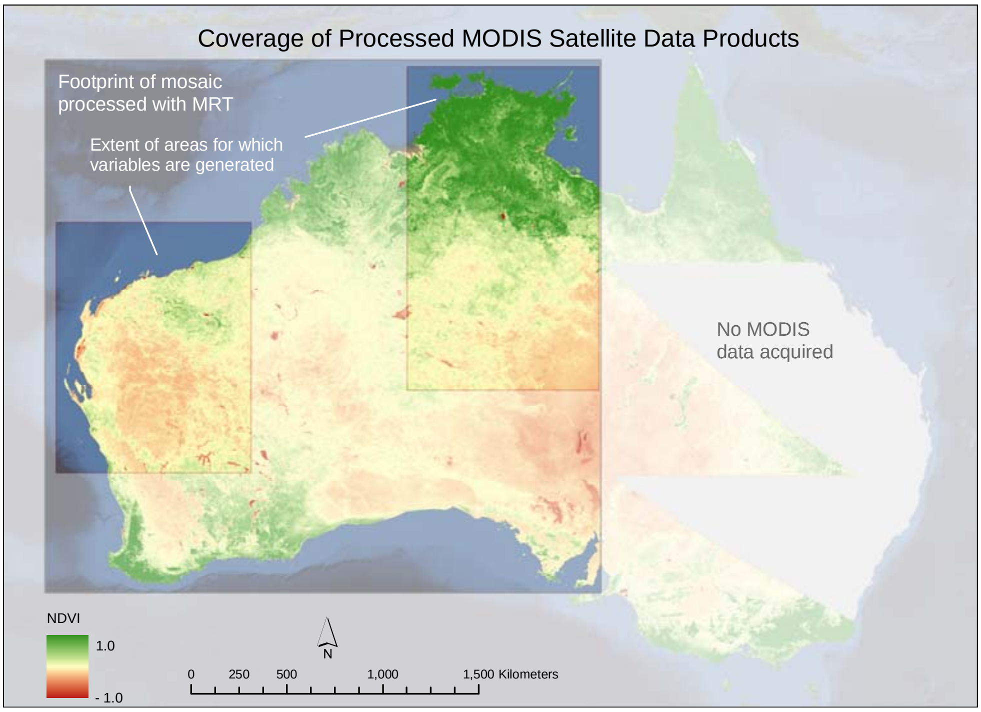


Figure 6.3 Extent of areas covered during the successive processing steps, using the NDVI as an example

6.2.2 Extracting MODIS Vegetation Indices

The MODIS NBAR product MCD43A4 comprises seven nadir reflectance data layers (termed scientific datasets - SDS), that have been computed for MODIS bands 1-7 at the mean solar zenith angle of a 16-day period). Out of these, only bands 1 (red), 2 (NIR) and 3 (blue) are required for the extraction of NDVI and EVI. Natively, values are encoded as integers, using a scaling factor of 10,000. The previously generated GeoTiff mosaics were imported to ArcGIS, masked for pixels that contain no data due to the presence of water, cloud cover or other effects, and transformed into NDVI and EVI images using the equations given in Section 4.2.4.2. To account for the scaling factor, the results were multiplied by 0.0001.

The presence of surface water or bare land such as mine sites, industrial areas or densely populated areas would bias the regional statistics of land surface temperature and vegetation dynamics. An NDVI threshold of 0.1 was determined empirically to delineate these areas and create a dynamic low NDVI mask for each 8-day period.

6.2.3 Extracting MODIS Land Surface Temperature

The MODIS Land Surface Temperature product MOD11A2 comprises 12 SDSs (Wan 2009), of which the layers “Daily daytime 1km grid Land Surface Temperature (LST_Day_1km)”, “Quality control for daytime LST and emissivity (QC_Day)”, “Daily nighttime 1km grid Land Surface Temperature (LST_Night_1km)”, and “Quality control for nighttime LST and emissivity (QC_Night)” were used for this study.

LST is only produced for pixels that are on land or inland water, and are in clear-sky conditions at a confidence of >=95% over land <= 2000 m above sea level, and at a confidence of >= 66% over lakes (Wan 2009). Information on the quality of the retrieved LST and Emissivity values for each pixel is found in the Quality Control (QC_day and QC_night) layers. Pixels with limited quality, denoted by the following flags were masked out: “not produced due to cloud effects”, “not produced due to reasons other than cloud”, “average emissivity error >= 0.02”, “average LST error > 2K”. The remaining pixels were corrected for the scaling factor by multiplying with 0.02 and stored as GeoTiff images for LST night and LST day.

In a subsequent step, data gaps resulting from the removal of poor quality pixels were filled in a two stage process. Using the low NDVI mask, small spatial gaps that are not water or bare ground, with a width of less than five pixels were replaced by the mean LST value within a radius of six pixels. Interpolation of land surface temperature across wider gaps is not advisable due to the large spatial variation in land cover. Therefore, in a second step, temporal gaps not wider than two consecutive epochs were linearly interpolated on a pixel basis. The approach to fill only small gaps enures that no data are artificially generated where there aren’t enough valid data initially.

6.2.4 Extraction of Precipitation Rates from TRMM

The post real-time TRMM 3B42 product provides instantaneous precipitation rates at a 0.25° (about 25 km) grid resolution time-stamped at 3-hourly intervals. The data used within this project are daily (9.00 am to 9.00 am) rainfall accumulates for the Australian continent that were processed within an intercomparison study of precipitation time series of TRMM and interpolated surfaces from BoM rain gauge observations (Renzullo 2008). These data covering the period between 1999 and 2009 were originally obtained from the NASA Goddard Space Flight Center Distributed Data Archive Center (GSFC DAAC). The area covered by these data extends between longitudes 109.625° and 154.125°E, and latitudes 9.625° and 44.125°S. To be compatible with the already processed datasets, the TRMM data were converted from a floating point file format to the GeoTiff format and clipped to the extent of the Australian mainland.

6. 3 Development of Bioclimatic Variables

6.3.1 Selection of Seasonal Variables and Temporal Aggregation Intervals

As defined in the previous chapter, virus data are summarised over 12 months, which include the period of highest vector activity before and after the wet season. The environmental and climatic conditions over that period, which lasts approximately from December to May, will determine virus activity and need to be aggregated into seasonal variables for later use in model building. This step is necessary to reduce the data layers collected for each year to a manageable number before analysis, whilst retaining as much information as possible (Robinson, Rogers, and Williams 1997b). In this section the types of variables as well as the aggregation periods are defined, considering ecological principles as well as the availability of remotely sensed data.

A series of environmental variables that are relevant to epidemiological studies can be derived from MODIS LST, NDVI, EVI, and TRMM precipitation time series, by time series aggregation. In particular, daily/monthly/annual mean value maps of minimum/mean/maximum temperature or accumulated rainfall have been previously identified as relevant ecological indicators (Hay et al. 1996). Other ecologically important variables for insect or plant development are annual or monthly growing degree days, or vegetation phenological parameters such as length of growing season or amplitude of seasonal green-up, which are determined annually.

Seasonal variables may either describe climatic and environmental conditions in absolute terms (e.g. maximum seasonal NDVI or minimum winter temperature), or in relation to long term trends to identify unusually dry, wet, cold or hot seasons. For example, Chalke (2006) used unusual change in early or maximum greenness in comparison with a five-year average. Previous studies developing BTV models for Africa and Europe have also used seasonal change, or rates of change as predictor variables (Purse, Tatem, et al. 2004; Tatem et al. 2003). However, for this study using MODIS data alone, the time series is considered too short to deliver reasonable multi-annual statistics. Moreover, the continuing acquisition of data in future will result in the instability of the long-term average, which needs constant adjustment. Variables are therefore defined independently for each year, using absolute values subsumed over specific aggregation periods. The simplicity of this method also facilitates biological interpretation of the results (Robinson, Rogers, and Williams 1997b).

The aggregation periods identified as most suitable for this study follow the observed and documented peak of virus activity, as well as the meteorological seasons (Table 6.1). Also the months of the previous winter with cold nights in some areas, are important determinants for vector survival and the southern distribution limit of the virus (Bishop, Spohr, and Barchia 2004b).

Table 6.1 Aggregation periods used for the development of bioclimatic variables. Note that the start and end dates for MODIS composites need to be shifted one day forward between March and December in leap years (2000, 2004, 2008)

Aggregation period	**Calendar Months**	**MODIS compositing period** **Start date – End date**
Annual	November - October	1.11. – 31.10.
Bluetongue Season	November - May	1.11. – 1.6.
Summer	December - February	3.12. – 25.2.
Autumn	March – May	26.2. – 1.6.
Previous winter	June - August	2.6. - 28.8.

The compositing periods of MODIS LST and NBAR products, which slightly differ from calendar months have been additionally defined. Because the NBAR product is generated every 8-days like the LST product, but is composited over 16 days, one epoch less than for LST will be taken into account to cover the same period. The availability of data from visible and infrared bands is limited particularly during the wet season in the northernmost parts of Australia. The processed time series have therefore been analysed for the proportion of missing data after quality filtering and gap filling (Figure 6.4), in order to determine which factors can be derived for each aggregation period and region. Extraction of precipitation rates and accumulates from TRMM are not affected, because the microwave sensors that are predominantly used in the generation of the 3B42 precipitation product are not affected by cloud cover.

As Figure 6.4 shows, particularly during the summer months, up to about 40% of data are missing in the Northern Territory. The highest proportion of missing data is found in the night LST data. This effect has also been found by Neteler (2010), who analysed LST time series in north Italy. It can be explained by the different algorithm used to detect cloud contamination during the night overpass, which produces a less accurate cloud mask (Ackerman et al. 1998). Pixels which have been assigned a clear-sky flag with low confidence are automatically removed during the production of the LST product.

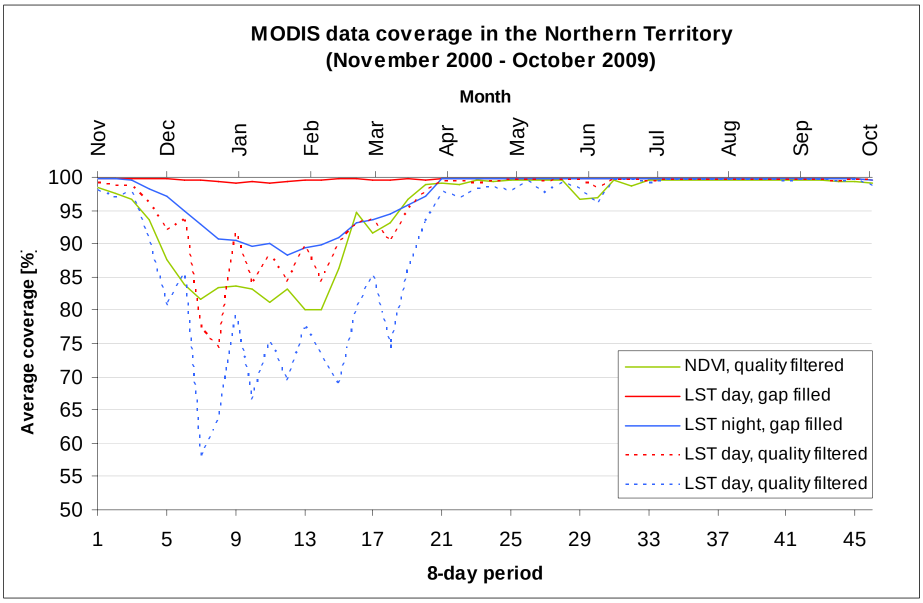


Figure 6.4 Average percentage of valid pixels in quality filtered and gap filled (for LST) time series between November 2000 and October 2009

As illustrated in Figure 6.5, the availability of data is generally very high in the semiarid Pilbara region, except for a small outlier at epoch 19, which is caused by cyclone activity in February 2002 over that area.

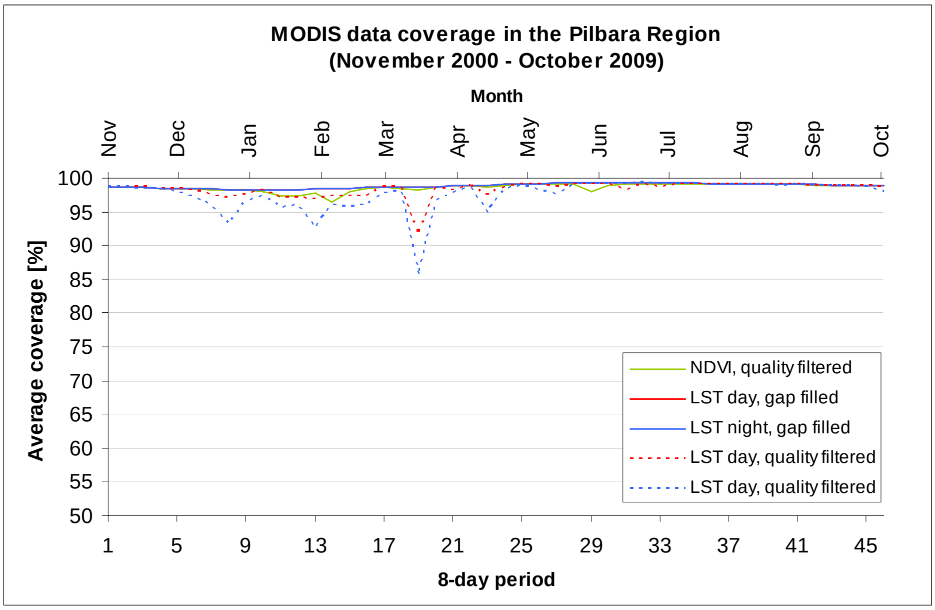


Figure 6.5 Average percentage of valid pixels in quality filtered and gap filled (for LST) time series between November 2000 and October 2009

Consequently, there should not be a limitation to the use of any of the proposed variables in that area, which experiences extensive cloud-free periods. However, it is not sensible to calculate average statistics such as mean daily temperatures over several months from data with large gaps as in the Northern Territory. An overview of the two study areas in Figure 6.6 demonstrates that for some areas in the North of

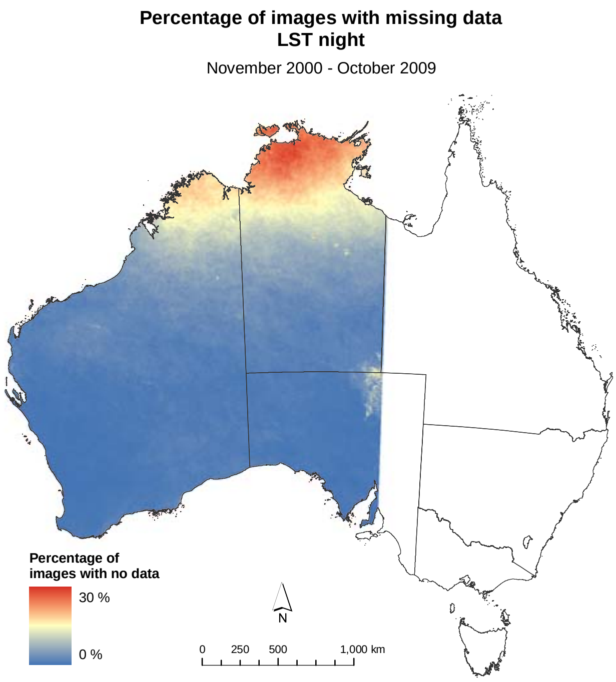


Figure 6.6 Percentage of missing LST night images between November 2000 and October 2009

Australia, valid unprocessed data on night LST are missing for as many as 30% of the 8-day periods. Therefore, variables based on accumulation, such as Growing Degree Days, cannot be determined for these areas. As a consequence, instead of using mean variables for night temperatures, only maximum and minimum values from the 8-daily MODIS datasets are determined for the NT. Also average daily temperatures that involve night temperature data been excluded as well as any derived variables like Growing Degree Days.

Table 6.2 Overview of bioclimatic variables (x = variable produced)

Variable	Short Name	Pilbara	NT
Vegetation / Phenology			
Maximum NDVI, season	maxndviss	X	X
Maximum EVI, season	maxeviss	X	X
Small Integral under seasonal NDVI curve, annual	smint	X	X
Temperature			
Mean day temperature of warmest 8-day period, season	maxlstdss	x	X
Mean day temperature of warmest 8-day period, summer	maxlstdsu	x	X
Mean day temperature of warmest 8-day period, autumn	maxlstdau	x	X
Mean day temperature of warmest 8-day period, previous winter	maxlstdpw	x	X
Minimum night temperature of coldest 8-day period, season	minlstnss	x	
Minimum night temperature of coldest 8-day period, summer	minlstnsu	x	
Minimum night temperature of coldest 8-day period, autumn	minlstnau	x	
Minimum night temperature of coldest 8-day period, previous winter	minlstnpw	x	X
Mean day temperature, season	meanlstdss	x	X
Mean day temperature, summer	meanlstdsu	x	X
Mean day temperature, autumn	meanlstdau	x	X
Mean day temperature, previous winter	meanlstdpw	x	X
Mean night temperature, season	meanlstnss	x	
Mean night temperature, summer	meanlstnsu	x	
Mean night temperature, autumn	meanlstnau	x	
Mean night temperature, previous winter	meanlstnpw	x	X
Mean daily temperature (day and night), season	meanlstss	x	
Mean daily temperature (day and night), summer	meanlstsu	x	
Mean daily temperature (day and night), autumn	meanlstau	x	
Mean daily temperature (day and night), previous winter	meanlstpw	x	X
Growing Degree Days, annual	gdda	x	
Growing Degree Days, season	gddss	x	
Growing Degree Days, summer	gddsu	x	
Growing Degree Days, autumn	gddau	x	
Precipitation			
Accumulated rain, summer	rsu	x	X
Accumulated rain, autumn	rau	x	X
Accumulated rain, season	rss	x	X

For the Pilbara the whole set of variables listed in Table 6.2 can be derived. The generation of each variable is detailed below.

6.3.2 Maximum Vegetation Indices

The maximum NDVI and EVI values over the period between November and May have been derived from the filtered VI datasets on a pixel basis for each year. Maximum VI values represent the maximum green biomass. In an semi arid to arid environment these variables may be used to delineate areas that either have green vegetation year-round or had enough rain to support growth of vegetation (e.g. annual grasses), which also gives an indication of the moisture levels needed for vector survival. In an epidemiological context, maximum NDVI has been used for example in modelling the distribution of *C. imicola* in Morocco (Baylis et al. 1998), and analysing factors related to tsetse fly habitats in Southern Africa (Robinson, Rogers, and Williams 1997b).

Using the maximum VI value sampled over a certain time period is less sensitive to cloud cover, compared to mean VI variables, which rely on data of consistent quality over that period. An alternative way to generate smooth continuous NDVI time series by removing noise and data gaps is presented below. This approach will allow for temporal characterisation of the growing season, by the use of phenological variables. However, for metrics that are unrelated to phenological timing, such as maximum NDVI, the benefits of noise reduction techniques, which introduce inaccuracies, are less evident (Hird and McDermid 2009). The use of the original data to derive maximum VI is hence preferred (Reed et al. 1994).

6.3.3 Vegetation Phenology

Vegetation phenological variables are important parameters characterising a growing season in terms of start and end date, the amount of green-up, either at a point in time or accumulated over the duration of the season or the rate of change in greenness. Many of these parameters are used in agricultural management to assess for example primary productivity or rangeland degradation, and it is anticipated that some of them are related to the occurrence of BTV and its vectors, which are strongly related to their bovine hosts and hence the availability of quality pastures.

A number of methods exist that derive phenology from time series of NDVI or EVI, and most of them follow a two-step approach as explained in Section 4.2.4.3. In the first step, the often noisy vegetation index time series are smoothed, either by applying a filter or fitting a function. The fitted curve is then analysed for points that exceed a certain VI threshold, or for changes in curvature that are relevant for the growing cycle. The TIMESAT program developed by Jönsson and Eklundh (2002, 2004) fits a smooth continuous curve to time series of VI data using Savitzky–Golay filtering (SG), asymmetric Gaussian (AG), or double logistic (DL) functions, and an adaptive upper envelope to account for negatively biased noise such as cloud. The software has mainly been used to extract phenological parameters from AVHRR and MODIS NDVI time series, e.g. in the Italian rice growing areas (Boschetti et al. 2009), the African Sahel Zone (Heumann et al. 2007), as well as the Rangelands of the Northern Territory (Graham, Trueman, and Yates 2008).

TIMESAT has been selected for this study, because it not only provides an efficient processing environment for large datasets, but also offers three smoothing techniques, from which the best fitting can be chosen for a particular area. The software is freely available for non-commercial academic research.

The first decision to be made is on the vegetation index to be used. As stated by Huete et al. (2002), EVI shows some advantages over NDVI in high biomass regions, where NDVI tends to saturate. It is also less sensitive to atmospheric effects and soil background. It has therefore been used to derive global phenology products (e.g. by Ganguly et al. 2010; Zhang et al. 2003). However, its future availability as part of the MODIS continuity program is uncertain, due to the proposed changes to the specifications of the blue band (Huete et al. 2006), which is crucial for the calculation of EVI. NDVI on the other hand is the most widely used index and hence a large archive of historical data from different sensors is available for retrospective studies. Schnur, Xie, and Wang (2010) found that NDVI is stronger correlated to soil moisture in a semi-arid setting, and the initial assessment of MODIS derived NDVI by Huete et al. (2002) also demonstrated that NDVI has a higher dynamic range over semi-arid regions. For those reasons it was decided to use NDVI instead of EVI time series to derive phenological parameters for the Australian landscape which is dominated by low biomass vegetation species (Gill et al. 2009).

TIMESAT is available as a tool within MATLAB® (The MathWorks 2008), as well as a set of Fortran 2003 command line programs. While the MATLAB® GUI offers tools for data exploration, selection and calibration of the smoothing function, large datasets are most efficiently processed with the Fortran executables. TIMESAT requires the input rasters to be in binary format and the NDVI rasters have therefore been exported from ArcGIS as binary float files (*.flt). To ensure that a full growing season is always covered, TIMESAT generates one less season than the number of years of supplied data (Eklundh and Jönsson 2010). For this study to analyse the nine years between November 2000 and October 2009, six months of additional data have been added on either side. The function fitting is executed in steps. Firstly, the number of seasons and their approximate timing is determined. Secondly, TIMESAT filters the data (SG filter) or fits a smooth function to the data (a least-squares fitted asymmetric Gaussian or Double Logistic smooth function). After the fitting has been achieved, the seasonality parameters are computed and written to output files. For the full description of the mathematical and methodological foundation of the process see Jönsson and Eklundh (2002, 2004).

The time series of 460 epochs (equivalent to 10 years of data) for selected locations have been analysed to select the appropriate smoothing technique and calibration parameters. It was found that the adapted SG filter consistently achieved the closest fit particular in areas with irregular growing seasons (see Figure 6.7).

The SG filter allows data smoothing without forcing a given mathematical function (e.g. Gaussian or Logistic curves) to fit the data time series, and thus reducing artefact creation (Boschetti et al. 2009; Chen et al. 2004; White and Nemani 2006). As seen in the example in Figure 6.7 for a pixel in the Carnarvon Basin, the method identified season start and end dates correctly, while preserving the characteristics of original data.

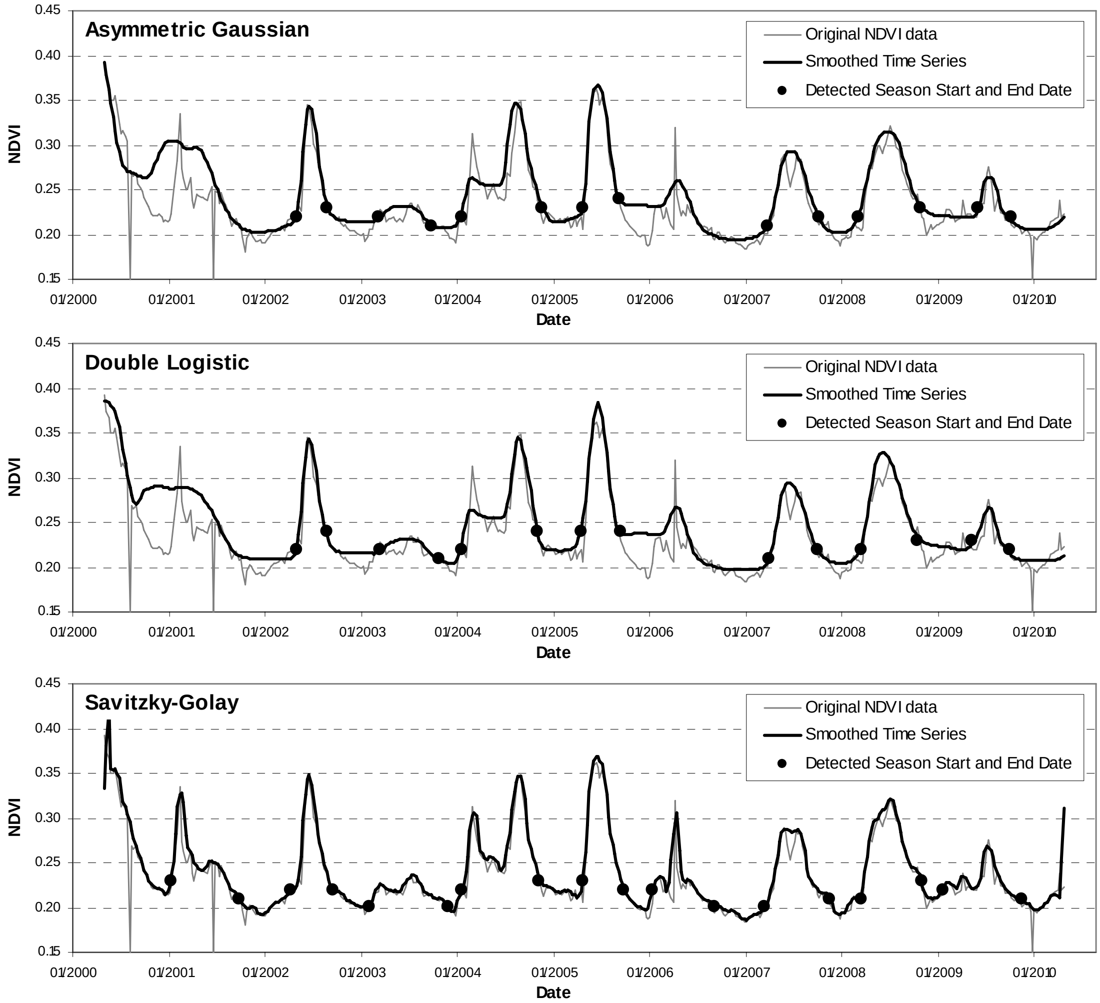


Figure 6.7 Comparison of smoothing techniques applied to NDVI time series for a pixel at the Carnarvon Basin at 114.5082°E, 23.6457°S

TIMESAT processes time series extracted pixel by pixel, checks for anomalous events, missing data and noise (Boschetti et al. 2009). To overcome internal memory limits, the study area had to be disaggregated into tiles of 250 x 250 pixels. The resulting phenological parameter maps were later merged to the original mosaic. Only data with a minimum NDVI value of 0.1 were processed (see section 6.2.2). Time series with mean amplitude of less than 0.05 NDVI units were excluded to overcome frequently occurring phenology anomaly values for start and end of the growing season associated with the relatively high noise. Three iterations for upper envelope adaptation were run to preserve the width and height of the annual NDVI curve, reducing the negative bias of the residual atmospherically related noise that lowers the values in the filtered data. The SG filter window size was set to four epochs.

Figure 6.8 below illustrates time series smoothed with TIMESAT for selected pixels. While most of the study area could be processed using TIMESAT, pixels with weak or noisy time series were unable to be processed due to a lack of clear growing seasons (e.g. sample sites 3 and 4). In some cases, TIMESAT would, for example, not return a valid growing season for one year, but assign the growing season to the following year. Pixels were therefore also checked for anomalies in season length, and those exceeding a length of growing season threshold of 68 weeks (60 epochs) were excluded.

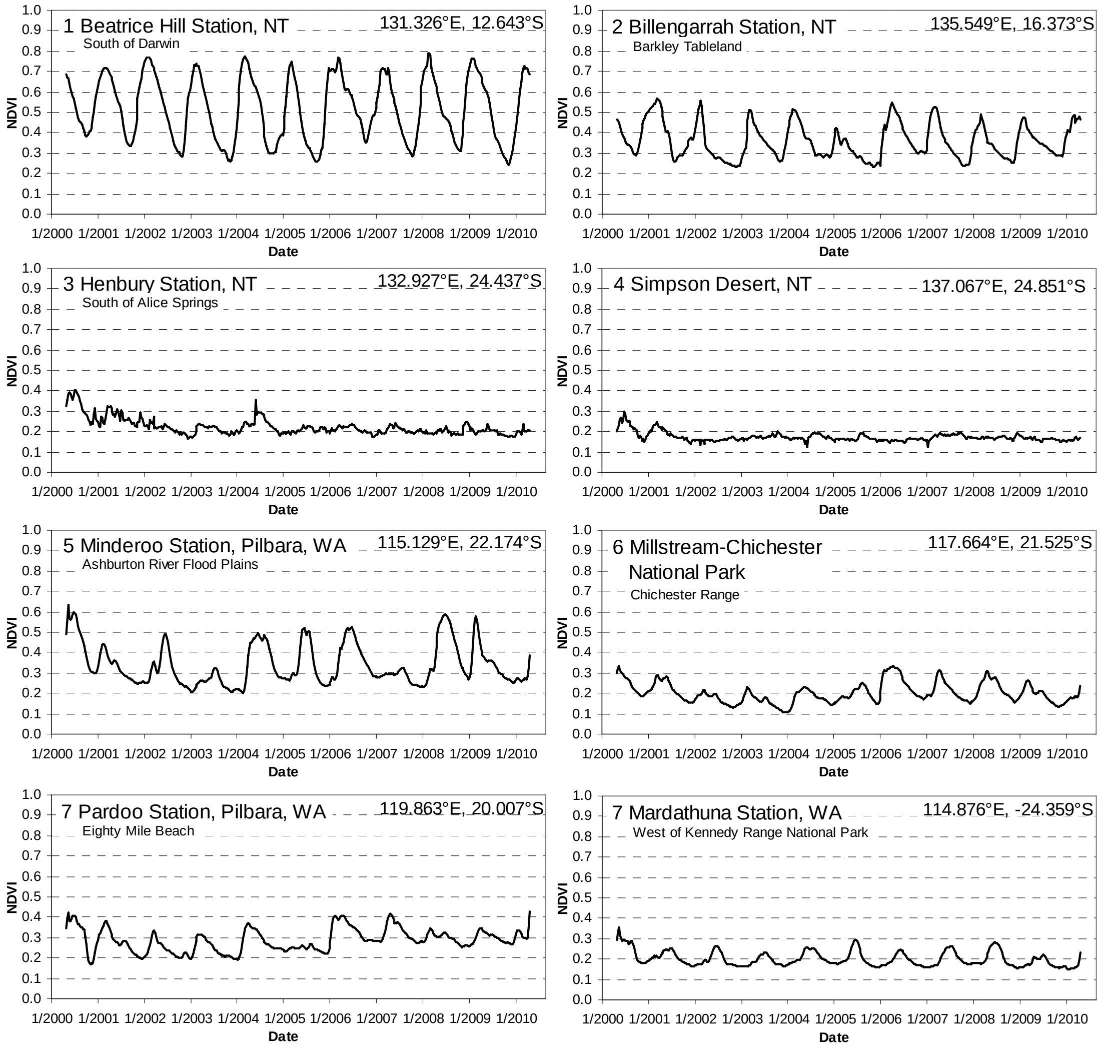


Figure 6.8 Sample NDVI time series from the Pilbara and the Northern Territory representing typical landscapes. Time series like those shown in samples number 3 and 4 have been excluded from analysis due to undetectable growing seasons

From the phenological parameters available within TIMESAT (see Figure 4.6 in Section 4.2.4.3), only the small integrated NDVI (SiNDVI) was estimated. The

SiNDVI metric was extracted from the smoothed NDVI time series for each of the nine years between November 2000 and October 2009. It is defined as the area under the vegetation curve during the growing season and above the mean of the base value (i.e. the mean of the NDVI values measured before and after the season). The start and end of the growing season were estimated as 15% of the annual amplitude from the left (pre season) and right (post season) minimum levels, respectively. The small integrated NDVI is strongly correlated with primary productivity and total phytomass (Holm, Cridland, and Roderick 2003), particularly in semi-arid regions. It thus provides an indication of the productivity of the area for pastoral purposes, i.e. how many cattle can be sustained and therefore provide a reservoir for arbovirus vectors. The SiNDVI tiles for each study area were extracted as binary raster files in TIMESAT and converted to GeoTiff and remerged in ArcGIS.

6.3.4 Minimum, Maximum and Mean Land Surface Temperature

Most *Culicoides* vector species have been found to be active within a particular temperature range (generally between 10° and 35°), where oviposition, feeding, and flight occurs (Sellers 1992). Above or below these temperatures, adult *Culicoides* midges are quiescent. Minimum and maximum temperatures are also considered the most important factors for the survival of *Culicoides* vectors and have therefore often been used as variables to analyse and model their distribution (e.g. Baylis, Meiswinkel, and Venter 1999; Bishop, Barchia, and Harris 1995; Cameron 2000a; Conte et al. 2003; Purse, Tatem, et al. 2004; Tatem et al. 2003; Ward and Thurmond 1995). While high daily maximum temperatures during summer may increase the risk of desiccation, low temperatures at night, the time when vectors are typically most active, will slow down vector activity. During the winter months when temperatures fall below a certain threshold, the vectors will disappear from endemic areas such as southeast Australia (Bishop, Barchia, and Harris 1995). Average temperatures are also known to relate to levels of vector activity and hence the risk for virus transmission.

Maximum day temperatures in summer and autumn and minimum night temperatures in autumn and winter have therefore been identified as crucial variables for the development of the BTV distribution model, together with average day, night and daily temperatures, over periods for which enough data were available (see Table

6.2). Due to the nature of the MODIS product utilised, only 8-daily averages of day and night time temperatures can be derived. Thus the maximum and minimum values that have been extracted from the processed LST day and LST night data represent the average day and average night temperature of the warmest and coldest eight days, respectively, in any aggregation period. Due to the large amount of missing data on night temperature in the NT, average daily temperature variables have been generated for the Pilbara only. Several variables were generated for a pixel only if data were available for more than 50% of the epochs in the aggregation period.

6.3.5 Growing Degree Periods

Besides the minimum and maximum temperature limits that determine vector survival, the duration of favourable conditions are an important factor particularly for the development stage of insects. For this reason, Growing Degree Days (GDD), which is a temperature-based index used e.g. to predict flowering of plants, insect molting (Pasotti et al. 2006), and the risk for West Nile virus transmission (Liu et al. 2009), were considered for this study. The GDD index estimates heat accumulation from the daily mean temperature minus a base temperature, usually calculated year-wise from the winter minimum to the end of a year (Neteler 2010).

Here, the traditional GDD calculation, which uses daily air temperature measurements, has been adapted to the available MODIS LST data and the ecology of the vectors (Equation 6.1).

$$GDD_{LST} = \begin{cases} T_{mean} - T_{base} & if \quad T_{\max} > T_{mean} > T_{base} \\ 0 & if \quad T_{mean} \le T_{base} \\ T_{\max} & if \quad T_{mean} \ge T_{\max} \end{cases} \tag{6.1}$$

where GDD_{LST} is the average number of degree days per day in an 8-day MODIS LST compositing period and T_{mean} is the mean temperature of the 8-day period. If the mean temperature is below the base temperature T_{base}, no GDD_{LST} will be accrued, because all insect development is expected to cease below that temperature. A maximum cut-off temperature T_{max} is also defined, acknowledging that no further increase in the insect's growth rate is expected above that temperature. The temperatures for T_{base} and T_{max} have been set to 17°C and 36°C, respectively, informed by the findings of Bishop et al. (1996), who investigated development rates of *Culicoides* in dung pads at different temperatures. Growing Degree Days were accumulated for the Pilbara annually, seasonally, as well as over the summer and autumn months (Table 6.2).

It is recognised that these quasi GDD measures are not directly comparable to the index use in agriculture, due to differences in base and cut-off temperatures, the fact that LST is used instead of air temperature and GDD have been calculated from 8-daily average temperatures. However, the variables generated here support the analysis of spatial and temporal patterns in the temperature regime relevant to the ecology of *Culicoides* vectors.

6.3.6 Accumulated Rainfall

Studies of the association between rainfall and the occurrence of BTV in cattle in North Eastern Australia provide several findings of relevance for this research. Ward and Thurmond (1995) identified correlations between BTV seroconversion and rainfall two to three months previously, with the effect of rainfall on the risk for seroconversion being highest in the preceding month. Considering that Bluetongue seroconversion in Queensland cattle generally occurs in late autumn and early winter, the authors suggest that autumn rainfall is likely to be important for the detection of BTV in that area. Translated to the Northern Territory and Western Australia, where virus activity outside the endemic region generally occurs between January and June (see Figure 5.10 and Animal Health Australia (2001)), this indicates that rainfall from early summer through to autumn may be important for BTV occurrence.

Consequently, several seasonal rainfall accumulation totals were calculated from the daily rainfall data for the periods covering the wet season (November to May), summer (December to February) and autumn (March to May) months. While there is an overlap between variable classes, they each contain distinct information on the wet season pattern of rainfall.

6. 4 Spatial Aggregation of Bioclimatic Variables at a Pastoral Property Level

The nature of the seroconversion dataset from NAMP with location information only given at a property level demands the application of an aggregation approach for the environmental variables to describe the conditions on the whole station.

6.4.1 Definition of Sampling Areas for Bioclimatic Variables

Since the environmental conditions will be analysed for their correlation with virus occurrence, they should ideally be sampled from locations where BTV transmission is most likely to occur. These areas, earlier referred to as the focus or nidus of the disease are found where hosts and vector congregate. In regions with small farms, it is relatively easy to delineate the origin of the tested cattle with an accuracy of a few kilometres or less, if cattle are kept in an enclosure or paddock near the homestead or farmhouse. In such cases bioclimatic variables may be sampled at a buffer around the homestead (Guis et al. 2007), or, if that is the origin of an infected cattle, at a particular paddock.

In the rangelands of Northern Australia, however, where the size of a typical property is 1,850 km^2 on average in the Pilbara and around 2,800 km^2 in the Northern Territory, such an approach is not practical. Figure 6.9 below demonstrates the dimension of a Pilbara cattle station and the location of the homestead with Glenflorrie Station as an example.

Except for some sentinel herds, the true location of infection cannot be determined accurately, as cattle are mainly free roaming over large distances. The majority of cattle spend most of the year far from the homestead and it is only during the muster that they are driven to the yards where they can be bled for BTV and other arbovirus antibodies. Although fenced paddocks exist and at the time of testing, pastoralists might still be able to determine the paddock from which a cattle herd was driven to the yards (as experienced by the author during a field trip), this information is not recorded in the database. Moreover, spatial information about fence lines is incomplete and is therefore of limited use for this study.

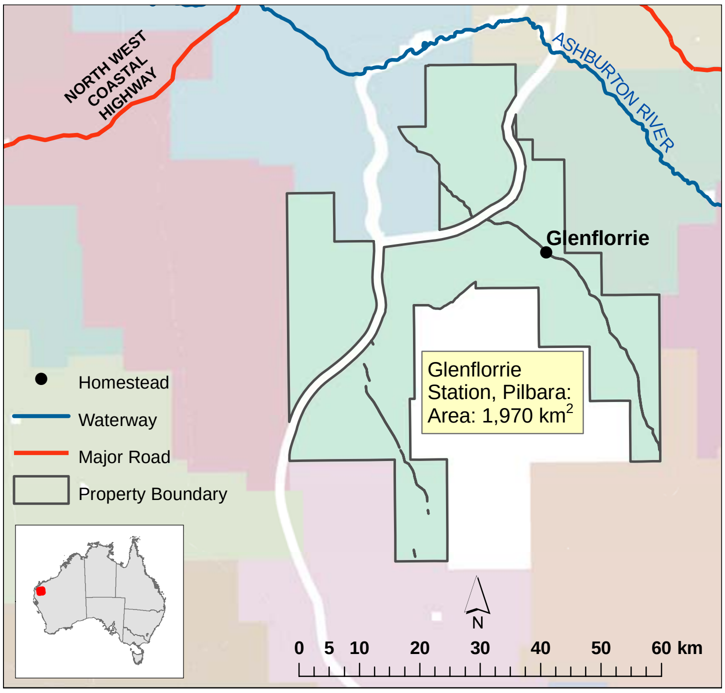


Figure 6.9 Glenflorrie Station and surrounding properties in the Pilbara

Environmental variable sampling will therefore involve large areas and there are two approaches that are tested and explained below:

1. Determine the station average for each of the variables;
2. Use ancillary information to determine the likely location of livestock to weight those areas higher when calculating the station average of each variable.

6.4.2 Station Averaging Approach

For the calculation of the station average, the whole station area was considered of equal importance, regardless of any factors that favour or exclude the presence of host and vector habitats. Only pixels with low NDVI values, as well as built-up areas, mines, road reserves, perennial water courses and lakes, and swamps from the GEODATA TOPO 250K Series 3 (Geoscience Australia 2006) have been excluded from the analysis. Using the zonal statistics function in ArcGIS, the average of each variable from Table 6.2 was determined for all pastoral properties in the NAMP database and summarised in a table for each region for the seasons 2000/2001 to 2008/2009 (see Appendices A and C).

6.4.3 Weighted Station Average Approach

An alternative to the station average approach has been developed based on the basic needs for cattle to survive, which are water and food. The availability and location of these two resources can help identify areas where cattle are most likely to graze and hence develop a habitat for vectors and a focus for BTV. Those areas are then weighted higher in calculation of the station average of the bioclimatic variables as described below. The approach was tested for the Pilbara initially due to the availability of suitable data, and can be applied to other areas if it proves to be superior to the simple station average.

Particularly in the warmer months of the year, cattle congregate around water points, permanent or temporal water bodies to drink and seek shade during the heat of the day. However, these areas are often heavily overgrazed and cattle are required to walk further away from the water points towards the end the day. This is also the time when humidity levels increase and *Culicoides* midges are most active. Cattle are travelling up to 8 - 10 km (Hodder and Low 1978), depending on the quality of pasture, terrain and other limiting factors like fence lines. Initially, it was intended to weight areas around water points or other sources of permanent waters higher. However, analyses of the distribution of watering points showed that 80% of station properties are within 10 km from a water point. Hence, cattle are able to search for the best pasture while still being in reach of a source of water.

For this reason, the availability of palatable vegetation that would attract cattle is considered to be more important for the estimation of cattle density. The Rangeland Land System dataset compiled by the Department of Agriculture Western Australia (see Section 5.4.4) provided a very useful source of information not only about the predominant vegetation type found in each land system, but also about the carrying capacity of each land system, i.e. how many hectares of land are needed to sustain a cattle unit (CU). CU is a standard measure equivalent to seven dry sheep equivalents (DSE), which is a unit of stocking rate frequently used among graziers in Australia that equates to an intake of ~7 MJ of metabolisable energy per day (Walcott and Zuo 2003). The data are static and do not reflect any changes in management that influence the actual number of cattle (e.g. through destocking as a result of drought stress or overgrazing). However, they give an indication about areas of different pastoral potential and can be used to disaggregate a station as described below. Unfortunately, an equivalent rangeland land system dataset is not currently available for the NT to apply the disaggregation approach in that area.

Based on the carrying capacity data (given in CU / ha) and the area of a land system within a property, the potential number of cattle for each land system was determined. This number in relation to the potential total number of cattle on a station determines the weight for each land system in the calculation of the weighted average (Equation 6.2).

$$\bar{y} = \sum_n \bar{y}_i w_i \qquad (6.2)$$

where $\bar{y}$ is the weighted station average of an environmental variable, n is the number of land systems comprising a property, $\bar{y}$ is the average of an environmental variable for a land system i, and w_i is the weight assigned to each land system based on carrying capacity and area as follows:

$$w_i = \frac{carryingcapacity_i\, area_i}{\sum_n carryingcapacity_i\, area_i} \qquad (6.3)$$

The average variable values for each land system have been determined with the ArcGIS zonal statistics function and the weighted averages were summarized in tables for the nine seasons from 2000/2001 to 2008/2009. As before, pixels with low NDVI values, as well as built-up areas, mines, road reserves, perennial water courses and lakes, and swamps from the topographic dataset have been excluded from the analysis.

Figure 6.10 illustrates the land systems that comprise Glenflorrie Station in the Pilbara and the weights that have been assigned to each Land System, considering the potential number of cattle it can sustain. A summary of the weighted environmental variables can be found in Appendix B.

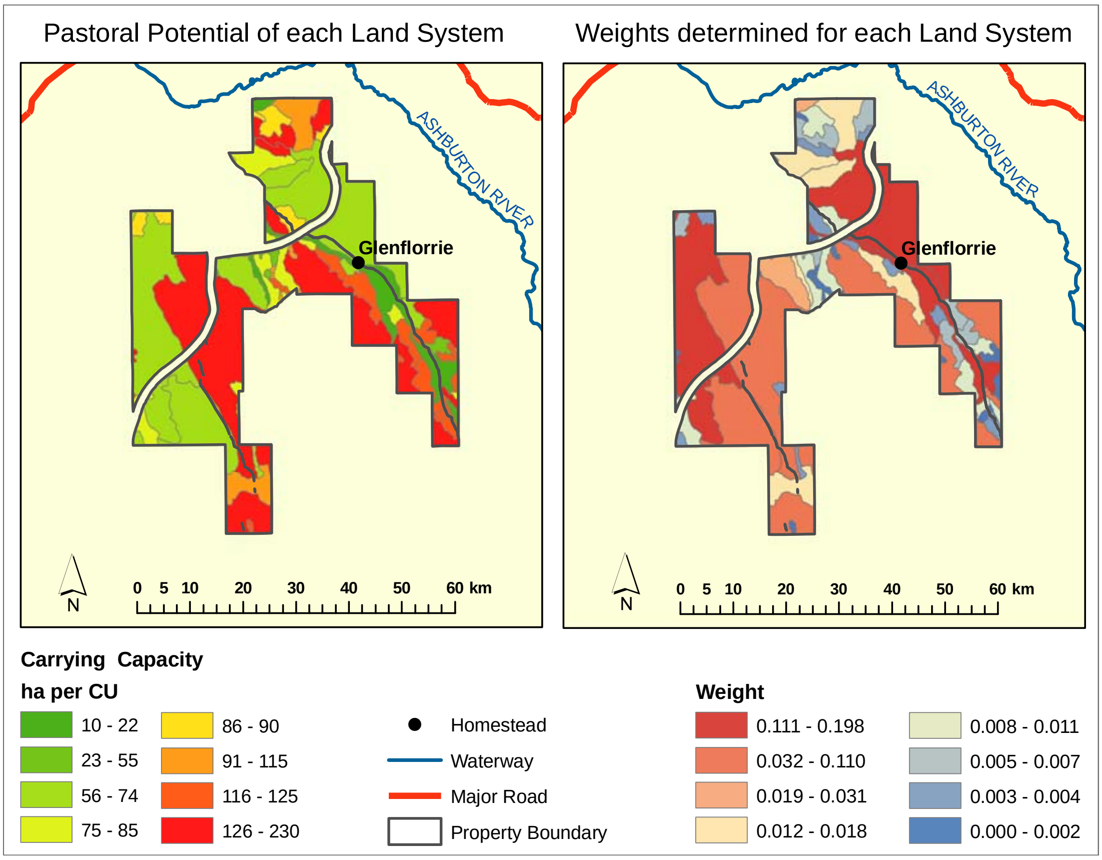


Figure 6.10 Carrying capacity of Land Systems at Glenflorrie Station and the weights used in the weighted station average calculation

6. 5 Summary

In this chapter, the workflow for the generation of bioclimatic variables has been described. The initial data processing steps, including data acquisition, reprojection, merging and quality filtering were outlined, followed by the extraction of the various environmental parameters from MODIS and TRMM data products.

After the definition of the aggregation periods (annual, seasonal, summer, winter and autumn), the various variables (maximum NDVI, integrated NDVI, minimum, maximum and mean land surface temperatures, Growing Degree Days and accumulated rainfall) were derived for these periods, using the geoprocessing environment of ArcGIS and custom Python scripts. Problems were highlighted in areas where data are missing due to the effects of cloud cover during the wet season, which resulted in a reduced set of useful variables in the Northern Territory. Approaches were then presented to aggregate the environmental variable on a pastoral property level, either using a simple averaging method or a weighted average approach based on the potential cattle density of different land systems.

In the following chapter the station summaries of the environmental variables will be analysed for their correlation with the occurrence of BTV. Distribution models will then be built with the variables that show significant correlation and are most important ecologically.

CHAPTER 7

DEVELOPING A PREDICTIVE MODEL OF BTV DISTRIBUTION BASED ON BIOCLIMATIC VARIABLES

In the previous chapter the process involved in the generation of remotely sensed bioclimatic variables was described. This chapter continues with the spatial analyses of relationships between these bioclimatic variables and BTV occurrence, upon which a spatial distribution model can be developed. Following the structuring of the predictor and response variables in a database, the development of a BTV distribution model is carried out in four stages. After the predictor variables have been analysed for correlation with BTV, the set of significant variables are used for the development of models for the Pilbara and the Northern Territory. The best fitting models are then used for the generation of annual prediction maps, which will be assessed using external data from a season that have not been included in model building. Issues of spatial autocorrelation are also addressed.

7. 1 Organising and Screening the Serological and Environmental Data

The serological data collected by the NAMP collaborators are centrally stored in a web based information system NAMP*Info* (Cameron 2000b, 2004), where they can be extracted for a particular time span and jurisdiction (i.e. state or territory). Besides the bleeding date, the information recorded includes the unique ID, latitude and longitude of each site, the total number of cattle tested and the number of infected cattle. Data can either be viewed online or downloaded as Excel worksheets, as was done for this project. In this way, serological data from both serological surveys and sentinel herds were initially obtained for the whole area of Western Australia and the Northern Territory from January 2000 to December 2009. From these data, which contain information about Bluetongue, Akabane and EHD viruses, relevant information was extracted only for Bluetongue virus for the study period from November 2000 to October 2009. Samples obtained as part of the process of recruiting new sentinel cattle were excluded as those cattle have not been at risk of being infected. Also, data from all sites that are not fully inside the study area limits as defined in Chapter 5 have been excluded. The location information for the NAMP sites was also assessed for inconsistencies using the property boundary datasets mentioned in Chapter 5. Generally, NAMP collaborators record the location of a homestead or the yards where bleeding took place, by means of latitude and longitude. Until recently, according to the former NAMP coordinator for WA, Richard Norris, coordinates were obtained from a standard atlas (personal communication, March 4, 2008). Also, some sites have been entered into the database that are within the boundaries of the same property, either because samples were taken at different yards within the property or due to human error. Data from such duplicated sites were reattributed to one site and like the other NAMP sites linked to the property polygon via the unique NAMP ID. Boundaries of properties that were missing in the pastoral property dataset, such as some of the research stations or feedlots at the export harbours, were obtained from online cadastral datasets (Landgate 2009; Northern Territory of Australia 2008) or digitised from Google Earth satellite imagery.

Table 7.1 shows an extract of the resulting data, which comprise 135 observations from 50 different sites in the Pilbara and 859 observations from 63 different sites in the NT. A full overview of the data can be found in Appendices A and B.

Table 7.1 Extract of data compiled from NAMP*Info*

Site_ Num[1]	**State**	**Bleed_ Date**	**Season**	**Bleed_ Type**[2]	**Virus_ short**[3]	**Num_ total**[4]	**Num_ seroconv**[5]	**Comment**[6]
W134	WA	12/09/2006	2005	Serosurv	BTV	30	0	Changed from W138
W134	WA	10/05/2007	2006	Serosurv	BTV	29	0	Changed from W138
W136	WA	22/09/2006	2005	Serosurv	BTV	30	0	
W137	WA	19/09/2006	2005	Serosurv	BTV	30	30	
…	…	…		…	…	…		
W141	WA	27/09/2006	2005	Serosurv	BTV	30	24	

1) unique ID assigned within then NAMP*Info* database; 2) type of survey (serological survey or sentinel herd); 3) acronym for virus (BTV, AKA, or EHF); 4) number of animals sampled; 5) number of animals seroconverted; 4) any changes made to the original data

As can be seen in this example, some properties have been tested multiple times, which may violate the assumption that the observations are independent. However, due to the fact that for most of the surveys cattle have been sourced from different areas of the often very large pastoral properties makes the observations sufficiently independent for this study. Considering the already small sample size, the pragmatic decision was made to keep all remaining observations for further analysis.

Following the screening process, a file geodatabase was set up in ArcGIS, where all tabular data of serology and the extracted bioclimatic variables are managed together with the spatial property datasets. To create a suitable structure for the analysis of virus - environment relationships the serological status of each of the tested properties was summarized per year as a dichotomous variable (1: presence; 0: absence) and merged with the bioclimatic variables for those years as illustrated in Table 7.2 below. For the complete dataset see Appendices C to E.

Table 7.2 Extract from the dataset developed for the analysis of correlations between the predictor environmental variables and BTV occurrence response variable

NAMP ID	**Station_name**	**Year**	**BT_status**	**maxndviss**	**maxlstdsu**	**…**	**Rau**
108	Crown	2001	1	0.726	35.848		243.06
108	Crown	2002	1	0.735	31.607		166.10
T029	Helen Springs	2000	0	0.503	42.249		177.98
…	…	…	…	…	…	…	…
T075	Buchanan Downs	2004	1	0.527	47.208	…	38.172

Table 7.3 below provides a summary of the number of tested properties as well as the farm level seroprevalence for both study areas. More detailed analyses, such as seroprevalence standardised by the age of animals tested were not feasible due to the lack of suitable data collected through the NAMP.

Table 7.3 Number of tested properties and seroprevalence in the Pilbara and the Northern Territory

	Pilbara		**Northern Territory**	
Year	**No. of tested properties**	**Prevalence (95% confidence interval)**	**No. of tested properties**	**Prevalence (95% confidence interval)**
2000/2001	30	0.13 (0.03-0.31)	14	0.36 (0.13-037)
2001/2002	13	0.46 (0.19-0.75)	18	0.67 (0.41-0.87)
2002/2003	15	0.33 (0.12-0.62)	25	0.68 (0.46-0.85)
2003/2004	7	0.14 (0.00-0.58)	23	0.74 (0.52-0.90)
2004/2005	8	0.13 (0.00-0.53)	18	0.28 (0.10-0.53)
2005/2006	16	0.06 (0.00-0.30)	10	0.80 (0.44-0.97)
2006/2007	9	0.22 (0.03-0.60)	17	0.70 (0.44-0.90)
2007/2008	8	0.00 (0.00-0.48)	37	0.54 (0.37-0.71)
2008/2009	7	0.00 (0.00-0.53)	38	0.71 (0.54-0.85)

7. 2 Selection of Variables to be Used in Model Development

The initial set of environmental variables developed has been selected on ecologically sound principles using knowledge about BTV ecology, but also considering the availability of data of sufficiently high quality. This section statistically analyses the relationship between BTV presence and each of the explanatory variables in order to identify the significant predictor variables for model building. The analyses are conducted for the station average and weighted station average variables of the Pilbara region and the station averages of the Northern Territory.

7.2.1 Analyses of Associations between Bioclimatic Variables and BTV Status

As a first step, univariate analyses were conducted using the statistical environment R (R Development Core Team 2010) to identify those variables which are most able to discriminate between BTV positive and negative properties. Using a non-parametric Kruskal-Wallis test (Kruskal and Wallis 1952), variables showing statistically significant differences between the two groups (BTV positive and BTV negative properties) could be identified. The hypothesis to be tested is that the same environmental conditions are present on cattle stations where BTV has been found as on those where the virus is absent. The test is similar to the parametric one way Anova, but has the advantage that it does not require the variables to be normally distributed (Moore, McCabe, and Craig 2009). It is also better suited for small sample sizes, which is another characteristic of the data used in this study. If the number of different groups equals two as with presence/absence data, the Kruskal-Wallis test is equal to the Mann-Whitney test. As with many other non-parametric procedures these techniques do not work with the original measurements, but instead with the ranks of the measurements, as described in detail by Zar (1999). Boxplots were generated for all variables to visually investigate their correlation with BTV positive and BTV negative sites (some of the key variables are shown in Figures 7.1 to 7.5). The entire test results are tabulated in Table 7.4 and discussed below.

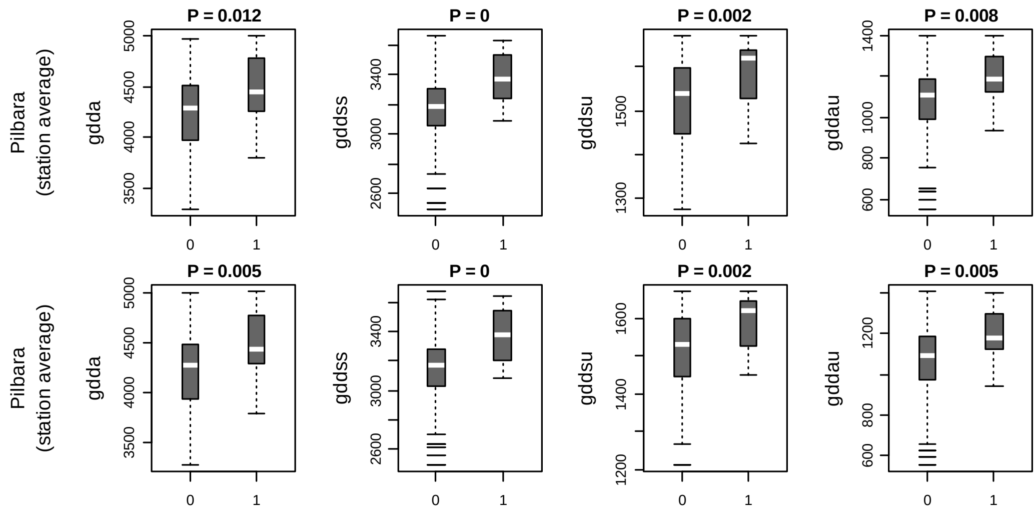


Figure 7.1 Relationship between selected Growing Degree Day variables and BTV status (0 = negative, 1 = positive), with the p-value indicating the significance of the group differences

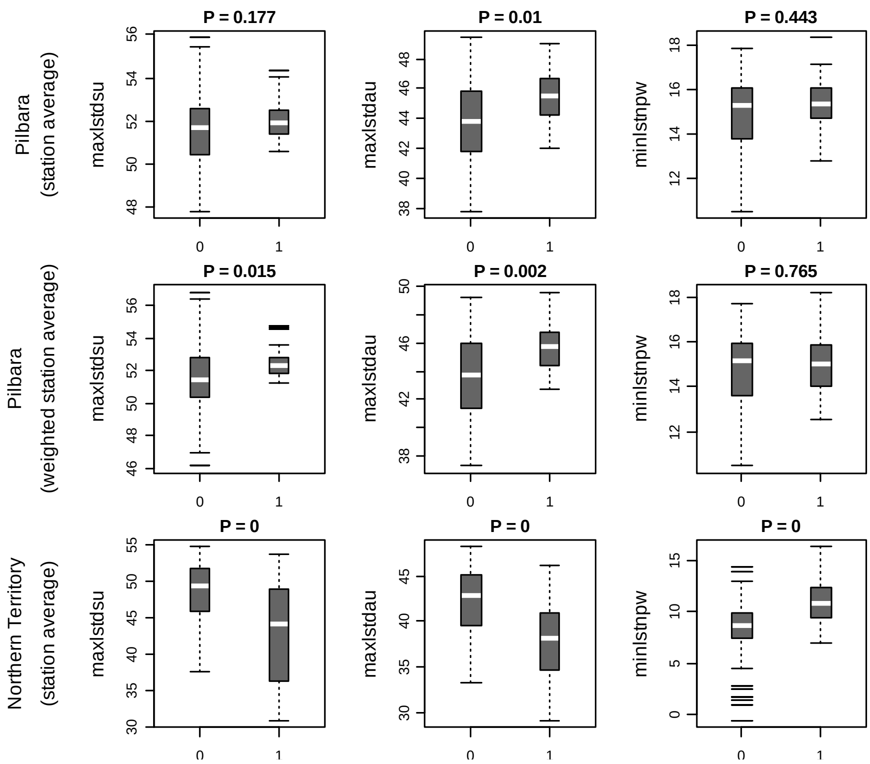


Figure 7.2 Relationship between selected minimum and maximum temperature variables and BTV status (0 = negative, 1 = positive), with the p-value indicating the significance of the group differences

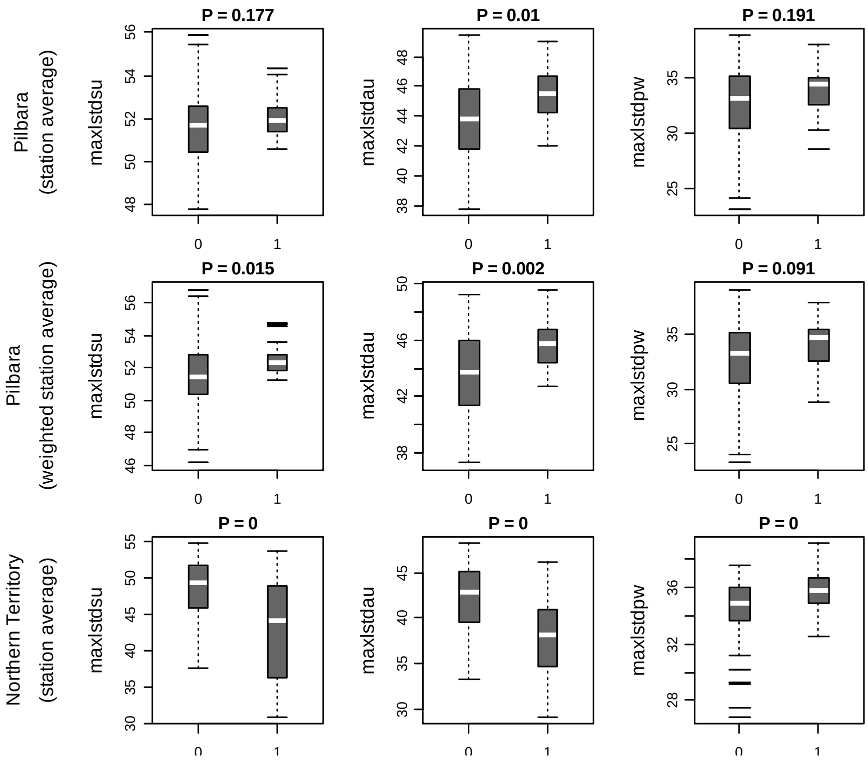


Figure 7.3 Relationship between selected mean temperature variables and BTV status (0 = negative, 1 = positive), with the p-value indicating the significance of the group differences

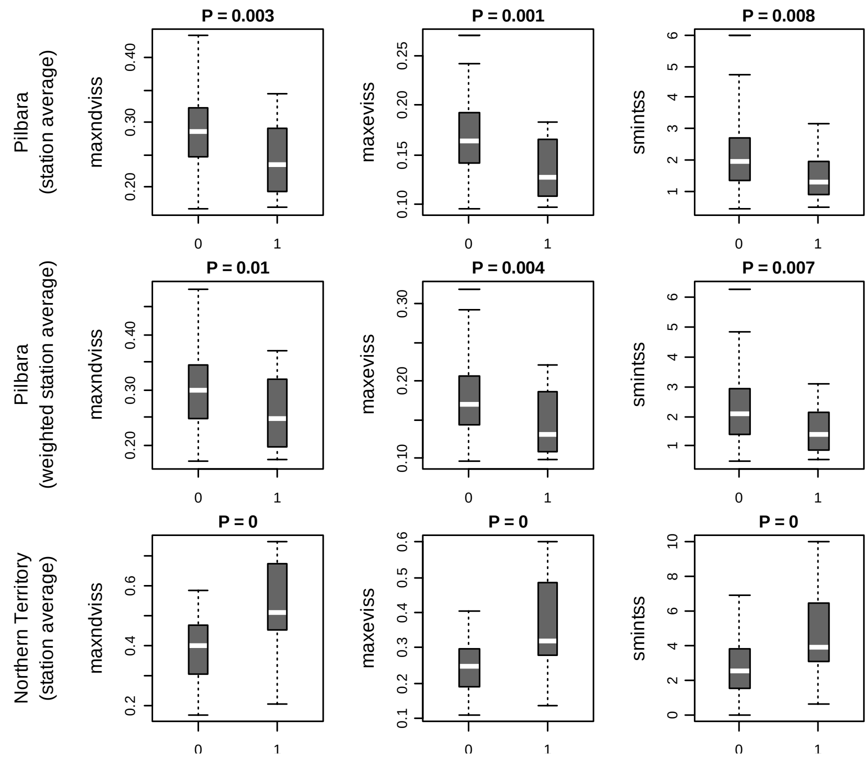


Figure 7.4 Relationship between vegetation variables and BTV status (0 = negative, 1 = positive), with the p-value indicating the significance of the group differences

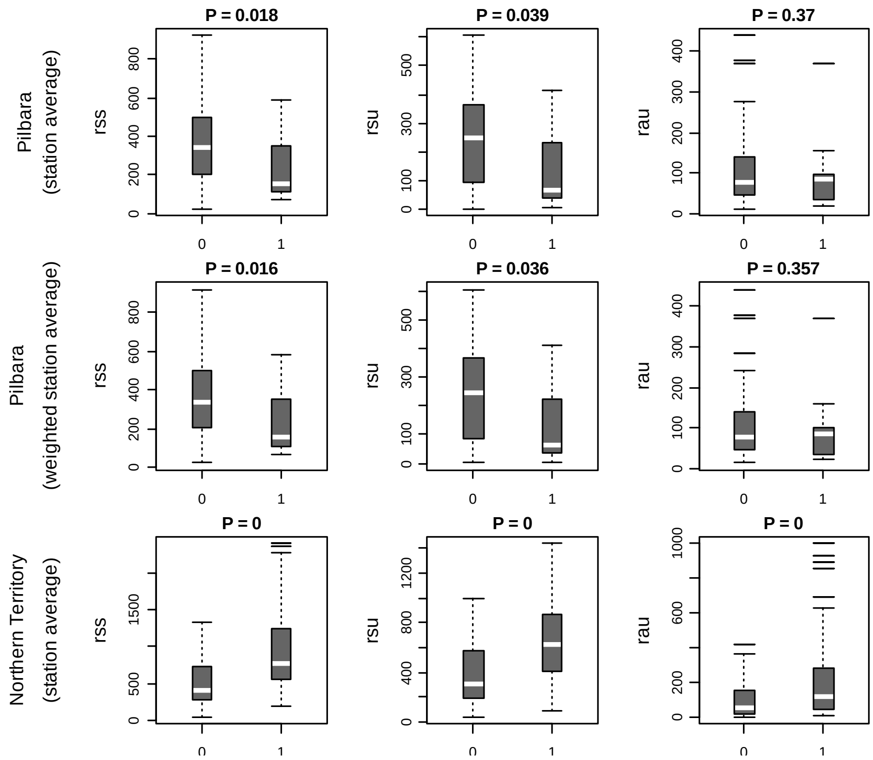


Figure 7.5 Relationship between rainfall variables and BTV status (0 = negative, 1 = positive), with the Kruskal-Wallis p-value given

The scatterplots reveal some notable differences between the effects of environmental conditions on the BTV status at the two study areas. Results from the Northern Territory show that the association between BTV presence/absence and NDVI, temperature and rain fits well with what is currently known about the ecology of the virus. Higher vegetation index values, rainfall accumulates and winter temperatures are found at BTV positive sites, while higher temperatures during the warmer months are associated with virus absence. The latter effect can be explained by the cessation of vector activity at higher temperatures due to desiccation, particularly in central Australia.

All variables are significantly different between positive and negative sites (Table 7.4) and are therefore equally capable of explaining differences between positive and negative sites, which is needed to develop a robust model. Although only observable at the least significant digits of the p-value and therefore not shown in Table 7.4, the strongest difference was found between the vegetation and rainfall variables.

Table 7.4 Test statistics for the Pilbara and Northern Territory study areas

Region (aggregation level)	Pilbara (station average) n = 76		Pilbara (weighted station average) n = 76		Northern Territory (station average) n = 162	
Variable (see Table 6.2)	**Chi-square**	**p-value**	**chi-square**	**p-value**	**chi-square**	**p-value**
maxndviss	9.1204	0.0025**	6.7186	0.0095**	39.1673	<0.0001**
maxeviss	11.8884	0.0006**	8.3101	0.0039**	37.8558	<0.0001**
smint	7.0148	0.0081**	7.2738	0.0070**	27.1438	<0.0001**
maxlstdss	1.4867	0.2227	5.4082	0.0200*	14.8629	0.0001**
maxlstdsu	1.8185	0.1775	5.9468	0.0147*	25.2792	<0.0001**
maxlstdau	6.5936	0.0102*	9.1692	0.0025**	35.8284	<0.0001**
maxlstdpw	1.7112	0.1908	2.8481	0.0915	12.7371	0.0004**
minlstnss	12.2257	0.0005**	8.3345	0.0039**		
minlstnsu	11.7228	0.0006**	10.4855	0.0012**		
minlstnau	4.5444	0.0330*	3.6934	0.0546		
minlstnpw	0.5885	0.4430	0.0893	0.7651	32.1725	<0.0001**
meanlstdss	4.4761	0.0344*	7.4496	0.0063**	24.5983	<0.0001**
meanlstdsu	1.5066	0.2197	2.6083	0.1063	32.8723	<0.0001**
meanlstdau	1.5565	0.2122	3.4945	0.0616	14.4972	0.0001**
meanlstdpw	1.1276	0.2883	2.1244	0.1450	24.1942	<0.0001**
meanlstnss	4.8419	0.0278*	5.7324	0.0167*		
meanlstnsu	9.3172	0.0023**	8.7828	0.0030**		
meanlstnau	0.8850	0.3468	0.6199	0.4311		
meanlstnpw	1.1796	0.2774	0.2308	0.6309	24.9716	<0.0001**
meanlstss	14.2811	0.0002**	16.6944	<0.0001**		
meanlstsu	0.4823	0.4874	0.3105	0.5774		
meanlstau	2.4668	0.1163	2.2924	0.1300		
meanlstpw	1.0767	0.2994	1.2508	0.2634	25.86522	<0.0001**
gdda	6.2660	0.0123*	7.8511	0.0051**		
gddss	12.6233	0.0004**	14.1593	0.0002**		
gddsu	9.2673	0.0023**	10.0706	0.0015**		
gddau	7.0577	0.0079**	7.8964	0.0050**		
rsu	5.5976	0.0180*	5.8292	0.0158*	34.61466	<0.0001**
rau	4.2732	0.0387*	4.4077	0.0358*	33.69828	<0.0001**
rss	0.8034	0.3701	0.8474	0.3573	17.95233	<0.0001**

**: The difference between groups is statistically significant ($p \leq 0.01$)
*: The difference between groups is statistically significant ($p \leq 0.05$)
n: Number of records

The differences between the positive and negative sites are generally less significant for the Pilbara. The most significant differences between presence and absence sites were found for the variables summarising vegetation indices, night land surface temperature, mean seasonal temperatures, and growing degrees days (Table 7.4). The effects vary slightly between variables generated using the station average approach and variables based on the weighted station average, the later of which shows higher significance in group differences for smintss, and the various maxlst, gdd and rain variables.

Unexpectedly, the box plots show a negative relationship between BTV presence and the usually important variables related to rainfall, humidity and vegetation. According to the data, the higher NDVI values are related to BTV absence, as are higher rainfall figures. If these variables were included in the model, a higher probability for BTV presence would be predicted for drier regions, such as the Great Sandy Desert. This is contradictory to the ecology of the BTV vectors, which are unlikely to occur in those regions due to the lack of both humidity and cattle.

The effects are mainly related to a bias towards negatively tested properties (out of 76 samples, only 16 are BTV positive), which may provide suitable habitats for *Culicoides* vectors, but where BTV has not been detected for several reasons. In contrast to the Northern Territory, the Pilbara has been declared BTV infected very recently and BTV is still not considered endemic to the area. Therefore, in years where BTV was not present in the Pilbara there is a natural bias towards negative test results. Factors other than environment and climate may be driving virus occurrence (see the maps in Figure 5.4), particularly during the first year of BTV introduction. The outbreak that was detected at the Kooline and Mt Stuart stations in the central Pilbara only infected neighbouring stations, while more distant properties tested BTV negative during an extensive surveillance campaign. The following season (2001/2002), BTV seemed to have spread further, infecting properties to the east and south of the original detection. This trend continued in 2002/2001. However, the following years, surveillance activities were gradually reduced, and therefore so was the detection of BTV. For this reason it is not known, if virus activity was lower due to changes in the environment or due to reduced surveillance activities. As indicated in Section 2.2.3, the economic impacts of declaring an area as BTV infected are nowhere else in Australia as large as they are in the Pilbara. This also needs to be considered in the analysis of the data, since NAMP surveillance depends on the collaboration of pastoralists. Further analyses were conducted to investigate the effect of study area boundaries and include only data from sites closer to the original outbreak between longitudes 114° 55' and 118° 49'E and latitudes 19° 34' and 25° 10'S, while excluding sites to the far east and south. The rationale behind this strategy is that higher NDVI and rainfall figures are generally found in the south of the region, while BTV is absent due to the lower temperatures. According to R. Norris (personal communication, March 4, 2008), BTV has not been found along the coast east of Port Hedland for unknown reasons. Also excluded were data from the season 2000/2001, when the virus had not yet established. However, as shown in Figure 7.6, similar associations were found between the reduced samples and *maxndviss*, *smintss*, *rsu* and *rau*:

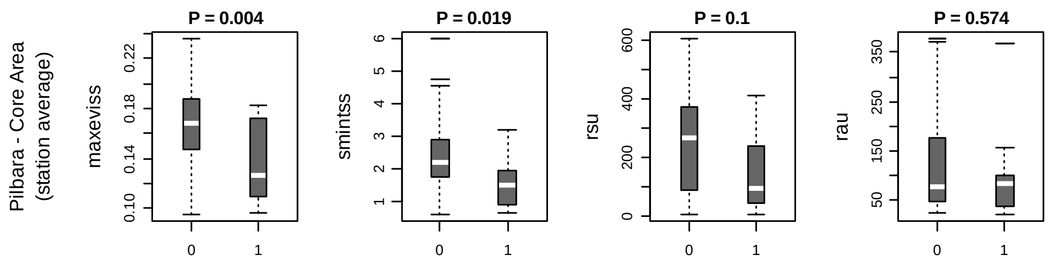


Figure 7.6 Relationship between vegetation variables and rain variables and BTV status (0 = negative, 1 = positive) based on 46 observations from the area around the initial BTV outbreak in the Pilbara, with the p-value indicating the significance of the group differences

In summary, some of the measures, particulary the GDD variables, are promising predictor variables for the Pilbara, with significant differences between positive and negative properties for all aggregation periods. However, given the behaviour of the other variables and with knowledge of the nature of the NAMP data as discussed above, these results cannot be fully trusted. Following further discussions with NAMP coordinators and entomologists familiar with the surveillance activities in the Pilbara, it was acknowledged that the surveillance data from this region are unsuitable for model development. Model development was therefore only progressed further for the Northern Territory.

7.2.2 Assessment of Correlations Between Predictor Variables

One of the basic assumptions underlying the regression methods to be used in this study is the independence of the predictor variables. Collinearity in the predictor variables is a crucial problem, which may lead to inaccuracy of the model by inflating the variance of the model parameters. A common observation is that two highly correlated predictors can both appear non-significant even though each would explain a significant proportion of the deviance if considered individually (Guisan, Edwards, and Hastie 2002). Although it is less of a problem for predictive models, if the model parameters are to be interpreted, it may become difficult to assess the individual importance of each collinear predictor variable. Careful selection of the variables during the model building process is therefore required.

In order to identify possible collinearity between variables they have been analysed pair-wise for correlations. The data divide naturally into two groups, namely temperature variables, and rainfall and vegetation variables. They were therefore analysed in those groups (Tables 7.5 and 7.6). The results will be considered when building the model and deciding which predictor variables to include or exclude.

Table 7.5 Pearson correlation coefficients for rainfall and vegetation variables

	maxndviss	maxeviss	smintss	rss	rsu	Rau
maxndviss	1	0.978	0.666	0.839	0.815	0.658
maxeviss	0.978	1	0.602	0.849	0.796	0.703
rmintss	0.666	0.602	1	0.531	0.539	0.401
rss	0.839	0.849	0.531	1	0.942	0.842
rsu	0.815	0.796	0.539	0.942	1	0.627
rau	0.658	0.703	0.401	0.842	0.627	1

Table 7.6 Pearson correlation coefficients for temperature variables

	maxlstdss	maxlstdsu	maxlstdau	maxlstdpw	minlstnpw	meanlstdss	meanlstdsu	meanlstdau	meanlstdpw	meanlstnpw	Meanlstpw
maxlstdss	1	0.685	0.664	-0.257	-0.423	0.886	0.843	0.727	-0.175	-0.315	-0.255
maxlstdsu	0.685	1	0.832	-0.331	-0.642	0.646	0.733	0.382	-0.581	-0.691	-0.666
maxlstdau	0.664	0.832	1	-0.401	-0.591	0.737	0.744	0.608	-0.569	-0.645	-0.636
maxlstdpw	-0.257	-0.331	-0.401	1	0.621	-0.345	-0.423	-0.268	0.543	0.645	0.62
minlstnpw	-0.423	-0.642	-0.591	0.621	1	-0.396	-0.526	-0.157	0.709	0.889	0.836
meanlstdss	0.886	0.646	0.737	-0.345	-0.396	1	0.96	0.913	-0.212	-0.341	-0.288
meanlstdsu	0.843	0.733	0.744	-0.423	-0.526	0.96	1	0.783	-0.34	-0.48	-0.428
meanlstdau	0.727	0.382	0.608	-0.268	-0.157	0.913	0.783	1	-0.018	-0.124	-0.072
meanlstdpw	-0.175	-0.581	-0.569	0.543	0.709	-0.212	-0.34	-0.018	1	0.812	0.956
meanlstnpw	-0.315	-0.691	-0.645	0.645	0.889	-0.341	-0.48	-0.124	0.812	1	0.947
meanlstpw	-0.255	-0.666	-0.636	0.62	0.836	-0.288	-0.428	-0.072	0.956	0.947	1

As can be seen in Table 7.6, there is considerable correlation observable between vegetation and rainfall. Strong correlation was found between *rss* (seasonal rain) and *rsu* (summer rain), indicating that most rainfall occurs during the summer months.

The strongest correlation was present between *maxndvi* and *maxevi*, which suggest using only one of the two in a model. In relation to temperature (Table 7.5), the highest correlation has been found between the two variables *meanlstdsu* and *meanlstdau* and the derivative seasonal mean day temperature *meanlstdss*, and similarly between the two variables *meanlstdpw* and *meanlstnpw* and the derived mean temperature in winter, *meanlstpw*.

7. 3 Developing the Distribution Model

7.3.1 Generalised Linear Models Versus Generalised Additive Models

Based on the comparison of different modelling techniques in Section 3.3, GLM and GAM approaches were both considered for this study. To be able to decide which method is the most appropriate, the nature of the relationship between predictor variables and BTV occurrence needs to be analysed. Some variables might be characterised by a linear response, which can be sufficiently accurately modelled using a GLM. However, non-linear responses to changes in environmental variables are often found in ecological and epidemiological modelling, e.g. rising temperature might initially increase vector activity, but after reaching an optimum temperature range, an additional increase in temperature might have an adverse effect. In such cases, one approach would be to categorise the variables (e.g. define specific temperature ranges for which the response is linear) as demonstrated by Austin, Nicholls and Margules (1990). Nevertheless, even after the transformation of variables and the addition of higher order terms, GLMs can still be an inadequate modelling procedure (Yee and Mitchell 1991). Early exploratory analyses using GLMs were abandoned due to their low explanatory power, compared to GAMs.

In contrast to a GLM, the response curve of a GAM is determined by the data and can take any shape. In a GAM, linear functions of the variables are replaced by so called smoothers, which gives additional flexibility for the modelling process. According to Hastie and Tibshirani (1990) a smoother is a non-parametric tool for summarising the trend of a response measurement as a function of one or more predictor measurements. The name refers to the characteristic that an estimate of the trend is produced that is less variable than the response itself. Examples of smoothers include running means, kernel smoothers, regression splines and natural splines. The non-parametric nature of GAMs also makes them very useful analytical tools for investigating the shape of the response curve for each variable. Some software implementations of the GAM approach, such as in R (Wood 2006) allow for the combination of variables with linear and non linear responses. Hence the question is no longer, if a GLM or a GAM should be used, but which variables show a linear response and can be parameterised in the model and which variables require a non-parametric curve due to their non-linearity. An example is shown in Figure 7.7, where one of the variables in a GAM can be described by a linear function. Full details about the modelling process are given below.

7.3.2 Developing the Generalised Additive Model

Generalised additive models were fitted using the gam() function from the R 'mgcv' package (version 1.7–1) (Wood 2010), starting with a model that includes all predictor variables with a Kruskal Wallis $p < 0.2$. A stepwise exclusion approach was then employed, removing the least significant variables during each iteration, until all variables were significant ($p < 0.05$). The p-value given for each smooth term is approximate and based on the test statistic motivated by Nychka's (1988) analysis of the frequentist properties of Bayesian confidence intervals for smoothers (Wood 2010). Where variables had the same or a similar p-value, those variables that are known to be important for the BTV cycle were retained in the model. Hence, the model was developed utilising expert knowledge as well as statistics. This minimises the risk of potentially using relationships which may be statistically significant but have no grounding in the ecological process being modelled. Several models were developed using this hybrid approach and the best model was chosen by maximising the discriminatory ability, given by the area under the receiver operator characteristic (ROC) curve (Pearce and Ferrier 2000). As described in Section 3.5 the area under the ROC curve (AUC) is a measure of the model's ability to correctly distinguish between presence and absence and can be interpreted in a straightforward manner. A value of 1 indicates perfect discrimination, whereas a value of 0.5 indicates that the model performs no better than a random guess (Fawcett 2006). Hosmer and Lemeshow (2000) considered values above 0.7 to provide reasonable discrimination and the larger the AUC the better the model at predicting group membership.

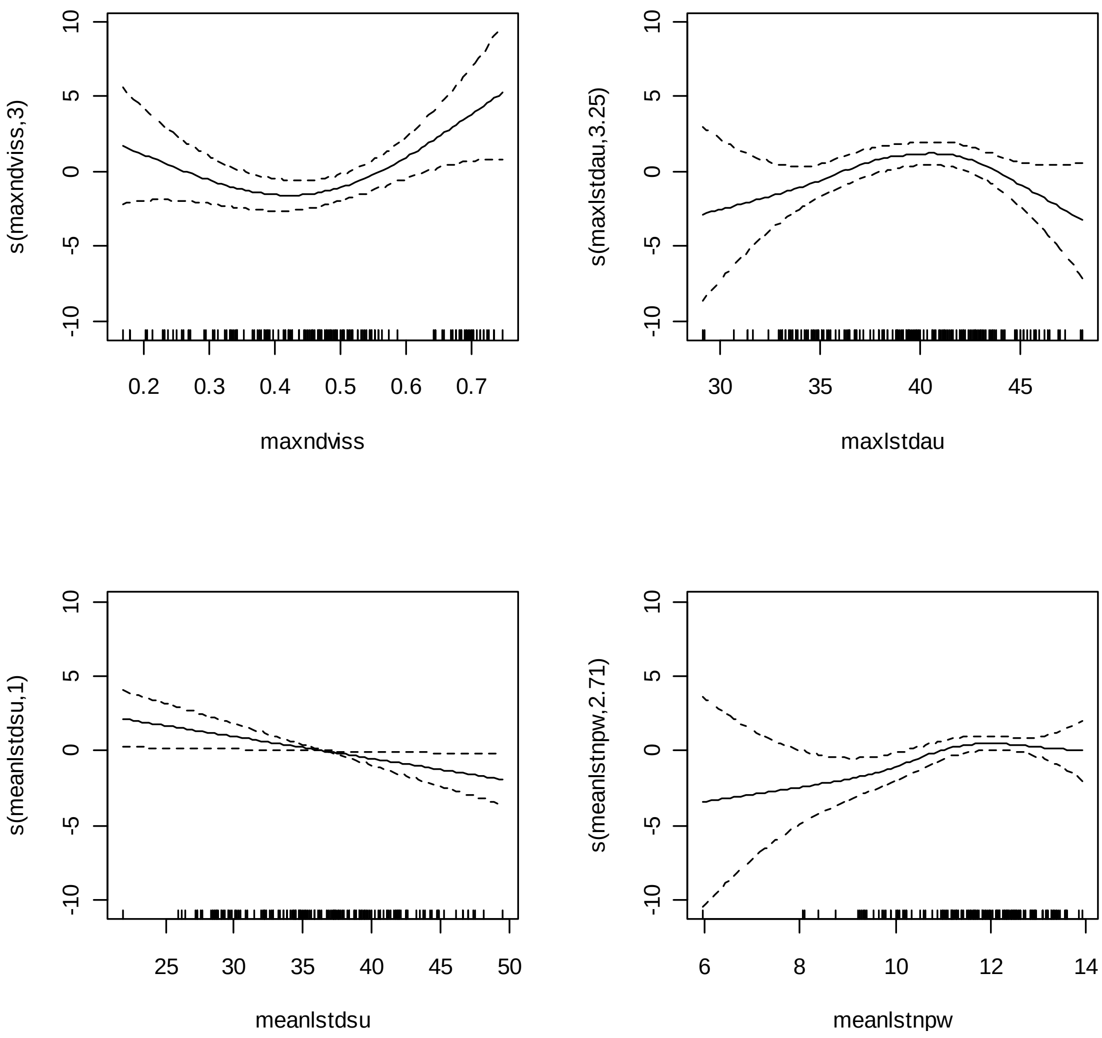


Figure 7.7 Smoothed fits to the variables maxndviss, maxlstdau, meanlstdau and meanlstnpw used in the final BTV distribution model for the Northern Territory (solid line). Dashed lines give ~95% confidence intervals

As summarised in Table 7.7 the four predictor variables that gave the best fit are maximum seasonal NDVI (*maxndviss*), mean day temperature of the warmest 8-day period in autumn (*maxlstdau*), mean day temperature in summer (*meanlstdsu*) and mean night temperature of the previous winter months (*meanlstnpw*). The GAM plot (Figure 7.7) shows the smoothers for these four covariates and the 95% confidence interval. The x-axis on the plots of covariate effects on the presence of Bluetongue illustrates the density of samples used for each covariate in the model. The plots show that the effect of one of the four variables on the outcome can be expressed by a linear function, while the other three variables were best described by an unimodal smoothing function (Figure 7.7).

Table 7.7 Significance of smooth (maxndviss, maxlstdau, meanlstnpw) and parametric (meanlstdsu) model terms in the BTV distribution model

Model terms	Df/edf	Chi-square	p-value
s(maxndviss)	3.001	11.001	0.0117*
s(maxlstdau)	3.254	9.551	0.0282*
s(meanlstnpw)	7.0148	7.699	0.0241*
meanlstdsu	1	5.087	0.0416*

*: The variable is statistically significant ($p \leq 0.05$)

In none of the models that have been developed, were more than four of initially 17 predictor variables significant. This may be explained by the relatively small sample size of 167 (96 BTV positive and 66 BTV negative). According to the "rule of thumb" of Harrell, Lee and Mark (1996) it is suggested that not more than six variables be used to achieve a stable model for this sample size. The final model has an AUC of 0.8644, which demonstrates an excellent predictive ability according to the classification described by Hosmer and Lemeshow (2000). The ROC plot for the model that has been developed with data for the seasons 2000/2001 to 2007/2008 is shown below (Figure 7.8). Further validation of the model was conducted using external data not included in model building from the season 2008/2009 and is described in Section 7.4.

Unfortunately, the model developed for the NT is not transportable back to the Pilbara due to large differences between the regions in regards to the climatic and environmental conditions. Investigations showed that predictor variables that have been identified as being significant to explain BTV seropositivity in the NT are not significant when applied to data from the Pilbara.

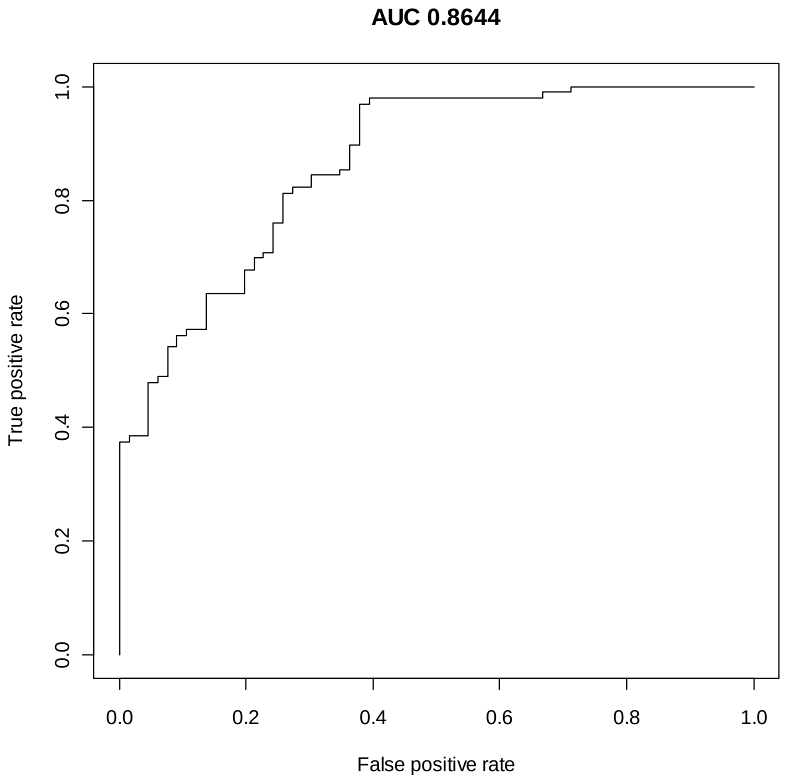


Figure 7.8 ROC plot of sensitivity (true positive rate) versus 1-specificity (false positive rate) for the final GAM based on data from 2000/2001 to 2007/2008

7.3.3 Spatial Effects

So far the effects of spatial autocorrelation (reviewed in Section 3.4) have not been considered when building the so called fixed effects GAM. Looking at the distribution of virus occurrence in Figure 5.8 suggests that the observed seropositivity may not be related to environmental factors alone (first order effects), but also may depend on the presence or absence of the virus on neighbouring stations. To identify such unaccounted for second-order effects, a typical approach is to examine the model residuals for evidence of spatial autocorrelation (see Pfeiffer et al. 2008). This involves the definition of “neighbourhood” between pastoral properties, either by distance or by adjacency, e.g. through sharing a common boundary. If there is evidence for spatial autocorrelation, the model can be extended to account for the spatial dependence between sites.

The peculiarities of the data that are dealt with in this study and the resulting model however exacerbate the situation. The samples that have been used for model building describe the BTV status over several years and some stations have multiple representations. Consequently, residuals would have to be analysed for each year separately. In the case of evidence for autocorrelation and considering that the effects will vary between years, distribution models would be needed to be developed on an annual basis. Given that the fixed effects model has originally been built from eight years of data comprising only 162 samples, reducing the sample size to between ten (season 2005/2006) and 25 samples annually (season 2002/2003) would lead to instability in the model. It was therefore concluded that, although spatial autocorrelation may be present between the dependant variables, the data in this study do not support further investigations. The previously developed stable and ecologically meaningful model is used to generate annual prediction maps as described below.

7.3.4 Predicting the Probability of BTV Seropositivity

Based on the final fixed effects GAM, annual prediction maps were generated using R. In contrast to the station average variables used for model development, the predictions were performed on a pixel basis, using the GeoTiff rasters of the bioclimatic variables. In order to be able to process the whole study area, the nominal spatial resolution had to be reduced to 1 km to avoid computer memory limitations. The results are illustrated in Figures 7.9 to 7.12, showing the probability that cattle tested in an area are BTV seropositive. Standard error maps indicate spatial variations in the accuracy of the predictions.

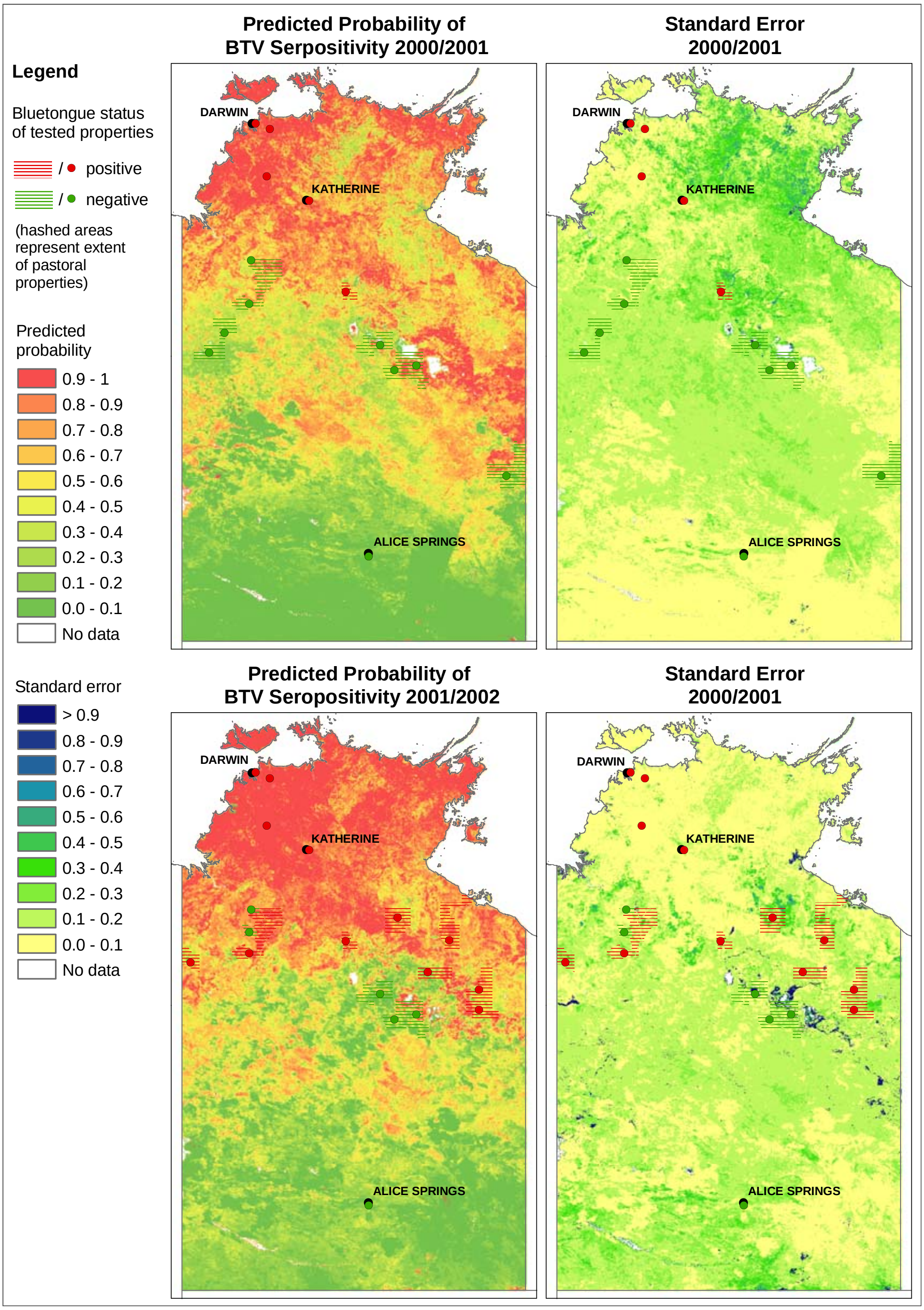


Figure 7.9 Predicted BTV seropositivity in the NT for the seasons 2000/2001 and 2001/2002 in relation to the surveyed presence/absence data with standard error maps indicating the spatially varying accuracy of the predictions

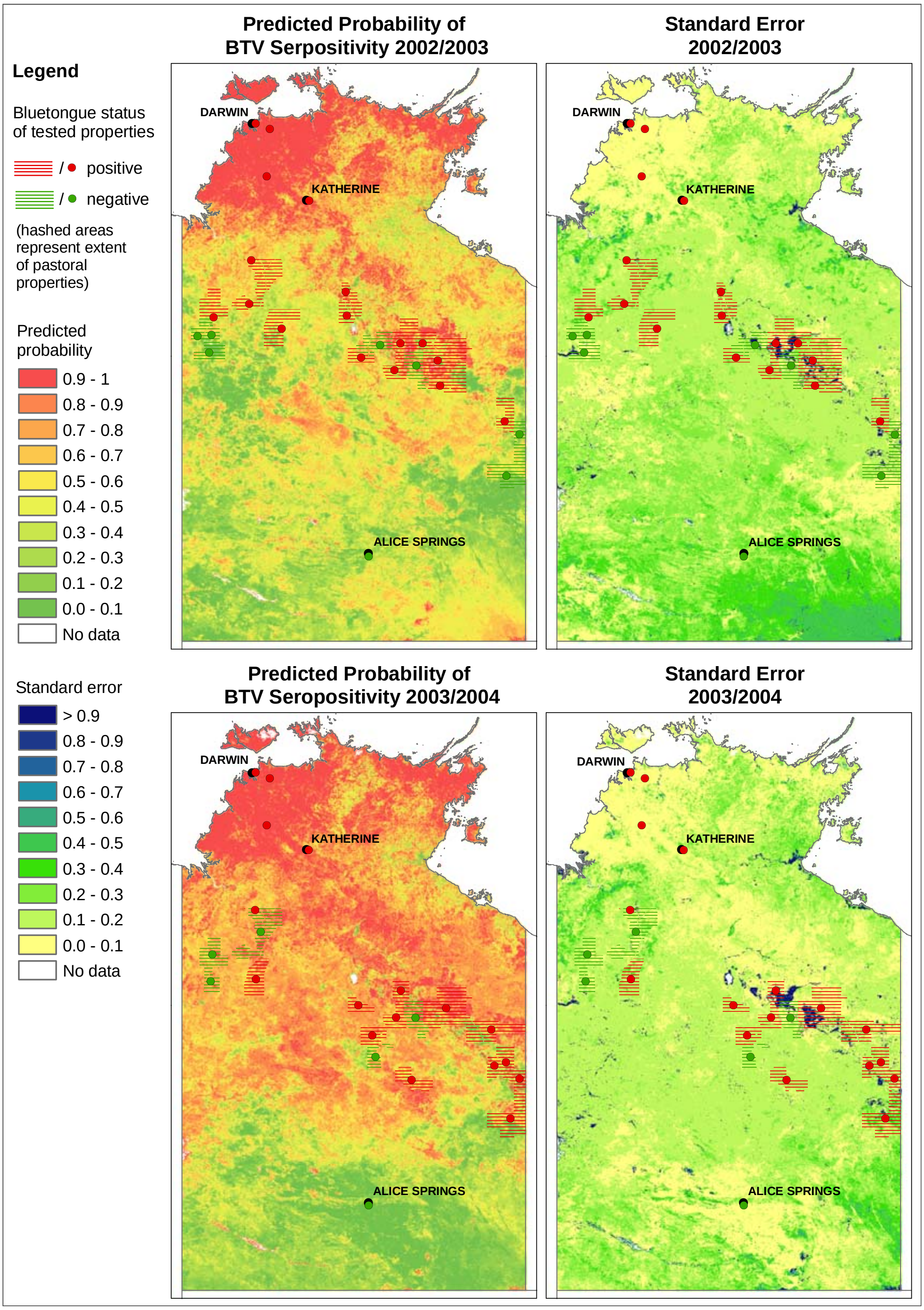


Figure 7.10 Predicted BTV seropositivity in the NT for the seasons 2002/2003 and 2003/2004 in relation to the surveyed presence/absence data with standard error maps indicating the spatially varying accuracy of the predictions

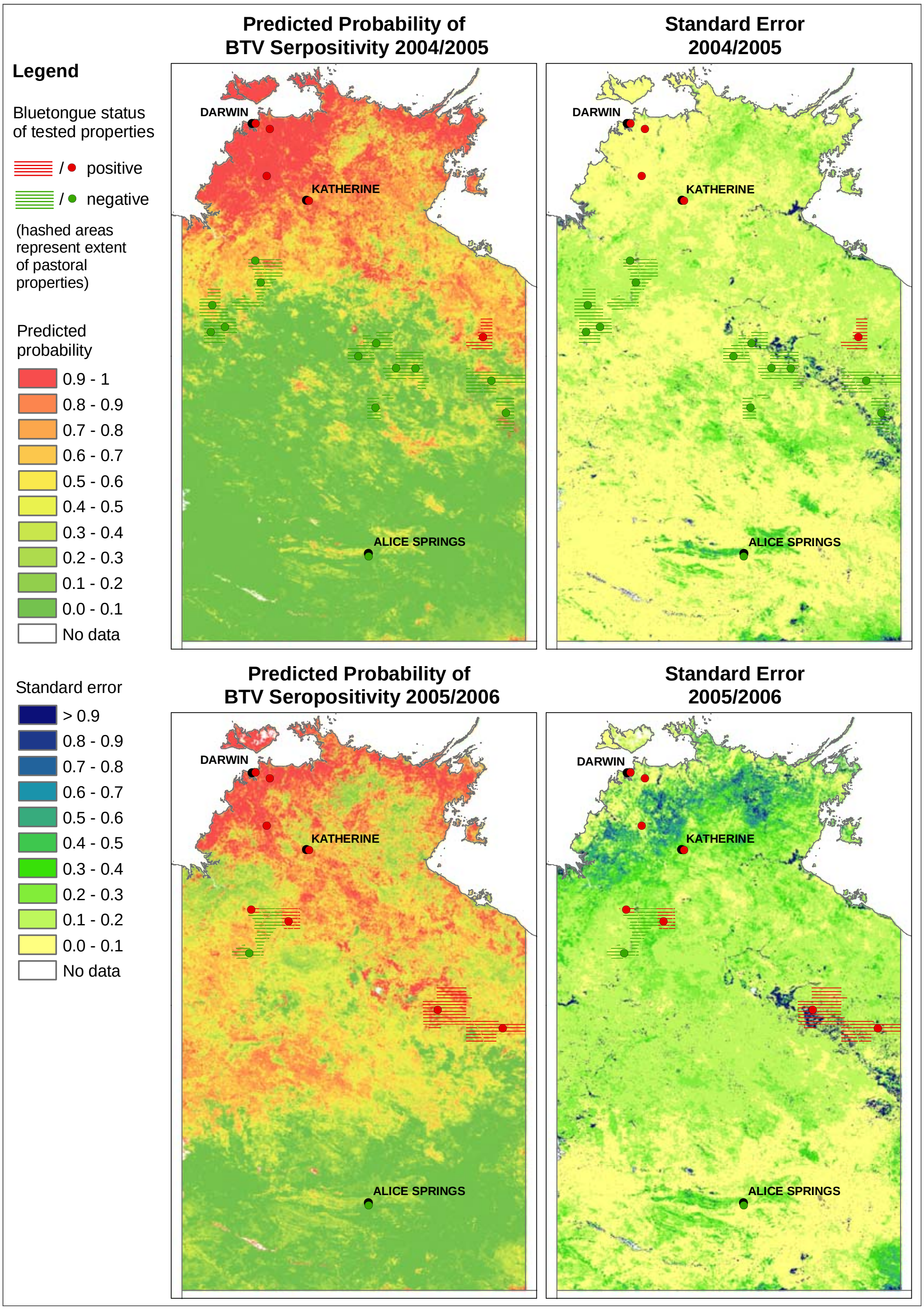


Figure 7.11 Predicted BTV seropositivity in the NT for the seasons 2004/2005 and 2005/2006 in relation to the surveyed presence/absence data with standard error maps indicating the spatially varying accuracy of the predictions.

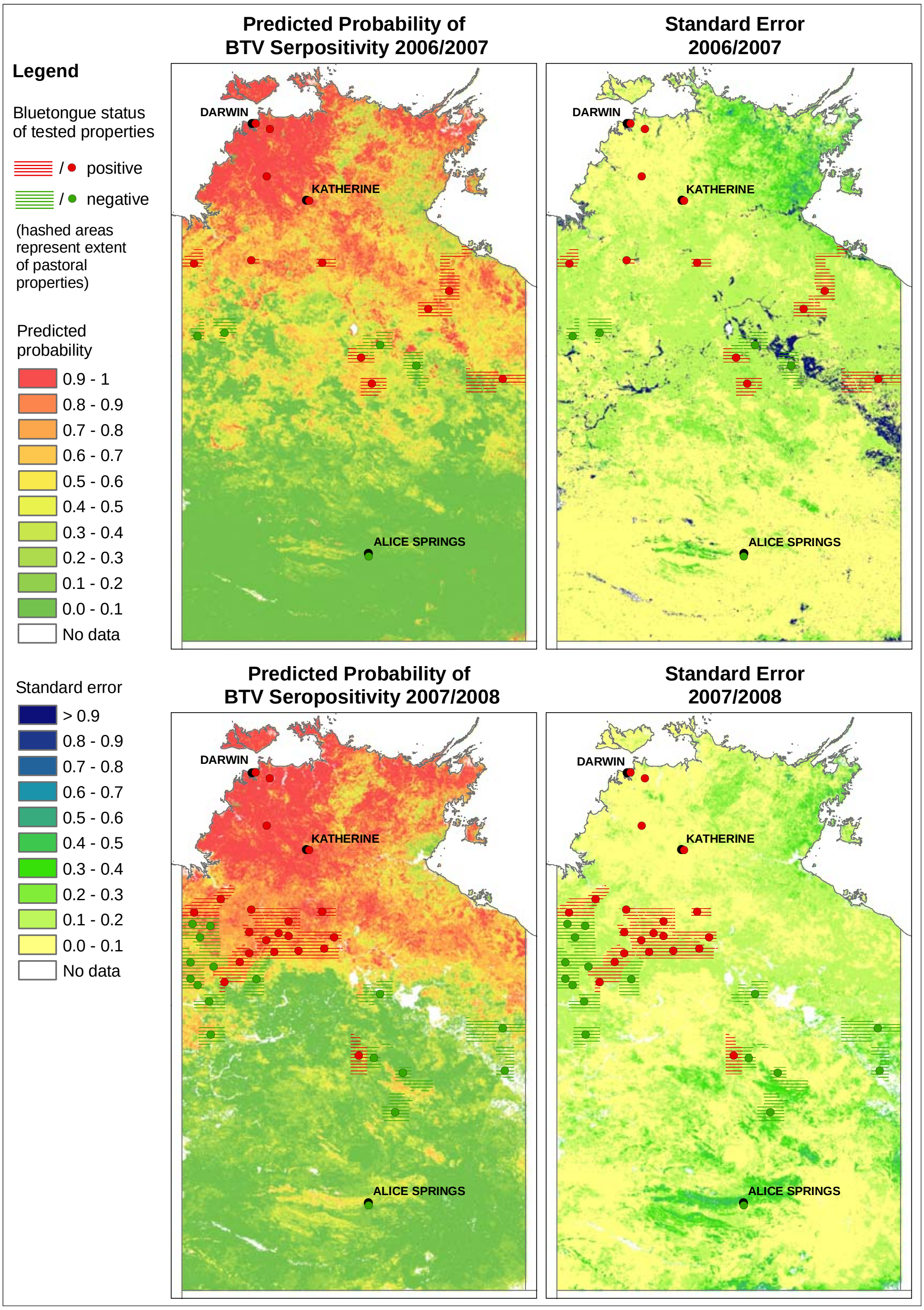


Figure 7.12 Predicted BTV seropositivity in the NT for the seasons 2006/2007 and 2007/2008 in relation to the surveyed presence/absence data with standard error maps indicating the spatially varying accuracy of the predictions.

The predictions are based on data from serological tests conducted on pastoral properties and hence the resulting probability correctly indicates the likelihood that cattle tested in an area will return seropositive status. It needs to be noted that areas outside the bounds of pastoral properties are unlikely to support virus survival due to the lack of cattle as the major group of hosts. Nevertheless, area-wide prediction maps have been generated to delineate areas where the environmental conditions might in principal provide suitable host and vector habitats. Although, there is no evidence that native animals are involved in BTV transmission, recent laboratory experiments in Morocco (Batten et al. in press) have demonstrated that camels, which are plentiful in central Australia, may act as hosts for BTV. Knowing about areas with a higher probability for virus transmission also aids in logistic planning of livestock movement and if necessary, precautionary measures can be taken to avoid contact between hosts and potentially infected vectors.

7. 4 Model Validation

Besides the internal validation as part of model development, external validation of the model was conducted with data from the season 2008/2009, which were not used for model development. This way it can be determined if the model built from previous years has the capability to predict the probability of detecting BTV seropositivity in the following season. Model validation was performed in two ways:

i) Predict the probability for detecting BTV in 2008/2009 based on station average variables, which haven’t been included in model development and assess the results against the serological test results from that season.

ii) Determine the maximum probability for seropositivity for each cattle station from the 2008/2009 prediction map. Based on a cut-off probability, a station is flagged BTV positive or negative and then compared to the test data from that season.

For the first approach, station average environmental variables were generated for 2008/2009 as described in Chapter 6. A prediction map was then computed using the existing GAM model (Figure 7.13). The discriminatory ability of the model in regards to the new season has been assessed using the area under the ROC curve.

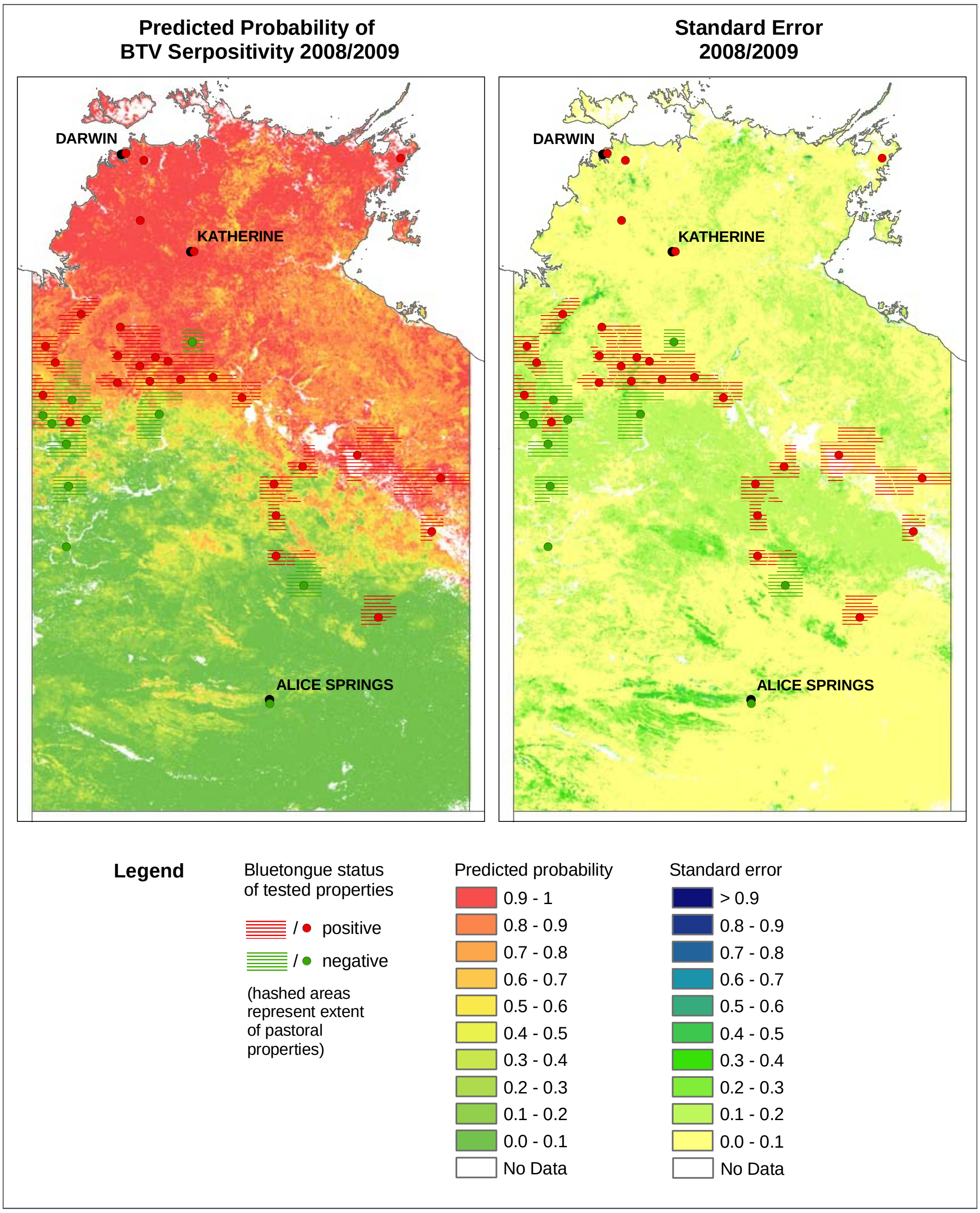


Figure 7.13 Predicted BTV seropositivity in the NT for the season 2008/2009 in relation to the surveyed presence/absence data with standard error map indicating the spatially varying accuracy of the prediction

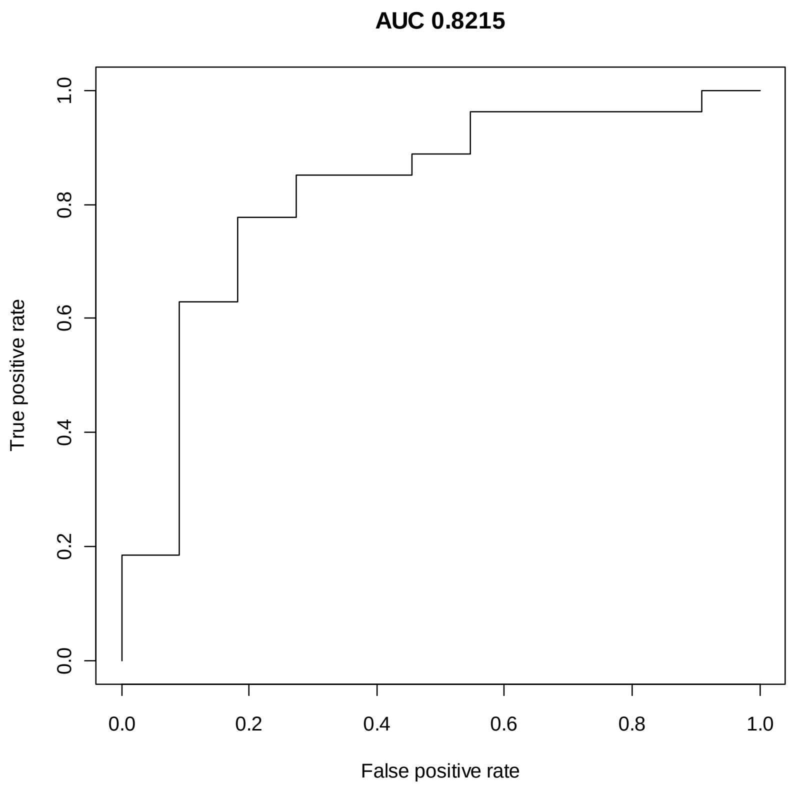


Figure 7.14 ROC plot for the predictions of BTV presence in 2008/2009

With an AUC of 0.8215 (see Figure 7.14) it can again be demonstrated that the model has excellent discriminatory capabilities based on the classification by Hosmer and Lemeshow (2000). This assessment is based on the data from 38 stations tested between November 2008 and October 2009.

While probability maps are advantageous as they retain the original information, there are many application areas where it is desirable to translate the probability maps into binary presence/absence maps. This is particularly important in decision making processes, e.g. when the boundary around an infected zone needs to be redrawn based on the predicted presence of a disease. To derive a binary (dichotomous) map, a cut-off point must be defined and compared to each probability to assign value of 1 to pixels with a probability above the threshold and a value of 0 otherwise. However, defining an appropriate probability threshold is no simple task and the wrong choice can heavily influence the perceived accuracy of the predictions. Although often a cut-off point of 0.5 is chosen for convenience, here a cut-off point has been selected that maximises both specificity and specificity (Hosmer and Lemeshow 2000). This choice is facilitated by the graph in Figure 7.15

(based on samples from all years), where a probability of 0.6 seems to be the optimal choice as this is where the sensitivity and specificity curves cross. Examining a similar plot based on the samples from 2008/2009 shown in the inset in Figure 7.15 suggested the same cutoff point.

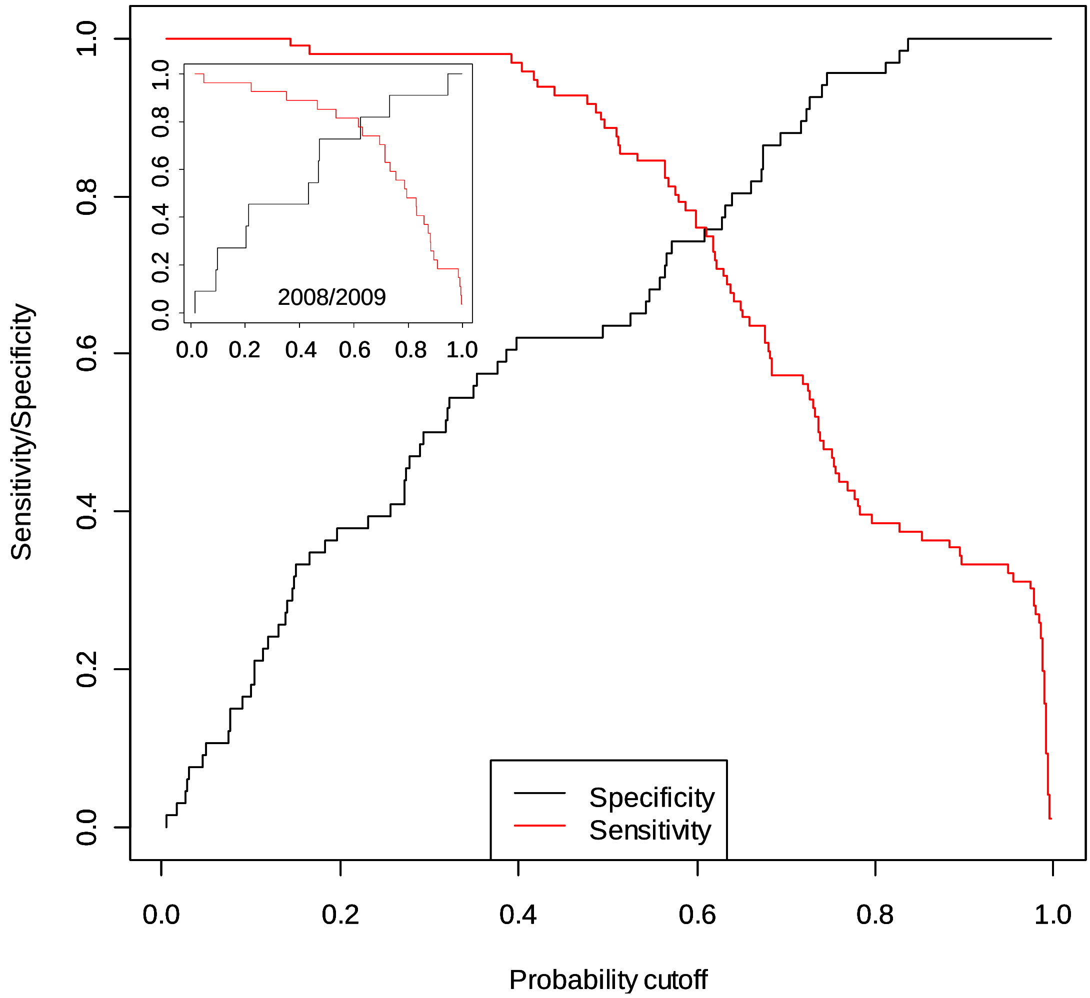


Figure 7.15 Plot of sensitivity and specificity versus all possible cutoff points to determine the optimum cut-off value for classification. The inset shows the plot for the 2008/2009 data only

Since the BTV status is only available at a station level, the maximum value of the predicted probability was determined for each station based on the 2008/2009 prediction map. A station was considered BTV positive if the maximum predicted probability exceeded the cutoff point of 0.6. It is acknowledged that using the maximum probability for BTV occurrence increases the false positive rate as all except two of the tested sites have been classified as BTV positive (Figure 7.16b). Due to the inherent noise in the data, it is likely that somewhere on a station pixel with a high probability is found. Therefore an alternative classified dataset was derived using the predictions made on a station level for all stations in the NT. This approach does not summarise pixel-based probabilities for a station, but works directly with the probabilities determined on a station level using the average environmental variables (Figure 7.16a). From these classified datasets, contingency tables were generated (Tables 7.8 and 7.9), from which a variety of measures can be extracted for the assessment of model performance (summarised in Table 7.10). See Section 3.5 for the equations.

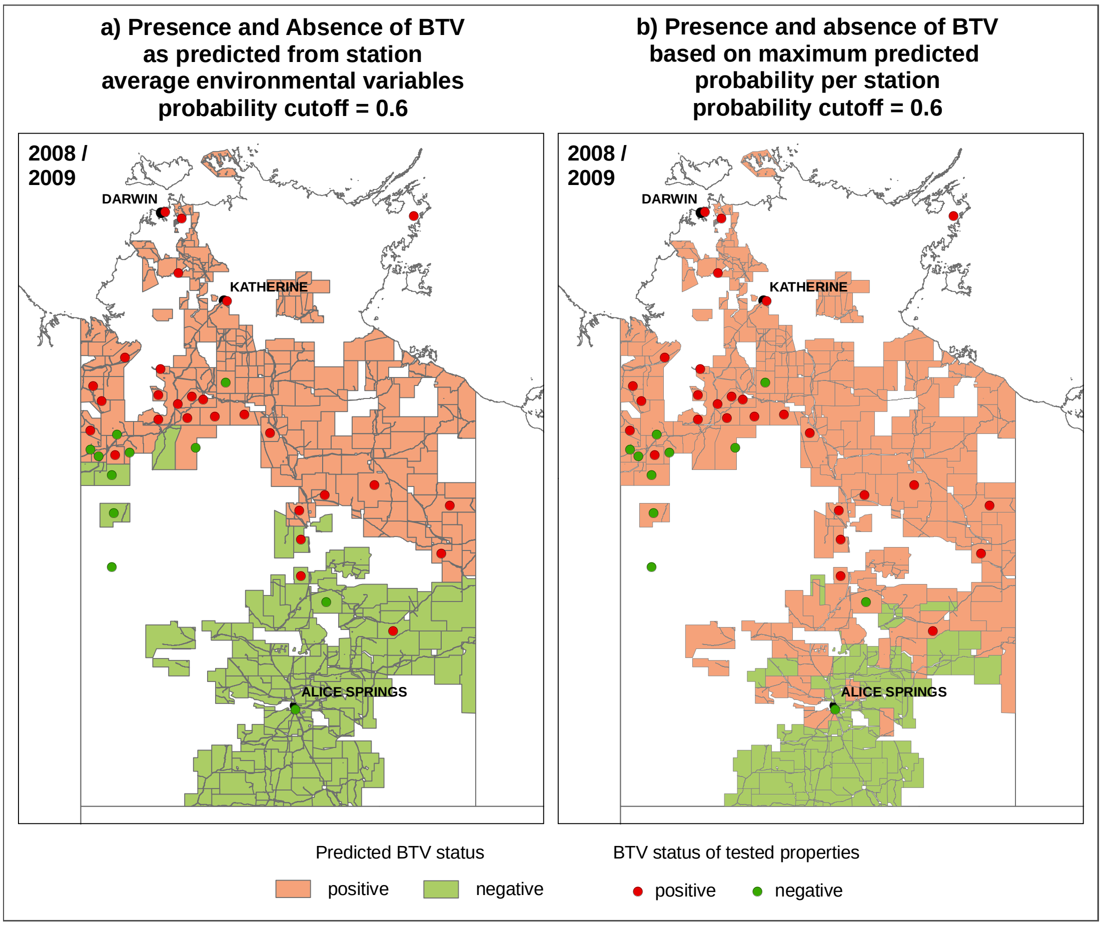


Figure 7.16 Binary prediction maps for the NT in 2008/2009, based on a cutoff probability of 0.6. (a) shows the station level prediction using the average environmental variables and (b) shows the station maximum of the pixel based prediction

Table 7.8 Confusion matrix based on predictions from station average variables

	Observed		
Predicted	BTV positive	BTV negative	**Total**
BTV positive	22	3	25
BTV negative	5	8	13
Total	27	11	38

Table 7.9 Confusion matrix based on maximum predicted probability per station

	Observed		
Predicted	BTV positive	BTV negative	**Total**
BTV positive	27	9	36
BTV negative	0	2	2
Total	27	11	38

Table 7.10 Accuracy measures for the classified predicted presence/absence maps

Measure	**Predictions from station average variables**	**Maximum predicted probability per station**
Correct classification rate	78.9%	76.3%
Sensitivity	81.5%	100%
Specificity	72.7%	18.2%
False positive rate	27.3%	81.8%
False negative rate	18.5%	0%
Positive predictive power	88%	75%
Negative predictive power	61.5%	100%
Cohen's Kappa	0.514	0.24

7. 5 Discussion of Model Results

7.5.1 Model and Prediction Results

The univariate analysis of associations between the environmental variables at BTV positive and BTV negative sites has found a significant difference between the two groups for all variables in the Northern Territory. However, during model building it was found that variables that were initially considered important, such as maximum and minimum temperatures and rainfall, had to be dropped from the model in the early stages due to a low p-value.

The minimum and maximum variables from MODIS may be less important, as they do not represent the true minimum and maximum daily temperatures. Mean temperature variables were more highly rated, and with mean day temperature in summer and mean night temperature in winter well represented in the model. As expected, maximum NDVI has been the single most important variable with the lowest p-values throughout the model building process. The importance of rainfall for BTV presence could not be proved. A reason might be that strong rainfall events, which are more frequent in the tropical North of Australia than light rain and are also better detectable by TRMM, can limit vector activity. NDVI on the other hand has been related to the effects of rainfall on the ground (increased humidity, soil moisture, increased plant growth) which more directly influence vector habitat conditions. EVI, which contains similar information, was excluded from the model due to collinearity with NDVI and the disadvantages discussed earlier. The small NDVI integral which was the only phenological variable used for model development was not included in the final model. However, its strong relationship with maximum seasonal NDVI suggests that no information is lost by excluding it from the model. In addition, generating phenological variables requires data for six more months after the season ends, whereas all of the variables that are currently present in the model describe the conditions of the most crucial period in the BTV cycle early in the year and are available by the end of June. Considering processing time, the model results may be available in early July. This means that the latest predictions would be available to NAMP coordinators for their annual meeting in August each year, where decisions are made on zone boundary changes and the focus of future surveillance activities.

Model coefficients and the shape of the smooth functions in Figure 7.7 indicate that the probability of BTV presence is generally higher in areas with high NDVI, although this relationship is not linear. High average summer day temperatures on the other hand decrease the probability of BTV presence, which can be explained by the risk of desiccation, particularly in the southern arid part of the Northern Territory. Maximum autumn day temperatures, or more precisely the average day temperature of the warmest 8-day period in autumn has a positive effect on BTV presence up to about 40°C, but higher temperatures seem to reduce the likelihood of finding the virus. Higher mean day temperatures in winter positively contribute to the probability of BTV detection.

As illustrated in Figures 7.9 to 7.11 the predictions from the GAM model consistently spatially replicate the distribution of BTV in cattle tested between 2000 and 2009. In particular the season 2004/2005, for which dry and hot conditions were experienced throughout the study area with associated low virus activity, demonstrates the predictive capabilities of the model. The general pattern of decreasing BTV presence probability from North to South is present throughout the years analysed, but the divide between high and low probability varies between the years and largely follows the observed BTV presence. Also, smaller patches of high and low probability are depicted well (e.g. season 2003/2004) and are confirmed by the test results.

Comparison of predicted and observed BTV occurrence also reveals that some positive test results are found in areas of low predicted probability. However, often there is a small area within a cattle station with a high probability. Without the knowledge of the true geographical origin of the tested animals, one can assume that they could have come from these areas. It is therefore recommended that the maximum observed probability be used as a guideline, when deciding if a property is to be declared BTV positive or negative.

7.5.2 Model Performance

Assessment of the models predictive and discriminatory ability has been performed as described in the previous section. The area under the ROC curve has been used as a measure for the discriminatory ability of the model, which according to the classification by Hosmer and Lemeshow (2000) is excellent for both internal and external validation. For the season 2008/2009, from which data have not been included in model building, the AUC is only slightly lower.

The predicted probability maps have also been classified into presence/absence maps using a cutoff value of 0.6 to maximise both sensitivity and specificity. It was found that using the station average variables for predictions on a station level resulted in the highest overall accuracy (Cohen’s Kappa). However, using the maximum predicted probability per station decreased the likelihood of false negative classifications, which is a crucial factor in epidemiology. While economically it might not seem appropriate to declare a station BTV infected if only a small area has a high probability of representing a focus for the virus, for Biosecurity reasons, it might be the less risky approach.

In summary, the necessity to develop and assess a model using station aggregates is certainly one of the limitations of the study. While it is still possible to identify areas of higher BTV probability on the prediction maps, one must be aware that the variables used for model development are not directly related to those areas, but represent the station average conditions. Nevertheless, validation results are promising and are well suited to complement present surveillance. Particularly in areas that are less accessible on the ground the remote sensing based prediction model is advantageous by providing estimates of infection probability for almost the entire study area.

7. 6 Preliminary Tests of the Model’s Forecasting Capabilities

The NAMP technical group holds its annual meeting each August, when a review of recent BTV activity is provided by the state coordinators. Upon their recommendations and based on the latest test results, proposed zone changes are finalised. Additionally, any changes to the location of monitoring sites are decided upon. Currently, the only underlying data base for these decisions is a web-based map showing the serological status of the tested properties. An area-wide estimate of the probability for BTV serpopositivity based on bioclimatic factors is not available to support the planning of monitoring activities and the definition of zone boundaries.

To demonstrate that the approach developed in this study is useful for the timely delivery of model results to decision makers, a preliminary prediction map was generated from bioclimatic variables derived for the season 2009/2010 (Figure 7.17). This map is based on the previously described model developed from data collected between 2000/2001 and 2007/2008. Due to time limitation and the fact that not all test results had been entered into the NAMP database, no detailed validation was conducted, but the ground surveillance results available as of November 25, 2010, have been plotted on the prediction map for illustration. The aggregation periods of the variables that have been selected for the final model enabled the predictions to be available by the end of June. While this is not to be considered as “Forecasting” in a sense that the probability of BTV seropositivity could be predicted before the beginning of the BTV activity season, the prediction results are available area-wide before all ground surveillance data are accessible through the NAMP database.

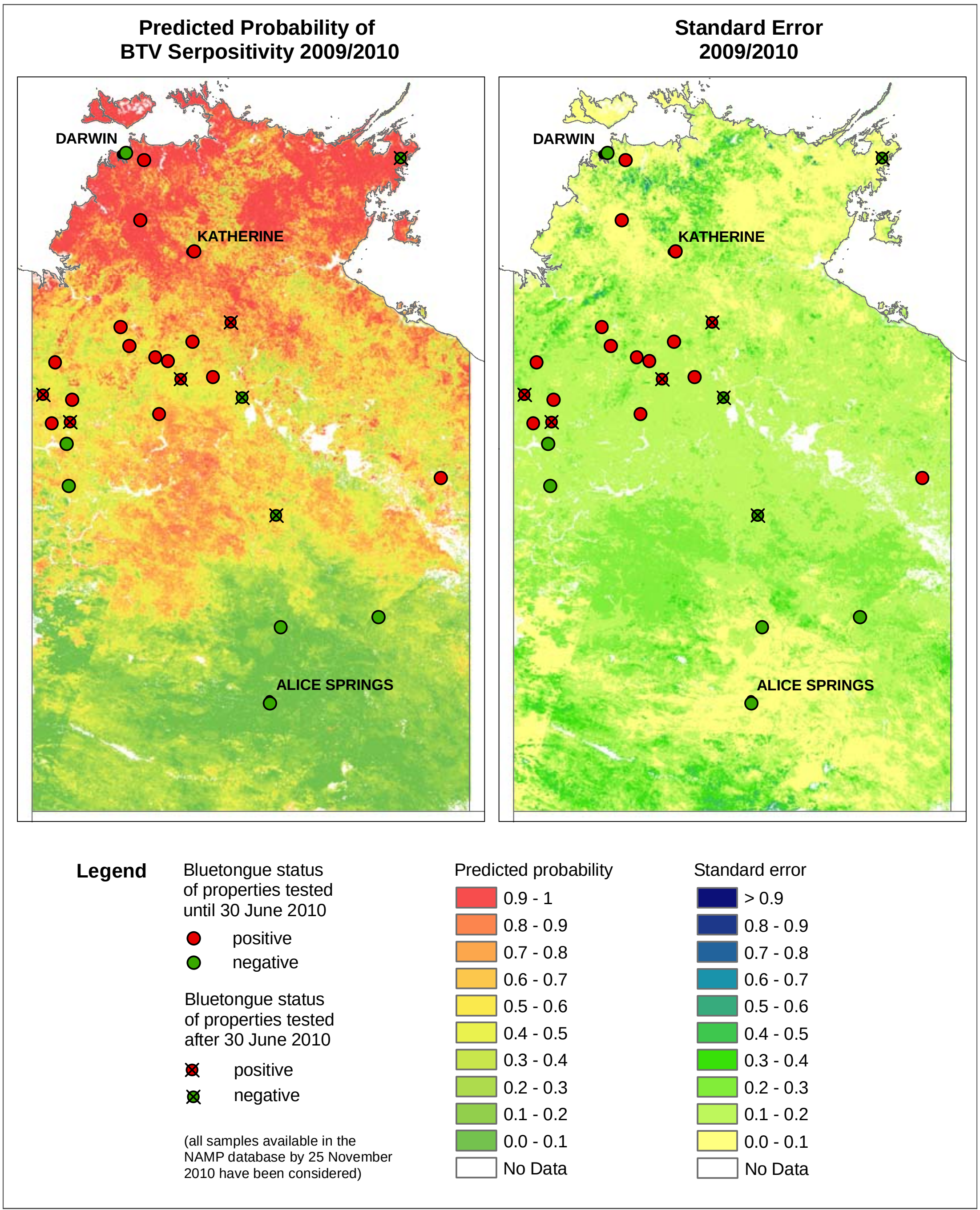


Figure 7.17 Preliminary predicted BTV seropositivity in the NT for the season 2009/2010 in relation to the surveyed presence/absence data with the standard error map indicating the spatially varying accuracy of the prediction

As can be seen in Figure 7.17, particularly in areas where test results became available after the production of the prediction map, the model has correctly identified stations at increased risk for seropositivity. It is expected that model performance can be further improved through recalibration by including data from the season preceding the forecast period, which in this case 2008/2009.

As a consequence of presenting the results for 2009/2010 to NAMP facilitators during the meeting held in Geelong in August 2010, previously unmonitored possible risk area have been identified, where vector trapping is likely to be intensified in future. Also stakeholders from the federal and state government Departments of Agriculture and Primary Industries were interested in seeing the predictive capabilities of the model, which can aid in demonstrating Australia's Biosecurity efforts to trade partners.

7. 7 Summary

Following an initial selection of variables based on their ability to discriminate between BTV positive and negative sites, variables were also assessed for the ecological meaning of their associations with BTV. All variables showed significant differences in the Northern Territory, and most showed significant differences in the Pilbara, although at a lower magnitude. Differences in effects between the station average variables and the weighted station average based on carrying capacity were small and not uniform across variables. Unfortunately, further analyses of the environment virus relationships unveiled discrepancies in the effects caused by some of the key variables in the Pilbara. Therefore, model development was progressed only for the Northern Territory.

A Generalised Additive Model was developed using a stepwise exclusion approach informed by both statistical significance and the ecological meaning of each variable. The best performing model according to the area under the ROC curve of 0.8644 is based on maximum seasonal NDVI (*maxndviss*), mean day temperature of the warmest 8-day period in autumn (*maxlstdau*), the mean day temperature in summer (*meanlstdsu*) and the mean night temperature during the previous winter (*meanlstnpw*) as the predictor variables. Possible implications of spatial autocorrelation that might be present between the dependant variables have been discussed. However, considering the small annual sample size of the multi-annual dataset used to develop the model further investigations into approaches to account for spatial effects were not conducted.

The spatial patterns in the annual predicted probability maps generated from the model corresponded well with the serological status of the tested properties. External model validation was performed with data from the season 2008/2009. The very good discriminatory ability was again confirmed with an AUC of 0.8215. Assessment of model performance was also conducted using binary presence/absence maps. Depending on the classification method a correct classification rate between 76.3 and 78.9% could be achieved, while importantly the false negative rate was very low.

It was also demonstrated in Section 7.5 that the model's capability to generate timely area-wide prediction maps may provide useful information for decision making within the management of the NAMP.

CHAPTER 8

CONCLUSIONS AND RECOMMENDATIONS

The presence of Bluetongue Virus and other infectious diseases in Australia requires an efficient and effective surveillance mechanism to control and minimise the risk for animal health and facilitate safe trade of livestock. Both aspects are important from a Biosecurity perspective and also for the livestock industries, which are a major contributor to the Australian economy.

This study demonstrated feasible alternatives to the current labour and cost intensive surveillance approaches that produce data with large temporal and spatial gaps and may compromise the integrity of the system in the future. Spatial sciences and remote sensing technology provide efficient means of gaining information about environmental conditions on the ground that can be related to the presence of BTV hosts and vectors and hence define a risk area for transmission. This research has investigated a number of data sources of environmental and climatic data and developed a robust and cost-effective methodology to generate environmental variables to model the distribution of BTV.

This chapter summarises the achievements of the project and gives recommendations for improvements and future research.

8. 1 Conclusions

A methodology for the spatial and temporal prediction of BTV has been implemented as a number of successive steps that have been defined to meet the aims set out in Chapter 1. These steps are reiterated and dealt with individually below.

8.1.1 Review of Bluetongue Epidemiology in Australia to Identify the Environmental Factors Relating to Host and Vector Dynamics

An extensive review of Bluetongue ecology in Australia has provided an up to date compilation of what is currently known about competent and in principle vectors, susceptible hosts and their habitats. It was found that except for *C. brevitarsis*, little is still known about the breeding habitats of other *Culicoides* vectors in the Australasian region. The environmental factors that are hypothesised to be related to the presence of BTV have therefore been based on the ecology of *C. brevitarsis*, which has the most widespread distribution of all vectors found in Australia. The factors relating to vector survival and activity include rainfall, atmospheric humidity, air and surface temperature, while vegetation structure and condition are more important to sustain a critical mass of ruminant hosts. Furthermore, wind has been associated with long range dispersal, but was not considered in this research which has concentrated on mapping the general habitat suitability.

This study also compiled valuable information about Bluetongue epidemiology for areas that have so far received little attention, such as the Pilbara in WA and the Northern Territory. Within the period under investigation, the Pilbara has experienced its first outbreak of BTV, followed by varying levels of activity characteristic for an epidemic area. More recently, the discovery of the competent vector *C. wadai* has been documented for the Pilbara. It is anticipated that this thesis will provide a valuable reference for future research in the area, particularly with the consideration that the pool of entomologists with knowledge about the ecology of *Culicoides* midges in Australia is small.

8.1.2 Identify Relevant Spatial Data Suitable for the Definition of Environmental Factors that relate to the Distribution of BTV

A variety of data sources have been assessed for their capability to provided relevant environmental data on the factors previously identified at the spatial and temporal resolution appropriate for this study. These resolution requirements were mainly governed by the underlying serological data and the spatial and temporal scope of the study. Operating in an area with a tropical climate and therefore extensive cloud cover particularly in the months during and after the wet season demanded a high temporal resolution in order to obtain sufficient data coverage at least on a fortnightly to monthly basis. The spatial resolution on the other hand was chosen to be comparatively low to account for the large area to be analysed on a regional scale and to minimise processing time. Also, the predominantly climatic factors chosen for this study act on a regional scale. Other criteria defined for data selection included the cost of data acquisition, the level of pre-processing and data quality documentation.

Satellite data products from MODIS and TRMM were selected for this research based on the above criteria and the successful applications of MODIS data in previous epidemiological studies. The application of TRMM precipitation estimates for arboviral studies is original to this study and a related project on MVEV (Schuster et al. 2009).

Although ground-based meteorological datasets have been considered initially, the complete spatial coverage provided by the remote sensing products utilised is a distinct advantage while preserving the same patterns as observed by weather stations. For land surface temperature the spatial coverage is limited to areas with clear sky conditions.

Due to time constraints, limited human resources, and the lack of suitable data, a comprehensive assessment of the satellite data products with ground truth data could not be conducted. The selection of data products is therefore mainly based on published validation studies and metadata, complemented by exploratory data analysis to detect larger error in the datasets. These analyses led to the discovery of a problem in the MODIS vegetation index product due to a shifted cloud mask, which was not previously known to the research community.

8.1.3 Developing an Efficient and Cost-effective Methodology for the Generation of Bioclimatic Variables

The multi-stage process of turning the satellite data from MODIS and TRMM into meaningful bioclimatic variables (describing vegetation condition, land surface temperature and precipitation) as input for model development has been largely implemented in a professional GIS environment. Satellite data covering almost 10 years between April 2000 and November 2009 were merged, reprojected and quality filtered using automated scripts driving the MODIS Reprojection Tool and the geoprocessing environment of ArcGIS. The entire collection of raster datasets was stored in the standard GIS compatible GeoTiff format. The resulting time series of environmental and climatic raster datasets were accumulated into seasonal variables, and as demanded by the locational precision of the virus data, aggregated on a pastoral property level using an areal mean.

The whole process of generating bioclimatic variables has been implemented in an efficient manner and the scripts developed can be reused in future, to semiautomatically process new data as they become available. However, should the prediction of BTV become operational, it is recommended that a more powerful dedicated processing environment be set up to replace the standard commercial off the shelf hardware used in this study.

8.1.4 Assessing the Relationship Between BTV and the Environment

A number of bioclimatic factors have been summarised over four aggregation periods: annual (November to October), seasonal (November to May), summer (December to February), autumn (March to May) and the previous winter (June to August). The hypothesis is that these variables relate to the serological status of a pastoral property in a particular year (per definition from 1 November to 31 October). The choice of aggregation period was informed by the observed annual cycle of virus activity.

Univariate analyses were initially conduced to identify those variables that showed the most significant difference between BTV positive and negative sites and were therefore most suitable for model development due to their discriminatory qualities. While investigations showed that all of the candidate variables were significantly different for the Northern Territory, the effect was less obvious in the Pilbara. Moreover, some of the variable groups (vegetation indices and rainfall) showed an unexpected response in virus presence. Following further investigations and discussions with NAMP coordinators and entomologists it was concluded that the sampling strategy currently employed in the Pilbara does not provide sufficiently reliable data for the development of an ecologically sound model.

The final set of variables contributing most to explaining the distribution of BTV in the Northern Territory was identified during model building and comprises the following four variables:

- maximum seasonal NDVI (*maxndviss*);
- mean day temperature of the warmest 8-day period in autumn (*meanlstdau*);
- mean day temperature in summer (*meanlstdsu*); and
- mean night temperature during the previous winter (*meanlstdnpw*).

The model building process also identified some of the minimum and maximum temperature variables and also rainfall as least significant. These observations in the first case may be explained by the fact that the 8-daily MODIS composite data do not provide the true minimum and maximum temperatures. The reason for excluding precipitation from the model indicates that individual rainfall events are less important for vector ecology than for example the resulting increase of NDVI, which has been identified as most significant variable.

The necessity to summarise both virus and environmental data spatially (on a property level) and temporally (on an annual or seasonal basis) can be seen as one of the major limitations of this study. Much of the information about direct linkages between environmental variability and the occurrence of BTV is lost through this process. Since it is not known where tested cattle might have been infected with the virus, the environmental conditions preceding the infection cannot be accurately determined. An alternatively weighted average approach has been implemented in the Pilbara where suitable data on carrying capacity are available. This method provided better means for discrimination between BTV positive and negative sites for some variable groups (e.g. small integrated NDVI, maximum day temperatures, growing degree days, rain), while for others (e.g. maximum NDVI, minimum night temperatures) it did not provide an advantage over the simpler station average approach. This suggests that the application of the station average in areas where suitable carrying capacity data do not exist, which is the case in the Northern Territory, does not create a disadvantage.

8.1.5 Developing a Spatio-temporal Model to Predict the Distribution of BTV

For the development of a virus distribution model as described in Chapter 7, a GAM approach was chosen. This is a non-parametric extension of the generalised linear and logistic regression models frequently used in ecological and epidemiological modelling. The major advantage of GAMs is their support of response curves not bound to linear or higher order functions, which rarely describe ecological processes appropriately.

Amongst the candidate models that have been developed using a stepwise exclusion approach, the best fitting model has been selected based on the maximisation of the area under the ROC curve (AUC) metric. The final model has been confirmed to possess excellent discriminatory abilities with an AUC of 0.8644.

Although the model did not account for possible spatial dependencies between response variables due to the multi-annual data used for model development (see Section 7.3.3) it can be considered a spatio-temporal model. The spatial component is given by reference to the environmental conditions at a particular location or sampled over a particular spatial reference unit. The temporal component is given by including data that have been sourced over several years and the annual estimates of BTV seropositivity that have been facilitated by the model.

Annual prediction maps have been produced, which resemble the spatial patterns of serological status as determined by conventional surveillance, with the additional advantage of providing an area-wide estimate of potential virus activity based on suitable environmental conditions. Classified prediction maps have been generated to aid decision makers in officially declaring the serological status of a pastoral property and defining boundaries of the BTV infected zone. Additionally, the pixel based probability maps help to identify areas that principally provide suitable conditions for virus transmission and should therefore be primarily targeted when planning strategic sampling locations.

Model validation with external data from the season 2008/2009 has demonstrated that the model is capable of describing the spatial extent of potential seropositivity in the current season with a relatively high accuracy, with the degree of success depending on the measure used for assessment. The AUC of 0.8215 has again shown that the model has excellent discriminatory abilities in relation to predicting BTV seropositivity on the basis of station average bioclimatic variables.

8.1.6 Ability of the Model to Complement Ground Based Surveillance

Ample evidence has been given so far that the presented environmental data and the modelling approach are well suited to reproduce what can be observed on the ground. However, there is no doubt that the model can only be as good as the input data and as such, the results of this study are seen as complimentary to the data produced by conventional surveillance. What this study has demonstrated well, is that the spatial gaps between the sampled pastoral properties may be filled to provide a more complete image of the actual extent of potential virus activity.

The model can also be used to provide early predictions of seropositivity risk in the current season. This has been demonstrated at a meeting of the NAMP technical committee in Geelong in August 2010, where a prediction map for the season 2009/2010 was presented. This map was compiled by the model built with data from 2000/2001 to 2007/2008, but using the most recent bioclimatic variables. The fact that the model uses data collected during the previous winter as well as the summer and autumn months means that after data acquisition and processing a prediction can be generated at the end of June each year. Depending on the timing of the annual muster, most data collected as part of serological surveys are not available in the NAMP database much earlier than the predictions. The model therefore has the capability of acting as an early indicator for potential virus activity hotspots, where monitoring should be intensified.

As mentioned before, the strength of a model is determined by the data it is built upon. It is therefore suggested that the increasing archive of virus and environmental data be used to gradually recalibrate the model, if the major aim is to provide an early prediction of virus presence before the annual NAMP meeting to be held in August. By providing such a prediction and identifying pastoral properties which might host the virus, the risk of undesired events such as BTV infected cattle being exported can be minimised. Stakeholders from the state and federal Departments of agriculture therefore indicated strong interest in the results of this research at the latest NAMP meeting.

8.1.7 Contribution to Knowledge about the Interaction Between the Environment and the Presence of BTV in the North of Australia

In conclusion, while this study was predominantly dedicated to the investigation of options for the application of spatial data and technology in the area of epidemiology, it has also provided new insights into the role of environment factors in the distribution of an important livestock pathogen. From a set of environmental variables, those which in combination may best describe the presence of the virus have been highlighted. The initially hypothesised importance of NDVI was confirmed, as well as the role of temperature. In contrast, accumulated rainfall variables were excluded from the model due to their low statistical significance. As discussed previously this may be explained through the relative importance of other more indirect measures of rainfall effects on the ground.

8. 2 Recommendations

During the implementation of this research some limitations have been identified, but also opportunities for strengthening and expanding the current approach. Recommendations and directions for future research are given below.

8.2.1 Optimisation of Monitoring

This research has clearly demonstrated the limitations of using data from an operational surveillance system such as NAMP, which has been designed predominantly for fulfilling international Biosecurity requirements. In order to facilitate more in-depth spatio-temporal studies of virus environmental relationships based on NAMP data, the following improvements are recommended from the viewpoint of a spatial scientist:

- Recording spatial information more accurately, including the location of vector traps, bleeding sites and if known the approximate location where the tested cattle have been held prior to bleeding;
- Maintain a core network of sentinel herds in strategic locations which are tested at regular intervals to provide a continuous record of virus activity data and facilitate comparison of inter-annual variations. The Northern Territory provides a good example for such a network, which is based on governmental research stations; and
- Where possible, select the sites for serological surveys based on the perceived risk (e.g. informed by previous survey results and modelled probability).

It has been acknowledged that any additional monitoring sites cause additional operational costs, but the costs of losing the good reputation that Australian BTV surveillance currently enjoys as evident in various publications (e.g. Gibbs and Greiner 1994; Racloz, Griot, and Stärk 2006) may be much higher.

8.2.2 Investigation of Alternative Variables and Data Sources

One of the major aims of this research is to identify factors that are important for the ecology of BTV and they have been extensively discussed in Chapters 2 and 3. However, time constraints demanded the use of largely pre-processed and validated datasets, which have not been available for all factors. Further research is therefore necessary to investigate the association of other factors with the virus. Of particular interest are the effects of humidity, air temperature, landscape structure, and cattle density. Potential data sources need to be identified and assessed.

Potential for future research has also been identified in the 2.5 decades of data from AVHRR, which could be analysed to make full use of the long records of epidemiological data from more than 30 years of arbovirus surveillance on Australia. Also the definition of alternative aggregation periods for the bioclimatic variables is worth investigating, perhaps using the well known BIOCLIM set of variables (Busby 1991) as a guideline.

In the case of future continuation of this research, the Collection 6 MODIS data products (to be made available in early 2011) will need to be investigated for changes from the current Collection 5 data used in this study. It is likely that Collection 5 processing will be phased out in the foreseeable future and the effects of using alternative Collection 6 datasets on the model outcome requires further research.

8.2.3 Applicability of Methodology to Other Regions and Arboviruses

The present approach of using environmental and climate data from remote sensing satellites to model virus distribution is not limited to BTV. As reviewed in Chapters 3 and 4, similar approaches have been applied to a variety of other viruses and emerging diseases. Within Australia there exist a number of arboviruses that may provide an ideal test bed for the methodology. These include Akabane virus, which like BTV is predominantly transmitted by *Culicoides brevitarsis* and may therefore provide additional explanation for observed presence of BTV in an area.

It has further been suggested by the members of the NAMP technical committee that research should be expanded to the eastern states of Australia. Not only have these parts of the country a longer tradition in Bluetongue epidemiological research, also the typical size of a farm / pastoral station is smaller than in northern Australia, allowing for a more accurate determination of environmental factors related to BTV.

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APPENDICES

APPENDIX A

NAMP TEST RESULTS FOR BTV IN THE PILBARA FROM SAMPLES COLLECTED BETWEEN 1 NOVEMBER 2000 AND 31 OCTOBER 2009

Site_ num	State	Bleed_ date	Season	Virus_ short	Bleed_ type	Num_ total	Num_ seroconv	Comment
F60	WA	21/06/2002	2001	BT	Sentinel	17	0	
F60	WA	15/05/2003	2002	BT	Sentinel	17	2	
F60	WA	27/09/2006	2005	BT	Sentinel	10	0	
F60	WA	9/10/2009	2008	BT	Sentinel	10	0	
W006	WA	14/08/2001	2000	BT	Serosurv	12	0	
W014	WA	12/09/2001	2000	BT	Serosurv	25	0	
W014	WA	9/09/2003	2002	BT	Serosurv	20	0	
W015	WA	12/09/2001	2000	BT	Serosurv	19	0	
W015	WA	19/06/2006	2005	BT	Serosurv	30	0	
W015	WA	21/08/2007	2006	BT	Serosurv	27	0	
W023	WA	14/08/2001	2000	BT	Serosurv	13	0	
W023	WA	24/09/2001	2000	BT	Serosurv	16	0	
W023	WA	14/06/2006	2005	BT	Serosurv	30	0	
W023	WA	10/06/2009	2008	BT	Serosurv	30	0	
W024	WA	30/07/2001	2000	BT	Serosurv	20	0	
W026	WA	14/08/2001	2000	BT	Serosurv	15	0	
W034	WA	23/08/2001	2000	BT	Serosurv	15	0	
W034	WA	20/09/2001	2000	BT	Serosurv	9	0	
W034	WA	9/09/2003	2002	BT	Serosurv	23	0	changed from W109
W039	WA	6/12/2002	2002	BT	Serosurv	55	4	
W039	WA	30/08/2005	2004	BT	Serosurv	30	0	
W047	WA	12/12/2000	2000	BT	Sentinel	20	0	
W047	WA	31/07/2001	2000	BT	Sentinel	18	0	
W048	WA	14/08/2001	2000	BT	Serosurv	12	0	
W064	WA	23/05/2001	2000	BT	Sentinel	8	1	
W065	WA	12/09/2001	2000	BT	Serosurv	15	0	
W065	WA	9/09/2003	2002	BT	Serosurv	22	0	
W066	WA	15/08/2001	2000	BT	Serosurv	20	1	
W066	WA	24/09/2001	2000	BT	Serosurv	21	0	
W067	WA	14/08/2001	2000	BT	Serosurv	12	0	
W069	WA	14/08/2001	2000	BT	Serosurv	4	0	
W069	WA	13/01/2004	2003	BT	Serosurv	37	0	
W070	WA	15/06/2001	2000	BT	Serosurv	10	1	
W071	WA	3/09/2001	2000	BT	Serosurv	15	0	
W072	WA	3/09/2001	2000	BT	Serosurv	16	0	
W072	WA	31/07/2002	2001	BT	Serosurv	11	0	
W072	WA	7/08/2002	2001	BT	Serosurv	9	0	
W072	WA	29/06/2006	2005	BT	Serosurv	29	0	
W073	WA	14/08/2001	2000	BT	Serosurv	14	1	
W073	WA	15/06/2001	2000	BT	Serosurv	20	1	
W073	WA	7/08/2002	2001	BT	Serosurv	20	16	
W074	WA	14/08/2001	2000	BT	Serosurv	12	0	
W075	WA	20/09/2001	2000	BT	Serosurv	20	0	
W075	WA	27/09/2002	2001	BT	Serosurv	52	8	
W075	WA	14/09/2005	2004	BT	Serosurv	30	0	
W076	WA	14/08/2001	2000	BT	Serosurv	11	0	
W076	WA	9/09/2003	2002	BT	Serosurv	20	0	
W076	WA	31/07/2007	2006	BT	Serosurv	40	0	
W076	WA	20/08/2002	2001	BT	Sentinel	25	0	
W076	WA	11/08/2004	2003	BT	Sentinel	12	0	
W076	WA	31/07/2007	2006	BT	Sentinel	22	0	

Site_ num	State	Bleed_ date	Season	Virus_ short	Bleed_ type	Num_ total	Num_ seroconv	Comment
W076	WA	18/06/2009	2008	BT	Sentinel	24	0	
W077	WA	14/08/2001	2000	BT	Serosurv	11	0	
W078	WA	14/08/2001	2000	BT	Serosurv	15	0	
W078	WA	31/05/2002	2001	BT	Serosurv	20	0	
W079	WA	14/08/2001	2000	BT	Serosurv	12	0	
W080	WA	20/09/2001	2000	BT	Serosurv	20	0	
W080	WA	24/06/2008	2007	BT	Serosurv	30	0	changed from W150
W081	WA	24/09/2001	2000	BT	Serosurv	21	0	
W081	WA	26/07/2007	2006	BT	Serosurv	30	0	
W082	WA	14/08/2001	2000	BT	Serosurv	13	0	
W082	WA	30/07/2001	2000	BT	Serosurv	20	0	
W082	WA	21/06/2002	2001	BT	Serosurv	20	4	
W082	WA	14/09/2005	2004	BT	Serosurv	27	2	
W082	WA	10/07/2007	2006	BT	Serosurv	30	1	
W082	WA	24/06/2008	2007	BT	Serosurv	30	0	
W084	WA	28/09/2001	2000	BT	Serosurv	21	0	
W084	WA	31/10/2003	2002	BT	Serosurv	21	1	
W084	WA	30/05/2003	2002	BT	Sentinel	13	0	
W084	WA	3/06/2004	2003	BT	Sentinel	16	0	
W085	WA	26/06/2008	2007	BT	Serosurv	30	0	
W085	WA	26/06/2008	2007	BT	Serosurv	30	0	
W085	WA	19/04/2002	2001	BT	Sentinel	24	0	
W085	WA	19/04/2002	2001	BT	Sentinel	24	0	
W085	WA	8/04/2003	2002	BT	Sentinel	20	0	
W085	WA	8/04/2003	2002	BT	Sentinel	20	0	
W085	WA	30/08/2004	2003	BT	Sentinel	9	0	
W085	WA	30/08/2004	2003	BT	Sentinel	9	0	
W085	WA	30/08/2005	2004	BT	Sentinel	15	0	
W085	WA	30/08/2005	2004	BT	Sentinel	15	0	
W086	WA	11/06/2002	2001	BT	Sentinel	20	1	
W087	WA	9/10/2001	2000	BT	Serosurv	22	0	
W087	WA	3/05/2006	2005	BT	Serosurv	31	0	
W088	WA	4/06/2002	2001	BT	Serosurv	20	17	
W088	WA	23/09/2003	2002	BT	Serosurv	18	16	changed from W111
W088	WA	30/03/2004	2003	BT	Sentinel	24	1	changed from W111
W088	WA	10/09/2004	2003	BT	Sentinel	19	0	changed from W111
W089	WA	14/06/2002	2001	BT	Serosurv	14	0	
W089	WA	4/12/2002	2002	BT	Serosurv	47	0	
W089	WA	19/06/2006	2005	BT	Serosurv	25	0	
W089	WA	11/06/2002	2001	BT	Sentinel	14	0	
W089	WA	16/06/2003	2002	BT	Sentinel	14	0	
W093	WA	7/08/2002	2001	BT	Serosurv	20	18	
W094	WA	23/08/2002	2001	BT	Serosurv	20	0	
W094	WA	5/11/2005	2005	BT	Serosurv	20	4	
W094	WA	17/08/2006	2005	BT	Serosurv	30	0	
W094	WA	24/07/2007	2006	BT	Serosurv	30	0	
W095	WA	19/11/2002	2002	BT	Serosurv	55	9	
W095	WA	30/08/2005	2004	BT	Serosurv	32	0	
W096	WA	28/08/2007	2006	BT	Serosurv	31	0	
W096	WA	8/04/2003	2002	BT	Sentinel	18	0	
W096	WA	9/08/2006	2005	BT	Sentinel	11	0	

Site_ num	State	Bleed_ date	Season	Virus_ short	Bleed_ type	Num_ total	Num_ seroconv	Comment
W098	WA	14/08/2007	2006	BT	Serosurv	21	0	
W098	WA	22/12/2003	2003	BT	Sentinel	29	0	
W098	WA	21/05/2004	2003	BT	Sentinel	23	0	
W098	WA	3/09/2004	2003	BT	Sentinel	19	0	
W098	WA	8/02/2005	2004	BT	Sentinel	18	0	
W098	WA	31/05/2005	2004	BT	Sentinel	18	0	
W098	WA	25/07/2006	2005	BT	Sentinel	23	0	
W098	WA	13/08/2008	2007	BT	Sentinel	9	0	
W098	WA	15/06/2009	2008	BT	Sentinel	10	0	
W099	WA	1/12/2003	2003	BT	Serosurv	28	0	
W099	WA	8/01/2008	2007	BT	Serosurv	21	0	
W099	WA	14/05/2004	2003	BT	Sentinel	28	0	
W099	WA	8/09/2005	2004	BT	Sentinel	21	0	
W099	WA	1/11/2006	2006	BT	Sentinel	27	0	
W100	WA	23/11/2004	2004	BT	Serosurv	50	0	
W100	WA	1/09/2005	2004	BT	Sentinel	16	0	
W100	WA	22/06/2006	2005	BT	Sentinel	16	0	
W101	WA	14/08/2003	2002	BT	Serosurv	20	0	
W101	WA	8/11/2005	2005	BT	Serosurv	30	0	
W110	WA	9/09/2003	2002	BT	Serosurv	22	0	
W112	WA	23/09/2003	2002	BT	Serosurv	17	0	
W126	WA	8/11/2005	2005	BT	Serosurv	30	0	
W127	WA	8/11/2005	2005	BT	Serosurv	30	0	
W127	WA	26/05/2009	2008	BT	Serosurv	30	0	
W128	WA	3/05/2006	2005	BT	Serosurv	30	0	
W128	WA	25/06/2008	2007	BT	Serosurv	30	0	
W129	WA	3/05/2006	2005	BT	Serosurv	30	0	
W129	WA	25/06/2008	2007	BT	Serosurv	29	0	
W133	WA	8/08/2001	2000	BT	Serosurv	8	0	changed from W068
W133	WA	10/08/2006	2005	BT	Serosurv	30	0	
W133	WA	21/08/2007	2006	BT	Serosurv	30	1	
W133	WA	18/09/2008	2007	BT	Serosurv	30	0	
W133	WA	30/09/2009	2008	BT	Sentinel	11	0	

APPENDIX B

NAMP TEST RESULTS FOR BTV IN THE NORTHERN TERRITORY FROM SAMPLES COLLECTED BETWEEN 1 NOVEMBER 2000 AND 31 OCTOBER 2009

Site_ num	State	Bleed_ date	Season	Virus_ short	Bleed_ type	Num_ total	Num_ seroconv	Comment
108	NT	9/11/2000	2000	BT	Sentinel	24	2	changed from T027
108	NT	14/12/2000	2000	BT	Sentinel	24	0	changed from T027
108	NT	11/01/2001	2000	BT	Sentinel	24	3	changed from T027
108	NT	15/02/2001	2000	BT	Sentinel	24	9	changed from T027
108	NT	15/03/2001	2000	BT	Sentinel	24	4	changed from T027
108	NT	12/04/2001	2000	BT	Sentinel	24	0	changed from T027
108	NT	24/05/2001	2000	BT	Sentinel	24	0	changed from T027
108	NT	14/06/2001	2000	BT	Sentinel	24	0	changed from T027
108	NT	23/08/2001	2000	BT	Sentinel	14	3	changed from T027
108	NT	6/09/2001	2000	BT	Sentinel	14	0	changed from T027
108	NT	11/10/2001	2000	BT	Sentinel	14	1	changed from T027
108	NT	15/11/2001	2001	BT	Sentinel	14	1	changed from T027
108	NT	13/12/2001	2001	BT	Sentinel	24	0	changed from T027
108	NT	10/01/2002	2001	BT	Sentinel	24	0	changed from T027
108	NT	7/02/2002	2001	BT	Sentinel	24	0	changed from T027
108	NT	7/03/2002	2001	BT	Sentinel	24	1	changed from T027
108	NT	11/04/2002	2001	BT	Sentinel	24	16	changed from T027
108	NT	10/05/2002	2001	BT	Sentinel	24	6	changed from T027
108	NT	13/06/2002	2001	BT	Sentinel	24	1	changed from T027
108	NT	5/07/2002	2001	BT	Sentinel	24	0	changed from T027
108	NT	15/08/2002	2001	BT	Sentinel	24	0	changed from T027
108	NT	4/10/2002	2001	BT	Sentinel	24	0	changed from T027
108	NT	7/11/2002	2002	BT	Sentinel	24	4	changed from T027
108	NT	5/12/2002	2002	BT	Sentinel	24	5	changed from T027
108	NT	2/01/2003	2002	BT	Sentinel	24	10	changed from T027
108	NT	13/02/2003	2002	BT	Sentinel	24	1	changed from T027
108	NT	13/03/2003	2002	BT	Sentinel	24	0	changed from T027
108	NT	10/04/2003	2002	BT	Sentinel	24	2	changed from T027
108	NT	8/05/2003	2002	BT	Sentinel	24	9	changed from T027
108	NT	6/06/2003	2002	BT	Sentinel	24	3	changed from T027
108	NT	30/06/2003	2002	BT	Sentinel	24	3	changed from T027
108	NT	10/07/2003	2002	BT	Sentinel	24	0	changed from T027
108	NT	7/08/2003	2002	BT	Sentinel	24	0	changed from T027
108	NT	4/09/2003	2002	BT	Sentinel	24	1	changed from T027
108	NT	16/10/2003	2002	BT	Sentinel	24	0	changed from T027
108	NT	6/11/2003	2003	BT	Sentinel	24	1	changed from T027
108	NT	4/12/2003	2003	BT	Sentinel	23	0	changed from T027
108	NT	8/01/2004	2003	BT	Sentinel	24	5	changed from T027
108	NT	5/02/2004	2003	BT	Sentinel	24	4	changed from T027
108	NT	11/03/2004	2003	BT	Sentinel	24	8	changed from T027
108	NT	8/04/2004	2003	BT	Sentinel	23	1	changed from T027
108	NT	7/05/2004	2003	BT	Sentinel	23	0	changed from T027
108	NT	8/07/2004	2003	BT	Sentinel	24	0	changed from T027
108	NT	12/08/2004	2003	BT	Sentinel	24	1	changed from T027
108	NT	9/09/2004	2003	BT	Sentinel	23	0	changed from T027
108	NT	7/10/2004	2003	BT	Sentinel	23	0	changed from T027
108	NT	4/11/2004	2004	BT	Sentinel	23	0	changed from T027
108	NT	2/12/2004	2004	BT	Sentinel	23	0	changed from T027
108	NT	6/01/2005	2004	BT	Sentinel	23	0	changed from T027
108	NT	3/02/2005	2004	BT	Sentinel	23	1	changed from T027
108	NT	3/03/2005	2004	BT	Sentinel	23	2	changed from T027
108	NT	7/04/2005	2004	BT	Sentinel	23	8	changed from T027
108	NT	5/05/2005	2004	BT	Sentinel	23	8	changed from T027
108	NT	2/06/2005	2004	BT	Sentinel	11	0	changed from T027
108	NT	7/07/2005	2004	BT	Sentinel	24	0	changed from T027
108	NT	4/08/2005	2004	BT	Sentinel	24	0	changed from T027
108	NT	1/09/2005	2004	BT	Sentinel	24	0	changed from T027
108	NT	6/10/2005	2004	BT	Sentinel	23	0	changed from T027
108	NT	3/11/2005	2005	BT	Sentinel	23	0	changed from T027

Site_ num	State	Bleed_ date	Season	Virus_ short	Bleed_ type	Num_ total	Num_ seroconv	Comment
108	NT	1/12/2005	2005	BT	Sentinel	23	0	changed from T027
108	NT	5/01/2006	2005	BT	Sentinel	23	3	changed from T027
108	NT	2/02/2006	2005	BT	Sentinel	23	9	changed from T027
108	NT	2/03/2006	2005	BT	Sentinel	23	1	changed from T027
108	NT	6/04/2006	2005	BT	Sentinel	23	2	changed from T027
108	NT	4/05/2006	2005	BT	Sentinel	23	7	changed from T027
108	NT	6/07/2006	2005	BT	Sentinel	23	0	changed from T027
108	NT	6/09/2006	2005	BT	Sentinel	23	0	changed from T027
108	NT	4/10/2006	2005	BT	Sentinel	23	0	changed from T027
108	NT	2/11/2006	2006	BT	Sentinel	22	0	changed from T027
108	NT	7/12/2006	2006	BT	Sentinel	22	0	changed from T027
108	NT	4/01/2007	2006	BT	Sentinel	22	0	changed from T027
108	NT	1/02/2007	2006	BT	Sentinel	22	0	changed from T027
108	NT	1/03/2007	2006	BT	Sentinel	22	0	changed from T027
108	NT	5/04/2007	2006	BT	Sentinel	22	0	changed from T027
108	NT	3/05/2007	2006	BT	Sentinel	21	2	changed from T027
108	NT	7/06/2007	2006	BT	Sentinel	21	3	changed from T027
108	NT	1/07/2007	2006	BT	Sentinel	24	0	changed from T027
108	NT	2/08/2007	2006	BT	Sentinel	24	0	changed from T027
108	NT	6/09/2007	2006	BT	Sentinel	24	0	changed from T027
108	NT	4/10/2007	2006	BT	Sentinel	24	0	changed from T027
108	NT	1/11/2007	2007	BT	Sentinel	24	0	changed from T027
108	NT	6/12/2007	2007	BT	Sentinel	24	2	changed from T027
108	NT	3/01/2008	2007	BT	Sentinel	24	1	changed from T027
108	NT	7/02/2008	2007	BT	Sentinel	24	9	changed from T027
108	NT	6/03/2008	2007	BT	Sentinel	24	4	changed from T027
108	NT	3/04/2008	2007	BT	Sentinel	24	2	changed from T027
108	NT	8/05/2008	2007	BT	Sentinel	23	3	changed from T027
108	NT	5/06/2008	2007	BT	Sentinel	24	0	changed from T027
108	NT	3/07/2008	2007	BT	Sentinel	24	0	
108	NT	7/08/2008	2007	BT	Sentinel	24	0	
108	NT	4/09/2008	2007	BT	Sentinel	24	0	
108	NT	2/10/2008	2007	BT	Sentinel	24	0	
108	NT	6/11/2008	2008	BT	Sentinel	23	0	
108	NT	4/12/2008	2008	BT	Sentinel	23	2	
108	NT	8/01/2009	2008	BT	Sentinel	23	4	
108	NT	19/02/2009	2008	BT	Sentinel	23	13	
108	NT	5/03/2009	2008	BT	Sentinel	23	3	
108	NT	2/04/2009	2008	BT	Sentinel	23	1	
108	NT	7/05/2009	2008	BT	Sentinel	23	0	
108	NT	4/06/2009	2008	BT	Sentinel	23	0	
108	NT	1/07/2009	2008	BT	Sentinel	22	0	
108	NT	6/08/2009	2008	BT	Sentinel	21	0	
108	NT	3/09/2009	2008	BT	Sentinel	21	0	
108	NT	1/10/2009	2008	BT	Sentinel	21	0	
120	NT	16/11/2000	2000	BT	Sentinel	20	0	
120	NT	5/12/2000	2000	BT	Sentinel	24	0	
120	NT	7/06/2001	2000	BT	Sentinel	20	0	
120	NT	13/07/2001	2000	BT	Sentinel	20	0	
120	NT	20/08/2001	2000	BT	Sentinel	20	0	
120	NT	21/09/2001	2000	BT	Sentinel	20	0	
120	NT	18/10/2001	2000	BT	Sentinel	25	0	
120	NT	14/12/2001	2001	BT	Sentinel	20	0	
120	NT	25/01/2002	2001	BT	Sentinel	20	0	
120	NT	4/03/2002	2001	BT	Sentinel	20	0	
120	NT	9/04/2002	2001	BT	Sentinel	20	0	
120	NT	15/05/2002	2001	BT	Sentinel	20	0	
120	NT	3/06/2002	2001	BT	Sentinel	20	0	
120	NT	4/07/2002	2001	BT	Sentinel	20	0	

Site_ num	State	Bleed_ date	Season	Virus_ short	Bleed_ type	Num_ total	Num_ seroconv	Comment
120	NT	29/08/2002	2001	BT	Sentinel	20	0	
120	NT	2/10/2002	2001	BT	Sentinel	20	0	
120	NT	7/11/2002	2002	BT	Sentinel	20	1	
120	NT	11/12/2002	2002	BT	Sentinel	20	0	
120	NT	2/01/2003	2002	BT	Sentinel	20	0	
120	NT	5/02/2003	2002	BT	Sentinel	20	0	
120	NT	18/03/2003	2002	BT	Sentinel	16	0	
120	NT	30/04/2003	2002	BT	Sentinel	15	6	
120	NT	19/06/2003	2002	BT	Sentinel	18	6	
120	NT	26/07/2003	2002	BT	Sentinel	13	0	
120	NT	30/08/2003	2002	BT	Sentinel	18	1	
120	NT	31/10/2003	2002	BT	Sentinel	19	3	
120	NT	4/12/2003	2003	BT	Sentinel	23	0	
120	NT	4/01/2004	2003	BT	Sentinel	19	3	
120	NT	1/02/2004	2003	BT	Sentinel	23	0	
120	NT	1/03/2004	2003	BT	Sentinel	23	0	
120	NT	1/04/2004	2003	BT	Sentinel	18	0	
120	NT	1/05/2004	2003	BT	Sentinel	23	0	
120	NT	1/06/2004	2003	BT	Sentinel	23	0	
120	NT	15/08/2004	2003	BT	Sentinel	16	5	
120	NT	15/09/2004	2003	BT	Sentinel	21	2	
120	NT	5/10/2004	2003	BT	Sentinel	21	0	
120	NT	9/12/2004	2004	BT	Sentinel	16	0	
120	NT	2/03/2005	2004	BT	Sentinel	14	0	
120	NT	11/04/2005	2004	BT	Sentinel	14	0	
120	NT	3/05/2005	2004	BT	Sentinel	12	0	
120	NT	9/06/2005	2004	BT	Sentinel	19	0	
120	NT	21/07/2005	2004	BT	Sentinel	19	0	
120	NT	13/09/2005	2004	BT	Sentinel	8	0	
120	NT	13/10/2005	2004	BT	Sentinel	14	0	
120	NT	7/12/2005	2005	BT	Sentinel	20	0	
120	NT	14/01/2006	2005	BT	Sentinel	20	0	
120	NT	16/02/2006	2005	BT	Sentinel	20	0	
120	NT	15/03/2006	2005	BT	Sentinel	20	0	
120	NT	12/04/2006	2005	BT	Sentinel	20	0	
120	NT	13/05/2006	2005	BT	Sentinel	20	0	
120	NT	23/06/2006	2005	BT	Sentinel	20	7	
120	NT	16/08/2006	2005	BT	Sentinel	20	3	
120	NT	14/09/2006	2005	BT	Sentinel	19	3	
120	NT	12/10/2006	2005	BT	Sentinel	20	1	
120	NT	14/12/2006	2006	BT	Sentinel	20	5	
120	NT	25/01/2007	2006	BT	Sentinel	20	0	
120	NT	28/02/2007	2006	BT	Sentinel	20	0	
120	NT	28/03/2007	2006	BT	Sentinel	20	0	
120	NT	20/04/2007	2006	BT	Sentinel	20	0	
120	NT	29/06/2007	2006	BT	Sentinel	20	1	
120	NT	30/07/2007	2006	BT	Sentinel	19	0	
120	NT	28/08/2007	2006	BT	Sentinel	17	0	
120	NT	12/10/2007	2006	BT	Sentinel	19	1	
120	NT	21/12/2007	2007	BT	Sentinel	20	0	
120	NT	24/01/2008	2007	BT	Sentinel	20	0	
120	NT	20/02/2008	2007	BT	Sentinel	20	0	
120	NT	19/03/2008	2007	BT	Sentinel	20	0	
120	NT	11/04/2008	2007	BT	Sentinel	20	1	
120	NT	23/05/2008	2007	BT	Sentinel	19	0	
120	NT	18/06/2008	2007	BT	Sentinel	20	1	
120	NT	30/07/2008	2007	BT	Sentinel	20	0	
120	NT	19/08/2008	2007	BT	Sentinel	20	0	
120	NT	22/09/2008	2007	BT	Sentinel	20	0	

Site_ num	State	Bleed_ date	Season	Virus_ short	Bleed_ type	Num_ total	Num_ seroconv	Comment
120	NT	22/10/2008	2007	BT	Sentinel	19	0	
120	NT	16/12/2008	2008	BT	Sentinel	20	0	
120	NT	20/01/2009	2008	BT	Sentinel	19	0	
120	NT	10/02/2009	2008	BT	Sentinel	19	0	
120	NT	25/03/2009	2008	BT	Sentinel	19	1	
120	NT	16/04/2009	2008	BT	Sentinel	18	4	
120	NT	29/05/2009	2008	BT	Sentinel	19	2	
120	NT	17/06/2009	2008	BT	Sentinel	20	0	
120	NT	15/07/2009	2008	BT	Sentinel	19	0	
120	NT	24/08/2009	2008	BT	Sentinel	19	2	
120	NT	20/09/2009	2008	BT	Sentinel	17	1	
165	NT	14/04/2004	2003	BT	Serosurv	21	2	
165	NT	29/11/2006	2006	BT	Serosurv	20	1	
165	NT	3/08/2004	2003	BT	Sentinel	15	0	
165	NT	12/04/2005	2004	BT	Sentinel	15	0	
165	NT	28/07/2005	2004	BT	Sentinel	15	0	
165	NT	18/05/2006	2005	BT	Sentinel	9	1	
165	NT	4/04/2007	2006	BT	Sentinel	19	0	
165	NT	15/08/2007	2006	BT	Sentinel	18	0	
165	NT	11/06/2008	2007	BT	Sentinel	18	0	
165	NT	21/04/2009	2008	BT	Serosurv	60	9	
165	NT	21/04/2009	2008	BT	Sentinel	13	5	
179	NT	24/11/2000	2000	BT	Sentinel	20	0	
179	NT	31/01/2001	2000	BT	Sentinel	20	0	
179	NT	28/02/2001	2000	BT	Sentinel	20	0	
179	NT	11/04/2001	2000	BT	Sentinel	20	0	
179	NT	9/05/2001	2000	BT	Sentinel	20	0	
179	NT	20/06/2001	2000	BT	Sentinel	20	0	
179	NT	11/07/2001	2000	BT	Sentinel	20	0	
179	NT	15/08/2001	2000	BT	Sentinel	20	0	
179	NT	13/09/2001	2000	BT	Sentinel	20	0	
179	NT	12/10/2001	2000	BT	Sentinel	20	0	
179	NT	14/11/2001	2001	BT	Sentinel	20	0	
179	NT	12/12/2001	2001	BT	Sentinel	20	0	
179	NT	7/02/2002	2001	BT	Sentinel	20	0	
179	NT	7/03/2002	2001	BT	Sentinel	20	0	
179	NT	10/04/2002	2001	BT	Sentinel	20	0	
179	NT	9/05/2002	2001	BT	Sentinel	20	0	
179	NT	5/06/2002	2001	BT	Sentinel	20	0	
179	NT	9/07/2002	2001	BT	Sentinel	20	0	
179	NT	7/08/2002	2001	BT	Sentinel	20	0	
179	NT	10/09/2002	2001	BT	Sentinel	20	0	
179	NT	30/10/2002	2001	BT	Sentinel	20	0	
179	NT	30/11/2002	2002	BT	Sentinel	20	0	
179	NT	24/12/2002	2002	BT	Sentinel	20	0	
179	NT	30/01/2003	2002	BT	Sentinel	20	0	
179	NT	28/02/2003	2002	BT	Sentinel	20	0	
179	NT	30/03/2003	2002	BT	Sentinel	20	0	
179	NT	29/04/2003	2002	BT	Sentinel	20	0	
179	NT	30/05/2003	2002	BT	Sentinel	20	0	
179	NT	30/06/2003	2002	BT	Sentinel	21	0	
179	NT	7/08/2003	2002	BT	Sentinel	20	0	
179	NT	3/09/2003	2002	BT	Sentinel	20	0	
179	NT	2/10/2003	2002	BT	Sentinel	20	0	
179	NT	11/11/2003	2003	BT	Sentinel	20	0	
179	NT	3/12/2003	2003	BT	Sentinel	20	0	
179	NT	10/02/2004	2003	BT	Sentinel	20	0	
179	NT	2/03/2004	2003	BT	Sentinel	20	0	
179	NT	18/05/2004	2003	BT	Sentinel	20	0	

Site_ num	State	Bleed_ date	Season	Virus_ short	Bleed_ type	Num_ total	Num_ seroconv	Comment
179	NT	8/06/2004	2003	BT	Sentinel	20	0	
179	NT	6/07/2004	2003	BT	Sentinel	20	0	
179	NT	4/08/2004	2003	BT	Sentinel	20	0	
179	NT	1/09/2004	2003	BT	Sentinel	20	0	
179	NT	1/10/2004	2003	BT	Sentinel	20	0	
179	NT	2/11/2004	2004	BT	Sentinel	20	0	
179	NT	1/12/2004	2004	BT	Sentinel	20	0	
179	NT	1/02/2005	2004	BT	Sentinel	20	0	
179	NT	2/03/2005	2004	BT	Sentinel	20	0	
179	NT	5/04/2005	2004	BT	Sentinel	20	0	
179	NT	4/05/2005	2004	BT	Sentinel	19	0	
179	NT	4/07/2005	2004	BT	Sentinel	20	0	
179	NT	3/08/2005	2004	BT	Sentinel	20	0	
179	NT	1/09/2005	2004	BT	Sentinel	19	0	
179	NT	4/10/2005	2004	BT	Sentinel	20	0	
179	NT	1/11/2005	2005	BT	Sentinel	20	0	
179	NT	1/12/2005	2005	BT	Sentinel	20	0	
179	NT	3/01/2006	2005	BT	Sentinel	20	0	
179	NT	2/02/2006	2005	BT	Sentinel	20	0	
179	NT	1/03/2006	2005	BT	Sentinel	20	0	
179	NT	4/04/2006	2005	BT	Sentinel	19	0	
179	NT	3/05/2006	2005	BT	Sentinel	19	0	
179	NT	1/06/2006	2005	BT	Sentinel	19	0	
179	NT	1/08/2006	2005	BT	Sentinel	19	0	
179	NT	12/09/2006	2005	BT	Sentinel	20	0	
179	NT	3/10/2006	2005	BT	Sentinel	20	0	
179	NT	7/11/2006	2006	BT	Sentinel	20	0	
179	NT	7/12/2006	2006	BT	Sentinel	20	0	
179	NT	3/01/2007	2006	BT	Sentinel	20	0	
179	NT	7/02/2007	2006	BT	Sentinel	20	0	
179	NT	1/03/2007	2006	BT	Sentinel	20	0	
179	NT	11/04/2007	2006	BT	Sentinel	20	0	
179	NT	15/05/2007	2006	BT	Sentinel	20	0	
179	NT	5/06/2007	2006	BT	Sentinel	20	0	
179	NT	10/07/2007	2006	BT	Sentinel	20	0	
179	NT	14/09/2007	2006	BT	Sentinel	20	0	
179	NT	11/10/2007	2006	BT	Sentinel	20	0	
179	NT	20/11/2007	2007	BT	Sentinel	20	0	
179	NT	12/12/2007	2007	BT	Sentinel	20	0	
179	NT	8/01/2008	2007	BT	Sentinel	19	0	
179	NT	5/02/2008	2007	BT	Sentinel	20	0	
179	NT	4/03/2008	2007	BT	Sentinel	20	0	
179	NT	1/04/2008	2007	BT	Sentinel	20	0	
179	NT	8/05/2008	2007	BT	Sentinel	20	0	
179	NT	5/06/2008	2007	BT	Sentinel	20	0	
179	NT	8/07/2008	2007	BT	Sentinel	20	0	
179	NT	13/10/2008	2007	BT	Sentinel	25	0	
179	NT	5/11/2008	2008	BT	Sentinel	25	0	
179	NT	4/12/2008	2008	BT	Sentinel	25	0	
179	NT	7/01/2009	2008	BT	Sentinel	24	0	
179	NT	4/02/2009	2008	BT	Sentinel	25	0	
179	NT	4/03/2009	2008	BT	Sentinel	24	0	
179	NT	8/04/2009	2008	BT	Sentinel	25	0	
179	NT	6/05/2009	2008	BT	Sentinel	25	0	
179	NT	4/06/2009	2008	BT	Sentinel	22	0	
179	NT	13/07/2009	2008	BT	Sentinel	25	0	
179	NT	2/09/2009	2008	BT	Sentinel	25	0	
179	NT	7/10/2009	2008	BT	Sentinel	25	0	
190	NT	15/11/2000	2000	BT	Sentinel	14	0	

Site_ num	State	Bleed_ date	Season	Virus_ short	Bleed_ type	Num_ total	Num_ seroconv	Comment
190	NT	12/12/2000	2000	BT	Sentinel	14	0	
190	NT	15/11/2000	2000	BT	Sentinel	16	0	changed from T028
190	NT	12/12/2000	2000	BT	Sentinel	15	0	changed from T028
190	NT	16/01/2001	2000	BT	Sentinel	13	1	
190	NT	6/02/2001	2000	BT	Sentinel	14	0	
190	NT	6/04/2001	2000	BT	Sentinel	22	0	
190	NT	8/05/2001	2000	BT	Sentinel	21	1	
190	NT	14/06/2001	2000	BT	Sentinel	22	1	
190	NT	4/07/2001	2000	BT	Sentinel	22	0	
190	NT	8/08/2001	2000	BT	Sentinel	20	0	
190	NT	7/09/2001	2000	BT	Sentinel	21	0	
190	NT	5/10/2001	2000	BT	Sentinel	22	0	
190	NT	9/11/2001	2001	BT	Sentinel	22	0	
190	NT	4/12/2001	2001	BT	Sentinel	22	0	
190	NT	16/01/2001	2000	BT	Sentinel	16	1	changed from T028
190	NT	6/02/2001	2000	BT	Sentinel	16	0	changed from T028
190	NT	7/03/2001	2000	BT	Sentinel	16	0	changed from T028
190	NT	6/04/2001	2000	BT	Sentinel	16	4	changed from T028
190	NT	8/05/2001	2000	BT	Sentinel	16	1	changed from T028
190	NT	13/06/2001	2000	BT	Sentinel	15	2	changed from T028
190	NT	11/01/2002	2001	BT	Sentinel	20	0	
190	NT	8/02/2002	2001	BT	Sentinel	17	0	
190	NT	15/03/2002	2001	BT	Sentinel	19	0	
190	NT	10/04/2002	2001	BT	Sentinel	20	0	
190	NT	14/05/2002	2001	BT	Sentinel	20	0	
190	NT	18/06/2002	2001	BT	Sentinel	20	1	
190	NT	17/07/2002	2001	BT	Sentinel	12	1	
190	NT	20/08/2002	2001	BT	Sentinel	12	2	
190	NT	10/09/2002	2001	BT	Sentinel	12	0	
190	NT	9/10/2002	2001	BT	Sentinel	12	1	
190	NT	12/11/2002	2002	BT	Sentinel	12	1	
190	NT	6/12/2002	2002	BT	Sentinel	12	0	
190	NT	9/10/2002	2001	BT	Sentinel	10	0	changed from T028
190	NT	12/11/2002	2002	BT	Sentinel	10	0	changed from T028
190	NT	6/12/2002	2002	BT	Sentinel	10	0	changed from T028
190	NT	14/01/2003	2002	BT	Sentinel	12	0	
190	NT	18/02/2003	2002	BT	Sentinel	12	0	
190	NT	18/03/2003	2002	BT	Sentinel	12	2	
190	NT	11/04/2003	2002	BT	Sentinel	12	1	
190	NT	6/05/2003	2002	BT	Sentinel	15	4	
190	NT	1/06/2003	2002	BT	Sentinel	15	1	
190	NT	10/07/2003	2002	BT	Sentinel	13	0	
190	NT	14/08/2003	2002	BT	Sentinel	13	0	
190	NT	15/09/2003	2002	BT	Sentinel	15	0	
190	NT	15/10/2003	2002	BT	Sentinel	15	0	
190	NT	18/11/2003	2003	BT	Sentinel	13	0	
190	NT	3/12/2003	2003	BT	Sentinel	14	0	
190	NT	14/01/2003	2002	BT	Sentinel	10	1	changed from T028
190	NT	18/02/2003	2002	BT	Sentinel	10	1	changed from T028
190	NT	18/03/2003	2002	BT	Sentinel	10	2	changed from T028
190	NT	11/04/2003	2002	BT	Sentinel	10	4	changed from T028
190	NT	10/07/2003	2002	BT	Sentinel	12	0	changed from T028
190	NT	14/08/2003	2002	BT	Sentinel	12	0	changed from T028
190	NT	15/09/2003	2002	BT	Sentinel	12	0	changed from T028
190	NT	15/10/2003	2002	BT	Sentinel	12	0	changed from T028
190	NT	18/11/2003	2003	BT	Sentinel	12	0	changed from T028
190	NT	3/12/2003	2003	BT	Sentinel	12	0	changed from T028
190	NT	16/01/2004	2003	BT	Sentinel	14	5	
190	NT	18/02/2004	2003	BT	Sentinel	14	1	

Site_ num	State	Bleed_ date	Season	Virus_ short	Bleed_ type	Num_ total	Num_ seroconv	Comment
190	NT	26/03/2004	2003	BT	Sentinel	15	1	
190	NT	27/04/2004	2003	BT	Sentinel	15	6	
190	NT	28/05/2004	2003	BT	Sentinel	14	0	
190	NT	18/08/2004	2003	BT	Sentinel	11	2	
190	NT	20/09/2004	2003	BT	Sentinel	11	3	
190	NT	19/10/2004	2003	BT	Sentinel	11	2	
190	NT	11/11/2004	2004	BT	Sentinel	11	1	
190	NT	7/12/2004	2004	BT	Sentinel	10	0	
190	NT	16/01/2004	2003	BT	Sentinel	11	8	changed from T028
190	NT	18/02/2004	2003	BT	Sentinel	12	3	changed from T028
190	NT	26/03/2004	2003	BT	Sentinel	12	0	changed from T028
190	NT	27/04/2004	2003	BT	Sentinel	15	6	changed from T028
190	NT	28/05/2004	2003	BT	Sentinel	14	0	changed from T028
190	NT	21/06/2004	2003	BT	Sentinel	15	0	changed from T028
190	NT	20/07/2004	2003	BT	Sentinel	15	0	changed from T028
190	NT	18/08/2004	2003	BT	Sentinel	15	0	changed from T028
190	NT	20/09/2004	2003	BT	Sentinel	15	0	changed from T028
190	NT	19/10/2004	2003	BT	Sentinel	15	1	changed from T028
190	NT	11/11/2004	2004	BT	Sentinel	15	1	changed from T028
190	NT	7/12/2004	2004	BT	Sentinel	15	1	changed from T028
190	NT	21/01/2005	2004	BT	Sentinel	11	0	
190	NT	17/02/2005	2004	BT	Sentinel	11	1	
190	NT	15/03/2005	2004	BT	Sentinel	11	0	
190	NT	15/04/2005	2004	BT	Sentinel	10	0	
190	NT	26/07/2005	2004	BT	Sentinel	12	4	
190	NT	19/08/2005	2004	BT	Sentinel	12	1	
190	NT	19/09/2005	2004	BT	Sentinel	12	0	
190	NT	25/10/2005	2004	BT	Sentinel	12	0	
190	NT	15/11/2005	2005	BT	Sentinel	13	0	
190	NT	6/12/2005	2005	BT	Sentinel	13	0	
190	NT	21/01/2005	2004	BT	Sentinel	15	1	changed from T028
190	NT	17/02/2005	2004	BT	Sentinel	15	0	changed from T028
190	NT	15/03/2005	2004	BT	Sentinel	14	0	changed from T028
190	NT	15/04/2005	2004	BT	Sentinel	15	1	changed from T028
190	NT	4/05/2005	2004	BT	Sentinel	8	0	changed from T028
190	NT	27/06/2005	2004	BT	Sentinel	10	0	changed from T028
190	NT	26/07/2005	2004	BT	Sentinel	10	0	changed from T028
190	NT	19/08/2005	2004	BT	Sentinel	10	0	changed from T028
190	NT	19/09/2005	2004	BT	Sentinel	10	0	changed from T028
190	NT	25/10/2005	2004	BT	Sentinel	10	0	changed from T028
190	NT	15/11/2005	2005	BT	Sentinel	10	0	changed from T028
190	NT	6/12/2005	2005	BT	Sentinel	10	0	changed from T028
190	NT	4/01/2006	2005	BT	Sentinel	14	0	
190	NT	7/02/2006	2005	BT	Sentinel	14	0	
190	NT	8/03/2006	2005	BT	Sentinel	14	0	
190	NT	5/04/2006	2005	BT	Sentinel	14	0	
190	NT	8/05/2006	2005	BT	Sentinel	14	1	
190	NT	5/06/2006	2005	BT	Sentinel	14	0	
190	NT	28/08/2006	2005	BT	Sentinel	15	0	
190	NT	25/09/2006	2005	BT	Sentinel	15	0	
190	NT	25/10/2006	2005	BT	Sentinel	15	0	
190	NT	22/11/2006	2006	BT	Sentinel	15	0	
190	NT	20/12/2006	2006	BT	Sentinel	14	0	
190	NT	4/01/2006	2005	BT	Sentinel	10	1	changed from T028
190	NT	7/02/2006	2005	BT	Sentinel	9	1	changed from T028
190	NT	8/03/2006	2005	BT	Sentinel	9	0	changed from T028
190	NT	5/04/2006	2005	BT	Sentinel	9	0	changed from T028
190	NT	8/05/2006	2005	BT	Sentinel	9	0	changed from T028
190	NT	5/06/2006	2005	BT	Sentinel	9	1	changed from T028

Site_ num	State	Bleed_ date	Season	Virus_ short	Bleed_ type	Num_ total	Num_ seroconv	Comment
190	NT	28/08/2006	2005	BT	Sentinel	8	0	changed from T028
190	NT	25/09/2006	2005	BT	Sentinel	8	0	changed from T028
190	NT	25/10/2006	2005	BT	Sentinel	8	0	changed from T028
190	NT	22/11/2006	2006	BT	Sentinel	8	0	changed from T028
190	NT	20/12/2006	2006	BT	Sentinel	8	0	changed from T028
190	NT	17/01/2007	2006	BT	Sentinel	14	0	
190	NT	21/02/2007	2006	BT	Sentinel	14	0	
190	NT	30/03/2007	2006	BT	Sentinel	14	0	
190	NT	24/04/2007	2006	BT	Sentinel	14	0	
190	NT	15/05/2007	2006	BT	Sentinel	14	1	
190	NT	15/08/2007	2006	BT	Sentinel	10	0	
190	NT	7/09/2007	2006	BT	Sentinel	7	1	
190	NT	17/01/2007	2006	BT	Sentinel	8	0	changed from T028
190	NT	21/02/2007	2006	BT	Sentinel	8	0	changed from T028
190	NT	30/03/2007	2006	BT	Sentinel	8	0	changed from T028
190	NT	24/04/2007	2006	BT	Sentinel	8	0	changed from T028
190	NT	15/05/2007	2006	BT	Sentinel	8	1	changed from T028
190	NT	15/08/2007	2006	BT	Sentinel	10	0	changed from T028
190	NT	7/09/2007	2006	BT	Sentinel	9	0	changed from T028
190	NT	15/10/2007	2006	BT	Sentinel	8	1	
190	NT	15/10/2007	2006	BT	Sentinel	9	1	changed from T028
190	NT	19/11/2007	2007	BT	Sentinel	8	0	
190	NT	19/11/2007	2007	BT	Sentinel	9	0	changed from T028
190	NT	12/12/2007	2007	BT	Sentinel	8	0	
190	NT	12/12/2007	2007	BT	Sentinel	9	0	changed from T028
190	NT	8/01/2008	2007	BT	Sentinel	8	0	
190	NT	8/01/2008	2007	BT	Sentinel	9	3	changed from T028
190	NT	5/02/2008	2007	BT	Sentinel	8	6	
190	NT	5/02/2008	2007	BT	Sentinel	9	6	changed from T028
190	NT	3/03/2008	2007	BT	Sentinel	8	0	
190	NT	3/03/2008	2007	BT	Sentinel	9	0	changed from T028
190	NT	2/04/2008	2007	BT	Sentinel	8	0	
190	NT	2/04/2008	2007	BT	Sentinel	9	0	changed from T028
190	NT	16/05/2008	2007	BT	Sentinel	8	0	
190	NT	16/05/2008	2007	BT	Sentinel	9	0	changed from T028
190	NT	6/06/2008	2007	BT	Sentinel	8	0	
190	NT	6/06/2008	2007	BT	Sentinel	9	0	changed from T028
190	NT	6/08/2008	2007	BT	Sentinel	23	0	
190	NT	2/09/2008	2007	BT	Sentinel	23	0	
190	NT	24/10/2008	2007	BT	Sentinel	23	0	
190	NT	26/11/2008	2008	BT	Sentinel	23	1	
190	NT	16/12/2008	2008	BT	Sentinel	23	4	
190	NT	2/01/2009	2008	BT	Sentinel	23	0	
190	NT	20/02/2009	2008	BT	Sentinel	23	0	
190	NT	9/03/2009	2008	BT	Sentinel	23	8	
190	NT	6/04/2009	2008	BT	Sentinel	23	10	
190	NT	5/05/2009	2008	BT	Sentinel	23	0	
190	NT	1/06/2009	2008	BT	Sentinel	22	0	
190	NT	6/07/2009	2008	BT	Sentinel	26	0	
190	NT	18/08/2009	2008	BT	Sentinel	26	1	
190	NT	15/09/2009	2008	BT	Sentinel	26	0	
190	NT	6/10/2009	2008	BT	Sentinel	25	0	
194	NT	13/09/2003	2002	BT	Serosurv	81	1	
194	NT	22/04/2004	2003	BT	Serosurv	20	2	
194	NT	31/05/2007	2006	BT	Serosurv	32	1	
194	NT	14/07/2004	2003	BT	Sentinel	20	0	
194	NT	14/10/2004	2003	BT	Sentinel	20	0	
194	NT	28/06/2005	2004	BT	Sentinel	19	0	
195	NT	10/01/2001	2000	BT	Sentinel	16	0	

Site_ num	State	Bleed_ date	Season	Virus_ short	Bleed_ type	Num_ total	Num_ seroconv	Comment
195	NT	30/03/2001	2000	BT	Sentinel	16	0	
195	NT	30/07/2001	2000	BT	Sentinel	19	0	
195	NT	30/11/2001	2001	BT	Sentinel	18	0	
195	NT	9/05/2002	2001	BT	Sentinel	20	0	
195	NT	20/08/2002	2001	BT	Sentinel	26	0	
195	NT	19/12/2002	2002	BT	Sentinel	26	0	
195	NT	17/03/2003	2002	BT	Sentinel	26	0	
195	NT	6/06/2003	2002	BT	Sentinel	26	0	
195	NT	23/09/2003	2002	BT	Sentinel	25	0	
195	NT	8/12/2003	2003	BT	Sentinel	25	0	
195	NT	26/03/2004	2003	BT	Sentinel	22	0	
195	NT	15/10/2004	2003	BT	Sentinel	22	0	
195	NT	7/04/2005	2004	BT	Sentinel	18	0	
195	NT	21/05/2007	2006	BT	Sentinel	7	0	
196	NT	4/05/2004	2003	BT	Serosurv	97	2	
196	NT	7/07/2007	2006	BT	Serosurv	29	4	
196	NT	29/06/2009	2008	BT	Serosurv	23	2	
198	NT	21/07/2003	2002	BT	Serosurv	100	10	
198	NT	17/05/2004	2003	BT	Serosurv	100	3	
198	NT	25/10/2006	2005	BT	Serosurv	38	3	
198	NT	4/06/2009	2008	BT	Serosurv	30	2	
202	NT	27/08/2003	2002	BT	Serosurv	100	0	
202	NT	29/07/2004	2003	BT	Serosurv	93	1	
204	NT	9/09/2004	2003	BT	Serosurv	101	1	
204	NT	21/04/2009	2008	BT	Serosurv	30	3	
220	NT	7/05/2004	2003	BT	Serosurv	99	0	
220	NT	19/08/2005	2004	BT	Serosurv	60	0	
220	NT	24/06/2008	2007	BT	Serosurv	22	0	
220	NT	29/05/2009	2008	BT	Serosurv	30	2	
221	NT	26/08/2003	2002	BT	Serosurv	98	1	
221	NT	29/06/2009	2008	BT	Serosurv	28	4	
225	NT	21/08/2002	2001	BT	Serosurv	67	27	
225	NT	7/07/2007	2006	BT	Serosurv	26	8	
A97	NT	19/08/2003	2002	BT	Serosurv	101	3	
E19	NT	5/10/2002	2001	BT	Serosurv	83	3	
E19	NT	15/05/2004	2003	BT	Serosurv	18	0	
E19	NT	14/05/2006	2005	BT	Serosurv	18	0	
E19	NT	16/10/2006	2005	BT	Serosurv	16	0	
E19	NT	21/05/2008	2007	BT	Serosurv	39	1	
E19	NT	9/01/2001	2000	BT	Sentinel	16	0	
E19	NT	18/04/2001	2000	BT	Sentinel	16	0	
E19	NT	29/05/2001	2000	BT	Sentinel	16	0	
E19	NT	10/07/2001	2000	BT	Sentinel	20	0	
E19	NT	12/10/2001	2000	BT	Sentinel	19	0	
E19	NT	8/02/2002	2001	BT	Sentinel	19	0	
E19	NT	23/04/2002	2001	BT	Sentinel	19	0	
E19	NT	28/08/2002	2001	BT	Sentinel	14	0	
E19	NT	10/10/2002	2001	BT	Sentinel	20	0	
E19	NT	1/01/2003	2002	BT	Sentinel	20	1	
E19	NT	27/03/2003	2002	BT	Sentinel	20	0	
E19	NT	15/05/2003	2002	BT	Sentinel	20	0	
E19	NT	1/06/2003	2002	BT	Sentinel	20	0	
E19	NT	1/07/2003	2002	BT	Sentinel	20	0	
E19	NT	10/09/2003	2002	BT	Sentinel	20	0	
E19	NT	9/10/2003	2002	BT	Sentinel	20	2	
E19	NT	21/12/2003	2003	BT	Sentinel	20	0	
E19	NT	22/03/2004	2003	BT	Sentinel	19	0	
E19	NT	30/04/2004	2003	BT	Sentinel	15	0	
E19	NT	20/09/2004	2003	BT	Sentinel	16	0	

Site_ num	State	Bleed_ date	Season	Virus_ short	Bleed_ type	Num_ total	Num_ seroconv	Comment
E19	NT	8/10/2004	2003	BT	Sentinel	19	0	
E19	NT	14/12/2004	2004	BT	Sentinel	18	0	
E19	NT	20/04/2005	2004	BT	Sentinel	17	0	
E19	NT	10/07/2005	2004	BT	Sentinel	16	0	
E19	NT	15/05/2009	2008	BT	Serosurv	31	1	
E19	NT	12/07/2009	2008	BT	Serosurv	30	2	changed from T085
T016	NT	14/11/2000	2000	BT	Sentinel	22	2	
T016	NT	12/12/2000	2000	BT	Sentinel	20	1	
T016	NT	22/01/2001	2000	BT	Sentinel	21	2	
T016	NT	13/02/2001	2000	BT	Sentinel	21	2	
T016	NT	12/03/2001	2000	BT	Sentinel	22	0	
T016	NT	10/04/2001	2000	BT	Sentinel	21	8	
T016	NT	11/05/2001	2000	BT	Sentinel	22	7	
T016	NT	20/06/2001	2000	BT	Sentinel	22	0	
T016	NT	9/07/2001	2000	BT	Sentinel	22	0	
T016	NT	8/08/2001	2000	BT	Sentinel	22	0	
T016	NT	5/09/2001	2000	BT	Sentinel	22	0	
T016	NT	3/10/2001	2000	BT	Sentinel	22	0	
T016	NT	2/11/2001	2001	BT	Sentinel	22	0	
T016	NT	4/12/2001	2001	BT	Sentinel	21	0	
T016	NT	4/01/2002	2001	BT	Sentinel	22	0	
T016	NT	5/02/2002	2001	BT	Sentinel	22	0	
T016	NT	6/03/2002	2001	BT	Sentinel	22	0	
T016	NT	9/04/2002	2001	BT	Sentinel	22	0	
T016	NT	9/05/2002	2001	BT	Sentinel	22	1	
T016	NT	3/06/2002	2001	BT	Sentinel	22	3	
T016	NT	4/07/2002	2001	BT	Sentinel	21	1	
T016	NT	8/10/2002	2001	BT	Sentinel	21	2	
T016	NT	6/11/2002	2002	BT	Sentinel	20	3	
T016	NT	1/12/2002	2002	BT	Sentinel	22	0	
T016	NT	14/01/2003	2002	BT	Sentinel	22	2	
T016	NT	6/02/2003	2002	BT	Sentinel	22	0	
T016	NT	12/03/2003	2002	BT	Sentinel	22	1	
T016	NT	1/04/2003	2002	BT	Sentinel	22	0	
T016	NT	1/05/2003	2002	BT	Sentinel	21	2	
T016	NT	10/06/2003	2002	BT	Sentinel	22	1	
T016	NT	12/08/2003	2002	BT	Sentinel	22	0	
T016	NT	16/09/2003	2002	BT	Sentinel	22	1	
T016	NT	8/10/2003	2002	BT	Sentinel	22	1	
T016	NT	12/11/2003	2003	BT	Sentinel	22	0	
T016	NT	16/12/2003	2003	BT	Sentinel	20	0	
T016	NT	14/01/2004	2003	BT	Sentinel	22	0	
T016	NT	12/02/2004	2003	BT	Sentinel	22	1	
T016	NT	10/03/2004	2003	BT	Sentinel	21	0	
T016	NT	6/04/2004	2003	BT	Sentinel	22	5	
T016	NT	18/05/2004	2003	BT	Sentinel	22	11	
T016	NT	10/06/2004	2003	BT	Sentinel	22	2	
T016	NT	16/06/2004	2003	BT	Sentinel	22	3	
T016	NT	13/07/2004	2003	BT	Sentinel	21	0	
T016	NT	9/08/2004	2003	BT	Sentinel	21	0	
T016	NT	14/09/2004	2003	BT	Sentinel	22	0	
T016	NT	27/10/2004	2003	BT	Sentinel	22	0	
T016	NT	18/11/2004	2004	BT	Sentinel	22	0	
T016	NT	23/12/2004	2004	BT	Sentinel	22	1	
T016	NT	17/01/2005	2004	BT	Sentinel	22	0	
T016	NT	14/02/2005	2004	BT	Sentinel	22	0	
T016	NT	7/03/2005	2004	BT	Sentinel	22	0	
T016	NT	18/04/2005	2004	BT	Sentinel	22	3	
T016	NT	9/05/2005	2004	BT	Sentinel	22	3	

Site_ num	State	Bleed_ date	Season	Virus_ short	Bleed_ type	Num_ total	Num_ seroconv	Comment
T016	NT	2/06/2005	2004	BT	Sentinel	22	3	
T016	NT	18/07/2005	2004	BT	Sentinel	18	0	
T016	NT	22/08/2005	2004	BT	Sentinel	18	2	
T016	NT	12/09/2005	2004	BT	Sentinel	18	0	
T016	NT	27/10/2005	2004	BT	Sentinel	18	0	
T016	NT	21/11/2005	2005	BT	Sentinel	18	0	
T016	NT	12/12/2005	2005	BT	Sentinel	18	0	
T016	NT	21/02/2006	2005	BT	Sentinel	18	4	
T016	NT	13/03/2006	2005	BT	Sentinel	18	5	
T016	NT	12/04/2006	2005	BT	Sentinel	18	3	
T016	NT	3/05/2006	2005	BT	Sentinel	18	2	
T016	NT	5/06/2006	2005	BT	Sentinel	18	0	
T016	NT	15/08/2006	2005	BT	Sentinel	20	0	
T016	NT	13/09/2006	2005	BT	Sentinel	20	0	
T016	NT	9/10/2006	2005	BT	Sentinel	24	0	
T016	NT	21/11/2006	2006	BT	Sentinel	24	0	
T016	NT	18/12/2006	2006	BT	Sentinel	24	0	
T016	NT	29/01/2007	2006	BT	Sentinel	24	0	
T016	NT	26/02/2007	2006	BT	Sentinel	24	0	
T016	NT	20/03/2007	2006	BT	Sentinel	24	0	
T016	NT	23/04/2007	2006	BT	Sentinel	24	0	
T016	NT	21/05/2007	2006	BT	Sentinel	23	1	
T016	NT	12/06/2007	2006	BT	Sentinel	24	2	
T016	NT	17/07/2007	2006	BT	Sentinel	24	0	
T016	NT	20/08/2007	2006	BT	Sentinel	23	0	
T016	NT	13/09/2007	2006	BT	Sentinel	25	0	
T016	NT	29/10/2007	2006	BT	Sentinel	25	3	
T016	NT	27/11/2007	2007	BT	Sentinel	25	2	
T016	NT	18/12/2007	2007	BT	Sentinel	25	2	
T016	NT	22/01/2008	2007	BT	Sentinel	25	3	
T016	NT	12/02/2008	2007	BT	Sentinel	25	1	
T016	NT	7/03/2008	2007	BT	Sentinel	25	0	
T016	NT	10/04/2008	2007	BT	Sentinel	25	3	
T016	NT	13/05/2008	2007	BT	Sentinel	25	2	
T016	NT	11/06/2008	2007	BT	Sentinel	25	1	
T016	NT	25/08/2008	2007	BT	Sentinel	22	1	
T016	NT	26/09/2008	2007	BT	Sentinel	23	0	
T016	NT	28/10/2008	2007	BT	Sentinel	23	0	
T016	NT	25/11/2008	2008	BT	Sentinel	23	0	
T016	NT	10/12/2008	2008	BT	Sentinel	23	0	
T016	NT	6/01/2009	2008	BT	Sentinel	23	0	
T016	NT	24/02/2009	2008	BT	Sentinel	23	8	
T016	NT	10/03/2009	2008	BT	Sentinel	23	10	
T016	NT	8/04/2009	2008	BT	Sentinel	23	2	
T016	NT	6/05/2009	2008	BT	Sentinel	23	0	
T016	NT	1/06/2009	2008	BT	Sentinel	23	1	
T016	NT	21/07/2009	2008	BT	Sentinel	22	0	
T016	NT	27/08/2009	2008	BT	Sentinel	22	0	
T016	NT	22/09/2009	2008	BT	Sentinel	22	0	
T016	NT	30/10/2009	2008	BT	Sentinel	22	0	
T017	NT	7/11/2000	2000	BT	Sentinel	22	0	
T017	NT	25/01/2001	2000	BT	Sentinel	16	0	
T017	NT	27/02/2001	2000	BT	Sentinel	15	1	
T017	NT	23/03/2001	2000	BT	Sentinel	11	2	
T017	NT	16/05/2001	2000	BT	Sentinel	12	6	
T017	NT	3/08/2001	2000	BT	Sentinel	21	0	
T017	NT	11/01/2002	2001	BT	Sentinel	25	0	
T017	NT	14/02/2002	2001	BT	Sentinel	25	1	
T017	NT	25/03/2002	2001	BT	Sentinel	25	6	

Site_ num	State	Bleed_ date	Season	Virus_ short	Bleed_ type	Num_ total	Num_ seroconv	Comment
T017	NT	18/04/2002	2001	BT	Sentinel	25	10	
T017	NT	22/05/2002	2001	BT	Sentinel	25	1	
T017	NT	21/06/2002	2001	BT	Sentinel	25	0	
T017	NT	18/07/2002	2001	BT	Sentinel	25	0	
T017	NT	16/08/2002	2001	BT	Sentinel	25	0	
T017	NT	30/09/2002	2001	BT	Sentinel	24	1	
T017	NT	22/11/2002	2002	BT	Sentinel	23	0	
T017	NT	21/01/2003	2002	BT	Sentinel	23	1	
T017	NT	10/02/2003	2002	BT	Sentinel	23	6	
T017	NT	19/03/2003	2002	BT	Sentinel	22	3	
T017	NT	24/04/2003	2002	BT	Sentinel	23	3	
T017	NT	19/05/2003	2002	BT	Sentinel	23	0	
T017	NT	21/07/2003	2002	BT	Sentinel	24	0	
T017	NT	13/08/2003	2002	BT	Sentinel	24	0	
T017	NT	30/09/2003	2002	BT	Sentinel	23	1	
T017	NT	7/11/2003	2003	BT	Sentinel	20	0	
T017	NT	9/12/2003	2003	BT	Sentinel	23	1	
T017	NT	16/01/2004	2003	BT	Sentinel	20	0	
T017	NT	26/02/2004	2003	BT	Sentinel	24	0	
T017	NT	6/04/2004	2003	BT	Sentinel	24	4	
T017	NT	17/05/2004	2003	BT	Sentinel	24	4	
T017	NT	16/06/2004	2003	BT	Sentinel	23	0	
T017	NT	14/07/2004	2003	BT	Sentinel	24	2	
T017	NT	27/08/2004	2003	BT	Sentinel	22	0	
T017	NT	30/09/2004	2003	BT	Sentinel	22	0	
T017	NT	4/11/2004	2004	BT	Sentinel	22	0	
T017	NT	7/12/2004	2004	BT	Sentinel	22	0	
T017	NT	31/01/2005	2004	BT	Sentinel	22	0	
T017	NT	23/02/2005	2004	BT	Sentinel	22	0	
T017	NT	29/03/2005	2004	BT	Sentinel	22	0	
T017	NT	26/04/2005	2004	BT	Sentinel	22	1	
T017	NT	23/05/2005	2004	BT	Sentinel	22	4	
T017	NT	28/06/2005	2004	BT	Sentinel	18	3	
T017	NT	8/08/2005	2004	BT	Sentinel	22	4	
T017	NT	12/10/2005	2004	BT	Sentinel	25	1	
T017	NT	9/11/2005	2005	BT	Sentinel	25	1	
T017	NT	5/01/2006	2005	BT	Sentinel	25	9	
T017	NT	7/02/2006	2005	BT	Sentinel	22	3	
T017	NT	18/04/2006	2005	BT	Sentinel	18	2	
T017	NT	25/05/2006	2005	BT	Sentinel	19	2	
T017	NT	26/06/2006	2005	BT	Sentinel	21	0	
T017	NT	5/10/2006	2005	BT	Sentinel	25	1	
T017	NT	29/11/2006	2006	BT	Sentinel	23	0	
T017	NT	15/02/2007	2006	BT	Sentinel	22	0	
T017	NT	23/04/2007	2006	BT	Sentinel	22	0	
T017	NT	21/06/2007	2006	BT	Sentinel	22	1	
T017	NT	1/08/2007	2006	BT	Sentinel	22	0	
T017	NT	20/09/2007	2006	BT	Sentinel	22	0	
T017	NT	22/10/2007	2006	BT	Sentinel	22	0	
T017	NT	13/12/2007	2007	BT	Sentinel	20	0	
T017	NT	14/01/2008	2007	BT	Sentinel	20	0	
T017	NT	6/02/2008	2007	BT	Sentinel	20	4	
T017	NT	7/03/2008	2007	BT	Sentinel	19	3	
T017	NT	15/04/2008	2007	BT	Sentinel	20	14	
T017	NT	12/05/2008	2007	BT	Sentinel	20	0	
T017	NT	16/06/2008	2007	BT	Sentinel	20	0	
T017	NT	31/10/2008	2007	BT	Sentinel	18	0	
T017	NT	26/11/2008	2008	BT	Sentinel	17	0	
T017	NT	29/12/2008	2008	BT	Sentinel	18	2	

Site_ num	State	Bleed_ date	Season	Virus_ short	Bleed_ type	Num_ total	Num_ seroconv	Comment
T017	NT	4/02/2009	2008	BT	Sentinel	18	0	
T017	NT	31/01/2009	2008	BT	Sentinel	18	0	
T017	NT	26/02/2009	2008	BT	Sentinel	18	0	
T017	NT	23/03/2009	2008	BT	Sentinel	18	0	
T017	NT	28/04/2009	2008	BT	Sentinel	18	6	
T017	NT	22/05/2009	2008	BT	Sentinel	18	0	
T017	NT	1/08/2009	2008	BT	Sentinel	23	0	
T017	NT	3/09/2009	2008	BT	Sentinel	18	0	
T017	NT	1/10/2009	2008	BT	Sentinel	23	0	
T021	NT	1/12/2004	2004	BT	Serosurv	100	0	
T021	NT	7/07/2007	2006	BT	Serosurv	31	0	
T021	NT	4/10/2008	2007	BT	Serosurv	30	0	
T021	NT	19/06/2008	2007	BT	Serosurv	31	0	
T021	NT	7/05/2008	2007	BT	Serosurv	34	2	
T021	NT	19/12/2000	2000	BT	Sentinel	12	0	
T021	NT	15/05/2001	2000	BT	Sentinel	19	0	
T021	NT	8/08/2001	2000	BT	Sentinel	14	0	
T021	NT	28/05/2009	2008	BT	Serosurv	34	0	
T029	NT	15/12/2000	2000	BT	Sentinel	8	0	
T029	NT	20/01/2001	2000	BT	Sentinel	7	0	
T029	NT	25/01/2001	2000	BT	Sentinel	7	0	
T029	NT	31/07/2001	2000	BT	Sentinel	17	0	
T029	NT	10/07/2002	2001	BT	Sentinel	20	0	
T029	NT	17/09/2002	2001	BT	Sentinel	19	0	
T029	NT	2/12/2002	2002	BT	Sentinel	19	0	
T029	NT	4/04/2003	2002	BT	Sentinel	16	0	
T029	NT	18/06/2003	2002	BT	Sentinel	19	0	
T029	NT	6/04/2005	2004	BT	Sentinel	30	0	
T029	NT	19/12/2006	2006	BT	Sentinel	20	0	
T029	NT	18/07/2007	2006	BT	Sentinel	13	0	
T029	NT	7/07/2008	2007	BT	Sentinel	11	0	
T032	NT	14/09/2002	2001	BT	Serosurv	60	7	
T032	NT	12/11/2000	2000	BT	Sentinel	9	1	
T032	NT	4/04/2001	2000	BT	Sentinel	6	0	
T032	NT	3/08/2001	2000	BT	Sentinel	12	0	
T032	NT	27/10/2001	2000	BT	Sentinel	6	0	
T032	NT	22/04/2002	2001	BT	Sentinel	11	0	
T032	NT	8/10/2002	2001	BT	Sentinel	10	1	
T032	NT	20/12/2002	2002	BT	Sentinel	9	0	
T032	NT	10/04/2003	2002	BT	Sentinel	4	1	
T033	NT	3/09/2003	2002	BT	Serosurv	100	0	
T033	NT	25/05/2004	2003	BT	Serosurv	60	2	
T033	NT	31/08/2004	2003	BT	Serosurv	100	0	
T033	NT	3/05/2001	2000	BT	Sentinel	53	0	
T034	NT	25/05/2004	2003	BT	Serosurv	91	2	
T034	NT	22/05/2008	2007	BT	Serosurv	36	0	
T036	NT	25/04/2003	2002	BT	Serosurv	90	0	
T036	NT	19/06/2008	2007	BT	Serosurv	31	0	
T036	NT	17/08/2001	2000	BT	Sentinel	25	0	
T036	NT	14/05/2009	2008	BT	Serosurv	33	0	
T037	NT	7/07/2004	2003	BT	Serosurv	93	1	changed from 193
T037	NT	18/07/2005	2004	BT	Serosurv	61	0	
T037	NT	16/10/2001	2000	BT	Sentinel	212	0	
T037	NT	1/02/2002	2001	BT	Sentinel	187	0	
T037	NT	6/09/2002	2001	BT	Sentinel	100	0	
T037	NT	17/09/2002	2001	BT	Sentinel	153	0	
T037	NT	7/12/2002	2002	BT	Sentinel	26	0	
T037	NT	30/07/2003	2002	BT	Sentinel	177	3	
T037	NT	19/02/2004	2003	BT	Sentinel	147	2	

Site_ num	State	Bleed_ date	Season	Virus_ short	Bleed_ type	Num_ total	Num_ seroconv	Comment
T037	NT	7/07/2009	2008	BT	Serosurv	30	1	changed from 193
T038	NT	22/07/2002	2001	BT	Serosurv	81	4	
T039	NT	24/07/2002	2001	BT	Serosurv	87	20	
T040	NT	25/07/2002	2001	BT	Serosurv	80	8	
T040	NT	11/11/2004	2004	BT	Serosurv	54	14	changed from T056
T041	NT	1/08/2002	2001	BT	Serosurv	80	27	
T042	NT	5/09/2002	2001	BT	Serosurv	60	3	
T042	NT	27/06/2008	2007	BT	Serosurv	37	0	changed from T69
T042	NT	15/05/2009	2008	BT	Serosurv	31	1	
T043	NT	11/10/2002	2001	BT	Serosurv	66	0	
T043	NT	26/04/2008	2007	BT	Serosurv	40	5	changed from T061
T043	NT	1/07/2009	2008	BT	Serosurv	32	9	changed from T061
T043	NT	1/07/2009	2008	BT	Serosurv	32	9	
T044	NT	17/04/2003	2002	BT	Serosurv	89	0	
T044	NT	17/04/2003	2002	BT	Sentinel	25	0	
T044	NT	15/05/2003	2002	BT	Sentinel	22	0	
T044	NT	11/06/2003	2002	BT	Sentinel	22	0	
T044	NT	14/07/2003	2002	BT	Sentinel	25	0	
T044	NT	29/08/2003	2002	BT	Sentinel	25	0	
T044	NT	24/09/2003	2002	BT	Sentinel	25	0	
T044	NT	14/11/2003	2003	BT	Sentinel	25	0	
T044	NT	18/12/2003	2003	BT	Sentinel	25	0	
T044	NT	6/01/2004	2003	BT	Sentinel	22	0	
T044	NT	21/03/2004	2003	BT	Sentinel	23	0	
T044	NT	28/04/2004	2003	BT	Sentinel	22	0	
T044	NT	6/05/2005	2004	BT	Sentinel	15	0	
T044	NT	12/08/2005	2004	BT	Sentinel	15	0	
T044	NT	8/09/2009	2008	BT	Serosurv	31	1	
T045	NT	7/07/2007	2006	BT	Serosurv	26	10	
T046	NT	14/07/2003	2002	BT	Serosurv	100	0	
T046	NT	19/10/2007	2006	BT	Serosurv	33	0	
T046	NT	18/06/2008	2007	BT	Serosurv	30	0	
T046	NT	16/05/2009	2008	BT	Serosurv	32	0	
T046	NT	25/08/2009	2008	BT	Serosurv	33	0	
T047	NT	14/07/2003	2002	BT	Serosurv	100	2	
T047	NT	20/05/2004	2003	BT	Serosurv	92	0	
T047	NT	16/07/2005	2004	BT	Serosurv	65	0	
T047	NT	21/08/2008	2007	BT	Serosurv	32	0	changed from T079
T047	NT	28/05/2009	2008	BT	Serosurv	33	0	changed from T079
T048	NT	1/04/2003	2002	BT	Serosurv	93	2	
T048	NT	3/06/2009	2008	BT	Serosurv	36	0	changed from T084
T049	NT	5/06/2003	2002	BT	Serosurv	98	2	
T049	NT	3/06/2004	2003	BT	Serosurv	100	2	
T050	NT	15/04/2003	2002	BT	Serosurv	103	4	
T051	NT	29/05/2003	2002	BT	Serosurv	92	3	
T051	NT	4/06/2004	2003	BT	Serosurv	96	8	
T051	NT	2/06/2005	2004	BT	Serosurv	62	0	
T051	NT	11/04/2008	2007	BT	Serosurv	50	0	
T054	NT	27/08/2004	2003	BT	Serosurv	100	1	
T054	NT	17/07/2008	2007	BT	Serosurv	23	0	changed from T077
T057	NT	25/05/2006	2005	BT	Serosurv	20	6	
T057	NT	8/06/2008	2007	BT	Serosurv	36	2	
T058	NT	7/07/2007	2006	BT	Serosurv	28	5	
T058	NT	5/06/2008	2007	BT	Serosurv	30	9	
T059	NT	19/07/2007	2006	BT	Serosurv	22	17	
T059	NT	22/05/2008	2007	BT	Serosurv	29	27	
T060	NT	6/04/2008	2007	BT	Serosurv	34	0	
T060	NT	6/04/2008	2007	BT	Serosurv	34	0	
T060	NT	2/09/2009	2008	BT	Serosurv	35	0	

Site_ num	State	Bleed_ date	Season	Virus_ short	Bleed_ type	Num_ total	Num_ seroconv	Comment
T063	NT	22/05/2008	2007	BT	Serosurv	35	2	
T064	NT	23/05/2008	2007	BT	Serosurv	35	1	
T064	NT	11/05/2009	2008	BT	Serosurv	35	4	
T065	NT	24/05/2008	2007	BT	Serosurv	30	6	
T065	NT	14/07/2009	2008	BT	Serosurv	32	1	
T066	NT	24/05/2008	2007	BT	Serosurv	31	2	
T066	NT	18/05/2009	2008	BT	Serosurv	32	6	
T067	NT	10/06/2008	2007	BT	Serosurv	35	9	
T067	NT	9/06/2009	2008	BT	Serosurv	32	12	
T068	NT	18/06/2008	2007	BT	Serosurv	33	0	
T068	NT	25/08/2009	2008	BT	Serosurv	35	0	
T070	NT	27/06/2008	2007	BT	Serosurv	32	0	
T070	NT	9/06/2009	2008	BT	Serosurv	31	16	
T071	NT	30/06/2008	2007	BT	Serosurv	29	0	
T071	NT	2/03/2009	2008	BT	Serosurv	20	0	
T072	NT	1/07/2008	2007	BT	Serosurv	30	2	
T073	NT	24/06/2008	2007	BT	Serosurv	34	6	
T073	NT	15/06/2009	2008	BT	Serosurv	35	13	
T074	NT	8/07/2008	2007	BT	Serosurv	24	1	
T074	NT	26/08/2009	2008	BT	Serosurv	35	30	
T075	NT	3/07/2008	2007	BT	Serosurv	23	7	
T076	NT	30/07/2008	2007	BT	Serosurv	38	0	
T078	NT	30/07/2008	2007	BT	Serosurv	33	0	
T078	NT	9/06/2009	2008	BT	Serosurv	31	2	
T080	NT	1/03/2009	2008	BT	Sentinel	8	0	
T080	NT	4/02/2009	2008	BT	Sentinel	9	0	
T080	NT	15/03/2009	2008	BT	Sentinel	8	4	
T080	NT	15/04/2009	2008	BT	Sentinel	7	4	
T080	NT	15/05/2009	2008	BT	Sentinel	8	1	
T082	NT	11/05/2009	2008	BT	Serosurv	31	1	
T083	NT	28/05/2009	2008	BT	Serosurv	31	0	
T086	NT	23/09/2009	2008	BT	Serosurv	32	0	
T087	NT	16/09/2009	2008	BT	Serosurv	12	1	

APPENDIX C

SUMMARY OF BTV STATUS AND AVERAGE ENVIRONMENTAL CONDITIONS OF NAMP SITES IN THE PILBARA

Site ID	year	BTV status	maxndviss	Maxeviss	smintss	maxlstdss	maxlstdsu	maxlstdau	Maxlstdpw	Minlstnss	minlstnsu	minlstnau	Minlstnpw	meanlstdss	Meanlstdsu	meanlstdau	meanlstdpw	Meanlstnss
F60	2001	0	0.176	0.117	0.700	51.433	49.561	48.035	36.684	27.836	27.276	27.744	16.973	41.803	42.562	39.480	31.368	23.294
F60	2002	1	0.181	0.103	0.636	53.072	51.882	48.972	36.614	28.705	28.706	26.831	15.503	43.819	45.886	39.480	31.368	23.294
F60	2005	0	0.396	0.231	4.554	50.926	50.491	43.838	33.680	28.058	28.042	26.389	15.917	43.113	46.830	37.836	31.199	23.572
F60	2008	0	0.321	0.190	2.611	50.966	50.966	44.445	34.545	27.836	27.276	27.505	17.285	43.440	47.077	38.763	30.180	24.178
W006	2000	0	0.233	0.127	1.302	53.836	53.839	41.334	30.561	28.947	28.951	24.799	11.623	42.892	48.115	36.441	25.830	22.272
W014	2000	0	0.323	0.199	3.283	54.171	52.883	41.930	35.270	27.909	27.547	27.285	16.030	42.345	43.402	39.634	29.341	23.363
W014	2002	0	0.305	0.179	2.205	50.613	50.395	44.760	37.127	28.214	28.216	25.354	15.133	42.345	43.402	37.883	30.021	22.821
W015	2000	0	0.304	0.179	1.913	52.735	52.717	43.361	34.912	29.230	29.229	26.968	15.162	43.945	48.611	38.337	29.286	24.641
W015	2005	0	0.334	0.193	2.954	54.164	54.164	43.660	30.328	30.608	30.608	26.990	15.740	44.680	50.016	37.837	28.305	24.865
W015	2006	0	0.211	0.126	0.582	52.490	52.490	47.267	33.723	29.230	29.229	28.403	17.660	45.989	51.852	39.923	28.370	25.987
W023	2000	0	0.317	0.173	2.708	49.357	49.061	40.647	34.998	27.951	27.876	26.801	16.790	42.783	46.148	38.476	28.868	23.975
W023	2005	0	0.378	0.209	4.732	51.595	51.383	41.064	31.692	29.284	29.285	25.436	16.063	41.840	46.159	36.023	29.041	24.112
W023	2008	0	0.296	0.159	2.919	51.845	51.845	43.207	32.714	28.335	28.294	26.801	16.613	43.416	47.741	38.540	28.152	24.884
W024	2000	0	0.315	0.174	2.493	51.163	51.104	42.664	36.076	27.803	27.783	25.495	15.291	43.830	48.285	38.539	29.843	23.986
W026	2000	0	0.344	0.183	3.187	50.411	50.293	39.851	34.049	27.931	27.931	24.871	15.194	44.514	47.692	39.788	27.842	23.575
W034	2000	0	0.381	0.230	3.222	51.404	50.275	41.155	35.926	27.930	27.640	27.084	15.575	42.173	42.963	39.777	28.850	23.098
W034	2002	0	0.316	0.192	1.967	52.261	51.647	45.975	37.928	28.314	28.313	25.907	14.407	42.173	42.963	36.961	29.840	22.347
W039	2002	1	0.190	0.100	0.732	51.474	51.469	44.652	31.118	28.691	28.697	25.756	13.448	41.778	46.699	34.433	24.110	21.851
W039	2004	0	0.183	0.095	0.658	52.874	52.874	48.654	27.761	31.059	31.060	27.164	13.007	41.178	45.832	34.759	24.015	22.607
W047	2000	0	0.325	0.196	2.619	53.985	53.197	42.285	36.107	27.623	27.605	26.174	15.534	44.182	45.550	41.407	29.364	23.274
W048	2000	0	0.317	0.165	2.375	49.600	49.287	41.324	31.896	28.401	28.402	24.960	13.811	43.295	47.937	36.870	25.874	23.220
W064	2000	1	0.309	0.176	1.942	51.414	51.395	42.779	34.413	29.470	29.469	26.405	15.659	43.296	47.704	37.707	28.188	25.217
W065	2000	0	0.424	0.271	4.253	48.896	48.143	39.907	34.609	28.044	27.939	27.138	16.887	40.322	39.808	39.478	28.828	23.048
W065	2002	0	0.379	0.237	2.886	51.362	51.319	41.631	37.670	27.799	27.791	25.282	15.114	40.322	39.808	34.841	29.256	22.367
W066	2000	1	0.228	0.130	1.091	53.230	53.229	44.211	34.740	30.647	30.646	27.938	14.329	44.917	49.756	38.815	28.481	24.564
W067	2000	0	0.248	0.124	1.933	50.826	50.629	41.700	32.572	27.763	27.764	23.950	11.631	42.466	46.856	36.449	24.386	22.047
W069	2000	0	0.258	0.153	1.864	50.722	50.481	41.341	32.373	28.504	28.523	25.340	15.884	42.375	45.802	37.243	26.537	23.587
W069	2003	0	0.280	0.165	2.373	52.605	52.543	41.349	29.614	30.599	30.553	24.897	14.907	42.375	45.802	37.243	26.537	23.587
W070	2000	1	0.294	0.173	1.546	50.906	50.900	43.231	34.514	30.216	30.216	27.012	15.125	44.209	48.984	38.354	28.145	25.178

Site ID	year	BTV status	maxndviss	maxeviss	smintss	maxlstdss	maxlstdsu	maxlstdau	maxlstdpw	minlstnss	Minlstnsu	minlstnau	minlstnpw	meanlstdss	meanlstdsu	meanlstdau	meanlstdpw	meanlstnss
W071	2000	0	0.313	0.177	2.113	50.859	50.658	43.703	38.770	28.049	27.698	27.508	16.585	44.420	46.878	41.116	31.823	23.425
W072	2000	0	0.323	0.191	1.706	50.044	49.851	43.583	35.660	27.398	27.394	25.977	14.967	43.478	47.754	38.528	29.885	23.234
W072	2001	0	0.280	0.152	2.107	50.526	50.507	44.497	35.839	27.467	27.438	26.278	16.050	41.687	43.254	38.545	29.227	22.727
W072	2005	0	0.376	0.210	3.499	52.504	52.505	41.282	30.639	28.866	28.827	26.858	16.237	45.019	49.912	38.672	29.772	23.414
W073	2000	1	0.319	0.175	2.446	50.606	50.579	41.986	34.325	28.917	28.905	26.353	15.212	43.042	47.542	37.529	27.997	24.413
W073	2001	1	0.289	0.159	2.247	51.569	51.577	43.198	34.367	29.988	29.995	26.821	16.356	40.906	42.545	37.293	28.817	23.333
W074	2000	0	0.297	0.163	2.485	50.016	49.824	39.361	30.785	27.543	27.543	23.756	12.359	41.477	45.626	35.455	23.591	22.134
W075	2000	0	0.288	0.170	1.812	50.223	49.957	43.749	34.033	28.634	28.634	26.592	15.114	43.980	48.368	39.079	29.141	23.910
W075	2001	1	0.247	0.137	1.227	51.355	51.355	46.507	34.639	28.725	28.715	27.544	15.994	41.905	43.891	38.311	28.060	23.053
W075	2004	0	0.223	0.126	1.151	52.960	52.960	49.291	30.582	31.187	31.181	28.930	15.762	44.271	47.963	39.295	28.245	23.956
W076	2000	0	0.329	0.208	3.796	51.776	51.298	41.812	35.617	27.969	27.851	27.246	16.286	41.485	41.836	39.994	28.868	23.435
W076	2001	0	0.305	0.193	1.851	49.009	47.832	44.617	34.152	27.559	27.556	25.750	16.494	40.100	41.547	36.695	30.070	22.783
W076	2002	0	0.300	0.183	2.294	51.856	51.840	44.259	36.738	28.392	28.394	25.324	15.665	41.485	41.836	36.695	30.070	22.783
W076	2003	0	0.317	0.192	2.707	50.390	50.129	42.210	32.882	27.438	27.440	25.311	17.864	41.485	41.836	39.994	28.868	23.435
W076	2006	0	0.292	0.177	1.915	52.050	51.871	49.429	36.614	27.969	27.851	27.521	15.795	43.965	45.885	41.330	30.548	24.644
W076	2008	0	0.296	0.180	2.136	50.456	50.455	43.848	34.889	27.559	27.556	27.246	16.753	43.436	48.258	37.121	30.095	24.132
W077	2000	0	0.280	0.168	2.120	51.122	51.080	41.160	34.949	28.360	28.360	25.855	16.950	43.180	44.758	39.977	28.033	23.949
W078	2000	0	0.280	0.170	1.838	52.341	52.127	42.179	34.061	28.608	28.599	26.619	16.038	41.682	43.641	37.831	26.490	24.457
W078	2001	0	0.303	0.186	2.093	51.798	48.867	42.578	32.884	29.830	29.829	26.064	15.387	40.873	42.315	37.177	28.353	23.062
W079	2000	0	0.241	0.153	1.048	51.171	51.171	44.195	31.838	27.778	27.738	26.980	15.637	42.740	47.261	37.764	27.385	23.226
W080	2000	0	0.274	0.168	1.354	49.905	49.901	43.824	33.716	26.982	26.980	25.643	15.618	43.901	48.020	39.447	29.546	22.864
W080	2007	0	0.256	0.150	1.405	54.153	54.076	44.556	34.395	26.982	26.980	27.906	16.824	41.702	44.852	37.143	25.561	22.322
W081	2000	0	0.302	0.179	1.632	49.766	49.759	43.791	34.736	28.147	28.144	25.921	14.736	43.976	47.944	39.407	29.527	23.525
W081	2006	0	0.218	0.126	0.536	53.346	53.346	48.507	34.627	28.147	28.144	26.922	16.452	46.246	51.380	41.073	28.533	24.698
W082	2000	0	0.300	0.162	1.929	52.195	52.189	44.315	37.169	27.638	27.416	27.135	16.062	44.908	48.921	39.895	31.641	23.686
W082	2001	1	0.244	0.125	1.752	52.669	52.512	45.946	36.907	27.837	27.656	27.171	15.925	43.315	45.287	39.801	30.873	23.165
W082	2004	1	0.296	0.145	2.319	53.959	53.960	48.840	35.051	29.116	29.025	27.905	17.115	46.616	49.730	41.993	30.970	24.143
W082	2006	1	0.242	0.130	0.896	52.450	52.446	46.848	35.378	27.638	27.416	27.541	16.514	46.117	51.126	40.745	31.168	24.778
W082	2007	0	0.319	0.158	2.955	55.926	55.857	44.154	38.625	27.638	27.416	27.135	15.609	40.433	43.651	34.414	28.385	23.172

Site ID	year	BTV status	maxndviss	maxeviss	smintss	maxlstdss	maxlstdsu	maxlstdau	maxlstdpw	minlstnss	minlstnsu	minlstnau	minlstnpw	meanlstdss	Meanlstdsu	meanlstdau	meanlstdpw	meanlstnss
W084	2000	0	0.344	0.210	2.647	53.935	53.688	42.268	35.934	27.384	27.376	25.831	15.601	44.806	46.364	41.982	30.376	23.401
W084	2002	1	0.280	0.172	1.941	53.254	52.169	47.605	37.930	28.643	28.644	25.586	14.211	44.806	46.364	38.258	30.205	22.321
W084	2003	0	0.328	0.199	2.151	53.507	52.427	42.977	34.202	27.567	27.567	25.804	15.858	44.806	46.364	41.982	30.376	23.401
W085	2001	0	0.281	0.160	1.622	49.635	49.636	45.548	33.904	26.586	26.576	25.120	15.018	41.371	43.329	38.133	26.873	21.484
W085	2002	0	0.211	0.126	0.873	50.813	50.813	46.843	31.515	28.385	27.910	27.499	14.056	43.079	47.174	38.133	26.873	21.484
W085	2003	0	0.261	0.160	1.866	51.870	51.874	44.304	30.029	26.740	26.727	25.915	13.785	43.079	47.174	38.553	28.782	21.873
W085	2004	0	0.385	0.221	2.810	50.694	50.657	47.932	30.281	27.766	27.227	27.456	15.156	43.600	47.484	38.980	26.795	21.948
W085	2007	0	0.355	0.211	3.361	53.293	53.280	44.418	32.994	26.101	26.095	26.790	16.083	40.765	43.729	36.836	24.129	21.440
W086	2001	1	0.191	0.100	0.985	51.731	51.741	44.520	32.181	28.699	28.704	26.126	15.102	40.806	43.835	35.779	25.601	23.086
W087	2000	0	0.247	0.154	1.229	49.424	49.326	43.143	33.113	29.440	29.440	26.845	15.486	42.494	47.220	37.141	28.021	24.306
W087	2005	0	0.270	0.159	2.203	50.492	50.373	43.159	29.009	29.104	29.105	26.684	14.546	42.032	47.059	35.374	25.751	24.076
W088	2001	1	0.201	0.109	0.984	51.260	51.262	45.187	33.119	29.374	29.377	26.718	15.618	41.189	43.767	36.687	26.286	23.323
W088	2002	1	0.179	0.096	0.674	52.104	52.050	47.181	33.165	31.035	31.030	27.834	15.101	42.639	47.619	36.687	26.286	23.323
W088	2003	1	0.208	0.110	1.669	54.286	54.303	44.204	28.554	30.601	30.609	26.468	14.102	42.639	47.619	36.915	26.974	24.258
W089	2001	0	0.179	0.106	0.559	52.842	52.842	45.866	31.749	28.403	28.404	25.396	13.235	41.119	44.843	35.374	23.993	21.947
W089	2002	0	0.180	0.100	0.608	52.606	52.605	45.921	32.105	28.117	28.117	25.974	13.335	42.885	47.997	35.374	23.993	21.947
W089	2005	0	0.350	0.198	3.717	52.315	52.324	38.872	28.830	29.089	29.002	24.220	11.917	42.036	49.226	33.651	22.894	22.591
W093	2001	1	0.195	0.111	1.387	53.993	54.072	46.217	34.644	30.042	30.065	27.012	15.062	42.948	45.455	38.523	28.287	23.641
W094	2001	0	0.255	0.134	1.768	51.946	51.860	45.466	36.628	27.796	27.618	27.159	15.781	42.857	44.384	39.772	30.849	23.215
W094	2005	1	0.343	0.182	3.184	52.398	52.380	44.399	32.412	28.876	28.871	26.431	16.178	44.834	49.750	38.494	29.781	23.408
W094	2006	0	0.242	0.133	0.876	51.885	51.883	47.254	35.061	27.739	27.722	27.317	16.432	45.993	51.114	40.718	30.817	24.815
W095	2002	1	0.169	0.105	0.499	51.956	51.924	45.896	30.226	28.801	28.773	27.184	12.767	43.072	47.822	37.210	25.259	22.402
W095	2004	0	0.245	0.147	1.247	51.991	51.991	48.278	27.202	31.264	31.264	28.406	13.730	42.650	47.313	36.654	24.513	22.929
W096	2002	0	0.167	0.102	0.460	51.800	51.799	44.987	29.446	28.672	28.670	27.252	12.660	42.227	47.097	36.303	24.212	22.424
W096	2005	0	0.229	0.138	1.345	50.903	50.907	43.035	26.894	28.800	28.790	27.083	13.020	41.259	47.514	34.060	22.669	23.001
W096	2006	0	0.203	0.120	1.032	51.070	51.071	46.029	29.725	28.830	28.830	27.947	15.166	42.572	48.988	36.215	22.292	23.821
W098	2003	0	0.337	0.170	3.321	55.477	55.413	43.449	32.988	29.659	29.667	24.869	14.755	44.756	48.156	39.739	27.407	23.421
W098	2004	0	0.216	0.114	0.819	55.879	55.879	46.339	35.121	30.585	30.583	26.447	16.212	44.574	47.662	39.169	30.653	23.498
W098	2005	0	0.434	0.236	5.986	54.822	54.131	38.436	32.118	29.718	29.713	24.248	13.261	43.257	49.095	35.401	29.744	23.452

Site ID	year	BTV status	maxndviss	maxeviss	smintss	maxlstdss	maxlstdsu	maxlstdau	maxlstdpw	minlstnss	minlstnsu	minlstnau	minlstnpw	meanlstdss	meanlstdsu	meanlstdau	meanlstdpw	meanlstnss
W098	2006	0	0.338	0.167	1.843	51.754	51.744	47.287	34.567	28.328	28.328	27.283	16.153	46.997	52.008	41.354	28.947	24.561
W098	2007	0	0.307	0.147	2.311	53.624	52.768	46.842	36.125	28.328	28.328	27.701	14.306	39.471	43.615	31.075	27.662	22.303
W098	2008	0	0.319	0.168	2.518	54.567	54.571	44.652	32.130	29.594	29.598	24.435	14.577	42.651	48.361	36.268	26.798	23.316
W099	2003	0	0.246	0.121	1.945	52.161	52.161	42.522	24.487	29.108	29.108	23.676	11.478	39.579	45.097	32.738	22.934	20.704
W099	2004	0	0.220	0.110	0.842	51.753	51.753	44.730	25.309	28.850	28.850	24.531	10.498	39.829	45.497	32.391	21.998	21.222
W099	2006	0	0.240	0.119	1.056	51.865	51.865	44.384	28.812	28.349	28.349	25.404	13.056	41.939	49.435	34.867	19.433	21.878
W099	2007	0	0.219	0.112	1.151	53.258	53.257	44.388	31.521	28.349	28.349	24.646	12.337	36.795	42.766	28.283	19.825	19.676
W100	2004	0	0.260	0.151	1.795	50.898	50.884	47.161	23.179	29.360	29.359	25.928	11.394	41.358	47.376	34.212	21.271	21.758
W100	2005	0	0.341	0.200	3.312	50.978	50.689	39.006	24.063	27.136	26.770	25.142	11.681	40.894	48.108	32.584	20.658	21.383
W101	2002	0	0.297	0.162	2.122	52.504	52.484	43.516	33.299	29.641	29.582	24.362	12.949	41.884	46.418	35.094	25.966	21.461
W101	2005	0	0.364	0.200	4.017	54.672	54.334	37.825	31.392	29.901	29.893	23.872	12.441	41.125	47.912	32.325	27.049	22.876
W110	2002	0	0.392	0.242	2.953	51.653	51.659	41.061	36.992	28.063	28.064	24.984	15.111	40.233	40.566	35.453	27.990	22.219
W112	2002	0	0.212	0.126	0.766	50.925	50.925	46.503	30.089	28.192	27.508	27.949	13.010	42.681	46.873	37.751	25.516	21.317
W126	2005	0	0.279	0.150	2.492	51.394	51.416	38.473	26.863	27.733	27.749	23.257	10.554	39.790	47.986	30.003	22.314	20.931
W127	2005	0	0.270	0.157	1.870	51.429	51.386	45.890	29.788	28.852	28.835	27.473	14.627	42.854	47.616	36.507	26.486	23.544
W127	2008	0	0.233	0.141	1.009	52.824	52.824	45.355	31.112	28.434	28.332	26.866	13.894	44.105	50.040	37.939	27.797	24.270
W128	2005	0	0.255	0.151	1.576	50.365	50.365	45.372	29.375	27.304	27.042	27.140	14.054	42.325	47.157	36.281	26.094	22.499
W128	2007	0	0.260	0.153	1.691	54.908	54.908	46.053	32.439	26.750	26.505	27.756	15.742	40.620	44.806	35.032	23.898	21.966
W129	2005	0	0.239	0.141	1.135	49.974	49.974	45.415	30.121	27.215	26.979	26.948	14.441	42.469	46.762	36.920	26.883	22.182
W129	2007	0	0.273	0.162	2.071	54.605	54.603	46.052	32.943	26.530	26.374	27.316	16.264	41.211	44.828	36.406	24.529	21.893
W133	2000	0	0.278	0.164	1.667	49.501	49.455	41.844	33.924	29.959	29.959	26.786	16.080	42.502	46.890	37.181	28.157	25.353
W133	2005	0	0.307	0.176	2.829	52.150	52.152	42.684	29.477	30.716	30.717	27.164	16.031	42.927	47.866	36.551	26.943	25.255
W133	2006	1	0.214	0.122	0.871	51.263	51.262	45.844	32.597	29.959	29.959	29.258	18.340	44.584	50.025	39.260	26.941	26.555
W133	2007	0	0.264	0.149	1.990	52.510	52.450	45.586	34.715	29.959	29.959	29.376	17.509	39.892	43.895	33.724	25.691	24.312
W133	2008	0	0.255	0.150	1.774	51.720	51.720	44.362	30.788	30.231	30.228	26.786	15.710	43.765	48.995	38.071	27.717	26.434
W154	2008	0	0.172	0.092	0.799	53.010	52.995	41.324	23.860	25.587	25.591	22.778	8.598	39.388	46.797	31.759	20.324	20.425

site ID	year	BTV status	meanlstnsu	meanlstnau	meanlstnpw	meanlstss	meanlstsu	meanlstau	meanlstpw	gdda	gddss	gddsu	gddau	rss	rsu	rau
F60	2001	0	25.932	21.008	13.720	33.766	13.951	13.451	22.544	4963.271	3548.542	1582.713	1352.435	33.097	9.914	23.183
F60	2002	1	24.938	21.008	13.720	34.705	34.247	13.451	22.544	4997.325	3629.545	1637.185	1394.169	86.434	51.202	35.232
F60	2005	0	25.359	22.044	13.925	31.457	37.090	31.773	22.562	4541.748	3051.749	1445.339	1016.893	573.491	373.569	199.848
F60	2008	0	26.313	22.010	13.034	32.549	34.051	27.590	21.607	4606.327	3249.335	1488.479	1215.751	312.660	268.115	43.543
W006	2000	0	25.368	19.462	9.930	31.718	36.282	26.205	17.880	3723.478	2963.297	1493.700	883.846	355.749	272.130	61.969
W014	2000	0	25.207	21.709	13.768	32.321	34.413	29.171	21.555	4367.755	3154.825	1406.428	1169.062	593.518	545.357	48.112
W014	2002	0	25.207	20.459	13.164	33.016	34.413	12.966	21.593	4714.922	3355.858	1588.116	1166.819	482.430	327.773	152.412
W015	2000	0	27.129	22.631	13.713	33.186	35.721	29.882	21.500	4476.958	3306.879	1486.846	1235.686	327.082	301.248	25.036
W015	2005	0	27.962	22.006	13.797	32.563	38.524	31.403	21.051	4598.128	3166.478	1550.413	1028.530	423.056	225.627	197.411
W015	2006	0	29.554	23.517	14.020	35.742	38.989	29.922	21.195	4964.612	3664.778	1671.908	1397.310	109.977	27.546	78.255
W023	2000	0	25.740	22.472	14.945	31.670	33.747	28.699	21.907	4270.659	3091.791	1402.934	1123.035	423.781	367.020	42.513
W023	2005	0	26.679	21.791	14.836	31.021	36.876	30.863	21.939	4287.512	2906.966	1376.236	934.266	922.845	544.600	378.243
W023	2008	0	26.993	22.656	13.445	31.670	33.699	26.726	20.798	4428.767	3186.635	1475.758	1160.044	423.781	367.020	42.513
W024	2000	0	26.240	22.120	13.707	32.397	34.749	29.263	21.775	4405.826	3206.188	1451.897	1177.200	447.227	389.054	47.410
W026	2000	0	25.939	21.296	12.855	30.864	33.350	27.317	20.348	3979.905	2909.807	1363.149	990.453	567.380	488.819	54.436
W034	2000	0	25.011	21.462	13.049	30.998	32.750	28.223	20.949	4050.379	2925.698	1303.259	1078.088	530.323	491.164	39.159
W034	2002	0	25.011	19.486	12.317	33.448	32.750	12.521	21.078	4765.496	3383.688	1571.433	1211.762	421.406	279.937	140.602
W039	2002	1	25.673	18.073	10.108	31.892	35.260	11.671	17.109	3791.141	3093.341	1569.647	937.916	206.441	148.009	56.584
W039	2004	0	26.409	18.787	10.007	33.873	36.186	27.836	17.011	3956.585	3302.826	1631.330	1146.637	106.814	17.744	74.934
W047	2000	0	24.989	21.936	13.352	32.253	34.855	28.903	21.358	4318.108	3147.465	1442.588	1142.673	661.488	607.750	49.390
W048	2000	0	26.603	19.736	11.333	30.920	33.719	26.917	18.603	3880.763	2920.472	1393.802	956.201	491.624	412.450	43.394
W064	2000	1	27.968	22.800	14.213	32.666	35.105	29.377	21.200	4395.695	3239.747	1466.089	1188.200	444.457	413.647	26.539
W065	2000	0	24.665	21.665	13.683	30.056	32.154	27.232	21.255	3886.699	2762.082	1273.317	984.957	583.760	482.626	101.036
W065	2002	0	24.665	19.620	13.397	32.307	32.154	12.098	21.326	4612.780	3215.688	1493.141	1133.227	564.845	423.631	139.734
W066	2000	1	27.823	21.579	12.855	33.405	36.114	29.634	20.668	4418.664	3299.461	1482.413	1211.226	375.778	349.719	25.600
W067	2000	0	25.502	18.723	9.532	30.890	34.365	26.001	16.959	3676.165	2889.972	1434.127	864.476	512.776	424.315	59.259
W069	2000	0	26.160	20.818	12.231	31.529	33.993	28.075	19.384	4036.820	3039.986	1402.890	1069.609	569.734	496.894	34.209
W069	2003	0	26.160	20.818	12.231	32.147	33.993	28.075	19.384	4174.932	3081.046	1575.794	914.818	545.278	348.028	190.163
W070	2000	1	28.161	22.508	13.488	32.747	35.131	29.306	20.817	4356.282	3235.711	1455.345	1181.309	413.488	393.378	20.073

site ID	year	BTV status	meanlstnsu	meanlstnau	meanlstnpw	meanlstss	meanlstsu	meanlstau	meanlstpw	gdda	gddss	gddsu	gddau	rss	rsu	rau
W071	2000	0	24.868	22.452	14.440	32.686	34.541	30.148	23.132	4631.378	3277.350	1442.433	1261.857	337.051	290.285	45.033
W072	2000	0	25.186	21.942	13.086	32.207	34.436	29.403	21.486	4328.126	3186.472	1442.866	1190.203	277.108	250.786	25.890
W072	2001	0	25.619	20.262	12.284	33.356	14.005	13.083	20.755	4615.689	3459.923	1642.989	1233.455	70.984	1.204	69.683
W072	2005	0	25.740	21.407	13.396	31.728	37.285	31.180	21.584	4405.156	3082.592	1528.720	985.716	417.204	141.587	275.589
W073	2000	1	27.022	22.096	13.966	32.120	34.384	28.929	20.981	4257.445	3145.260	1423.607	1145.060	462.266	413.166	36.606
W073	2001	1	26.224	20.565	13.197	33.727	13.996	12.866	21.007	4690.349	3449.390	1636.833	1196.247	133.071	32.205	100.801
W074	2000	0	25.144	18.968	9.936	30.034	33.390	25.438	16.764	3507.461	2741.909	1374.872	810.213	442.098	360.536	50.553
W075	2000	0	26.179	22.359	12.809	32.479	35.074	29.296	20.975	4301.287	3233.039	1488.113	1180.022	298.607	280.825	17.783
W075	2001	1	26.257	20.282	12.060	33.945	14.289	13.021	20.060	4605.295	3511.530	1645.342	1281.197	103.137	12.813	90.186
W075	2004	0	26.982	21.347	12.275	34.924	37.273	30.719	20.260	4393.063	3505.954	1633.686	1321.113	88.409	21.294	56.891
W076	2000	0	25.401	21.801	13.720	31.442	33.496	28.503	21.294	4154.452	3020.446	1362.980	1105.684	557.811	507.131	50.100
W076	2001	0	25.443	20.311	13.411	32.460	13.662	12.667	21.740	4705.764	3326.887	1450.533	1281.577	369.038	332.496	35.822
W076	2002	0	25.401	20.311	13.411	33.023	33.496	12.667	21.740	4695.707	3345.666	1561.055	1186.748	642.636	448.491	191.577
W076	2003	0	25.401	21.801	13.720	32.015	33.496	28.503	21.294	4471.932	3171.260	1509.906	1073.053	616.048	408.560	204.831
W076	2006	0	27.158	22.544	14.480	33.784	34.787	28.171	22.514	4754.452	3404.638	1643.903	1159.550	507.302	64.364	439.920
W076	2008	0	26.444	21.446	12.841	31.442	33.617	28.095	21.468	4693.454	3255.631	1489.815	1192.817	557.811	507.131	50.100
W077	2000	0	25.589	22.546	13.704	31.880	34.406	28.569	20.869	4215.108	3090.579	1419.097	1110.651	635.053	561.514	45.406
W078	2000	0	27.173	21.680	13.421	31.967	33.924	28.736	19.955	4188.081	3105.128	1391.144	1126.549	492.468	422.361	46.157
W078	2001	0	25.533	20.294	12.457	33.070	13.822	12.773	20.405	4661.087	3350.613	1549.370	1180.838	446.877	258.950	187.861
W079	2000	0	25.492	21.756	12.162	32.421	35.384	29.106	19.773	4108.114	3213.843	1505.789	1161.633	215.594	197.956	17.638
W080	2000	0	24.763	21.770	12.719	32.228	34.704	29.448	21.133	4297.657	3214.802	1483.033	1195.292	264.881	248.952	15.929
W080	2007	0	24.712	20.497	12.663	33.503	37.755	30.569	19.112	4432.347	3380.092	1603.489	1184.266	205.157	124.276	80.058
W081	2000	0	25.470	22.295	13.016	32.542	35.023	29.619	21.272	4390.360	3260.933	1494.995	1210.833	283.783	263.001	20.703
W081	2006	0	27.610	23.003	13.649	34.880	37.814	30.210	21.091	4845.724	3604.276	1669.412	1358.119	69.348	20.279	47.519
W082	2000	0	25.570	22.260	14.134	33.240	35.503	30.385	22.887	4716.203	3355.464	1493.496	1284.359	363.582	316.677	39.859
W082	2001	1	25.720	20.970	13.456	34.297	14.410	13.578	22.165	4971.142	3582.333	1655.419	1303.208	96.880	4.495	92.381
W082	2004	1	26.834	21.751	13.536	35.447	37.246	31.077	22.253	4783.261	3591.765	1633.011	1388.235	216.864	56.397	155.497
W082	2006	1	27.768	22.799	14.250	34.891	38.196	29.866	22.709	5001.974	3606.288	1668.369	1347.454	112.342	46.316	64.634
W082	2007	0	25.701	20.749	13.884	33.764	39.447	31.772	21.134	4709.293	3385.181	1567.451	1217.942	282.579	99.940	177.920

site ID	year	BTV status	meanlstnsu	meanlstnau	meanlstnpw	meanlstss	meanlstsu	meanlstau	meanlstpw	gdda	gddss	gddsu	gddau	rss	rsu	rau
W084	2000	0	25.198	21.958	13.118	32.251	35.170	28.814	21.747	4377.652	3147.857	1464.881	1134.419	635.912	580.473	47.838
W084	2002	1	25.198	19.369	12.119	34.004	35.170	12.815	21.162	4822.002	3488.926	1603.504	1281.055	331.826	238.517	91.459
W084	2003	0	25.198	21.958	13.118	32.995	35.170	28.814	21.747	4642.389	3288.061	1529.853	1157.798	343.670	237.137	105.055
W085	2001	0	23.802	19.638	11.971	32.476	13.645	12.889	19.422	4231.662	3315.774	1590.932	1189.255	73.546	4.091	69.412
W085	2002	0	23.658	19.638	11.971	32.774	33.566	12.889	19.422	4263.243	3335.041	1594.696	1201.690	26.549	5.645	20.816
W085	2003	0	23.658	20.736	12.179	31.825	33.566	28.885	20.480	3985.322	3161.832	1543.481	1092.399	136.428	122.421	13.116
W085	2004	0	24.188	20.248	12.159	32.556	35.416	29.644	19.477	3942.290	3239.391	1567.210	1197.266	115.406	9.191	104.391
W085	2007	0	23.252	20.222	12.004	32.108	35.995	29.645	18.067	4026.987	3164.535	1566.360	1016.679	274.278	136.171	134.699
W086	2001	1	26.519	19.668	11.663	32.963	14.266	12.369	18.632	4233.211	3294.946	1611.903	1106.669	146.530	42.198	104.329
W087	2000	0	26.904	22.236	12.858	32.421	34.926	29.160	20.439	4212.556	3210.564	1468.462	1167.061	303.725	277.491	26.234
W087	2005	0	27.824	20.729	12.470	31.669	36.972	29.567	19.110	4334.688	3083.807	1553.208	964.931	377.266	248.811	128.455
W088	2001	1	26.522	20.190	11.816	33.449	14.316	12.647	19.051	4378.085	3381.968	1641.294	1156.059	124.314	35.834	88.388
W088	2002	1	27.366	20.190	11.816	33.492	35.144	12.647	19.051	4267.675	3357.988	1622.555	1133.999	147.440	110.818	36.312
W088	2003	1	27.366	21.628	12.558	32.863	35.144	28.439	19.766	4070.633	3167.308	1609.363	971.266	323.617	179.795	137.351
W089	2001	0	25.594	18.354	9.934	32.816	14.339	11.948	16.963	4046.858	3268.922	1616.980	1073.677	147.164	57.090	85.931
W089	2002	0	25.956	18.354	9.934	32.269	35.219	11.948	16.963	3815.242	3139.947	1603.658	953.482	210.948	131.776	75.155
W089	2005	0	27.471	18.176	9.676	29.541	36.749	26.954	16.285	3621.985	2637.606	1442.766	635.759	502.264	249.743	248.820
W093	2001	1	26.985	20.372	11.914	34.118	14.673	13.144	20.101	4562.351	3430.151	1620.290	1175.276	167.084	71.926	95.039
W094	2001	0	25.863	20.931	13.159	34.056	14.291	13.518	22.004	4862.494	3553.271	1643.077	1299.719	91.157	4.879	86.263
W094	2005	1	25.744	21.336	13.886	31.907	37.916	31.784	21.834	4478.976	3101.161	1485.658	1038.872	588.588	219.894	368.665
W094	2006	0	27.674	23.164	13.789	34.572	37.747	29.915	22.303	4889.658	3563.753	1659.741	1328.000	89.598	26.257	62.068
W095	2002	1	25.613	19.383	10.565	32.790	35.597	12.576	17.912	3983.271	3277.405	1623.697	1079.593	73.097	37.101	34.776
W095	2004	0	26.314	19.921	10.668	33.516	36.717	29.167	17.590	3928.194	3272.494	1630.375	1148.674	154.793	11.298	140.245
W096	2002	0	25.690	19.457	10.639	32.740	35.296	12.391	17.425	3920.598	3261.466	1636.703	1062.400	72.503	37.830	30.329
W096	2005	0	27.267	19.344	10.552	31.049	37.095	28.084	16.610	3941.137	2972.934	1549.828	892.607	360.988	235.240	123.967
W096	2006	0	27.768	21.326	10.977	32.778	37.391	26.702	16.634	3969.480	3230.304	1667.784	1027.716	88.867	14.448	71.283
W098	2003	0	25.985	20.839	12.080	33.354	33.338	26.871	19.744	4399.964	3181.794	1554.823	1024.466	449.138	254.886	184.754
W098	2004	0	26.826	19.936	11.792	35.779	37.070	30.288	21.223	4744.081	3605.855	1633.316	1371.465	153.735	79.339	57.103
W098	2005	0	26.757	19.944	12.573	30.887	37.244	29.552	21.159	3910.848	2739.311	1363.156	769.154	891.668	520.690	370.535

site ID	year	BTV status	meanlstnsu	meanlstnau	meanlstnpw	meanlstss	meanlstsu	meanlstau	meanlstpw	gdda	gddss	gddsu	gddau	rss	rsu	rau
W098	2006	0	28.268	21.286	12.842	32.984	37.926	27.672	20.895	4430.939	3259.939	1641.480	1044.980	245.405	81.242	135.078
W098	2007	0	24.731	18.877	11.467	33.670	40.138	31.320	19.565	4469.937	3319.373	1547.901	1171.633	212.738	135.523	75.733
W098	2008	0	26.648	19.712	10.950	30.624	34.173	24.976	18.874	4399.914	3168.285	1494.513	1079.341	576.242	502.101	48.838
W099	2003	0	23.849	17.827	8.355	30.511	35.065	24.956	15.645	3343.494	2791.516	1598.300	656.128	304.189	132.032	149.806
W099	2004	0	24.951	17.603	8.234	31.909	34.473	25.283	15.116	3516.106	3007.648	1620.579	949.129	137.375	21.763	80.363
W099	2006	0	26.273	18.856	8.348	31.464	37.182	23.250	13.891	3650.065	2996.671	1621.807	833.750	195.602	114.176	73.200
W099	2007	0	23.103	15.968	7.620	30.916	37.854	26.862	13.723	3428.938	2862.912	1448.132	860.365	269.356	212.781	52.746
W100	2004	0	25.516	18.345	9.136	32.059	36.040	26.726	15.204	3513.951	3071.060	1614.470	981.482	139.988	23.596	104.068
W100	2005	0	26.096	17.025	8.488	28.668	36.446	26.278	14.573	3290.536	2496.129	1370.963	602.855	492.735	263.601	229.078
W101	2002	0	26.442	17.668	9.545	32.636	33.100	11.983	17.756	4226.339	3176.706	1579.597	993.053	349.251	221.540	110.375
W101	2005	0	26.987	18.768	11.492	31.263	36.927	27.321	19.270	3928.523	2832.672	1476.476	755.499	509.120	354.844	154.010
W110	2002	0	24.441	19.191	14.598	31.932	31.597	12.154	21.294	4460.015	3147.802	1495.140	1069.324	545.859	363.125	181.688
W112	2002	0	24.173	19.108	10.755	32.464	34.096	12.636	18.135	4017.914	3268.081	1605.312	1119.223	39.604	20.190	19.021
W126	2005	0	25.892	16.036	8.141	28.868	34.834	24.304	15.228	3354.816	2545.250	1441.865	552.718	470.314	335.446	119.692
W127	2005	0	26.816	20.928	12.578	32.149	37.234	29.645	19.532	4466.343	3177.288	1577.560	1035.680	311.554	202.374	109.178
W127	2008	0	27.484	21.581	12.950	32.734	35.713	27.855	20.373	4333.237	3333.856	1577.760	1242.703	261.867	245.670	16.196
W128	2005	0	25.519	20.122	11.826	31.293	36.567	29.511	18.960	4198.728	3061.543	1525.384	1010.646	289.498	163.971	124.155
W128	2007	0	24.321	20.080	11.723	32.842	37.428	29.711	17.811	4105.326	3259.487	1594.571	1076.120	228.636	100.963	126.271
W129	2005	0	24.829	20.118	12.102	31.552	36.532	29.956	19.492	4319.625	3120.790	1516.151	1086.417	300.641	179.713	120.864
W129	2007	0	24.064	20.282	12.162	32.728	36.969	29.988	18.345	4150.646	3255.851	1580.553	1088.766	275.836	151.568	121.937
W133	2000	0	27.873	23.250	14.136	32.600	34.960	29.466	21.147	4346.822	3236.904	1462.250	1196.753	392.861	367.343	25.517
W133	2005	0	28.773	22.038	14.169	32.102	37.918	30.695	20.556	4506.367	3110.691	1531.028	998.129	501.295	285.109	216.186
W133	2006	1	30.437	23.820	14.334	35.100	38.320	29.294	20.637	4779.816	3564.117	1671.964	1305.046	114.669	30.597	79.797
W133	2007	0	27.430	21.033	13.535	34.055	40.231	31.540	19.613	4516.912	3388.945	1620.204	1164.647	269.452	91.718	174.403
W133	2008	0	29.751	23.482	13.949	32.600	35.663	27.379	20.833	4455.262	3300.423	1545.392	1212.687	392.861	367.343	25.517
W154	2008	0	24.945	16.040	7.685	28.768	33.799	21.752	14.005	3026.248	2606.212	1524.291	714.427	267.801	187.294	68.603

APPENDIX D

SUMMARY OF BTV STATUS AND WEIGHTED AVERAGE ENVIRONMENTAL CONDITIONS OF NAMP SITES IN THE PILBARA

site ID	year	BTV status	maxndviss	maxeviss	smintss	maxlstdss	maxlstdsu	maxlstdau	maxlstdpw	minlstnss	Minlstnsu	minlstnau	Minlstnpw	meanlstdss	meanlstdsu	meanlstdau	meanlstdpw	meanlstnss
F60	2001	0	0.176	0.113	0.655	52.064	50.151	48.644	37.225	27.701	27.121	27.611	16.568	42.144	42.834	39.852	31.661	23.115
F60	2002	1	0.180	0.104	0.574	53.758	52.453	49.630	37.134	27.963	28.479	26.567	15.107	44.319	46.417	39.852	31.661	23.115
F60	2005	0	0.415	0.244	4.864	51.588	51.160	44.146	34.193	27.895	27.880	26.215	15.635	43.699	47.604	38.202	31.613	23.349
F60	2008	0	0.337	0.202	2.550	51.511	51.511	44.623	34.994	27.701	27.121	27.343	17.193	43.909	47.605	39.132	30.506	23.996
W006	2000	0	0.242	0.133	1.358	53.886	53.889	41.355	30.539	28.903	28.906	24.783	11.471	42.970	48.203	36.510	25.864	22.238
W014	2000	0	0.345	0.220	3.662	52.699	51.573	40.914	34.830	27.669	27.357	26.886	16.040	41.698	42.649	39.151	29.086	23.194
W014	2002	0	0.318	0.199	2.388	49.922	49.626	44.076	36.575	27.669	27.989	25.352	15.012	41.698	42.649	37.010	29.593	22.583
W015	2000	0	0.343	0.206	1.913	53.292	53.278	43.755	35.319	29.086	29.085	26.808	14.670	44.475	49.319	38.609	29.675	24.479
W015	2005	0	0.372	0.225	3.095	55.138	55.138	43.651	30.517	30.508	30.508	26.922	15.414	45.154	50.963	37.713	28.739	24.671
W015	2006	0	0.227	0.136	0.620	53.234	53.234	47.991	34.015	29.086	29.085	28.291	17.364	46.590	52.628	40.287	28.528	25.878
W023	2000	0	0.338	0.185	2.747	49.637	49.285	40.810	35.279	27.896	27.811	26.761	16.607	43.128	46.596	38.714	29.053	23.904
W023	2005	0	0.395	0.220	4.768	52.080	51.861	40.968	32.025	29.202	29.204	25.414	15.951	42.290	46.721	36.215	29.335	24.073
W023	2008	0	0.311	0.168	2.882	52.161	52.159	43.282	32.891	28.298	28.245	26.761	16.501	43.586	47.912	38.713	28.286	24.819
W024	2000	0	0.320	0.177	2.504	51.308	51.247	42.743	36.155	27.773	27.753	25.478	15.209	43.878	48.329	38.568	29.886	23.958
W026	2000	0	0.382	0.206	3.502	50.892	50.700	39.602	34.269	27.680	27.680	24.541	14.734	44.877	48.122	40.048	28.009	23.281
W034	2000	0	0.427	0.263	3.668	50.236	49.134	40.670	35.858	27.764	27.397	27.139	15.337	41.481	42.086	39.345	28.739	22.860
W034	2002	0	0.340	0.212	2.072	51.927	51.180	45.755	37.993	27.764	28.040	25.802	14.271	41.481	42.086	36.434	29.633	22.127
W039	2002	1	0.190	0.100	0.716	51.648	51.644	44.794	31.230	29.036	28.685	25.732	13.398	41.936	46.877	34.555	24.162	21.821
W039	2004	0	0.184	0.096	0.646	53.066	53.066	48.795	27.857	31.026	31.026	27.121	12.935	41.320	46.004	34.866	24.098	22.573
W047	2000	0	0.331	0.203	2.559	53.787	52.839	42.258	36.021	27.403	27.388	26.139	15.338	44.325	45.436	41.869	29.593	23.136
W048	2000	0	0.327	0.171	2.546	49.722	49.457	41.169	31.752	28.170	28.171	24.841	13.751	43.380	48.050	36.916	25.873	23.055
W064	2000	1	0.372	0.221	2.263	52.297	52.285	42.722	34.581	29.132	29.132	25.765	14.390	44.025	48.590	38.203	28.458	24.740
W065	2000	0	0.484	0.319	4.740	47.675	46.946	38.639	34.144	27.766	27.629	26.755	16.918	39.601	38.827	39.074	28.637	22.611
W065	2002	0	0.440	0.285	3.420	51.142	51.108	41.145	37.516	27.766	27.543	24.752	14.306	39.601	38.827	34.034	28.499	21.916
W066	2000	1	0.254	0.148	1.236	53.607	53.607	44.425	34.823	30.619	30.619	27.680	13.640	45.588	50.559	39.310	28.839	24.224
W067	2000	0	0.249	0.125	1.923	50.986	50.783	41.802	32.703	27.751	27.753	23.900	11.582	42.588	46.972	36.558	24.456	22.015
W069	2000	0	0.267	0.156	1.946	49.995	49.776	40.540	31.897	28.480	28.488	25.229	16.045	42.242	46.013	36.637	26.230	23.445
W069	2003	0	0.284	0.168	2.359	52.775	52.636	41.195	29.331	29.794	30.349	24.894	14.855	42.242	46.013	36.637	26.230	23.445
W070	2000	1	0.326	0.199	1.598	51.703	51.687	43.822	34.963	29.516	29.516	26.411	13.744	45.300	50.332	39.113	28.624	24.584

site ID	year	BTV status	maxndviss	maxeviss	smintss	maxlstdss	maxlstdsu	maxlstdau	maxlstdpw	minlstnss	minlstnsu	minlstnau	minlstnpw	meanlstdss	meanlstdsu	meanlstdau	meanlstdpw	meanlstnss
W071	2000	0	0.334	0.192	2.185	50.977	50.661	44.014	39.152	27.912	27.514	27.435	15.994	44.876	47.293	41.593	32.213	23.179
W072	2000	0	0.341	0.204	1.724	49.604	49.457	43.333	35.001	27.363	27.360	25.990	14.921	43.401	47.736	38.396	29.907	23.211
W072	2001	0	0.296	0.161	2.266	50.483	50.466	44.282	35.859	27.473	27.434	26.201	15.975	41.402	42.936	38.378	29.002	22.733
W072	2005	0	0.406	0.229	3.985	52.506	52.506	40.739	30.621	28.856	28.813	27.039	16.161	44.997	50.024	38.465	29.882	23.416
W073	2000	1	0.357	0.203	2.161	52.530	52.510	43.316	35.302	28.922	28.913	26.185	14.744	44.168	49.037	38.115	28.810	24.445
W073	2001	1	0.329	0.188	2.411	52.933	52.935	43.976	35.669	30.341	30.338	27.257	15.783	42.035	43.617	38.346	29.314	23.247
W074	2000	0	0.299	0.165	2.480	50.067	49.858	39.339	30.791	27.500	27.500	23.711	12.263	41.500	45.607	35.501	23.628	22.101
W075	2000	0	0.291	0.172	1.848	50.228	49.963	43.696	33.991	28.621	28.621	26.595	15.123	43.954	48.340	39.051	29.120	23.915
W075	2001	1	0.250	0.138	1.240	51.297	51.297	46.464	34.618	28.726	28.718	27.552	15.962	41.885	43.878	38.271	28.021	23.047
W075	2004	0	0.226	0.127	1.169	52.964	52.964	49.237	30.557	31.185	31.180	28.919	15.741	44.239	47.938	39.258	28.218	23.966
W076	2000	0	0.358	0.236	3.998	50.173	49.788	40.636	34.576	27.702	27.609	26.731	16.519	40.351	40.397	39.178	28.375	23.240
W076	2001	0	0.327	0.215	1.983	47.316	46.163	43.554	33.498	27.348	27.344	25.610	16.834	38.753	40.010	35.730	29.178	22.516
W076	2002	0	0.330	0.211	2.596	50.465	50.479	42.864	35.766	27.702	28.136	25.254	15.462	40.351	40.397	35.730	29.178	22.516
W076	2003	0	0.344	0.217	3.148	49.039	48.789	41.318	32.543	27.348	27.341	25.261	17.699	40.351	40.397	39.178	28.375	23.240
W076	2006	0	0.333	0.209	2.344	50.298	50.105	47.587	35.793	27.702	27.609	27.210	15.632	42.968	44.718	40.532	29.975	24.442
W076	2008	0	0.307	0.199	2.222	49.226	49.223	42.851	34.228	27.348	27.344	26.731	16.680	41.988	46.567	35.996	29.596	23.942
W077	2000	0	0.284	0.171	2.093	51.284	51.243	41.257	35.105	28.222	28.222	25.775	16.783	43.301	44.889	40.068	28.129	23.850
W078	2000	0	0.299	0.180	2.045	52.754	52.594	42.160	34.315	28.452	28.446	26.410	15.838	41.779	43.718	37.880	26.605	24.272
W078	2001	0	0.320	0.196	2.198	52.086	49.023	42.531	33.093	29.607	29.607	25.808	15.193	40.935	42.303	37.255	28.532	22.908
W079	2000	0	0.247	0.158	1.106	51.279	51.279	44.174	31.865	27.723	27.680	26.978	15.687	42.823	47.351	37.839	27.465	23.199
W080	2000	0	0.279	0.172	1.369	49.850	49.846	43.800	33.739	26.904	26.901	25.572	15.542	43.922	48.048	39.463	29.570	22.790
W080	2007	0	0.259	0.152	1.456	54.128	54.048	44.560	34.428	26.904	26.901	27.837	16.817	41.720	44.830	37.215	25.544	22.281
W081	2000	0	0.319	0.189	1.744	49.716	49.711	43.458	34.487	28.213	28.209	25.931	14.736	43.931	47.904	39.338	29.487	23.535
W081	2006	0	0.225	0.131	0.578	53.258	53.258	48.316	34.529	28.213	28.209	26.950	16.508	46.212	51.400	40.999	28.513	24.787
W082	2000	0	0.302	0.162	1.915	52.341	52.334	44.550	37.598	27.526	27.318	27.065	15.898	45.225	49.236	40.228	31.880	23.523
W082	2001	1	0.250	0.129	1.816	52.863	52.728	46.128	37.212	27.665	27.439	27.124	15.774	43.556	45.496	39.962	31.183	23.042
W082	2004	1	0.312	0.155	2.402	54.611	54.613	49.621	35.350	28.966	28.818	27.884	16.846	46.928	50.042	42.336	31.057	23.996
W082	2006	1	0.246	0.132	0.854	52.332	52.331	47.037	35.471	27.526	27.318	27.289	16.181	46.523	51.668	41.001	31.416	24.637
W082	2007	0	0.337	0.170	3.058	56.487	56.375	44.304	38.881	27.526	27.318	27.013	15.353	40.484	43.877	34.239	28.391	23.020

site ID	year	BTV status	maxndviss	maxeviss	smintss	maxlstdss	maxlstdsu	maxlstdau	maxlstdpw	minlstnss	minlstnsu	minlstnau	minlstnpw	meanlstdss	meanlstdsu	meanlstdau	meanlstdpw	meanlstnss
W084	2000	0	0.372	0.228	2.960	53.025	52.647	41.699	35.749	27.314	27.305	25.857	15.556	44.371	45.523	42.072	30.226	23.277
W084	2002	1	0.297	0.190	2.113	52.928	51.774	47.087	37.933	27.314	28.439	25.428	14.017	44.371	45.523	37.708	30.008	22.235
W084	2003	0	0.354	0.221	2.151	53.398	51.918	42.640	34.181	27.449	27.417	25.806	15.957	44.371	45.523	42.072	30.226	23.277
W085	2001	0	0.286	0.163	1.652	49.650	49.650	45.591	33.914	26.596	26.586	25.031	15.010	41.312	43.207	38.083	26.851	21.427
W085	2002	0	0.208	0.125	0.872	50.793	50.792	46.862	31.469	26.033	27.651	27.466	14.011	43.055	47.150	38.083	26.851	21.427
W085	2003	0	0.259	0.160	1.876	51.676	51.680	44.269	29.989	26.596	26.548	25.805	13.788	43.055	47.150	38.528	28.819	21.802
W085	2004	0	0.397	0.231	2.979	50.673	50.647	47.897	30.262	27.579	26.968	27.331	15.137	43.606	47.456	39.028	26.734	21.849
W085	2007	0	0.363	0.218	3.518	53.221	53.209	44.178	32.877	26.033	26.025	26.728	16.083	40.742	43.702	36.844	24.002	21.383
W086	2001	1	0.191	0.102	0.985	51.871	51.885	44.539	32.254	28.653	28.657	26.049	14.992	40.867	43.901	35.822	25.617	23.039
W087	2000	0	0.248	0.156	1.184	49.594	49.481	43.386	33.301	29.458	29.458	26.934	15.574	42.739	47.496	37.350	28.182	24.310
W087	2005	0	0.274	0.164	2.221	50.677	50.576	43.257	29.153	29.060	29.060	26.755	14.459	42.251	47.306	35.549	25.854	24.063
W088	2001	1	0.202	0.111	0.978	51.588	51.591	45.469	33.394	29.405	29.406	26.665	15.540	41.487	44.087	36.958	26.420	23.279
W088	2002	1	0.182	0.099	0.679	52.446	52.381	47.454	33.394	29.792	31.096	27.705	15.043	42.941	47.929	36.958	26.420	23.279
W088	2003	1	0.211	0.112	1.628	54.717	54.728	44.473	28.765	29.405	30.561	26.565	14.039	42.941	47.929	37.201	27.174	24.251
W089	2001	0	0.184	0.109	0.592	52.958	52.958	45.974	31.788	28.407	28.408	25.358	13.199	41.136	44.895	35.358	23.937	21.936
W089	2002	0	0.186	0.103	0.659	52.817	52.816	46.000	32.194	29.082	28.134	25.963	13.329	42.979	48.101	35.358	23.937	21.936
W089	2005	0	0.356	0.202	3.836	52.469	52.482	38.764	28.969	29.092	29.006	24.251	11.907	42.137	49.335	33.727	22.941	22.588
W093	2001	1	0.220	0.125	1.574	54.501	54.542	46.207	34.805	29.874	29.890	26.428	14.482	43.012	45.449	38.690	27.995	23.262
W094	2001	0	0.265	0.141	1.848	51.490	51.377	45.032	36.339	27.603	27.408	27.026	15.527	42.440	43.818	39.398	30.850	23.085
W094	2005	1	0.344	0.185	3.088	52.249	52.225	44.684	32.378	28.654	28.646	26.487	16.152	44.583	49.346	38.438	29.653	23.271
W094	2006	0	0.240	0.133	0.865	51.597	51.595	47.303	35.156	27.554	27.541	27.159	16.399	45.828	50.870	40.644	30.795	24.597
W095	2002	1	0.174	0.109	0.524	52.123	52.087	46.063	30.277	28.522	28.645	27.107	12.578	43.208	47.978	37.228	25.253	22.262
W095	2004	0	0.256	0.154	1.315	52.153	52.153	48.430	27.263	31.189	31.189	28.280	13.558	42.842	47.565	36.794	24.568	22.813
W096	2002	0	0.169	0.103	0.473	51.954	51.954	45.093	29.513	28.806	28.646	27.205	12.584	42.321	47.210	36.335	24.232	22.376
W096	2005	0	0.236	0.142	1.434	51.037	51.044	43.019	26.921	28.798	28.791	27.029	12.966	41.345	47.616	34.115	22.717	22.964
W096	2006	0	0.209	0.123	1.072	51.191	51.192	46.127	29.786	28.806	28.806	27.925	15.139	42.665	49.102	36.286	22.341	23.806
W098	2003	0	0.356	0.183	3.196	56.325	56.234	43.270	33.613	29.622	29.542	24.671	14.102	45.185	48.605	40.107	27.650	23.059
W098	2004	0	0.221	0.117	0.862	56.829	56.828	47.204	35.746	30.176	30.175	26.140	15.671	44.942	47.943	39.478	31.038	23.055
W098	2005	0	0.459	0.257	6.299	56.145	55.430	37.936	32.785	29.669	29.668	24.248	12.699	43.695	49.776	35.477	30.158	23.174

site ID	year	BTV status	maxndviss	maxeviss	smintss	maxlstdss	maxlstdsu	maxlstdau	maxlstdpw	minlstnss	minlstnsu	minlstnau	minlstnpw	meanlstdss	meanlstdsu	meanlstdau	meanlstdpw	meanlstnss
W098	2006	0	0.369	0.184	1.872	51.970	51.967	48.027	34.811	28.062	28.062	27.041	15.408	47.829	52.947	42.051	29.357	24.111
W098	2007	0	0.328	0.158	2.303	54.548	53.706	47.630	36.660	28.062	28.062	27.575	13.604	39.649	44.037	30.660	28.097	22.042
W098	2008	0	0.347	0.185	2.544	55.470	55.471	44.882	32.811	29.622	29.623	24.060	14.282	42.933	48.726	36.472	26.900	22.864
W099	2003	0	0.244	0.121	1.915	52.266	52.266	42.657	24.575	26.281	29.112	23.707	11.495	39.743	45.265	32.885	23.091	20.729
W099	2004	0	0.215	0.109	0.787	51.855	51.855	44.859	25.377	28.860	28.860	24.540	10.495	39.958	45.641	32.491	22.091	21.230
W099	2006	0	0.235	0.118	1.012	51.992	51.991	44.541	28.896	28.404	28.404	25.441	13.083	42.046	49.553	34.955	19.466	21.890
W099	2007	0	0.217	0.112	1.115	53.338	53.337	44.428	31.633	28.404	28.404	24.661	12.350	36.816	42.792	28.276	19.880	19.676
W100	2004	0	0.263	0.153	1.830	51.007	50.991	47.212	23.197	29.404	29.403	25.957	11.364	41.408	47.442	34.228	21.310	21.777
W100	2005	0	0.347	0.204	3.428	51.027	50.738	38.745	24.016	27.118	26.744	25.056	11.627	40.954	48.205	32.601	20.674	21.413
W101	2002	0	0.319	0.178	2.181	52.716	52.702	42.887	33.356	28.461	29.370	24.207	12.748	41.793	46.501	34.659	25.857	21.329
W101	2005	0	0.390	0.222	4.247	55.214	54.848	37.251	31.678	29.786	29.773	23.796	12.260	41.128	48.139	32.014	27.104	22.756
W110	2002	0	0.461	0.291	3.733	51.393	51.403	39.313	37.000	27.705	27.722	24.391	14.031	39.195	39.211	33.857	25.142	21.652
W112	2002	0	0.214	0.127	0.777	51.061	51.060	46.645	30.231	26.608	27.533	27.974	13.011	42.811	47.024	37.786	25.610	21.329
W126	2005	0	0.275	0.150	2.398	51.509	51.531	38.540	27.004	27.717	27.733	23.315	10.489	39.845	48.038	30.020	22.433	20.935
W127	2005	0	0.274	0.161	1.879	51.539	51.502	46.188	29.807	28.785	28.765	27.488	14.594	42.945	47.712	36.598	26.527	23.478
W127	2008	0	0.237	0.144	1.028	52.891	52.891	45.428	31.122	28.351	28.235	26.849	13.765	44.181	50.127	38.009	27.803	24.164
W128	2005	0	0.260	0.154	1.629	50.385	50.384	45.412	29.380	27.299	27.045	27.126	14.005	42.395	47.235	36.334	26.148	22.508
W128	2007	0	0.264	0.155	1.712	54.968	54.968	46.155	32.489	26.748	26.511	27.760	15.682	40.647	44.839	35.046	23.918	21.961
W129	2005	0	0.244	0.144	1.173	50.027	50.027	45.357	30.133	27.213	27.025	26.899	14.499	42.468	46.779	36.891	26.890	22.199
W129	2007	0	0.281	0.167	2.189	54.622	54.620	45.928	32.927	26.515	26.382	27.267	16.319	41.218	44.848	36.404	24.520	21.884
W133	2000	0	0.302	0.177	1.884	50.235	50.191	42.082	34.337	29.876	29.876	26.742	15.798	42.973	47.419	37.534	28.296	25.262
W133	2005	0	0.329	0.188	3.111	53.012	53.010	42.962	29.756	30.615	30.616	27.108	15.874	43.490	48.655	36.837	27.231	25.153
W133	2006	1	0.224	0.128	0.876	51.879	51.879	46.420	32.840	29.876	29.876	29.216	18.209	45.168	50.724	39.655	27.191	26.428
W133	2007	0	0.281	0.159	2.168	53.167	53.098	46.311	35.156	29.876	29.876	29.278	17.206	40.319	44.484	33.846	25.897	24.203
W133	2008	0	0.276	0.162	1.940	52.390	52.390	44.671	31.116	30.154	30.143	26.742	15.510	44.300	49.631	38.495	27.831	26.333
W154	2008	0	0.172	0.094	0.771	53.057	53.038	41.330	23.877	25.543	25.548	22.726	8.580	39.432	46.877	31.811	20.324	20.324

site ID	year	BTV status	meanlstnsu	meanlstnau	meanlstnpw	meanlstss	meanlstsu	meanlstau	meanlstpw	gdda	gddss	gddsu	gddau	rss	rsu	rau
F60	2001	0	25.842	20.736	13.303	33.920	13.986	13.472	22.482	4986.619	3571.195	1594.801	1360.400	33.191	9.891	23.300
F60	2002	1	24.811	20.736	13.303	34.867	34.338	13.472	22.482	5016.990	3645.612	1644.652	1400.786	85.935	51.031	34.904
F60	2005	0	25.191	21.807	13.451	31.562	37.308	31.882	22.532	4555.137	3063.536	1458.156	1013.560	574.482	373.674	200.735
F60	2008	0	26.156	21.801	12.604	32.629	34.271	27.555	21.555	4629.884	3267.546	1496.967	1217.695	312.939	268.306	43.635
W006	2000	0	25.349	19.405	9.823	31.720	36.289	26.198	17.843	3719.728	2962.878	1493.731	883.382	354.804	271.912	60.314
W014	2000	0	25.025	21.560	13.786	31.587	33.607	28.571	21.436	4199.080	3027.241	1355.964	1112.052	613.113	559.400	53.634
W014	2002	0	25.025	20.131	12.994	32.596	33.607	12.699	21.294	4620.777	3292.828	1561.746	1141.650	494.059	339.527	151.789
W015	2000	0	27.032	22.376	13.365	33.210	35.762	29.845	21.520	4492.348	3305.100	1483.643	1231.996	332.823	306.463	25.531
W015	2005	0	27.825	21.708	13.482	32.632	38.843	31.532	21.110	4585.231	3159.947	1545.238	1023.163	423.700	227.493	196.192
W015	2006	0	29.516	23.312	13.701	35.940	39.394	29.710	21.114	4997.396	3676.317	1671.906	1405.868	108.755	27.605	76.849
W023	2000	0	25.713	22.355	14.770	31.699	33.783	28.677	21.912	4281.052	3094.769	1404.141	1121.009	423.880	367.057	42.574
W023	2005	0	26.614	21.738	14.642	31.075	37.064	30.994	21.989	4291.994	2908.142	1377.090	932.849	919.850	541.667	378.180
W023	2008	0	26.966	22.556	13.291	31.699	33.783	26.713	20.789	4430.566	3186.854	1476.419	1155.873	423.880	367.057	42.574
W024	2000	0	26.232	22.073	13.593	32.402	34.767	29.244	21.740	4406.114	3206.954	1452.520	1175.410	444.954	387.224	47.139
W026	2000	0	25.762	20.887	12.364	30.697	33.351	26.943	20.186	3930.976	2874.097	1361.893	954.581	567.912	489.460	54.073
W034	2000	0	24.889	21.133	12.718	30.446	32.177	27.784	20.729	3900.193	2825.205	1266.767	1035.509	534.673	496.739	37.934
W034	2002	0	24.889	19.133	12.104	33.136	32.177	12.316	20.869	4706.918	3342.286	1552.410	1194.750	427.438	290.676	136.134
W039	2002	1	25.670	18.020	10.036	31.947	35.324	11.687	17.099	3800.572	3099.041	1572.021	940.456	205.607	147.737	56.099
W039	2004	0	26.395	18.737	9.922	33.927	36.274	27.886	17.010	3964.897	3307.410	1631.569	1148.740	106.527	17.646	74.782
W047	2000	0	24.886	21.749	13.241	32.059	34.519	28.876	21.417	4291.071	3118.669	1424.531	1140.101	672.710	618.300	49.006
W048	2000	0	26.492	19.478	11.146	30.843	33.774	26.728	18.510	3863.275	2909.763	1400.008	941.931	487.040	410.356	40.823
W064	2000	1	27.724	22.086	13.187	32.359	34.928	28.849	20.823	4298.151	3172.142	1449.793	1137.521	446.511	415.018	27.080
W065	2000	0	24.405	21.030	13.069	29.321	31.351	26.514	20.853	3659.731	2611.171	1212.616	915.077	610.556	505.127	105.329
W065	2002	0	24.405	18.994	13.139	31.870	31.351	11.781	20.819	4483.104	3132.914	1463.040	1093.612	570.922	420.193	149.457
W066	2000	1	27.625	21.082	12.251	33.299	36.097	29.410	20.545	4393.885	3274.265	1478.780	1190.119	375.557	350.682	24.288
W067	2000	0	25.476	18.683	9.481	30.911	34.394	26.006	16.969	3684.968	2893.844	1435.236	865.460	511.695	423.724	58.865
W069	2000	0	26.026	20.700	12.160	31.223	33.792	27.645	19.195	3980.609	2999.326	1394.359	1036.856	567.026	494.842	33.266
W069	2003	0	26.026	20.700	12.160	32.059	33.792	27.645	19.195	4147.555	3063.131	1572.976	901.661	541.148	345.962	188.023
W070	2000	1	27.775	21.710	12.416	32.569	35.068	28.960	20.520	4306.497	3197.962	1449.894	1148.187	414.440	394.360	19.993

site ID	year	BTV status	meanlstnsu	meanlstnau	meanlstnpw	meanlstss	meanlstsu	meanlstau	meanlstpw	gdda	gddss	gddsu	gddau	rss	rsu	rau
W071	2000	0	24.753	22.065	13.925	32.647	34.505	30.068	23.069	4616.956	3266.028	1438.092	1253.912	331.092	284.949	44.553
W072	2000	0	25.161	21.915	13.035	32.067	34.278	29.310	21.471	4304.073	3163.082	1433.546	1181.570	275.402	249.257	25.709
W072	2001	0	25.621	20.242	12.217	33.306	13.945	13.039	20.610	4608.956	3451.503	1643.369	1226.121	69.142	1.072	67.977
W072	2005	0	25.721	21.395	13.407	31.649	37.257	31.183	21.645	4368.693	3061.001	1527.403	963.677	424.405	141.359	283.021
W073	2000	1	27.122	22.094	13.544	32.641	35.019	29.297	21.177	4387.609	3219.445	1449.950	1180.497	432.135	389.074	34.621
W073	2001	1	26.422	20.248	12.642	34.307	14.263	13.024	20.978	4761.476	3504.118	1651.350	1225.416	130.660	26.790	103.805
W074	2000	0	25.110	18.926	9.880	30.011	33.379	25.401	16.754	3502.045	2737.150	1374.038	806.759	444.863	363.856	50.126
W075	2000	0	26.187	22.364	12.791	32.466	35.071	29.266	20.956	4296.300	3230.170	1487.989	1177.096	297.804	280.074	17.729
W075	2001	1	26.264	20.261	12.041	33.935	14.288	13.007	20.031	4601.416	3510.314	1645.350	1280.231	102.792	12.895	89.749
W075	2004	0	26.992	21.360	12.260	34.914	37.263	30.707	20.239	4390.334	3504.788	1633.700	1320.137	88.280	21.366	56.817
W076	2000	0	25.176	21.563	13.768	30.634	32.588	27.855	21.071	3962.734	2871.013	1296.937	1046.357	563.117	510.220	52.415
W076	2001	0	25.167	19.981	13.369	31.796	13.344	12.399	21.273	4507.304	3195.760	1382.774	1235.654	367.594	333.018	33.790
W076	2002	0	25.176	19.981	13.369	32.322	32.588	12.399	21.273	4528.314	3229.007	1514.845	1135.837	648.779	452.623	193.756
W076	2003	0	25.176	21.563	13.768	31.433	32.588	27.855	21.071	4315.285	3073.656	1469.630	1031.502	619.834	413.781	203.579
W076	2006	0	26.973	22.294	14.324	32.965	34.145	27.714	22.150	4562.971	3286.390	1598.657	1102.154	502.687	62.098	437.535
W076	2008	0	26.278	21.227	12.517	30.634	32.760	27.592	21.057	4539.512	3154.837	1446.939	1153.931	563.117	510.220	52.415
W077	2000	0	25.548	22.396	13.533	31.895	34.478	28.518	20.831	4214.441	3092.540	1423.549	1105.758	632.972	560.574	45.876
W078	2000	0	27.006	21.473	13.257	31.921	33.865	28.665	19.931	4180.111	3093.862	1384.722	1119.817	486.552	422.419	44.341
W078	2001	0	25.427	20.075	12.214	33.025	13.797	12.741	20.373	4652.715	3339.565	1544.581	1173.052	450.417	255.893	194.477
W079	2000	0	25.462	21.731	12.122	32.413	35.390	29.080	19.793	4108.767	3212.102	1506.408	1159.195	216.022	198.650	17.372
W080	2000	0	24.694	21.685	12.708	32.201	34.658	29.438	21.139	4293.654	3209.915	1480.621	1194.209	262.324	246.423	15.901
W080	2007	0	24.644	20.487	12.681	33.475	37.691	30.530	19.113	4432.025	3377.209	1601.675	1183.610	208.900	127.811	80.305
W081	2000	0	25.491	22.279	12.980	32.465	34.928	29.537	21.234	4369.618	3243.432	1485.585	1203.111	285.800	264.422	21.285
W081	2006	0	27.747	23.025	13.724	34.876	37.896	30.079	21.118	4856.220	3601.733	1668.348	1357.006	72.474	21.467	49.425
W082	2000	0	25.349	22.168	13.884	33.299	35.565	30.403	22.882	4731.979	3365.476	1496.644	1286.303	348.400	303.468	39.113
W082	2001	1	25.633	20.844	13.237	34.374	14.439	13.563	22.210	4980.110	3597.363	1658.161	1316.077	94.267	4.194	90.071
W082	2004	1	26.639	21.711	13.281	35.580	37.292	31.198	22.169	4785.925	3597.262	1633.425	1391.558	213.613	51.364	157.471
W082	2006	1	27.583	22.743	14.038	34.823	38.228	29.860	22.727	5002.133	3606.190	1667.855	1348.146	104.274	41.053	61.990
W082	2007	0	25.512	20.678	13.750	33.728	39.626	31.872	21.071	4686.248	3372.611	1562.308	1206.751	271.743	93.300	174.701

site ID	year	BTV status	meanlstnsu	meanlstnau	meanlstnpw	meanlstss	meanlstsu	meanlstau	meanlstpw	gdda	gddss	gddsu	gddau	rss	rsu	rau
W084	2000	0	25.076	21.797	13.029	31.782	34.566	28.433	21.628	4269.401	3068.520	1433.349	1097.540	656.206	599.711	49.589
W084	2002	1	25.076	19.157	12.092	33.683	34.566	12.641	21.050	4779.994	3451.654	1580.327	1269.362	341.490	239.493	100.765
W084	2003	0	25.076	21.797	13.029	32.815	34.566	28.433	21.628	4627.653	3266.882	1522.340	1145.327	341.969	232.095	108.414
W085	2001	0	23.698	19.620	11.988	32.429	13.594	12.849	19.420	4217.749	3306.379	1587.760	1185.245	72.231	3.755	68.443
W085	2002	0	23.572	19.620	11.988	32.728	33.452	12.849	19.420	4251.027	3329.270	1592.407	1200.252	24.479	5.436	18.973
W085	2003	0	23.572	20.672	12.183	31.742	33.452	28.852	20.501	3961.388	3147.470	1537.479	1087.020	133.219	120.675	11.659
W085	2004	0	24.067	20.170	12.161	32.463	35.361	29.600	19.447	3916.056	3222.977	1562.712	1189.078	115.961	8.133	106.206
W085	2007	0	23.147	20.214	11.988	31.993	35.885	29.564	17.995	3987.473	3139.385	1562.145	997.827	277.903	136.906	137.527
W086	2001	1	26.497	19.595	11.557	32.969	14.264	12.370	18.587	4227.574	3294.335	1612.701	1105.009	146.329	41.274	105.053
W087	2000	0	26.898	22.247	12.783	32.522	35.033	29.254	20.483	4240.621	3227.468	1474.121	1176.111	302.914	276.907	26.007
W087	2005	0	27.816	20.730	12.423	31.730	37.023	29.609	19.139	4349.996	3093.391	1558.584	968.279	376.515	248.507	128.008
W088	2001	1	26.519	20.105	11.659	33.596	14.381	12.688	19.039	4404.294	3401.624	1645.709	1167.968	124.904	35.335	89.472
W088	2002	1	27.386	20.105	11.659	33.602	35.303	12.688	19.039	4284.248	3366.683	1624.555	1139.824	145.016	109.364	35.415
W088	2003	1	27.386	21.598	12.433	32.982	35.303	28.532	19.804	4088.511	3181.648	1612.676	980.701	322.409	180.324	135.420
W089	2001	0	25.590	18.329	9.879	32.864	14.347	11.939	16.908	4057.543	3275.446	1619.573	1076.041	147.443	57.151	86.186
W089	2002	0	25.985	18.329	9.879	32.321	35.243	11.939	16.908	3823.555	3144.984	1603.906	957.311	211.111	131.632	75.404
W089	2005	0	27.478	18.163	9.655	29.562	36.801	26.997	16.298	3612.160	2635.256	1445.072	629.371	502.057	249.829	248.374
W093	2001	1	26.673	19.891	11.235	34.146	14.637	13.051	19.615	4528.171	3412.358	1617.081	1159.985	169.139	70.669	98.423
W094	2001	0	25.721	20.808	13.108	33.769	14.149	13.404	21.979	4795.165	3513.877	1633.742	1279.595	91.989	4.736	87.241
W094	2005	1	25.608	21.225	13.789	31.817	37.598	31.599	21.721	4461.283	3087.431	1482.799	1033.683	585.277	215.428	369.823
W094	2006	0	27.406	23.014	13.606	34.431	37.477	29.832	22.200	4862.563	3550.121	1656.001	1321.348	87.652	24.521	62.007
W095	2002	1	25.515	19.191	10.367	32.827	35.593	12.537	17.810	3989.182	3281.961	1627.198	1080.030	72.125	36.322	34.496
W095	2004	0	26.210	19.790	10.490	33.540	36.747	29.137	17.529	3929.762	3274.488	1630.383	1148.797	155.705	11.115	141.337
W096	2002	0	25.672	19.378	10.550	32.776	35.314	12.382	17.391	3926.881	3265.429	1638.146	1063.414	72.427	37.807	30.280
W096	2005	0	27.230	19.296	10.485	31.060	37.151	28.094	16.601	3943.254	2974.118	1551.063	891.153	360.963	235.091	124.086
W096	2006	0	27.750	21.307	10.927	32.811	37.423	26.705	16.634	3973.658	3232.916	1668.252	1028.400	88.863	14.483	71.286
W098	2003	0	25.827	20.297	11.430	33.434	33.293	26.490	19.540	4392.706	3175.929	1558.253	1012.600	452.399	257.769	184.866
W098	2004	0	26.467	19.407	11.046	35.970	37.216	30.201	21.042	4763.658	3615.721	1633.815	1379.795	150.703	76.177	57.306
W098	2005	0	26.540	19.620	11.895	30.845	37.205	29.443	21.026	3837.104	2698.367	1356.409	734.277	895.339	517.933	377.109

site ID	year	BTV status	meanlstnsu	meanlstnau	meanlstnpw	meanlstss	meanlstsu	meanlstau	meanlstpw	gdda	gddss	gddsu	gddau	rss	rsu	rau
W098	2006	0	27.911	20.778	12.206	32.899	38.158	27.548	20.781	4397.373	3241.380	1641.676	1028.249	245.011	80.604	135.486
W098	2007	0	24.604	18.538	10.861	33.828	40.429	31.414	19.479	4472.686	3320.960	1556.652	1162.308	211.853	135.590	74.925
W098	2008	0	26.278	19.196	10.158	30.459	34.320	24.599	18.529	4378.461	3155.256	1493.418	1061.622	573.250	500.022	48.237
W099	2003	0	23.871	17.854	8.366	30.550	35.192	25.052	15.728	3351.962	2796.439	1599.654	658.505	301.476	131.083	148.062
W099	2004	0	24.969	17.605	8.233	31.968	34.568	25.369	15.162	3529.063	3016.386	1621.571	954.391	136.823	21.763	80.025
W099	2006	0	26.280	18.871	8.353	31.555	37.234	23.278	13.910	3668.815	3009.939	1625.047	840.625	194.912	113.683	73.034
W099	2007	0	23.103	15.972	7.603	30.974	37.917	26.913	13.741	3441.614	2872.176	1452.243	863.242	270.575	213.667	53.066
W100	2004	0	25.545	18.349	9.121	32.100	36.080	26.726	15.216	3519.022	3075.366	1615.283	983.020	139.396	23.414	103.589
W100	2005	0	26.133	17.052	8.482	28.632	36.493	26.289	14.578	3281.918	2492.095	1371.118	595.314	492.755	263.446	229.251
W101	2002	0	26.400	17.424	9.469	32.506	32.944	11.894	17.663	4183.560	3140.818	1566.656	971.963	347.315	221.262	108.722
W101	2005	0	26.888	18.642	11.331	31.211	36.867	27.087	19.217	3892.362	2804.047	1474.775	728.305	508.860	355.614	152.992
W110	2002	0	24.241	18.246	15.483	31.216	30.715	11.608	20.312	4275.267	3013.842	1452.643	993.679	550.079	366.935	182.329
W112	2002	0	24.210	19.096	10.740	32.531	34.134	12.641	18.175	4035.806	3277.939	1609.797	1121.424	39.148	20.169	18.612
W126	2005	0	25.860	16.081	8.112	28.911	34.856	24.323	15.272	3367.016	2553.952	1445.379	556.010	463.924	333.828	114.549
W127	2005	0	26.737	20.884	12.496	32.171	37.275	29.670	19.511	4464.139	3180.052	1581.075	1035.656	305.204	195.870	109.332
W127	2008	0	27.386	21.467	12.807	32.716	35.767	27.864	20.305	4329.461	3334.401	1578.679	1242.317	258.974	243.374	15.600
W128	2005	0	25.547	20.105	11.780	31.304	36.612	29.523	18.964	4198.186	3063.159	1527.480	1009.234	288.509	163.316	123.971
W128	2007	0	24.349	20.038	11.667	32.870	37.478	29.722	17.793	4107.167	3261.845	1596.427	1076.090	227.377	100.806	125.197
W129	2005	0	24.828	20.143	12.145	31.551	36.526	29.999	19.517	4325.728	3121.284	1516.239	1086.852	299.501	180.601	118.860
W129	2007	0	24.042	20.285	12.201	32.703	36.977	29.987	18.361	4151.362	3252.744	1580.898	1085.539	282.317	156.629	123.166
W133	2000	0	27.823	23.094	13.877	32.674	35.051	29.444	21.087	4359.128	3242.567	1463.517	1194.657	397.091	371.820	25.269
W133	2005	0	28.741	21.864	13.931	32.261	38.167	30.811	20.581	4519.431	3119.432	1540.358	994.025	504.401	286.810	217.591
W133	2006	1	30.339	23.660	14.088	35.317	38.698	29.351	20.639	4811.313	3577.816	1671.984	1314.530	114.920	30.654	79.659
W133	2007	0	27.397	20.828	13.321	34.282	40.532	31.658	19.609	4537.145	3399.007	1627.791	1165.762	269.951	88.155	178.657
W133	2008	0	29.670	23.353	13.649	32.674	35.940	27.337	20.740	4489.004	3316.216	1549.745	1213.970	397.091	371.820	25.269
W154	2008	0	24.859	15.921	7.586	28.747	33.849	21.761	13.955	3015.323	2599.179	1523.816	710.030	269.233	186.272	71.055

APPENDIX E

SUMMARY OF BTV STATUS AND AVERAGE ENVIRONMENTAL CONDITIONS OF NAMP SITES IN THE NORTHERN TERRITORY

site ID	year	BTV status	maxndvissall	maxevissall	smintss	maxlstdss	maxlstdsu	maxlstdau	maxlstdpw	minlstnpw	meanlstdss	Meanlstdsu	meanlstdau	meanlstdpw	meanlstnpw	meanlstpw	rss	rsu	rau
108	2000	1	0.718	0.505	6.630	38.222	34.519	30.651	36.237	12.413	29.116	28.435	28.274	30.560	15.555	23.057	1914.786	1292.955	493.966
108	2001	1	0.726	0.522	7.590	37.498	35.848	33.293	34.247	11.328	30.238	28.880	30.761	30.863	17.022	23.942	1348.896	922.204	243.064
108	2002	1	0.735	0.532	6.542	37.343	31.607	33.471	36.104	12.617	30.635	28.653	31.119	32.416	14.849	23.633	1389.148	1071.307	166.099
108	2003	1	0.747	0.579	7.034	41.303	37.438	31.341	35.718	14.755	28.841	27.632	28.256	33.265	17.199	25.232	1931.793	1164.826	625.092
108	2004	1	0.692	0.531	4.963	35.828	35.320	33.437	34.942	12.099	30.883	30.067	30.655	30.473	15.470	22.971	1229.827	864.744	253.924
108	2005	1	0.734	0.599	8.871	39.691	33.745	29.122	37.433	12.465	27.511	26.405	26.525	33.347	17.106	25.227	2394.810	1103.649	992.777
108	2006	1	0.724	0.529	6.566	35.337	30.832	31.362	35.294	11.757	28.688	27.323	28.288	28.638	14.986	21.812	2356.750	1361.961	927.409
108	2007	1	0.703	0.490	6.456	35.000	34.287	32.365	35.623	10.392	28.921	27.235	29.677	29.767	15.352	22.559	1869.711	1253.317	480.831
108	2008	1	0.716	0.528	7.330	35.387	33.114	32.011	33.122	12.966	29.520	28.899	29.174	31.373	15.847	23.610	1914.786	1292.955	493.966
120	2000	0	0.511	0.315	4.833	41.943	37.601	34.758	34.495	13.060	33.498	33.660	31.186	30.560	16.283	23.422	1067.733	826.484	181.950
120	2001	0	0.506	0.321	4.517	43.071	41.109	38.830	34.562	13.867	35.164	33.818	35.285	31.992	17.582	24.787	949.013	763.153	52.080
120	2002	1	0.458	0.275	2.990	46.143	46.254	38.594	35.258	12.506	38.126	40.289	34.717	30.947	14.695	22.821	979.315	679.797	238.702
120	2003	1	0.511	0.315	4.995	46.327	39.936	35.747	35.939	14.290	33.532	32.228	31.662	31.894	17.138	24.516	1267.427	1017.407	211.246
120	2004	0	0.476	0.332	3.439	44.772	45.062	39.007	35.601	11.931	37.186	37.567	35.176	30.436	15.791	23.113	814.456	571.349	171.949
120	2005	1	0.492	0.316	4.977	44.304	41.090	35.984	37.130	13.392	33.172	34.733	28.879	32.076	17.197	24.637	1238.218	584.440	558.969
120	2006	1	0.453	0.285	3.050	47.140	47.280	39.434	36.152	13.537	35.826	37.206	32.324	28.838	15.575	22.206	526.139	258.323	224.023
120	2007	1	0.444	0.280	3.115	47.176	41.453	38.369	35.563	11.235	35.647	34.347	33.967	29.384	15.278	22.331	916.416	845.369	22.211
120	2008	1	0.511	0.324	4.745	44.179	40.707	37.903	34.250	14.154	33.397	30.377	33.964	30.848	16.420	23.634	1067.733	826.484	181.950
165	2003	1	0.465	0.318	2.937	49.238	48.681	42.158	37.069	9.717	36.233	34.340	34.439	31.731	13.084	22.407	582.026	480.616	69.924
165	2004	0	0.342	0.238	2.275	47.354	51.866	44.837	36.199	8.079	37.114	36.908	35.084	30.700	11.913	21.307	362.199	320.439	14.597
165	2005	1	0.480	0.328	5.638	45.992	52.118	39.427	34.566	9.842	32.450	36.234	25.766	30.687	13.658	22.172	658.379	273.582	325.499
165	2006	1	0.417	0.287	2.484	42.819	49.290	43.293	36.159	9.121	34.031	34.439	31.365	27.243	11.324	19.283	217.761	119.996	93.066
165	2007	0	0.268	0.189	1.349	54.463	51.673	44.087	34.436	6.708	42.761	45.279	38.560	26.933	10.520	18.727	243.188	216.866	4.247
165	2008	1	0.548	0.392	4.419	52.900	51.935	39.598	34.666	9.796	37.043	36.020	34.141	30.444	12.725	21.584	996.418	777.243	130.895
179	2000	0	0.468	0.294	3.283	50.228	50.228	42.877	27.497	1.412	36.603	42.065	30.107	22.907	5.353	14.130	512.298	312.957	156.203
179	2001	0	0.391	0.249	2.707	45.494	45.494	40.196	26.821	4.502	36.233	37.959	34.019	21.481	6.323	13.902	416.340	304.319	7.290
179	2002	0	0.324	0.223	1.352	48.942	48.942	41.250	30.164	-0.556	39.442	43.904	34.393	24.659	3.161	13.910	347.994	111.088	16.861
179	2003	0	0.258	0.160	2.058	54.770	54.770	46.467	29.221	1.693	41.829	46.657	35.886	24.657	5.551	15.104	320.989	118.280	182.617
179	2004	0	0.180	0.109	0.551	53.783	52.121	47.012	33.017	2.823	44.373	49.522	38.196	23.393	6.912	15.152	42.847	36.849	0.332
179	2005	0	0.251	0.158	0.000	52.340	52.340	45.353	29.289	2.465	41.719	47.498	34.874	22.625	6.314	14.469	149.411	84.332	38.437
179	2006	0	0.269	0.183	1.465	55.649	52.150	48.163	34.792	1.743	42.534	46.674	36.068	24.052	4.555	14.303	149.981	78.949	55.538

site ID	year	BTV status	maxndvissall	maxevissall	smintss	maxlstdss	maxlstdsu	maxlstdau	maxlstdpw	minlstnpw	meanlstdss	meanlstdsu	meanlstdau	meanlstdpw	meanlstnpw	meanlstpw	rss	rsu	rau
179	2007	0	0.180	0.114	0.240	53.199	53.052	45.700	31.541	0.944	42.432	48.130	36.710	23.729	4.611	14.170	60.884	48.359	0.000
179	2008	0	0.311	0.219	1.620	50.869	49.172	46.019	28.182	2.603	40.518	44.230	36.245	23.416	4.749	14.082	512.298	312.957	156.203
190	2000	1	0.671	0.485	0.000	40.849	32.046	34.082	37.438	14.516	30.555	29.603	29.691	32.348	17.467	24.907	1860.855	1250.943	492.642
190	2001	1	0.692	0.514	0.000	39.189	33.525	34.225	34.094	15.613	30.534	29.087	30.946	32.138	18.474	25.306	1361.753	852.163	259.731
190	2002	1	0.697	0.525	0.000	37.326	33.638	34.609	36.887	14.252	31.255	28.559	32.565	32.652	16.840	24.746	1583.739	1189.864	221.738
190	2003	1	0.703	0.536	0.000	39.859	32.696	33.804	36.588	16.316	29.910	28.644	29.839	34.195	19.178	26.686	1990.178	1264.732	581.404
190	2004	1	0.677	0.518	0.000	40.442	32.889	34.387	35.691	13.734	30.679	28.467	31.523	31.549	17.408	24.479	1374.235	907.622	350.094
190	2005	1	0.713	0.550	0.000	38.332	33.960	31.640	37.842	14.704	29.089	28.604	27.673	32.892	19.061	25.977	2273.058	1027.450	885.539
190	2006	1	0.684	0.524	0.000	36.645	32.804	34.879	36.439	13.513	30.713	30.041	30.208	30.603	16.184	23.394	1932.067	1012.638	852.109
190	2007	1	0.668	0.492	0.000	35.034	32.079	34.526	37.055	13.856	30.497	28.881	31.250	31.478	17.517	24.497	1890.273	1323.720	428.018
190	2008	1	0.680	0.495	0.000	34.663	34.309	34.488	35.404	15.682	25.799	18.496	31.425	33.102	17.616	25.359	1860.855	1250.943	492.642
194	2002	1	0.339	0.206	2.830	51.525	51.569	40.607	35.728	9.338	39.935	42.171	35.511	30.924	11.920	21.422	703.320	595.468	84.178
194	2003	1	0.374	0.228	4.771	48.423	42.648	39.921	34.339	10.128	37.189	35.219	35.810	30.069	13.650	21.860	730.048	605.793	114.203
194	2004	0	0.230	0.140	0.612	54.024	54.202	48.048	34.314	8.309	44.943	47.452	40.984	28.900	12.760	20.830	320.284	227.674	45.791
194	2006	1	0.332	0.205	2.596	47.580	47.716	42.487	35.441	10.085	39.288	41.109	35.377	27.503	12.226	19.865	367.075	145.775	194.160
195	2000	0	0.587	0.402	6.905	42.049	43.104	34.841	32.835	7.701	30.425	31.519	28.243	27.897	10.761	19.329	761.622	584.304	99.146
195	2001	0	0.484	0.327	2.403	40.485	47.513	42.023	32.447	8.275	33.656	35.804	31.212	29.794	12.740	21.267	286.350	247.478	11.727
195	2002	0	0.539	0.371	3.423	44.183	53.744	39.489	34.925	7.185	32.926	35.277	28.254	30.433	9.854	20.144	520.364	458.918	49.844
195	2003	0	0.487	0.327	4.360	41.771	46.772	39.983	34.971	8.671	30.847	29.895	28.741	30.442	12.534	21.488	576.695	481.008	73.568
195	2004	0	0.342	0.238	1.518	41.226	51.181	45.015	35.521	7.406	33.311	33.868	31.304	29.572	11.739	20.655	355.891	292.731	26.798
195	2006	0	0.414	0.273	2.620	38.321	48.179	42.795	36.224	8.943	31.153	31.921	28.609	26.833	10.882	18.858	237.394	121.444	108.926
196	2003	1	0.337	0.202	3.156	48.266	46.109	42.285	34.878	10.368	38.477	37.253	36.733	29.561	13.605	21.583	508.775	394.934	100.465
196	2006	1	0.309	0.185	2.031	49.293	48.803	42.042	35.237	10.419	40.004	41.967	36.076	27.133	12.410	19.772	196.049	93.802	84.324
196	2008	1	0.293	0.182	2.719	51.295	50.948	43.731	33.696	10.350	40.497	41.533	36.927	28.915	12.658	20.786	854.063	539.149	224.367
198	2002	1	0.546	0.384	3.266	42.742	53.191	41.431	36.069	8.192	32.208	33.346	28.652	31.151	10.687	20.919	497.744	416.542	69.444
198	2003	1	0.548	0.381	5.243	41.244	47.777	39.068	36.490	9.553	28.942	27.692	26.526	31.748	13.510	22.629	646.967	544.277	75.390
198	2005	1	0.546	0.384	6.579	40.026	52.340	36.734	35.649	10.197	27.648	30.872	21.972	31.670	14.019	22.845	658.430	337.553	279.060
198	2008	1	0.515	0.377	4.744	53.364	52.535	39.180	35.065	9.748	35.926	34.952	33.907	31.054	12.747	21.900	904.935	705.079	117.616
202	2002	0	0.342	0.238	1.701	50.850	54.330	44.292	34.573	6.068	39.433	41.657	34.706	30.409	9.212	19.810	337.135	295.543	14.503
202	2003	1	0.385	0.278	2.163	50.320	52.698	43.858	36.863	7.234	27.283	25.997	21.870	31.112	11.393	21.252	468.854	400.640	37.056
204	2003	1	0.332	0.225	1.916	47.892	48.343	43.726	34.998	9.327	33.871	32.752	30.903	29.271	12.731	21.001	471.139	404.208	43.699

site ID	year	BTV status	maxndvissall	maxevissall	smintss	maxlstdss	maxlstdsu	maxlstdau	maxlstdpw	minlstnpw	meanlstdss	meanlstdsu	meanlstdau	meanlstdpw	meanlstnpw	meanlstpw	rss	rsu	rau
204	2008	1	0.440	0.317	3.827	52.509	52.096	41.835	33.220	9.090	38.320	37.798	35.473	28.733	11.928	20.331	799.419	571.660	139.596
220	2003	0	0.305	0.185	2.428	49.773	48.159	43.123	34.633	8.970	40.005	39.586	37.537	29.617	12.575	21.096	477.333	375.883	89.070
220	2004	0	0.207	0.126	0.077	52.554	52.805	47.261	34.881	8.613	44.138	47.020	40.124	28.676	12.458	20.567	272.441	160.280	61.743
220	2007	0	0.233	0.144	0.558	51.701	50.447	45.815	33.667	8.584	42.330	44.388	39.201	26.326	11.011	18.668	189.916	167.728	9.684
220	2008	1	0.279	0.171	2.077	51.224	50.597	44.617	33.442	9.779	41.318	43.027	37.603	28.118	12.070	20.094	763.631	450.441	228.382
221	2002	1	0.476	0.292	4.226	49.866	50.943	36.296	35.863	10.299	36.878	38.870	32.294	30.818	12.873	21.846	843.657	662.705	159.027
221	2008	1	0.484	0.299	4.948	47.838	45.915	37.546	33.521	11.566	35.182	34.352	32.946	29.589	14.210	21.899	1107.934	804.284	209.650
225	2001	1	0.465	0.290	3.861	44.961	44.140	39.422	35.130	12.955	36.399	36.315	35.207	32.014	16.589	24.302	669.297	581.708	63.117
225	2006	1	0.480	0.308	4.118	46.745	44.399	36.426	35.916	13.507	35.620	36.731	31.750	28.918	15.538	22.228	733.228	486.086	227.639
A97	2002	1	0.489	0.335	2.966	47.922	53.209	41.115	34.840	8.059	36.353	38.732	31.468	30.123	10.525	20.324	446.940	389.090	42.493
E19	2000	0	0.527	0.336	5.932	44.061	38.809	36.700	36.601	11.407	34.559	34.722	32.304	31.718	14.841	23.280	1135.096	848.951	221.827
E19	2001	1	0.545	0.354	5.349	45.774	41.652	40.599	35.601	12.714	36.338	34.426	36.472	32.487	17.049	24.768	851.128	695.446	24.100
E19	2002	1	0.465	0.281	3.132	49.372	49.801	39.352	36.407	11.031	39.270	41.819	35.146	31.902	13.403	22.652	891.124	624.598	222.738
E19	2003	0	0.548	0.355	5.564	48.737	42.665	36.776	36.932	12.959	34.499	32.572	32.492	33.098	16.149	24.624	1182.996	989.136	162.604
E19	2004	0	0.469	0.292	3.551	49.058	49.583	41.280	36.650	10.269	39.232	40.691	36.172	31.628	14.994	23.311	700.681	459.259	195.511
E19	2005	0	0.532	0.346	5.938	46.630	44.071	35.382	37.372	11.836	34.263	35.926	29.572	32.520	16.427	24.474	1058.635	552.914	420.595
E19	2007	1	0.493	0.308	3.859	50.495	45.778	39.159	35.947	10.078	37.801	37.541	35.030	30.243	13.780	22.011	790.953	710.933	33.206
E19	2008	1	0.538	0.350	4.875	47.577	45.077	38.874	35.556	12.772	35.988	33.719	35.054	31.790	15.058	23.424	1135.096	848.951	221.827
T016	2000	1	0.676	0.472	7.250	40.585	32.792	33.795	36.797	11.771	29.926	28.364	29.047	32.356	14.372	23.364	1679.193	1200.797	391.275
T016	2001	1	0.682	0.467	7.389	41.051	33.706	36.823	36.207	11.369	31.611	29.221	32.976	32.994	15.790	24.392	1210.663	946.612	90.984
T016	2002	1	0.700	0.504	6.462	42.533	40.446	34.886	39.076	10.903	33.090	32.138	32.457	34.033	13.351	23.692	1105.043	767.286	228.507
T016	2003	1	0.718	0.535	8.001	45.396	34.357	33.577	37.318	13.161	31.348	29.050	30.088	33.368	16.465	24.916	1774.483	1314.536	385.799
T016	2004	1	0.701	0.507	6.775	41.677	41.677	35.427	35.808	10.720	33.412	33.641	32.595	31.754	14.225	22.989	1203.970	860.647	215.116
T016	2005	1	0.714	0.542	9.998	33.871	31.588	29.176	37.320	11.527	27.475	27.296	26.314	33.276	16.473	24.874	1936.883	1045.712	686.629
T016	2006	1	0.707	0.528	7.211	41.762	33.477	32.929	36.760	10.532	30.685	29.601	28.906	30.150	13.587	21.869	1267.827	615.690	585.094
T016	2007	1	0.695	0.515	7.347	38.894	36.505	32.999	35.617	9.252	31.293	30.438	30.866	30.535	13.077	21.806	1943.150	1376.173	467.076
T016	2008	1	0.713	0.522	7.742	39.191	31.827	34.352	34.885	11.736	30.413	27.479	31.250	31.747	14.578	23.163	1679.193	1200.797	391.275
T017	2000	1	0.646	0.437	7.381	41.484	33.634	33.519	37.160	10.344	31.098	29.652	29.814	31.542	14.534	23.038	1483.928	1014.791	408.130
T017	2001	1	0.656	0.467	6.422	41.935	36.109	37.654	35.619	11.514	32.923	30.981	33.969	32.742	16.485	24.613	1226.243	860.645	76.260
T017	2002	1	0.684	0.484	6.040	44.413	40.324	36.383	36.966	10.915	35.066	34.383	33.398	32.548	13.328	22.938	1216.580	805.427	275.403
T017	2003	1	0.645	0.416	6.356	46.273	36.082	33.902	36.093	13.431	32.710	30.246	31.025	32.833	16.434	24.633	1928.084	1438.182	438.080

site ID	year	BTV status	maxndvissall	maxevissall	smintss	maxlstdss	maxlstdsu	maxlstdau	maxlstdpw	minlstnpw	meanlstdss	meanlstdsu	meanlstdau	meanlstdpw	meanlstnpw	meanlstpw	rss	rsu	rau
T017	2004	1	0.642	0.439	6.107	41.464	40.112	36.210	35.591	11.421	33.968	32.826	33.372	31.114	14.594	22.854	988.763	642.599	235.639
T017	2005	1	0.689	0.510	8.511	39.107	34.898	33.050	37.622	12.464	30.066	30.353	27.909	33.368	16.605	24.987	1627.014	860.172	618.268
T017	2006	1	0.681	0.493	6.598	44.767	38.182	35.037	36.974	11.413	33.265	32.316	30.839	29.824	14.098	21.961	792.063	411.178	351.906
T017	2007	1	0.658	0.458	6.572	43.676	36.697	36.457	34.527	8.428	33.523	32.174	32.540	31.015	13.632	22.323	1081.684	886.600	140.599
T017	2008	1	0.641	0.454	5.663	44.273	42.539	36.402	35.188	11.002	33.206	30.194	33.367	31.814	14.881	23.347	1483.928	1014.791	408.130
T021	2000	0	0.446	0.257	4.284	46.864	43.724	35.180	35.113	10.009	35.834	37.312	32.038	29.692	12.904	21.298	1324.398	887.665	365.435
T021	2004	0	0.343	0.192	1.791	52.668	52.950	44.874	35.762	9.150	41.769	44.309	38.086	30.234	13.749	21.992	456.392	266.920	175.894
T021	2006	0	0.384	0.219	3.161	50.967	49.908	42.944	37.338	10.150	39.863	42.463	34.597	28.478	12.170	20.324	269.041	124.785	140.319
T021	2007	1	0.380	0.221	2.195	52.099	47.954	42.438	34.035	7.492	40.201	40.535	38.141	27.795	12.292	20.043	385.485	300.474	17.230
T021	2008	0	0.396	0.239	3.493	49.678	48.143	43.015	34.937	11.075	39.329	38.944	37.400	30.041	13.442	21.741	1324.398	887.665	365.435
T029	2000	0	0.503	0.333	6.259	42.182	42.249	33.279	33.936	8.690	32.035	34.471	28.039	28.960	12.209	20.584	1019.658	735.775	177.982
T029	2001	0	0.421	0.272	1.918	43.054	47.990	45.012	31.750	9.602	36.497	37.661	34.861	29.027	14.109	21.568	338.557	302.448	1.895
T029	2002	0	0.501	0.344	3.807	47.586	53.755	37.965	36.165	8.471	35.244	37.915	30.009	31.164	11.022	21.093	714.500	640.341	56.330
T029	2004	0	0.271	0.178	0.619	45.866	52.731	46.428	34.443	7.671	37.597	39.262	34.964	28.730	12.408	20.569	363.368	268.125	46.145
T029	2006	0	0.449	0.295	3.529	40.595	47.635	40.612	36.149	9.554	32.845	34.062	29.516	27.283	11.812	19.547	355.560	160.365	179.740
T029	2007	0	0.261	0.177	0.878	52.496	50.483	45.163	34.875	8.008	42.603	44.764	39.202	27.477	11.829	19.653	397.576	302.462	67.836
T032	2000	1	0.553	0.319	7.158	40.206	37.620	33.131	35.126	9.543	31.535	32.237	28.659	29.946	14.081	22.014	1146.101	879.081	174.839
T032	2001	1	0.514	0.300	3.739	45.949	44.327	41.835	33.123	11.634	37.298	37.182	36.144	29.791	15.904	22.847	530.966	431.818	23.577
T032	2002	1	0.559	0.327	5.043	50.595	50.916	35.540	35.906	10.469	37.258	40.068	32.431	31.193	13.042	22.118	887.193	718.459	149.271
T033	2000	0	0.459	0.309	4.521	45.362	46.717	43.199	33.403	7.228	35.323	36.063	33.432	29.003	10.570	19.787	611.822	443.349	62.954
T033	2002	0	0.367	0.243	1.908	50.831	53.072	43.074	33.301	7.453	40.188	43.525	34.612	28.428	9.930	19.179	289.948	249.208	13.889
T033	2003	1	0.202	0.135	0.651	50.281	52.101	46.208	34.385	7.930	39.380	41.296	35.005	28.872	11.722	20.297	351.545	312.735	17.839
T034	2003	1	0.423	0.261	4.523	50.087	48.104	39.681	36.870	10.802	36.746	35.034	34.907	32.403	14.013	23.208	913.350	780.165	98.533
T034	2007	0	0.342	0.211	1.802	52.429	49.300	44.808	35.402	9.560	41.947	42.561	39.577	28.965	12.547	20.756	343.856	254.180	40.815
T036	2000	0	0.437	0.247	4.105	47.345	45.798	34.330	35.469	8.302	34.903	37.792	29.302	29.415	11.499	20.457	1144.245	774.676	281.930
T036	2002	0	0.377	0.217	2.588	49.385	52.916	43.460	36.142	8.299	38.855	41.968	34.272	30.653	10.771	20.712	427.960	315.886	78.070
T036	2007	0	0.333	0.199	1.696	52.510	49.799	43.649	34.273	9.501	41.331	41.855	39.198	27.456	12.027	19.742	252.521	193.620	10.168
T036	2008	0	0.339	0.205	2.542	49.909	49.179	45.147	34.496	9.605	40.643	40.322	38.732	29.257	12.121	20.689	1144.245	774.676	281.930
T037	2000	0	0.535	0.355	5.987	44.454	44.371	35.094	32.800	8.259	33.074	34.854	29.759	27.977	11.324	19.651	851.409	595.638	155.469
T037	2001	0	0.436	0.278	2.263	44.721	47.334	43.677	31.835	8.838	37.550	39.086	35.645	29.215	13.160	21.188	347.104	299.265	9.473
T037	2002	1	0.505	0.337	3.748	49.187	53.034	38.216	34.891	7.623	36.945	39.864	31.472	30.544	10.305	20.425	586.016	530.217	37.374

site ID	year	BTV status	maxndvissall	maxevissall	smintss	maxlstdss	maxlstdsu	maxlstdau	maxlstdpw	minlstnpw	meanlstdss	meanlstdsu	meanlstdau	meanlstdpw	meanlstnpw	meanlstpw	rss	rsu	rau
T037	2003	1	0.421	0.271	3.281	46.542	45.109	40.938	34.519	9.076	35.722	34.358	33.987	30.004	12.597	21.301	600.775	502.756	80.534
T037	2004	0	0.313	0.214	1.392	47.641	51.721	45.238	35.942	8.049	38.809	39.780	36.278	30.042	12.243	21.142	345.540	276.131	30.042
T037	2008	1	0.485	0.352	4.202	52.127	50.585	41.852	34.134	9.637	38.226	37.254	35.613	30.320	11.984	21.152	851.409	595.638	155.469
T038	2001	1	0.462	0.298	3.324	50.525	50.977	41.505	32.910	10.793	39.551	41.196	36.601	30.225	14.455	22.340	343.657	309.705	5.096
T039	2001	1	0.480	0.307	2.287	48.776	49.488	42.792	32.496	9.635	39.173	40.574	37.208	29.808	13.895	21.852	383.991	351.327	6.717
T040	2001	1	0.421	0.256	3.335	49.224	48.611	41.053	33.501	11.704	39.007	39.364	37.119	30.481	15.470	22.975	454.156	383.305	36.873
T040	2004	1	0.326	0.206	2.388	52.761	50.375	43.026	34.366	10.113	39.922	39.281	37.321	29.893	14.015	21.954	482.735	405.375	37.605
T041	2001	1	0.519	0.313	3.491	47.895	46.151	40.327	36.865	13.169	38.055	38.223	36.433	33.310	16.473	24.892	574.035	474.010	25.689
T042	2001	1	0.423	0.257	3.244	46.103	44.763	42.644	35.750	13.268	38.490	37.239	38.696	32.575	17.680	25.127	703.304	595.944	25.904
T042	2007	0	0.394	0.238	2.721	51.552	47.554	41.217	35.983	11.299	39.274	39.157	37.417	29.997	14.572	22.285	568.300	511.215	32.609
T042	2008	1	0.424	0.265	3.532	47.927	44.567	41.549	36.211	12.885	38.365	36.918	37.122	31.882	15.365	23.624	1228.965	827.169	356.669
T043	2001	0	0.465	0.296	4.212	44.565	41.860	40.662	34.718	14.425	36.548	34.895	36.887	31.741	18.493	25.117	820.646	677.248	14.072
T043	2007	1	0.455	0.281	3.091	49.616	42.144	38.870	35.090	11.047	36.434	35.158	34.702	29.386	15.224	22.305	750.071	680.087	23.470
T043	2008	1	0.473	0.295	3.799	46.445	44.268	39.389	33.963	14.265	35.915	34.053	34.747	30.621	16.187	23.404	1120.104	840.032	220.978
T044	2002	0	0.436	0.250	2.501	51.360	51.742	42.105	36.529	9.077	40.491	43.261	35.844	30.862	11.344	21.103	487.072	361.657	91.806
T044	2003	0	0.485	0.291	5.689	49.075	43.837	37.461	35.647	10.800	34.661	32.904	32.859	32.070	14.036	23.053	960.133	803.580	104.251
T044	2004	0	0.353	0.194	1.850	52.042	52.704	45.180	35.081	8.526	42.055	44.852	38.170	29.540	13.276	21.408	407.989	249.314	145.882
T044	2008	1	0.421	0.256	3.475	49.118	47.705	43.155	35.201	10.647	39.039	38.115	37.531	30.205	13.052	21.628	1247.997	855.984	323.664
T045	2006	1	0.494	0.303	3.520	45.439	42.889	38.375	34.990	11.488	36.295	37.346	32.743	27.277	13.909	20.593	483.590	346.604	124.722
T046	2002	0	0.406	0.240	2.432	51.754	51.674	42.193	36.251	7.702	40.591	43.741	36.027	30.740	10.241	20.490	469.740	312.348	115.445
T046	2006	0	0.428	0.246	3.635	51.102	49.884	42.738	37.596	8.913	39.293	42.657	33.445	28.600	11.413	20.006	257.566	95.440	155.178
T046	2007	0	0.447	0.269	3.552	50.459	46.432	39.555	34.260	8.829	38.519	39.493	35.772	27.875	11.763	19.819	356.655	306.793	15.881
T046	2008	0	0.434	0.270	3.029	48.179	47.077	43.183	34.620	9.604	39.110	38.220	37.531	29.769	12.144	20.957	1142.752	773.982	319.710
T047	2002	1	0.397	0.235	2.370	48.838	48.911	40.927	37.247	11.419	39.319	41.876	35.512	31.748	13.526	22.637	678.112	475.310	160.207
T047	2003	0	0.470	0.287	4.575	48.074	42.569	37.893	35.754	13.011	35.521	34.254	33.521	32.231	15.986	24.108	1170.214	954.460	164.605
T047	2004	0	0.368	0.217	2.304	49.055	49.053	41.679	35.979	10.887	39.864	41.419	36.972	30.783	15.303	23.043	604.981	369.435	205.615
T047	2007	0	0.416	0.249	3.148	49.980	46.628	39.935	35.312	9.709	38.161	38.330	35.966	29.044	14.045	21.545	562.925	483.118	27.370
T047	2008	0	0.430	0.265	3.994	46.984	43.631	40.569	34.650	12.503	36.969	35.455	35.859	30.270	14.824	22.547	1261.847	886.911	328.881
T048	2002	1	0.384	0.236	3.079	52.428	52.047	41.576	35.835	9.362	41.817	44.897	36.790	30.895	11.758	21.326	683.266	510.991	137.296
T048	2008	0	0.381	0.242	3.679	51.692	49.623	43.038	35.720	11.242	40.130	39.738	37.527	30.952	13.511	22.231	1270.907	793.023	402.598
T049	2002	1	0.573	0.396	3.782	34.128	52.947	39.446	36.120	7.315	25.351	26.227	22.552	30.842	10.105	20.473	666.015	602.150	52.971

site ID	year	BTV status	maxndvissall	maxevissall	smintss	maxlstdss	maxlstdsu	maxlstdau	maxlstdpw	minlstnpw	meanlstdss	meanlstdsu	meanlstdau	meanlstdpw	meanlstnpw	meanlstpw	rss	rsu	rau
T049	2003	1	0.554	0.371	5.934	31.818	44.190	36.948	35.493	8.712	22.926	21.875	21.284	30.893	12.930	21.911	736.935	619.352	92.001
T050	2002	1	0.538	0.369	3.375	44.893	53.531	40.796	37.070	9.207	33.525	34.431	30.159	31.957	11.857	21.907	558.302	493.363	56.594
T051	2002	1	0.389	0.270	2.256	51.874	53.778	42.720	34.714	8.051	39.811	41.816	35.018	30.313	10.786	20.550	364.092	315.500	14.666
T051	2003	1	0.335	0.240	1.856	50.311	49.835	44.148	36.228	9.209	33.474	32.257	29.799	30.232	12.729	21.480	491.023	406.485	56.317
T051	2004	0	0.244	0.183	1.136	39.790	51.249	46.962	36.169	7.853	29.182	29.306	26.143	30.045	11.607	20.826	264.036	220.583	21.073
T051	2007	0	0.168	0.124	0.365	53.875	52.499	46.016	33.682	7.605	43.724	47.054	39.213	25.522	10.517	18.019	152.481	119.262	1.395
T054	2003	1	0.293	0.178	2.168	50.869	49.762	42.144	34.101	8.963	40.249	40.840	36.762	29.427	12.404	20.915	428.514	365.954	32.983
T054	2007	0	0.231	0.144	0.358	51.291	50.156	45.575	32.893	8.597	41.919	44.833	38.310	25.209	10.718	17.963	183.818	134.298	8.860
T057	2005	1	0.558	0.363	6.720	45.584	42.348	34.626	37.680	11.185	33.122	34.693	28.558	32.906	16.208	24.557	1117.060	593.139	421.821
T057	2007	1	0.517	0.328	4.619	50.431	42.250	38.223	36.008	10.325	36.307	34.677	34.341	30.462	13.641	22.052	854.496	772.343	33.309
T058	2006	1	0.472	0.303	3.838	47.652	45.279	39.298	38.521	14.306	37.427	39.115	33.447	31.083	16.467	23.775	557.800	276.558	243.909
T058	2007	1	0.484	0.303	4.145	47.072	42.681	38.221	36.222	11.941	36.211	35.403	34.789	30.416	15.686	23.051	825.334	714.452	54.348
T059	2006	1	0.512	0.319	3.797	46.314	43.763	37.971	34.810	11.030	36.192	37.616	32.453	27.581	13.278	20.430	420.730	173.919	223.854
T059	2007	1	0.565	0.358	4.894	49.976	41.646	36.457	35.808	8.424	34.808	33.204	32.686	29.400	13.271	21.336	805.410	714.106	49.946
T060	2007	0	0.294	0.174	1.516	51.706	49.893	43.534	33.956	8.863	41.321	42.518	38.636	27.204	11.268	19.236	245.456	139.091	14.566
T060	2008	0	0.298	0.179	2.207	50.442	48.084	45.513	34.053	8.679	41.363	41.876	38.831	28.270	11.242	19.756	1036.150	736.351	190.109
T063	2007	1	0.388	0.230	2.398	50.137	46.358	41.201	34.456	9.488	38.762	38.891	36.707	28.233	13.518	20.875	429.347	330.344	26.536
T064	2007	1	0.518	0.332	3.907	52.755	49.591	38.840	36.526	10.554	38.387	38.401	34.702	30.749	13.394	22.072	859.873	779.999	43.103
T064	2008	1	0.565	0.375	4.431	50.784	49.846	40.395	36.334	12.256	37.699	36.111	35.926	32.391	14.353	23.372	1096.806	798.890	242.210
T065	2007	1	0.458	0.292	3.273	52.286	46.348	39.831	35.542	9.982	39.297	39.465	35.912	29.989	13.905	21.947	574.344	490.528	47.550
T065	2008	1	0.480	0.311	4.303	48.923	46.955	40.827	36.167	12.962	38.151	37.106	36.413	31.931	15.302	23.617	1229.697	846.289	323.627
T066	2007	1	0.481	0.294	3.093	51.964	45.021	39.163	34.132	10.307	37.678	37.172	34.970	28.729	14.445	21.587	716.272	655.112	32.284
T066	2008	1	0.524	0.335	4.336	46.187	43.303	39.454	34.541	14.198	35.439	33.311	35.105	30.935	16.291	23.613	1140.661	834.634	220.833
T067	2007	1	0.468	0.288	3.518	47.658	42.699	38.868	37.053	10.535	36.652	35.583	35.155	30.708	15.352	23.030	765.244	687.529	26.698
T067	2008	1	0.505	0.318	4.585	46.383	37.445	38.823	36.229	13.994	34.140	30.241	35.422	33.399	16.710	25.054	1217.914	920.673	263.604
T068	2007	0	0.421	0.254	3.474	50.559	45.914	39.505	34.745	9.777	38.242	38.713	35.912	28.625	12.967	20.796	461.177	385.189	22.618
T068	2008	0	0.426	0.262	3.391	47.337	45.425	42.294	34.947	10.929	38.189	36.702	37.194	30.235	13.308	21.772	1121.559	737.124	335.154
T070	2007	0	0.495	0.312	4.263	50.157	44.950	39.805	37.058	11.856	37.910	37.338	35.821	30.912	15.091	23.002	738.140	646.731	43.188
T070	2008	1	0.507	0.327	4.942	48.230	43.108	39.650	36.436	13.456	36.975	34.779	36.078	32.628	15.879	24.253	1170.693	790.145	342.802
T071	2007	0	0.214	0.130	0.523	52.021	50.265	44.782	31.493	7.017	42.271	46.146	37.438	24.172	9.044	16.608	110.587	87.440	2.101
T071	2008	0	0.232	0.140	1.259	51.271	51.136	46.207	31.049	7.614	41.487	43.973	37.326	25.310	9.869	17.590	822.777	580.400	168.698

site ID	year	BTV status	maxndvissall	maxevissall	smintss	maxlstdss	maxlstdsu	maxlstdau	maxlstdpw	minlstnpw	meanlstdss	meanlstdsu	meanlstdau	meanlstdpw	meanlstnpw	meanlstpw	rss	rsu	rau
T072	2007	1	0.238	0.144	0.932	52.164	51.444	45.770	33.519	8.269	42.773	44.910	39.411	26.593	10.537	18.565	186.808	166.848	12.305
T073	2007	1	0.484	0.293	3.760	50.816	44.199	38.102	33.916	10.135	37.052	36.991	34.195	28.006	13.386	20.696	584.077	495.009	61.152
T073	2008	1	0.510	0.319	5.218	46.649	44.647	38.518	33.768	12.111	35.537	34.645	34.016	29.855	14.511	22.183	1220.799	861.244	276.743
T074	2007	1	0.468	0.284	4.212	49.945	43.159	37.937	34.148	8.251	36.397	35.856	34.021	28.124	12.915	20.520	668.793	547.317	79.252
T074	2008	1	0.474	0.298	5.128	48.520	47.487	38.993	32.606	11.261	35.949	35.474	33.919	28.954	13.947	21.451	1133.852	810.350	230.973
T075	2007	1	0.527	0.317	5.021	52.756	47.208	37.162	34.313	7.187	36.225	35.489	33.430	28.264	12.850	20.557	742.835	673.838	38.172
T076	2007	0	0.390	0.245	2.918	48.858	43.809	39.738	36.412	9.984	37.143	35.859	35.704	30.439	15.882	23.160	808.498	740.273	28.280
T078	2007	0	0.427	0.259	3.479	50.013	47.163	39.727	36.804	11.753	38.706	38.815	36.391	30.495	15.820	23.158	720.064	637.243	35.901
T078	2008	1	0.460	0.291	4.337	47.737	42.988	40.105	36.045	14.381	37.121	34.945	36.347	32.290	16.769	24.529	1163.803	794.957	328.286
T080	2008	1	0.745	0.512	10.806	39.199	30.712	31.687	30.026	16.571	27.757	26.018	26.839	25.817	18.833	22.325	1694.567	903.100	692.240
T082	2008	1	0.254	0.154	1.386	49.304	48.925	45.069	31.546	8.673	40.267	42.062	36.816	25.751	11.041	18.396	848.884	568.147	197.289
T083	2008	0	0.584	0.368	5.716	44.611	41.163	36.297	32.627	12.669	32.664	29.899	32.560	29.269	15.115	22.192	1198.832	860.888	249.907
T086	2008	0	0.240	0.134	1.635	51.178	50.763	47.074	32.992	7.122	43.418	45.988	39.536	27.928	9.952	18.940	849.545	503.389	235.560
T087	2008	1	0.242	0.154	1.170	53.883	53.877	46.616	29.679	6.629	42.114	45.386	37.928	25.211	9.058	17.135	631.167	420.357	135.344