School of Earth and Planetary Sciences

Classification and use of landform information

to increase the accuracy of land condition monitoring

in Western Australian pastoral rangelands

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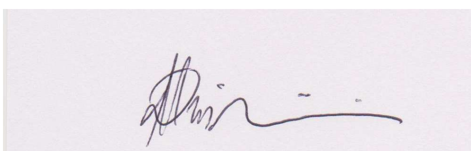
Declaration

To the best of my knowledge and belief, this thesis contains no material previously published or written by another person, except where due reference has been made.

I would like to acknowledge the traditional land owners and custodians of the Perth area and the East Kimberley Region in Western Australia, and to advise that this thesis may contain images and names of deceased Aboriginal people.

This thesis contains no material which has been accepted for the award of any other degree or diploma in any university and is less than 100,000 words in length excluding footnotes, bibliography and appendices.



Student signature

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Abstract

Rangeland monitoring in Western Australia (WA) was initiated in the 1950's and was influenced by the theory and practices of condition assessment in the United States of America (USA) during the 1930's and 40's. There has been steady progress in both monitoring philosophy and techniques since this time trending towards geographic information systems (GIS), spatial sciences and remote sensing. Examples of pastoral monitoring of rangelands in WA include projects such as Pastoral Lease Assessment using Geospatial Analysis (PLAGA).

The PLAGA project was designed to assess pastoral lease degradation in WA in conjunction with the Department of Food and Agriculture (DAFWA) with the aim of identifying areas in poor landscape condition and to provide an early warning system by highlighting areas trending towards poor condition. The soil-landscape hierarchy of WA is comprised of 6 levels. PLAGA currently provides quality assurance at the land system level, level 4.

A land system is defined in mapping terms as a regional unit with landscape criteria consisting of relief/modal slope class, landform pattern and generic type of soil parent material. The next level in the soil-landscape hierarchy is a land unit, level 5, a local unit with landscape criteria consisting of landform element and morphological type. The aim of this research was to develop landscape data at a land unit level in order to improve the performance of methods such as PLAGA.

Landforms are a major component of the landscape description of land units. Landform mapping in the WA rangelands was found to be limited, with existing landscape variables consisting of vegetation and geology. Methods were explored using LandSerf software to include landforms as a landscape variable to be used in land unit predictive modelling.

To develop land unit scale data, predictive models and methods were tested using the landscape variables. The models tested were a Binary Weighted Overlay (BWO), a Fuzzy Weighted Overlay (FWO) and an adaptation of the Weights of Evidence (WofE) model, a Positive WofE (PWofE) model.

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Bow River Station field trip team (from left): Shirley Purdie, Deanna Wilson (Myself), Bruce Thomas, Balau Wah community field assistant and community dog.

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Terms and Acronyms

ADAM	Australian Data Archive for Meteorology
APAI	Australian Postgraduate Award Industry
ARC	Australian Research Council
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
AVHRR	Advanced Very High-Resolution Radiometer
BLM	Bureau of Land Management
BRS	Bow River Station
BWO	Binary Weighted Model
CSIRO	Commonwealth Scientific Industrial Research Organisation
DAFWA	Department of Agriculture and Food of Western Australia
DEM	Digital Elevation Model
EM	Electromagnetic
ESRI	Environmental Science Research Institute
FPR	False Positive Rate
FWO	Fuzzy Weighted Model
GDA	Geocentric Datum of Australia
GIS	Geographic Information Science/Systems
GPS	Global Position System
GRASS	Geographic Resource Analysis Support System
GSWA	Geological Survey of Western Australia
HP	Highest Position
IUCN	International Union for Conservation of Nature
Km	Kilometres
LN	Necessity ratio
LS	Sufficiency ratio
LU	Land Unit
MDBSIS	Murray-Darling Basin Soil Information Strategy
MGA	Map Grid of Australia
MS	Microsoft

NDVI	Normalised Difference Vegetation Index
NOAA	National Oceanic and Atmospheric Administration
NIR	Near Infra-Red
OBIA	Object Based Image Analysis
OID	Object Identification
OS	Operating Systems
PLAGA	Pastoral Lease Assessment using Geospatial Analysis
PLB	Pastoral Lands Board
PVT	Predictive Value Theory
PWofE	Positive Weights of Evidence
RCM	Rangeland Condition Monitoring
ROC	Receiver Operating Characteristics
SCS	Soil Conservation Service
SRTM	Shuttle Radar Topographic Mission
TM	Thematic Mapper
TPR	True Positive Rate
USA	United States of America
USFS	United States Forestry Services
WA	Western Australia
WO	Weighted Overlay
WofE	Weights of Evidence
WRI	World Resource Institute
2D	2-Dimesional
3D	3-Dimensional

1 Introduction

1.1 Project background

Western Australia (WA) has an area of approximately 2,529,875 square kilometres (km²) (Geoscience Australia: Geographic Information. 2004) with Crown Leaseholds (mostly pastoral) covering approximately 900,000 km² (Geoscience Australia: Geographic Information. 1993) of that area. Crown leaseholds, which are Crown Land that has been allocated to pastoralists (Donnelly 2012), extend across a range of landscapes, from tropical grasslands in the north to arid shrub lands in the south and include approximately 452 pastoral stations comprised of 507 pastoral leases. In general, pastoral leases in WA are extremely large, with an average size of 1,850 km² (Novelly 2008/2009). Most of the States pastoral leases occur in the Kimberley, Pilbara, Gascoyne, Murchison, Goldfields and Nullarbor regions (Department of Lands. 2015b) (Figure 1.1). In accordance with the Land Administration Act 1997 (WA) (Department of Premier and Cabinet. 2015), Pastoral Lands Board (PLB) that administer the Act and therefore are the statutory authority which monitor pastoral leases to ensure compliance with regulations outlined in this Act.

Prior to 2009, pastoral leasehold monitoring was limited to field inspections conducted by the Department of Food and Agriculture of Western Australia (DAFWA) that produced Pastoral Land Condition (PLC) reports prepared for the WA Pastoral Lands Board (PLB) (Department of Lands. 2015a) in accordance with the Land Administrations Act 1997. This method was limited due to the large number and extensive size of pastoral leaseholds, DAFWA's limited resources, and the resulting infrequency of inspections. As a result of these inadequacies, Rangeland Condition Monitoring (RCM) commenced to support existing monitoring techniques. RCM involves voluntary self-reporting by lessees and land managers by collecting objective data (including plant identification) and photographic evidence from a number of rangeland condition monitoring sites on their lease(s) (Department of Lands. 2015a). RCM is supported by DAFWA, who provide advice to lessees and land managers on 'assessing rangeland condition, managing stocking rates appropriate to sustainable use of pasture growth, management planning and remediation of existing problems' (Ryan 2015).

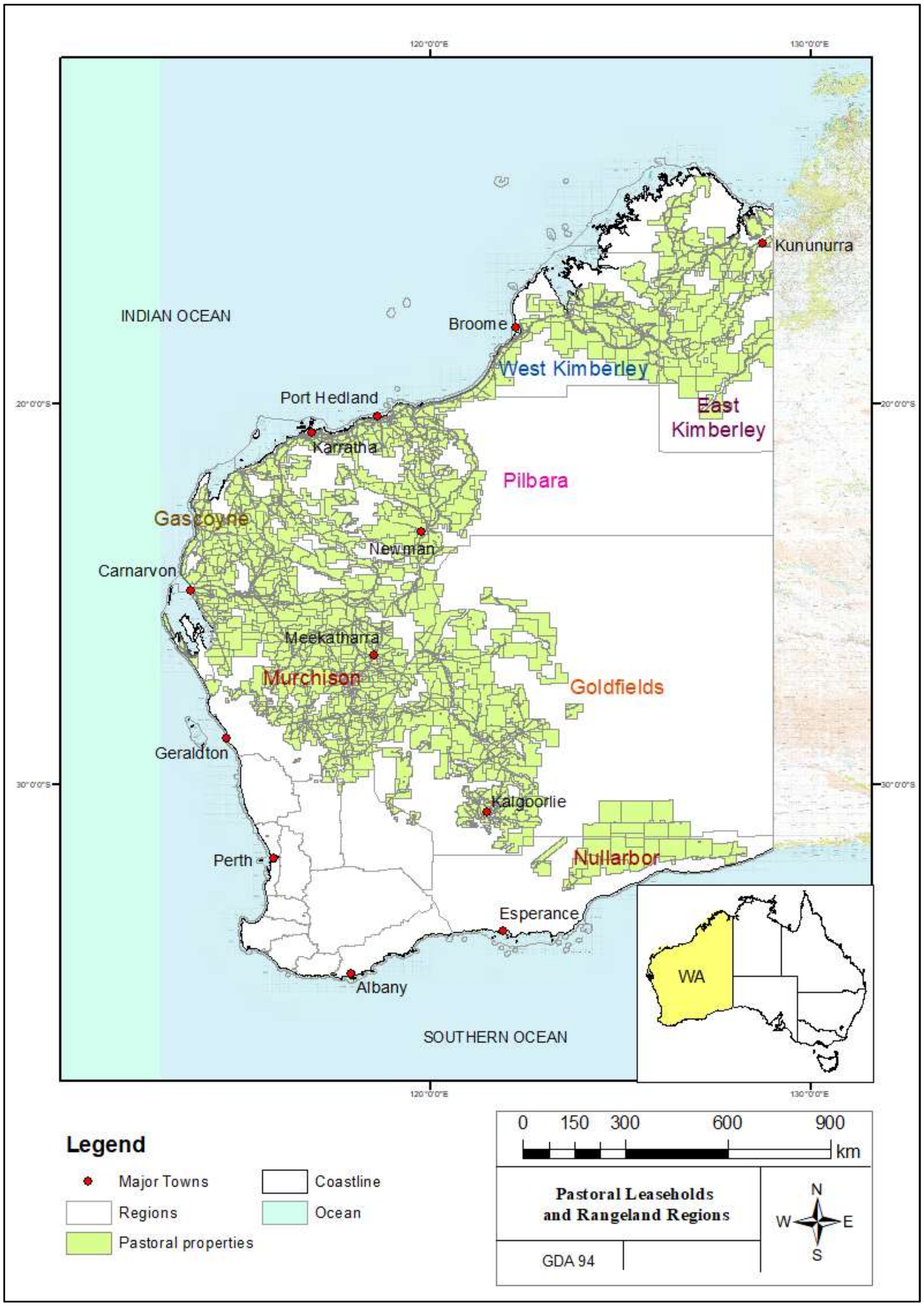


Figure 1.1 Pastoral leasehold and rangeland regions in Western Australia.

1.2 The problem outlined

Rangeland surveys in Western Australia (WA) have been conducted since the 1950's and were instigated by the Commonwealth Scientific Industrial Research Organisation (CSIRO). Since then, there have been a variety of regional surveys conducted by government departments and interested bodies; including mining companies, overseen by the Department of Agriculture and Food of Western Australia (DAFWA). The soil-landscape hierarchy for regional surveys in WA comprises of six nested levels of mapping. The highest level of the hierarchy is a Region – subdivided into Provinces. The Provinces are subdivided into Zones and the Zones into Land Systems. Land Systems are subdivided by Land Subsystems and Phases (equivalent to land units in rangeland mapping).

Landscape data for WA pastoral rangelands are currently published at land system, and in some cases land unit scale. Generally, land systems are too low resolution to provide relevant decision-making information for pastoral lease assessments. The limitation of low-resolution data impacts advances in geospatial analysis monitoring by incorrectly estimating rangeland conditions, including vegetation cover. These incorrect estimations of rangeland conditions therefore impact other geospatial monitoring techniques such as Pastoral Lease Assessment using Geospatial Analysis (PLAGA). PLAGA is one suggested technique that was trialled by DAFWA. Designed to aid pastoral monitoring systems, PLAGA uses a remote sensing approach to monitoring vegetation conditions, where remote sensing imagery is used to study changes of vegetation over time through temporal analysis.

Research on PLAGA monitoring has identified limitations in the accuracy and precision of vegetation cover trend analyses. Current data at property boundary scale (refer to field observations in Section 5.6 and Table 5.11) are too heterogeneous to precisely locate vegetation and landscape degradation. PLAGA was initiated to add 'efficacy to existing ground-based sampling that had previously been conducted along tracks' (Robinson, pers. comm., 2010). PLAGA was designed to identify conditions of specific areas and provide an early warning system by highlighting trends toward poor vegetation condition. The limitation in data quality prompted further research into increasing the resolution from the current property scale ‘boundaries’ of data to land system and potentially land unit scale, where a greater degree of homogeneity exists in features including landforms, vegetation and soils. Only limited land unit scale data is available for the rangelands in WA due to accessibility issues, cost and the time-consuming nature of ground-based sampling.

Pastoral lease landscape data in WA exists as both individual land surface units (i.e. vegetation, soil and landforms) and as parcels of land surface data (i.e. land systems and land units). There is a great variability of resolution within available land surface data in WA due to *ad hoc* surveys having been conducted on a project by project basis.

1.2.1 Land systems

Land systems are described as ‘an area or group of areas through which there is a recurring pattern of topography, soils and vegetation’ (Christian and Stewart (1953) in (Payne 2011)). Recurring patterns can be seen using aerial photographs and other remotely sensed techniques. The patterns assume similarities in land surface units that require field reconnaissance for accuracy. Land system boundaries are usually mapped from 1:50,000 scale aerial photographs that can then be reproduced as topographic maps or pastoral plans.

1.2.2 Land sub-systems

The main difference between land systems and land subsystems is the level of detail at which soil information is mapped. Land subsystems are defined as “a local unit based on landform element and morphological type, and soil associations” (Van Gool 2005).

1.2.3 Land units

Land unit boundaries exist with greater homogeneity than both land systems and land subsystems. A land unit is ecologically homogeneous at the scale of interest, approximately 1: 10,000 according to accessibility, land unit coverage is limited and is currently mapped using field-based surveys. A major issue with field-based surveys is accessibility and cost of sampling. Sampling is commonly restricted to tracks that only represent a small fraction of the total area of a pastoral lease that can also preference introduced species that grow in the clearings and artificial drainage introduced by a variety of access transportation. Land unit boundary mapping exists for only a few pastoral stations in WA rangelands.

1.3 Problem statement

Current soil-landscape hierarchy data used for Western Australian pastoral rangeland condition monitoring are mostly at a land system scale (approximately 1:250,000). This is comparatively low-resolution data compared with intensive agricultural areas including the south-west regions of Western Australia (Schoknecht 2004) where landscapes are mapped between 1:20,000 to 1:250,000 scale, between a phase and land system respectively. The scale of the landscape data adversely impacts pastoral rangeland condition monitoring due to lack of homogeneity. Pastoral rangeland condition monitoring aims to prevent and/or limit degradation of native flora and fauna caused not only by grazing livestock such as cattle and sheep, but also feral animals including donkeys, camels, horses and goats; and native animals including kangaroos, where populations of these animals have increased due to artificial drainage. Artificial drainage is contributed to by a number of factors including man-made tracks, livestock and other animal movement within the property. Invasive weeds such as mesquite, Parkinsonia, saffron thistle, Bathurst burr and horehound (Van Vreeswyk 2008) can also be found growing as a consequence of this artificial drainage.

Although land unit data have greater homogeneity and would provide more accurate results for land condition monitoring, these data are limited, being currently mapped using field based regional surveys hampered by accessibility issues and cost of sampling. As a result of these issues, land unit boundaries exist for very few pastoral stations within WA rangelands.

1.4 Project significance

By improving the accuracy of rangeland condition monitoring this project will help prevent and/or limit degradation by protecting biodiversity and unique ecosystems in WA pastoral rangelands allowing continuance and improvement of agriculture practices in these remote areas. Degradation affects vegetation, soil stability, landform stability, ecosystem balance, ecology, climate and weathering erosion thereby affecting agriculture and consequently human survival strategies.

1.5 Project objectives

The overall objective of this research is to develop a method for upscaling data to a land unit scale for a selected study area. The upscaling of data would use available/existing land surface information and data, with the output result applied to other study areas and pastoral leases in the WA rangelands for improved rangeland condition monitoring. The land unit data could also be added and used in land condition monitoring programs such as PLAGA to assess the effect that smaller parcels of land have on vegetation indices. To create data at the land unit scale, these input land surface units are required to be as homogeneous as possible. WA land surface data exists for vegetation, soil, geology and a number of other physiographical features however not for landforms. The specific objectives are to:

- Analyse and create landform data using a Digital Elevation Model (DEM);
- Analyse homogeneity of exiting land surface data;
- Analyse three predictive model techniques to find a 'best suited' to predicting land units in the study area using land surface datasets including landforms;
- Predict 'most likely' land units for land systems in the study area;
- Correlate predicted 'most likely' land units with existing land unit data;
- Report on findings with accuracy of results.

1.6 Thesis structure

Chapter 1 – Introduction to pastoral rangeland monitoring in Western Australia, including a brief history from its early years in the State until recent developments towards remote sensing and geospatial techniques. An outline is given of the project, the significance and objectives.

Chapter 2 – Literature review of pastoral rangeland monitoring, pastoral lease assessment and previous attempts to predict land unit data.

Chapter 3 – Background of the Bow River Station study area including a description of the land unit model. The East Kimberley Region is described in terms of climate, physiography, topography, drainage, weathering, erosion and landscape variables.

Chapter 4 – A description of geomorphometry and spatial modelling including landform classification techniques using GIS and data source for predictive modelling.

Chapter 5 – Includes a description of landform classification for the study area and the development of relative relief and elevation using a SRTM DEM and testing of local existing landscape variables - vegetation and geology.

Chapter 6 – Test modelling techniques to predict 'most likely' land units in the study area. Three prediction modelling techniques were tested: a Binary Weighted Overlay (BWO) model, a Fuzzy Weighted Overlay (FWO) model and a Positive Weights of Evidence (PWofE) model. The modelling techniques used landscape variables as evidence, these include, vegetation, geology, landforms, elevation and relative relief.

Chapter 7 – Results from the three prediction models were checked using confirmation analysis. Confirmation analysis included Receiver Operating Characteristics (ROC) plots and contingency tables to cross-check *posterior* proportions with *prior* proportions. A brief comparison was included between the predicted 'most likely' land units and field data.

Chapter 8 – Conclusions and recommendations for landform classification and prediction modelling techniques for the Bow River Station study area. A review of landform classification and land unit prediction modelling to increase accuracy of land condition monitoring in pastoral rangelands. Recommendations for future research in the fields of landform classification, classification of landscape evidence data, and prediction modelling in pastoral rangelands.

2 Western Australia pastoralism and monitoring systems

Western Australia (WA) is the largest state of Australia, occupying 2,529,875 square kilometres comprised of numerous pastoral, mining, residential, commercial and government boundaries. Monitoring land parcels in vast settings such as the Kimberley Region of WA can be challenging especially when many areas, including pastoral leases, are remote and have limited access; these areas are commonly referred to as pastoral rangelands.

2.1 Pastoral rangeland monitoring

Isolated sheep stations were first established in valleys around the Ord and Fitzroy Rivers in the Kimberley Region of WA, in the late 1870's, led by surveyor Alexander Forrest (Crowley and De Garis 1969). However, early pastoralism in Australia was restricted to areas of natural and reliable water sources, mainly along river systems and in the vicinity of springs and soaks. Pastoralism in isolated locations such as the Kimberley rangelands didn't expand until suitable water boring and dam-building technologies were developed (Russell 2007). The pastoral rangelands of WA show greater diversity and heterogeneity of ecosystems than other rangelands around the world (Harrington et al. 1984).

In WA, pastoral rangeland monitoring is closely linked to pastoral rangeland management and natural resource assessment which was originally developed to manage domestic and livestock grazing on native vegetation. The techniques developed in WA were influenced by the theories and practices of range condition monitoring established during the 1930s and 1940s in the United States of America (USA) by that country's federal agencies such as Forest Services (USFS), Bureau of Land Management (BLM) and Soil Conservation Service (SCS) (Russell 2007). However, the pastoral rangelands in WA differ strongly from those in the USA in having more diverse climatic conditions and therefore more significant seasonal changes.

In WA, pastoral rangeland monitoring commenced in the early 1950's, designed to compare vegetation changes over time. One of the main reasons for pastoral rangeland monitoring is to measure the degree of landscape degradation caused by human activities including cattle and sheep grazing. Pastoral rangelands are used extensively for livestock grazing due to the abundance of palatable vegetation; predominately perennial plant species such as grasses, forbs and shrubs. These species not only provide animals with nutrition, but also protect the soil surface from wind and water erosion (McKeon et al. 2004). Pastoral properties in the northern rangelands are predominately cattle stations. Since pastoral lease monitoring began in WA, the practice has passed through three main stages: Phase 1 (early 1950's to late 1960's) involved understanding vegetation growth and growth dynamics; Phase 2 (early 1970's to late 1980's) concerned systematic studies of broad-scale rangeland condition and trend information; Phase 3 (early 1990's to recent) has concentrated on landscape model standardisation and stability of monitoring. In recent years, there have been advances in remote sensing technologies that have seen the development of new geospatial monitoring techniques, including technologies used in landscape degradation monitoring. A suggested technology was Pastoral Lease Assessment using Geospatial Analysis (PLAGA), which uses remotely sensed imagery in temporal analysis to detect changes in vegetation cover quality. PLAGA is a set of tools that were designed to aid field inspections and other monitoring techniques, by increasing confidence in the quality, and improving the efficiency of ground-based traverses (Matternicht 2007).

2.1.1 Pastoral Lease Assessment using Geospatial Analysis (PLAGA)

The PLAGA project was designed to aid pastoral lease monitoring in the rangelands of Western Australia (WA), by providing the Department of Food and Agriculture (DAFWA), additional information on pastoral lease degradation. PLAGA was initiated to add efficacy to existing ground-based sampling and was designed to identify vegetation conditions of specific areas and provide an early warning system. Poor vegetation condition implies, pasture degradation, where excessive grazing and climatic variability interact to cause the loss of 'desirable' perennial grasses and shrubs, that in turn leads to increased weathering and soil erosion (McKeon et al. 2004).

The PLAGA project offered a remote sensing approach that was both cost efficient and replicable quantitative analysis, providing feedback for pastoral rangeland leaseholds.

PLAGA was promoted to provide quality assurance of WA pastoral rangeland leases by examining different vegetation indices for different areas on the lease by 'evaluating imagery of varying spatial resolutions; developing measures to infer condition changes relative to an expected condition or benchmark; and interrogating the historical archives of satellite remote sensing (temporal analysis) that is now at our disposal' (Robinson 2012). The soil-landscape hierarchy of WA is comprised of 6 levels. PLAGA provided quality assurance at the land system level, level 4, defined as a *regional unit* with landscape criteria consisting of relief/modal slope class, landform pattern and generic type of soil parent material (Schoknecht 2004). Based on trials, PLAGA identified that 'optimal' remotely sensed vegetation index indices for vegetation, changed over relatively short distances in geographic space. Essentially, the PLAGA project was designed to test the condition of vegetation, with the results assigned a condition-based rate, outlined by condition indictors (Table 2.1).

Table 2.1 Criteria used to assign a vegetation condition rating using PLAGA (adapted from Robinson, 2009).

Rating	**Condition Indicators**
Very Good	Cover and composition of shrubs, perennial herbs and grasses is near optimal, free of obvious reductions in palatable species or increases in unpalatable species liable to reduce production potential.
Good	Perennials present include all or most of the palatable species expected; some less palatable or unpalatable species may have increases, but total perennial cover is not very different from the optimal.
Fair	Moderate loses of palatable perennials and/or increases in unpalatable shrubs or grasses, but most palatable species still present; foliar cover is less than sites rated as good or very good unless unpalatable species have increases.
Poor	Conspicuous loses of palatable perennials; foliar cover is either decreased through a general loss of perennials or increased by invasion of unpalatable species.
Very Poor	Few palatable perennials remain; cover is either greatly reduced, with much bare soil, arising from loss of desirables, or has become dominated by a proliferation of unpalatable species.

Research on PLAGA monitoring identified inaccuracies in the precision of the vegetation condition indicators. Current quality assurance boundaries at the land system and property scale are too heterogeneous to precisely locate vegetation and landscape degradation. This limitation prompted further research into increasing the resolution of available land surface data to land unit scale in the soil-hierarchy of WA (refer to Section 1.2).

A major challenge for remote sensing techniques in WA is the lack of adequate ground sampling data at the lease and paddock scale available to make informed decisions. Data availability is strongly influenced by a study area's accessibility, and the cost of ground-based sampling often restricted to tracks representing a small fraction of the total leasehold. Tracks can also bias the data based on their distribution due to landscape constraints and can alter vegetation patterns as particular plants may grow more abundantly closer to tracks due to increase space, sunlight and accumulated water. Tracks may also act as artificial drainage.

2.2 Previous attempts to upscale land surface information in the Ord River Catchment

Previous land use information in the WA pastoral rangelands was collected collaboratively by the Department of Food and Agriculture Western Australia (DAFWA) and Commonwealth Scientific and Industrial Research Organisation (CSIRO) Land and Water as part of the Ord-Bonaparte Research Program (Prince 2009). Recognising that traditional methods for geomorphological mapping require extensive fieldwork that is both expensive and time consuming, the purpose of this research was to use a modelling approach to improve the quality and resolution of land-resource mapping in the Ord River Catchment within the State of Western Australia's border. The research also aimed to build on existing knowledge and activities to develop effective tools, methods, processes and strategies to support policy, planning and management for sustainability for East Kimberley resources, starting in the Ord River Catchment.

The methods used for this work were based on developments made for the Murray-Darling Basin Soil Information Strategy (MDBSIS) (Bui 1998, Bui and Moran 2003), with this method chosen to provide information on soils for natural-resource management and planning at the catchment level. Land system mapping (nominal scale 1:250,000) conducted by CSIRO over 50 years ago (published in the 1970s), regional vegetation mapping by Beard (1979) (Schoknecht 2003), geological maps (1:250,000 scale), elevation and terrain attributes (acquired from a Digital Elevation Model (DEM) using TAPES-G), were the primary data sources used. TAPES-G (Gallant and Wilson 1996) was the chosen analysis method for initial terrain analysis on gridded DEMs in the Ord-Bonaparte Program. During the research, the survey area was extended to include land in the north of the Ord River Catchment up to the coast (Keep River Catchment).

The main landscape datasets available in the Ord-Bonaparte Program were at the land system scale, covering the Kimberley and encompassing large areas where soils, vegetation and topography are considered homogeneous. In fact, these regions display a high degree of heterogeneity when viewed at higher resolution. The mapping of these land-system datasets was proposed and then initiated in the late 1940, primarily using monochrome aerial photography captured for military purposes. The methodology in these early land system surveys was essentially photo interpretation, supported by some ground-truthing, datasets were later refined by government agencies in specific States and Territories. The East Kimberley was one of the first regions in Australia to be analysed as part of a land system study, following the Katherine-Darwin region, the surveys' aims were to identify areas suitable for agriculture, and in the East Kimberley, the eventual outcome was the development of the Ord Irrigation Scheme (Goudie 2004).

The initial modelling process for the Ord-Bonaparte Program used C5.0 software (RuleQuest Research. 2015) to discover patterns and delineate categories, assemble data into classes and then make predictions. The technique used existing mapping, climate data, remotely sensed datasets (Landsat imagery (30 m spectral resolution), Digital Elevation Models (30 m – 250 m)) and targeted field work combined with expert-driven modelling to derive land units for the study areas. Two DEMs were used to identify 12 predictor datasets (Schoknecht 2003). The resultant C5.0 software model used all of the relevant available digital datasets and required an additional 9 weeks of fieldwork to collect extra training data; three iterations of the model were produced over an 18-month period from 2002 to 2003.

The C5.0 software model used a data mining algorithm that extracting patterns from data, but only if these patterns existed. The result was a single layer, with this new layer displaying only the desired pattern, with the pattern limited to available data. The C5.0 software had previously been successful in building decision trees for the Murray-Darling Basin project, using digital lithology, digital elevation, terrain attributes and Landsat MSS as input layers. As an example, in the Goondiwindi-Inverell training area, 83% of the area was correctly predicted by the model (Bui 1998). Unfortunately, the same success was not evident for the Ord-Bonaparte Program. Areas outside of the training data, for land units, were correctly predicted only 3% (refer to Figure 2.1 and Table 2.2) of the time on average (which was a problem since these areas were eventually used as ground truth), with prediction adjacent to, but outside, the training data area fair to poor, and the quality of prediction dropping off rapidly with distance from the training site (Schoknecht 2003).

Figure 2.1 An example of combined land unit output for the Ord-Bonaparte Program. Approximate size of map is 3km by 2km. The legend displays the land unit codes (Schoknecht 2003).

Table 2.2 Prediction success using C5.0 software for Ord-Bonaparte Program (Schoknecht 2003).

Land unit attribute	**Prediction success (%)**	
	Sites within training data polygons	*Sites outside training data polygons*
Landform	53	24
Geology	73	34
Soil	45	16
Vegetation	39	15
Land unit	26	3

Post-project analysis of the project suggested that the main reasons that the C5.0 software modelling approach was unsuccessful were; lack of homogeneous training data; absence of representative training data in some areas; inability to predict patterns of land surface (vegetation, soil, landforms) without human intervention; lack of weight allocation for suggestive predicting data; and, lack of high-resolution datasets over the entire Ord-Bonaparte area. After the unsatisfactory output from three attempted models, a decision was made to abandon the C5.0 modelling approach, and Schoknecht (2003) suggests for future success of land unit mapping in the Ord-Bonaparte basin:

• High-resolution digital datasets of predictor variables (especially terrain, geology) all stored in the same datum and projection;

• Aerial photography;

• Incorporation of expert knowledge at all stages of the mapping process; and

• Representative field data.

According to Schoknecht (2003), four out of the five reasons for why this method was not successful relate to the lack of high-resolution data in the region, with the remaining factor relating to lack of field-based data.

Following the abandonment of the C5.0 modelling approach, land unit mapping was revised for the Ord-Bonaparte Program using a hybrid between traditional techniques and digital data. The revised technique used digital datasets, with expert knowledge that successfully prepared a land unit map for Carlton Hill pastoral lease, that was extended to three other stations in the Ord River Catchment, Bow River, Ivanhoe and Violet Valley pastoral leases.

2.3 Chapter summary

Western Australia (WA) pastoral rangeland monitoring commenced in the 1950's designed for comparison of vegetation changes over time. Several methods of rangeland monitoring have been trialled in pastoral rangelands of WA, with advances in technology including remote sensing and geospatial analysis. Pastoral lease monitoring developed to help maintain and reduce landscape and vegetation degradation, impacted by livestock and introduced vegetation species, influenced by methods used in the USA.

PLAGA was introduced as a possible tool to aid field inspections, that tests the conditions of vegetation. The limitations of PLAGA and other remote sensing methods is the lack of adequate ground sampling data at lease or paddock scale to make informed decision making.

An attempt was made to upscale the available land surface data in the study area using C5.0 software as part of the Ord-Bonaparte Program. This upscaling method using the C5.0 modelling approach was unsuccessful and was therefore abandoned. Mapping for the Ord-Bonaparte Program was revised, following recommendations, using a hybrid between traditional methods and digital data, that produced land unit scale data for four pastoral leases in the Ord River Catchment.

3 Land unit mapping and the East Kimberley study area

Land units are a component of landscape classification that are essentially estimations of natural boundaries derived using a variety of techniques including stereoscopic analysis of aerial photographs and confirmation of these boundaries during field surveys. Field surveys are generally not used for adjusting or finding new boundaries, but principally to support the composition of the aerial photo interpretation. Land units are defined by relationships between individual elements predominately, vegetation, soil and landforms. Landforms and geology are typically directly linked to soil and vegetation where soils relate to minerals formed from eroded and weathered rocks, with many plants' dependent on the soil type. This relationship is commonly referred to as the soil-landscape model, with soil-landscape units being fairly spatially predictable, where a stable landscape produces higher correlation between soil and landscape units. The landscape essentially forms a continuous biological surface, and it has been said (Irvin 2000), that any schemes of sub-division are somewhat arbitrary although they are commonly necessary in landscape modelling.

The Kimberley landscape has been evolving over the last 250 million years, affected by climate and erosion predominately water, wind and ice movement. The landscape was shaped during a geological event of collision and uplift between older rocks and sediments of the Kimberley Basin forming planation surfaces, preserved today as remnants, as high planar surfaces referred to as the Kimberley Plateau. Areas around the edge of the Kimberley Plateau have been eroded and form the Low Kimberley surface country, with locally uniform hills and ridge tops becoming progressively lower towards the coast. In areas beyond the plateau country, the hills have been levelled out and are covered by sandplains forming the Great Sandy and Tanami Deserts (Tyler 2000). According to Petheram, Kok, and Bartlett-Torr (2003), the soils and vegetation are varied in the Kimberley Region, and are distinctive to the main physiographic regions (i.e. East Kimberley), with soil derived from their respective geological formations, supporting a variety of vegetation.

3.1 The land unit model

A land unit is an expression of a landscape model, which is ecologically homogeneous at the scale of interest. Land units are described in Zonneveld (1989), and follow an holistic (from the Greek word *Holon*, based on the theory of holism) assumption, where the units consist of hierarchical 'wholes'. Zonneveld (1989) explained, that holism is where a large scale 'body' cannot be described using the smallest elements but should be examined at various hierarchical levels. Soil, vegetation and landforms are considered by some ecological scientists as 'wholes' and hence can be classified using sets of diagnostic characteristics identifying their formation on the theory of holism. A crucial concept of a 'whole' is that it either remains the same over a period of time or shows only slow gradual change.

Land units are considered as sets of tangible internal and external relationships, including; real operational factors, conditional factors, positional factors and hereditary factors. An example of operational factors is the amount and composition of minerals that are readily absorbed by plant roots that can be used by the plants as nutrients, operation factors are the biological relationships. Other factors such as soil pH, absorption capability, and humus (the upper-most organic component of soil) content are also contributing factors to nutrient absorption by plants. Conditional factors are real measurements of land units through internal and external relationships including: slope, soil texture, absorption complex and soil cover. A more indirect land unit relationship is the positional factor, that includes the knowledge that water runs downhill, and that calcareous rocks will influence its lower surrounds in certain ways, and that the sun shines mostly on a particular aspect of a hill at certain times of year (Zonneveld 1989). The visual pattern of a landscape on a map reveals much of the positional relationship and a good place to establish a landscape study is to observe objects for similarities and differences.

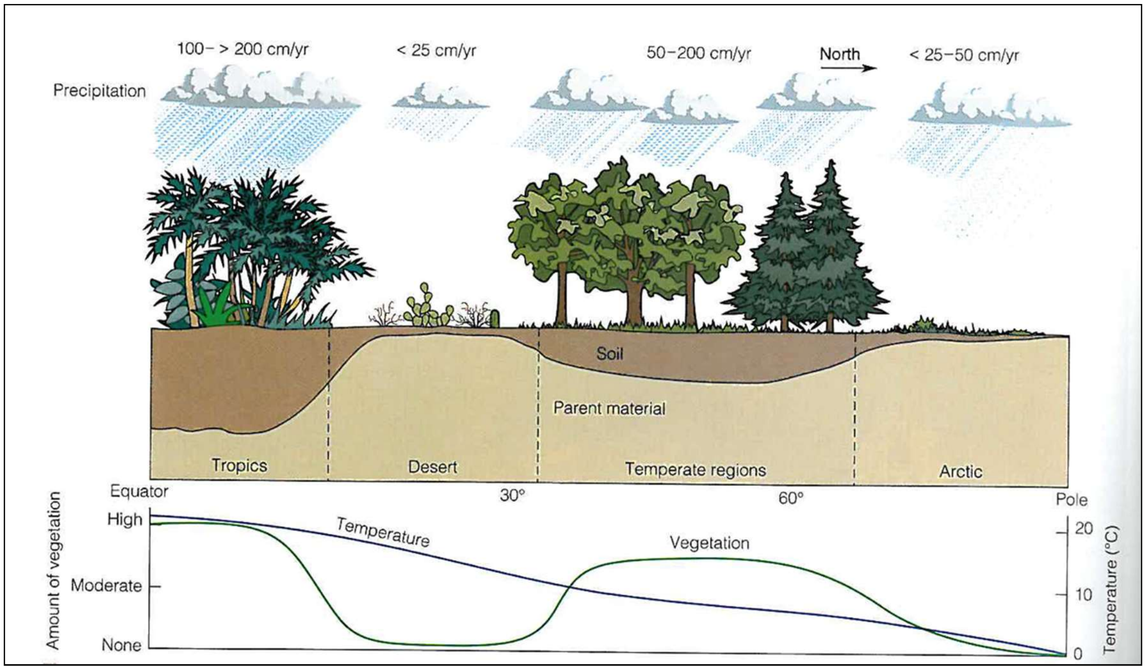
Mapping the Earth's ecosystems requires the stratification of the landscape into mapping units according to a combination of ecological features, primary climate, physiography, surficial material, bedrock geology, soil and vegetation. Common scales are 1:100,000, 1: 50,000 to 1:20,000, though larger scales of 1:10,000 and even 1:5,000 can be used depending on project objectives (Fraser et al. 2012). Project objectives can predetermine the scale and with this the mapping units change instinctively, instead of mapping an Earth systems or cycles, the mapping units can be localised becoming more homogenous, including land units. The project, the scale and location all effect the level of interconnectivity, where interconnectivity refers to the state or quality of being connected together.

Mapping of land units is generally carried out by trained photo-interpreters who can delineate land units that are relatively homogeneous using their knowledge of landforms, geomorphic processes, vegetation structure in relation to the environment and the relationship between soils. Aerial photograph interpretation of the land units lacks congruency which is ultimately unavoidable, each interpreter will slightly vary when interpreting soils, landforms and vegetation. By recognising land unit boundaries during field surveys, interpolation can be used to predict and infer information and land unit boundaries in areas beyond the initial study area (Hengl and Rossiter 2003), where field surveys are not a viable option.

The Earth is comprised of four main systems that are influenced internally and externally, effecting biodiversity and natural ecosystems, these are:

- Hydrosphere includes the *hydrological cycle*
- The atmosphere includes the *atmospheric cycle*
- Solid Earth includes the *rock cycle*
- The Biosphere includes *biochemistry*

These four main systems are interconnected and their influence can be seen in Figure 3.1, which identifies this interconnectivity and how elements of the landscape can be interpreted and inferred by their natural position on the Earth.



*The geographic orientation of Figure 3.1 is diagrammatic with North representing north of the equator (northern hemisphere).

Figure 3.1 Interconnectivity of the main Earth systems, from Murphy and Nance (1999).

Using interconnectivity as the underlying model, a hypothesis was proposed for this research work, to use known landscape elements to predict land unit parcels of land with bounding limits founded on the assumption that land units have a high degree of homogeneity. Consideration for a prediction model involved finding a controlled environment where landscape information was available for many landscape elements, considering whether individual landscape elements can be combined to form a single land unit, and how many elements are required for accurate results. A study area was chosen in the Kimberley Region of WA because data existed at land unit scale which allowed more homogeneous interconnectivity to exist between the landscape features. The study area was chosen from four Kimberley stations: Bow River, Ivanhoe, Carlton Hill and Violet Valley, where land unit surveys were performed as part of the Ord-Bonaparte Program.

It was assumed that two or more landscape variables (i.e. geology and landforms) could be used to produce a land unit boundary data in a prediction model. If only two landscape variables were used to predict a land unit, then the reasoning behind the position would be compromised because not all elements of the land unit would have been included in the prediction calculation. Only using two landscape variables to predict a land unit would therefore not be a true representation of the land unit or of the term interconnectivity of the land unit. All landscape variables are required to be included in the prediction model for true interconnectivity of a land unit. Similarly, if landscape elements were used to predict land units in areas outside a single physiographic region, East Kimberley study area, as mentioned in Petheram, Kok, and Bartlett-Torr (2003), they might not have the same interconnected pattern. Clustered patterns were assumed for 'whole' landscape variables within a land unit. A suggestion of how the clustering pattern might infer land unit boundaries can be seen in Figure 3.2, where interconnection is shown between vegetation, landforms, geology and slope, with variation in geology type, slope type and landform type considered for vegetation.

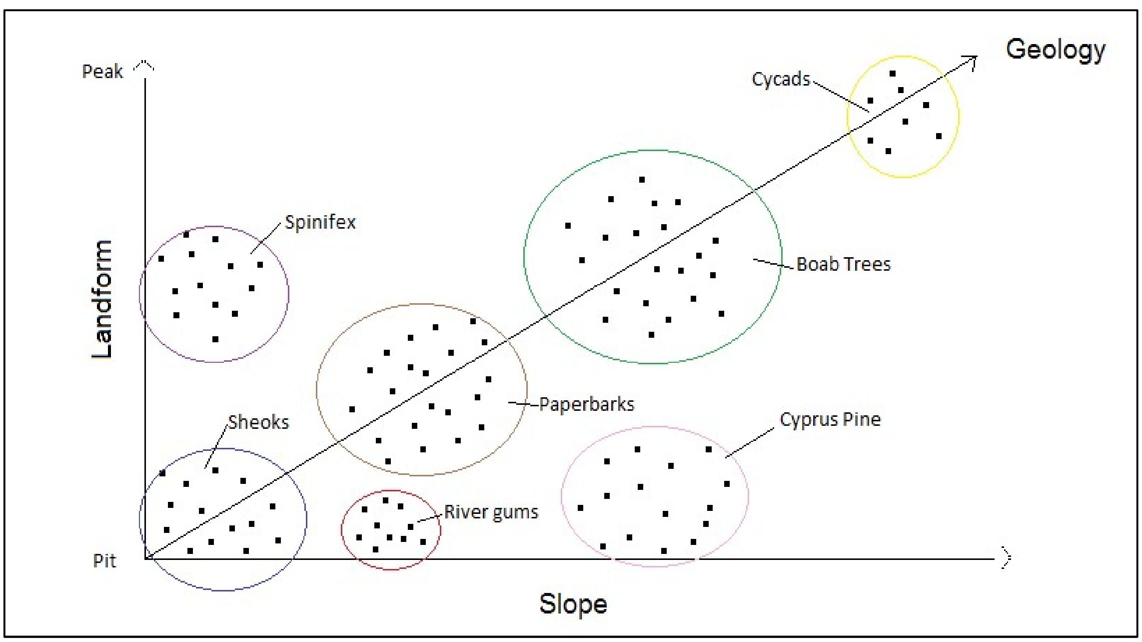


Figure 3.2 Hypothetical diagram showing associations between vegetation, landform, slope and geology supporting interconnectivity for a prediction model.

3.2 East Kimberley study area

The WA pastoral rangelands can be divided into five regions: Kimberley, Pilbara, Gascoyne, Murchison, Goldfields and Nullarbor. The Kimberley Region covers a total area of approximately 422,000 km² occupying one sixth of the entire state (Department of Regional Development and the North West and Kimberley Regional Development Advisory Committee (WA) 1986). Mapping of soils, landscapes and vegetation in the rangelands of WA commenced in 1953 with surveys of the land and pastoral resources of the North Kimberley area by the CSIRO (Speck 1960). Subsequently, CSIRO land system surveys covered the Wiluna-Meekatharra (Mabbutt 1963), West Kimberley (Speck 1964) and Ord-Victoria (Stewart 1970) areas. In the 1960s the Department of Lands and Surveys commenced a program of rangeland surveys in the Kimberley and Pilbara, these surveys classified the land into broad pasture types, mainly for the purpose of estimating paddock and station carrying capacities. By the end of the decade, responsibility for mapping rangeland areas became a joint responsibility of the Department of Agriculture and the Department of Lands and Surveys, using a procedure similar to CSIRO, but replacing the concept of land systems with rangeland types in which recurring patterns of pastures and landforms occur. In early 2000s, following the abandonment of the initial C5.0 modelling approach (refer to Section 2.2), hybrid land unit surveys commenced on four stations; Bow River, Ivanhoe, Carlton Hill and Violet Valley in the East Kimberley rangelands, as part of the Ord-Bonaparte Program. Current landscape, soil and vegetation descriptions for land systems for the Kimberley Region can be found in the Department of Food and Agriculture (DAFWA) "Land systems of the Kimberley Region" Technical Bulletin No. 98 (Payne 2011). The main purpose of the Technical Bulletin was to consolidate descriptions of landscapes, soils and vegetation of the East Kimberley Region of WA from a succession of surveys carried out since the 1940s. The Technical Bulletin land system descriptions are comprised of 'nested' spatially explicit land units, with approximate percentages.

The study area for this thesis is the East Kimberley of WA, with particular focus on the Bow River Station, shown in Figure 3.3, representing part of the Ord River Catchment.

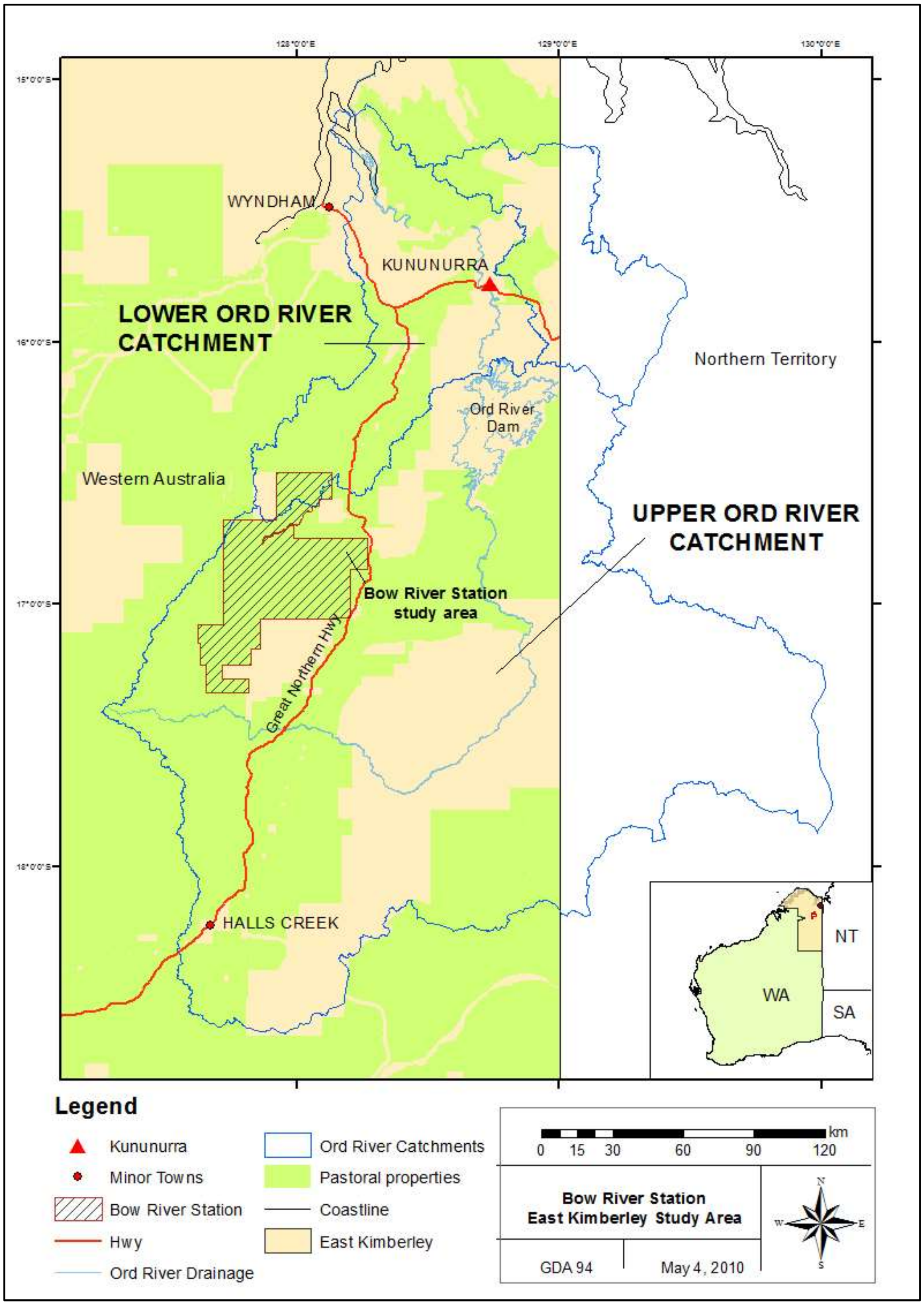


Figure 3.3 Bow River Station within the Ord River Catchment.

Bow River Station was chosen from the four possible stations for the diversity in topography and its relative central location. The station is approximately 3017 km² in area, diverse in topography, has a relative central location in the East Kimberley river catchment and has land condition information available at the land unit scale. This land unit data has been made available by DAFWA for this research.

3.2.1 Climate and physiography

Bow River Station and the East Kimberley Region in general, have a semi-arid monsoonal tropical climate with average annual minimum and maximum temperatures 20.3˚C and 35.0˚C respectively, and average annual rainfall 723.8 mm. The closest active weather station to Bow River Station homestead is approximately 80 km away at Warmun (Figure 3.4), located at 17.0156°S, 128.2175°E, 203 m elevation (Bureau of Meteorology. 2011).

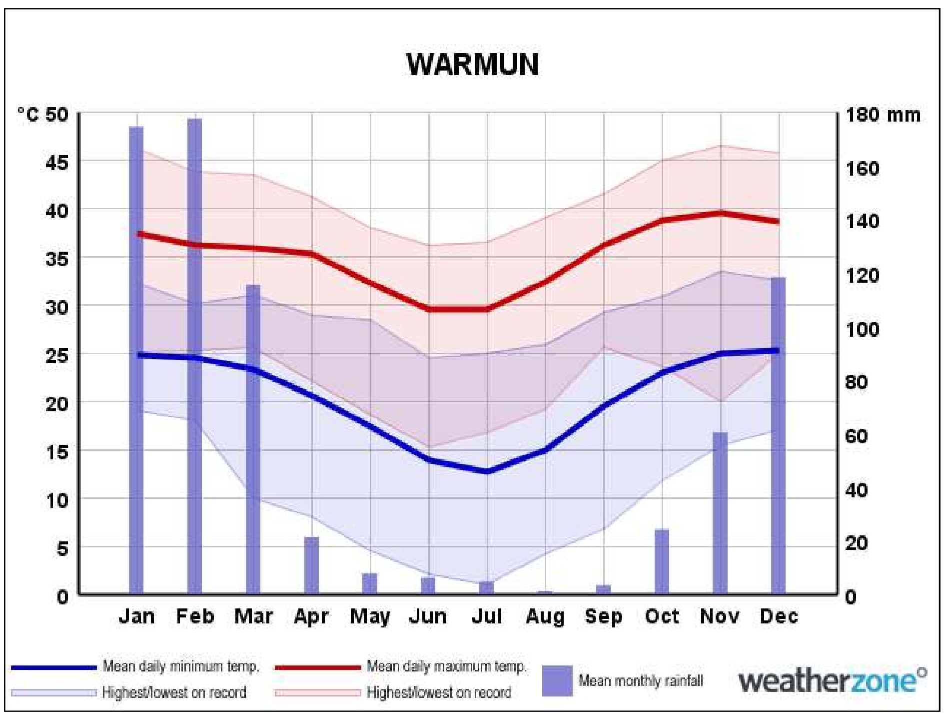


Figure 3.4 Warmun weather station average annual statistics (Bureau of Meteorology. 2011).

Climate data are collected by weather stations located throughout Australia and are monitored by the Bureau of Meteorology (Bureau of Meteorology 2010). The bureau weather stations record a variety of weather phenomena, including temperature, humidity, rainfall, pressure, sunshine, wind, cloud and visibility. All weather data recorded at operating stations are stored in the Bureau's climate database - the Australian Data Archive for Meteorology (ADAM) (Bureau of Meteorology 2010).

The physiography of the Bow River Station forms part of the low Kimberley hill country that stretches for approximately 130 kilometres on either side of the Great Northern Highway. The landforms within the region have evolved through time due to the effects of uplift, climate, erosion and weathering, and vary from flat-top plateaux to vast sand covered plains. Geologically, either side of the Great Northern Highway in the East Kimberley between Bow River and the Duffer Range consists of rocks collectively called the Tickalara Metamorphics. The Tickalara Metamorphics form rugged, boulder-strewn hills and plateaus. These hills in places can reach up to 500 metres above sea level traversed by rivers and creeks that have a valley relief of up to 250 m. The rocks in this area were formed during a time of collision between the Kimberley and the rest of Australia, more precisely the Archean Craton of Western Australia. The original rocks metamorphosed to form new mineral assemblages and rock types. Examples include sandstones metamorphosed to schists, granites metamorphosed to gneisses and limestones metamorphosed to marbles (Tyler 2000). The King Leopold and Durack Ranges are the main ranges in the area, with the highest peaks being Mt Ord (930 m) and Mt Hann (854 m).

3.2.2 Topography and drainage

East Kimberley topography and drainage have developed in response to local geology and geological events. Drainage radiates from the central highlands to the northern coast and also drains from the south and east into the Ord, Margaret, Lennard and Fitzroy river systems. The flood plain surrounding this drainage provides valuable water to the pastoral leases (Petheram, Kok, and Bartlett-Torr 2003). On Bow River Station, the Bow and Wilson rivers are the main streams that flow out of the station towards to Ord River dam in the direction of the coast, these rivers form part of the Ord River Catchment.

3.2.3 Weathering and erosion

According to Murphy and Nance (1999), weathering is a degeneration process of the land surface as the result of interaction with water, ice and air, most commonly, it refers to the breakdown and weakening of rocks although consequent cementation and hardening of surfaces can also occur in weathered zones or regolith. Erosion is the wearing away of the land surface by rivers, mass movements (e.g. landslides), glaciers, waves and the wind. The differentiation between erosion and weathering is that erosion implies the movement of material from its' original place of origin whereas weathering is 'in situ'.

Water on Bow River Station is most abundant during the wet season from November to March (Figure 3.4) with most of the water falling during tropical thunderstorms and cyclones varing geographically and topographically. The wet season feeds intermittent creeks and rivers that flow through valleys and lowlands replenishing pastures, providing much needed fodder for the livestock. The wet season is also an active time for erosion and weathering, when many creeks and rivers flood, carrying sediment and rock material from place of origin, that with time, reshapes gorges and valleys. With the onset of the dry season, creeks and rivers start to retreat with water evaporating or seeping into the underlying aquifers. Vegetation dries out allowing seeds to set for regrowth in the following wet season (Twidale and Campbell 2005).

Water contributes greatly to weathering and erosion and is an important part of the natural ecosystem continuing to change the physiography of the landscape.

3.3 Soils and Vegetation

There is a wide range of soil and vegetation associated within the Kimberley and is distinctive of the main physiographical regions. The four main groups of soils and their associated vegetation according to Petheram, Kok, and Bartlett-Torr (2003) are:

a. **The stony, skeletal soils of the ranges and plateaux and areas of deep sandy soils in the valley floors,** comprised of shallow, stony soils with areas of extensive mixed sandy soils. These soils support forest corridors found within sandy soils of small valleys associated with seepage and running water and within the saline and fringing coastal soils of the northern Kimberley.

The trees of this physiographic group are generally smaller on the stony range country, with spinifex species more prolific and on the stony hillsides, generally low pastoral value.

b. **Grey and brown heavy, soils of the savannahs and grasslands of the plains,** including the flood plains of rivers. These areas also have outcrops of basalt, limestone and mudstones that form heavy clays soils that are favourable of productive grass species. According to Petheram, Kok, and Bartlett-Torr (2003), the Kimberley savannahs and grasslands are the richest grazing areas for the region. Grass species found in this physiographic group include: Mitchell (*Astrebla* spp.), Flinders (*Iseilema* spp.) and bundle-bundle (*Dichanthium fecundum*) along with edible tree species such as the rosewood (*Terminalia volucris*).

c. **Brown soils of the river flood plains** include soils that fringe the rivers comprised of recent alluvium that are usually brown or grey in colour and of sandy loam or light clay texture, supporting a variety of edible grasses and trees that form narrow corridors along the river systems and are generally called grassy woodland vegetation. This physiographic group is highly regarded for pastoral purposes.

d. **Deep reddish sandy soils,** are extensive in nature and found in the West and East Kimberley. These soils support a variety of small woodland trees mainly *Eucalyptus* and *Acacia* species, in addition, these soils support spinifex and other coarse grasses including *Sorghum* and *Aristida* species.

This physiographic group is generally considered as having a low carrying capacity for pastoral purposes. However, areas south of the Fitzroy River and merging into the desert support soft spinifex which is useful pasture.

3.3.1 East Kimberley soil types

In the Kimberley, the soil types are Rudosols and Tenosols, however a number of other soil types are present including: Sodosols, Chromosols, Vertosols, Dermosols, Ferrosols, Kandosols and minor Hydrosols.

Rudosols are minimally developed soils consisting of materials that have not been greatly affected by pedological (soil-forming) processes, these soils have minimal development of the A1 horizon or the presence of a B horizon in fissures of the parent rock. McKenzie (2004) describes Rudosols as consisting of vast red sand sheets with variably spaced longitudinal dunes that extend for long distances. The Rudosol environment varies widely, with rainfall between 200 mm in the deserts and more than 1000 mm in the tropics of the Kimberley Region. Topography for Rudosols, ranges from sandplains to rugged, dissected quartzite and sandstone plateaus and partly eroded mesas and butts. Vegetation varies from spinifex in the open deserts to eucalypt woodlands and open forests in higher rainfall Rudosols of the tropics and subtropics (McKenzie 2004).

Tenosols are widespread and the dominant soil of WA, McKenzie (2004) describes these soils as slightly developed soils (with the exception of the A horizon) with the B horizon only weakly expressed in terms of colour, texture, structure and presence of segregation of pedogenic (soil-forming) origin. There is considerable diversity within the Tenosols in regards to their properties, vastly occurring as red soil on sandplains and minor yellow soils with a small clay increase with depth. There are large areas in Western Australia of red loamy soils with red-brown hardpan at shallow depths (0.3 – 1.0 m). Tenosols are found in a range of physical environments spanning rainfall variations between 200 mm to 2000 mm. Vegetation associated with Tenosols are diverse, in arid zones, the most widespread community are spinifex, of the sand plains, mulga (*Acacia aneura*) shrubland and woodlands are common, and in northern and eastern Australia, eucalypt woodlands and open forest are almost universal. Most areas with Tenesols are used for sheep and cattle grazing of native pastures.

3.3.2 East Kimberley pasture vegetation types

There are several vegetation types which are important to pastoralists in the East Kimberley Region, most of these pastures are grasses, providing important fodder for livestock. With reference to McKenzie (2004) and Petheram, Kok, and Bartlett-Torr (2003), the following are the common pasture species for the East Kimberley study area.

a. **Mitchell (*Astrebla* spp.)** – Hoop Mitchell Grass, Weeping Mitchell Grass, Barley Mitchell Grass, Bull Mitchell Grass are the most common found in the Kimberley Region. The most palatable for livestock is the Barley Mitchell Grass that occur on dark crackling clay flood-plains associated with major rivers, other Mitchell Grass varieties can also be observed in this physiography.

b. **Flinders (*Iseilema* spp.)** – Red Flinders is a tufted annual grass that grows to 75 cm high, this fast-growing grass is confined to cracking clays and medium-textured red earths and is associated with Mitchell grasses (*Astrebla spp.)* and Bluegrasses (*Dichanthium spp.)* on black soil pasture lands of the Kimberley Region. Being an annual, the Red Flinders Grass is prominent in the late wet season, depending greatly on seasons, it is valuable livestock fodder both green and as dry hay.

c. **Bluegrass (*Dichanthium fecundum*)** - Curly Blue Grass and Bundle-Bundle are two forms of this species found throughout the Kimberley Region. These grasses are tufted, leafy perennials ranging from 50 to 100 cm in height showing association with black soil pasture lands to the deep soils above 700 mm isohyte in the West Kimberley Region. It is regarded as a key decreaser[1] species and excellent fodder, especially following summer rains, when the nutritional value is increased, when the plants reach maturity the nutrition value steadily declines.

[1] Decreaser species are those that tend to disappear from pasture under heavy stocking.

d. **Rosewood (*Terminalia volucris*)** – Rosewood is a 'top feed' species growing as a small tree to approximately 8 m high; with finely fissured bark that loses all of its leaves in the dry season, new leaves appearing with the flowers and fruit. This species occurs on black-soil plains and also in seasonal swampy areas with clayey soil and occasionally in deeper sandy soils along rivers or creeks. The new leaves provide valuable fodder at the driest time of the year.

3.4 Chapter summary

This chapter includes a description of land units and land unit mapping. Land units provide estimations of natural boundaries derived using a variety of techniques and are defined by relationships between individual elements predominately, vegetation, soil and landforms.

The study area is part of the Kimberley Region of WA, that has been evolving over the last 250 million years. It has diverse climate, physiography, topography and drainage, all interconnected via the hydrological cycle, atmospheric cycle, rock cycle and biochemistry that have shaped the landscape both internally and externally. The natural environment can be broken up into different units or landscape variables, that differ in homogeneity, due to the interconnectivity of the individual elements, including soil, rocks, vegetation and landforms. A parcel of land is identified as never being entirely homogenous when using natural features however it can be thought of as near-homogeneous for mapping purposes and monitoring features.

The Bow River Station study area was chosen for its diversity in topography, relative central location in the East Kimberley Region. Bow River Station is described as one of only a few pastoral rangeland stations that have been mapped to a land unit level during the revised Ord-Bonaparte Program, which makes it suitable for confirmation analysis to check for land unit accuracy.

4 GIS, geomorphometry, spatial modelling, data source

In this study, Geographic Information Science (GIS) is used to assist landscape variable classification to a land unit scale for the East Kimberley study area of WA, by visual representation of data, application of analysis techniques and presentation of results. The analysis techniques include visualisation, exploratory and confirmatory analysis for both landform classification and the building of predictive models. Visualisation includes data display, data overlay, attribute identification, graphs and tables, exploratory analysis involves manipulation of original datasets, data processing and construction of new datasets to encourage formulation of results and confirmatory analysis using maps, graphs and tables to test the hypotheses and to determine the relationships within the data.

It is hypothesised in this research that there is interconnectivity within landscape variables, where landscape variables exist as ‘wholes’ and can be used to delineate land units, these variables include vegetation, soil and landforms as primary landscape variable. This hypothesis aims to prove that spatial landscape data, as individual variables, and GIS software can be used to produce land units at a level of accuracy and precision that can be incorporated into pastoral monitoring projects such as PLAGA.

The assumption has been made that the spatial data used in this research were at a high resolution, from reliable sources, with minimal measurement or representation error. Higher resolution spatial data exists for the pastoral rangelands however was not available for this research. The software available for analysis and presentation purposes in this research required consideration for propagation errors and transformation errors that would be involved with when constraining the spatial data to coordinate systems, pixel size consistency and scale to allow final comparison of techniques and results. Spatial data models were investigated for appropriateness to meet the needs of the hypothesis and for compatibility with available data. The structure chart in Figure 4.1 identifies preparation steps for landform classification and the land unit prediction modelling techniques.

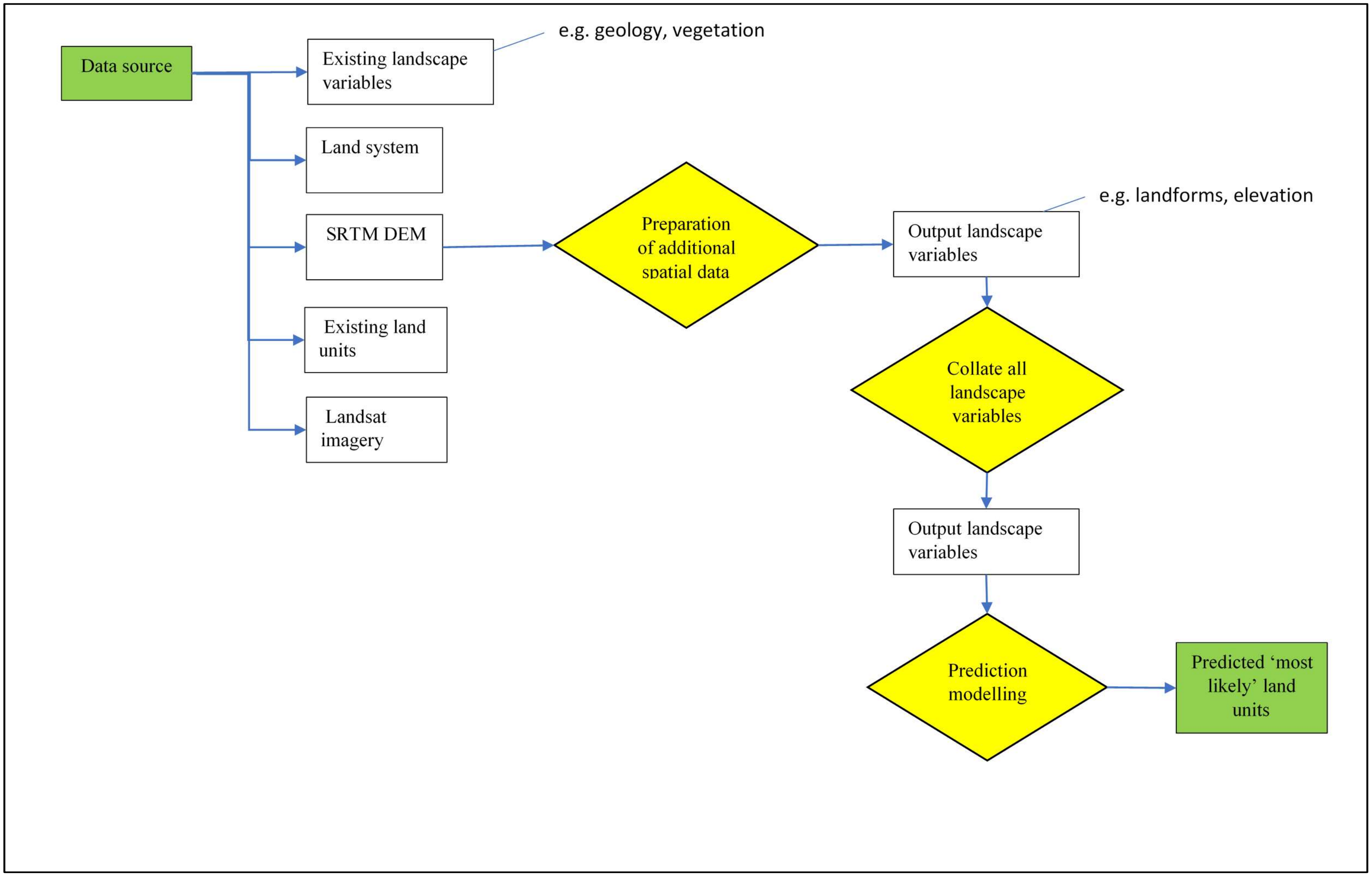


Figure 4.1 Structure chart for spatial modelling techniques.

4.1 Geomorphometry

According to Pike (2009), the science of geomorphometry is described as quantitative land-surface analysis and is generally regarded as an activity within more established fields, ranging from geography to geomorphology to soil science, it is essentially a mix of earth and computer sciences, and engineering and mathematics, sometimes referred to as analytical cartography and GIS. Geomorphometry refines the way elevation data is processed, described and visualised by focusing on the continuous land surface and on discrete features such as landforms. The functional aspect of geomorphometry is the extraction of measures (land-surface parameters) and spatial features (land-surface objects) from digital topography.

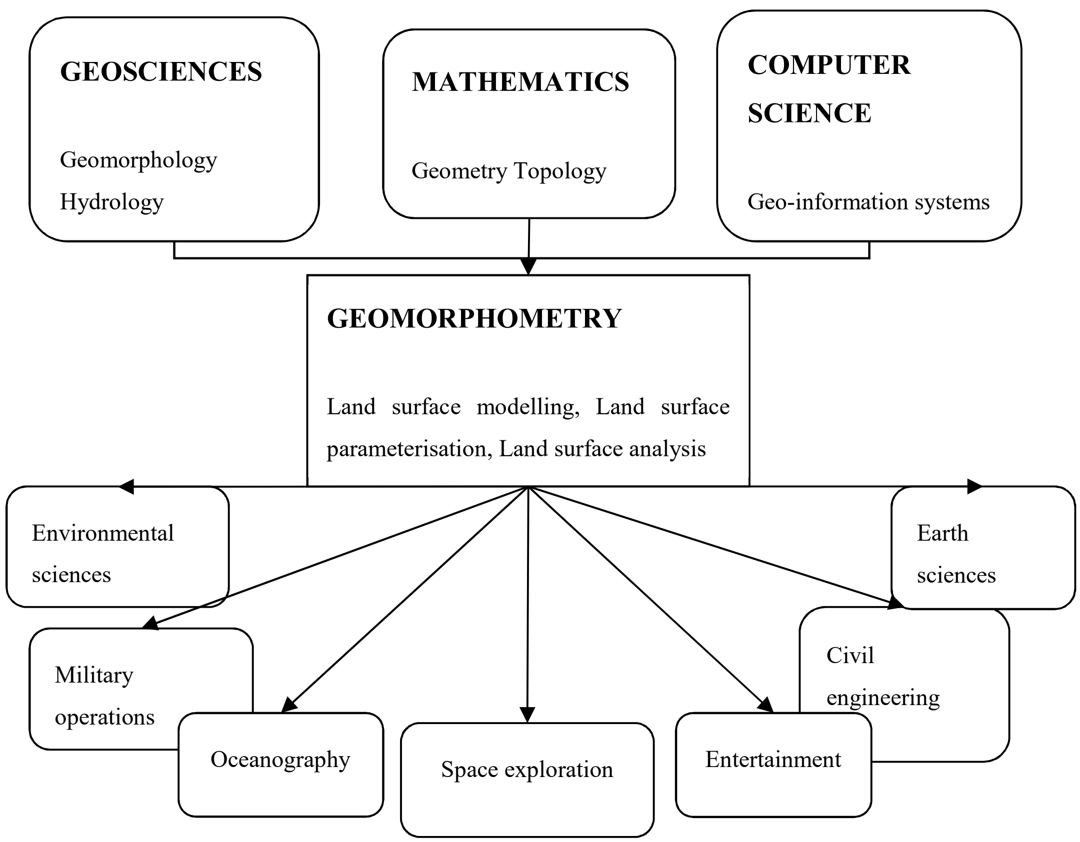


Figure 4.2 Relationship between source and end-users; geomorphometry (adapted from Pike (2009) pp.4).

There are two principal modes of geomorphometry: *specific*, addressing discrete objects (i.e. landforms) and *general*, addressing the continuous land surface. The morphometry of landforms is considered part of quantitative geomorphology (Rhoads and Thorn 1993).

The principals for using geomorphometric analysis for calculating quantities over a 'grid of interest' i.e. a raster GIS (or DEM), involves working with neighbourhood analysis. Most morphometric algorithms work through neighbourhood operations; where patterns are derived from the 'grid of interest', with pixels analysed and grouped according to the association with neighbouring pixels.

Quantitative descriptors or measures of the land surface (landscape variables in this research), are defined by topographic attributes, landform parameters, morphometric variables, terrain information and geomorphometric attributes (Pike 2009).

4.2 The development of landform classification

Since the landform classification process was first proposed by Gauss in 1828, a large number of techniques and models have been researched and tested. Gauss identified that the eponymous Gaussian function, defined by normal curves could be used to replicate and automate manual landform classification and mapping (MacMillan 2009). A similar system was developed by Troeh (1964, 1965), which partitions the land surface into four gravity-specific classes, with the intention of recognising relative accumulation mechanisms, based on the signs of the tangential and profile curves (MacMillan 2009). Both the Gauss and Troeh techniques can be applied to any land surface to produce landform pattern results. There are a wide range of examples where these techniques have been used and adapted for specific geographic locations, including Hammond's landform classification (1954, 1964) for the USA, and Speight (1974, 1990, 2009), for classification of landforms in Australia.

According to Speight (1994), there are approximately 40 landform 'patterns' and 80 landform 'elements' currently defined in Australia. Landform 'elements' provide a greater level of detail, where soil-point observations are taken at 20 m radius distance, compared with landform 'patterns' where soil-point observations are taken at approximately 300 m radius distance. Landform 'patterns' are mostly defined using attributes such as: relief, modal slope, stream channel occurrence, mode of geomorphological activity, geomorphological agent, geomorphological activity and components of landform 'elements'. Landform 'elements' are defined by attributes that include: slope, morphological type, dimensions, mode of geomorphological activity and geomorphological agent (Speight, 1994).

Traditional methods of landform and landscape classification involved drawing estimated boundaries onto aerial photographs through stereoscopic analysis, with these boundaries then confirmed and assessed through field surveys (Hengl and Rossiter 2003).

Field observations are primarily used to characterise the composition of units used in the photo interpretation rather than adjust or find boundaries. It has also been considered that, for many areas, it is important to first establish landform classes, usually by aerial photos, which can then be used to build soil maps, as landform delineations are usually directly associated to the natural soil types.

4.2.1 Hammond's landform classification technique

According to Hammond (1964), landform analysis historically was limited to three dimensional coordinates of points that described the planimetric location and elevation, and were used to create contour maps. He identified that the landform information collected for their specific properties on an element-by-element basis, as seen in other fields such as climate and agriculture; landforms were collated in terms of 'wholes'. He suggested that element-by-element landform analysis was not being used, possibly since some landform phenomena are not very readily seen, for example, surface geometry such as slope and aspect don't automatically fall into separable properties, since they have no clear cut-off boundaries.

Hammond (1964) proposed that geographers interested in landforms, should consider a move away from descriptive to quantitative, or move away from visually perceived landscapes to specific characteristics, with specific characteristics including: relief, slope, topographic profile. Class boundaries are identified as arbitrary and limited, so that combinations of landform types do not become too complex during description or depiction. The coarsest level of the hierarchy is slope, defined by four classes; six classes of relief define the next level, followed by four classes of profile at the finest hierarchy level. This concept is particularly useful for defining gently sloping areas and has the advantage of differentiating between tableland topography where gentle slopes are primarily in the uplands, and the gentler slopes associated with hills and valley topography in the lowlands (Gallant 2005).

Slope is essentially a feature of the earth's solid surface, including both terrestrial and submarine surfaces. Slope elements are assumed to be of small, but unspecified, dimensions, and as finite surfaces in space, slope elements may be planar, cylindrical, conical, spherical, or of any other configuration, including highly irregular forms. Slopes are currently produced by exogene (external) processes, and endogene (internal) processes of vulcanism, orogeny, and epeirogeny (Strahler 1968).The principles of slope are driven by two scale dependent classes of physical stresses, gravitational and molecular, that act on earth materials, having certain characteristic properties (elastic solid, plastic solid, fluid), and yielding stresses, including strain as rupture, plastic flow, and or fluid flow, that generate distinctive landform types (Strahler 1992).

Relief is defined as the difference in elevation between the high and low points, for a study area, on a land surface. Its estimation is described by visualising two surfaces that are continuous and gently curved, where one of the surfaces passes through all the major crests in the area and the other surface passes through all the drainage depressions. The average vertical separation between these two surfaces is the measure of relief. Relief is the quantitative characteristic for the terms: *mountains*, *hills*, *low hills*, *rises* and *plains*, as used as types of erosional landform patterns (Speight 1990).

Topographic profiles were described by Sayles (1978) as forms or features which cover the Earth surface extending to underlying random structures, in which they represent the complex interaction of many physical processes that operate over a wide range of lengths and scales. One method for measuring the complexity of topographic profile, recognised by Mandelbrot (1977), is using fractals. A fractal is a scaling property represented as a parameter of the surface topography, it is collectively referred to as fractional dimension, and can be used as a measure of clustering, to identify patterns, however the fractal model only describes the rate of change of the parameters within a specific size and does not describe an entire surface (Brown 1986). The Hammond (1964), landform classification method uses observations of the topographic position of only gentle slopes, therefore is not a complete representation of a topographic profile. The Hammond classification method was used in this research to assist landform classification by following the Hammond (1964) five main steps in analysing and classifying landforms, these are:

1. Selecting an analysis window, a moving average window, that is neither too small to cut individual slopes into parts therefore distorting the determination of local relief, nor too large that it includes areas of excessive diversity, or that extend local relief figures by adding in long regional slopes (Gallant 2005).

2. Calculating the percentage of slope characteristics in the analysis window;

3. Categorising local relief;

4. Classifying topographic profile;

5. Generating a landform map.

The five steps allow landform classification together with defined cut-off boundaries outlined in Table 4.1 as Table I – Hammond’s Landform Classification Rules and Table II – Hammond’s Landform Classes (Gallant 2005).

Table 4.1 Hammond's Landform Classification Scheme – Table I and Table II (Gallant 2005).

Table I – Hammond's Landform Classification Rules

% Local Area Gently Sloping	Local Topographic Relief (m)	Profile Type (topographic position of the gentle slope)
A. >80	1. 0-30	a. >75% in lowland
B. 50-80	2. 30-91	b. 50-75% in lowland
C. 20-50	3. 91-152	c. 25-50% in lowland
D. <20	4. 152-305	d. <25% in lowland
	5. 305-914	
	6. >914	

[1]Column categories are hierarchic, from left (most general) to right (finest).

Table II – Hammond's Landform Classes

Plains	
A1	Flat plains
A2	Smooth plains
B1	Irregular plains, slight relief
B2	Irregular plains
Tablelands	
B3c,d	Tablelands, moderate relief
B4c,d	Tablelands, considerable relief
B5c,d	Tablelands, high relief
B6c,d	Tablelands, very high relief
Plains with Hills or Mountains	
A,B3a,b	Plains with hills
B4a,b	Plains with high hills
B5a,b	Plains with low mountains
B6a,b	Plains with high mountains
Open Hills and Mountains	
C2	Open low hills
C3	Open hills
C4	Open high hills
C5	Open low mountains
C6	Open high mountains
Hills and Mountains	
D3	Hills
D4	High hills
D5	Low mountains
D6	High mountains

4.2.2 Landform classification using GIS

In general, landform classification can be performed either manually or automatically. Manual systems of geomorphic classification are commonly hierarchical, sub-dividing land surfaces into increasing greater detail at increasing higher resolutions. Manual classifications tend to be synoptic and synthetic, and are therefore not a perfect representation of nature, nor are they as accurate as field surveys. Automated classification is a technique that tries to replicate and improve manual classification, using technologies such as GIS.

Automated classifications can be either supervised or unsupervised. In a supervised classification, the features have already been identified and therefore can form the foundations of training samples, for example, similar landforms types can be grouped as an area or polygon and given a label. Once all the training samples have been grouped and labelled for a study area, multivariate statistics can be used to establish the relationships within and between the groups, these multivariate statistics also include slope and curvature limitations. These statistics can then be stored as signature files or classes. There are two final stages of automated supervised classification, these are:

- Evaluation and, if necessary, editing classes, and

- Final classification using signatures for the study area.

The two main input data for an automated supervised classification are the input raster data (e.g. DEM) to analyse, and the desired classes (Mather 2006).

In automated unsupervised classification, grouping areas of similar features might not be easy or there might be insufficient information to group the features with a good degree of certainty. In these situations, it is not possible to estimate the statistical mean centres of classes for classification or even the number of classes that might exist, therefore classification is 'unsupervised' and left to automated multivariate statistics. The multivariate statistics use spatial differences of points including slope and curvature variations together with frequency distribution of the points to determine which class the features belong (Mather 2006). In ArcGIS there are a range of signature values that are used to statistically separated groups into spectral and spatial differences that are then given a class label (Environmental Science Research Institute Inc (ESRI) 1999-2010).

In Australia, landform features are classed and labelled using Australian standard nomenclature, these are defined by Speight (2009a) as: crest (peaks), ridge, flat (plains), depressions (pits), channels and slope. When a class cannot be uniquely grouped as a class, as seen in Figure 4.3 for peaks and ridges, there remains a level of doubt, and this doubt is reflected in classification used of a study area.

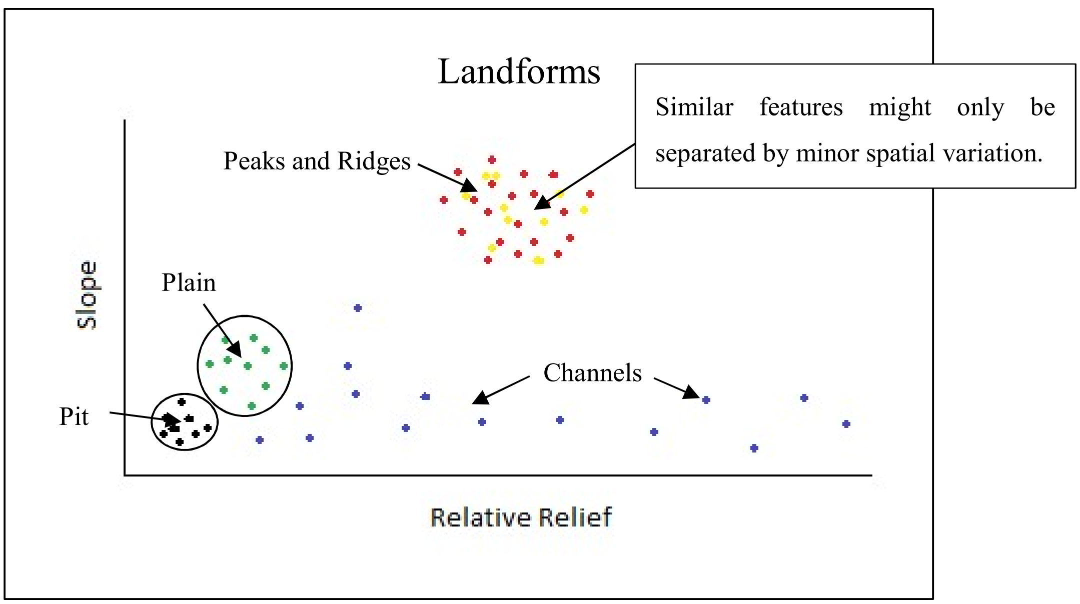


Figure 4.3 Hypothetical grouping of features into classes for classification techniques.

According to Speight (2009a), landform descriptions and classifications are rarely developed sufficiently to meet the needs of land-use planning, for example, the landform scheme developed for the 'Australian Soil and Land Survey, Field Handbook' (Speight 2009a) was produced as a record of observations rather than inferences.

Maps displaying landforms can either show landform ‘elements’ or landform ‘patterns’. Based on their characteristic dimension of about 600 m, landform ‘patterns’ are best depicted at a 1: 200,000 scale, whereas landform ‘elements’ with their characteristic dimensions of 40 m are best illustrated at a scale of 1: 15,000.

The main benefits of landform classes in soil and land surveys are that they have direct application for land-use planning, are useful for finding relationships to support the extrapolation of point observations, and they help to predict changes in the land following various land use and help identify areas of land degradation.

4.3 Selecting spatial modelling techniques software

Geographical Information Systems (GIS) are considered an integral part of mapping and spatial analysis and have shown significant development since they were first introduced during the 1960’s. Everything that occurs on Earth, occurs in space and time, therefore can be measured both spatially and temporally. An object on Earth can be described by its location, and an event occurring at a location can be recorded in time. A spatial model is comprised of spatial and temporal data, together with attributes that describe both the location and the event of an object; this relationship is referred to as trispace (space, time, attribute) (Wegener 2000). The ability to capture, analyse and present these data is useful for a number of disciplinary fields. Historically, GIS was used for topographic and cadastral mapping, thematic mapping, civil engineering, geography, mathematical studies, soil science, surveying, photogrammetry, urban and rural planning, utility networks, and remote sensing and image analysis, with a large variety of specific software for each individual field (Burrough 1986).

According to Fotheringham (2000) advances in spatial modelling using GIS can be considered both a step forward and a step backwards. He identifies the inability of a single GIS package to cater for all needs in such a broad spectrum of applications for GIS. The negative consequences of using GIS for spatial modelling, include outdated modelling methods and the inability of untrained users to produce reliable results. There have however been advances in spatial modelling using GIS, these include, integration of disciplinary fields for robust analysis and modelling purposes, and an increase in the number of specialised software available.

Wegener (2000) describes the main fields in which GIS are used today as being categorised into two main groups, environmental sciences and social sciences. The environmental sciences include: atmospheric and hydrological modelling, land surface-subsurface processes, biological/ecological systems and integrated modelling including a combination of two or more of the other groups of environmental models. The social sciences include: economic, geographical, sociological and transport engineering modelling or integrated modelling using a combination of two or more of the other specialised groups of social science models.

There are still many different GIS software packages that explore spatial data and provide specialised analysis techniques, including software packages that specialise in geomorphometric analysis. Software functionality and its ability to produce reliable results are the main criteria when choosing a suitable package, however, price, availability, expertise and users software knowledge are equally important in the decision-making process. The following figure summarises the main focus point of analysis for software packages that specialise in geomorphometric analysis.

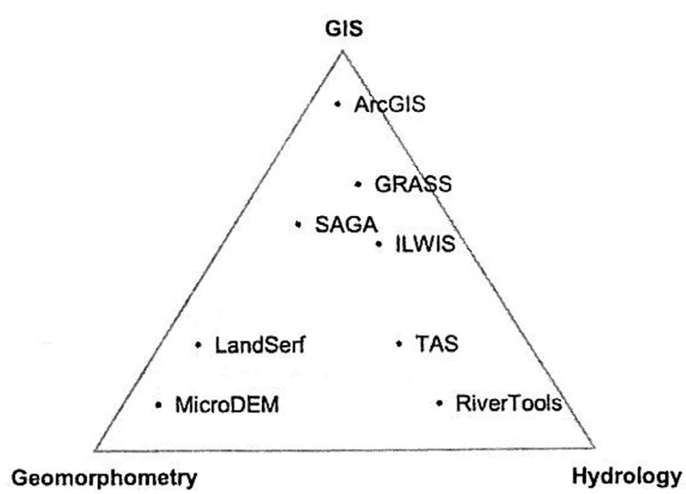


Figure 4.4 Approximate focus of GIS software packages ((Wood 2009d).

The two main software choices for the research as part of this thesis are, the free but closed source software (LandSerf) and the commercial software package (ArcGIS). ArcGIS was one of the earliest software packages used for geomorphometric analysis (more than 20 years), however the disposition of the software was not focused around terrain analysis and therefore was limited in geomorphometric analysis (refer to Section 4.3.1). Terrain-based geomorphometric analysis software is limited (refer to Figure 4.3), because many software packages focus on providing a wide range of GIS functionality, provide large user communities and substantial user support and therefore are more limited on specialised GIS including terrain-based geomorphometric analysis (Wood 2009d). This limitation in specialised terrain-based GIS led to the development of the education-focused GIS software package called LandSerf. LandSerf performs semi-automated terrain analysis and landform classification. Other software packages tested during the decision making process of this included the fully open source software Geographic Resources Analysis Support System (GRASS) (GRASS Development Team 2010) and Object-Based Image Analysis (OBIA) software eCognition (XD 2009).

Different software packages use different Operating Systems (OS). An OS is comprised of the hardware and software components of the software 'package' and allows for different architecture and processing capacities. The most common OS are Microsoft (MS) Windows, UNIX, OS X and Linux (McHoes 2014). MS Windows is a common operating system for GIS software packages including both ArcGIS and LandSerf. Both ArcGIS and LandSerf are window application computer programs that use Graphic User Interface (GUI), which could be considered more user-friendly when compared with a console application.

There are similarities when using ArcGIS and LandSerf in that both can be adapted using script, however the scripting language varies between the two software, with ArcGIS using Python scripting language, and LandSerf using a Java-like language called LandScript syntax. Data created in both software packages can be saved in various formats that can be interchanged between compatible software.

4.3.1 Environmental Systems Research Institute (ESRI): ArcGIS

Environmental Systems Research Institute (ESRI) produces a collection of software products collectively known as ArcGIS. ArcGIS has been in existence since the early 1980's using various UNIX OS platforms, moving to a MS Windows OS platform in the 1990's. The current ArcGIS 10.5 runs within a MS Windows OS using the Python 2.7.8 scripting language (ESRI 2016). The ArcGIS software suite consists of ArcCatalogue (data management), ArcMap (2D data analysis and display), ArcScene (3D analysis) and ArcGlobe (3D global analysis). The main use of ArcGIS in this research was to aid landform classification and to develop a prediction model.

The ArcGIS suite is limited in terrain-based classification, the method for classification and segmentation in an ArcGIS environment is using a segment mean shift approach, which involves the use of spectral detail, spatial detail, minimum segment size in pixels and segment boundaries. The mean shift approach uses a 'moving window that calculates an average pixel value to determine which pixels should be included in each segment, as the window moves over the image, it iteratively recomputes the value to make sure that each segment is suitable. The result is a grouping of image pixels into a segment characterised by an average value, represented by a colour' (Environmental Science Research Institute Inc (ESRI) 1999-2010). There are also a number of separate functions for terrain analysis in ArcGIS, including a curvature function, a slope function and a shaded relief function. These functions provide information about an elevation raster or DEM in regards to the terrain, however are not presented as a complete tool to be used for landform classification, therefore identifies ArcGIS limitations in terrain-based geomorphometric analysis.

The main suite of tools to aid terrain classicisation and modelling in ArcGIS include the Spatial Analyst and 3D Analyst toolboxes. The Spatial Analyst toolbox contains parameters to process a DEM into slope, aspect, hillshade, contours and two-dimensional curvature, with an additional Spatial Analyst extension tool that allows the user to create contours and a value/count histogram. The 3D Analyst toolbox contains parameters to create and manage terrain datasets in three dimensional environments that can also be viewed in ArcScene. The 3D Analyst extension tool allows transformation of elevation data including DEMs and contours into a Triangular Irregular Networks (TIN), that can be used to delineate linear and network features such as drainage (Environmental Science Research Institute Inc (ESRI) 1999-2010).

ArcGIS is the most widely used GIS software globally and has a large amount of functionality for visualisation, exploratory analysis and for confirming results. Most government departments and industry in Australia that perform spatial analysis use ArcGIS. ArcGIS has the ability to export and import data, to and from other software providers and in a variety of formats including text files, excel files, cartographic files, image files and elevation models. ArcGIS products allow different work environments for both manipulating data and for map layout; data analysis and spatial modelling can be performed using the data view window, and then saved as a map or image in the layout view window.

4.3.2 LandSerf

Numerous software packages are capable of landform classification including LandSerf, ArcGIS, GRASS (Geographic Resources Analysis Support System (GRASS Development Team 2010)), and eCognition (2009), although out of these, LandSerf is the only software dedicated to terrain and geomorphometric analysis. LandSerf is a free, closed source software, refer to Section 4.3.

LandSerf is specifically designed for terrain and geomorphometric analysis with much of the functionality designed to process DEMs. LandSerf has similar functions to the r.param scale command in GRASS, although the terrain analysis tools in LandSerf are more refined and specialised for landform classification, and LandSerf is considered more 'user-friendly' than GRASS. LandSerf uses a Java-like scripting language called LandScript, and can operate on MS Windows, Mac, Linux and UNIX operating systems. Issuing commands within a script makes it is easy to document, reuse and share the operation sequences (Wood 2009c).

LandSerf was developed through research by Wood (1996), who identified a number of issues surrounding the characterisation of land surfaces represented by DEMs, and therefore developed a set of software tools suitable for use in a raster-based Geographical Information System (GIS). Overall, LandSerf software has three specific objectives: to identify spatial patterns, to identify scale dependency and to allow visualisation of results. Therefore, LandSerf is a platform for performing scale-based analysis of DEMs, with the performance of *multiscale surface characterisation* (Wood 2009a) central to the design. When LandSerf was developed, the only other software capable of performing multi-scale surface characterisation was GRASS, using the module *r.param* scale, also based on Wood's (1996) research.

The central design of LandSerf, multiscale surface characterisation, was based on the idea that measurements of surface characteristics are dependent on the scale in which they are made (Wood 2009a). Scale in this context encompasses the spatial extent of the measurement and the spatial resolution of the sampling. LandSerf uses a number of graphical and visualisation techniques to explore the relationships between space, scale and morphometry. The size of an image on a screen is governed by a combination of factors, including the resolution and scale. The resolution of an image on screen, is the distance on the ground, corresponding to a pixel, which is generally unrelated to the resolution of the data. For example, if a DEM with a raster format of 10,000 rows by 10,000 columns is displayed on the screen with 1,000 rows and 1,000 columns, the display uses every tenth pixel in each direction (Bonham-Carter 1994).

LandSerf is particularly suited to geomorphometric analysis where graphical interpretation of the land surface using spatial data is intended, and where scale is also a factor of consideration. Firstly, land-surface parameters are measured at a scale which is determined by setting the local window size depending on which parameter is to be estimated. Secondly, the variation in land-surface parameters with scale can be explicitly considered by plotting 'signatures' of scale, at points over the surface, or by finding the points where the land-surface is at its most extreme e.g. mountain peaks are regarded as land surface extremes. Thirdly, the variation in land-surface parameters can be explored visually through the use of 'mipmapping' in a dynamic 3D environment (Wood 2009a), where mipmapping is described as a real-time block-based terrain rendering algorithm that aims to reduce processing time when compared with prior techniques such as quadtree rendering, where the terrain is divided into square tiles created by binary division with quadratically diminishing size (de Boer 2000).

LandSerf uses derivatives of coefficients to define quadratic surfaces, where quadratic surfaces are defined as, natural 3D extensions of the so-called conics (ellipses, parabolas, and hyperbolas), for land surface parameters and landform classification, that can be used in multivariate calculus (Rogness 2016). LandSerf uses first derivatives and partial second-derivatives of a bi-quadratic polynomial, the bi-quadratic polynomial expression is represented by:

$$z = ax^2 + by^2 + cxy + dx + ey + f \tag{4.1}$$

where z is the estimate of elevation at any point (x, y) and a to f represent the six coefficients that define the quadratic surface, however, the way in which each of these six coefficients is estimated makes LandSerf unique. LandSerf finds the six coefficients by solving six simultaneous equations using a matrix method; a raster grid is fitted to a scale window that best suits the study area or required output resolution, and then a 'best fit' quadratic surface is estimated using least squares regression. These coefficients are further simplified by regular spacing of the grid cells in the raster, and making the raster coordinate system symmetrical in the x and y directions (Wood 1996).

Overall, LandSerf has both strengths and weaknesses for geomorphometric analysis. On the positive side, LandSerf is free software that runs on most operating system platforms, and it has a geomorphometric focus, visual control and interpretation, and performs semi-automated landform classification, with both raster and vector input and output capabilities in many formats. Some of the negatives of LandSerf are the fact that it is a specialised software package focusing almost solely on geomorphometric analysis, and its limited memory management impedes performance, and limits the size and number of data that can be processed at one time. Wood (2009a) explains, that each raster cell is stored as a 32-bit floating point number, so a 1000 x 1000 cell raster requires 4 MB of heap memory, combining this with the memory for display and undoable copies of editable rasters, a size of around 3000 x 3000 cell raster is the practical limit before performance degradation becomes evident in results with minimal relevant meaning.

LandSerf is appropriate for terrain-based geomorphometric analysis for a number of reasons, however mostly due to the application of parameterisation of geomorphometric surfaces, where parameterisation is described as "the numerical description of continuous surface form" (Pike 1993). LandSerf takes into consideration that "terrain description is exhaustive if it describes all aspects of the surface form" (Wood 1996), and uses a number of numerical descriptors of the continuous land surface including slope, curvature, aspect, scale and edge effects, to aid landform classification and geomorphometric analysis.

4.4 Data sources

Data for this research were obtained from a variety of sources including the Department of Food and Agriculture of Western Australia (DAFWA) (Department of Food and Agriculture 2011), Landgate (Western Australia Land Information Authority. 2011), Geoscience Australia (Geoscience Australia: Department of Resources Energy and Tourism. 2007), US Geological Survey (United States Geological Survey. 2011) and the Bureau of Meteorology (Bureau of Meteorology 2010) websites. The initial data consist of point, line and polygon shapefiles, raster datasets and attribute tables, with most data readily compatible with ESRI ArcGIS software. Metadata were included in most original datasets, describing data source, author, date produced and coordinate system. The following table, Table 4.2, lists the datasets available for this research together with source, data type and format.

Table 4.2 Available Datasets.

Dataset	Source	Data type	Format
Aerial Photography: Bow_4564, Chamberlain_4464, Mount_Remarkable_4463, Turkey_Creek_4563	DAFWA	Continuous	Raster Mosaics
DEM	SRTM via DAFWA	Continuous	Raster
Landsat Imagery	NASA website	Continuous	Raster
Drainage	DAFWA	Discrete	Vector
Pastoral Properties	DAFWA	Discrete	Vector
Vegetation	DAFWA	Categorical	Vector
Land units	DAFWA	Categorical	Vector
Land systems	DAFWA	Categorical	Vector
Geology	DMP	Categorical	Vector
Field Data	GPS field survey	Discrete	Vector

4.4.1 Coordinate systems

The study area is located in the North East of Western Australia that lies in zone 52 of the Map Grid of Australia (MGA52) coordinate system. The reference datum for MGA52 is the Geocentric Datum of Australia 1994 (GDA94). All data was converted firstly to GDA94, geographic coordinates - latitude and longitude, and then transformed onto the map grid MGA52. The map grid coordinate system - MGA52 allow the data to be viewed in easting and northing space and allows metric measurements.

The specifications for the Geocentric Datum of Australia 94 (GDA94) are:

- *Datum:* Geocentric Datum of Australia (GDA)
- *Geographical coordinate set:* Geocentric Datum of Australia 1994 (GDA94) (latitude and longitude)
- *Grid coordinates:* (Universal Transverse Mercator, using the GRS80 ellipsoid) Map Grid of Australia 1994 (MGA94)
- *Reference Frame:* ITRF92 (International Terrestrial Reference Frame 1992)
- *Epoch:* 1994.0
- *Ellipsoid:* GRS80
- *Semi-major axis (a):* 6,378,137.0 meters
- *Inverse flattening (1/f):* 298.257222101

4.4.2 The Digital Elevation Model (DEM)

According to Burrough (1986), a DEM is a model that represents the continuous variation of relief for the land surface. DEMs can be grouped into two categories, they are either a raster-based regular DEM, or a vector-based irregular DEM. Regular gridded DEMs represent the terrain surface as a regular matrix of point elevations that are essentially tessellations of square tiles with point elevations at the centre of each tile (Gallant 2000b). The regular grid of elevations allows plan-based coordinates to be calculated from the regular spaced grid points that can be transformed into point coordinates (x, y, z) (Evans 2009).

Two DEMs were used in this research, produced from the Shuttle Radar Topographic Mission (SRTM) elevation data and not publicly available at the time of this research.

Both DEMs were supplied by the Department of Food and Agriculture of Western Australia (DAFWA), and are enhanced versions of data produced by NASA, with striping and voids removed using methods developed by CSIRO Land and Water.

A preliminary version DEM (version 1) was used to develop and test landform classification for the study area. A second hydrologically enhanced DEM (version 2) was later obtained that emphasises drainage features. Methods developed using the preliminary DEM were applied to this second DEM to test for appropriateness and to assess improvement of results.

Enhancement for the second SRTM DEM (version 2) included a de-stripe mask. ‘Striping’ is an undesirable effect that is caused by remote sensing sensors, that occurs when one or more sensors scan an area for an image (Horn 1979). Each sensor has slightly different calibration and slightly different ‘gain’ and ‘offset’ creating lines or ‘stripes’ across the image. The ‘gain’ is the slope of the line relating to the pixel value and radiance, and the offset is associated with the average ‘gain’. This ‘striping’ effect can be removed if the ‘gain’ are accurately known, since the ‘scene radiance’ could be calculated from the sensor output using the inverses of these ‘gain’ (Mather 2006). The de-striping method involved for the SRTM DEM (version 2) indicated which ¼ x ¼ degree tiles had been affected by de-striping and which had not been de-striped. The striping magnitude layer showing the amplitude of the striping at 1 km resolution, with a void mask showing cells that had no-data in the raw SRTM. The voids were filled using a void filling algorithm, and a hydrology mask was applied at 1 second resolution showing the cells that were part of flattened water bodies (Pigram 2009). The hydrologically enhanced DEM aimed to improve landform classification due to more detail in drainage and depressions caused by land surface water features.

4.4.3 Field data collection

The study area for this research is primarily Bow River Station located in the East Kimberley Region of WA (refer to Section 3). Bow River Station is a cattle station operated by the indigenous Gija people (Wardrop 2009), and was chosen due to the availability of data at the land unit scale. Land unit data is only available for a small number of WA pastoral rangelands due to limitations on cost, accessibility and time. Bow River Station is part of the Ord River catchment, and was mapped as land units during the Ord-Bonaparte Program in the 1990's.

Data was collected during two field trips, firstly a trip to the West Kimberley to provide familiarity with the landscape, and secondly, to Bow River Station. Global Positioning Systems (GPS) waypoints, together with land surface descriptions were collected for information of the landforms, vegetation, geology and soils that could aid prediction model testing and confirmation analysis.

4.5 Accuracy measures

Geographic information is essentially a collection of information and links between places, time and properties on or near the Earth's surface. Geographic information has evolved mainly from the practical needs to solve geographic problems, however has also proven successful in other disciplinary fields including agriculture, landscape ecology and soil conservation (Zhang 2002). The complexity of the Earth's surface means that effective and accurate descriptions are almost impossible, therefore, a variety of techniques have been developed to simplify the world into something more manageable, this is known as generalisation (Longley 2005). Some degree of generalisation is always present, when producing data from a remote source, generalisation adds a degree of uncertainty into the data, and therefore represents a compromise on accuracy and precision which will affect the final results. Uncertainty and inaccuracies are present in the whole process of geographic analysis, arising through data acquisition, data processing and presentation of results. Once results are determined a degree of error (Mather 2006) may become evident when correlating with existing data, however this will not identify where the error initiated.

Inaccuracy and uncertainty initiate during data acquisition, data are dependent on the skill of data analysts and the precision of the acquisition instruments. Data may pass through many different transactions and custodians, each providing their own protocols and interpretations, therefore uncertainty is not so much in the data but more in the relationship between the data and the user. Nevertheless, data quality has improved through advances in field technologies, including GPS and improvements in laboratory techniques, such as digital image processing.

Spatial data can be in many forms including irregular points, regular points, contours, polygons, or grids. There are two main types of variables commonly used in models: continuous and categorical. Categorical variables are measured on discrete scales (nominal and ordinal), whilst continuous is measured on continuous scales (interval and ratio). Categorical variables include geology and soil type, while continuous variables include elevation, rainfall and temperature. Both variable types contain a degree of uncertainty, with spatial variation incorporated through polygon boundaries and grid cell generalisations, for example, in the classification of remotely sensed images where each cell is allocated a particular class, and the contiguous pixels of identical class are used to generate polygons (Zhang 2002), are some sources of uncertainty in spatial data.

According to Zhang (2002), it is best to consider uncertainties as part of the initial input into a model rather than considering where uncertainty might have occurred in the modelling process. The modelling process does however propagate uncertainty during the combination of input data and additional knowledge input.

Uncertainty can also be categorised into four classes: temporal, structural, metrical and transitional. Temporal describes uncertainty in past and future states, structural describes uncertainty due to complexity, metrical describes uncertainty in measurement and transitional describes uncertainty in explaining uncertain results (Rowe 1994).

Spatial data accuracy is determined by implementing well-defined statistics and tested methodologies for positional accuracy of maps and spatial data. The methodology for measuring accuracy compares collected field points, vector and raster data with higher accuracy sources, such as features readily visible or recoverable on the ground (Survey 2005).

A number of methods can be used to check for uncertainty and inaccuracy of results for both landform classification and predicted land units with existing data and point locations, including a confusion matrix, omission and commission calculations and Receiver Operating Characteristics (ROC) methods using a ROC plot.

A confusion matrix is commonly used to assess the accuracy of classification results. The matrix is a summary of the independent field observations compared with the classification results, showing the relationship between the two data sets in tabular form. There are two main accuracy outputs from the matrix, the user accuracy and the producer accuracy. The user accuracy is the probability that a result labelled as a category actually belongs to that category, and is the measure of commission error, whilst the producer accuracy is the probability that a result known to belong to a category is correctly labelled to that category, and is the measure of omission error (Zhang 2002). The comparison matrix can be presented as a table, commonly referred to as a frequency distribution table with the overall accuracy calculated by dividing the sum of the diagonals of the matrix by the total of all the elements. The overall accuracy reflects on the input data and modelling process. The sum of results for each row or column can also be compared for variation in total number of results.

A ROC plot is a graphical plot that can be used to illustrate the performance of binary classifier sets, for example, it can be used to compare various modelling methods or sets of data, or existing data with model output data. The graph curve on the ROC plot is created by plotting the True Positive Rate (TPR) against the False Positive Rate (FPR) at various threshold settings.

Models will never perfectly replicate reality. The most important outcome of the model will be how much it reduced uncertainty for future applications, and how important the results are for decision making. The use of reference data to check for accuracy of the results and the accuracy of the model are most importantly used to calibrate a model and to determine the parameters and rules of the model especially where reference data isn’t always available, like many pastoral rangelands in WA at a land unit scale. To test the parameters and rule of the model it is also useful to perform cross-validation, a process of testing the model in which a subset of an area is used for calibration and the rest of the area is used for validation (Longley 2005).

The land unit prediction model in this study has reference data available, that can be used to develop, calibrate and cross-validate the model, if the model passes these tests perhaps it can be applied in areas where reference data is not available.

4.6 Chapter summary

Geomorphometry is comprised of many science disciplines used to describe the Earths land surface in terms of quantitative observations and measurements. Geomorphometry was discussed in this chapter to describe the importance of quantitative descriptors such as landforms as part of greater land surface descriptors including land units.

Landform classification was discussed as a possible source of an additional landscape variable, with the aim of increasing the number of landscape variables, discussed as likely to increase the homogeneity of the landscape in a predicted land unit model. A discussion was made regarding how landforms can be categorised using Hammonds techniques and using GIS technologies.

GIS software were designed to solve numerous digital data problems using visualisation of data, explanation and exploration of digital patterns, development of models and confirmation analysis. Various types of software were discussed and how they are relevant to this research, with focus on LandSerf for landform classification and ArcGIS for presentation and prediction modelling. Data sources and coordinate systems are identified with a discussion on Digital Elevation Model's (DEM's). There is an introduction to the study area field trip and accuracy measures that will be used to check final results.

5 Development and testing of evidence variable layers

This chapter looks at techniques for classifying the landscape into evidence variable layers that can be used in a prediction model. Initial focus was on landform classification with landscape features including hills, gorges and flood plains. Landforms contribute to the character of the landscape and shape (morphology) as a result of physical land surface processes, for example, the action of water (fluvial action), action of wind, weathering, transportation of sediment, distribution of plant and animal species and movements within the earth's crust (Blaszczynski 1997). Landscape and land surface processes can be used in many evaluation studies including land use suitability studies, vegetation prediction modelling, fire hazard analysis, erosion studies, regional planning and land system inventories (Dragut and Blaschke 2006).

Other features of the landscape include living elements such as vegetation and wildlife, human elements that include land use, buildings and structures, and changeable elements such as weather conditions. The interaction of the atmosphere (air), biosphere (living things), hydrosphere (water) and lithosphere (rocks), all shape the physical environment of the land surface and therefore the natural landscape.

5.1 Landform classification

Landform and land surface field mapping in this study follow guidelines from the Australian Soil and Landscape Survey Field Handbook (Speight 2009a), that describes ways of breaking the landscape into natural components of the land. Landform components possess size, shape, orientation, relief and contextual position. Individual landform features can be derived using elevation from a DEM, that can be broken into local geometric parameters describing the shape of the land (e.g. slope, aspect, plan and profile curvature) and regional statistical parameters describing relative position of a point within its surroundings (e.g. local relief, deviation from the mean) (Blaszczynski 1997, Gallant 2000b, Klingseisen 2016, MacMillan 2009).

Table 5.1 Local geometric parameters for W.A. landforms (Speight 2009a).

Typical modal slope class	**Landform pattern types**
Precipitous > 100%	(Rare in Australia)
Very steep 56-100%	Mountains, escarpments, volcano, caldera
Steep 32-56%	Hills
Moderately inclined 10-32%	Low hills, karst, meteor craters
Gently inclined 3-10%	Rises, beach ridge plain, dunefield, lava plain, coral reef
Very gently inclined 1-3%	Pediments, alluvial fan, sand plain
Level <1%	Plains, sheet-flood plains, pediplain, peneplain, alluvial plain, flood plain, meander plain, bar plain, covered plain, anastomotic plain, stagnant alluvial plain, terrace, tidal flat, made land, playa plain

Table 5.2 Parameters for modal slopes for landforms (Speight 2009a).

Typical relief	**Landform pattern types**
Very high >300 m	*Mountains*, volcano
High 90-300 m	*Hills*, volcano, caldera, meteor crater
Low 30-90 m	*Low hills*, volcano, caldera, meteor crater
Very low 9-30 m	*Rises*, terrace, dunefield, lava plain, coral reef, peneplain, karst
Extremely low <9m	*Plain,* pediment, pediplain, sheet-flood fan, alluvial fan, alluvial plain, meander plain, bar plain, covered plain, anastomotic plain, stagnant alluvial plain, delta, playa plain, tidal flat, beach ridge plain, chenier plain, sand plain, made land

The information shown in Table 5.1 and Table 5.2 identifies the local geometric parameters (Table 5.1), and the modal slope parameters (Table 5.2), for Australian landforms (Speight 2009a) and were used to formulate a methodology to extract landform features from a DEM. The primary landforms in Australia are described as peaks, ridges, plains and channels, and this hierarchy is commonly used to describe and classify landforms in WA (Speight 1990), both local geometric parameters and the regional statistical parameters for landforms identify approximately five to six classes.

5.1.1 Landform classification using LandSerf

LandSerf (Wood 2009c) is software that uses a semi-automatic classification algorithm that can identify six morphometric/landform classes. This classification method can be adjusted to suit the dimensions of the landscape for the study area, by adjusting the slope and curvature parameters. Sequentially adjusting the settings will impact the classification of individual cells and therefore the final results.

LandSerf uses an adjustable sampling window for local landscape dimensions, including the size of the landforms, that might occur in the study area. A common sampling window for identifying landform features using a DEM is a 3 x 3 regular grid. The results can then be examined for relationships that might exist between the central cell and its' neighbours (Wood 1996). The classification process produces three point-based categories (pits, passes, and peaks), two line-based categories (channels and ridges) and one area-based category (plains).

The 3 x 3 regular grid approach as a sampling window, can be seen in Figure 5.1, showing how three of the morphometric/landform feature classes are interpreted by LandSerf software.

The semi-automated feature extraction algorithms assign individual cells of a DEM a single feature class, for example, a 3 x 3 sampling window has eight neighbours surrounding a central cell, each cell can be denoted as a positive or negative value depending on their elevation relative to the central cell; positive for higher and negative for lower than the central cell.

The pattern of these neighbours can then be used to define which landform feature class the cell belongs to as seen in Figure 5.1.

-	-	-
-	Peak	-
-	-	-

+	+	+
+	Pit	+
+	+	+

+	+	+
	Channel	
+	+	+

Figure 5.1 Cell classification (Adapted from (Wood 2007, Brown 2008)).

This cell classification method follows the Fowler and Little algorithm (Fowler 1979), that works in an iterative manner, requiring a number of passes before the final selection of elevation points. The Fowler and Little algorithm started with a 3 x 3 neighbourhood and identified peaks and pits, with the computer remembering these points, the next pass used a 2 x 2 neighbourhood to identify potential ridges and channels. A cell is a potential ridge point if it is higher than the three neighbours; it is a potential channel if it is lower than the three neighbours. The algorithm then searched along the potential ridges toward the peaks and toward the channels to pits, and connected the peaks to ridges and channels to pits (Brown 2008).

Simply described, the overall default landform classification (semi-automated feature extraction) method described by Wood (1996) follows these steps:

- Features are initially identified by their shape;
- A bivariate quadratic surface is fitted through a sampling window (kernel) using least squares regression;

- Separate quadratic functions are used to identify features:
- Pits and peaks are elliptic conic sections,
- Passes are hyperbolic conic sections,
- Ridges and channels are parabolic conic sections.

Using the above steps and initially a 3 x 3 sampling window, LandSerf was tested and used for the Bow River Station study area for classification of landforms.

5.1.2 LandSerf feature identification

LandSerf uses a number of tools that enable landform feature analysis and personalised landform classification. LandSerf essentially involves setting a sampling window scale to semi-automatically extract features, or to adjust landform settings to include elevation, curvature and slope. There is a tool to set slope tolerance – that determines how steep the surface can be while still being classified as a pit, pass or peak feature, and a tool for the curvature tolerance – that determines how convex/concave a feature must be before it can be considered part of a feature. Curvature is entered and recorded as a dimensionless ratio usually between the values 0.1 to 0.5, with larger values tending towards planar features (Wood 2009a).

There are two classification methods used by LandSerf, a feature network extraction or a fuzzy feature extraction. The feature network extraction is used to classify an area into a number of different landforms, while the fuzzy feature extraction tool is used to classify individual landforms, and is more useful to indicate the degree to which a location within the study area can be regarded as a peak, pit, channel etc. The feature network extraction tool allows emphasis on linear networks such as channel and ridges, where these landforms are treated as vector topology rather than raster cells, therefore displaying a degree of connectivity (Wood 2009b). Fuzzy feature extraction is designed to explore individual features e.g. *peaks*, by exploring the range of scales at which the feature is emphasised

(Wood 2009c). Out of the two classification methods, the feature network extraction method was used for the study area.

The initial feature network extraction of the study area SRTM DEM used the default settings to understand how the software classified landform feature classes of the study area. The sampling window was set at a 3 x 3 kernel, with the default slope and curvature tolerances set at 0; where all neighbouring cells were considered of equal importance.

The landform feature classes produced using the default settings showed similarities when compared with existing vector topographic features for the study area (Figure 5.2). The most notable differences were peaks identified on low elevations adjacent to drainage and passes and pits that formed linear boundaries that do not occur naturally as part of the Bow River landscape.

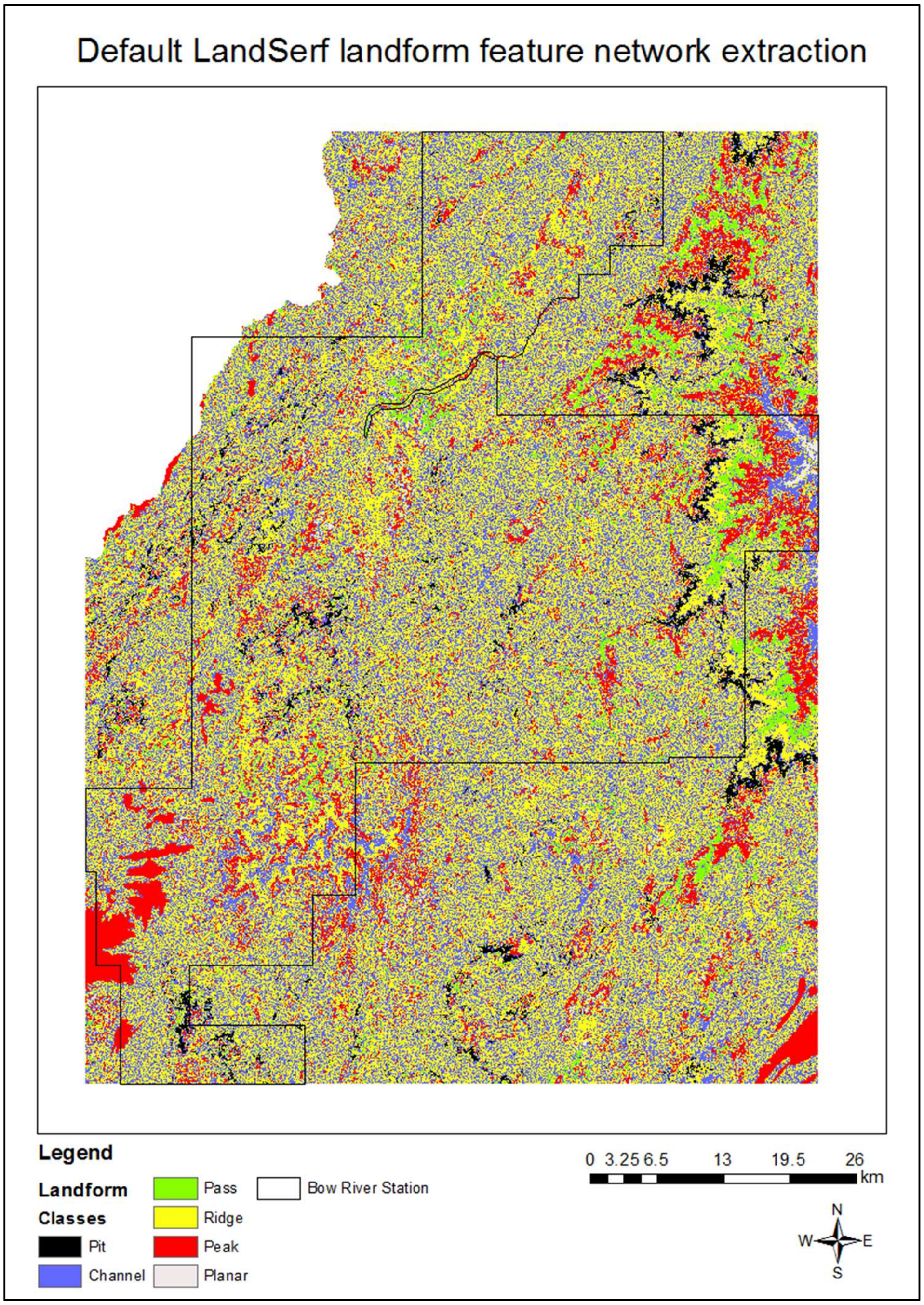


Figure 5.2 Default LandSerf feature network extraction using the 30 m SRTM DEM for the Bow River Station study area.

According to Wood (1996), LandSerf assumes 'that all locations that have a local slope must be either plains, form part of a channel or form part of a ridge and that pits, peaks and passes are assumed only to occur where local slope is zero'.

There are many ways to optimise the software settings in LandSerf, and after the initial test using the default 3 x 3 kernel feature network extraction, the settings were refined to suit the landscape and landforms of the Bow River Station study area.

5.1.3 Optimised LandSerf settings for the study area

To find the optimal LandSerf settings for the Bow River Station (BRS) study area involved finding settings that suited the landscape complexity of the study area. The landscape varies from major drainage systems (including Bow River) in the north-eastern quadrant of the study area, to boulder-strewn hills and plateaus associated with Tickalara metamorphic rocks of the Bow River ranges, predominately in the western quadrant of the study area. Associated peaks of the high lands and plateaus, and pits in low elevation, form the extremities of this landscape. Numerous passes and plains extend for tens of kilometres, that join the landscape between drainage systems and ‘hill country’.

Comparisons were made for varied sampling windows from a 3 x 3 kernel to a 64 x 64 kernel, with results for a sampling window greater than a 15 x 15 kernel, showing too much loss of detail of landscape. The various sampling window results were compared visually with existing topographic vector data using ArcMap, and also using ArcScene 3-dimensional representation. The optimum sampling window was found to be between a 3 x 3 kernel and 15 x 15 kernel. The sampling windows between these two kernels were tested using the interactive tools of LandSerf including the profile tool, surface feature profile and histogram tool.

The profile query tool was used to visually identify the variations in elevation across the DEM. Cross-section graphs of lines drawn across the DEM were tested for various locations and directions. Figure 5.3 shows a location with a decrease in elevation from the west (left) to the east (right). The graph compares the elevation on the *y* axis, with the line location on the *x* axis, for 1271 samples (pixel points).

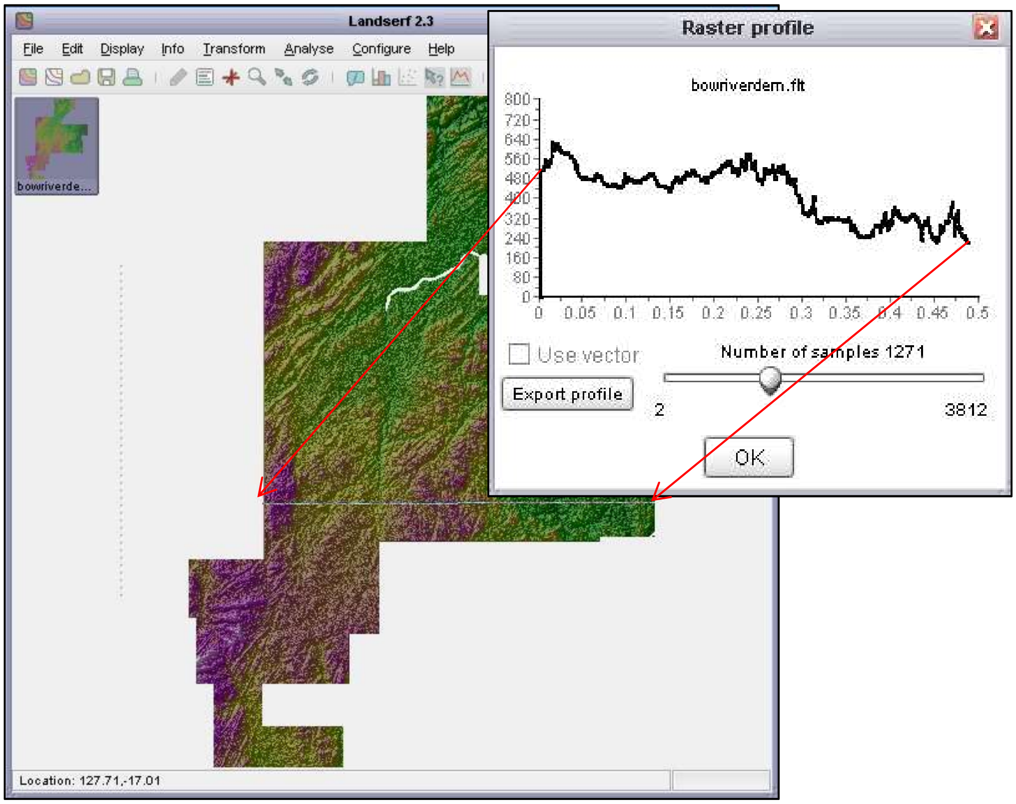


Figure 5.3 A profile query for the Bow River Station DEM.

The surface feature profile tool was used to show the potential landform classification of the DEM for small locations, as seen in Figure 5.4, it shows a location area (128 (Longitude), -17 (Latitude)), suggesting the landforms are channels (blue), ridges (yellow), pits (black) and passes (green). The graph compares the number of pixels for each landform (x axis) and the landform feature (y axis). The likelihood that a landform in this area is a *channel* is given a 0.74 probability, seen in the graph. This tool provided a quick test of possible landform feature classes.

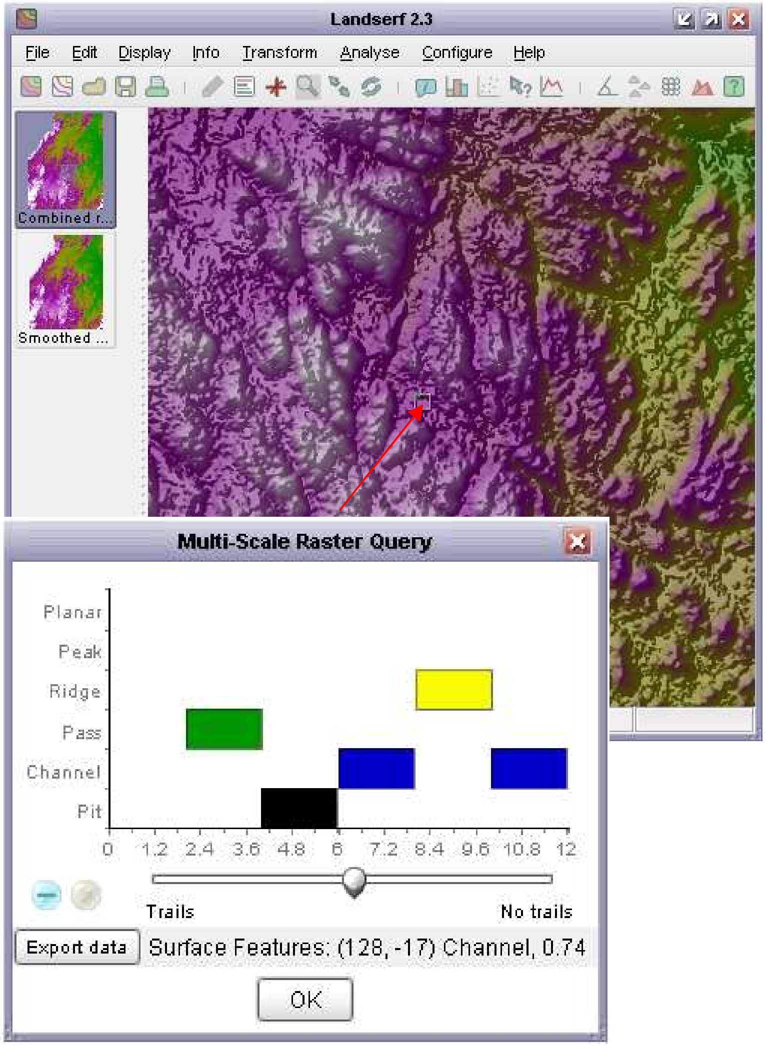


Figure 5.4 Feature extraction profile for a location (128, -17) of the DEM, with a 0.74 probability that the predominate landform would be a *channel*.

Finally, the histogram tool was used to for effectiveness of the feature network extraction when combining the sampling window, slope tolerance, curvature tolerance and distance decay to optimise the landform settings. The result was an overall analysis of the feature network extraction tool for the entire Bow River study area. The histogram displayed the number of pixels allocated to each landform, in other words, the histogram showed the landform frequency distribution (Figure 5.5) for the study area.

Figure 5.5 shows two different sampling windows for kernels 11 x 11 and 15 x 15. The results for the 11 x 11 kernel have more similarities with landforms when compared with aerial photographs and other digital data including drainage, elevation contours, geology, land use and land system boundaries.

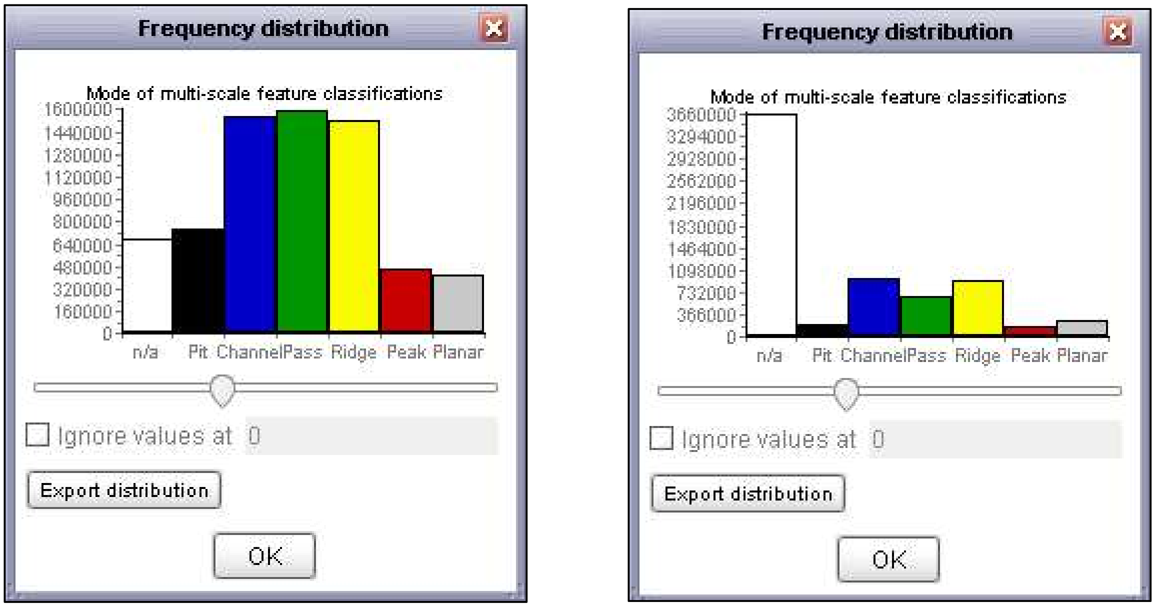


Figure 5.5 Comparison between sampling window kernels; 11 x 11 (left) and 15 x 15 (right).

The LandSerf interactive tool's results provided informed support for development of the landform classification settings, using comparisons between anticipated results and existing digital data about the landforms for the study area, therefore reducing the need to rely on 'trial and error' for classification settings. Using the results from the LandSerf interactive tool analysis, the optimal settings for landform classification for the study area using a DEM were found to be - a sampling window with a 11 x 11 kernel, 6 degree of slope which best suits the landscape maintaining optimal landform classification, 0 curvature tolerance and 0.1 distance decay (Figure 5.6), where the curvature tolerance and distance decay are both dimensionless ratios. The distance decay refers to the degree that neighbouring cells that are likely to be the same as neighbouring cells, a distance decay of 0 suggests that all cells are equal, by increasing the decay to > 0 then it suggests that the likelihood a neighbouring cell is the same decreases with that distance.

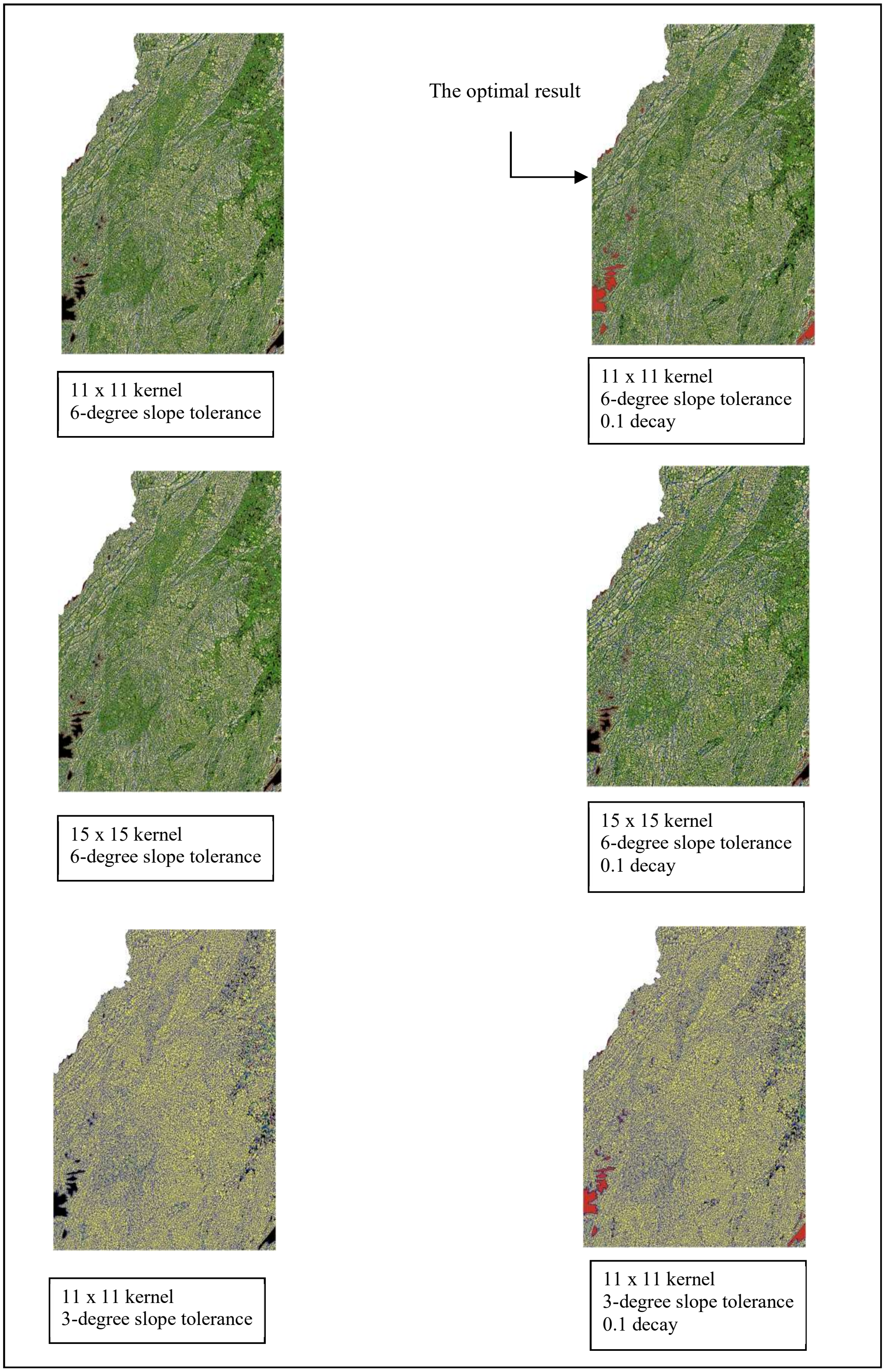


Figure 5.6 Results using different LandSerf setting for optimal feature extraction.

The optimal settings described above were applied to the feature network extraction tool. The output was a continuous representation of the land surface with cells assigned to one of the six feature classes: peak, channel, ridge, pass, pit or plain.

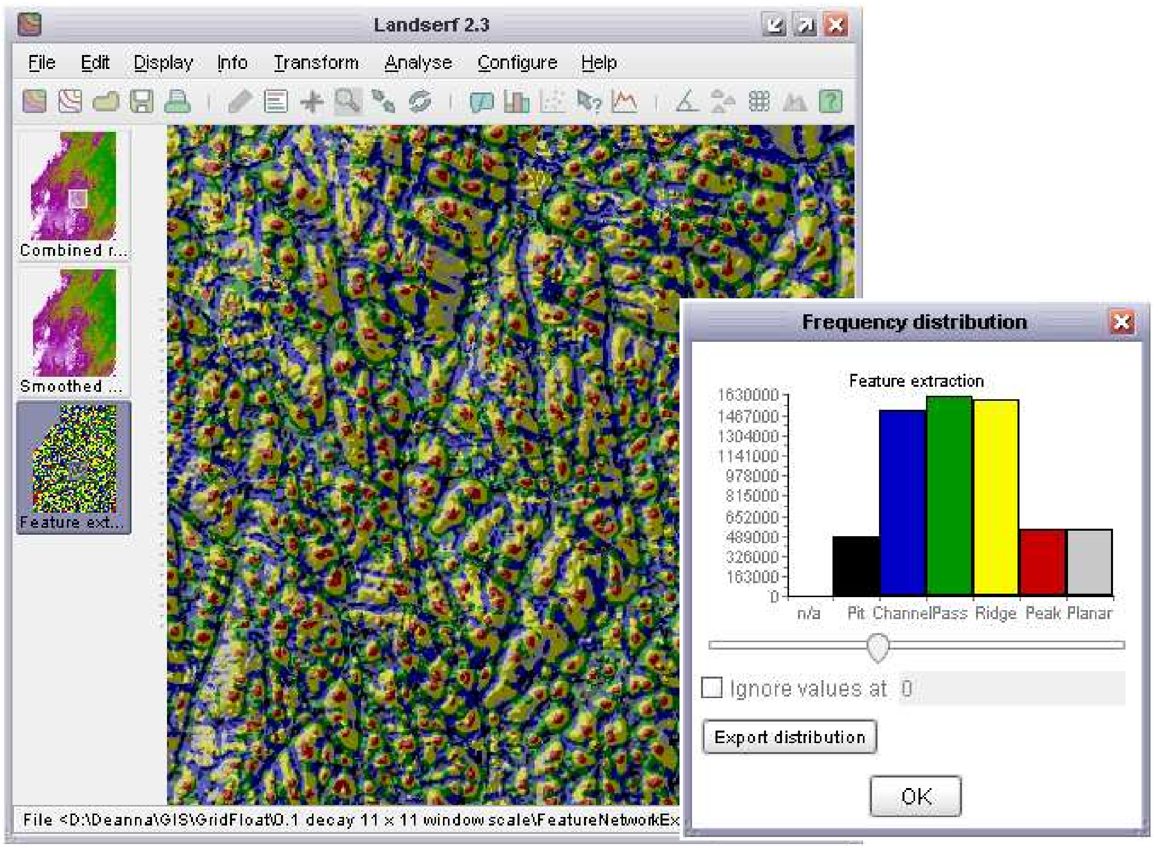


Figure 5.7 Feature network extraction of study area landforms.

To continue analysis of the landform classes seen in Figure 5.7, the results were converted from LandSerf rasters to floating point GRIDS to be used in ArcGIS.

5.1.4 LandSerf to ArcGIS

LandSerf is limited in spatial analysis tools and map presentation tools, therefore these limitations required further analysis and presentation of results to be completed using ArcGIS. All converted LandSerf data was georeferenced to the GDA94 datum to match other data for the study area. The methodology follows the structure chart presented in Figure 5.8.

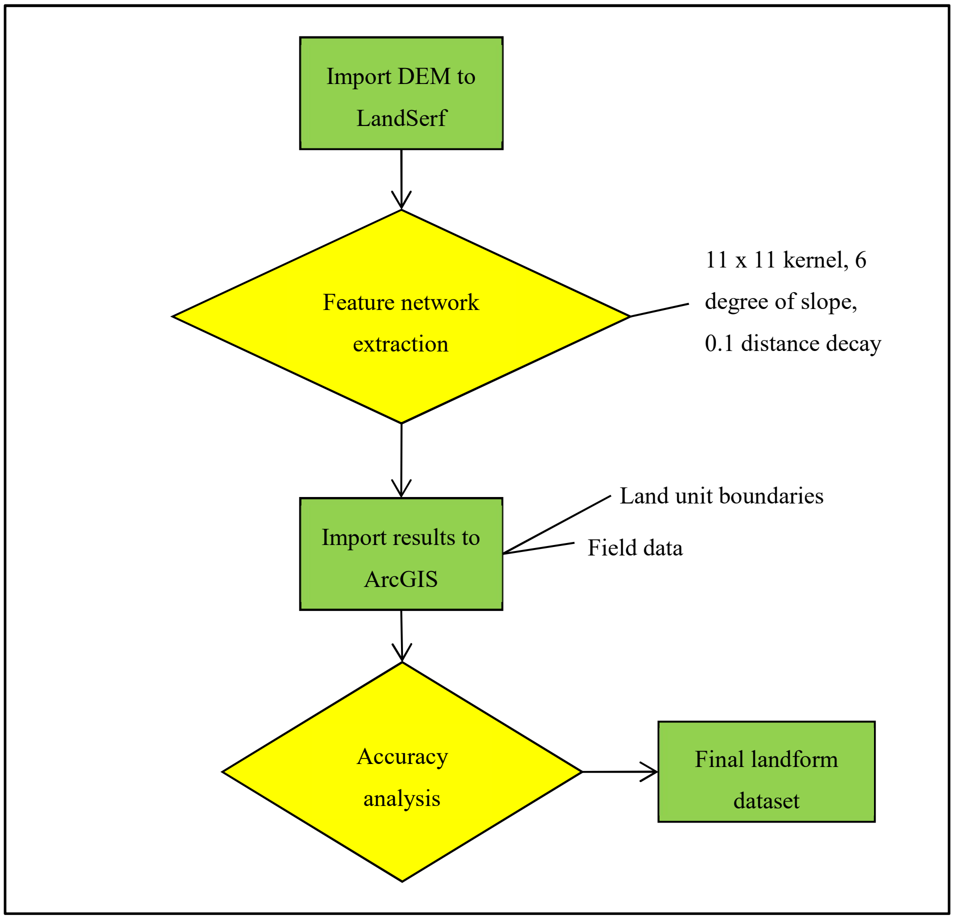


Figure 5.8 Landform classification from LandSerf to ArcGIS methodology.

When the landform data was imported into ArcGIS, the landform classes that were categorised and symbolised to match the results from LandSerf for consistency between software. The landform classes, now in ArcMap, were overlaid on a Landsat 2002 image to assess continuation of landform features on a wider scale and for geographic perspective as seen in Figure 5.9.

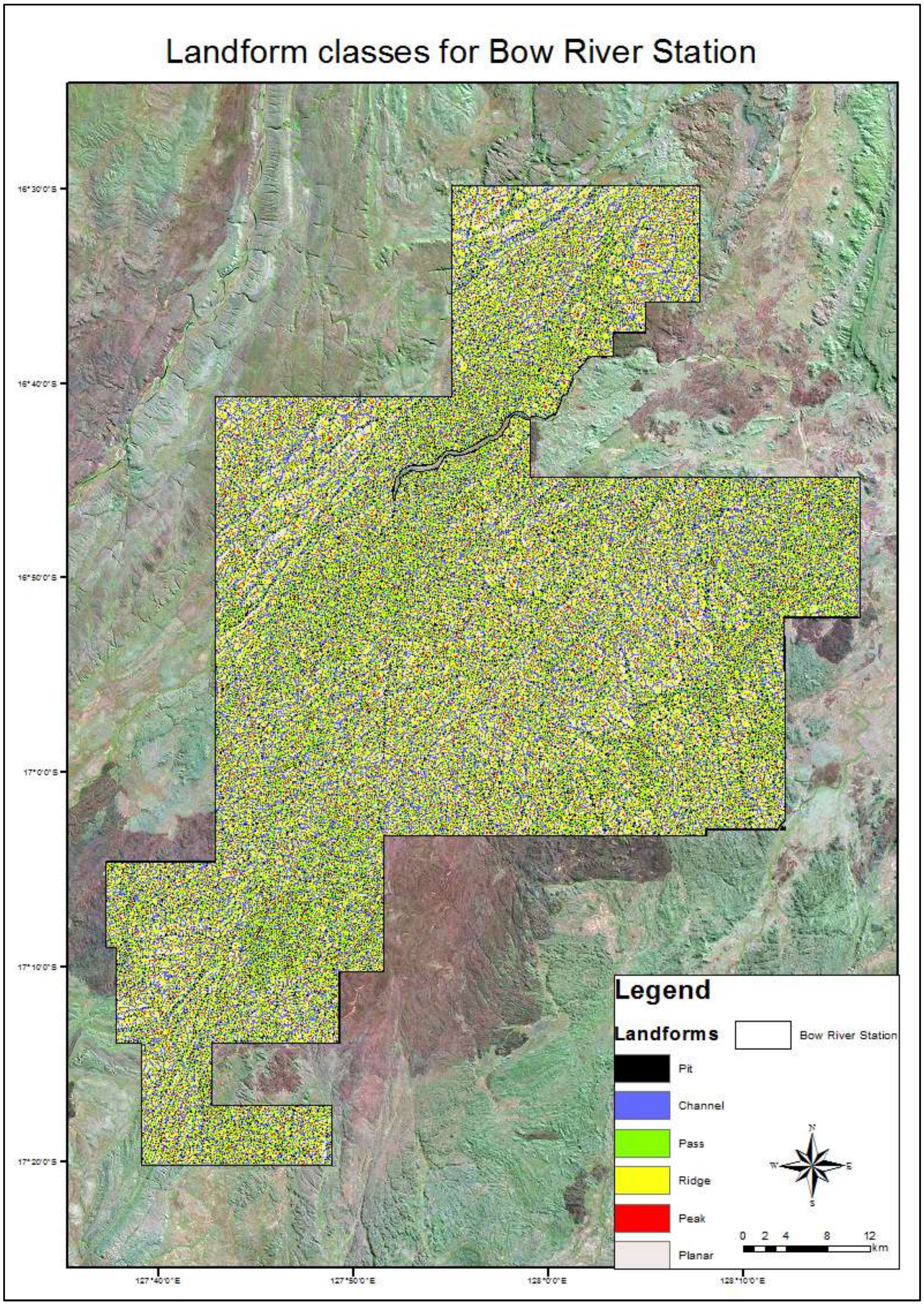


Figure 5.9 LandSerf landform classes presented in ArcMap in the Bow River Station study area boundary overlaid on Landsat 2002 imagery.

The landform classes were then draped with the land system boundaries to visually assess the patterns that might exist between the landforms and the land systems, as seen in Figure 5.10.

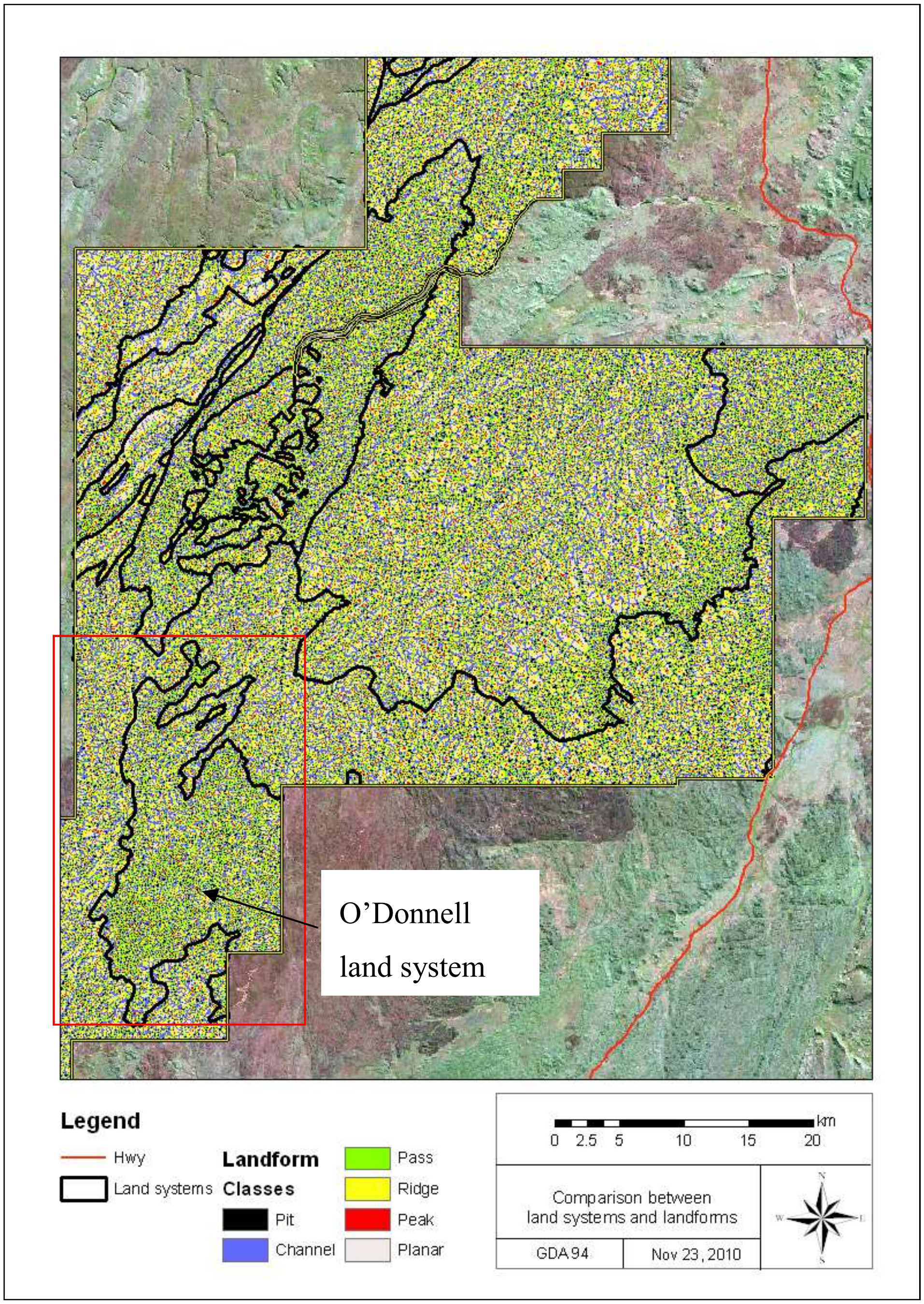


Figure 5.10 Land systems draped on landform results for the study area.

Visually there appeared to be some grouping of landform results that prompted closer investigation of individual land systems. The land systems names were devised by CSIRO field surveyors in 1949 (Payne 2011) to describe a soil-landscape hierarchy for the rangelands, with recurring patterns of landform, soils and vegetation, suitable for regional and pastoral property mapping.

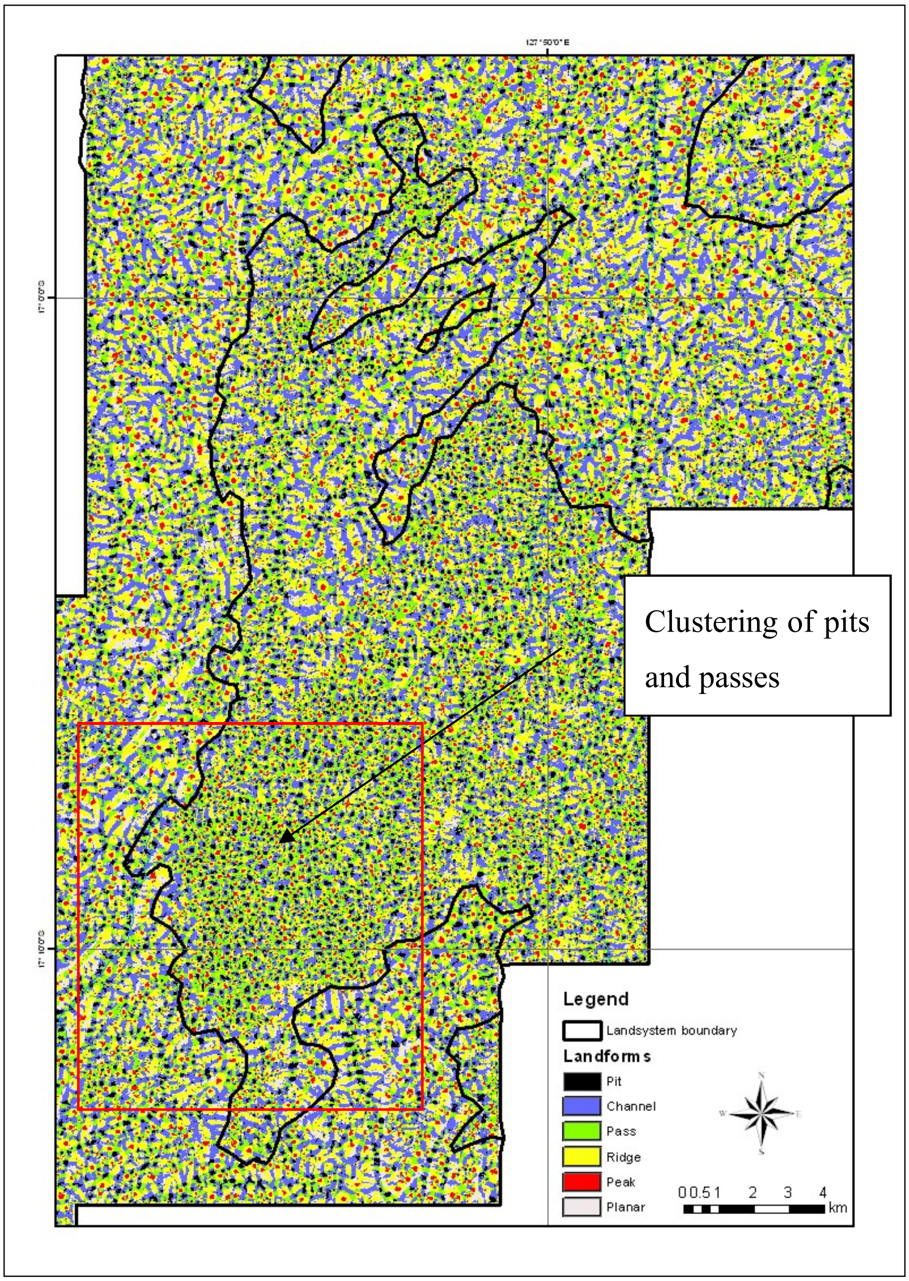


Figure 5.11 Landform results bounded by O'Donnell land system.

The landform results within the O'Donnell land system identified clustering of pits and passes as seen in Figure 5.11, where passes are described as linear features between two higher elevated areas, and a pit representing a point of low elevation.

The O'Donnell land system was chosen for this analysis for its diverse arrangement of land surface types. This land system is described as "stony undulating country with scattered hills, loamy skeletal soils, also restricted cracking clay plains, supporting open snappy gum woodlands with spinifex, arid short grasses and tussock grasses" (Payne 2011), and is approximately 22,814 hectares of landscape on Bow River Station.

Land units mapped as part of the Ord-Bonaparte Program (refer to Section 2.2) are described by Schoknecht (2003), as landscape units for mapping at 1:100,000 scale, bounded by the land systems, that are positioned in regards to proportion and combination of constituents - landforms, vegetation and soils.

Table 5.3 O'Donnell land system with land unit hierarchy.

Land unit	**Summary**	**Landform**
312Od_5	Gently undulating to rolling rises on granite. Red or brown sandy duplexes with minor stony soils and occasional outcrop.	Gently undulating to rolling rises
312Od_6	Level to undulating low plains on granite. Red or brown shallow loamy or sandy duplexes and red sandy or loamy earths.	Level to undulating low plains
312Od_7	Level to undulating gilgai plains on alluvium. cracking clays with or without self-mulching surfaces with gilgai micro-relief.	Level to undulating gilgai plains
312Od_8	Drainage floors and channels on alluvium. Alluvial soils.	Drainage floors and channels

The Ord-Bonaparte land units are part of the O'Donnell land system (312Od) that are divided into four units presented in Table 5.3.

These land units are within the O'Donnell land system that is part of the greater state soil-landscape mapping hierarchy of Western Australia, seen below in Figure 5.12.

Region: Kimberley	3
Province: Southern Kimberley Ranges	1
Zone: Bow River	2
Land system: O'Donnell	Od
Land unit: O'Donnell land unit 6	_8

Figure 5.12 O'Donnell land system placed in the state mapping hierarchy.

The O'Donnell 312Od_8 land unit boundary was draped on the landform results and is presented in Figure 5.13. The relationship between 312Od_8 land unit and the landform results show a unique and clustered pattern of landforms, predominately passes, pits and channels. The description of 312Od_8 is "drainage floors and channels on alluvium, and alluvial soils. Woodland of mixed Eucalyptus pruinosa and E. spp with Carissa lanceolata common and an understorey of tussock grasses including Themeda triandra" (Schoknecht 2003).

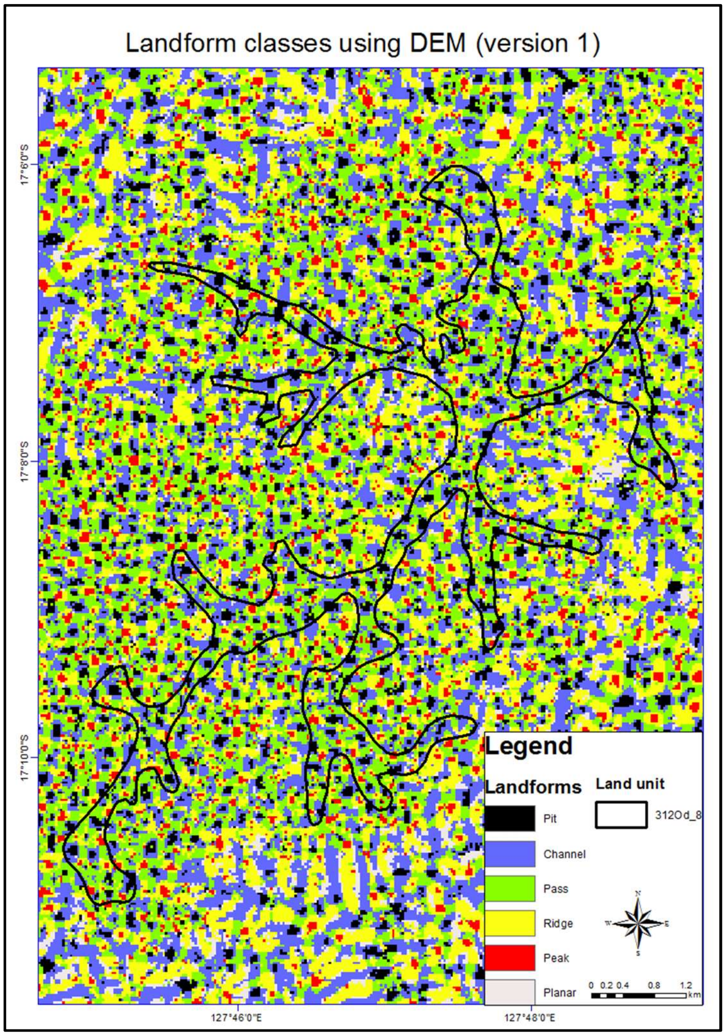


Figure 5.13 Landform results bounded by 312Od_8 land unit.

The approximate area of the land unit in Figure 5.13 is 1,073 hectares. The landscape and therefore description of the land unit contains features that are more homogeneous and therefore are a more accurate way of checking the precision of the landform results produced in LandSerf.

5.1.5 Landform classification using a hydrologically enhanced SRTM DEM.

A second more up to date hydrologically enhanced SRTM DEM became available to this research from DAFWA. The hydrologically enhanced SRTM DEM included a number of updated features; reduction of voids by gap filling, removal of systematic striping using

Fast Fourier Transform methods, offsets due to trees were detected and heights were adjusted to produce a bare-earth DEM, random noise was smoothed using a multiadaptive smoothing method that responded to spatial variations in topography and magnitude and finally the DEM was "subject to hydrological enforcement using the ANUDEM program (enhanced to improve performance of the SRTM DEM) driven by mapped streamlines at 1: 250,000 scale" (Gallant 2010).

Prior optimisation of landform settings for LandSerf were applied to the new SRTM DEM (version 2) including a 11 x 11 sampling window, 6 degrees of slope and 0.1 distance decay, to produce a new set of landform classes. The 'version 2' landform class results were uploaded into ArcMap and compared with Bow River Station land systems and land unit boundaries. Comparisons were also made between landform class results of DEM version 1 and version 2, using the Ord-Bonaparte land units. The proportions of these land units were converted from cell count statistics to graphically representation in MS Excel.

The difference in landform classification results can be graphically seen in Figure 5.14 and Figure 5.15, showing the dramatic decrease in passes (green) and increase in plains (grey).

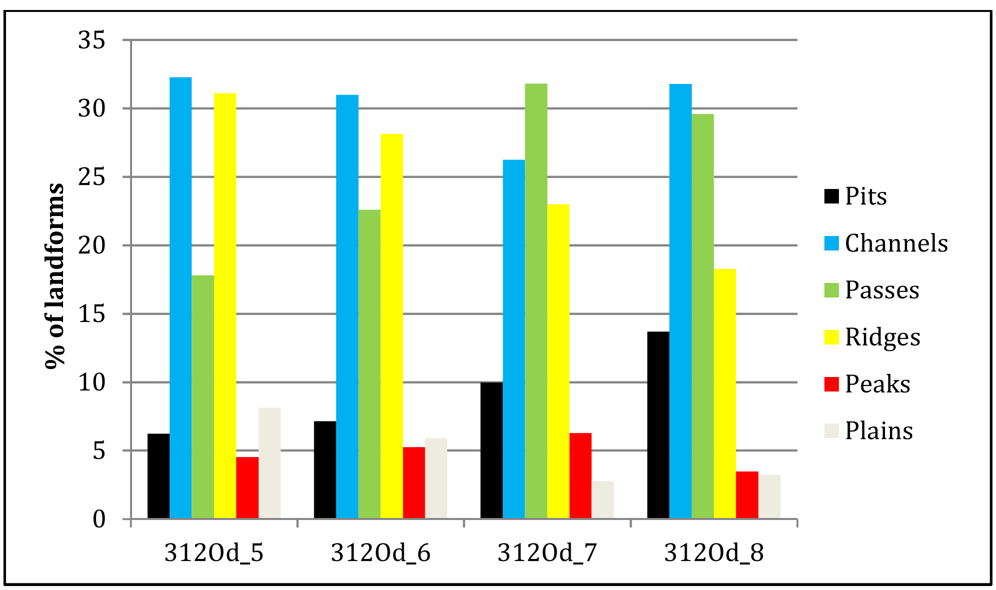


Figure 5.14 Version 1 DEM landform results for O'Donnell land units.

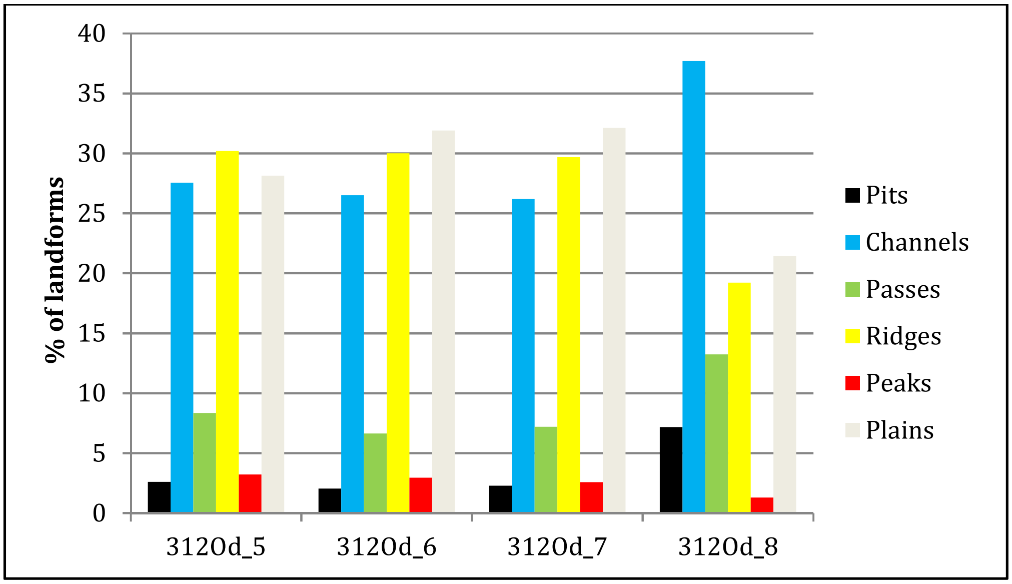
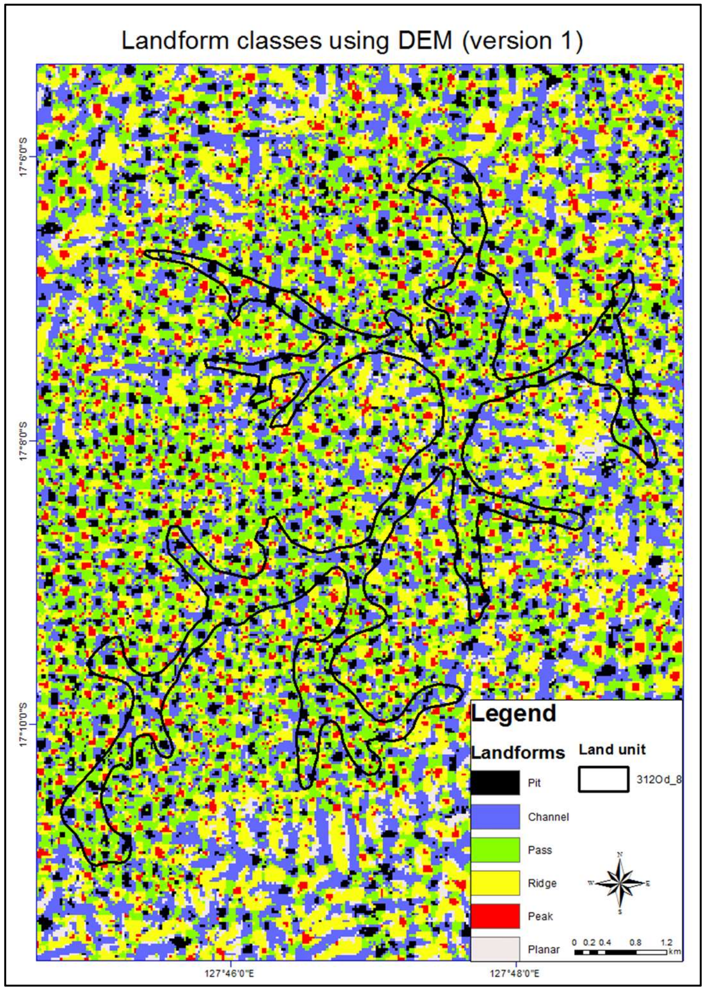


Figure 5.15 Version 2 DEM landform results for O'Donnell land units.

The mapped results of both DEM's were compared in ArcMap, identifying that the *plains* in most part have replaced the *pass* features, and the *peaks* (in this mostly drainage land unit) were also sparser than the results of DEM version 1.

LandSerf classification of both DEMs produced six landform classes - pits, channels, passes, ridges, peaks and plains. The landform results for O'Donnell land unit 8 (312Od_8) were compared for both DEMs, and as expected due to the hydrologically enhanced processing of the DEM version 2, the channel features are more defined and had apparent association with pits and passes as seen in Figure 5.16.



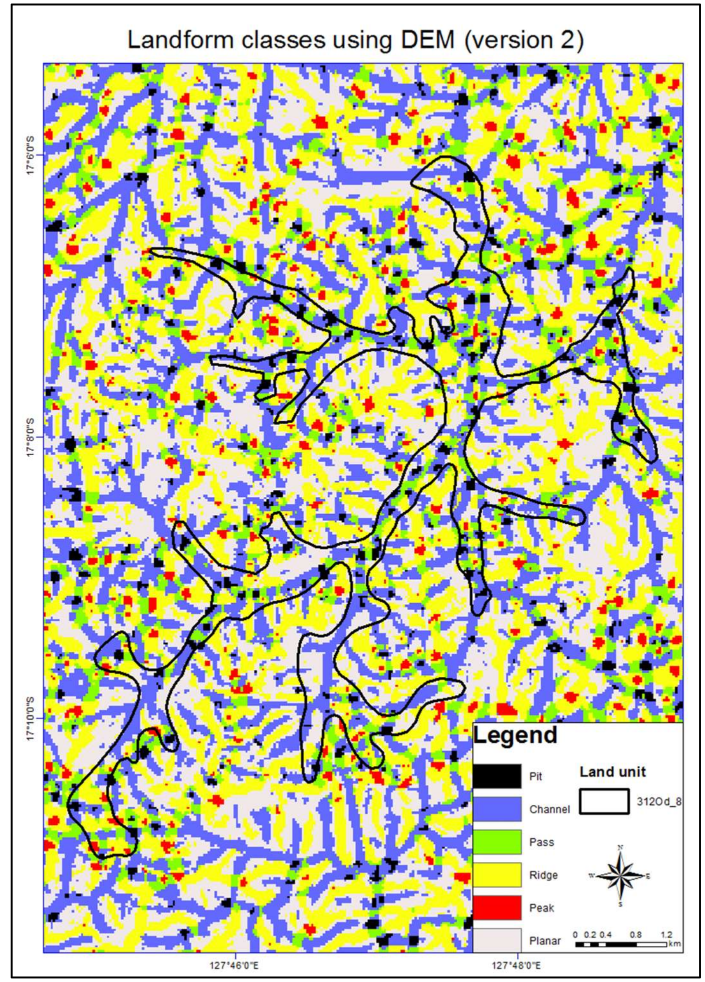


Figure 5.16 Comparison between LandSerf results for both the hydrologically enhanced SRTM DEM (left) and SRTM DEM (right).

5.1.6 Landform class comparison with landform field data

The landform class results from the SRTM DEM version 2 were compared with the field data collected during an organised field trip (refer to Section 5.4.1), with a total of 31 points collected on Bow River Station, however only 26 with descriptions could be used in the comparative study. The field trip data were limited to O'Donnell, Richenda and Pompey land unit's due to accessibility and time constraints. Table 5.4 shows the comparisons between the field trip descriptions, land unit descriptions, and LandSerf landform final results (version 2), where landforms are described as: 1 pit; 2 channels; 3 passes; 4 ridges; 5 peaks; 6 plains.

Table 5.4 Comparison between field, land unit and DEM landform data for O'Donnell land units.

Field description	**Field landform code**	**Ord-Bonaparte land unit description**	**Land unit landform code**	**LandSerf description**	**LandSerf landform code**
Drainage	2	312Od_8	2	No Value	N/A
Drainage	2	312Od_8	2	Ridge	4
Slope (Pass)	3	312Od_8	2	Channel	2
Plain	6	312Od_8	2	Channel	2
Plain	6	312Od_8	2	Channel	2
Pit	1	312Od_7	6	Pit	1
Drainage	2	312Od_6	6	Ridge	4
Drainage	2	312Od_6	6	Pass	3
Drainage	2	312Od_6	6	Ridge	4
Drainage	2	312Od_8	6	Ridge	4
Drainage	2	312Od_6	6	Plain	6
Drainage	2	312Od_6	6	Ridge	4
Pass	3	312Od_6	6	Pass	3
Pass	3	312Od_6	6	Pass	3
Slope (Pass)	3	312Od_6	6	Channel	2
Pass	3	312Od_6	6	Pass	3
Pass	3	312Od_6	6	Ridge	4
Pass	3	312Od_6	6	Ridge	4
Plain	6	312Od_7	6	Peak	5
Plain	6	312Od_6	6	Plain	6
Plain	6	312Od_6	6	Channel	2
Plain	6	312Od_6	6	Ridge	4
Plain	6	312Od_6	6	Ridge	4
Plain	6	312Od_6	6	Ridge	4

This comparison shows only a few landforms matched both the field landform codes and land unit codes, possibly due to the limited field data collected, with field data limited by lack of accessibility to the study area.

5.2 Other evidence layers derived from the DEM

Two topographic indices, relative relief and elevation, were derived from the hydrologically enhanced SRTM DEM (version 2) as independent evidence variable layers also used in a land unit prediction model (refer to Section 6).

5.2.1 Relative relief for Bow River Station

The relative relief was calculated for the Bow River Station study area to not only add another evidence layer but as an evidence layer to aid predicting of land units. The term *relative relief* refers to the 'relativeness' of the relief to its surrounding topography. To calculate the relative relief, the size of Bow River Station was required, which is 3,036.737488 km^2 and the physiography of the local landform features were needed. The physiography of the main landform features was found to range from plateaux, rolling hills to plains and channels. The main data source for calculating the relative relief was the SRTM DEM (version 2) with a cell resolution of approximately 27.77 m (~ 30 m).

For this research, the relative relief was calculated using the ArcGIS focal statistics tools and a moving average window. In Hammond's classification method (Hammond 1964) "a moving square window of 9.65 km (6 miles) on each side across a 1: 250,000 Army Service topographic maps with contour levels of 15.2 m to 61.0 m" was used to find the relative relief. This 'moving square window' scale was appropriate for Hammond's study area however these setting was adjusted for this research study area because, firstly, Hammond used topographic maps, not a DEM, and secondly, the Bow River Station study area is located in a different landscape setting compared to that of Hammonds study that was based in the United States. The variation in the landscape between the two study areas include landform elevations and landform types, with the physiography of the landforms in Hammonds study being more mountainous.

An initial check for obtaining relative relief values found that using the original Hammond's threshold values, and an averaged 10 km moving average window for the

Bow River Station study area DEM produced a 'blocky' result. A number of other moving average windows were tested to find a more appropriate kernel with less loss of detail. The tests found that a circular window 'best fit' the Bow River study area and best represented the landform physiography, and through trial and error testing, the kernel for the optimal circular neighbourhood sampling was found to be an 11 x 11 kernel. This kernel was the same scale used for landform classification in LandSerf, enforcing its suitability for the study area.

The elevation for the relative relief evidence layer was calculated for the study area using the focal statistics tool in ArcGIS with comparisons made with the elevations of the DEM, seen in Table 5.5. The focal statistic elevations were slightly different to the DEM elevation values because the focal statistics tool calculates the statistic of each cell within a specified neighbourhood, in this case, a neighbourhood of a 11 x 11 sampling window.

Table 5.5 Comparison between the DEM and focal statistics mean elevations.

	Mean (m)	**Standard Deviation (SD)**	**Range (m)**
DEM elevation (z_o)	347.983	144.564	41.3507 – 980.777
Focal statistic mean elevation - 11 x 11 cell mean focal statistics ($\bar{z}$)	348.01	143.83	45.79 – 966.35

The elevation 'residual analysis' technique outlined in Gallant (2000a), was applied to the focal statistic mean elevations to calculate the 'deviation of mean' between the two elevations. The formula to calculate the focal mean elevation was:

$$\bar{z} = \frac{1}{n_c} \sum_{i \in c} z_i \qquad (5.1)$$

where $\bar{z}$ is the mean DEM elevation and z is the elevation at the central point of *i* pixel cell, *n* is the number of pixel cells and $\sum$ is the sum of all pixel cells. The focal mean elevation values ranged from 45.79 to 966.35 m (refer to Table 5.5). The difference between the mean elevation of the DEM and focal statistics was calculated using:

$$diff = z_0 - \bar{z} \tag{5.2}$$

Where (z_o) are the DEM elevations and ($\bar{z}$) is the focal mean statistics elevations, with the difference between the mean elevations ranging from -138.52 to 113.22 m. The difference between the mean elevations were then normalised by dividing them by the standard deviations (SD) using the formula:

$$dev = \frac{z_0 - \bar{z}}{SD} \tag{5.3}$$

The normalised 'difference between the mean' calculated with Equation 5.3, are the 'deviation of the mean' values which ranged between -16.81 to 24.27, with most values between -1 to 1, with values higher and lower than 1 and -1, respectively, set to null as they represented outliers and possible errors.

The 'deviation from the mean' statistics were compared with the existing Ord-Bonaparte land units (refer to Section 2.2) to see if any patterns existed that could be used to categorise the 'deviation from the mean' statistics to create a relative relief evidence layer, seen in Table 5.6.

Table 5.6 The 'Deviation from the Mean' statistics for the O'Donnell land units.

Ord-Bonaparte land unit	**Area**	**Min**	**Max**	**Mean**	**SD**	**Sum**
312Od_5	0.001698	-1.83735	2.592094	-0.03651	0.635132	-1156.58
312Od_6	0.015592	-1.89007	2.798842	0.042977	0.511059	4546.946
312Od_7	0.002433	-1.8757	2.25673	0.045093	0.451749	1283.594
312Od_8	0.003376	-2.15761	3.042716	-0.4319	0.514174	-13885.6

The minimum and maximum values for the ‘deviation from the mean’ values ranged between -1 and 1, with a pattern seen between elevation and landform types. The interpretation of these patterns was set as -1 = ‘pitiness’, 1 = ‘peakiness’ and 0 = “planar”.

The ‘deviation of the mean’ values between -1 and 1 were compared graphically for all of the study area, with Ord-Bonaparte land units, as seen in Figure 5.17. The land units that should most ‘pitiness’ were drainage land units and the land units with most ‘peakiness’ were represented by hills and ridges.

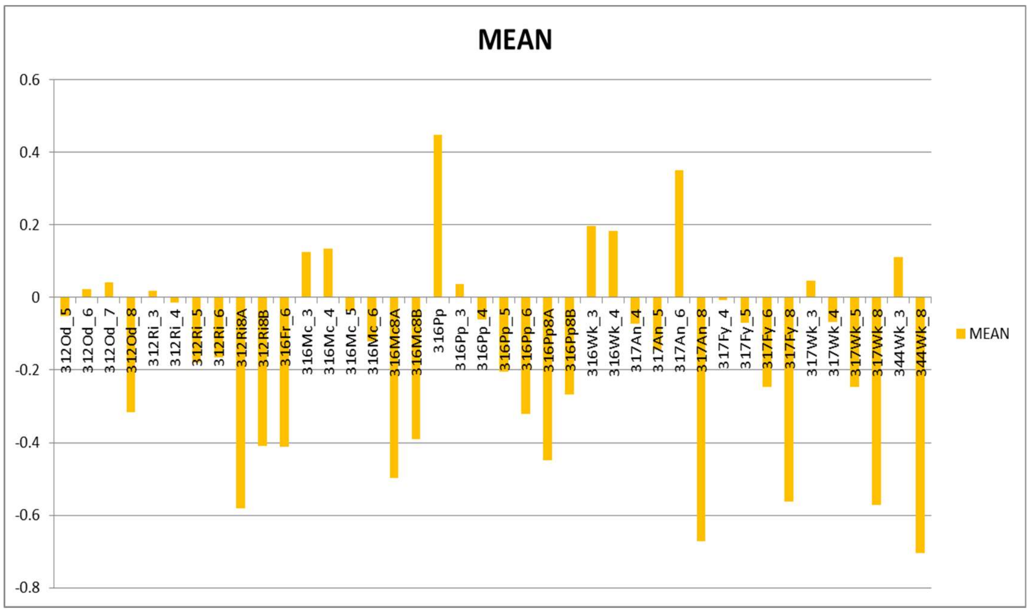


Figure 5.17 The mean values from the ‘deviation from the mean’ for each land unit.

The ‘deviation from the mean’ statistics and the land unit descriptions were further compared to identify patterns. The Ord-Bonaparte land units and ‘deviation from the mean’ *mean* statistic was spatially joined using a map unit column. The data were imported into Excel and arranged so that *mean* values were sorted from smallest to largest values; or ‘pitiness’ to ‘peakiness’. The sorting was extended to include the landform description column as seen in Table 5.7.

Table 5.7 Comparison between 'Deviation from the Mean' *mean* statistic and Ord-Bonaparte land unit descriptions.

Ord-Bonaparte land unit	Mean	Landform description
344Wk_8	-1.085	Narrow drainage floors, gentle slopes and streamlines
317An_8	-0.766	Narrow drainage floors and channels
312Ri8A	-0.734	Major watercourses, channels and banks
317Wk_8	-0.733	Narrow drainage floors, gentle slopes and streamlines
316Mc8A	-0.676	Major creek and river channels and banks
317Fy_8	-0.626	Drainage floors and channels
316Pp8A	-0.569	Channels and banks of major rivers and creeks
316Mc8B	-0.509	Drainage floors, usually less than 800 m wide with or without major central channels
312Od_8	-0.432	Drainage floors and channels
312Ri8B	-0.429	Drainage floors sometimes with channels
316Fr_6	-0.390	Level to undulating plains
316Pp_6	-0.322	Extremely low level to undulating plains
316Pp8B	-0.261	Drainage floors up to 500 m wide usually with channels
317Wk_5	-0.235	Gentle lower slopes
317Fy_6	-0.203	Level to undulating plains
316Pp_5	-0.188	Very low, gently undulating to rolling rises
312Ri_6	-0.160	Level to undulating plains
312Ri_5	-0.157	Very low gently undulating to rolling rises
317An_5	-0.136	Gently to moderately sloping lower footslopes and very low rises
316Mc_6	-0.091	Level to gently undulating plains
317An_4	-0.066	Low hills, mesas and associated upper slopes with much rock outcrop
312Od_5	-0.037	Gently undulating to rolling rises
317Wk_4	-0.032	Low undulating to steep hills and ridges
317Fy_5	-0.030	Very low rises
317Fy_4	0.013	Undulating to rolling low hills
316Mc_5	0.035	Very low gently undulating to rolling rises and plains
312Od_6	0.043	Level to undulating low plains
312Od_7	0.045	Level to undulating gilgai plains
312Ri_4	0.059	Undulating to steep low hills
316Pp_4	0.064	Low undulating to steep hills
312Ri_3	0.087	Rolling to steep high hills
344Wk_3	0.092	High hills ridges and plateaux and associated steep slopes and benches
317Wk_3	0.098	High hills ridges and plateaux and associated steep slopes and benches
316Pp_3	0.103	Rolling to steep high hills

Three cut-off points (as values) were determined using the above table, where there was a significant change in landform description, these cut-off points are:

<-0.24667 = channel, plain;

-0.24667 to -0.007367 = pass, plain, low hills, moderate hills;

> -0.007367 = moderate hills, high hills, pass, plains.

The cut-off values were applied to the Ord-Bonaparte land unit data in ArcGIS with the colour ramp symbology changed to show channels represented by blue, plains/ moderate elevations as yellow, and hills/higher elevations as red. The three categories for the relative relief evidence layer are presented in Figure 5.18

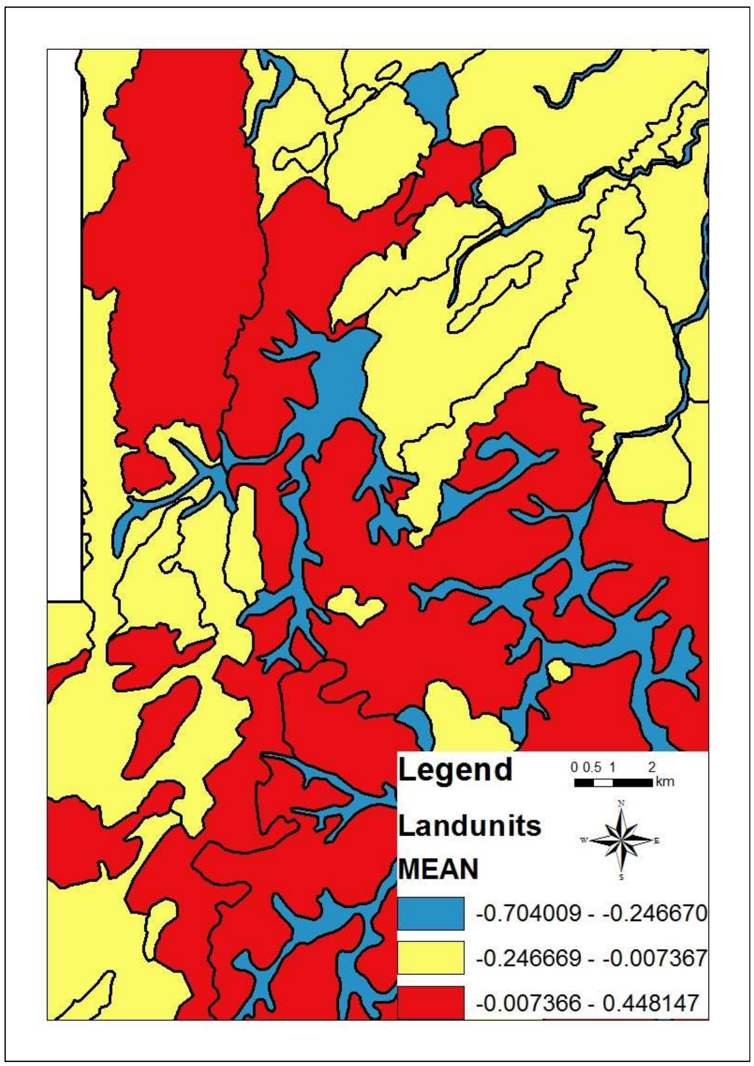


Figure 5.18 Relative relief evidence layer for the study area.

The relative relief results presented in Figure 5.18, show that not all categories match the land unit boundaries, which is to be expected because the resolution of the DEM is not the same as the Ord-Bonaparte land units. The 'deviation of the mean' statistics did identify patterns within landforms and were therefore used to produce a relative relief layer to would be used as a landscape variable in the land unit prediction model.

5.2.2 Elevation range

The elevation range dataset was created also derived from the hydrologically enhanced SRTM DEM (version 2). The DEM was categorised into elevations with 100-metre intervals, that involved extracting all elevations 100 m or less; 200 m or less; 300 m or less, resulting in 3 binary layers, where '0' value was data outside the range, and '1' was data within the elevation range. The three elevation layers were combined using addition calculations to produce a single elevation variable layer with 100 m intervals.

Elevation plays an integral role in landscape analysis, e.g. vegetation that are associated with changes in elevation. The range of elevation for the Bow River Station is between 41.35 – 980.78 m and was used as a landscape variable layer in the land unit predictive model.

5.3 Additional non-topographic evidence layers

Beside landforms, elevation and relative relief, two other landscape evidence variables were available for the study area, they were - vegetation and geology. The idea was to use and derive as many datasets with as high as possible resolution and accuracy to increase the possibility of accurately predicting land unit boundaries with minimum error. These two additional landscape elements were initially assessed to see if improvements could be made to their resolution and accuracy with focus on vegetation due to availability of additional data that could assist in a possible vegetation classification scheme.

Soil is the most difficult of the land surface variables to remotely class because much of the soil characteristics are defined below ground. Soil is defined by a soil profile that is a vertical section of a soil from the soil surface through its horizons to the host rock. Soil descriptions in the field require expert knowledge using a number of symbols for individual soil profiles. Soils are exposed to many external factors including underlying rock type, climatic factors – rainfall and evaporation and degradation factors such as weathering, erosion and compaction. From the surface only a very small part of the soil body is actually seen (McDonald 2009). A notable feature about soil is its clear association with vegetation and associated underlying geology. This research does not focus on the quantity, type and distribution of vegetation species or the intensive division between soil types and geological features but is aimed to show that relationships do exist and that patterns can be found using GIS.

Soil information for the pastoral rangelands of WA and for this research was only available at a scale of 1: 100,000, and as part of the rangeland land system dataset, therefore it could not be used for this study as an independent soil dataset. Soils surveys with resolution higher than a land system were only available in the south-west of Western Australia (Schoknecht 2004).

5.3.1 Vegetation

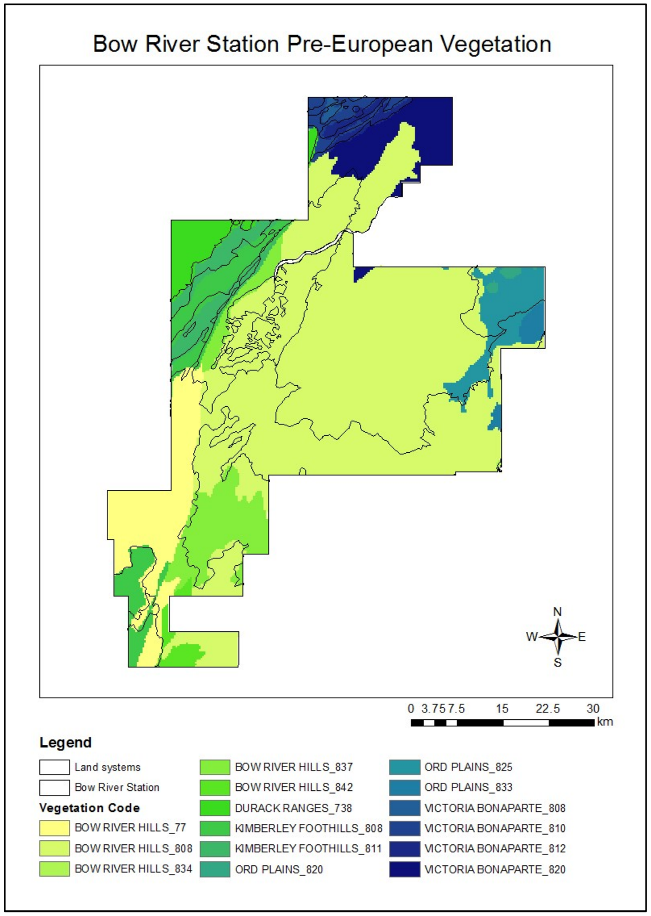
Vegetation data for the northern rangelands of Western Australia include a dataset of Pre-European vegetation, rangeland land system vegetation data and Landsat Thematic Mapper (TM) imagery that provides Near Infra-Red (NIR) bands useful for vegetation surveys. Vegetation in the WA rangelands is currently mapped as Pre-European vegetation, and available at 1: 250,000 scale. The Pre-European vegetation mapping was originally carried out by 'plotting interpretations from field traverses onto the aerial photo-mosaics' (Department of Agriculture 2005). The current version of the Pre-European vegetation dataset includes correction of original mapping errors and attribute capture errors. The land system vegetation data is 1:100,000 scale, providing higher resolution vegetation data, however this vegetation survey is not independent of the other landscape features (soil, landforms) within the land system. Landsat TM scenes cover the majority of rangeland agricultural areas in Western Australia and was available to download from the United States Geological Survey website (United States Geological Survey. 2011). Landsat TM can be used to remotely delineate vegetation boundaries in GIS by finding the NDVI value (Normalised Difference Vegetation Index), this is possible because healthy vegetation reflects near infrared radiation very strongly. This technique can be successful used to map vegetation however it requires some degree of field reconnaissance work and benefits from time series imagery for changes in vegetation over time.

Australia's vegetation varies in structure and species between biogeographic regions and vegetation surveys require expert knowledge for identification of individual species to improve on existing datasets. For the purpose of this research, the Pre-European vegetation dataset was chosen due to its specific focus on native vegetation (refer to Figure 5.19).

5.3.2 Geology

There have been numerous geological events that have shaped the East Kimberley Region of WA and there are consequently numerous geological features, including a variety of rock types and associated erosional and weathering by-products including materials that make the overlying soil profiles. For the purpose of this research, the main geological dataset available for the pastoral rangeland of WA was the 1: 100,000-scale geological dataset (refer to Figure 5.19).

Figure 5.19 shows the vegetation and geology datasets used in this research that aim to aid a land unit prediction model. These two landscape elements have been overlaid with the land system boundaries for comparative purposes and to show any relationships that might visibly exist.



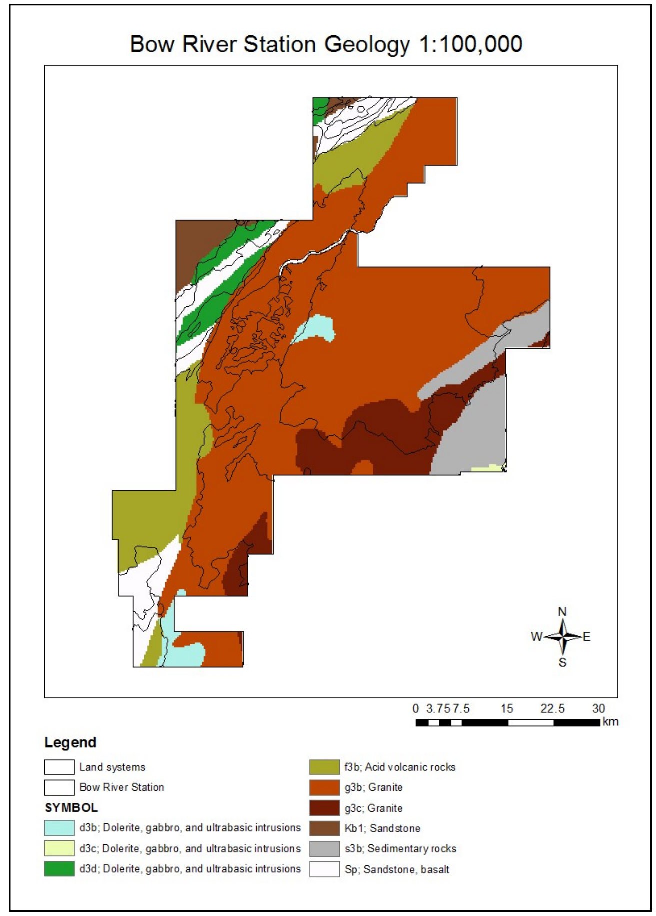


Figure 5.19 Vegetation and geology class boundaries for Bow River Station study area.

5.3 Comparison of evidence layers with mapped land units

The goal of landform classification was to create landform classes that could be used in a land unit prediction model. The landform classes needed to show that they were related, with some degree of accuracy, with real-world landforms at the land unit scale.

There are several factors that influence the quality of the derived morphological features (including landform classes) from a DEM that can lead to variations and quality of landform classification results. These factors include: topographic complexity and roughness of the terrain; source of elevation data (digitised/ground survey or remotely sensed) and DEM generation method; horizontal resolution (pixel size); vertical resolution (precision); algorithms used to calculate topographic attributes and landform classes (Thompson, Bell, and Butler 2001).

The elevation for the Bow River Station study area, ranks low on a global scale however, together with the local topography there are a number of complex formations, including numerous valleys, gorges and highlands such as plateaux, mesas and rolling hills (e.g. Bow River hills complex). These features are typically intricate and change in a space less than 30 m, that suggests a compromise in accuracy of classification of landforms both in horizontal and vertical space, when working with a 30 m DEM.

5.3.1 Individual landform feature analysis

Two landform classes were analysed for accuracy compared with previously digitally mapped landforms at the land unit scale. These two landform classes were *peaks* and *drainage/channels*, chosen for their prominent features; *peaks* are point features surrounded by negative elevation, and *channels* are linear features surrounded by positive elevation (refer to Figure 5.1). This analysis used the DEM, Landsat 2002 imagery, hillshade ('the hypothetical illumination of a surface'(Environmental Science Research Institute Inc (ESRI) 1999-2010)), land system and land unit boundaries.

The *peak* landforms were extracted from the LandSerf landform class results and converted into a layer where '1' represented *peaks*, and '0' represented all other landforms. Elevation values were added to the *peak*s by creating a *mask* of the DEM in ArcMap, and the symbology was changed to show to similarity in *peak* heights. The *peaks* were then displayed on a shaded relief DEM, overlaid with the Landsat 2002 image, to emphasis the location and clustering of this class, as seen in Figure 5.20.

Figure 5.20 shows that most *peaks* within O'Donnell land system have an elevation between 465.3 - 540.4 m (orange) and are mostly lower in elevation than those *peaks* on the outside of this land system. The mostly lower elevation and *peaks* corresponds with the O'Donnell land system described as 'stony undulating country with scattered hills'(Payne 2011).

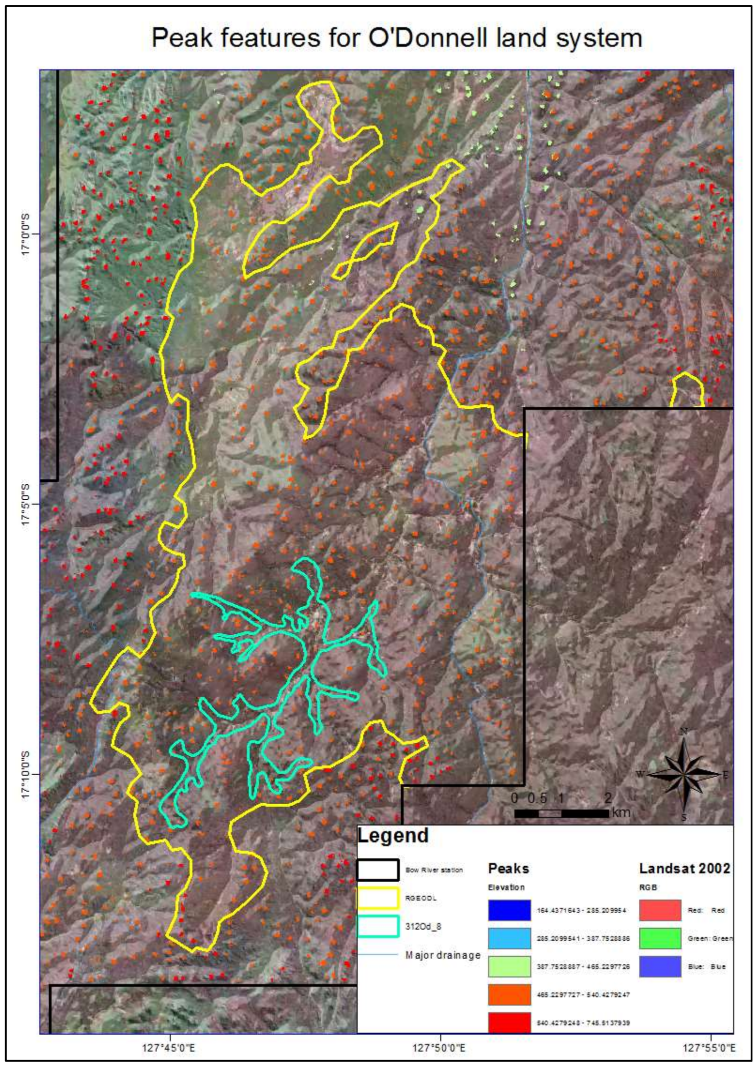


Figure 5.20 *Peaks* with elevation within the O'Donnell land system (yellow) and 312Od_8 (pale blue) land unit boundaries.

The LandSerf *channel* landform class was also tested for accuracy with existing digital data, with visual analysis used to see if any relationships existed with aerial photographs and satellite imagery.

The *channel* class identified more drainage lines when compared with the existing digital drainage data., seen in Figure 5.21, that shows the *channels* (LandSerf) overlaid on the DEM, bounded by both the O'Donnell land system (yellow) and the 312Od_8 O'Donnell land unit (pale blue), with 312Od_8 described as "Drainage floors and channels" (Schoknecht 2003).

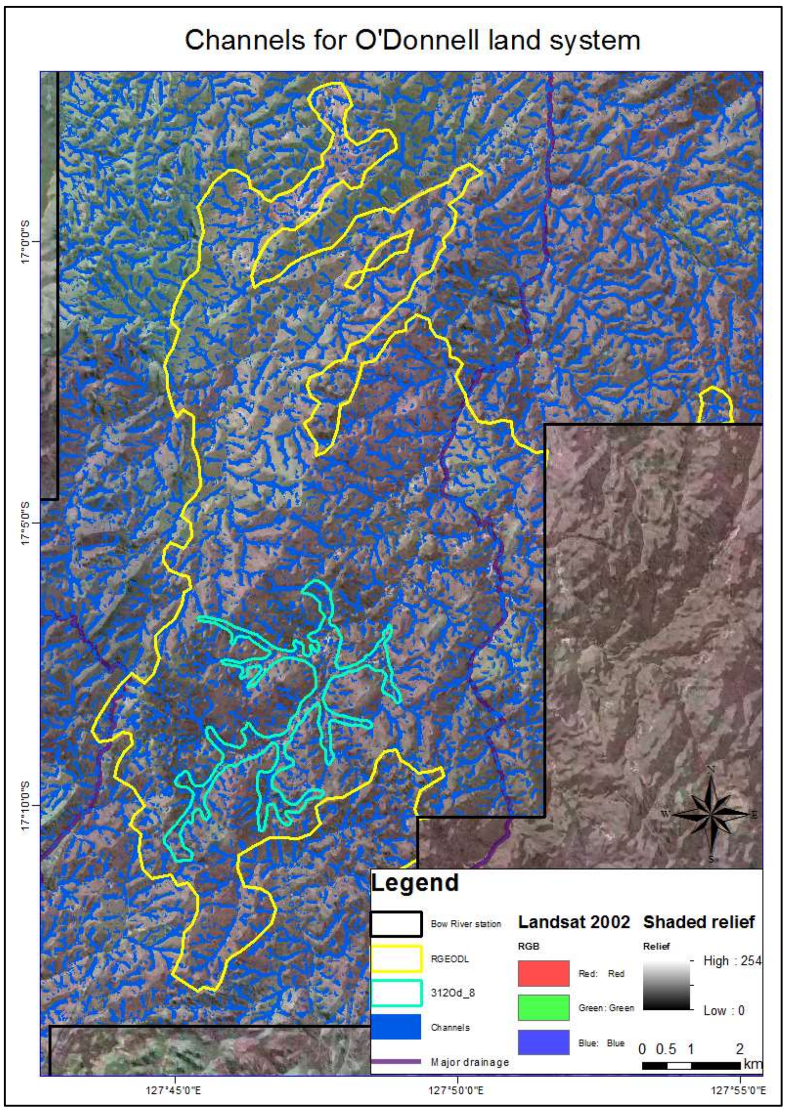


Figure 5.21 *Channels* bounded by the O'Donnell land system (yellow) and 312Od_8 (pale blue) land units.

The increased number of *channels* produced using LandSerf suggests that more drainage actually exists in the study area or the digitised drainage data didn't capture all possible drainage types including perennial, intermittent and tributaries. A comparison was made between the *channels* and existing digital drainage to see the difference between these two sets of drainage data.

Table 5.8 Comparison between existing digitised drainage data and LandSerf *channels* for Bow River Station study area.

	Number of pixels (30 m pixel size)	**Percentage of drainage (%)**
Digital drainage	2378	6.28
LandSerf channels	10243	27.07

In Table 5.8, the digital drainage makes up 6.28%, whilst the LandSerf *channels* comprised 27.07% drainage. Although this difference in percentage does not suggests why there is a difference in drainage, it does highlight the difference. According to Wood (2009c), the number of *channels* produced using LandSerf is 'the result of every negative linear feature adjacent to a slope being classed as a channel, that naturally may not be correct and would require field reconnaissance analysis to confirm state of flow' and also to confirm number and location of drainage.

5.4 Confirmation analysis and landform classification results

Confirmation analysis was used to compare the LandSerf landform class results with existing Ord-Bonaparte land units (refer to Section 2.2) for study area.

Random points were generated for the BRS study area (refer to Appendix 3 for point location map), with 100 points selected to test the relationship between the land units and landform class results. The descriptions of landforms were added to the 100 random points through statistics and attributes, using codes: - 1 Pits; 2 Channels; 3 Passes; 4 Ridges; 5 Peaks; 6 Plains. The landform codes were compared with the Ord-Bonaparte land unit descriptions using a frequency distribution table.

A frequency distribution table describes the frequency of variables, in this case, land units and landforms. Table 5.9 shows the frequency distribution of the 100 random point data, describing the relationship between the land units and the landform class data.

Table 5.9 Comparison between field points vs. LandSerf landforms codes.

	LandSerf landform codes						
Ord-Bonaparte land unit descriptions	**1**	**2**	**3**	**4**	**5**	**6**	**Total**
Channels and banks of major rivers and creeks	1		1				2
Drainage floors and channels			1				1
Drainage floors up to 500 m wide usually with channels			1	1			2
Extremely low level to undulating plains	1	1	1	1			4
Gentle lower slopes		2			1		3
Gentle lower slopes and level plains		1	1	2			4
High hills ridges and plateaux and associated steep slopes and benches	2	2	1			1	6
High rolling to steep bouldery hills				1	1		2
Level to gently undulating plains			4	1		1	6
Level to undulating plains		2		2			4
Low hills, mesas and associated upper slopes with much rock outcrop	1	3	1	1	1	1	8
Low undulating to steep hills	1	5	3	11	4	1	25
Low undulating to steep hills and ridges				1		1	2
Major creek and river channels and banks	1	1					2
Narrow drainage floors and channels		3				1	4
Narrow drainage floors, gentle slopes and streamlines	1	3	1			1	6
Rolling to steep high hills		5	2	1	1		9
Very low gently undulating to rolling rises and plains		1		1			2
Very low, gently undulating to rolling rises		2	3	3			8
Total	**8**	**31**	**20**	**26**	**8**	**7**	**100**
*1 Pits; 2 Channels; 3 Passes; 4 Ridges; 5 Peaks; 6 Plains							

The table identifies that the main LandSerf landform out of the 100 sample points were channels with a frequency of 31 points (highlighted), this can be compared with the drainage land unit descriptions (rows).

5.4.1 Bow River Station field reconnaissance study

A field trip was conducted on Bow River Station, which is a pastoral lease station in the East Kimberley Region of WA (refer to Section 3), situated along the Bow River and its tributaries. The area is accessible via the Great Northern Highway, through a number of minor roads and pastoral tracks maintained by the local aborigine community. The closest minor town is Warmun (Turkey Creek) and closet major towns are Halls Creek, Kununurra and Wyndham.

There are only three stations mapped to the land unit scale in this region including – Bow River, Ivanhoe and Carlton Hill, and of these stations, Bow River was chosen as a study area. The closest settlements to Bow River Station are the Warman/Turkey Creek aboriginal community and roadhouse, and the Violet Valley and Bow River aboriginal communities. Following correspondence with local government members and the local indigenous community elders, permission was granted for access to carry out a field trip for this research. The area is accessible via the Great Northern Highway, by a number of minor roads and pastoral tracks maintained by the station. The track conditions vary from localised flooding in the wet season to unstable cracking clays in the dry season.

During a 6-day field reconnaissance field trip, access was limited to the southern portion of the station, via the Violet Valley community, due to poor track conditions. The field trip was planned toward to end of the dry season, when the tracks would still be accessible, however due to early thunderstorm activity there was localised flooding on some tracks.

In Figure 5.22, the map shows the study area with 100 m intervals local relief, roads and tracks, settlements, important indigenous sites and digital drainage.

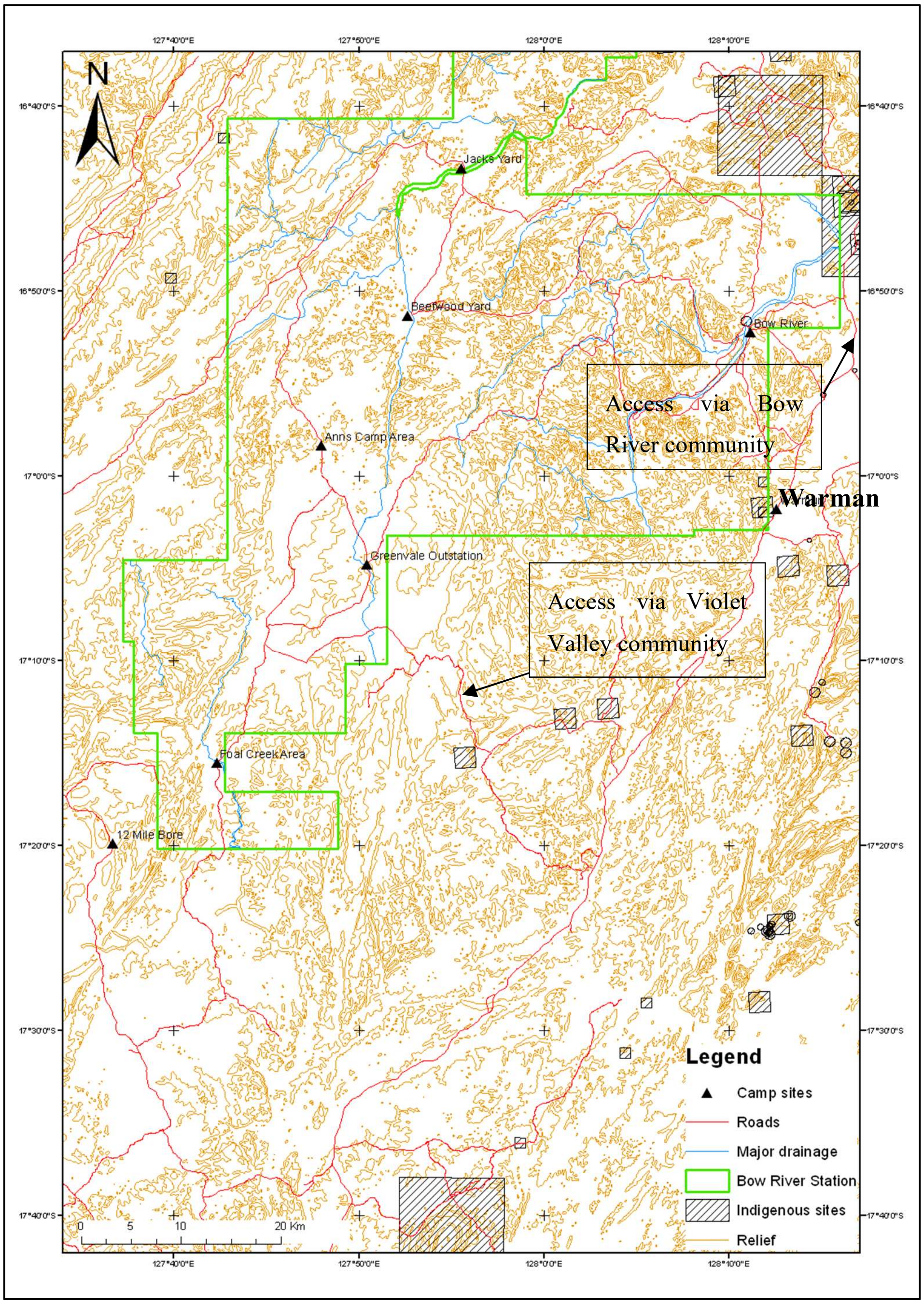


Figure 5.22 Bow River Station in the East Kimberley Region of WA.

The field trip involved visiting a total of 31 locations on the station, collecting GPS waypoints of local landforms, geology, vegetation and soils, and also track locations, stored on an ArcPad handheld device, that were later uploaded into ArcMap. Figure 5.23 shows the sites of the GPS waypoints and tracks overlaid on Landsat imagery.

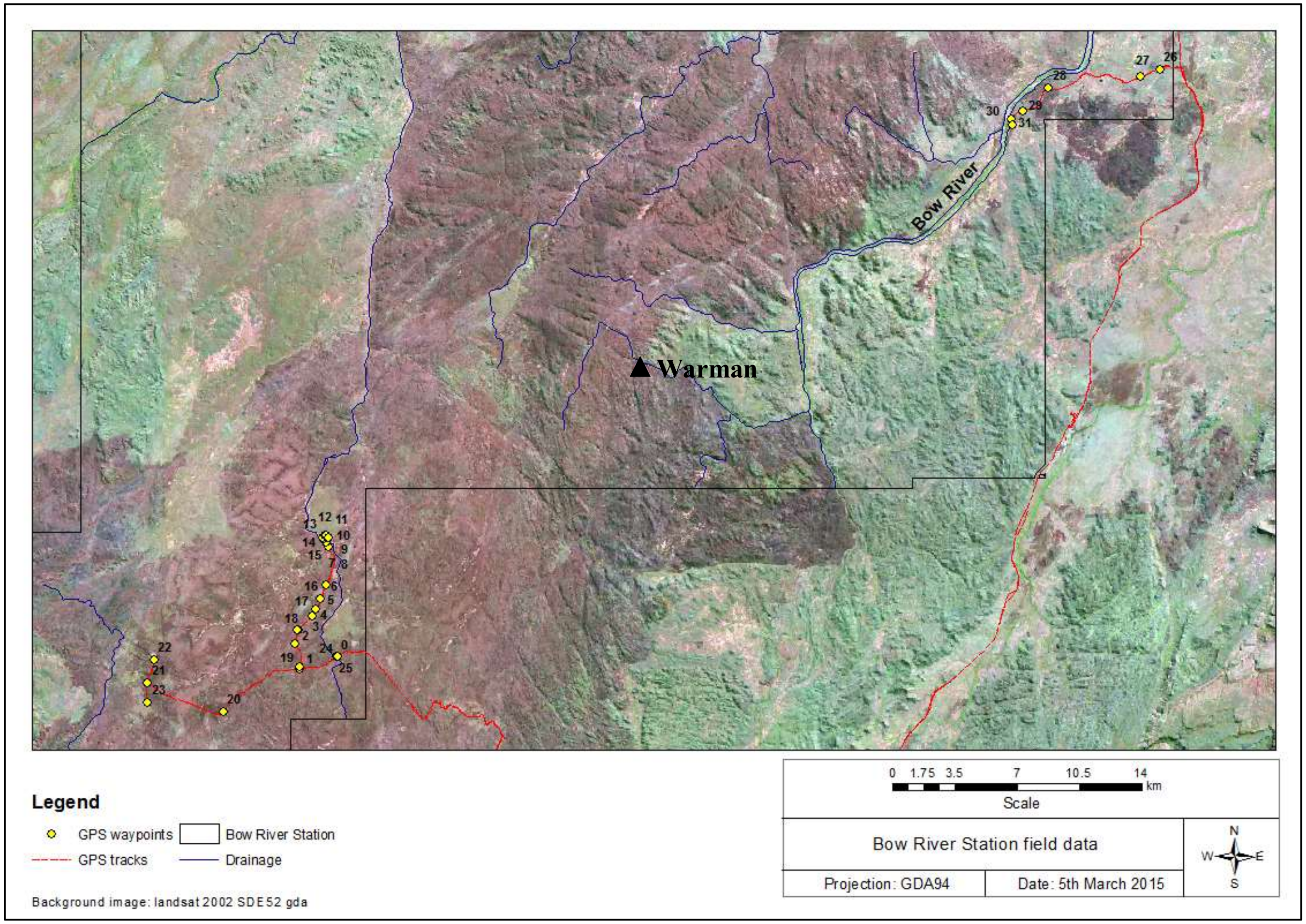


Figure 5.23 GPS waypoint location map for Bow River Station field trip.

A comparison was made between existing Ord-Bonaparte land unit descriptions (refer to Appendix 2) and the field trip point descriptions, with a summary seen in Table 5.10 and in Appendix 4 (including GPS photos). Out of a total of 31 field points collected, only 26 field points had landform descriptions. Using the points with landform descriptions, only 15 out of the 26 descriptions matched, which produced a 58% accuracy.

Table 5.10 Comparison between field trip descriptions and land unit description of landforms.

OID	GPS Waypoint	Field Description	Land unit	Land unit landform description	Yes/No
1	21	Plain	312Od_8	Drainage floors and channels	No
2	24	Plain	312Od_7	Level to undulating gilgai plains	Yes
3	22	Pit	312Od_7	Level to undulating gilgai plains	No
4	2	Drainage (Creek bed)	312Od_6	Level to undulating low plains	No
5	20	Drainage	312Od_6	Level to undulating low plains	No
6	25	Drainage	312Od_8	Drainage floors and channels	Yes
7	26	Plain	312Od_8	Drainage floors and channels	No
8	3	Drainage	312Od_6	Level to undulating low plains	No
9	19	Pass	312Od_6	Level to undulating low plains	Yes
10	4	Pass	312Od_6	Level to undulating low plains	Yes
11	18	Slope	312Od_6	Level to undulating low plains	Yes
12	5	Pass	312Od_6	Level to undulating low plains	Yes
13	6	Plain	312Od_6	Level to undulating low plains	Yes
14	17	Pass/Plain	312Od_6	Level to undulating low plains	Yes
15	7	Plain	312Od_6	Level to undulating low plains	Yes
16	8	Slope	312Od_8	Drainage floors and channels	No
17	9	Drainage	312Od_8	Drainage floors and channels	Yes
18	10	Drainage	312Od_8	Drainage floors and channels	Yes
19	11	Pass/Plain	312Od_6	Level to undulating low plains	Yes
20	16	Drainage	312Od_6	Level to undulating low plains	No
21	12	Plain	312Od_6	Level to undulating low plains	Yes
22	15	Plain	312Od_6	Level to undulating low plains	Yes
23	13	Drainage	312Od_6	Level to undulating low plains	No
24	14	Plain	312Od_6	Level to undulating low plains	Yes
25	32	Drainage	312Ri_6	Level to undulating plains	No
26	31	Plain	316Pp8A	Channels and banks of major rivers and creeks	No

5.5 Chapter summary

The existing landscape variable data for the study area was limited to vegetation and geology however a SRTM DEM was available for this research that allowed classification of landforms and other topographic indices, both relative relief and elevation.

LandSerf was used for landform classification shaped by regional statistical parameters. Local sampling windows were tested with the optimal dimensions found to be a 11 x 11 kernel with a 6 degree of slope and 0 curvature tolerance and distance decay, sampling the DEM for similar neighbouring cell values that created clustered landform patterns. The patterns resulted in six landform classes – pits, channel, passes, ridges, peaks and plain. These landform classes were exported as a raster that were imported into ArcGIS software for further manipulation and analysis.

ArcGIS was used to further develop and categorised the landform classes that were saved as a landscape variable to be used in the land unit prediction model. ArcGIS was also used to create relative relief and elevation data layers using the DEM. Relative relief was developed using deviation from the mean statistics that were spatially joined to the land units to identify height cut-off points using landform descriptions. The elevation was categorised into 100 m height intervals and saved.

The results for the landforms were checked for accuracy with existing Ord-Bonaparte Program land units and with field mapped point data. The landforms were found to be 58% accurate with the land unit and field mapped data that was considered adequate accuracy to be used as a landscape variable in the prediction model. To improve landform classification, it is recommended to use higher resolution DEM data that would increase the identification of minor landform features. The final set of landscape variable data included vegetation, geology, landforms, relative relief and elevation.

6 Predictive modelling

Spatial predictive models aim to predict ‘events’, in this case occurrence of land units, at specific locations. They are comprised of one or many decision-making support infrastructures including data, information, evidence, knowledge and wisdom.

A predictive model is about real world relationships, while a data model is essentially a set of constructs for describing and representing the real world in a digital environment (Longley 2005). Predictive models are generally divided into two categories: data driven and/or knowledge driven models, where the mathematics of data-driven models are drawn from data, and raw facts about a study area, and knowledge-driven models include expert knowledge about a situation, location or event. Both data and knowledge driven models can work simultaneously creating a more robust model, where raw data can be supported and/or added to by knowledge.

Analysis in a predictive model can be either deductive or inductive, where deductive models are based on theory, and inductive models are based on observed patterns (Kuiper 1999). This research uses inductive geomorphological model theory, where prior data and knowledge are used to build and create a suitable modelling method, also looking at ways to analyse and predict multi-class data, using multi class layers (predictor variables), that are commonly referred to as evidence layers (Romero-Calcerrada & Luque, 2006), which in this case are the landscape variables.

The modelling methods analysed and tested were a Binary Weighted Overlay (BWO), a Fuzzy Weighted Overlay (FWO) and a Positive Weights of Evidence (PWofE) models, which is a special case of a Weights of Evidence (WofE) model.

6.1 The predictive models

Two of the modelling methods tested were Weighted Overlay (WO) models that are based around a method that can uses a variety of input data as evidence, which can be manipulated to create layers, that can then be combined, commonly additively, to predict sites of interest. Both binary and fuzzy weighted models can be used for predicting sites/events, and there are many examples of comparisons between the two methods. BWO and FWO models are well adapted to GIS which provides a good geographic space and suitable tools allowing numerous data layers to be combined, confined to a set of rules, to produce predicted mapped units.

A BWO describes the data as either ‘suitable’ with values of 1, or ‘un-suitable’ by allocating zero values. A FWO allows an object a partial degree of belonging to a class, essentially allocating a degree of probability, resulting in an allocation assigned by probabilistic interpretation (Longley 2005).

An example of a comparison between traditional binary overlay and fuzzy overlay is presented in Sen (2017), where attempts were made to map habitat suitability surfaces for snow leopards, which are listed as Vulnerable on the IUCN Red List of Threatened Species because the global population is estimated to number less than 10,000 mature individuals. The models used data from various sources including Landsat images, and an ASTER DEM that was used to find the slope, relief, aspect, and ruggedness index of the area. The results from this case study, found that both the binary and fuzzy models successfully predicted habitat suitability surface for the snow leopards, with the suitability analysis identifying that the binary weighted overlay method was more successful than the fuzzy model. The models were validated using ground field observation data. The results showed that the fuzzy model tended to over-predict unsuitable habitats, with more than double the percentage of unsuitable habitats predicted than those observed in the field. The main obstacles to mapping snow leopards were the small number of ground field observations and their elusive nature and the harsh terrain and environment in which they exist (Sen 2017), which is a similar problem to mapping in WA pastoral rangelands due to inaccessibility.

The other modelling method tested was a WofE model, which is a data-driven and discrete multivariate statistical method that uses conditional probability to determine the relative importance of the phenomena as evidence. In this research a modification of WofE was used, using only positive weights. WofE models commonly use an application of Bayesian inference that has been used in population and community ecology although is becoming increasingly popular in ecological research and environmental decision-making (Romero-Calcerrada & Luque, 2006). WofE has been used in a variety of fields of research including the assessment of ground subsidence, mineral potential mapping, landslide studies and ground water predictions. It is essentially a method of combining multiple layers of evidence that support or reject a hypothesis.

WofE was originally developed in the field of mineral resource mapping, to determine patterns of clusters in mineral deposits, and their spatial association with particular geological features. In GIS, WofE approaches were developed by Bonham-Carter (1994), combining spatial software and weightings of evidence to predict features in landscapes. WofE involves considerably computations that involve a choice of weights (cf. fuzzy logic), that reflect spatial association between map patterns and known points (Bonham-Carter 1994). WofE models provide a good theoretical basis for prediction using a variety of variable data layers, however, strictly, WofE requires adequate known occurrences of the events/features (commonly as point locations) otherwise there may be an error in the estimate of weights; the population of predicted events/features might be under or overestimated if not enough known occurrences are included in the WofE model

An early example of how WofE has been used to predict the location of the mineral Gold (Au), involved several data layers that indicated the presence of Au deposits that were combined together to predict areas favourable to Au (with an associated explicit degree of accuracy) on a map, with the predicted mapped units used to assist informed decision making and planning (Bonham-Carter 1994).

A more recent example is the use of WofE for modelling wildfire probability by Jaafari (2017). The modelling of wildfires in the Zagros Mountains in Iran, involved preparing distribution maps of wildfire probability as predicted output. A weights of evidence model was used to investigate the relationship between historical wildfires in the region and a range of binary predictor maps that included topography, climate and human activities. The findings for this model were validated using receiver operating characteristics (ROC) plots, and it was found that wildfires are strongly dependent on the topographic characteristics of the landscape, but are also dependent on human infrastructure and human activities. These results were suggested as aids for land use planning and decision making for wildfire management such as allocation of fire infrastructure prior to the start of the main fire season in the region.

WofE has a number of strengths as a predictive model including an objective method of deriving weighting factors, combination of multiple map patterns and conversion of multi-state maps to binary maps for optimised contrast. In addition, data with incomplete spatial coverage can be accommodated in the model, with the uncertainty incorporated as a separate layer (masking out areas of relative uncertainty) (Bonham-Carter 1994).

There are however two main disadvantages with WofE modelling. Firstly, the input maps are assumed to be conditionally independent of each other with respect to the response variable (distribution of known sites), and the testing of conditional independence is only possible in a data-driven model. Secondly, there needs to be adequate known occurrences of the events/features otherwise there may be an error in the estimate of weights; the population of predicted events/features might be under or overestimated if not enough known occurrences are included in the WofE model. The WofE method was tried in a variety of regions, however according to Bonham-Carter (1994) the WofE method was not applicable to poorly explored regions or where the samples are of poor quality.

A precursor to WofE was the Prospector model (Hart 1978), that used a combination of Bayesian inference networks and modified Bayesian probability (Porwal 2015), allowing a number of variables to be used in pattern recognition together with expert input, to produce a predicted pattern for site selection. In an ideal situation, there is an abundance of data that can be used in the modelling process, however in this research, the study area has limited information and data regarding land units restricted to the Technical Bulletin (Payne 2011). In data poor systems, such as the study area used in this research, subjective *prior* conditional probabilities can be used as an alternative to existing data as they were in Prospector.

6.1.1 Predictive Value Theory (PVT)

Predictive Value Theory (PVT) is a framework that shows the relationship between positive and negative concepts, that allows for informed decisions. The PVT was originally developed for the medical sciences to help physicians make critical decisions such as whether "to administer or not administer a treatment, or to screen or not to screen say cancer" (Mitroff 2013). The PVT works equally well for general decision making by combining probability theory and logic to establish Sufficiency and Necessity, where Sufficiency and Necessity are the basis for establishing causal relationships between factors, variables etc. In Figure 6.1, the PVT framework identifies the Sufficiency and Necessity represented by positive and negative and are described by four cases. The four cases seen in Figure 6.1, are: Case 1 where 'T' and 'D' are positive = 'a', a True Positive relationship (Sufficiency ratio), Case 2 where 'T' is positive and 'D' is not positive ('Not D') = 'b', a False Positive relationship, Case 3 where 'T' is not positive and 'D' is positive = 'c', a True Negative relationship and Case 4 where 'T' is not positive and 'D' is not positive = 'd', a False Negative relationship (Necessity ratio) (Mitroff 2013).

	D	Not D
T	a. True Positive	b. False Positive
Not T	c. True Negative	d. False Negative

Figure 6.1 The Predictive Value Theory (PVT) framework.

Sufficiency and Necessity are related to Sensitivity and Specificity describe by Mitroff (2013) as the fundamentals of confidence probability and measurements between sets of data. The Specificity and the Sensitivity of the PVT framework are defined by: Specificity = d/(b + d), and Sensitivity = a/(a + c), where the Specificity measures the proportion of actual positives that are correctly identified and the Sensitivity measures the proportion of actual negatives that are correctly identified. These measures can be derived using ROC plot analysis by plotting the True Positive Rate (TPR) against the False Positive Rate (FPR) (refer to ROC plots in Section 4.5 and Section 7.2).

An early use of Sufficiency and Necessity ratios in a prediction model was the Prospector system (mentioned above) which was designed as a computer-based consultation system for mineral exploration (Hart 1978) but was based on earlier medical diagnosis models. The concept behind Prospector was to alert geologists to unsuspected possible mineral deposits that could be used to establish further mineral exploration. The methodology of Prospector, involved the ‘geologist telling the program the characteristics of a particular “prospect” of interest i.e. the geologic setting, structural controls, kinds of rocks/minerals, and alteration products present or suspected’. Prospector then ‘compared these observations with models of various kinds of ore deposits, noting the similarities, differences, and missing information’. The program then ‘engaged the geologist in a dialogue to obtain additional relevant information and to make an assessment of the mineral potential of the prospect’(Hart 1978).

6.1.2 Prediction model data sources

Land unit data and land information for the Bow River Station (BRS) study area were available from two sources; general descriptions and proportions (where proportions are not spatially explicit) presented in “Land Systems of the Kimberley Region” Technical Bulletin by Payne (2011) (refer to Appendix 1), and digital land unit data (refer to Appendix 2), mapped as part of the Ord-Bonaparte Program by DAFWA (Schoknecht 2003). The general descriptions and proportions found in the Technical Bulletin (Payne 2011), formed the foundations of the *prior* proportions that were used in the prediction models for the study area whilst the land unit data mapped by Schoknecht (2003) were reserved as “ground truth” to test the results.

Two main land systems were used to test the different modelling techniques; the Antrim and Wickham land systems, due primarily to their statistical variation of land unit proportions, but also due to their different geographical location within the study area. The Antrim land units have uneven proportions, seen in Table 6.1, whilst the majority of the Wickham land units are more evenly proportioned within the land system (refer to Table 6.2).

Table 6.1 Proportion of land units for Antrim land system.

Antrim land unit	**Proportion as a percent (%)**
ALU1	50
ALU2	40
ALU3	5
ALU4	2
ALU5	2
ALU6	1

Table 6.2 Proportion of land unit for Wickham land system.

Wickham land unit	**Proportion as a percent (%)**
WLU1	20
WLU2	20
WLU3	10
WLU4	20
WLU5	20
WLU6	4
WLU7	3
WLU8	3

The three different modelling techniques (refer to Section 6.1) were tested on these two land systems. The modelling techniques needed to take into consideration the facts that numerous land units exist in a land system and that the land units are comprised of many combinations of landscape variables. For example, Antrim land unit 1 (ALU1) is comprised of a combination of landscape variables, including a number of landform classes, described as mostly ‘mesas and buttes with steeply sloping margins’ in Payne (2011). The description of landform classes for ALU1 suggests that this particular land unit would have minimal pass, channel and pit landform classes but more peak, ridge and high plain landform classes. At least one or more classes of each of the landscape variables exist for each land unit and the land units are likely to be different or have different proportions for each land system. The different combination and number of landscape variables and classes for the land units is what makes the land systems unique. The aim of this chapter is to find a suitable modelling technique that 'best models' the landscape variables and classes to predict land unit boundaries for a land system. One of the main challenges of modelling natural landscape features is that they don't always follow rules and assumptions.

6.2 Binary Weighted Overlay (BWO) methodology

A Binary Weighted Overlay (BWO) model is a knowledge-based model that uses 'expert' opinion incorporated indirectly through interpreted mathematical values. The BWO model uses a binary system where values represent either unsuitable or suitable events, 0 or 1 respectively. Traditionally, according to Qui (2014), a binary weighted overlay was considered a simple method, where results are either a pass or fail for an "event".

A BWO model generally consists of a number of data layers as evidence about an event, with the analysis commonly raster with layers converted from vector to raster as required for modelling purposes. Each of the layers contains evidence as a geographic feature that can be either natural or manmade e.g. geology, soils, and/or roads. The layers are categorised into binary overlays, distance rasters and/or ranked categories. A typical site selection problem using binary layers is presented in the following structure chart:

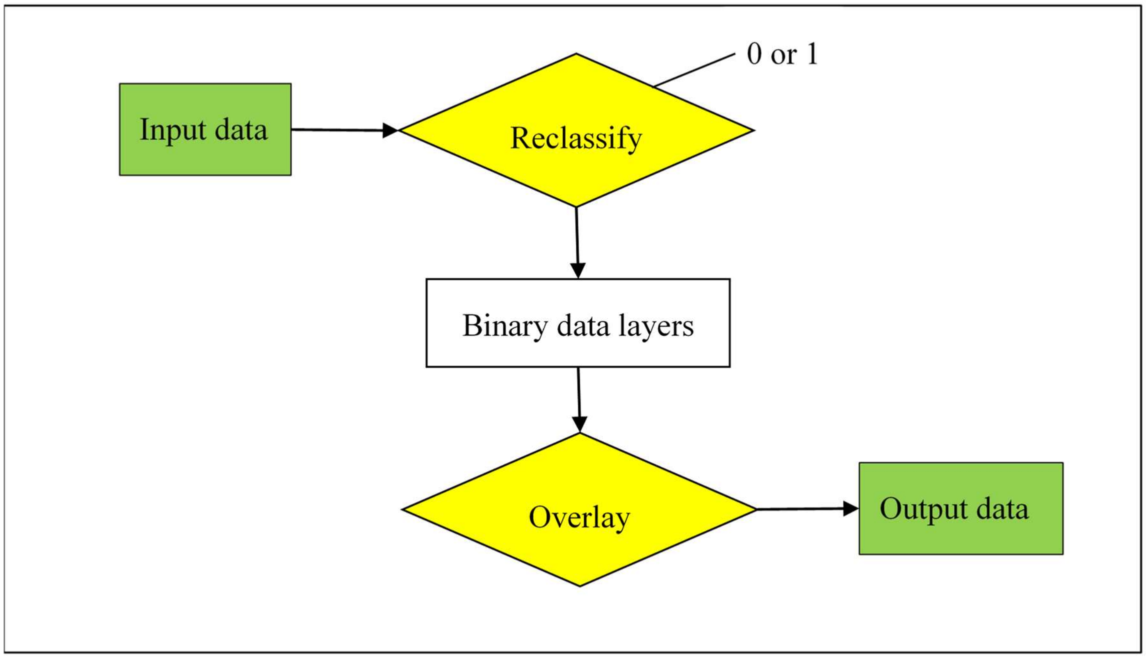


Figure 6.2 Architecture of a typical binary model.

The main stages of a BWO model consist of reclassification of any multi-classed evidence data as input to form the binary data layers, which is overlaid to locate 'sites' as output data.

Binary overlays are commonly used in 'site selection' problems, for example, city councils need to consider locations of waste disposal, and therefore seek landfill sites. Initially, a set of rules would be established that would consist of conditions that needed to be satisfied for an event. Using the 'set of rules', the conditions of a number of maps that contained a variety of variables i.e. topography, geology, watersheds, could be classified as either suitable or not suitable, which could start as a rank system or buffered distance map that could be further converted to a binary map represented by a value of 1 or 0 respectively for suitable and unsuitable locations for the landfill site. A classic example of this technique, Bonham-Carter (1994) shows how a variety of input variables, classified by suitability for landfill site and overlaid in an additive method can produce a predicted site selection output map as isolated polygons for an area of interest.

A more recent study investigated the environmental problem of wildfires. Rios-Pena (2017), predicted the occurrence of wildfires as an ‘event’ with a number of variables i.e. weather, vegetation cover, altitude and known wildfire sites, using a binary additive modelling technique, where all layers were added together for an output of predicted wildfire sites.

For the BWO model, the land unit evidence layers available as landscape variables were also converted to proportions for each landscape variable class i.e. the landscape variable ‘landform’ includes - ‘channel’, ‘peak’, ‘ridge’ classes.

To convert the landscape variable classes to proportions, the descriptions from the Technical Bulletin (Payne 2011) and the land unit proportions were compared. Using the landscape variable ‘landform’ as an example, the majority of landforms for Antrim land system identified in Antrim land unit 1 (refer to Table 6.1, with 50% of the land system belonging to ALU1), are described as ‘mesas and buttes with steeply sloping margins’, these can be linked to landforms such as ‘ridges’, ‘peaks’ and high ‘plains’, where mesa are described by Kearey (2001) as ‘steep-sided, flat topped plateau or promontory surrounded by flat erosional plains’, whilst buttes are ‘small isolated hills capped with resistant rock’. Peaks form the top of landscape features, with ridges being long narrow hilltops and plains associated with flat expanses of land with no quantified elevation (plains can be sea-level or on flat expanses on plateaus and mesas).

The description of Antrim land unit 1 (ALU1) according to Payne (2011) is presented in Table 6.3. This description is an example of only one land unit of the Antrim land system with the entire table presented in Appendix 4. These descriptions provide an approximate description and proportion for each class of the landscape variables and classes, and they are not accurate at an individual pastoral lease scale and therefore should only be taken as an estimate or guide to assist decision making for land unit modelling.

Table 6.3 Antrim land unit 1 description from (Payne 2011).

Unit	Approx. area (%)	Landforms	Soils	Vegetation
1	50	Mesas and buttes with steeply sloping margins	Mostly rock outcrops with basalt boulders and pockets of red clayey soils.	Bloodwood-southern box sparse low woodland with arid short grass or upland tall grass; snappy gum sparse low woodland with hard spinifex or arid short grass.

Because exising data and information regarding land unts was limited to the description in the Technical Bulletin (Payne 2011), it was necessary to derive 'subjective' likelihood values using information such as that shown in Table 6.3.

The landscape variables were broken up into classes and given a value incorperating a degree of 'expert knowledge' that they would occur in the land units for Antrim land system. The subjective liklihood values for Antrim land units are presented in Table 6.4.

Table 6.4 Subjective values of landform classes for Antrim land units.

	Pit	Channel	Pass	Ridge	Peak	Plain
ALU1	1	1	1	50	50	50
ALU2	1	1	1	60	80	1
ALU3	1	1	1	40	1	1
ALU4	1	5	70	1	1	80
ALU5	50	90	20	1	1	1
ALU6	50	100	1	1	1	1

The values in Table 6.4, show that ridges, peaks and plains all have an equal likelihood of existing in Antrim land unit 1 (ALU1) and channels are most likely to occur in Antrim land unit 6 (ALU6), with double the chance of pits. These values ranged between '0' and '100' representing the likelihood that a landscape variable class would occur in a land unit (refer to Appendix 5).

The values were used to create binary values, seen in Table 6.5, where ‘1’ represents a ‘suitable’ value and ‘0’ represents a ‘unsuitable’ value. The rule used to reclassify the landscape variable class values to binary values was:

IF *landscape variable class* ≥ 50% THEN 1, ELSE 0.

Table 6.5 Binary values of landform classes for Antrim land units.

RULE: If >= 50% then 1, else 0						
	Pit	**Channel**	**Pass**	**Ridge**	**Peak**	**Plain**
ALU1	0	0	0	1	1	1
ALU2	0	0	0	1	1	0
ALU3	0	0	0	0	0	0
ALU4	0	0	1	0	0	1
ALU5	1	1	0	0	0	0
ALU6	1	1	0	0	0	0

The binary values in Table 6.5 were then added to the attribute’s tables of the landscape variable raster layers in ArcGIS. A visual example of the reclassification of Table 6.5 is shown in Figure 6.3. Figure 6.3 shows that landforms for ALU1 are represented by dark grey (1) and all other landforms are represented as light grey (0).

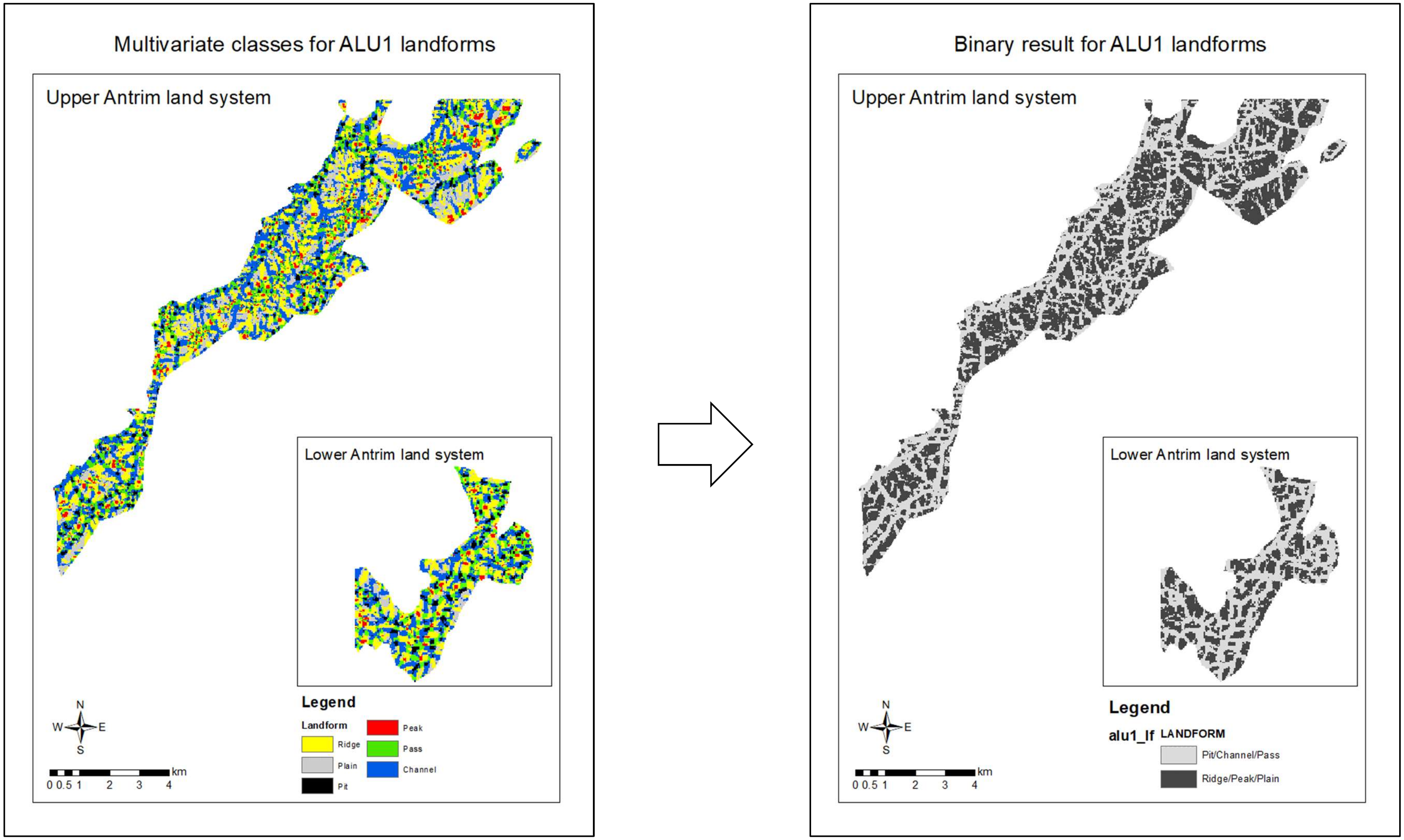


Figure 6.3 Conversion from multivariate to binary datasets for ALU1 landforms.

The binary rasters for all the landscape variables needed to be combined, however each landscape varaible as a collection of landscape variable classes also has a likihood value of occurring in a land unit. For example, the accuracy of the geology landscape variable raster was mapped with greater detail than the landform landscape varaible raster and therefore this should be represented in the overlay of the binary rasters.

6.2.1 Pairwise comparison of landscape variables

To represent the difference in data quality, data source and resolution between the landscape variables, weights were devised using pairwise comparison. The pariwise comparison matrix was devised as a scaling or ranking method for deriving weights for a set of activities according to their importance (Saaty 1977). Pairwise comparison involved ranking each of the landscape variables between '1' and '3', where '1' represents lowest quality data and '3' represents highest quality data. The relationship between the landscape variables was then compared in the "pairwise comparison matrix", e.g. the geology data is seen as twice as 'good' quality as the landform data in Table 6.6. The "pairwise comparison matrix" was then normalised using the total of each column, with results given in the "normalised score table" in Table 6.7.

Table 6.6 Pairwise comparison for the landscape variables.

Landscape variable	**Rank**				
Landform	1				
Geology	2				
Vegetation	2				
Relative Relief	3				
Elevation	3				
Pairwise comparison matrix					
	Landform	Geology	Vegetation	Relative Relief	Elevation
Landform	1	0.5	0.5	0.333333	0.333333
Geology	2	1	1	0.666667	0.666667
Vegetation	2	1	1	0.666667	0.666667
Relative Relief	3	1.5	1.5	1	1
Elevation	3	1.5	1.5	1	1
Total	11	5.5	5.5	3.666667	3.666667

Table 6.7 Normalised scores and criteria ranking for the landscape variables.

Normalised score table							
	Landform	Geology	Vegetation	Relative Relief	Elevation	Sum of rows	**Criteria ranking**
Landform	0.091	0.091	0.091	0.091	0.091	0.455	0.091
Geology	0.182	0.182	0.182	0.182	0.182	0.909	0.182
Vegetation	0.182	0.182	0.182	0.182	0.182	0.909	0.182
Relative Relief	0.273	0.273	0.273	0.273	0.273	1.364	0.273
Elevation	0.273	0.273	0.273	0.273	0.273	1.364	0.273
Total	1	1	1	1	1	5	

The normalised scores for each of the landscape variables were then totalled "as the sum of the rows", which was then divided by the total number of variables (6) to give the "criteria ranking" value. The "criteria ranking" value seen in Table 6.7 was multiplied by '100' to give a percentage, shown in Table 6.8, for each landscape variable that would be used as a weight in the modelling techniques.

Table 6.8 Landscape variable weights as percentage.

Landscape variables	**Weight (%)**
Landform	9
Geology	18
Vegetation	18
Relative Relief	27
Elevation	27

Landforms were given a rank of '1' because the landforms were sourced from the DEM using landform classification, where the accuracy was found to be 58% when compared with field data (refer to Section 5.6). The elevation and relative relief were ranked highest with an order of '3' because they were directly sourced from the DEM therefore reducing the likelihood of source error and also because the data resolution was 'highest' at 30 m.

The weights from Table 6.8 were used to overlay the binary landscape variable rasters using ArcGIS modelling tools using Equation 6.1.

(("%ALU1_e%" * 27) + ("%ALU1_g%" * 18) + ("%ALU1_v%" * 18) + ("%ALU1_lf%" * 9) + ("%ALU1_rr%" * 27))

(6.1)

Equation 6.1 shows Antrim land unit 1 (ALU1) as an example, with %ALU1_e% representing elevation, %ALU1_g% as geology, %ALU1_v% as vegetation, %ALU1_lf% as landforms and %ALU1_rr% as relative relief. The landscape variable weights, seen in Table 6.8 and Equation 6.1, were used for all modelling techniques (BWO, FWO and PWofE model) described in this research and for all land systems. The data quality, data source and resolution remained constant for all modelling techniques tested.

Equation 6.1 was added to a modelling tool in ArcGIS, using the “Raster Calculator” tool, as seen in Figure 6.4.

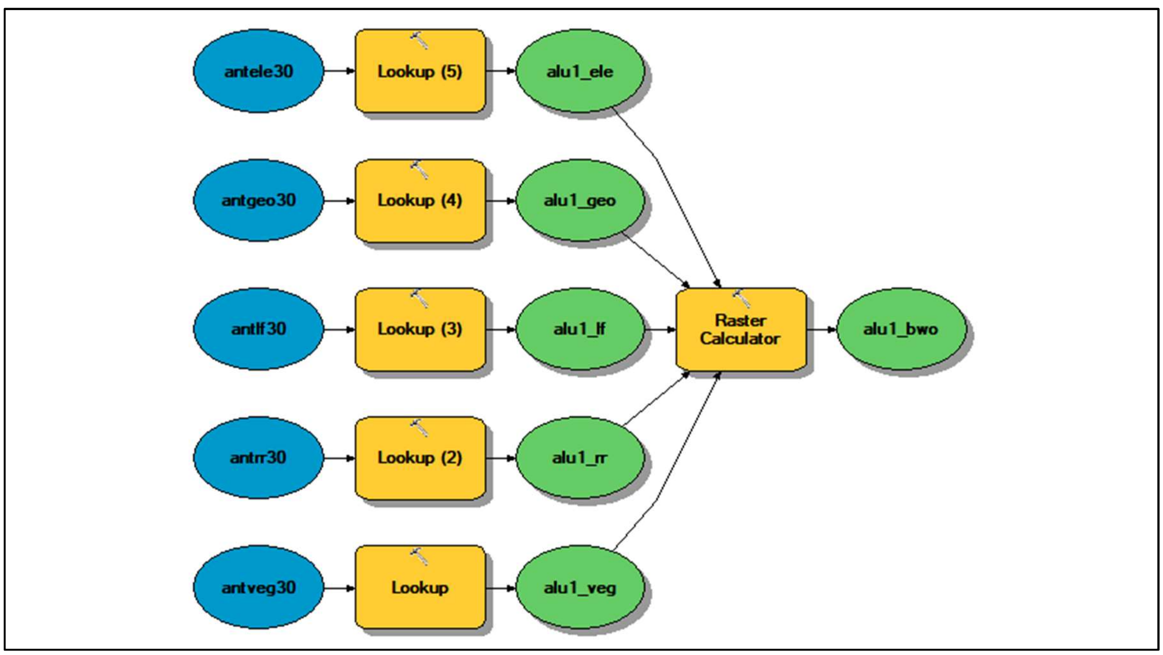


Figure 6.4 The ArcGIS modelling tool for ALU1.

The result of the ArcGIS modelling tool was graduated predicted BWO land units for Antrim land unit 1 (ALU1), shown in Figure 6.5.

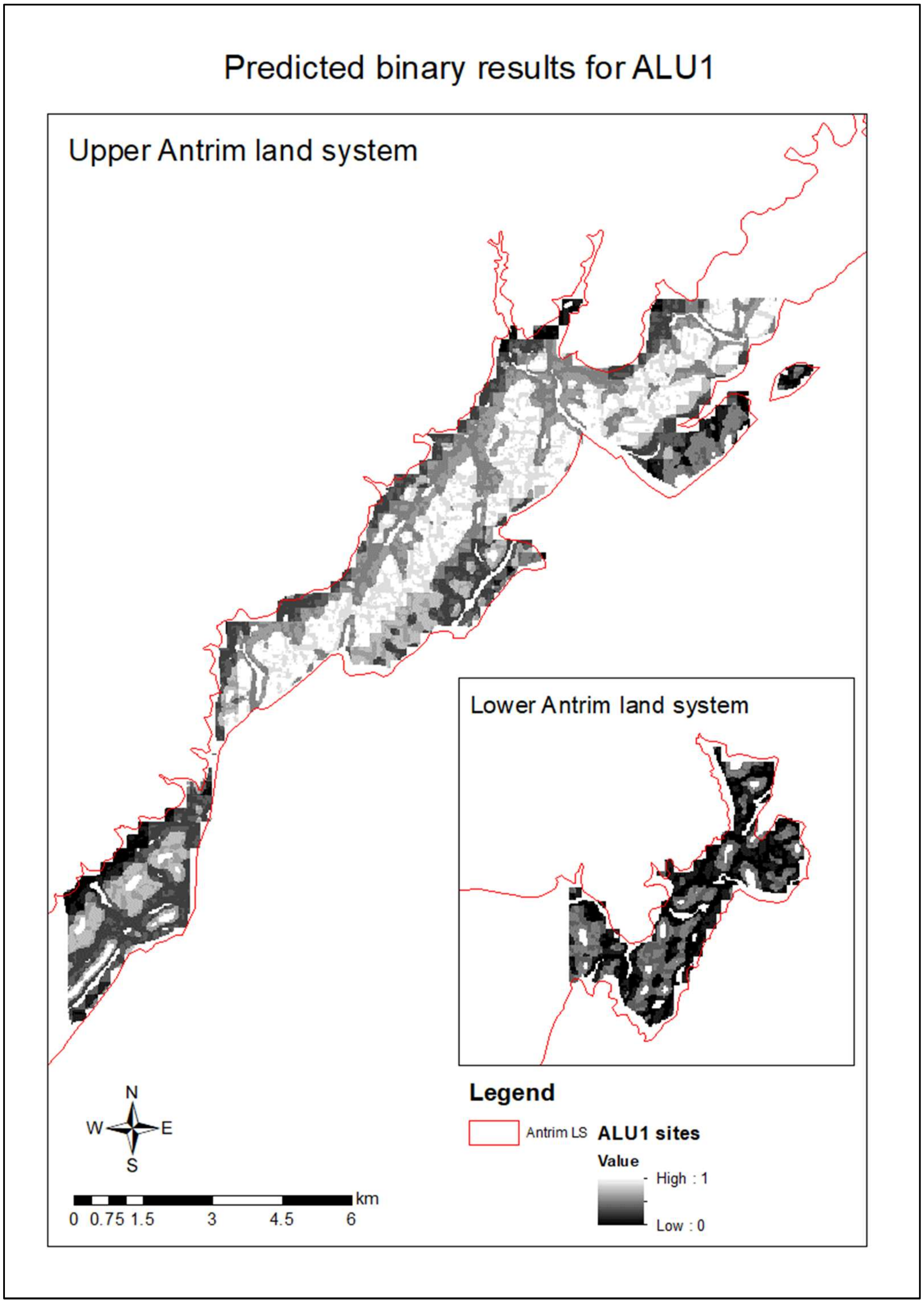


Figure 6.5 Antrim land unit 1 (ALU1) Binary Weighted Overlay (BWO) results.

The BWO model was tested on all Antrim land units of Antrim land system, with the results for ALU2 and ALU3 presented in Figures 6.6 and 6.7.

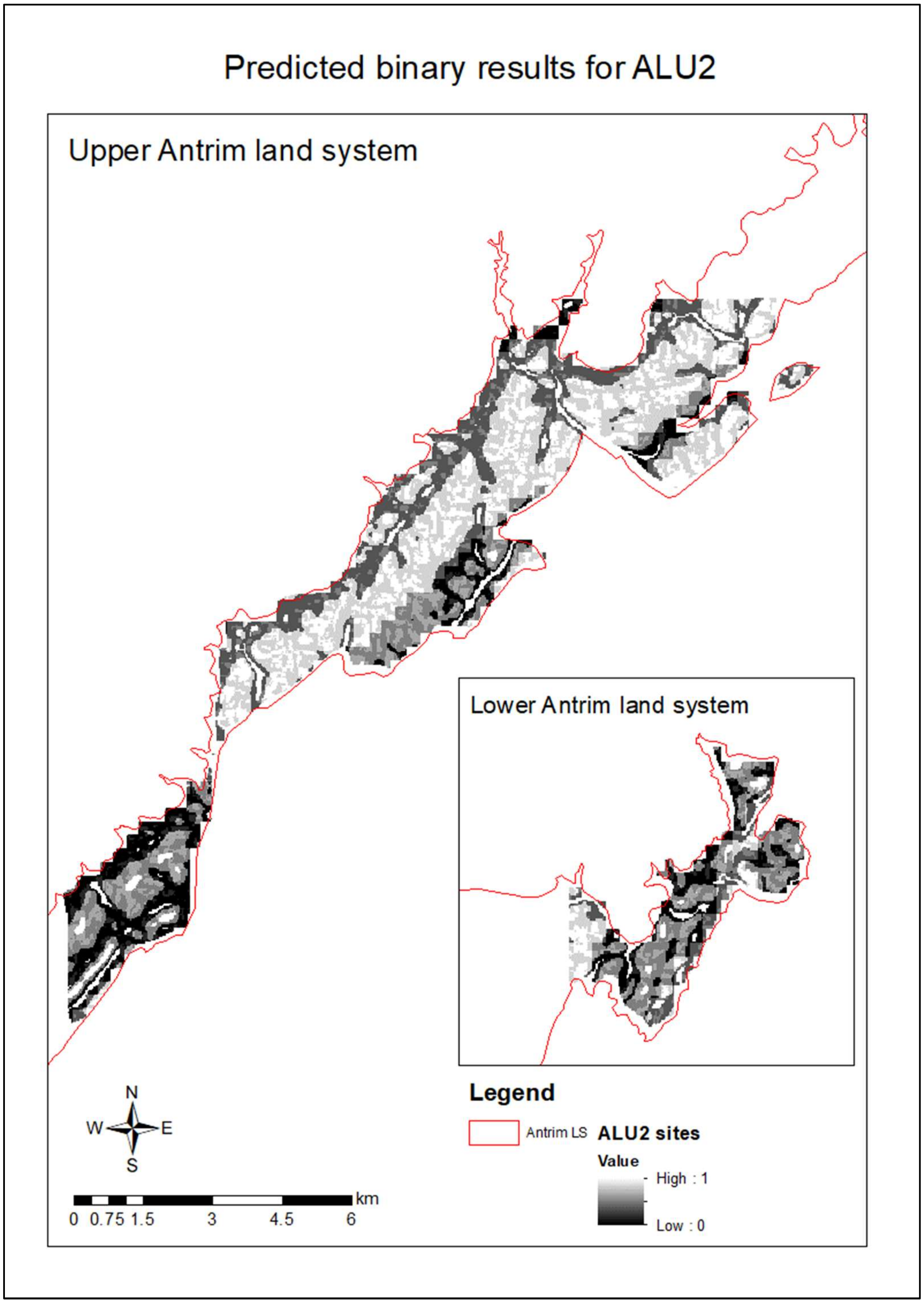


Figure 6.6 Antrim land unit 2 (ALU2) Binary Weighted Overlay (BWO) results.

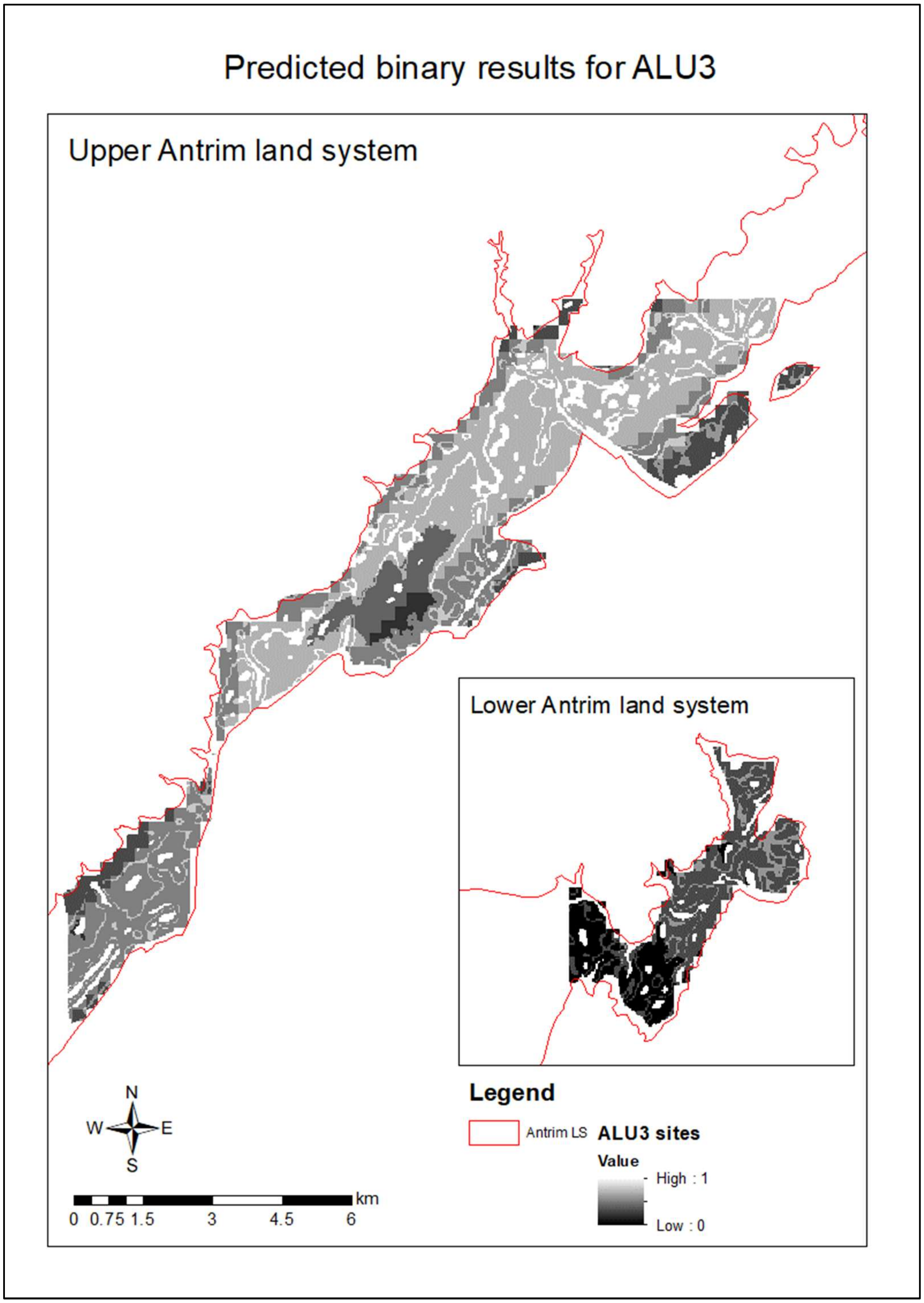


Figure 6.7 Antrim land unit 3 (ALU3) Binary Weighted Overlay (BWO) results.

Using the Binary Weighted Overlay (BWO) results, the predicted land units were ranked to find the 'most likely' land units within Antrim land system using the highest position tool in ArcGIS.

6.2.2 Calculating the predicted 'most likely' land units

In ArcGIS, there are many tools that can be used to combine rasters into a single map, one of these tools is the highest position 'ranking' tool, which calculates the highest position by estimating raster cells in an order allocated by the user. For a set of rasters, a rank is allocated as most likely to least likely, which in this research, allows the integrity of the land unit proportions to be maintained for the land system. The highest position tool in ArcGIS estimates "on a cell by cell basis the position of the raster with the maximum value in a set of rasters" (Environmental Science Research Institute Inc (ESRI) 1999-2010).

Figure 6.8 The highest position calculation method.

In Figure 6.8, the 'InRas1' represents an individual land unit (e.g. InRas1 = ALU1), with the OutRas representing the highest position result for a land system, or the 'most likely' land units.

6.2.3 The 'most likely' land units using the BWO model: Antrim land system

Antrim land system highest position ranking results for the BWO method can be seen in Figure 6.9, with values 1-5 representing Antrim land units 1-5, with Antrim land unit 6 not represented as it was likely outranked by more prominent land units with higher likelihood of existing.

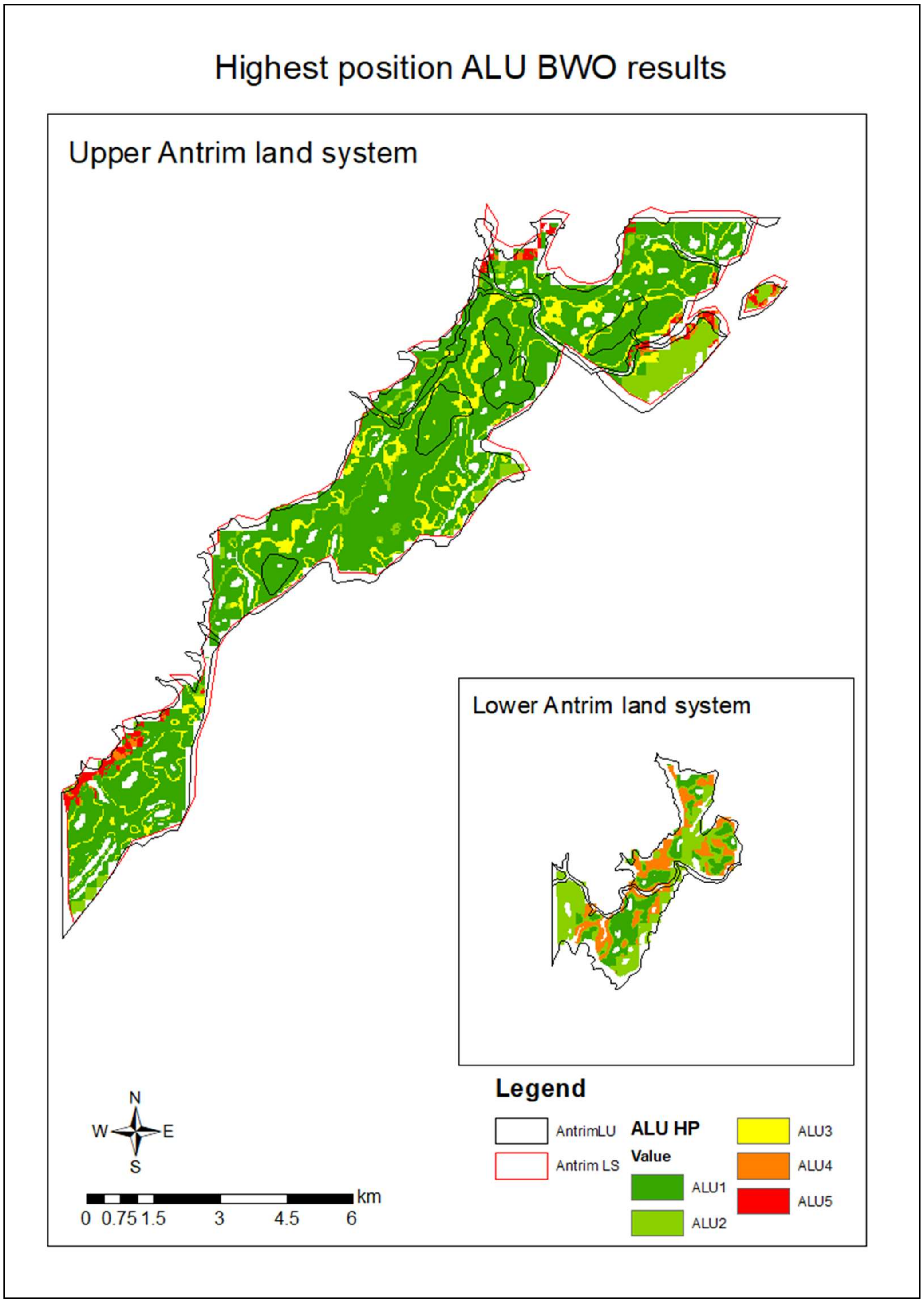


Figure 6.9 BWO model ‘most likely’ land units for Antrim land system.

The results in Figure 6.9 show the 'most likely' land units for Antrim land system represented by colours ranging from dark green to red, where these colours were used here only to show the difference in spatial location of the predicted 'most likely' land units. For the highest position tool, "if two or more of the input rasters contained the maximum value for a particular cell location, the position of the first 'ranked order' predicted land unit raster was returned as the result on the output raster" (Environmental Science Research Institute Inc (ESRI) 1999-2010). This means that the results for the 'most likely' land units using the highest position ranking tool were assigned a land unit not only on a cell by cell basis (or pixel by pixel) but also because of the order that the land units were input into the tool.

Only 5 out of the possible 6 land units were predicted, with Antrim land unit 6 (ALU6) not shown in Figure 6.9, likely due to it being a minor land unit within the Antrim land system with 1% *prior* proportion (refer to Table 6.1).

The land unit results have been overlaid with the Antrim land system and Antrim land unit boundaries, red and black lines respectively. These vector boundaries show a mismatch between the two sets of data that was introduced through differently data source and different mapping techniques in the form of irregular points, irregular contours, irregular polygons and possibly different mapping grids (refer to Section 4.5). There is also a mismatch seen between the vector boundaries and the raster results. Both data types contain a degree of uncertainty, with spatial variation incorporated through polygon boundaries and grid cell generalisations. For the purpose of this research, the mismatch does not affect the results however it will influence the confirmation results in Chapter 7.

6.2.4 The 'most likely' land units using the BWO model: Wickham land system

For comparative purposes, the BWO model was tested on Wickham land units, with the results presented in Figures 6.10, 6.11 and 6.12, for WLU1, WLU2 and WLU3, respectively.

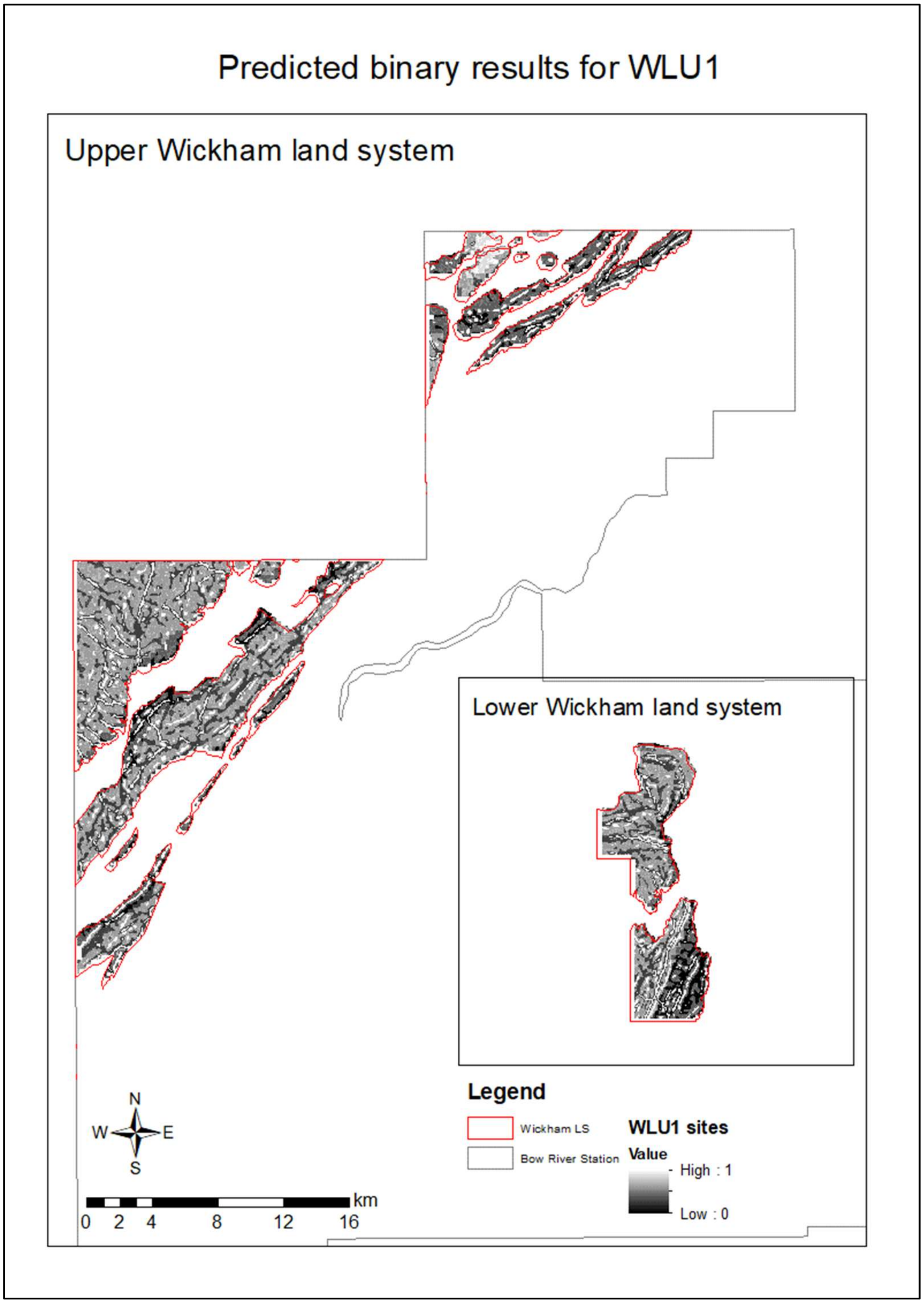


Figure 6.10 Wickham land unit 1 (WLU1) Binary Weighted Overlay (BWO) results.

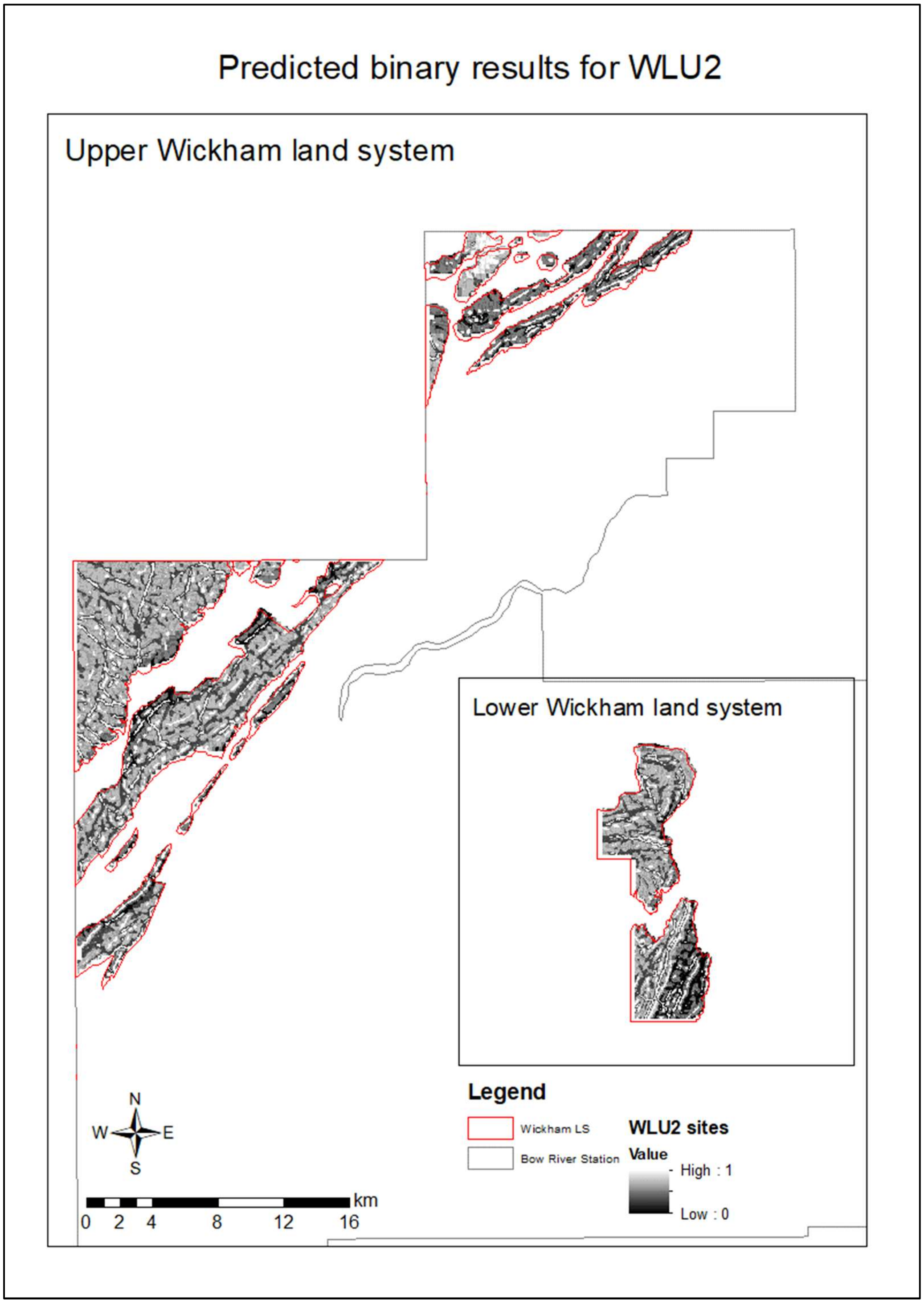


Figure 6.11 Wickham land unit 2 (WLU2) Binary Weighted Overlay (BWO) results.

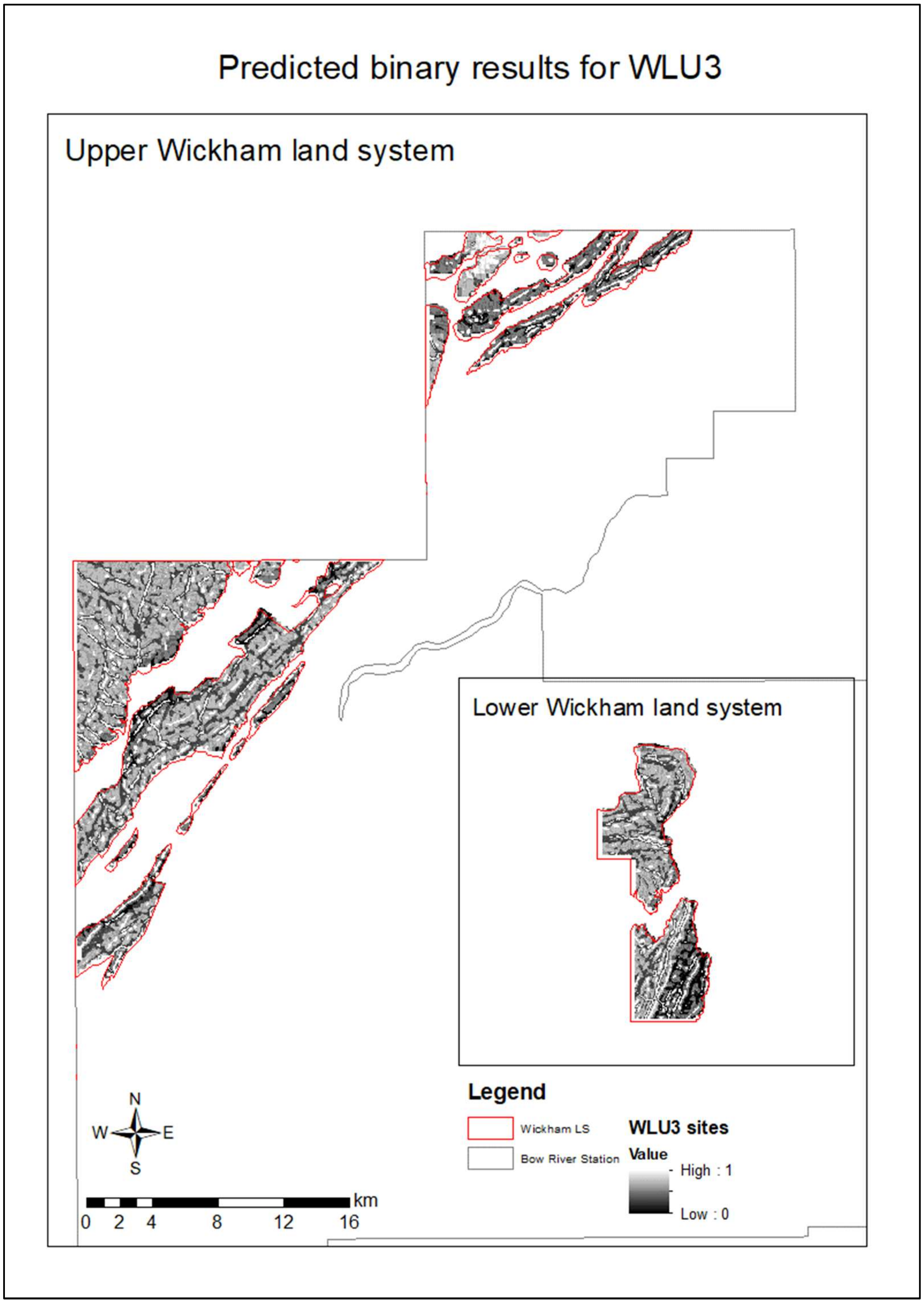


Figure 6.12 Wickham land unit 3 (WLU3) Binary Weighted Overlay (BWO) results.

The results of the BWO model for Wickham land units were then ranked using the highest position tool in ArcGIS (refer to Section 6.2.2) to find the 'most likely Wickham land units, seen in Figure 6.13.

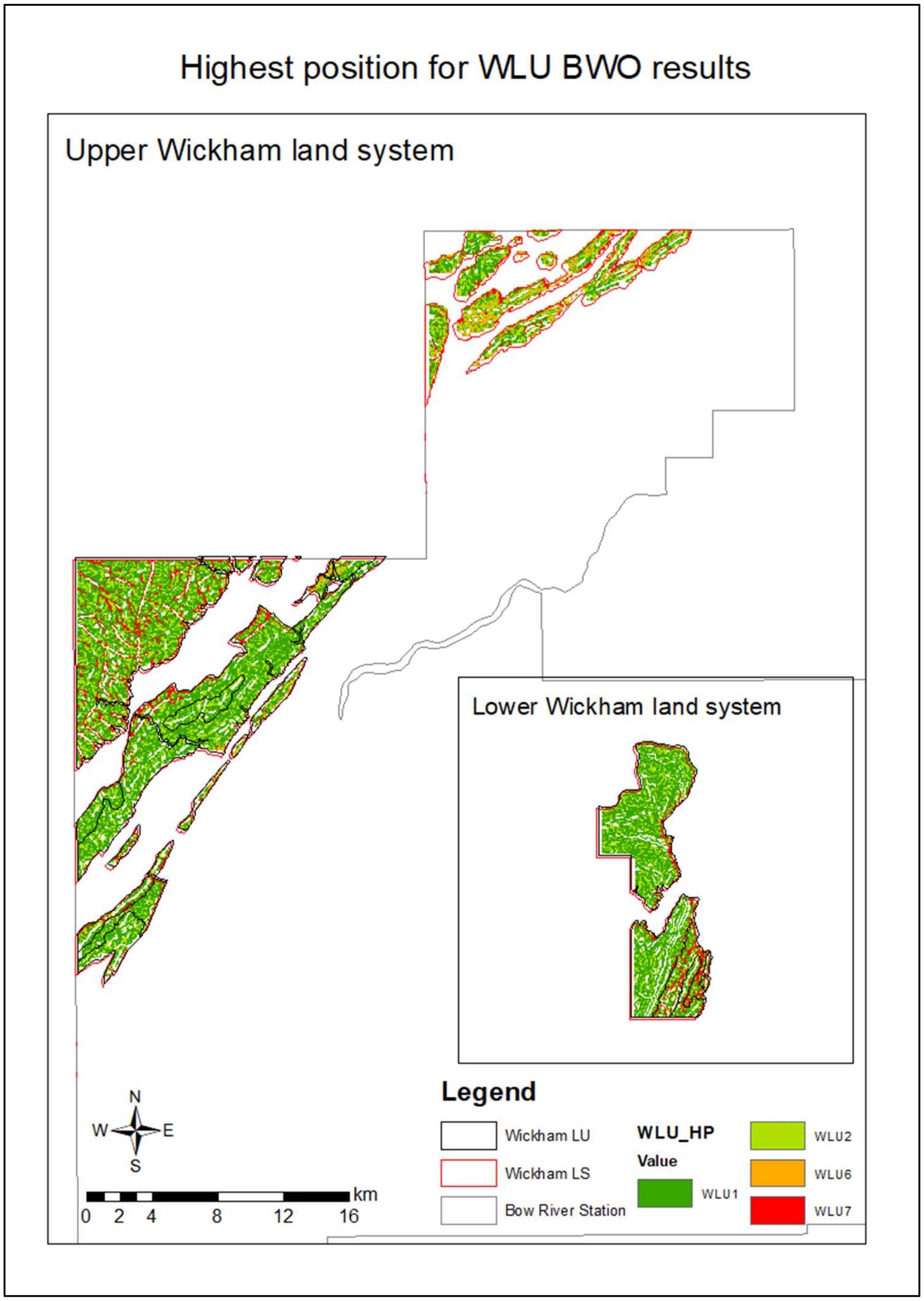


Figure 6.13 BWO model 'most likely' land units for Wickham land system.

The results for Wickham land system using the BWO model show that the 'most likely' land units, seen in Figure 6.13, suggest the four main land units are: WLU1, WLU2, WLU6 and WLU7.

6.2.5 Summary of BWO method

The BWO model used binary landscape variable rasters to predicted possible locations for land units of the study area. The process involved the conversion of multivariate data to binary data and then the combination of many binary data to produce unique landscape variable patterns for each land unit. The binary combination results were then ranked using the highest position tool in ArcGIS to find groupings and position of predicted 'most likely' land units.

The BWO model was tested on Antrim and Wickham land systems, producing two sets of 'most likely' land unit results, seen in Figures 6.9 and 6.13. The subjective value tables used to classify the multivariate landscape variable data of Antrim and Wickham land systems to binary raster data for the BWO model can be found in Appendix 6.

6.3 Fuzzy Weighted Overlay (FWO) methodology

Fuzzy models were introduced by Zadeh (1965), "as a mathematical way to represent vagueness in everyday life" (Bezdek 1994). FWO models can handle both multiclass and continuous data, and can be used in areas where training sites are limited (Porwal 2003). The FWO model is applicable for this study because both training sites and data are limited in the pastoral rangelands of WA. Another benefit of reducing the need to rely on training sites, is that there is a reduced tendency to over emphasise known sites.

The FWO model essentially breaks evidence layers into a number of classes, where each class it then given a fuzzy membership value of 'suitable class' between 0 and 1, where the classes may or may not sum to 1, nor do they have to sum to 1. A fuzzy membership, according to Liu (2009), is sometimes referred to as a signature, which removes the requirement of 'total membership' and provides a solution to the problem of threshold and decision rule uncertainty by allowing 'soft' thresholds and decisions. According to Porwal

(2015), an estimate of the probability that the class is suitable can be obtained through the probability of the 'signature' occurring, with the combination of all the 'signatures' identifying the significance of the class to that evidence layer.

Figure 6.14 presents a typically fuzzy model structure, comprising of the three main stages, these are: the fuzzifier, the inference engine and the defuzzifier. The fuzzifier or encoder has the function of converting input data from categories or numerical data into fuzzy values.

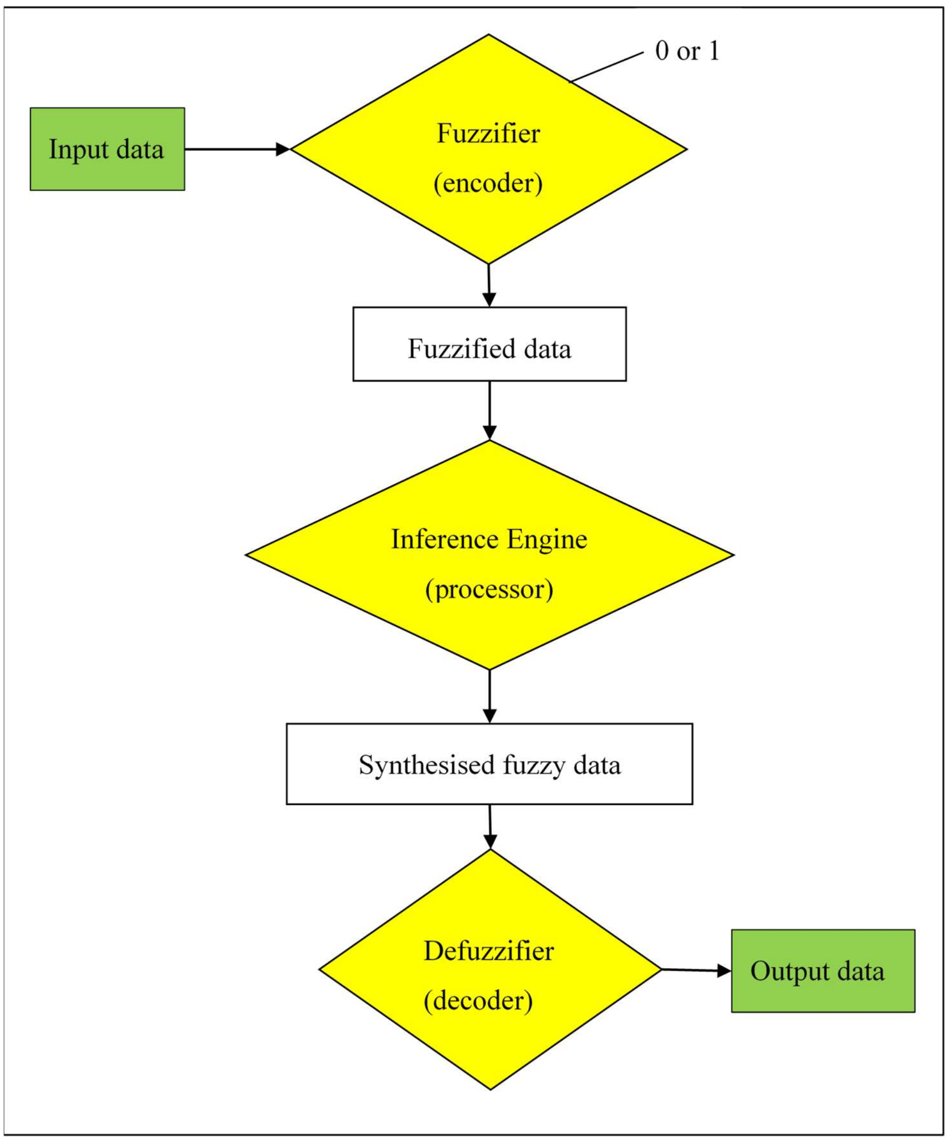


Figure 6.14 Architecture of a typical fuzzy model.

The fuzzy data with fuzzy values reflects the importance of each class in the 'site selection', for example, a plateau for a study area might have a high suitability and be allocated a value of 80%, whereas pits and channels might be allocated a value of 20% due to their low suitability. The FWO model allows the modeller to allocate values given prior knowledge and prior experience, within a range, in this case, between 0 and 100%. The landscape evidence layers e.g. landforms, were weighted using pairwise comparison (refer to Section 6.2.1).

One method of converting input data into fuzzy values is using a favourability order, that according to Malczewski (1999), is the simplest method for assessing the suitability of evidence variables, which in this research are the landscape variables. Favourability order can be either straight favourability (1 = most important, 2 = second important, etc…) or inverse favourability (1 = least important, 2 = second least important, etc…), the favourability and essentially the weight indicate the suitability of a class in relation to other classes. This favourability or weights represent the fuzzy values that will propagate through the model and ultimately determine the output data, therefore the fuzzification is the most important process in fuzzy modelling.

An inference engine or the fuzzy model processor is the "mind" of the fuzzy model, its function can be to filter out noise or create a synthesised fuzzy set, sometimes through standardisation. There are no general guidelines for the design of the inference engine except it should simulate the human-decision making process as close as possible (Porwal 2015), in this research, the inference engine used a simple overlay method.

The defuzzifier transforms the synthesised fuzzy set back into a data that expresses the result of the modelling. Described by (Porwal 2003), it can be a mathematical function or a subjectively or objectively defined threshold fuzzy value. The most important factor is that a small change in inputs of a fuzzy model should not cause a large change in the outputs.

The FWO is appropriate to studies where training site data are limited, where there is uncertainty in data and knowledge, where there is a need to model multi-class data and where expert opinion can be used in the modelling framework. The FWO also allows for subtle differences in landscape variables within land units to be retained.

The FWO processing for the Bow River Station study area and Antrim and Wickham land systems followed similar techniques to the BWO method using an overlay method. The prior proportions shown in Tables 6.1 and 6.2 were also used in the FWO model methodology.

Using the fundamentals of fuzzification and the necessity to use subjective *prior* conditional probabilities due to limited data availability for the study area, fuzzy values were derived using available data, information and expert knowledge. Because they were derived from various source data and information, they are described as ‘subjective’, in Table 6.9, because they include a degree of subjectiveness. The allocation of fuzzy values for the landscape variable classes, were represented by ‘0’ for ‘not suitable’, ‘1’ for a ‘low suitability’ chance and ‘100’ representing a ‘high suitability’ chance of existing within a land unit. The subjective fuzzy values for landforms of Antrim land system are presented in Table 6.9.

Table 6.9 Subjective fuzzy values for Antrim landforms.

Antrim fuzzy values							
Land units	**Pit**	**Channel**	**Pass**	**Ridge**	**Peak**	**Plain**	**Total (%)**
ALU1	1	1	1	50	50	50	153
ALU2	1	1	1	60	80	1	144
ALU3	1	1	1	40	1	1	45
ALU4	1	5	70	1	1	80	158
ALU5	50	90	20	1	1	1	163
ALU6	50	100	1	1	1	1	154
Total (%)	104	198	94	153	134	134	

The fuzzy values in Table 6.9 were converted to fuzzy memberships, where the allocation of a ‘membership’ to a fuzzy set, refers to the conversion of the fuzzy value to a value between ‘0’ and ‘1’, with ‘1’ representing high, and ‘0’ representing no membership. An example of the conversion between fuzzy values and fuzzy memberships can be described in the following formula:

ALU1 (channel 'fuzzy value')/Total (ALU1 'channels') = fuzzy membership

(6.2)

The fuzzy memberships for Antrim land system landforms are presented in Table 6.10. These were calculated for each of the landscape variables for each land unit of Antrim and Wickham land systems (refer to Appendix 7).

Table 6.10 Fuzzy memberships for Antrim landform variables.

Antrim landforms fuzzy memberships						
Land units	**Pit**	**Channel**	**Pass**	**Ridge**	**Peak**	**Total**
ALU1	0.01	0.01	0.33	0.33	0.33	1.0
ALU2	0.01	0.01	0.01	0.42	0.56	1.0
ALU3	0.02	0.02	0.02	0.89	0.02	1.0
ALU4	0.01	0.03	0.44	0.01	0.01	1.0
ALU5	0.31	0.55	0.12	0.01	0.01	1.0
ALU6	0.32	0.65	0.01	0.01	0.01	1.0

The fuzzy memberships in Table 6.10 were added to the attribute's tables in ArcGIS for each Antrim land unit, with an example of the ALU1 'signature' presented in Table 6.11.

Table 6.11 Fuzzy membership 'signature' values for ALU1.

Antrim Land Unit 1 - ALU1									
Elevation	Fuzzy value	Geology	Fuzzy value	Vegetation	Fuzzy value	Landform	Fuzzy value	Relief	Fuzzy value
500	0.38	Sp.	0.01	DR_738	0.01	Pit	0.01	Low	0.01
400	0.38	d3d	0.97	KF_808	0.01	Channel	0.01	Mod	0.01
300	0.24	g3b	0.01	KF_811	0.97	Pass	0.01	High	0.98
		kb1	0.01	BRH_77	0.01	Ridge	0.33		
						Peak	0.33		
						Plain	0.33		

To accommodate the six land units of the Antrim land system, six columns were added to the attributes tables of the landscape variable rasters, with the columns labelled ALU1 (Antrim land unit 1), ALU2 (Antrim land unit 2), etc. The fuzzy membership values (refer to Table 6.11) were added to the attribute columns of the landscape variable rasters (Antrim landforms 30 m pixel) in ArcGIS.

The fuzzy memberships for each of the landscape variable rasters and each of the land units (refer to Appendix 7) were combined. A model similar to that seen in Figure 6.4, was created for each land unit to calculate the weighted sum of the combined landscape variable fuzzy memberships for each land unit. The pairwise comparison weight (refer to Table 6.8) was applied to the landscape variable rasters for the FWO model to predict land units for Antrim land system.

The FWO model results for Antrim land units are shown in Figures 6.15, 6.16 and 6.17 as patterns of high and low values, representing high and low favourability.

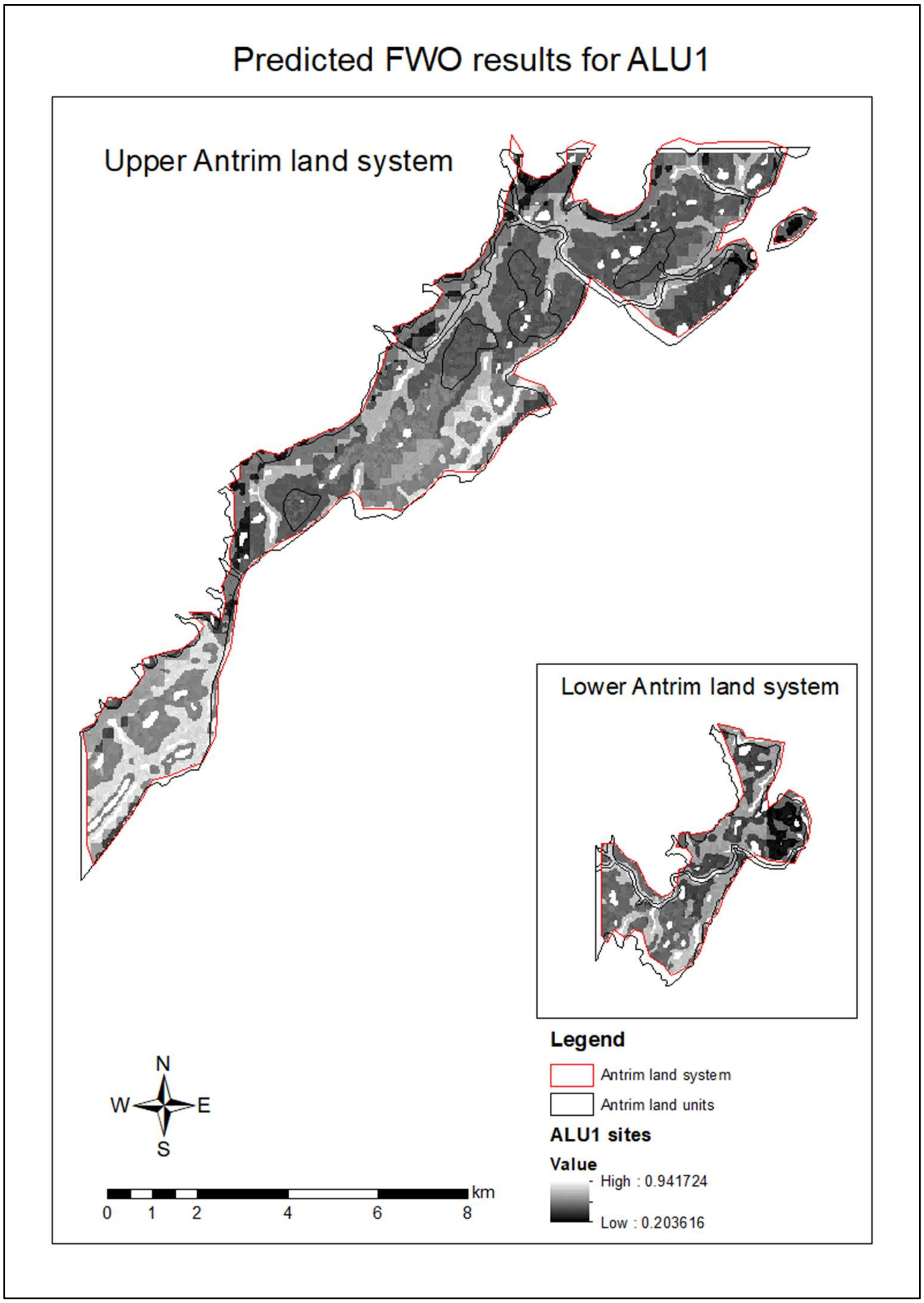


Figure 6.15 Antrim land unit 1 (ALU1) Fuzzy Weighted Overlay (FWO) results.

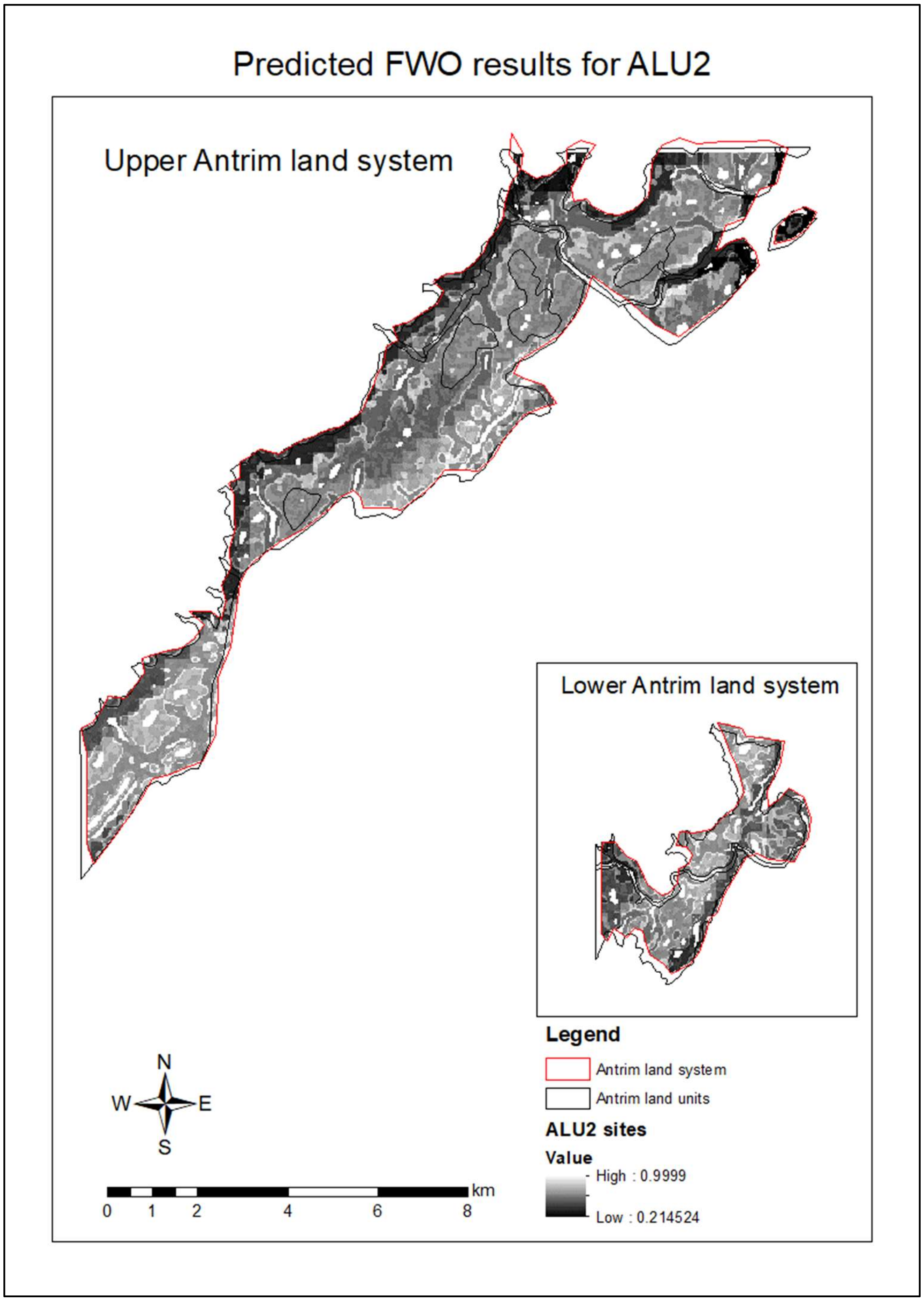


Figure 6.16 Antrim land unit 2 (ALU2) Fuzzy Weighted Overlay (FWO) results.

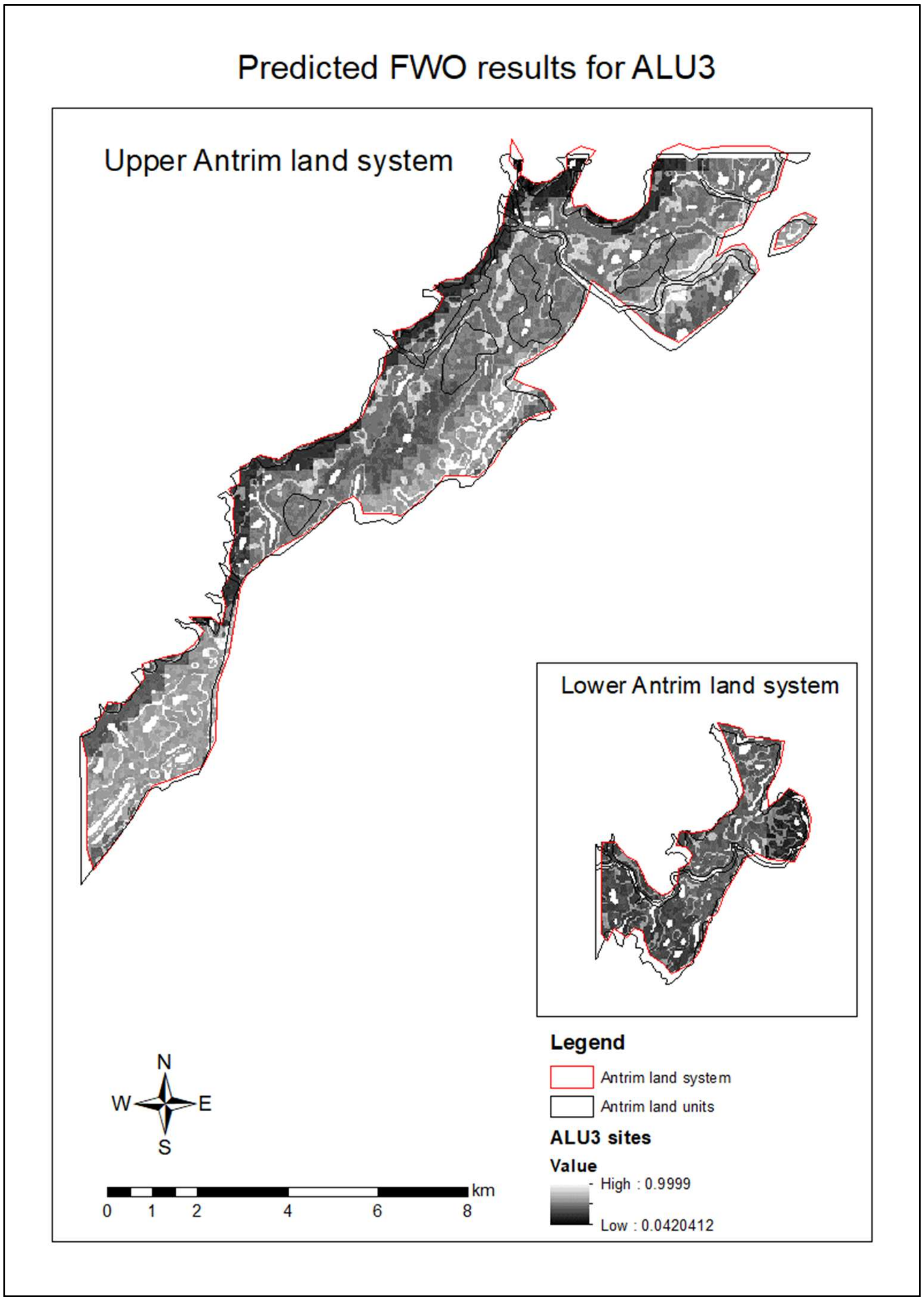


Figure 6.17 Antrim land unit 3 (ALU3) Fuzzy Weighted Overlay (FWO) results.

6.3.1 The 'most likely' land units using the FWO model: Antrim land system

The FWO model predicted individual fuzzy weight overlay rasters for each land unit that were combined to form a single prediction map using the highest position tool for Antrim land system.

The FWO model results were ranked using the proportions and positions (refer to Table 6.1) for Antrim land system, which were the same ranking as those used in Section 6.2.3 for the BWO model.

The results for the 'most likely' land units in Antrim land system for the FWO model, using the highest position tool are presented in Figure 6.18. The results show the same mismatch between the land unit and land system vector boundaries and also with the raster predicted model results. As with the BWO model (refer to Section 6.2.3), the mismatch seen between the vector boundaries and the raster results is related to data uncertainty, with spatial variation incorporated through polygon boundaries and grid cell generalisations. The mismatch again does not impact the results shown in Figure 6.18.

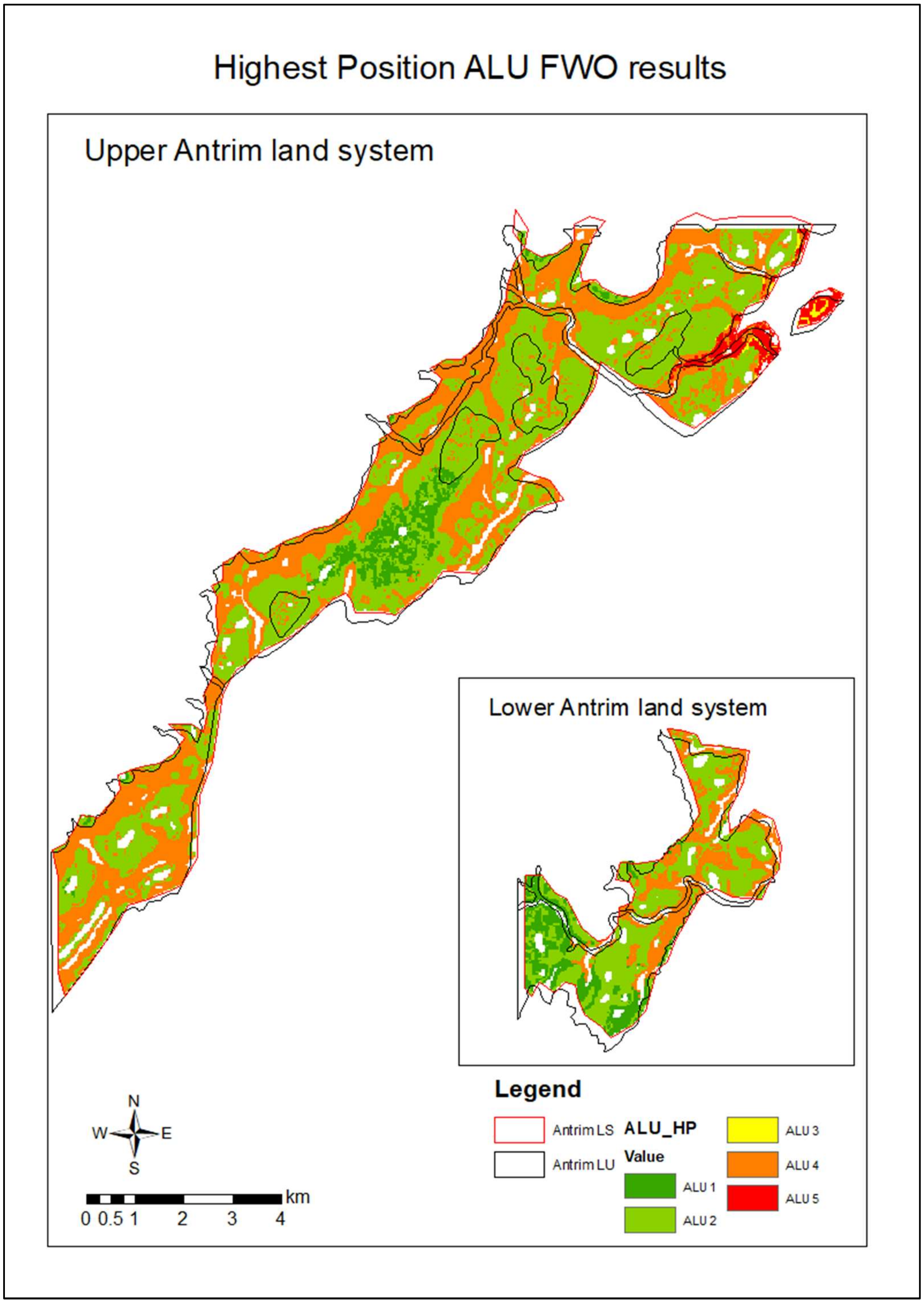


Figure 6.18 FWO model 'most likely' land units for Antrim land system.

6.3.2 The 'most likely' land units using the FWO model: Wickham land system

The FWO model was tested on Wickham land system to compare the effect of the modelling technique on the evenly proportioned land units of Wickham (refer to Table 6.2), with the results of the more uneven proportioned land units of Antrim (refer to Table 6.1) in Section 6.2.1. Wickham land system is described by Payne (2011), as having four land units with an equal ~20% chance of occurring in the land system and four other land units with considerably lower chance of occurrence (refer to Table 6.2 and Appendix 1).

Fuzzy values were created (refer to Appendix 7B) using the stages outlined in Section 6.3 using available data, information and expert knowledge. The values represent '0' for not suitable, '1' for low chance and '100' representing the highest chance within the land system. The subjective fuzzy values for landforms of Wickham land system are presented in Table 6.12.

Table 6.12 Subjective fuzzy values for Wickham landforms.

Wickham landform fuzzy values						
Land units	**Pit**	**Channel**	**Pass**	**Ridge**	**Peak**	**Plain**
WLU1	20	30	5	30	50	50
WLU2	5	5	5	50	50	50
WLU3	1	5	5	60	70	50
WLU4	1	5	5	80	50	1
WLU5	1	5	10	90	10	1
WLU6	1	50	80	1	1	1
WLU7	1	80	50	1	1	50
WLU8	5	100	50	1	1	1

The values in Table 6.12 were converted to fuzzy memberships by normalising the fuzzy values, where '1' is most likely to occur and '0' is no chance, as shown in Table 6.13.

Table 6.13 Fuzzy membership values for landforms of Wickham land units.

Wickham landforms fuzzy memberships							
Land units	**Pit**	**Channel**	**Pass**	**Ridge**	**Peak**	**Plain**	**Total**
WLU1	0.11	0.16	0.03	0.16	0.27	0.27	1.0
WLU2	0.03	0.03	0.03	0.30	0.30	0.30	1.0
WLU3	0.01	0.03	0.03	0.31	0.37	0.26	1.0
WLU4	0.01	0.04	0.04	0.56	0.35	0.01	1.0
WLU5	0.01	0.04	0.09	0.77	0.09	0.01	1.0
WLU6	0.01	0.37	0.60	0.01	0.01	0.01	1.0
WLU7	0.01	0.44	0.27	0.01	0.01	0.27	1.0
WLU8	0.03	0.63	0.32	0.01	0.01	0.01	1.0

The pairwise comparison weights (refer to Table 6.8) were again applied to the landscape variables to predict the Wickham land units using the FWO model (refer to Section 6.2.1). The FWO results for the predicted Wickham land units are shown in Figures 6.19, 6.20 and 6.21 for land units, WLU1, WLU2 and WLU3, respectively.

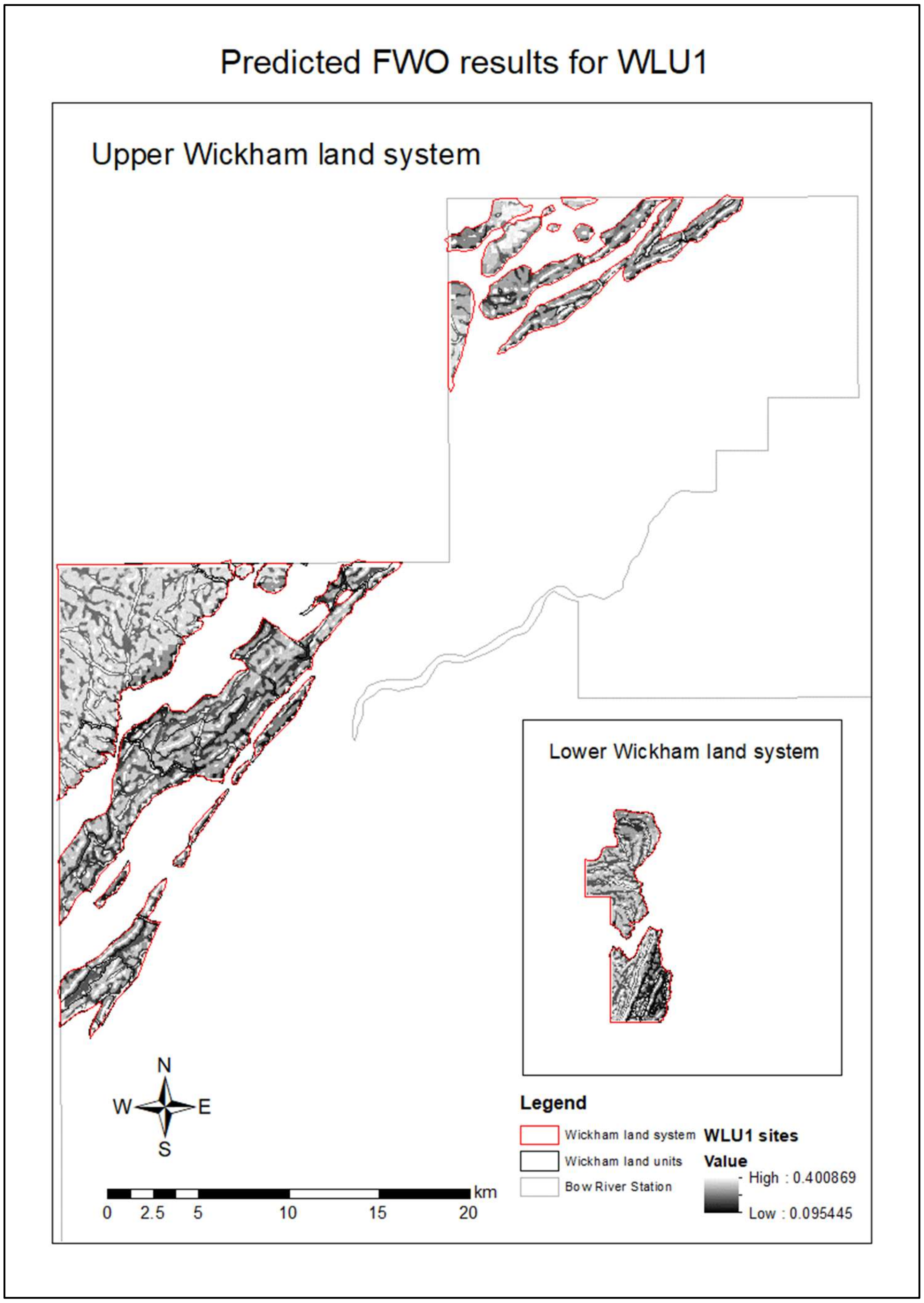


Figure 6.19 Wickham land unit 1 (WLU1) Fuzzy Weighted Overlay (FWO) results.

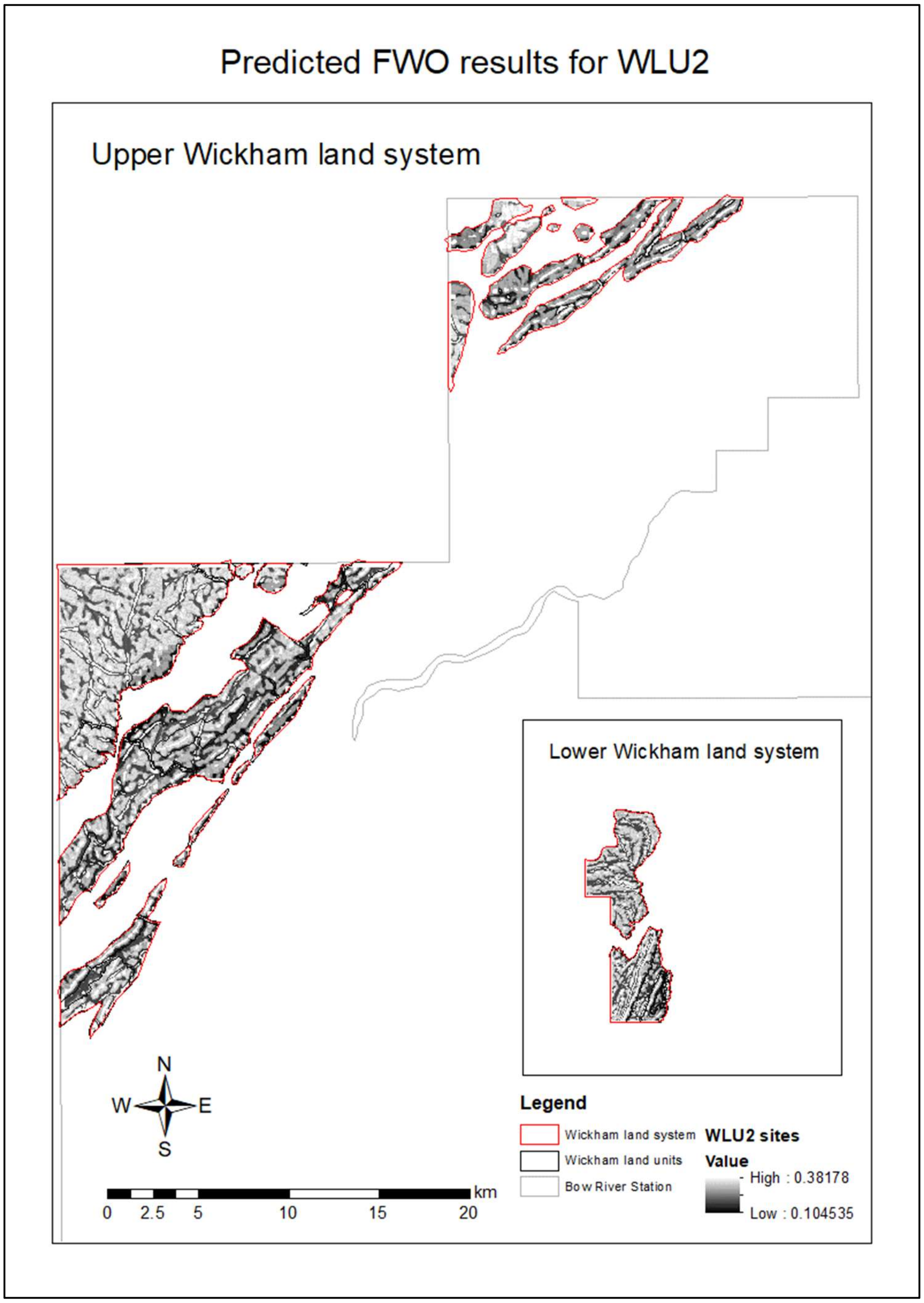


Figure 6.20 Wickham land unit 2 (WLU2) Fuzzy Weighted Overlay (FWO) results.

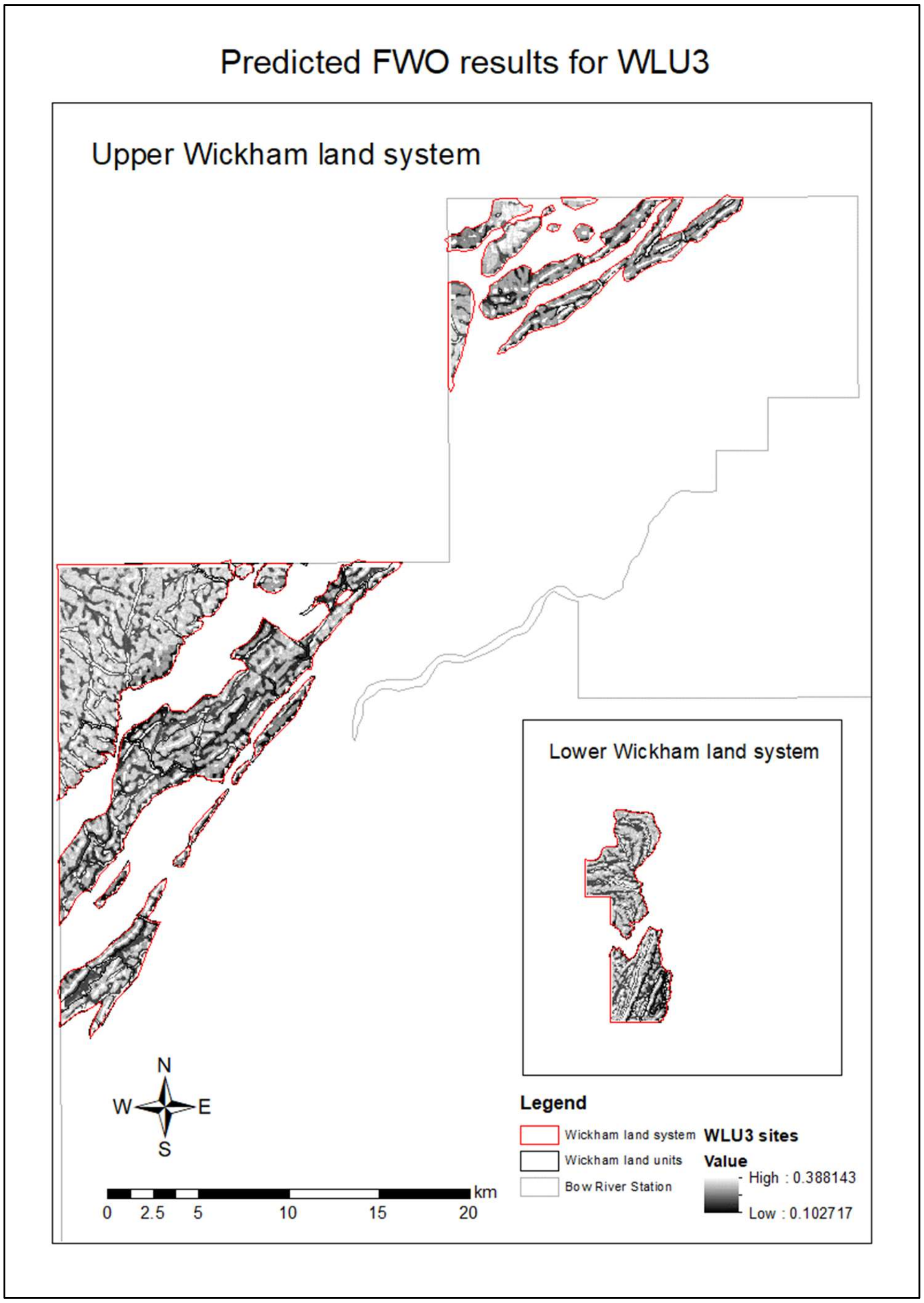


Figure 6.21 Wickham land unit 3 (WLU3) Fuzzy Weighted Overlay (FWO) results.

The FWO model predicted land unit results for Wickham land system were then ranked using the highest position tool in ArcGIS to find the 'most likely' land unit. The Wickham 'most likely' land units are presented in Figure 6.22.

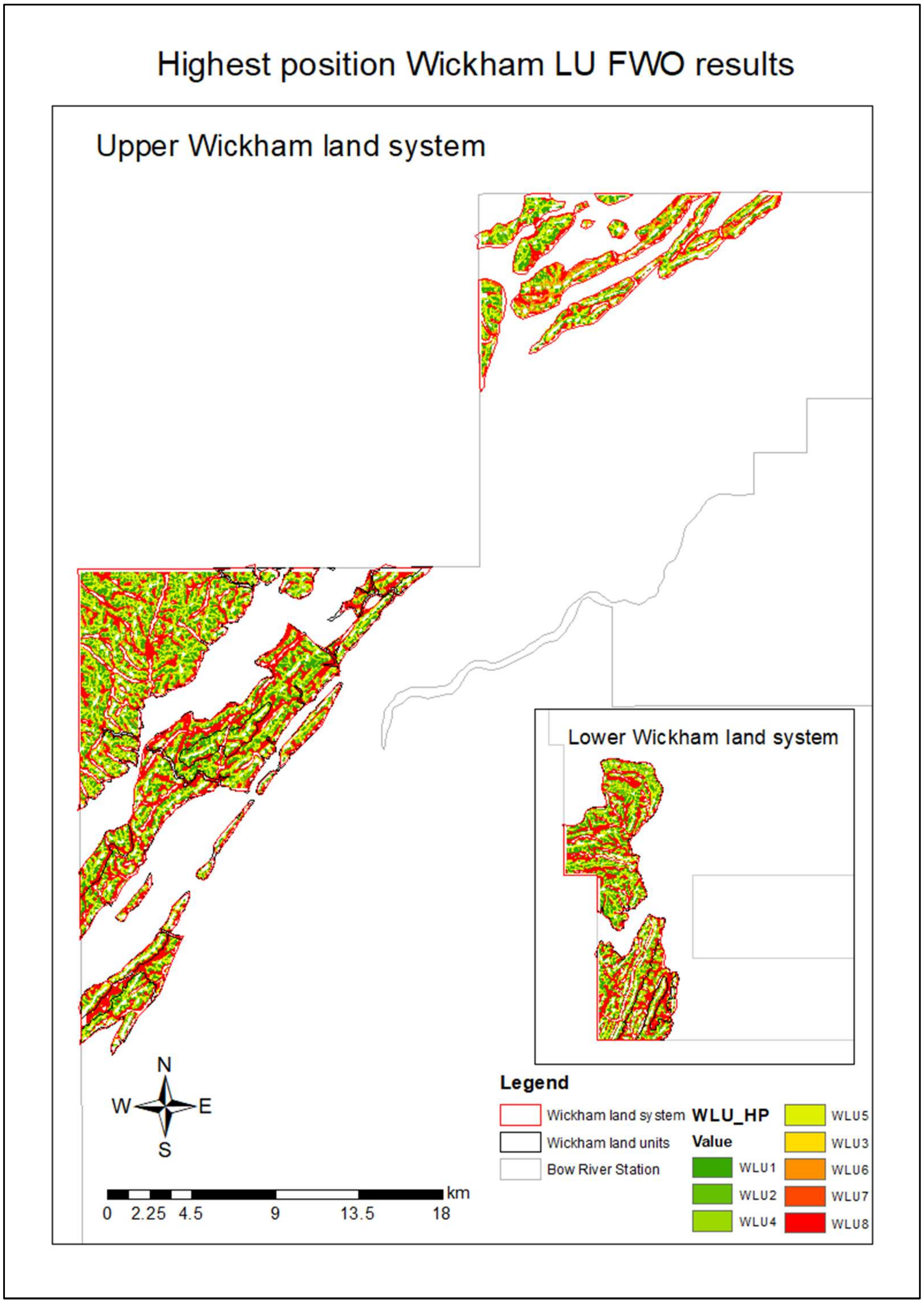


Figure 6.22 FWO model 'most likely' land units for Wickham land system.

The 'most likely' land units and highest position results seen in Figure 6.22 identify WLU1, WLU2, WLU4, and WLU5 as the predominant predicted land units for Wickham land system, which agrees with the *prior* proportions set out in Table 6.2.

6.3.3 Summary of FWO method

The FWO model allowed allocation of subjective fuzzy values using available data, information and expert knowledge to be included into the modelling technique, therefore enhancing even minor landscape variable classes of the land units. The FWO model was tested on Antrim and Wickham land systems with the 'most likely' land unit results shown in Figures 6.18 and 6.22, respectively.

A strength of the FWO model is that it incorporates expert knowledge to devise fuzzy values, and is applicable to study areas where data is limited, and where locations are remote, therefore not having to rely on existing data reduces the tendency to over emphases on known sites.

6.4 Positive Weights of Evidence (PWofE) modelling

The original WofE model is based on the idea that for any evidence layer, at any location in any area of interest, a binary pattern is either present or absent. WofE was developed initially using several binary layers containing presence and absence patterns, that were combined together to predict a binary presence and absence patterns for the predicted variable (Bonham-Carter, 1994).

The WofE model uses likelihood ratios, Sufficiency (LS) and Necessity (LN), to find the connection between variables that can be used in site prediction modelling. The LS are the ratios of conditional probabilities calculated in the presence of evidence (binary pattern is present) and the LN are the conditional probabilities calculated in the absence of evidence (binary pattern is absent) modified by the LS. These ratios are then used to modify the *prior* odds of the site existing. It is usual to use a logarithmic formulation to make the combination additive, so that if a zero value was encountered, it did not override other values (as it would in a multiplication process). The natural log of LS produces a positive weight and the natural log of the LN produces a negative weight. The difference between the modelling in this research, and the PVT framework (refer to Figure 6.1 that describes in more detail the relationship between LS and LN), is that there is only a hypothesis for Sufficiency (LS) and no hypotheses for Necessity (LN).

The Bow River Station (BRS) study area can be considered a ‘universe of discourse’ that refers to a collection of ‘objects under discussion’, or a set of entities that a model is based on (Corcoran 1999). The ‘objects under discussion’ in this research are the landscape variable classes, with the BRS study area ‘universe of discourse’ broken down into land systems and land units.

The ‘universe of discourse’ can also be described as bounded by the space of a Venn diagram. In Figure 6.23, the Venn diagram shows the relationship between a binary pattern and a deposit (Bonham-Carter 1994). The binary pattern describes ‘presence’ and ‘absence’ pieces of evidence, such as the presence/absence of a mineral deposit such as gold (Au). This is equivalent to the existence of a binary piece of landscape variable evidence such as “a landform is a plain”.

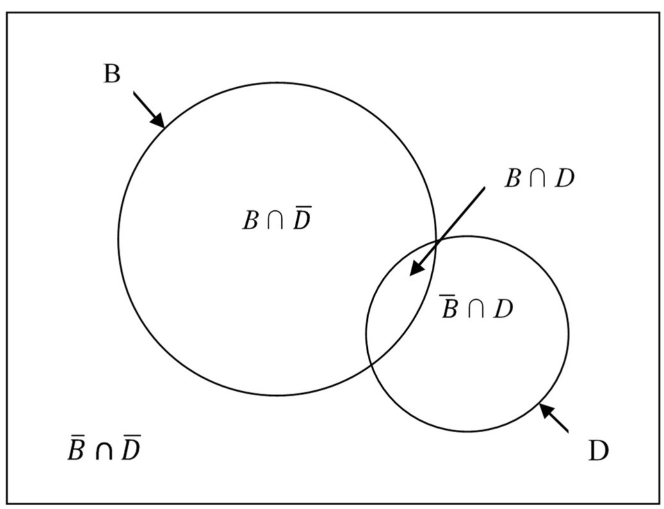


Figure 6.23 Venn diagram showing overlap between two binary layers.

Figure 6.23 shows a typical probabilistic relationship, where P(B) is the *prior* probability of the binary anomaly existing, P(D) is the *prior* probability of the deposit, with the various joint probability shown using the ∩ symbol. All of the probabilities will sum to a value of 1, within the 'universe of discourse' the bounds of the diagram.

However, in this research we need to consider that for any one 'D' (which represents a land unit) and each landscape variable there is a suite of possible 'b's' which are the different landscape variable classes (e.g. the landform variable layer includes pits, plains, channels, ridges, peaks and ridge classes). There will always be an intersection between one of the classes and 'D*'* (for any one land unit of a land system) and so there is never a possibility that $\bar{b} \cap \bar{D}$ and $\bar{b} \cap D$ can occur. Therefore, instead of the positive relationship being shown in a modified Venn diagram it is more appropriate to use a Euler diagram (refer to Figure 6.24), showing for any one land unit we have a probability space made up of *prior* probability of made up of a series of $\{b1 \cap D, b2 \cap D \ldots b\text{n} \cap D\}$ however many classes there are of the landscape evidence layer.

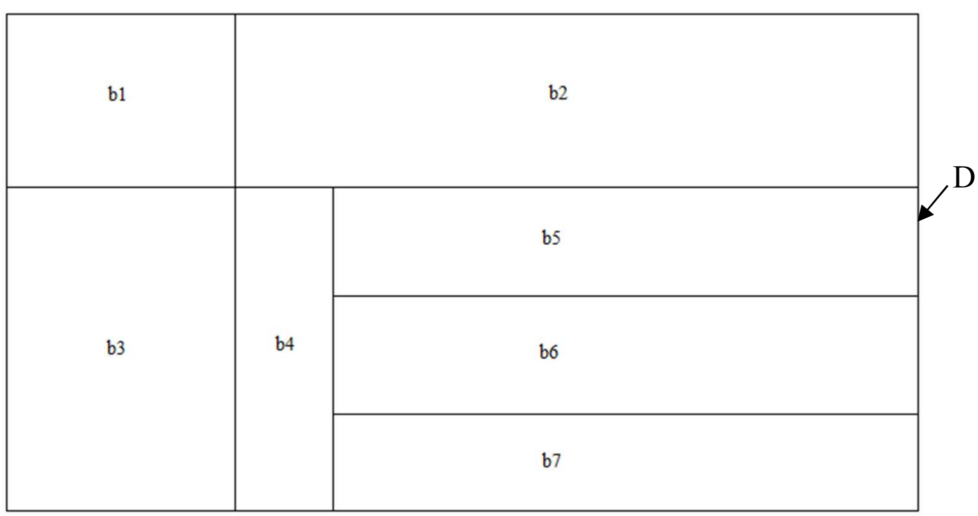


Figure 6.24 Euler diagram showing relationship between variable 'D' and classes 'b'.

The Euler diagram in Figure 6.24, shows the relationship between a variable 'D' and class B = {b_1, b_2… b_6} that essentially represent the landscape variables e.g. 'landforms' and the landscape variable classes e.g. pits, plains etc..., for this research.

In the work being carried out here, each evidence layer or landscape variable has a number of classes or categories. Whilst these were reduced to binary layers for the BWO method there is always a value at each location in the study area of the evidence layer. The PWofE method assumes that the entire study area has an equal chance of sites existing, meaning there is no situation where $P(\bar{B}|D) or\ P(\bar{B}|\bar{D})$ exists, and a Necessity ratio LN = $\frac{P(\bar{B}|D)}{P(\bar{B}|\bar{D}}$ will not exist and only a Sufficiency ratio LS = $\frac{P(B|D)}{P(B|\overline{\overline{D}})}$ is required for each landscape variable evidence class, for every one land unit of a land system.

6.4.1 Positive Weights of Evidence (PWofE) methodology

A traditional WofE model uses objective data on co-occurrences of predictor and predicted variables to set the weights, however in this research the study area had limited data therefore it was necessary to use data and information from the Technical Bulletin (Payne 2011), incorporating some expert knowledge, to derive subjective conditional probabilities for the PWofE model. The probabilities for the PWofE model were set the same as the FWO model (refer to Section 6.3) ranging in values between '0' and '1' for each landscape evidence variable class of each land unit for a land system. These subjective conditional probabilities were derived for each landscape evidence layer (E_n) class ($_j$), which can be expressed as E_{nj}, for each land unit i (LU_i).

As described above in Section 6.4.0, the PWofE model requires only Sufficiency ratios (LS), described in Bonham-Carter (1994) as likelihood ratios, which are defined as:

$$LS = \frac{P(E_{nj}|LU_i)}{P(E_{nj}|\overline{LU}_i)} \qquad (6.3)$$

where, $P\left(E_{nj}\middle|LU_i\right)$ is the probability that as evidence layer *n*, class *j* will be present, given that the land unit is i, and $P(E_{nj}|\overline{LU_i})$ is the probability that as evidence layer *n*, class *j* will be present, given that the land unit is NOT i.

The available information from the Technical Bulletin (Payne 2011), gives us the probability of a land unit *i* in any land system (e.g. Antrim land system) occurring given that evidence layer *n* class *j* exists - $P(LU_i|E_{nj})$. This refers back to the 'universe of discourse' (refer to Section 6.4.0), where the BRS study area is considered the 'universe of discourse', broken down into land systems and land units.

The $P(LU_i|E_{nj})$ can be converted to $P(E_{nj}|LU_i)$ using Bayes Theorem:

$$P(LU_i|E_{nj}) = \frac{P(LU_i,E_{nj})}{P(E_{nj})}$$

$$\text{and, } P(E_{nj}|LU_i) = \frac{P(E_{nj},LU_i)}{P(LU_i)} \tag{6.4}$$

since $P(LU_i|E_{nj})$ is the same as $P(E_{nj}|LU_i)$ then:

$$P(E_{nj}|LU_i) = \frac{P(LUi|E_{nj}) \text{ x } P(E_{nj})}{P(LU_i)} \tag{6.5}$$

Equation 6.5 can be used to solve for $P(E_{nj}|LU_i)$, using P(E*nj*), which are the *prior* probabilities of the landscape variable evidence classes, P(LU*i*), the *prior* probabilities of the land units in any land system, and P(LU*i*|E*nj*), the subjective conditional probabilities formulated through available information and expert opinion.

By analogy, $P(Enj|\overline{LU}i)$, the probability of an evidence class E*nj* existing given the absence of land unit *i,* may be found using the expression:

$$P(E_{nj}|\overline{LU}_i) = \frac{P(\overline{LU}i|E_{nj}) \text{ x } P(E_{nj})}{P(\overline{LU}_i)} \tag{6.6}$$

Where, the *prior* probabilities of the evidence layer class *nj* remain the same, however the *prior* probability of a land unit changes to the probability for the absence of land unit i $P(\overline{LU_i})$, expressed because of the fact that the *prior* probabilities must sum to 1. The *prior* probability for the absence of land unit *i* for any given evidence layer class is therefore also available.

In order to solve for $P(E_{nj}|LU_i)$ and $P(E_{nj}|\overline{LU}_i)$ and eventually LS (refer to Equation 6.3), the *prior* probabilities were all entered into matrices such as that shown in Table 6.14.

Table 6.14 shows the *prior* probabilities for the evidence classes for Antrim landforms (where E_{nj} = {Evidence landform $_{pit}$ ……… Evidence landform $_{plain}$}), the *prior* probabilities for Antrim land units (where LU_i = {ALU_1 ………. ALU_6}) and the subjective conditional probabilities given by $P(LU_i|E_{nj})$.

The *prior* probabilities of the evidence layer classes $P(E_{nj})$ were found using cell counts within the Antrim land system, the *prior* probabilities of the Antrim land units $P(LU_i)$ were given in the Technical Bulletin, the subjective conditional probabilities $P(LU_i|E_{nj})$ were developed using interpretation of descriptions in the Technical Bulletin and the *prior* probabilities for the absence of a land unit $P(\overline{LU}i)$ were found using subtraction: 1 - $P(LU_i)$.

Table 6.14 *Prior* probability matrices used to derive Sufficiency ratios (LS) for the PWofE model: Antrim landform evidence classes.

Evidence	*Prior* probability of all landform classes for Antrim land units										
Pit	0.06										
Channel	0.30										
Pass	0.15										
Ridge	0.28				*Prior* probabilities of Antrim land units $P(LU_i)$						
Peak	0.04				ALU1	ALU2	ALU3	ALU4	ALU5	ALU6	Sum
Plain	0.16				0.5	0.4	0.05	0.02	0.02	0.01	1
					Subjective conditional probabilities using Technical Bulletin $P(LUi\|Enj)$						
All Antrim landforms			*Prior* probabilities of class $P(En_j)$		ALU1	ALU2	ALU3	ALU4	ALU5	ALU6	Sum
		Pit	0.06	Pit	0.0065	0.0069	0.0222	0.0063	0.3067	0.3247	0.67
		Channel	0.30	Channel	0.0065	0.0069	0.0222	0.0316	0.5521	0.6494	1.27
		Pass	0.15	Pass	0.0065	0.0069	0.0222	0.4430	0.1227	0.0065	0.61
		Ridge	0.28	Ridge	0.3268	0.4167	0.8889	0.0063	0.0061	0.0065	1.65
		Peak	0.04	Peak	0.3268	0.5556	0.0222	0.0063	0.0061	0.0065	0.92
		Plain	0.16	Plain	0.3268	0.0069	0.0222	0.5063	0.0061	0.0065	0.87
So: $P(Enj) \times P(LU_i\|Enj) / P(LU_i)$			$P(Enj)$		$P(Enj\|LUi)$						
			0.06	Pit	0.001	0.001	0.026	0.018	0.895	1.894	
			0.30	Channel	0.004	0.005	0.136	0.484	8.439	19.849	
			0.15	Pass	0.002	0.003	0.066	3.313	0.918	0.097	
			0.28	Ridge	0.186	0.296	5.048	0.090	0.087	0.184	
			0.04	Peak	0.027	0.057	0.018	0.013	0.013	0.027	
			0.16	Plain	0.106	0.003	0.072	4.091	0.050	0.105	

					Prior probability of absence of Antrim land units $P(\overline{LUi})$						
					ALU1	ALU2	ALU3	ALU4	ALU5	ALU6	
					0.5	0.6	0.95	0.98	0.98	0.99	
					Prior probabilities (absence of land unit i) $P(\overline{LU}_i\|E_{nj})$						
And: $P(Enj) \times P(\overline{LU}i\|Enj)/P(\overline{LU}i)$			P(Enj)		ALU1	ALU2	ALU3	ALU4	ALU5	ALU6	
			0.06	Pit	0.667	0.667	0.651	0.667	0.367	0.349	
			0.30	Channel	1.262	1.262	1.247	1.237	0.717	0.619	
			0.15	Pass	0.601	0.601	0.586	0.165	0.485	0.601	
			0.28	Ridge	1.325	1.235	0.762	1.645	1.645	1.645	
			0.04	Peak	0.597	0.368	0.901	0.917	0.917	0.917	
			0.16	Plain	0.548	0.868	0.853	0.369	0.869	0.868	
							$P(E_{nj}\|\overline{LU}_i)$				
			P(Enj)		ALU1	ALU2	ALU3	ALU4	ALU5	ALU6	
			0.06	Pit	0.078	0.065	0.040	0.040	0.022	0.021	
			0.30	Channel	0.772	0.643	0.401	0.386	0.224	0.191	
			0.15	Pass	0.180	0.150	0.092	0.025	0.074	0.091	
			0.28	Ridge	0.752	0.584	0.228	0.477	0.477	0.472	
			0.04	Peak	0.049	0.025	0.039	0.038	0.038	0.038	
			0.16	Plain	0.177	0.234	0.145	0.061	0.143	0.142	

The matrices seen in Table 6.14, can be used to calculate the $P(E_{nj}|LU_i)$ and $P(E_{nj}|\overline{LU}_i)$ for each landscape evidence layer class for each land unit. To calculate the Sufficiency ratios (LS), Equation 6.3 simply needs to be substituted with values from the matrices. For example, to calculate the LS for Antrim land unit 1 (ALU1) in a case where 'pits' is the landform evidence layer class, (refer to Table 6.14), the equation will look like this:

$$\mathrm{LS} = \frac{P(E_{nj}|LU_i)}{P(E_{nj}|\overline{LU_i})} \rightarrow \mathrm{LS} = \frac{P(pit|ALU1)}{P(pit|\overline{ALU1})} \rightarrow \mathrm{LS} = \frac{0.001}{0.078} \rightarrow \mathrm{LS} = 0.001 \qquad (6.7)$$

Using Equation 6.7, the LS values are shown in Table 6.15, for the landform evidence classes of Antrim land system. The LS were calculated for each evidence class Enj and each land unit LUi for Antrim land system.

Table 6.15 Sufficiency ratios (LS) for Antrim landform evidence class layers.

Antrim land system						
	ALU1	**ALU2**	**ALU3**	**ALU4**	**ALU5**	**ALU6**
Pit	0.001	0.002	0.040	0.028	2.440	5.430
Channel	0.003	0.004	0.109	0.391	11.775	32.041
Pass	0.003	0.004	0.114	20.094	1.891	0.161
Ridge	0.140	0.240	6.621	0.055	0.053	0.112
Peak	0.045	0.154	0.020	0.014	0.014	0.029
Plain	0.193	0.003	0.084	11.099	0.057	0.121

The Sufficiency ratios (LS) were calculated for all the evidence layer classes Enj of all the land units LUi of a land system, for example, Table 6.16 shows two Antrim land units and some of the associated evidence classes.

Table 6.16 Example of LS values for Antrim land units (ALU1 and ALU6).

Antrim land system LS values					
	Landform	**Geology**	**Vegetation**	**Relief**	**Elevation**
	Pits	*Granite*	*Durack Ranges_738*	*Hills and high passes*	*400*
ALU1	0.001	0.020	0.016	1.815	0.655
ALU6	5.430	0.820	64.462	0.656	1.042

The Sufficiency ratios (LS) were then combined for each land unit of a land system to give the likelihood of a land unit existing. The combined LS were used to produce the *posterior* odds and *posterior* probabilities for each land unit of a land system. To calculate the *posterior* odds $O(LU_i|E_{nj})$, firstly the *prior* odds of the land unit *i* $O(LU_i)$ needed to be calculated using:

$$O(LU_i) = P(LU_i)/(1 - P(LU_i)), \text{ or } P(LU_i)/P(\overline{LU_i}) \qquad (6.8)$$

For example, for Antrim land unit 1 (ALU1) the *prior* odds are calculated using:

$$O(ALU_1) = 0.5/(1\text{-}0.5) = 1 \qquad (6.9)$$

Therefore, the 'odds' of the predicted land unit being ALU1, at any location within the Antrim land system are 1:1. These odds were calculated for all of the land units of each land system with the *prior* odds reflecting the base likelihood of the land units. The *prior* odds for Antrim land units are shown in Table 6.17.

Table 6.17 *Prior* odds for Antrim land units.

Antrim land system						
	ALU1	**ALU2**	**ALU3**	**ALU4**	**ALU5**	**ALU6**
***Prior* odds**	1	0.666667	0.052632	0.020408	0.020408	0.010101

The *prior* odds were then used together with the Sufficiency ratios (LS) to find the *posterior* odds for the land units. For each evidence layer E_n and each land unit, the expression is shown in Equation 6.10.

$$O(LU_i|E_{nj}) = O(LU_i) \times LS_{LU_{i_{E_{nj}}}} \qquad (6.10)$$

Where, $O(LU_i|E_{nj})$ is the *posterior* odds of land unit *i*, given by the *prior* odds $O(LU_i)$ of land unit *i*, multiplied by $LS_{LU_{i_{E_{nj}}}}$, the sufficiency ratio for land unit *i* and evidence layer *n*, class *j*.

The *posterior* odds calculation for any pixel, combining multiple evidence layers can be expressed in general terms n = {1, 2...$_m$} as:

$$O\ (LU_i|E_1 \cap E_2 \cap E_3 \cap \ldots E_m) = O\ (LU_i) \times \prod_{n=1}^{m}(LS_{LU_{i_{E_{nj}}}}) \qquad (6.11)$$

Where *j* indicates the class of each evidence layer that occurs in each pixel.

The *posterior* odds are then converted to *posterior* probabilities, where the *posterior* probability of a land unit *i*, given the presence of evidence class *j* is calculated using *posterior* probability = (*posterior* odds/1 + *posterior* odds), that can be expressed as:

$$P(LU_i|E_{nj}) = O(LU_i|E_{nj})/(1 + O(LU_i|E_{nj})) \qquad (6.12)$$

6.4.2 The 'most likely' land units using the PWofE model: Antrim land system

The PWofE method was tested on all Antrim land system using the equations provided in Section 6.4.1. Table 6.18 shows the proportion of each landform class for the Antrim land system (or the Antrim land units collectively).

Table 6.18 Proportion of landforms in Antrim land system.

Antrim landform cell count		
Value	**Count**	**Landform**
1	3199	Pit
2	16667	Channel
3	8079	Pass
4	15589	Ridge
5	2348	Peak
6	8912	Plain

The cell count (Count) in Table 6.18, suggest that 'channels' and 'ridges' are the main landform classes found in Antrim land system, therefore the PWofE prediction model results should reflect this for the land units.

The Sufficiency ratios (LS), *posterior* odds and *posterior* probabilities were calculated using equations 6.3 to 6.11 in Section 6.4.1 for each the Antrim land system. The 'model' in Figure 6.25 shows the structure of how this was calculated in ArcGIS.

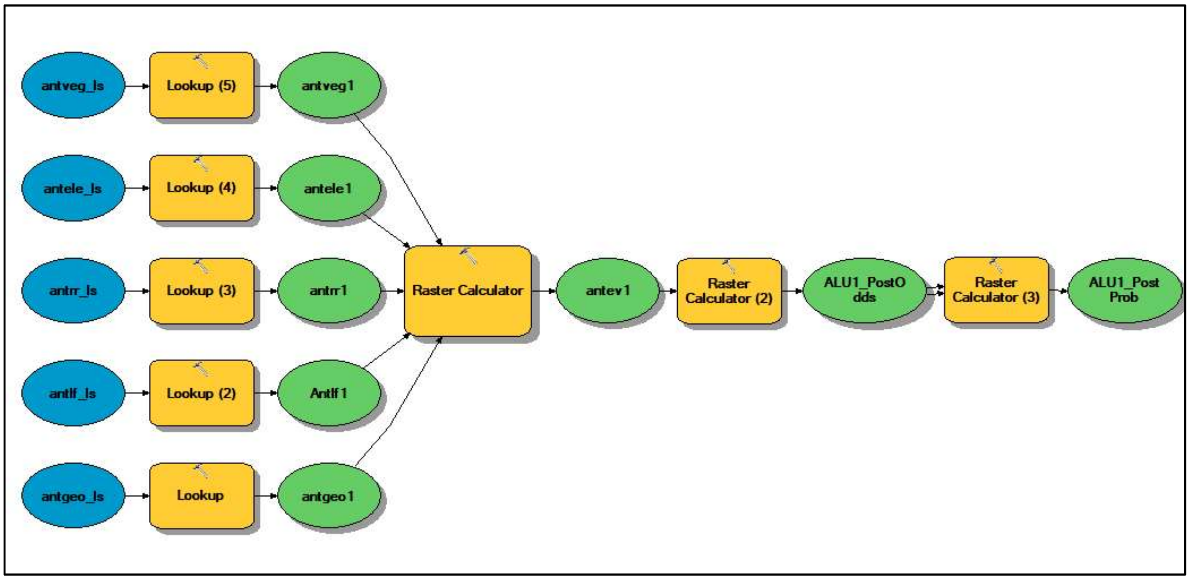


Figure 6.25 ArcGIS modelling tool for combining ALU1 Sufficiency ratios (LS).

Figure 6.25 shows that the LS of each landscape evidence data layer of ALU1 were extracted using the 'lookup' tool e.g. antlf_ls → antlf1. The individual LS were then combined using multiplication to produce the Product of the LS ratios (e.g. Antev1) for a land unit. A visual representation of this is presented in Figure 6.26, that shows the Product of the LS ratios for Antrim land unit 1 (ALU1).

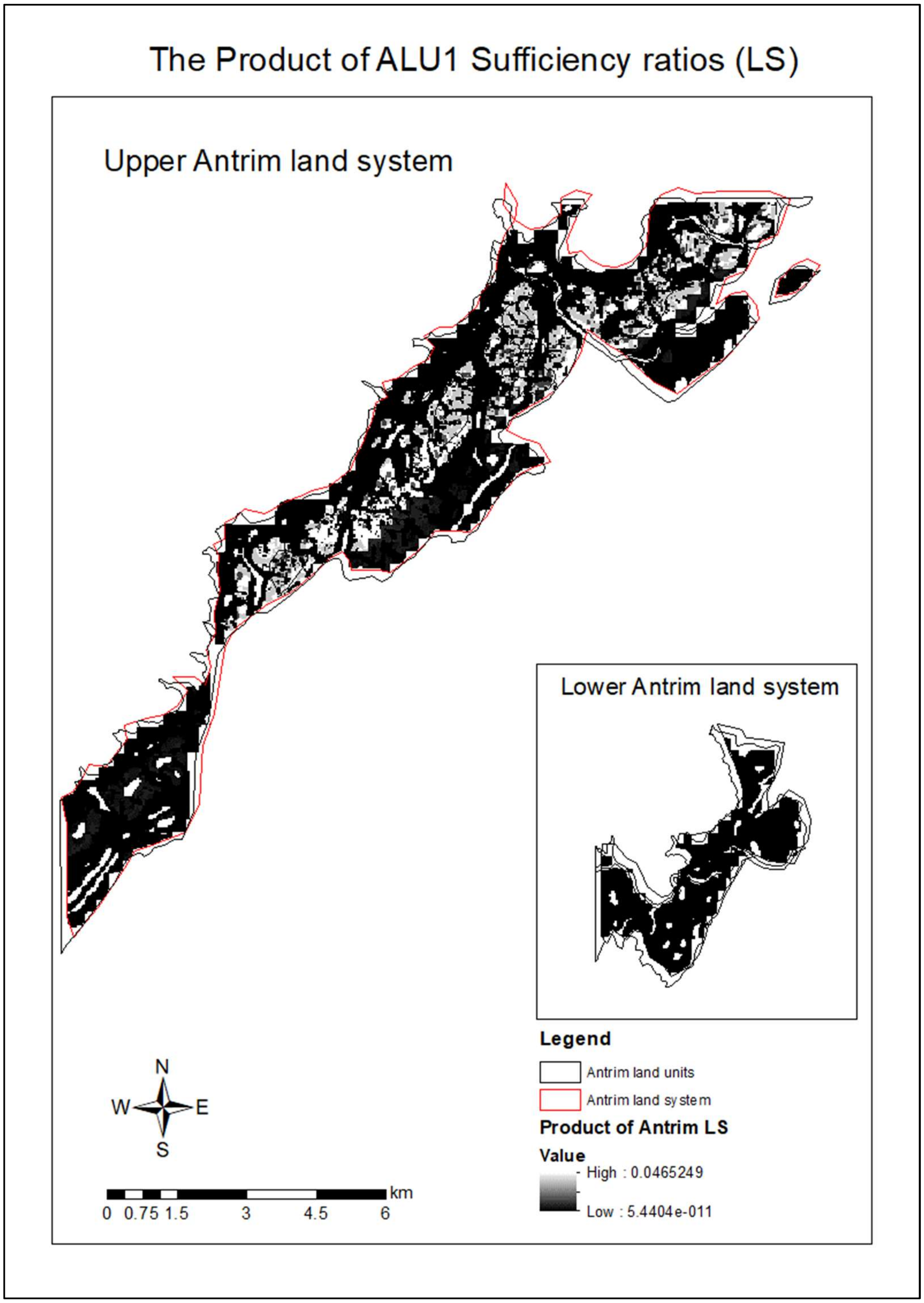


Figure 6.26 The Product of Antrim land unit 1 (ALU1) Sufficiency ratios (LS).

The *posterior* probabilities ALU1 and ALU2 are seen in Figures 6.27 and 6.28 respectively.

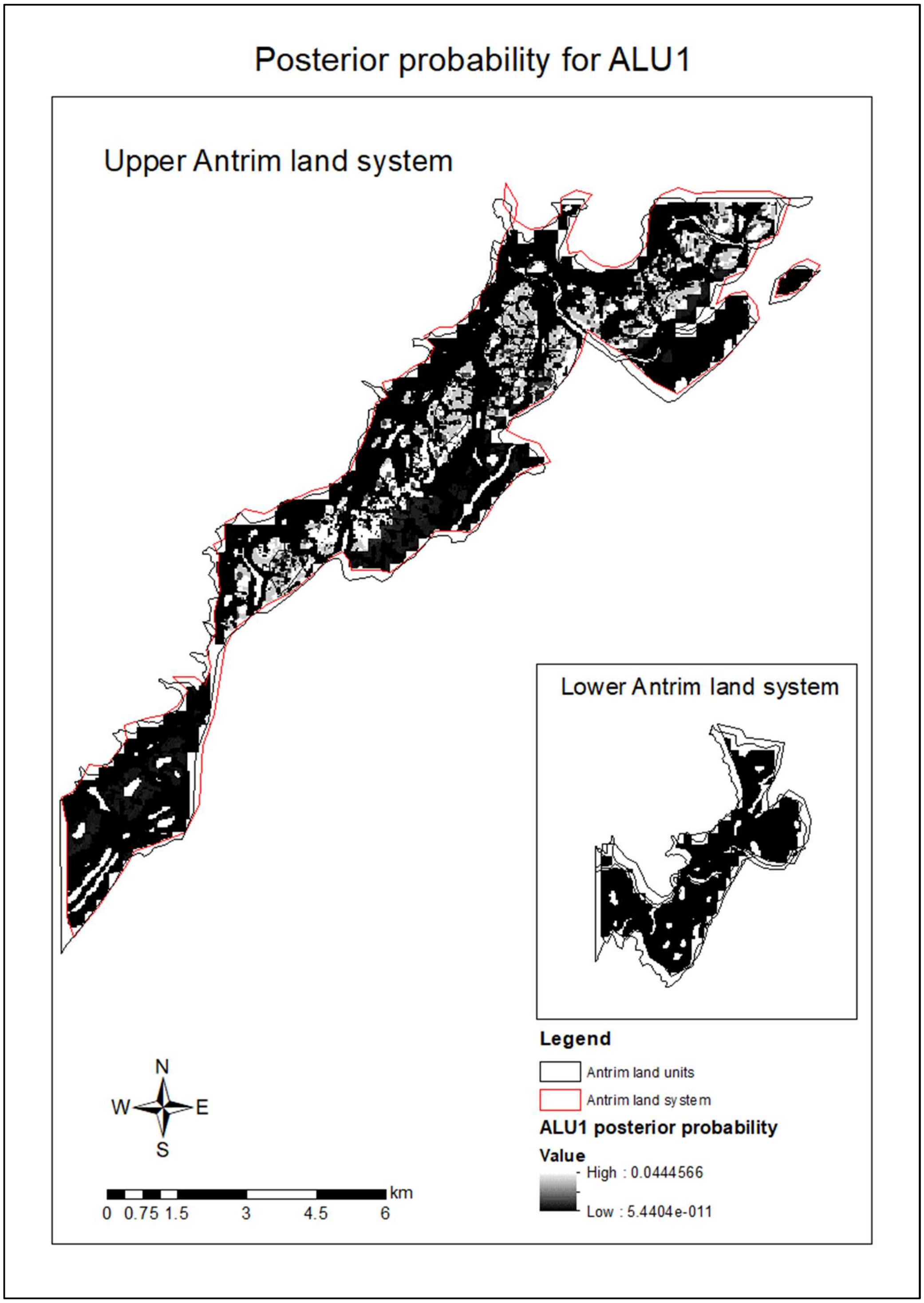


Figure 6.27 Antrim land unit 1 (ALU1) *posterior* probability results.

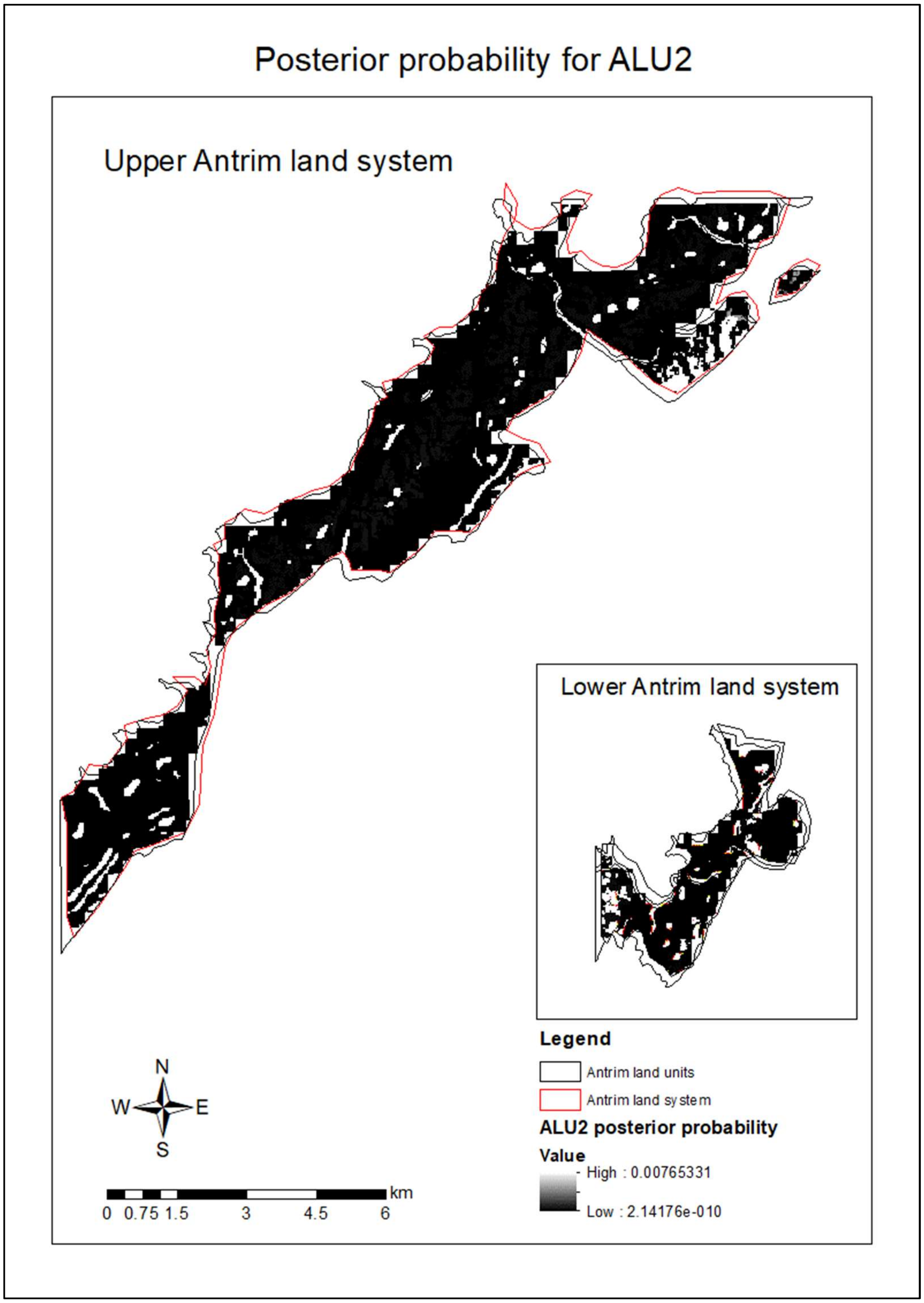


Figure 6.28 Antrim land unit 2 (ALU2) *posterior* probability results.

Finally, the results of the *posterior* probabilities were ranked using the highest position tool to find the 'most likely' land units for the Antrim land system, seen in Figure 6.29.

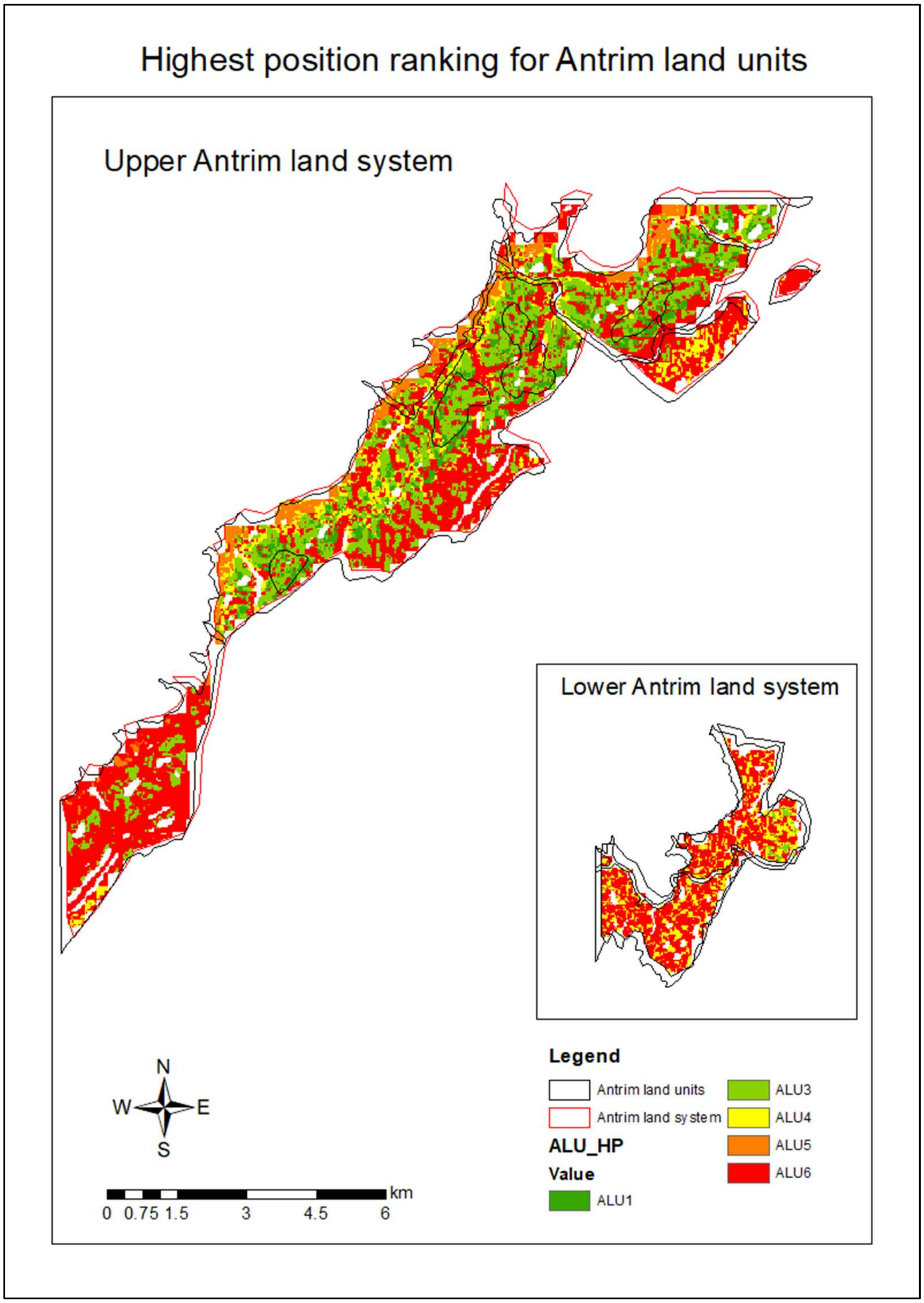


Figure 6.29 PWofE model 'most likely' land units for Antrim land system.

The 'most likely' land units (highest position values) seen in Figure 6.29 show a grouped or clustered pattern consistent with a grouped unit such as a land unit.

6.4.3 The 'most likely' land units using the PWofE model: Wickham land system

The PWofE method was also tested on Wickham land system, using the same methodology as for Antrim land system (refer to Section 6.4.2).

The Sufficiency ratios (LS) values for the landscape variables for Wickham land system were calculated (refer to Appendix 8B) and added as attributes to the raster landscape data in GIS that was used to calculate the *posterior* odds again using equations 6.3 to 6.11 in Section 6.4.1. The *posterior* odds were then converted to *posterior* probabilities for WLU1 and WLU2, shown in Figures 6.30 and 6.31.

The *posterior* probabilities were calculated for all Wickham land units, that were then entered as WLU1, WLU2, WLU4, WLU5, WLU3, WLU6, WLU7 and finally WLU8 into the highest position tool to produce the 'most likely' land units in ArcGIS (refer to Figure 6.32). The land units were entered into the highest position tool in this unordered style to reflect the *prior* proportions of the Wickham land units (refer to Table 6.2).

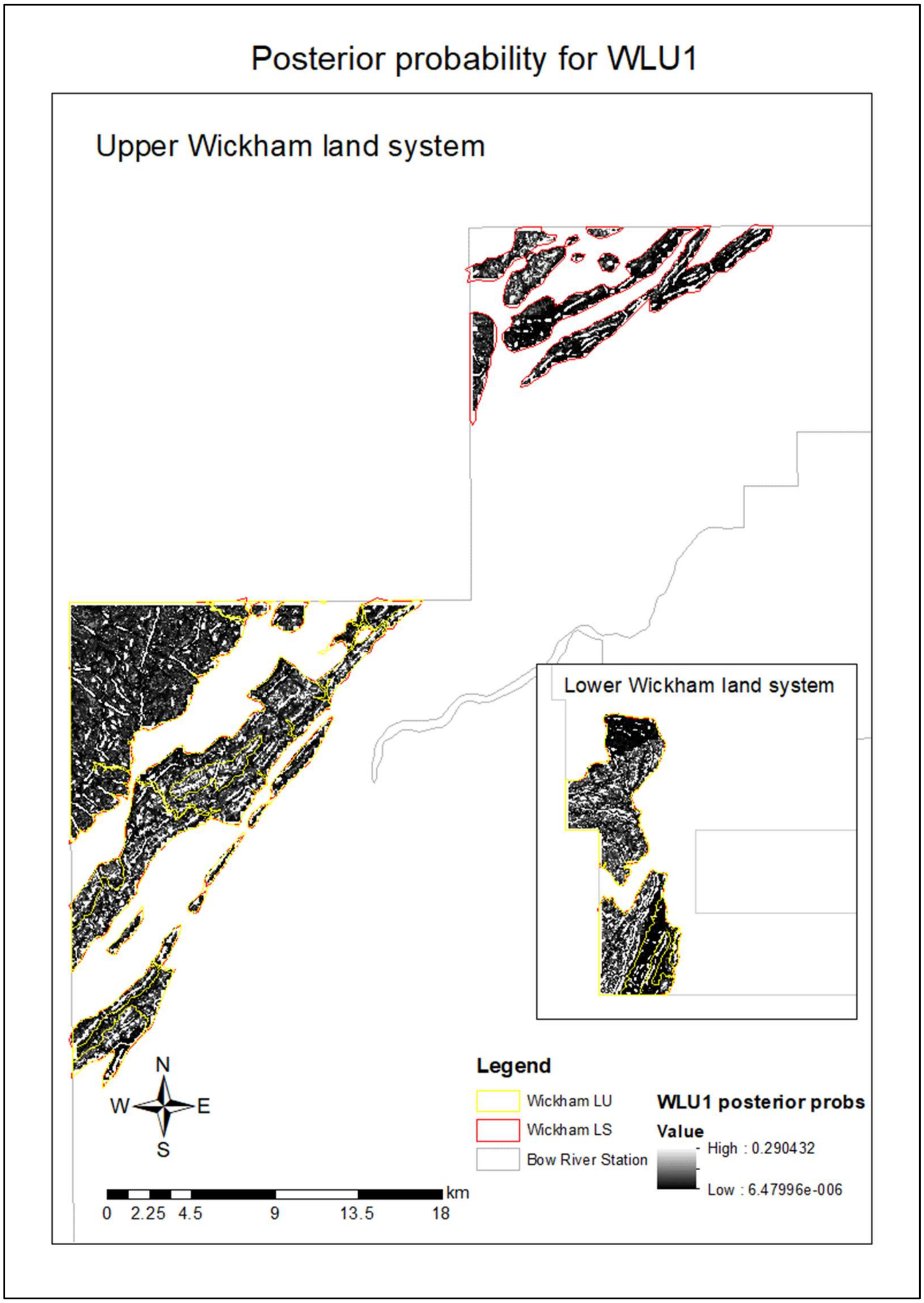


Figure 6.30 Wickham land unit 1 (WLU2) *posterior* probability results.

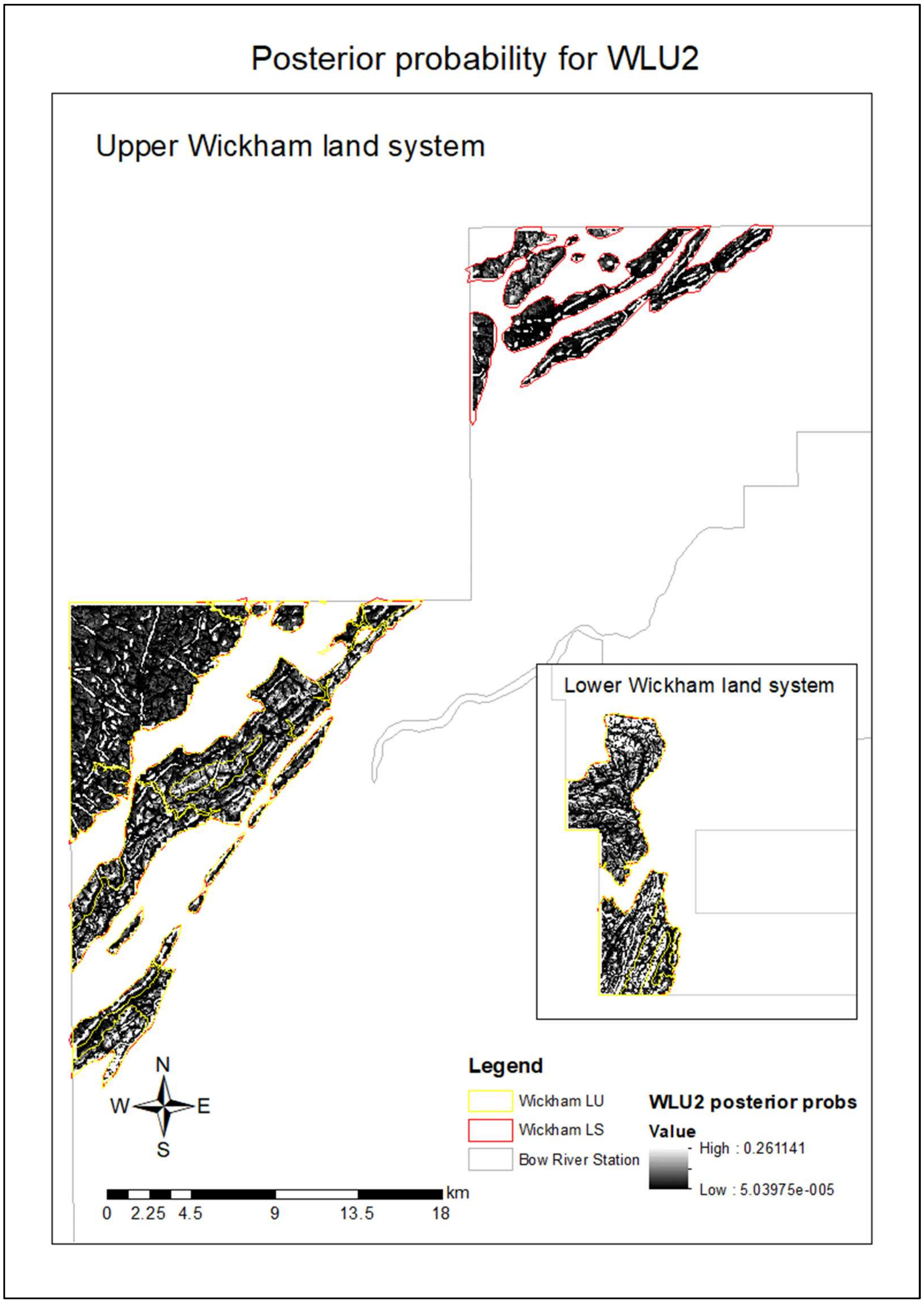


Figure 6.31 Wickham land unit 2 (WLU2) *posterior* probability results.

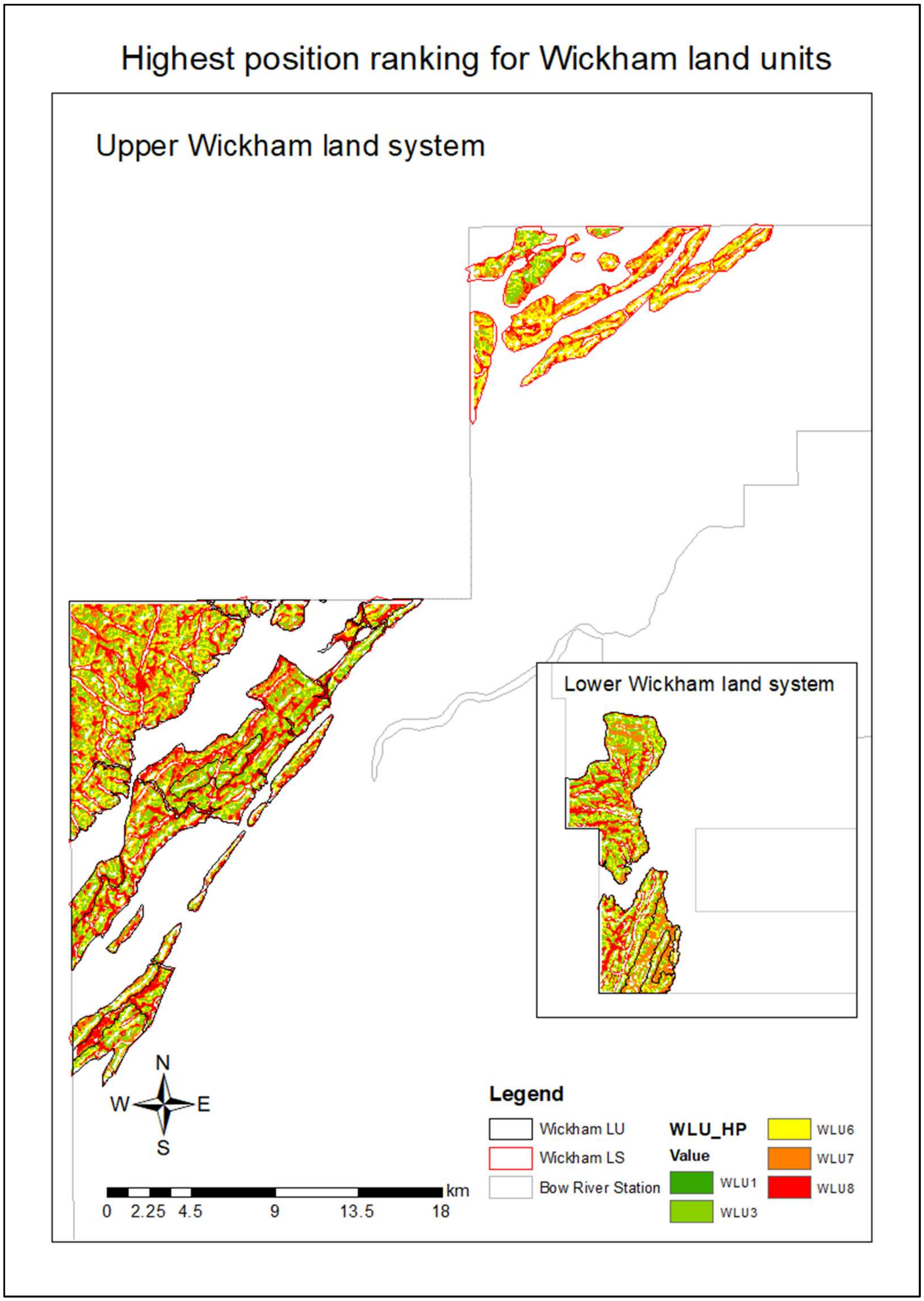


Figure 6.32 PWofE model ‘most likely’ land units for Wickham land system.

The ‘most likely’ land units for Wickham land system in Figure 6.32, reflect how the *posterior* probabilities were entered (mentioned above) with the results showing a slight clustered pattern, with WLU7 and WLU8 suggesting drainage patterns, WLU6 representing a minor unit, and WLU1 and WLU3 covering the majority of the land system. These patterns are comparable with the descriptions given in the Technical Bulletin (Payne 2011).

6.5 Chapter summary

Three prediction modelling techniques were tested, a Binary Weighted Overlay (BWO), a Fuzzy Weighted Overlay (FWO) and the modified WofE model: the PWofE model, using Antrim and Wickham land systems. The prediction models aimed to show that landscape variables can be used as evidence to predict land units by formalising existing knowledge into a basic set of rules. These rules have been applied to digital data in a GIS environment, where results were analysed using visualisation and exploration of digital patterns.

The ‘most likely’ land unit results for the three prediction models were developed and ranked using the highest position tool. The land units were ranked from most likely to least likely, based on *prior* proportions of the land units for the land systems.

The BWO model is a knowledge-driven modelling technique that used available data and information to determine the importance of events, as evidence, as either a ‘1’ or ‘0’, representing a positive or negative site selection for a study area.

The FWO is also a knowledge-driven modelling technique that also used all available data and information to derive the importance of events as evidence, however instead of allocating binary values, fuzzy values ranging between ‘0’ and ‘100’ were allocated to the evidence data, using expert knowledge, that were then standardised to create fuzzy memberships ranging between ‘0’ and ‘1’. The main difference of fuzzy memberships was that even small features would still be allocated a likelihood of a site selection that could favour of a land unit in the study area.

The Positive Weights of Evidence (PWofE) model is a 'special case' of the Weights of Evidence (WofE) model that used Sufficiency (LS) ratios to calculate *posterior* odds and *posterior* probabilities. The PWofE model used *prior* probabilities of land units, *prior* probabilities of landscape evidence layers and subjective conditional probabilities. The PWofE model was more suited to this research than the original WofE model because evidence existed only as positive values, with no evidence supporting the absence of land unit sites.

7 Confirmation analysis and final results

Confirmation analysis is used to assess the accuracy of results and can be used to determine the success of GIS modelling techniques. The results analysed in this chapter were created by three prediction modelling techniques: Binary Weighted Overlay (BWO) model, Fuzzy Weighted Overlay (FWO) model and a Positive Weights of Evidence (PWofE) model. Each modelling technique used landscape variables including vegetation, geology, landforms, relative relief and elevation data that were converted to a raster format with a common 30 m pixel cell size.

The accuracy of the predicted land units was tested using two methods - ROC plots and contingency tables, for both Antrim and Wickham land systems. A final test for accuracy used O'Donnell land system because it was the only land system accessible in the study area during the field trip, and therefore the only area where ground truth data points were collected. The results for the predicted O'Donnell land units were tested using ROC plots and contingency tables however a comparison was also made between the predicted 'most likely' land units and the field data descriptions.

7.1 Existing land unit data for the study area and its' uncertainties.

Two sets of land unit data existed prior to this research, they were the consolidated descriptions of landscapes, soil and vegetation of the Kimberley Region in the Technical Bulletin (Payne 2011) and the digitally mapped land units developed as a cost-effective land resource approach to mapping, at a suitable scale, that would see an upgrade to the Kimberley Region as part of the Ord-Bonaparte Program in the early 2000's (Schoknecht 2003).

The Technical Bulletin land unit descriptions and proportions were not spatially explicit but were able to be used as *prior* probabilities for the prediction modelling in Chapter 6, whilst the Ord-Bonaparte land units were not used this research until now, when they will be used for confirmation analysis. The accuracy of both sets of land units is not 100% and therefore they are both essentially estimates of land units for the region. Both sets of data were mapped using different techniques; the Ord-Bonaparte land units were mapped using a combination of traditional methods and digital data, whilst the Technical Bulletin land units are consolidated descriptions from a succession of surveys carried out since the 1940s (refer to Section 2.2).

The Ord-Bonaparte land units are used here as confirmation data, were mapped over several pastoral properties within the Ord and Keep River catchments, with the aim of producing land unit scale results. According to Schoknecht (2003), where training sites existed, predicted land unit results produced a reasonable degree of accuracy, whereas results with distance from the training sites produced fair to poor accuracy.

The 'most likely' land unit results for the three prediction models developed in Chapter 6 were initially visually compared with the Ord-Bonaparte land unit boundaries on GIS maps, however this comparison was inconclusive and therefore further confirmation analysis was carried out using spatial analysis techniques.

The Ord-Bonaparte Program included estimated land unit boundaries for the Bow River Station study area including Antrim and Wickham land systems. The land unit terminology used is described as e.g. "317An_4", where "An" refers to Antrim land system and "316Wk_3", where "Wk" refers to Wickham land system. To calculate the proportion of each Ord-Bonaparte land unit, the number of pixels for each of the land units, was divided by the total pixel cell count for the entire land system. The proportion of each land unit were then converted to percentages for comparison with the Technical Bulletin land unit percentages, shown in Tables 7.1 and 7.2, for Antrim and Wickham land systems, respectively.

Table 7.1 Proportion of the existing land units for Antrim land system.

Ord-Bonaparte land unit	Pixel cell count	Proportion	Ord-Bonaparte percentage (%)	Technical Bulletin land unit	Technical Bulletin percentage (%)
317An_4	39969	0.7253	73	ALU1	50
317An_5	9449	0.1715	17	ALU2	40
317An_6	3274	0.0594	6	ALU3	5
317An_8	2413	0.0438	4	ALU4	2
Total	55105			ALU5	2
				ALU6	1

Table 7.2 Proportion of existing land units for Wickham land system.

Ord-Bonaparte land unit	Cell Count	Proportion	Ord-Bonaparte percentage (%)	Technical Bulletin land unit	Technical Bulletin percentage (%)
316Wk_3	3114	0.0138	1	WLU1	20
316Wk_4	2092	0.0093	1	WLU2	20
317Wk_3	77492	0.3433	34	WLU3	10
317Wk_4	65625	0.2907	29	WLU4	20
317Wk_5	8181	0.0362	4	WLU5	20
317Wk_8	1910	0.0085	1	WLU6	4
344Wk_3	66782	0.2959	30	WLU7	3
344Wk_8	518	0.0023	0	WLU8	3
Total	225714				

There are a number of reasons why the estimated percentages do not match between the two sets of land unit data. Firstly, the Ord-Bonaparte land units were actually mapped and measured from spatial maps, whereas the Technical Bulletin land units are non-spatial estimates consolidated from existing surveys. Uncertainties also exist in all spatial analysis, in all or either the validity of the information (criterion uncertainties), the potential effect of the phenomena (threshold uncertainties), and/or the handling of information (decision rule uncertainties) (Liu 2009). The land unit data provided by both sources, Technical Bulletin and Ord-Bonaparte Program, show a degree of uncertainty. These uncertainties include: criterion uncertainty that arises from errors in the original data by the way of identification, measurement and data quality, threshold uncertainty that refers to the uncertainty of working with natural phenomena where boundaries are often enforced for convenience, however rarely so rigid in reality, and thirdly the decision rule uncertainties that are associated with incomplete data and spatial interpolation.

Inconsistencies can be seen in Tables 7.1 and 7.2, where there are differences in the proportion and number of land units from both sources for Antrim and Wickham land systems. This is true for many other land systems in the study area. This inconsistency has arisen from different mapping techniques, reasons for mapping and the compilation of data. The Technical Bulletin land systems were developed as general descriptions and to adopt a land system as a basic mapping unit, whilst the Ord-Bonaparte land units were actually mapped using traditional and digital data. Antrim land system is estimated to have six land units described in the Technical Bulletin by Payne (2011), however only four land units were mapped during the Ord-Bonaparte Program (Schoknecht 2003). The proportions of Antrim land units seen in Table 7.1, show that the Ord-Bonaparte land unit 317An_4 and the Technical Bulletin land unit ALU1 are the 'most likely' to occur land unit for Antrim land system, with an estimated 73% and 50% respectively.

It was possible to use descriptions of the land units to match the two sets of land units, creating an inferred relationship. Table 7.3 shows that the drainage land units ALU5 and ALU6 described in the Technical Bulletin can be matched with the Ord-Bonaparte land unit 317An_8.

Table 7.3 Inferred relationship between existing Antrim land unit data.

Ord-Bonaparte land unit	**Technical Bulletin land unit**	**Description**
317An_4	ALU1	Mesas and buttes, steeply sloping margins
317An_5	ALU2	Crests and slopes of rounded hills
317An_6	ALU3, ALU4	Moderate to gentle slopes and flat areas
317An_8	ALU5, ALU6	Drainage

Table 7.3 shows that the inconsistency of the two sets of land units has no effect on 'most likely to occur' land unit '317An_4' and 'ALU1'. The only land units affected for Antrim land system are the minor land units that make up around 10% altogether.

A similar comparison can be made for Wickham land system, however, as shown in Table 7.4, Wickham has the same number and similar descriptions of land units available from both sources.

Table 7.4 Relationship between existing Wickham land unit data.

Ord-Bonaparte land unit	**Technical Bulletin land unit**	**Description**
316Wk_3	WLU1	Plateaux of sandstone
316Wk_4	WLU2	Low to undulating steep hills and ridges including plateaux
317Wk_3	WLU3	Mesas, high hills and ridges – sandstone
317Wk_4	WLU4	Cuestas, low undulating to steep hills and ridges.
317Wk_5	WLU5	Hogbacks, ridges and gentle slopes.
317Wk_8	WLU6	Lower gentle floors, narrow drainage.
344Wk_3	WLU7	Slopes associated with streamlines.
344Wk_8	WLU8	Drainage

The Ord-Bonaparte Program land units were limited to only several pastoral properties in the Kimberley Region, including the study area, which was one of the reasons for choosing the study area for this research.

7.2 ROC plot analysis for the predicted land units

Receiver Operating Characteristics (ROC) plots were used to compare results from the prediction models with existing digital data. ROC plots can be used to determine the performance qualities of classes allocated by a human or by a mechanical device (Fielding 1997). The ROC plot was originally developed for processing many different formats of data essentially represented by ‘signals’. In this research, the ‘signals’ represent the land unit that is ‘most likely’ to exist as the highest position results.

ROC plots are essentially a measure of presence and absence of individual ‘signals’ within the existing boundaries, in this case, the presence and absence of predicted land units within and outside of existing land unit boundaries. This can be described using the Predictive Value Theory (refer to Section 6.1.1 and Figure 6.1), where the results found to be within the existing boundaries identify the proportions that are correctly predicted for a modelling technique and those that are outside the boundary are incorrectly predicted. Table 7.5 shows how the true positive rate and false positive rate or sensitivity and specificity (any increase in sensitivity would be accompanied by a decrease in specificity), respectively, can be used to test the accuracy of the predicted ‘most likely’ land unit data against the existing Ord-Bonaparte land unit data.

Table 7.5 A 2 x 2 sensitivity and specificity matrix (adapted from Tape (1993)).

	Predicted land unit (LU) - present	**Predicted land unit (LU) - absent**
Test positive – correct land unit	True positives	False positives
Test negative – incorrect land unit	False negatives	True negatives

The following graph in Figure 7.1 shows an example of ROC plot analysis, with the curves described as excellent, good and worthless results, the further the curve departs the 45-degree diagonal trendline, the more accurate the result.

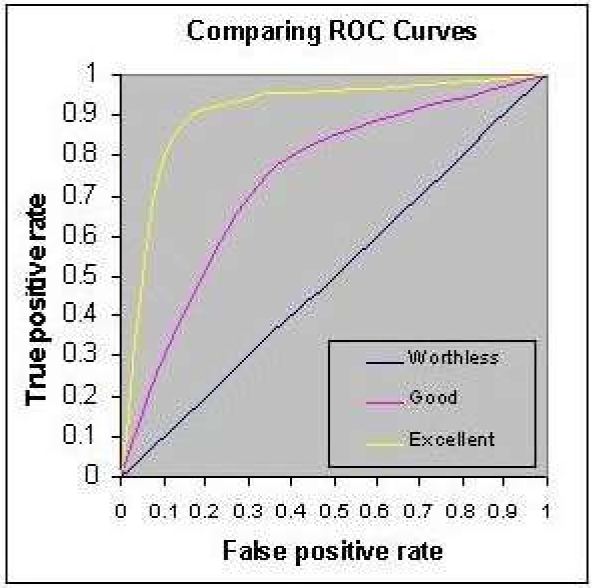


Figure 7.1 Comparing ROC plot curves, showing excellent, good and worthless results (Tape 1993).

The predicted results for the Bow River Station land units consist of thousands of pixels with the most likely land unit, calculated using the highest position method. Out of these, a random sample pool of 100 points was selected for each land unit and random sample pool of 100 points for outside of each land unit.

To plot the ROC plot charts, the two sets of 100 sample points were created for the 'most likely' (highest position results) to occur land units for each of the prediction model methods. The ROC plot method collates the true positives and false positives of the 'most likely' land unit within the land system. Essentially, the greater the sample pool of results the greater the chance for correct representation of the modelling technique accuracy.

The true positive and false positive values were used to calculate the 'rate' or relationship between the Ord-Bonaparte land unit data and predicted 'most likely' land unit data for any one particular land unit. This relationship was calculated by cumulating the response rate of the true and false positive values. Once the response rate was calculated for both false and positive values, the 'rate' was plotted as a ROC plot.

7.2.1 Antrim land unit ROC plot analysis

Comparisons were made between the BWO, FWO and PWofE models for Antrim land units using ROC plot analysis. Following the method outlined in Section 7.2, a ROC plot was produced for 317An_4 (ALU1), illustrated in Figure 7.2. The ROC plot shows that the results have a ROC plot curve close to the 45-degree diagonal. This 45-degree diagonal divides the ROC space (seen in Figure 7.1 as 'worthless') represents the cut-off between 'good' classification results (better than average), above the line, and 'poor' classification results (worse than average), below the line.

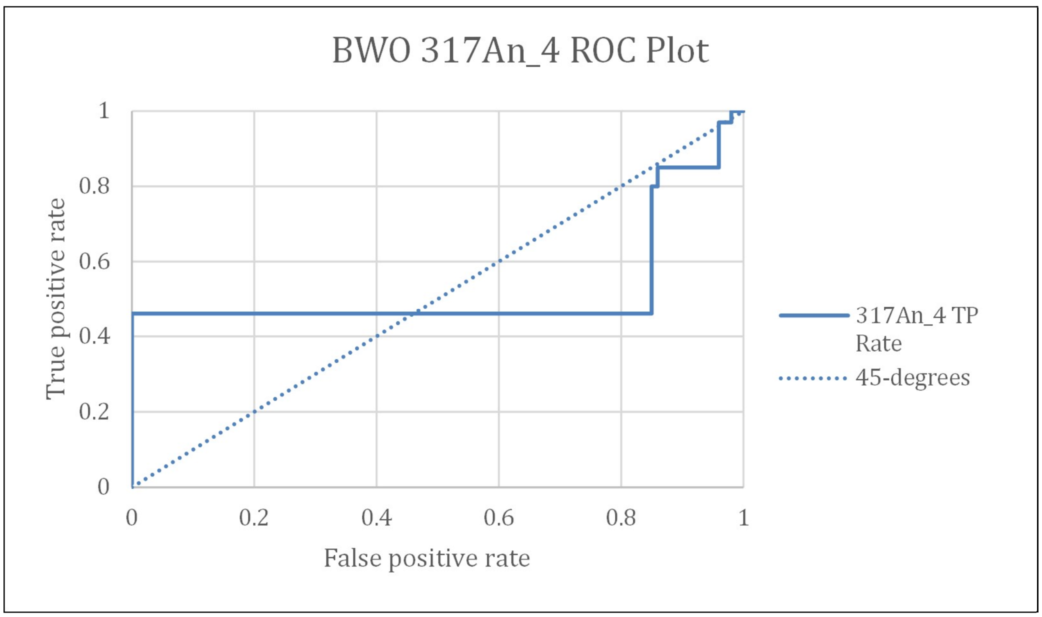


Figure 7.2 ROC plot for Ant4 (ALU1) using the BWO model with AUC = 0.5234.

A good measure for the capabilities of the modelling method is the Area Under the Curve or AUC. For the BWO 317An_4 results, in Figure 7.2, the AUC = 0.5234, which identifies failure to predict (refer to Table 7.6) effectively. The best possible prediction result would yield a point in the upper left corner or coordinate (0,1) of the ROC plot space, representing 100% true positive rate (sensitivity), where there were zero false negatives, and 100% false positive rate (specificity), with zero false positives. The (0,1) point is also called a 'perfect classification'.

A guideline to AUC values and their classification of accuracy is given in Table 7.6, showing the traditional academic point system (Tape 1993).

Table 7.6 Interpretation of AUC value accuracy for a ROC plot.

AUC value	Accuracy
0.90-1	Excellent
0.80-0.90	Good
0.70-0.80	Fair
0.60-0.70	Poor
0.50-0.60	Fail

The results for land unit 317An_4 using the FWO and PWofE models are presented in Figures 7.3 and 7.4, respectively.

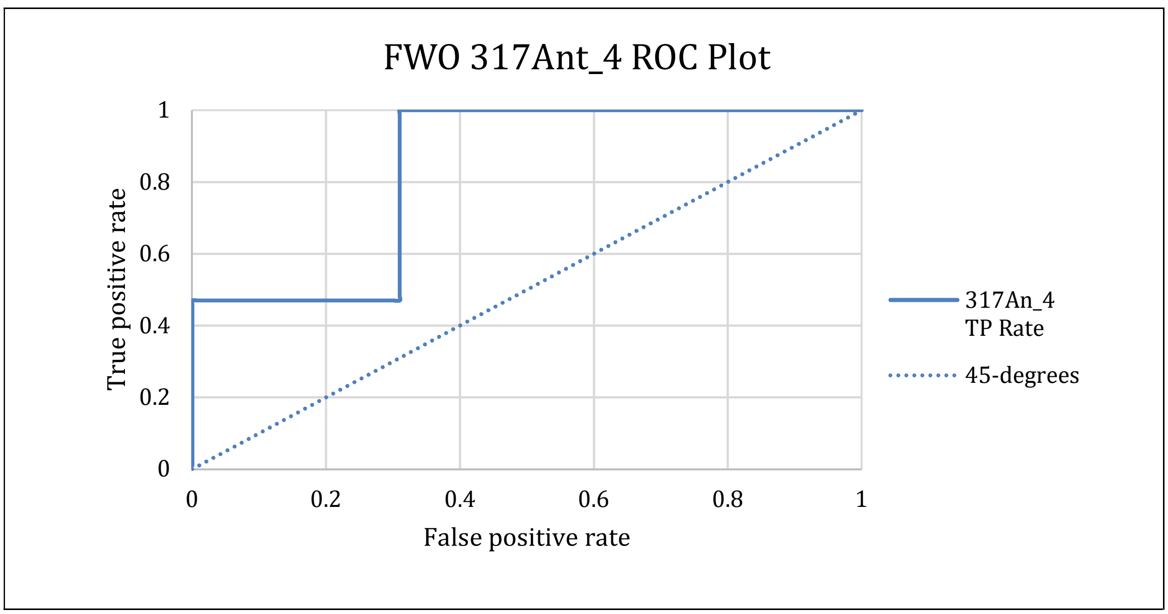


Figure 7.3 ROC plot for 317An_4 (ALU1) using the FWO model with AUC = 0.8357.

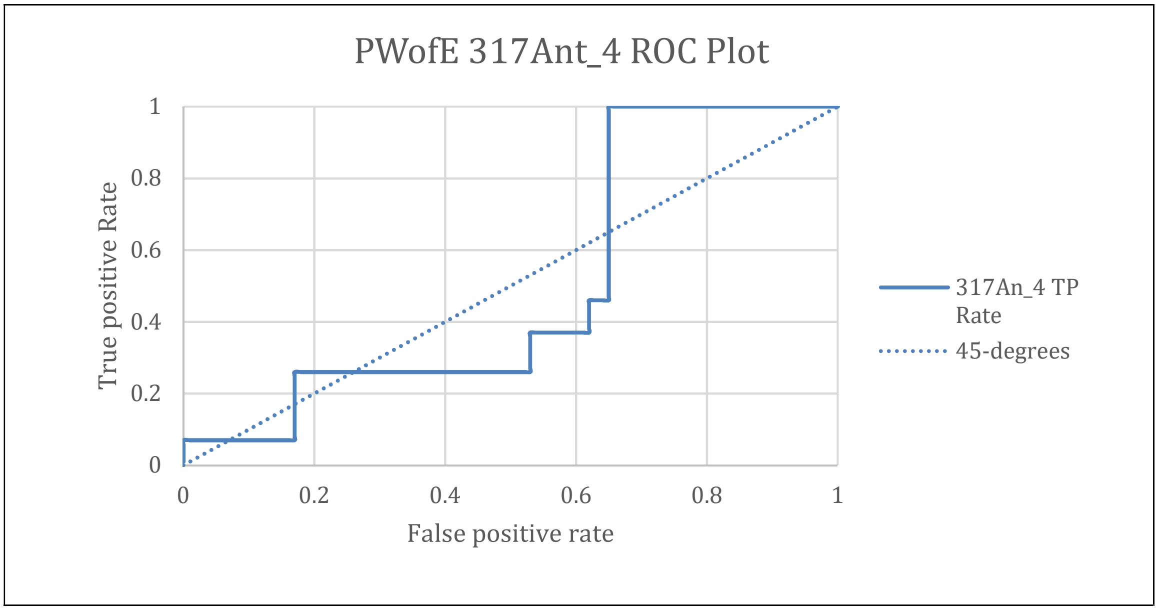


Figure 7.4 ROC plot for 317An_4 (ALU1) using the PWofE model with AUC = 0.5026.

The ROC plots seen in Figure 7.3 and 7.4 were compared with Figure 7.2, and show that the ROC plot curve furthest from the 45-degree diagonal trendline was produced by the FWO model. To further compare the accuracy of the 'most likely' land unit results using ROC plots, the AUC was calculated for the BWO, FWO and PWofE models, seen in Table 7.7, for Antrim land units.

Table 7.7 AUC for Antrim land unit ROC plots.

Antrim land units			
Ord-Bonaparte land units	**BWO AUC**	**FWO AUC**	**PWofE AUC**
317An_4	0.5234	0.7818	0.5026
317An_5	0.5058	0.9082	0.4078
317An_6	0.9197	0.972	0.7582
317An_8	0.8864	0.2974	0.5347

The highlighted (yellow) AUC values identify the 'best fit' land unit being '317An_6', an area of 'Moderate to gentle slopes and flat areas', predicted using all three modelling methods, with the 'best' overall performance by the Fuzzy Weighted Overlay (FWO) model identifying 3 out of 4 land units (green and yellow highlighted) with a 'fair' to 'excellent' accuracy measure (refer to Table 7.6), which concurred with the 45-degree diagonal measure for accuracy. The BWO, FWO and PWofE 'most likely' land unit results for Wickham land system were also tested.

7.2.2 Wickham land unit ROC plot analysis

The main difference between the Antrim and Wickham land units are the proportional spread of the land units within the land system. Antrim has graduated *prior* probability proportions outlined in the Technical Bulletin, whilst Wickham has evenly spread *prior* probability proportions (refer to Appendix 1).

Using the Ord-Bonaparte land units and 'most likely' land units from the three modelling techniques, ROC plots were created for the Wickham land units. The ROC plots for Wickham '316Wk_3' (WLU1) are presented in Figures 7.5, 7.6 and 7.7, for the BWO, FWO and PWofE models respectively.

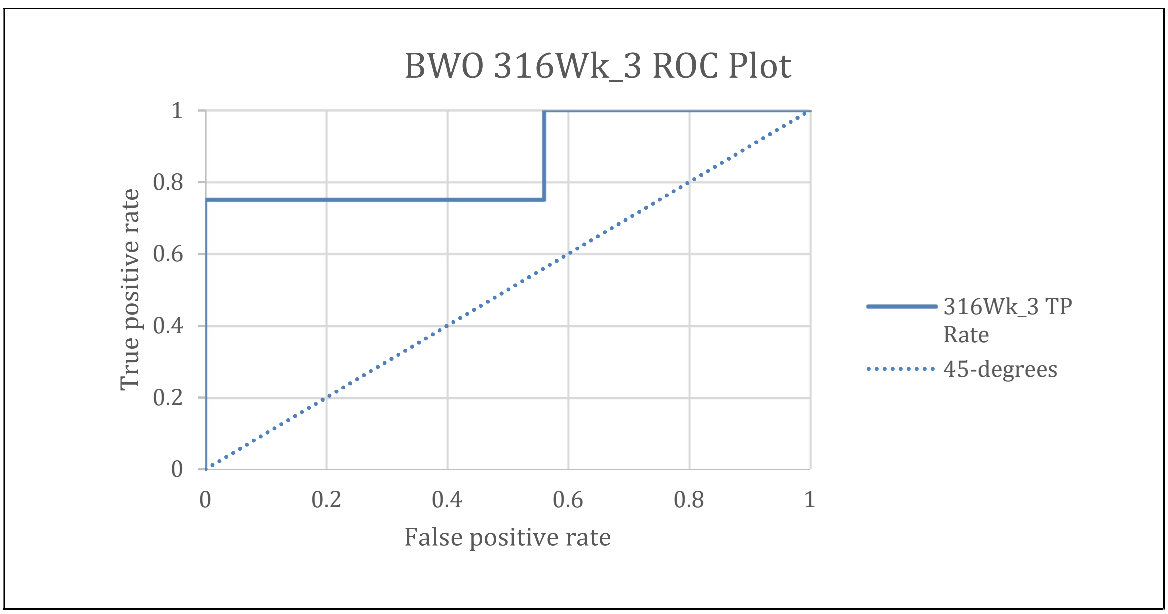


Figure 7.5 BWO 316Wk_3 (WLU1) ROC plot results with an AUC = 0.86.

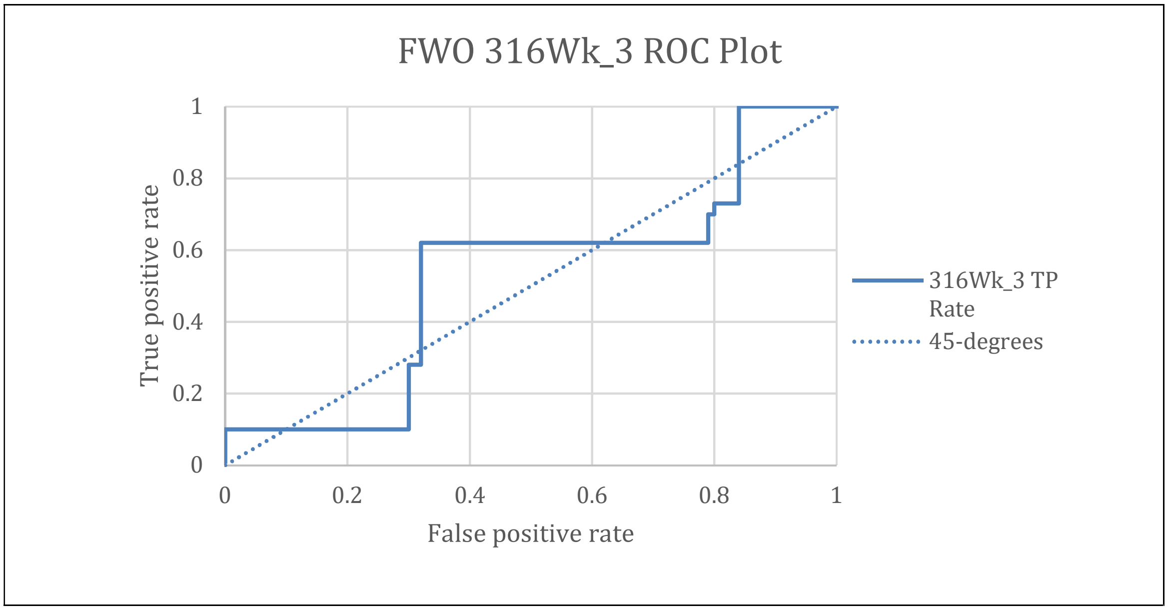


Figure 7.6 FWO 316Wk_3 (WLU1) ROC plot results with an AUC = 0.5848.

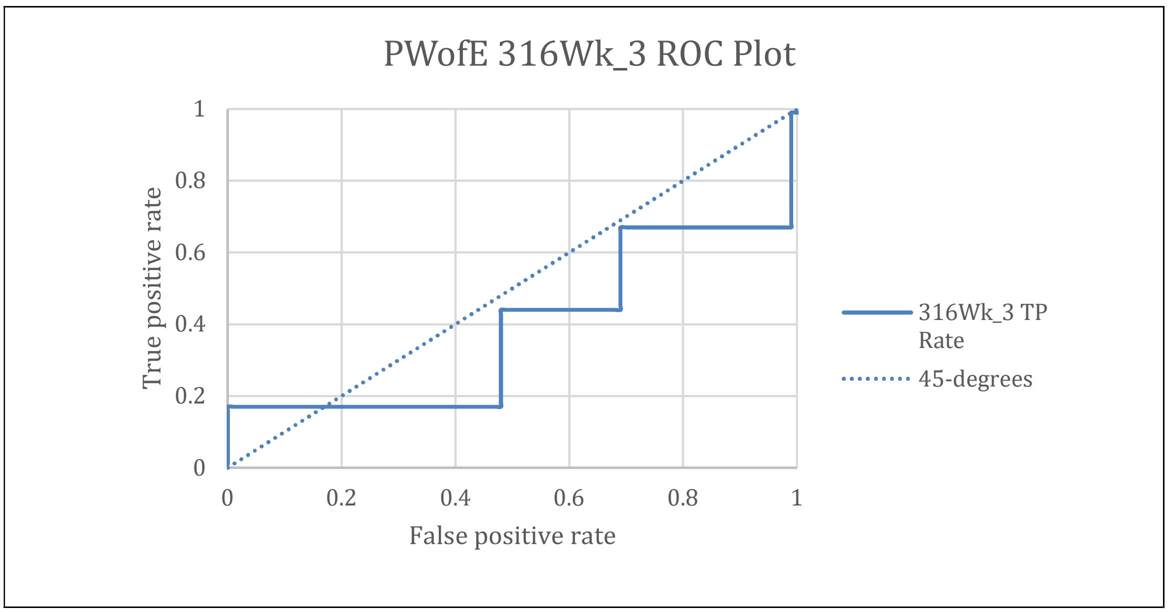


Figure 7.7 PWofE 316Wk_3 (WLU1) ROC plot results with an AUC = 0.3948.

Using the ROC plots, the curve furthest from the 45-degree diagonal trendline was the BWO model results. This was compared with the AUC values that were calculated for all of the Wickham land units and are presented in Table 7.8. The highlighted (yellow) AUC values show that the 'best fit' models to the land units. For the Wickham land system, the

Binary Weighted Overlay (BWO) model for land unit '316Wk_3' produced the best AUC = 0.86, and was best overall predictor with 4 out of 8 land units (green and yellow highlighted) with a 'fair' to 'excellent' accuracy (refer to Table 7.6).

Table 7.8 AUC results for Wickham land unit ROC plots.

Wickham land units			
Ord-Bonaparte land unit	**BWO AUC**	**FWO AUC**	**PWofE AUC**
316Wk_3	0.86	0.5848	0.3948
316Wk_4	0.4612	0.6135	0.409
317Wk_3	0.8128	0.6283	0.6334
317Wk_4	0.7445	0.4281	0.5265
317Wk_5	0.6796	0.4512	0.3382
317Wk_8	0.8548	0.5425	0.1094
344Wk_3	0.3696	0.7906	0.7486
344Wk_8	0.1856	0.3077	0.045

7.2.3 Summary of the ROC plot analysis

The ROC plot analysis results are presented for both Antrim and Wickham land systems and show that the accuracy varied between land systems and modelling techniques. The departure from the 45-degree diagonal trendline showed that the FWO model was best suited to Antrim land unit '317An_4', and the BWO model was best suited to Wickham land unit '316Wk_3'. The summary AUC values for Antrim land system seen in Table 7.7, show that all three models performed similar for land unit '317An_6', however overall the FWO model performed best for the suite of Antrim land units. The summary AUC values for Wickham in Table 7.8 show that the BWO model performed best for land unit '316Wk_3', and also best overall for Wickham land system. Overall, the AUC values for both land systems showed that the modelling techniques performed weakest for the drainage units '317An_8' and '344Wk_8'. This poorer performance of the modelling techniques for the drainage land units could be because these land units occupy significantly smaller areas than the other major land units, therefore they were missed or under sampled when using the 100 random point sampling system for the ROC plot accuracy analysis.

7.3 Contingency table analysis

To continue testing the BWO, FWO and PWofE modelling techniques, comparisons were made between the existing Ord-Bonaparte land units and the predicted 'most likely' land unit results using cross tabulation within a contingency table matrix.

A contingency table describes the frequency distribution of variables, in this case as pixel cell counts, with one variable in rows and the other in columns. The table commonly displays the dependent variable (the outcome) along the top row of the matrix and an independent variable on the side column (Grech 2018). The dependent variables in this research are the 'most likely' land units results, with the independent variables being the existing Ord-Bonaparte land unit data, as a confirmatory data set. The distribution between the dependent and independent variables yields information about the pattern such as 'frequency' and 'clustering' of the results. The contingency table method uses all pixels to compare 'most likely' land unit results and therefore is expected to have less bias when compared to the ROC plots. Using all pixels in the accuracy analysis reduces the chance of missing or under sampling minor land units.

7.3.1 Antrim land units contingency tables

A comparison was firstly made for the Antrim land system between the Ord-Bonaparte land units and the 'most likely' land unit results. A tally of the raster pixel cells was counted, using ArcGIS tools, to find the number of pixels for each 'most likely' land units within the existing Ord-Bonaparte land unit boundaries. The contingency tables for Antrim land system are displayed in Tables 7.9, 7.10 and 7.11 for the BWO, FWO and PWofE models, respectively.

In Table 7.11, the results suggest that some land units have no predicted pixels however it is possible that the modelling technique, in this case the PWofE modelling technique, has underestimated the prediction of minor land units, overestimated other land units.

Table 7.9 Contingency table for the Antrim BWO prediction model.

	ALU1 (HP1)	ALU2 (HP2)	ALU3, ALU4 (HP3, HP4)	ALU5, ALU6 (HP5, HP6)	Total
317An_4	25072	2643	4231	773	32719
317An_5	1981	3145	1876	0	7002
317An_6	2964	0	245	0	3209
317An_8	913	128	212	108	1361
Total	30930	5916	6564	881	44291
***Correctly predicted %**	81	53	4	12	0.645**

* Represents the percentage of modelled results that were correctly predicted for each land unit.

** The overall accuracy shown highlighted (yellow), is the sum of the diagonals, highlighted (green), divided by the total pixels, highlighted (blue).

Table 7.10 Contingency table for the Antrim FWO prediction model.

	ALU1 (HP1)	ALU2 (HP2)	ALU3, ALU4 (HP3, HP4)	ALU5, ALU6 (HP5, HP6)	Total
317An_4	1695	16695	15320	542	34385
317An_5	1237	3973	2195	0	7405
317An_6	61	2549	575	0	3185
317An_8	139	119	1115	248	1621
Total	3518	24667	20488	1049	46463
Correctly predicted %	48	16	3	24	0.140

Table 7.11 Contingency table for the Antrim PWofE prediction model.

	ALU1 (HP1)	ALU2 (HP2)	ALU3, ALU4 (HP3, HP4)	ALU5, ALU6 (HP5, HP6)	Total
317An_4	2456	0	11693	17829	31978
317An_5	0	0	2144	4697	6841
317An_6	599	0	1705	881	3185
317An_8	5	0	411	909	1325
Total	3060	0	15953	24316	43329
Correctly predicted %	80	0	11	4	0.117

The tables above show a number of relationships between the predicted (columns) and existing (rows) land unit data. The tables also show that on some cases the predicted 'most likely' land unit results were combined to match the inferred relationship, shown in Table 7.3. Table 7.9 has been highlighted (green) to show the number of pixels that correspond between the two predicted land units and the confirmatory data set e.g. 317An_4 and ALU1 (HP1). These pixel counts (highlighted green) represent the correctly predicted pixels for each land unit, that were then totalled and divided by the total number of pixels to calculate the overall accuracy highlighted (yellow). The overall accuracy represents the overall accuracy of the modelling technique for the land system. Table 7.9 shows that the overall accuracy using the BWO model for Antrim land units is 0.645 or 64%. This is considerably better than either of the other methods for Antrim land system, that had overall accuracies of 14% for the FWO model and 11.7% for the PWofE model.

The total of the columns shown in the contingency tables above, are the sum of all of the 'most likely' land unit pixels for that land unit, for example, in Table 7.9 the total number of pixels predicted for ALU1 was 30930 (highlighted red). The column totals show all pixels assigned by the model to that land unit. To calculate the percentage of correctly predicted pixels involved dividing the number of correctly predicted pixels by the total predicted pixels for the land unit. For example, to calculate the percentage of correctly predicted pixels for 317An_4 (ALU1), the correctly predicted pixels 25072 (highlighted green), were divided by the total pixels for the column 30930 (highlighted red), which equals 81%. The 81% represents the percent of pixels that were correctly predicted for 317An_4 (ALU1).

A summary of the correctly predicted percentages for Antrim 'most likely' land units are shown in Table 7.12 for all three modelling methods.

Table 7.12 Summary of correctly predicted land units for Antrim land system.

Antrim land system				
Ord-Bonaparte land unit	**Technical Bulletin land unit**	**BWO correctly predicted %**	**FWO correctly predicted %**	**PWofE correctly predicted %**
317An_4	ALU1	81	48	80
317An_5	ALU2	53	16	0
317An_6	ALU3, ALU4	4	3	11
317An_8	ALU5, ALU6	12	24	4

The labels for both the Ord-Bonaparte and Technical Bulletin land units have been included in Table 7.12, to show the relationship between the two sets of data, and for association with contingency tables. Table 7.12 shows that the BWO model correctly predicted 317An_4 (ALU1) with 81% correct, and that the PWofE model predicted the same land unit with 80% correct.

However, the contingency tables suggest that the BWO model performed best overall for the Antrim land system, with a good overall modelling accuracy (64.5%).

7.3.2 Wickham land units contingency tables

Contingency tables analysis was also applied to the Wickham modelling results. The results for Wickham land system are shown in Tables 7.13, 7.14 and 7.15, for the BWO, FWO and PWofE models, respectively.

Table 7.13 Contingency table for the Wickham BWO prediction model.

	WLU1 (HP1)	WLU2 (HP2)	WLU3 (HP5)	WLU4 (HP3)	WLU5 (HP4)	WLU6 (HP6)	WLU7 (HP7)	WLU8 (HP8)	Total
316Wk_3	1299	698	0	0	0	312	106	0	2415
316Wk_4	504	354	0	0	0	273	40	0	1171
317Wk_3	48792	21500	0	0	0	0	2127	0	72419
317Wk_4	39933	18469	0	0	0	155	5317	0	63874
317Wk_5	4551	2107	0	0	0	544	252	0	7454
317Wk_8	1030	321	0	0	0	139	96	0	1586
344Wk_3	35688	20601	0	0	0	0	8388	0	64677
344Wk_8	57	39	0	0	0	0	118	0	214
Total	131854	64089	0	0	0	1423	16444	0	213810
Correctly predicted %	1	1	0	0	0	10	51	0	0.047**

** The overall accuracy shown highlighted (yellow), is the sum of the diagonals divided by the total pixels.

Table 7.14 Contingency table for the Wickham FWO prediction model.

	WLU1 (HP1)	WLU2 (HP2)	WLU3 (HP5)	WLU4 (HP3)	WLU5 (HP4)	WLU6 (HP6)	WLU7 (HP7)	WLU8 (HP8)	Total
316Wk_3	263	413	0	856	59	177	109	545	2422
316Wk_4	211	154	7	14	373	162	50	215	1186
317Wk_3	17487	5585	614	2345	23030	303	1207	22263	72834
317Wk_4	12000	4286	358	1834	18411	913	1212	24961	63975
317Wk_5	1018	39	26	200	1514	387	54	4210	7448
317Wk_8	59	8	0	13	114	42	7	1343	1586
344Wk_3	17817	535	0	3334	22911	4394	418	15288	64697
344Wk_8	3	0	0	1	5	6	0	199	214
Total	48858	11020	1064	7741	67214	6384	3057	69024	214362
Correctly predicted %	1	1	58	24	2	1	14	0	0.023

Table 7.15 Contingency table for the Wickham PWofE prediction model.

	WLU1 (HP1)	WLU2 (HP2)	WLU3 (HP5)	WLU4 (HP3)	WLU5 (HP4)	WLU6 (HP6)	WLU7 (HP7)	WLU8 (HP8)	Total
316Wk_3	0	0	524	0	0	656	602	640	2422
316Wk_4	0	0	231	0	0	419	231	305	1186
317Wk_3	568	0	25315	0	0	15536	16984	14431	72834
317Wk_4	243	0	18675	0	0	11414	17299	16344	63975
317Wk_5	22	0	1253	0	0	1206	1281	3686	7448
317Wk_8	1	0	84	0	0	63	199	1239	1586
344Wk_3	0	0	18012	0	0	17102	16085	13498	64697
344Wk_8	0	0	0	0	0	5	17	192	214
Total	834	0	64094	0	0	46401	52698	50335	226672
Correctly predicted %	0	0	39	0	0	0	31	0	0.194

The tables above, show the accuracy of the modelling techniques for Wickham land system, with the overall accuracy highlighted (yellow). The overall accuracy for the PWofE model was best at 0.194 or 19.4%, and although weak, shows that this model performed best overall for the Wickham land system.

The 'most likely' land unit results for Wickham land system shown in Tables 7.13 and 7.15 suggest that like the modelling of Antrim land system (refer to Table 7.11), some land units have no predicted pixels possibly due overestimation or underestimation of other land units.

The correctly predicted percentages of the 'most likely' land units have been summarised in Table 7.16. The table shows that the FWO model predicted land unit 317Wk_3 (WLU3) with 58% correctly predicted, and the BWO model predicted land unit 344Wk_3 (WLU7) with 50% correctly predicted.

Table 7.16 Summary of correctly predicted land units for Wickham land system.

Wickham land system				
Ord-Bonaparte land unit	**Technical Bulletin land unit**	**BWO correctly predicted %**	**FWO correctly predicted %**	**PWofE correctly predicted %**
316Wk_3	WLU1	1	1	0
316Wk_4	WLU2	1	1	0
317Wk_3	WLU3	0	58	39
317Wk_4	WLU4	0	24	0
317Wk_5	WLU5	0	2	0
317Wk_8	WLU6	10	1	0
344Wk_3	WLU7	51	14	31
344Wk_8	WLU8	0	0	0

The contingency tables suggest that the PWofE model performed best overall for the Wickham land system, with an overall modelling accuracy (19.4%).

7.3.3 Summary of the contingency table results

The contingency tables provided a good evaluation for the accuracy of individual land units and the overall accuracy of the three modelling techniques applied to Antrim and

Wickham land systems. The contingency tables show that the BWO model performed best for Antrim land system with an overall model accuracy of 64.5%, and the PWofW model performed best for the Wickham land system with an overall accuracy of 19.4%. Although the accuracies for Antrim land system are only moderate, it does suggest the BWO model may be better suited to the more evenly proportioned land units of Antrim land system. The PWofE model has disappointingly low accuracy for the Wickham land system but may be better suited to the more statistically varied uneven proportioned land units of that land system.

The contingency tables also showed on a land unit by land unit basis that the BWO model produced the highest percentage of correctly predicted pixels for Antrim land unit 317An_4 (ALU1) at 81%, and the FWO model had the highest percentage of correctly predicted pixels for Wickham land unit 317Wk_3 (WLU3) with 58%. Although the accuracy of these two units is relatively high, this percentage is simply a reflection of how many 'most likely' land units were correctly predicted for those individual units, and does not reflect how the model performed for the entire land system, therefore the best measure for model accuracy remains the overall accuracy.

7.4 Comparison between O'Donnell 'most likely' land units and field data.

Highest position results (refer to Appendix 9) were calculated for O'Donnell land system to find the 'most likely' land units because it was the only land system visited during the field reconnaissance trip to the study area, and therefore the only land system with independent field data and descriptions.

The proportion of the O'Donnell land system for the Ord-Bonaparte land units were calculated and compared with the Technical Bulletin land unit proportions, presented in Table 7.17.

Table 7.17 Comparison between existing land units for O'Donnell land system.

Ord-Bonaparte land units	Ord-Bonaparte percentage (%)	Technical Bulletin land unit	Technical Bulletin percentage (%)
312Od_5	1	OLU1	12
312Od_6	1	OLU2	12
312Od_7	34	OLU3	51
312Od_8	29	OLU4	6
		OLU5	10
		OLU6	9

Table 7.18 identifies differences between the two existing land unit data, therefore an inferred relationship between land unit descriptions was investigated (the same as for Antrim existing land units – refer to Table 7.3). There are only four Ord-Bonaparte land units described by Schoknecht (2003) compared with the six Technical Bulletin land units from Payne (2011).

Table 7.18 Inferred relationship between the existing O'Donnell land unit data.

Ord-Bonaparte land unit	Technical Bulletin land unit	Description
312Od_5	OLU1, OLU2	Gentle undulating rolling rises - hills.
312Od_6	OLU3	Level to undulating low plains - interfluves.
312Od_7	OLU4, OLU5	Alluvial gilgai plains.
312Od_8	OLU6	Drainage.

ROC plots were again used to test the accuracy of the predicted land units using the three modelling methods – BWO, FWO and PWofE models. The ROC plots were used to calculate the AUC values for each of the modelling techniques of the O'Donnell land units and are presented in Table 7.19. The PWofE model produced the best AUC value for land unit 312Od_6 with an 'excellent' rating of 0.999 accuracy (refer to Table 7.6). The ROC plots for the FWO model showed more consistency, with 2 out of 4 AUC values greater than 0.7 (refer to Appendix 10) suggesting better than 'fair' accuracy.

Table 7.19 AUC results for O'Donnell land unit ROC plots.

Ord-Bonaparte land units	BWO AUC	FWO AUC	PWofE
312Od_5	0.6621	0.6632	0.3768
312Od_6	0.6616	0.7388	0.999
312Od_7	0.6079	0.7775	0.2642
312Od_8	0.4080	0.5096	0.3066

The AUC results only reflect the sample pool for each of the modelling techniques therefore the O'Donnell 'most likely' land unit results were checked using contingency tables to check the accuracy for the entire land system.

Contingency tables were again used to show the percentage of correctly predicted 'most likely' land units and to test the overall accuracy of the three modelling techniques for O'Donnell land system. The contingency tables for O'Donnell land system identified that the BWO model (refer to Table 7.20) performed best with an overall accuracy of 0.286, or 28.6%, with the contingency tables for the FWO and PWofE models presented as Appendix 11 for comparison.

Table 7.20 Contingency table for the O'Donnell BWO prediction model.

	OLU1, OLU2 (HP2, HP3)	OLU3 (HP1)	OLU4, OLU5 (HP6, HP4)	OLU6 (HP5)	Total
312Od_5	7051	10017	3622	3834	24524
312Od_6	60859	54423	27765	8918	151965
312Od_7	17191	9160	5574	484	32409
312Od_8	10824	13665	10416	3891	38796
Total	95925	87265	22363	17127	247694
Correctly predicted %	7	62	25	23	0.286

A summary of the correctly predicted 'most likely' land units is shown in Table 7.21. The table suggests that on a land unit by land unit basis that the PWofE model produced the highest percentage of correctly predicted pixels for land unit 312Od_6 (OLU3) with 100%. The other models also predicted good percentages for correct pixels for land unit

312Od_6 (OLU3). These results are promising because O'Donnell land unit 312Od_6 (OLU3) is the land unit with the highest *prior* probability given in the Technical Bulletin (Payne 2011), however in comparison the Ord-Bonaparte confirmatory land unit data suggests this land unit only makes up 1% of the land system (refer to Table 7.17).

Table 7.21 Summary of correctly predicted land units for O'Donnell land system.

O'Donnell land system				
Ord-Bonaparte land unit	**Technical Bulletin land unit**	**BWO correctly predicted %**	**FWO correctly predicted %**	**PWofE correctly predicted %**
312Od_5	OLU1, OLU2	7	7	5
312Od_6	OLU3	62	69	100
312Od_7	OLU4, OLU5	25	1	7
312Od_8	OLU6	23	23	20

Finally, comparisons were made between field data collected on site at BRS study area and the 'most likely' land unit results of all three modelling techniques. The field data was limited to a few dozen points however it provided a ground-truth insight into the accuracy of the final predicted land unit results. The field data included GPS locations and descriptions of landforms, geology, drainage and vegetation (refer to Appendix 4). Table 7.22 shows the comparison between the 'most likely' land units produced using the BWO model and the field data.

Table 7.22 Land unit comparison between field data and BWO model results.

O'Donnell land units – BWO model vs field data					
Waypoint	**Field Description**	**Elevation**	**Highest position result**	**Technical Bulletin land unit**	**Match**
025	Drainage – 'Sandy Creek', various scrub vegetation	519	1	OLU3	No
026	Plain – Boab trees	519	3	OLU2	No
027	Plain	527	3	OLU2	No
028		530	4	OLU5	
029		530	1	OLU3	
030		529	3	OLU2	
031	Plain – perennial grasses, sparse bloodwood trees	467	3	OLU2	No
032	Drainage	509	4	OLU5	Yes
033	Drainage	498	5	OLU6	Yes
034		501	2	OLU1	
035	Plain	512	5	OLU6	Yes
036	Lower slope	513	6	OLU4	Yes
037	Peak	519	2	OLU1	Yes
038	Mid slope	520	1	OLU3	Yes
039	Plain	513	1	OLU3	Yes
040		511	6	OLU4	
041	Plain	527	3	OLU2	No
042	Plain	522	3	OLU2	No
043	Plain	529	4	OLU5	Yes
044	Plain	519	1	OLU3	Yes
045		530	1	OLU3	
046	Plain	542	1	OLU3	Yes
047	Plain	538	3	OLU2	No
048	Plain	535	4	OLU5	Yes
049	Drainage	525	1	OLU3	No
050	Drainage	527	4	OLU5	Yes
					Agreement total = 60%

The comparison of 'most likely' BWO land units and the field data, where 'yes' represented a positive agreement of land unit descriptions, identified that the BWO model has a 60% agreement for O'Donnell land system. In comparison, the PWofE model suggested a 21% agreement, whilst the FWO model suggested an agreement of only 26% (refer to Appendix 12).

7.5 Chapter summary

In this chapter, methods were discussed and tested to check the accuracy of the three prediction models, comparing the results of Antrim, and Wickham land systems. The accuracy of the results was tested using Receiver Operating Characteristics (ROC) plots, contingency tables and field trip reconnaissance.

ROC plots were used to analyse the relationship between existing and predicted 'most likely' land units using a random 100 sample pool of result value points. The ROC plots were firstly analysed using a 45-degree diagonal trendline, with results above the 45-degree line indicating 'good' results and results under the line representing 'poor' results. ROC plots were also used to find the Area Under the Curve (AUC), that was calculated using integrals between predicted and existing land unit points, that resulted in values close to '1' indicating an 'excellent' relationship. The AUC analysis found that the FWO model was best suited to Antrim land system, the BWO model was best suited to Wickham land system and the FWO model was best suited to O'Donnell land system. The problem with relying on the ROC plot accuracy analysis for this research is that a 100-point sample pool could have missed or overestimated/underestimated the predicted 'most likely' land unit results.

Contingency tables were used to check the accuracy of every predicted 'most likely' land unit and the overall accuracy of the modelling techniques. The contingency tables used all pixel cells of predicted land units, resulting in a more accurate test for accuracy of results for the study area. The contingency tables identified that the BWO model performed best overall for the Antrim land system (64.5%), the PWofE model performed best overall for the Wickham land system (19.4%) and the BWO model performed best overall for the O'Donnell land system (28.6%). The contingency tables also showed on a land unit by land unit basis that the BWO model correctly predicted the highest percentage of accuracy for Antrim land unit 317An_4 (ALU1) at 81%, the FWO model correctly predicted

Wickham land unit 317Wk_3 (WLU3) with 58%, and that the PWofE model correctly predicted O'Donnell land unit 312Od_6 (OLU3) with 100%. Although the accuracy of these correctly predicted land units is quite high, especially for the PWofE model for land unit 312Od_6 (OLU3) with 100%, they do not directly identify which modelling technique is best suited to the land system. An individually correct land unit such as 312Od_6 (OLU3) might also be a minor unit as in this case when compared with the Ord-Bonaparte confirmatory data, that suggests 312Od_6 (OLU3) only occupies approximately 1% of the land system. The high percentage of pixels that were predicted for land unit 312Od_6 (OLU3) likely reflects the *prior* probability of the land unit given as 51% (refer to Table 7.17) that was applied during modelling. Therefore, it is best to use the overall accuracy for model suitability which in the case of O'Donnell land system, was found to be the BWO model with 28.6% compared with the PWofE model with 8% overall accuracy.

When comparing the ROC plots and contingency tables for accuracy of the three modelling techniques, the contingency tables gave better accuracy results for this research. The contingency tables gave better results because they included all pixels for the land systems, therefore including the minor predicted 'most likely' land units. Although the contingency tables included all pixels, they could not correct the fact that some of the pixels might have been incorrectly predicted as other land units. Both the ROC plots and contingency tables included 'most likely' land unit results that were underestimated or overestimated, which reflects the landscape variable class limitations.

Final confirmation analysis checked the accuracy of the 'most likely' lands units and field data. Field data was collected during a scheduled field trip to Bow River Station study area, with data mostly obtained for O'Donnell land system, due accessibility. Results were calculated using all three prediction modelling techniques for O'Donnell land system, with confirmation used to check the accuracy of these results. Predicted 'most likely' land units of O'Donnell land system were also check for accuracy by comparing the results with the field data descriptions. The comparison used an agreement tally of 'yes' the results and field data descriptions agree, and 'no' they don't agree. The comparison found that the

BWO model performed best overall for the O'Donnell land system with 60% agreement, followed by the FWO model with 26%, and the PWofE model with 26% agreement.

The accuracy of the modelling techniques varied for the different land systems, however the BWO model performed most consistently overall.

8 Conclusion and Recommendations

Pastoral leasehold in Western Australia (WA) require land condition monitoring to ensure compliance with the Land Administrations Act 1997 of WA, which ensures that the integrity of the natural ecosystems is maintained, by controlling degradation by livestock and other pastoral activities. Background investigation into pastoral rangelands of WA, identified that available land surveys were limited small scale ones conducted by Department of Agriculture and Food of Western Australia, DAFWA, other government departments and by corporations with interests other than pastoral (e.g. exploration companies).

Existing land surveys for the region mostly consist of landscape data published at a land system scale, and in some places land unit scale. Of these landscape datasets, most are incomplete or are merely estimates, due to inaccessibility and limited by the lack of availability of qualified field personnel.

The study area chosen for this research was Bow River Station (BRS) located in the Kimberley Region of WA. BRS was chosen as a suitable pastoral lease to use as a study area because of the amount of existing land surface data. The BRS study area provided landscape variable data (geology and vegetation), the Technical Bulletin land system data, and land unit scale data that was mapped during the Ord-Bonaparte Program in the early 2000s.

This research looked at methods to improve and upscale landscape variable datasets for the pastoral rangelands by looking at ways to predict land unit scale data that could be applied to pastoral lease monitoring programs such as Pastoral Lease Assessment using Geospatial Analysis, PLAGA. Spatial science and GIS technology, as part of this research, were used to provide an efficient and effective way to add to existing data and to analyse techniques for a predictive model. This chapter summarises this research and provides recommendations for improvements and future research in these subjects.

8.1 Conclusions

The conclusions for this research have been broken up into two main section, these were landform classification and land unit prediction modelling, with both sections using Bow River Station (BRS) as the study area. The results for both sections have been summarised and include conclusions on the accuracy.

8.1.1 Review of evidence variable layer classification for the study area

This research analysed methods for classification of landforms using a Digital Elevation Model (DEM) to improve and increase the available landscape data for the rangelands and pastoral leaseholds of WA. Data for the BRS study area included existing geology and vegetation landscape datasets and also information about the local topography, land systems and land units. With the aid of a Shuttle Radar Topographic Mission (SRTM) DEM additional landscape variable datasets were developed for the study area, using classification techniques. These datasets were landforms, elevation and relative relief. The aim of this classification (refer to Chapter 5) was to develop additional datasets to aid land unit prediction modelling. Land units comprise of a number of landscape elements and have a greater homogeneity than existing land systems scale data (refer to Section 3.1).

Landform classes were developed using the semi-automated LandSerf software and the SRTM DEM to produced six landform class: pits, passes, channels, ridges, peaks and plains for the study area. The landform data were saved as 30 m resolution rasters. The landform classes were checked for accuracy using a number of spatial analysis techniques. Initially, the landform classes were checked against the DEM using interactive tools in LandSerf including the 'profile query', 'multi-scale raster query' and 'frequency distribution' tools. It was found that the optimal LandSerf settings for landform classification in the study area were a 11 x 11 sampling window, with 6-degree slope tolerance and 0.1 distance decay (refer to Section 5.1.3). The optimal setting results were cross-checked with O'Donnell land system, with focus on correlation between channel/drainage patterns. The landform classes were coded and compared with field data descriptions for O'Donnell land system (refer to Table 5.4), that were collected as part of this study during a field trip to Bow River Station. The comparison with the field data found only minor similarities between the two sets of data. It was concluded that this was likely to be due to the field data representing only a small fraction of the land system.

The landform classes were further checked with the existing Ord-Bonaparte Program land units, and field data descriptions. Comparisons made using a frequency distribution table between the Ord-Bonaparte land unit descriptions and the LandSerf code descriptions found that channel landforms were the most frequent landform both for the existing land units and predicted landform. The comparison between the LandSerf landform classes and the field data descriptions found that 15 out of the 26 descriptions matched suggesting 58% agreement between the two sets of data. Due to limitation of only 26 field point locations 58% agreement was considered acceptable.

Two other topographic indices, elevation and relative relief, were also derived from the DEM for the study area. The relative relief was calculated using 'deviation from the mean' statistics that were compared with the O'Donnell land unit and the Ord-Bonaparte land unit descriptions to develop three cut-off points for channels, plains (<0.24667), pass, plains, low hills, moderate hills (-0.24667 to – 0.007367) and moderate hills, high hills, plains (>-0.007367) (refer to Section 5.2.1). The elevation dataset was developed by categorising the DEM into three 100 m intervals; 100 m, 200 m and 300 m, and saving as a new raster.

All datasets were saved with a 30 m resolution, using the coordinate system of Geocentric Datum of Australia 1994 (GDA94) and the projected Map Grid of Australia (MGA52) zone 52.

In conclusion, a SRTM DEM was used to produce landform, elevation and relative relief evidence variable data for the study area. The final landscape variable datasets available for the land unit prediction model now consisted of vegetation, geology, landforms, elevation and relative relief.

8.1.2 Review of predictive model techniques for Bow River Station study area

An aim of this research was to investigate models to predict land unit scale data that could be used to increase the accuracy of land condition monitoring in WA pastoral rangelands by using landform information. Up until the early 1990's most pastoral rangeland monitoring was aimed at understanding vegetation growth and growth dynamics, including studies to record rangeland condition and trend analysis. Many areas of the pastoral leases are remote with limited access. This was the driving force behind using remote sensing and geospatial techniques in the Pastoral Lease Assessment using Geospatial Analysis (PLAGA) project. One of the limitations of geospatial analysis is quality of data boundaries, where if the scale of data is too heterogeneous, detection of vegetation and landscape degradation becomes less accurate, creating the need for higher resolution data that is more homogenous. Three predictive modelling techniques for upscaling land system data were tested as part of this research; a Binary Weighted Overlay (BWO) model, that used binary data values, and a Fuzzy Weighted Overlay (FWO) model that used subjective fuzzy data values and a Positive Weights of Evidence (PWofE) model that also used *prior* probabilities of evidence classes, *prior* probabilities of land units and subjective conditional probabilities and is a 'special case' of a Weights of Evidence (WofE) model. The datasets developed in Chapter 5, were used as landscape evidence variables in the land unit prediction models.

The three modelling techniques were tested and comparisons were made to find the most suitable prediction model for the study area, as an example of the pastoral rangelands. The models were initially tested on the Antrim and Wickham land systems. These land systems were chosen primarily due to their statistical variation of land unit proportions, but also due to their different geographical locations in the study area. The Antrim land units have uneven proportions, whilst Wickham land units are more evenly proportioned. The results from the modelling techniques were checked by confirmation analysis, using ROC plots and contingency tables, in Chapter 7.

The methodology of the BWO model converted the multi-classed landscape variable raster data to binary rasters, with evidence classes favouring a land unit allocated a value of ‘1’ and all other classes allocated a value of ‘0’. The results for this model showed linear clustered patterns for the drainage units (refer to Figures 6.9 and 6.13 for Antrim and Wickham land systems respectively). Using ROC plots, the BWO model performed best for the Wickham land system, with 4 out of the 8 land units having AUC values greater than 0.7, which according to the traditional academic point system (refer to Table 7.6), suggests a greater than ‘fair’ prediction accuracy. Model validation using contingency tables also showed that the BWO model performed best overall for Antrim land system with 64.5% of land units predicted correctly.

The FWO model used available data and information to derived fuzzy values ranging between ‘0’ and ‘100’. The fuzzy values allowed the likelihood of small evidence feature classes to be allocated a value and have a slight chance of favouring a predicted land unit. The results for the FWO model are shown in Figures 6.18 and 6.22 (refer to Section 6.3) for Antrim and Wickham land systems, respectively. The results show that there are linear clustered patterns evident for the drainage units, with the distribution of the remaining predicted land units varied between the two land systems. ROC plot analysis found that the FWO model produced the best results for Antrim land system, with 3 out of 4 land units having an AUC value greater than 0.7, suggesting a better than ‘fair’ prediction result. Contingency tables showed that the FWO model performed well for land unit 317Wk_3 (WLU3) with 58% of the pixels correctly predicted, but also showed that overall the FWO model performed poorly overall for both land systems.

The PWofE model used Sufficiency ratios (LS) to find the ‘most likely’ land units for the Antrim and Wickham land systems. The LS were found using *prior* probabilities for the landscape evidence classes (E*nj*), prior probabilities for land units (LU*i*) and subjective conditional probabilities P(LU*i*|E*nj*). The results for the PWofE model show clustered patterns for the main land units of Antrim land system (refer to Figure 6.29), however no linear patterns for the drainage units were found. In comparison, the results of the model for Wickham land system (refer to Figure 6.32) did show linear clustered patterns for the drainage units. ROC plot analysis found that the PWofE model performed similarly for both Antrim and Wickham land systems, with AUC values mostly less than 0.7, suggesting ‘fair’ to ‘poor’ accuracy. However, the contingency tables suggested that the

PWofE model performed well for a few individual land units of both Antrim and Wickham, and performed best overall for the Wickham land system with only 19.4% accuracy.

A third land system, O'Donnell, used to test the three modelling techniques since it was the only land system with contemporary field data that could be used for ground truth accuracy analysis. The results for O'Donnell land system (refer to Appendix 9) show that the BWO model produced slight linear clustered patterns for the drainage units, which did not appear using the FWO and PWofE models. ROC plot analysis showed that the FWO model performed best, with 2 out 4 AUC values greater than 0.7, suggesting better than 'fair' accuracy. However, contingency tables suggested that the BWO model was best suited to modelling of the O'Donnell land system, but with only 28.6% overall accuracy (refer to Table 7.20). O'Donnell land system was the only land system with sufficient contemporary field data to compare the model results for accuracy. The comparison found that the BWO model produced the best accuracy with 12 out of the 20 field points matching the predicted 'most likely' land unit results, giving 60% accuracy.

Overall, confirmation analysis found that the BWO model performed best with accuracy ranging from 'fair' to 'excellent' for land systems of BRS study area. The accuracy did however vary between the land systems. This may suggest that different modelling techniques are suited to different land systems and/or areas. Similar concerns were identified for results from the PLAGA project, where an 'optimal' vegetation index was found to change in relatively small geographic space between adjacent land systems (Robinson 2012). The predicted 'most likely' land unit results from this research can only be considered an estimate of land units for the land systems in the study area.

Binary overlays have been used in the past to aid site selection problems, such as the example given in Section 6.2, where a number of variables were ranked as suitable and not suitable. The results from that example, found that in comparison with a fuzzy model, that the results of the binary overlay model were more successful. Both model results were checked for accuracy using field data, and it was found that the fuzzy model had doubled the percentage of output results than those observed in the field when compared with the binary model. The fuzzy model was also found to over-predict unsuitable sites.

This research focused on three land systems for Bow River Station, in the East Kimberley Region of WA, with results suggesting that modelling techniques varied between land units and land systems. The variability makes it difficult to suggest a suitable model to predict land units outside the three tested land systems.

8.2 Recommendations

This research aimed to increase the accuracy of land condition monitoring in pastoral rangelands of Western Australia (WA) by developing land unit scale data using spatial science and GIS technologies. The methodologies and techniques used in this research are proposed to support future studies in the subjects of landscape unit mapping, land surface prediction modelling and land condition monitoring.

8.2.1 Optimising landscape variable datasets

Landscape variable data for the WA rangelands is currently published at land system scale (1:50,000), and only in some places at a land unit scale (1:10,000). The landscape variable data available for this research were a geology dataset at 1:100,000 scale, and a vegetation dataset at 1:250,000 scale. All other landscape variables were developed using a hydrologically enhanced Shuttle Radar Topographic Mission (SRTM) Digital Elevation Model (DEM), with 30 m resolution (refer to Section 4.4.2), that was developed to support many applications including the study of landforms in arid and low relief areas of Australia (Gallant 2010).

Landscape variables that were derived using the hydrologically enhanced DEM included landforms, elevation and relative relief datasets. The detail and resolution of the classification were dependent on the 30 m resolution of the DEM, which provided a good resolution to identify and classify most features, however features less than 30 m were combined with adjacent features. This may have limited the detail of landscape variable classes that would ultimately be used in land unit prediction modelling. Landform features greater than 30 m were less effected by the DEM resolution, however the classification of these features could have included misclassified minor landforms. Higher resolution data could have improved landform classification by identifying minor landform features. It is recommended that any future landform classification use higher resolution DEM data, should it be available.

LandSerf software provided acceptable classification of landforms for this research, with 58% agreement (refer to Section 5.4.1) between results and the limited field data, and therefore could be used to classify landforms outside of the study area, in other remote areas of pastoral rangelands. LandSerf is cost-effective and runs on most operating system platforms. LandSerf is suited to geomorphometric analysis, allowing visual control and interpretation, and performs semi-automated landform classification, with both raster and vector input and output capabilities. However, the limitation of LandSerf is that it is a specialised software package focusing almost solely on geomorphometric analysis, it has limited memory management which impedes performance, and limits the size of data that can be processed at one time.

Other landscape variables used as evidence layers in this research included vegetation. Vegetation varies across the WA pastoral rangelands, with grasslands and vegetation in the northern regions adapted to monsoonal weather patterns, whilst further inland vegetation trend towards arid scrub adapted to the four calendar-based seasons. Mapping vast areas such as the pastoral rangelands of WA requires knowledge of the vegetation types and seasonal variability. Recommendations for future vegetation data sources include extensive field surveys and satellite imagery for both the wet and dry seasons for consecutive years, such as imagery collected by Landsat. Landsat represents the world's longest continuously acquired collection of remote sensing data, that can be used for work in the fields including agriculture, geology and global change research (Survey 2018).

Soil is a major component of the information in a land unit. Soil data is largely related to the underlying geology and bedrock material however climate also plays a major part especially in monsoonal zones. Soils are degenerated rocks that are either *in situ* or have been transported over small or large distances. Soils differ in chemistry of minerals and also differ in organic material. These differences are what allow different vegetation types to flourish or non-exist in certain areas. Depth of soil cover also produces variation in vegetation types. Analysing the source of parent material for soils can be difficult and almost impossible using solely remote sensing and geographic analysis techniques. The Geological Survey of Western Australia (GSWA) is developing techniques using terrain studies that focus on mapping underlying geology hidden beneath the overlying regolith. These technologies include state-wide airborne magnetic and radiometric coverage with approximately 400 m-line spacing. Data from that programme may be of use to future research (Beardsmore 2014). Soil analysis is identified as a great challenge in traditional remote sensing and identification is sometimes misleading due to colour variation seen in satellite imagery and aerial photographs. Soils in northern Western Australia often have a ferruginous coating or vegetation-related humus layer. Soil classification and analysis still requires a degree of field reconnaissance.

Object Based Image Analysis (OBIA) software has been suggested as a technique for future landform/landscape variable classification. OBIA software packages are not focused solely on geomorphometric analysis, allowing not only classification of landforms but also other landscape variables such as vegetation. OBIA uses a variety of data that can be used as a 'training set', where colours, shapes, textures and heights of features can be included in the classification process. OBIA also has advantages with semi-automated classification because it takes account not only of the attribute information in data layers but also considers the spatial arrangement and the proximity of those attributes, it also reduces human error by decreasing manual classification, and facilitates comparisons of results derived from other methods. OBIA also has limitations that were relevant to this research. OBIA using software such as eCognition (2009) is expensive since it requires considerable amounts of training data to perform supervised classification effectively. In this situation that data would have had to be collected by field work which was limited by the amount of funding that was provided by the Australian Research Council (ARC) linkage project – LP0882689.

Finally, field data is still one of the best methods for acquiring data and for mapping pastoral rangelands, especially for landscape variable features such as soil and geology.

Although field surveys are time consuming, expensive and can impinge on the natural ecosystems, they do however provide invaluable information on spatial variability, seasonal variations (vegetation) and minor land surface features. Field mapping is important for land surface features because often land unit elements are comprised of landscape variables with varying dimensions. According to Speight (2009b) a small area of land is known as a site, which can represent land surface features such as landforms, vegetation and soils. Of these features, different dimensions apply when considering mapping their extent, for example landform patterns might be measurable over a circle of 300 m radius compared with a soil body that might be smaller than 10 m radius. These differences in dimensions can lead to estimations or missed features when using remote sensing techniques, such as details when classifying landscape variables using a DEM with a 30 m scale.

Although a field trip was included as part of this research, it is recommended that in future research more field data be collected for study areas. The inclusion of more field data would improve understanding of the local area, increase landscape variable resolution available for pastoral rangeland prediction modelling, and would increase ground truth data for confirmation analysis.

8.2.2 Impact of spatial data on future predictive modelling

There is an underlying model of interconnectivity between landscape variables that was used as a hypothesis for the land unit prediction models. The assumption was made (refer to Section 3.1) that two or more landscape variables (i.e. geology and landforms) could be used to predict land unit scale data, however if only two landscape variables were used, then the reasoning behind the position would be compromised because not all elements that describe a land unit would have been included in the prediction calculation.

This research found that the BWO model produced the best overall accuracy using a binary value system for landscape variables to predict the interconnectivity of land units. The BWO results suggested that sometimes, as with example given in Section 6.2 for predicting wildfires (Rios-Pena 2017), a simple binary additive model may be all that is required. A recommendation for improving the BWO prediction model would be to include higher resolution landscape data, with the inclusion of field observations.

The limitations for pastoral lease monitoring in WA essentially stem from the lack of available high-resolution landscape variable data, which essentially would consist of a higher degree of homogeneity of landscape variable classes than those of currently mapped land systems for WA pastoral leases. Land system boundaries are mapped for all of the WA pastoral rangelands, with only a small proportion of pastoral rangelands mapped at a land unit scale. Generally, land systems are too low resolution to provide relevant decision-making information for pastoral lease assessments. The limitation of low-resolution data impacts advances in geospatial analysis monitoring by incorrectly estimating rangeland conditions, including vegetation cover. These incorrect estimations of rangeland conditions therefore impact other geospatial monitoring techniques such as Pastoral Lease Assessment using Geospatial Analysis (PLAGA) (refer to Section 1.2).

By improving the accuracy of rangeland condition monitoring in remote areas such as pastoral rangelands, allows continual improvements of agricultural practices, that are important to human survival. Land condition monitoring is important because it provides strategies to prevent and/or limit degradation of native flora and fauna, that helps protect vegetation, soil stability, landform stability, ecosystem balance, ecology and biodiversity.

Recent strategies have been implemented by many agencies and organisations to aid landscape conservation and guidance on how to conduct and coordinate climate adaptation planning associated with climate change (Theobald 2015). Immediate climate change in semi-arid rangeland regions of WA are predicted to be relatively small in comparison to natural variability, according to CSIRO climate change prediction modelling (CSIRO 2015). The relatively small predicted effects of climate change in these regions is due to two competing processes: an increase in atmospheric moisture associated with high temperatures favouring an increase in rainfall during the wet season, and, the slowing down of tropical circulation systems favouring a decrease in rainfall during the wet season. There are three main drivers to these effects in these semi-arid monsoonal rangeland regions of Australia, they are climate, fires and agricultural practices, including pastoral grazing by cattle and other herbivores. Greenhouse gases emitted in these regions include carbon dioxide, methane, carbon monoxide, nitrous oxide and other oxides of nitrogen, mostly contributed by herbivore grazing on woody vegetation, termites and other detritus feeders and fires. Recommended management strategies for the environment and land use in the rangeland regions include, reducing grazing livestock, halt clearing of woody vegetation and reduce the frequency of fires (Howden 1994).

Other climate management strategies to reduce greenhouse gases could include land unit prediction models incorporated in land conditional monitoring, allowing informed decisions of areas suitable for future land resource opportunities such as agroforestry. Agroforestry is an integrated agriculture and forestry production system that would help reduce the impact to the land and reduce accumulation of greenhouse gases in the atmosphere (Booth 1994). Increased land information and data would aid successful agroforestry systems, where success relies on identifying suitable trees for different geographical areas and ecosystems.

Methods to improve land-resource mapping and spatial landscape monitoring is not exclusive to WA, with previous studies conducted in the Ord River Catchment and Murray-Darling Basin (refer to Section 2.2). Spatial methods tested in this research, could be applied to rangelands of similar ecology, geology and climate, including those of southern Africa where good rangeland practices are seldomly enforced, and where access to areas are limited due to remoteness. However, to achieve high accuracy prediction models for any region both within and outside of the scope of this research, land unit scale data is suggested to present high resolution and be well supported by relevant field work for targeted resource.

Finally, rangelands cover approximately 87% of WA, with pastoral rangelands consisting 40% of that area for grazing livestock (Fletcher 2018). Rangelands are an important economic, ecological and cultural resource for both indigenous and non-indigenous populations, that require monitoring and conservation for future generations.

REFERENCES

2009. Definiens eCognition Developer 8 - User Guide. Trappentreustr. 1 D-80339 Munchen, Germany: Definiens AG.

Beardsmore, T.J. 2014. "GSWA's mineral systems research - helping to discover tomorrow's resourses." *GSWA 2014 extended abstracts: promoting the prospectivity of Western Australia.* Record 2014/2:5-9.

Bezdek, J.C. 1994. "Editorial: Fuzzy models - What are they, and why?" In *Fuzzy Logic Technology and Applications*, edited by R.J. Marks. New Jersey: The Institute of Electrical and Electronics Engineers, Inc. .

Blaszczynski, J.S. 1997. "Landform characterisation with geographic information systems." *Journal of Photogrammetry and Remote Sensing* 63 (2):183-191.

Bonham-Carter, Graeme. 1994. *Geographic information systems for geoscientists : modelling with GIS*. 1st ed. Vol. 13, *Computer methods in the geosciences*. New York: Pergamon.

Booth, T.H. 1994. "Determining the climatic requirements of trees suitable for agroforestry." Climate change: Significance for Agriculture and Forestry, Canberra, Australia.

Brown, D., Mountain, D., and Wood, J., . 2008. Automated and Subjective Terrain Feature Extraction: A Comparative Analysis

Brown, S.R., and Scholz, C.H., . 1986. "Broad Bandwidth Study of the Topography of Natural Rock Surfaces." *JGR* 90:12,575-12,582.

Bui, E. N., and C. J. Moran. 2003. "A strategy to fill gaps in soil survey over large spatial extents: an example from the Murray-Darling basin of Australia." *Geoderma* 111 (1-2):21-44.

Bui, E. N., Moran, C.J. and Simon, D.A.P. 1998. New geotechnical maps for the Murray-Darling basin. In *Technical Report 42/98*, edited by CSIRO Land and Water. Canberra: CSIRO Land and Water.

Bureau of Meteorology. 2010. "Bureau of Meteorology, Australian Government." [Australian Government Website]. Copyright Commonwealth of Australia, accessed June 22. http://www.bom.gov.au/.

Bureau of Meteorology. 2011. "Weatherzone." Fairfax Digital. http://www.weatherzone.com.au/climate/station.jsp?lt=site&lc=2032.

Burrough, P. A. 1986. *Principles of geographical information systems for land resources assessment*. Oxford Oxfordshire: Clarendon Press.

Corcoran, J. 1999. Universe of discourse. In *Cambridge Dictionary of Philosophy*. Cambridge, UP.

Crowley, F. K., and Brian K. De Garis. 1969. *A short history of Western Australia*. 2nd ed. South Melbourne, Vic.: Macmillan.

CSIRO. 2015. Climate Change in Australia - Projections for Australia's NRM Regions. In *Technical Report*, edited by P. Whetton: CSIRO.

de Boer, W.H. 2000. "Fast terrain rendering using geometrical mipmapping." *Flipcode*.

Department of Agriculture, WA. 2005. Metadata Statement. In *Pre-European Vegetation Theme*, edited by WA Department of Agriculture. Western Australia: Department of Agriculture.

Department of Food and Agriculture, Western Australia. 2011. "Department of Food and Agriculture, Western Australia." The Government of Western Australia. http://www.agric.wa.gov.au/.

Department of Lands. 2015a. "Pastoral Rangeland Monitoring." Government of Western Australia, accessed 26/02. http://www.lands.wa.gov.au/Pastoral-Leases/Pastoral-Rangeland-Monitoring/Pages/default.aspx.

Department of Lands. 2015b. "Roles and Functions." Government of Western Australia, accessed 26/02. http://www.lands.wa.gov.au/Pastoral-Leases/Pastoral-Lands-Board/Pages/default.aspx.

Department of Premier and Cabinet. 2015. "Land Administration Act 1997." State Law Publisher, accessed 26/02. http://www.slp.wa.gov.au/legislation/statutes.nsf/main_mrtitle_509_homepage.html.

Department of Regional Development and the North West, and Kimberley Regional Development Advisory Committee (WA). 1986. *Kimberley regional profile Western Australia*. Kununurra, W.A.

Donnelly, G.J. 2012. Fundamentals of Land Ownership, Land Boundaries, and Surveying. edited by Geoscience Australia: Intergovermental Commitee on Surveying and Mapping (ICSM).

Dragut, L., and T. Blaschke. 2006. "Automated classification of landform elements using object-based image analysis." *Geomorphology* 81 (3-4):330-344. doi: DOI 10.1016/j.geomorph.2006.04.013.

Environmental Science Research Institute Inc (ESRI). 1999-2010. "ESRI Desktop Help." Environmental Science Research Institute, Inc (ESRI), accessed July 28, 2010. http://help.arcgis.com/en/arcgisdesktop/10.0/help/index.html#/Understanding_multivariate_classification/009z000000pr000000/.

ArcGIS 10.4 for Server system requirements 10.4 (Feburary 2016). ESRI, USA.

Evans, I. S., and Hengl, T. 2009. "Mathematical and Digital Models of the Land Surface." In *Geomorphometry; Concepts, Software, Applications.*, edited by T. Hengl, and Reuter, H.I. Oxford, UK.: Elsevier.

Fielding, A.H., and Bell, J.F. 1997. "A review of methods for the assessment of prediction errors in conservation presence/absence models." *Environmental Conservation* 24 (1):38-49.

Fletcher, W., Ryan, K., . 2018. "Rangelands of Western Australia." Department of Primary Industries and Regional Development. https://www.agric.wa.gov.au/rangelands/rangelands-western-australia.

Fotheringham, A.S. 2000. "GIS-based Spatial Modelling: A Step Forwards or a Step Backwards?" In *Spatial Models and GIS*, edited by A.S. Fotheringham, and Wegener, M.,. USA and Canada: Taylor & Francis Inc. .

Fowler, R. J., and Little, J. J., . 1979. "Automatic extraction of Irregular Network digital terrain models." SIGGRAPH '79 Proceedings of the 6th annual conference on Computer graphics and interactive techniques

Fraser, Robert, Donald McLennan, Serguei Ponomarenko, and Ian Olthof. 2012. "Image-based predictive ecosystem mapping in Canadian arctic parks." *International Journal of Applied Earth Observation and Geoinformation* 14 (1):129-138. doi: 10.1016/j.jag.2011.08.013.

Gallant, A.L., Brown, D.D. and Hoffer, R.M. 2005. "Automated mapping of Hammond's Landforms." Geoscience and Remote Sensing Letters 2.

Gallant, J. C., Read, A., Dowling, T.I., and Hutchinson, M.F., . 2010. Enhanced digital elevation models from the SRTM data: The Australian experience and global prospects. In *American Geophysical Union*. The Smithsonian/NASA Astrophysics Data System: NASA.

Gallant, J.C. and Wilson, J.P. 2000a. "Primary Topographic Attributes." In *Terrain Analysis; Principles and Applications*, edited by J.C. and Wilson Gallant, J.P., 51-85. USA: John Wiley & Sons.

Gallant, J.C., and Wilson, J.P. 2000b. "Digital Terrain Analysis." In *Terrain Analysis: Principals and Applications*, edited by J.C. and Wilson Gallant, J.P.: John Wiley & Sons, Inc.

Gallant, John, and John Wilson. 1996. *TAPES-G: A grid-based terrain analysis program for the environmental sciences*. Vol. 22.

Geoscience Australia: Department of Resources Energy and Tourism. 2007. "Geoscience Australia

Topographic data and map specifications.". Geoscience Australia, accessed Sept 8, 2010. http://www.ga.gov.au/mapspecs/topographic/v5/section1.jsp#PositionalAccuracy .

Geoscience Australia: Geographic Information. 1993. "Land Tenure." Australian Government, accessed 26/02.

Geoscience Australia: Geographic Information. 2004. "Areas of Australia - States and Territories." Australian Government, accessed 26/02. http://www.ga.gov.au/scientific-topics/geographic-information/dimensions/area-of-australia-states-and-territories.

Goudie, Andrew. 2004. *Encyclopedia of geomorphology*. London: Routledge.

GRASS Development Team, . 2010. "GRASS History." Fondazione E. Mach - Research and Innovation Centre, Last Modified March, 2010, accessed May 20, 2010. http://grass.itc.it/devel/grasshist.html.

Grech, V. 2018. "WASP (Write a Scientific Paper) using Excel - 10: Contingency tables." *Early Human Development* 121:65-68.

Hammond, E.H. 1964. "Analysis of properties in land form geography: An application to broad-scale land form mapping." *New Approaches to the Geography of the United States*:11-19.

Harrington, G. N., M.H. Friedel, K.C. Hodgkinson, and J.C. Noble. 1984. *Management of Australia's rangelands*, edited by G. N. Harrington, A. D. Wilson and M. D. Young, 354p. East Melbourne: Commonwealth Scientific and Industrial Research Organization.

Hart, P.E., Duda, R. O., and Einaudi, M.T., . 1978. "Prospector - A computer-based consultation system for mineral exploration." *Mathematical Geology* 10 (5).

Hengl, T., and D. G. Rossiter. 2003. "Supervised landform classification to enhance and replace photo-interpretation in semi-detailed soil survey." *Soil Science Society of America Journal* 67 (6):1810-1822.

Horn, B.K.P., and Woodham, R.J.,. 1979. "Destriping Landsat MSS by Histogram Modification." *Computer graphics and Image processing* 10:69-83.

Howden, S.M., White, D. H., McKeon, G.M., Scanlan, J.C., and Carter, J.O., . 1994. "Methods for exploring management options to reduce greenhouse gas emissions from tropical grazing systems." Climate change: Significance for Agriculture and Forestry, Canberra, Australia.

Irvin, B. J., and Ventura, S.J. 2000. "Automated Landform Classification Methods for Soil-Landscape Studies." In *Terrain Analysis: Principals and Applications.*, edited by J.P. Wilson, and Gallant, J.C. Canada: John Wiley & Sons, Inc.

Jaafari, A., Gholami, D.M., and Zenner, E.K., . 2017. "A bayesian modeling of wildfire probability in the Zagros Mountains, Iran." *Ecological Informatics* 39:32-44.

Kearey, P. 2001. *The new Penguin dictionary of geology*. 2nd ed, *Penguin reference*. London: Penguin.

Klingseisen, B., Metternicht, G., Paulus, G., and Wilson, D.,. 2016. "Geomorphometric landscape analysis of agricultural areas and rangelands of Western Australia." In *Geopedology*, 361-375. Switzerland: Springer International Publishing.

Kuiper, J.A. and Wescott, K.L. 1999. "A GIS approach for predicting prehistoric site locations*." The Nineteenth Annual ESRI User Conference, San Diego, California.

Liu, J. G. and Mason, P. J. 2009. Descision Support and Uncertainty. In *Essential Image Processing and GIS for Remote Sensing*, edited by Ltd John Wiley & Sons.

Longley, P.A., Goodchild, M.F., Maguire, D.J. and Rhind, D.W. 2005. *Geographic Information Systems and Science*. Second Edition ed. Chichester, UK: John Wiley & Sons.

Mabbutt, J.A., Litchfield, W.H., Speck, N.H., Sofoulis, J., Wilcox, D.G., Arnold, J.M., Brookfield, M., and Wright, R.L., . 1963. General report on lands of Wiluna-Meekatharra area, Western Australia. In *Land Research Series*, edited by CSIRO. Melbourne, Victoria: Commonwealth Scientific and Industrial Research Organisation.

MacMillan, R.A., and Shary, P.A. 2009. "Landforms and Landform Elements in Geomorphometry." In *Geomorphometry; Concepts, Software and Applications*, edited by T. Hengl, and Reuter, H.I. Oxford, UK: Elsevier.

Malczewski, J. 1999. *GIS and multicriteria decision making*. Edited by University of Western Ontario Department of Geography. Canada: John Wiley & Sons, Inc.

Mandelbrot, B. B. 1977. *Fractals*. Edited by W.H. Freeman. San Francisco, California, U.S.A.

Mather, P. M. 2006. *Computer Processing of Remotely-Sensed Images, An Introduction*. Third ed. West Sussex, U.K.: John Wiley and Sons ltd. .

Matternicht, G., Novelly, P., Watson, I., Beeston, G and Robinson, T. 2007. Pastoral Lease Assessment using Geospatial Analysis, ARC Proposal. edited by Department of Food and Agriculture of Western Australia. Perth.

McDonald, R. C., and Isbell, R.F. . 2009. "Soil Profile." In *Australian Soil and Land Survey Field Handbook*, edited by A. Cloud, 147-200. Collingwood, Victoria: CSIRO Publishing.

McHoes, A., and Flynn, M., . 2014. "Understanding Operating Systems." In, ed A. McHoes, and Flynn, M., . USA: Cengage Learning.

McKenzie, Neil J. 2004. *Australian soils and landscapes : an illustrated compendium*. Collingwood, Vic.: CSIRO Publishing.

McKeon, G. M., Australian Greenhouse Office., Climate Variability in Agriculture R&D Program (Australia), and Queensland. Dept. of Natural Resources Mines and Energy. 2004. *Pasture degradation and recovery in Australia's rangelands : learning from history*, *Qnrme04130*. Indooroopilly, Qld.: Queensland Dept. of Natural Resources, Mines and Energy.

Mitroff, I.I., and Silvers, A., . 2013. "Probabilistic causality." *Technological Forecasting and Social Change* 80:1629-1634.

Murphy, Brendan, and Damian Nance. 1999. *Earth science today*, *The Brooks/Cole earth science and astronomy series*. Pacific Grove, Calif.: Brooks/Cole.

Novelly, P.E. and Thomas, P.W.E.,. 2008/2009. Annual Pastoral Land Conditon Report. edited by Pastoral Land Board of Western Australia. Western Australia: Department of Agriculture and Food, Western Australia.

Payne, A., and Schoknecht, N. 2011. Land systems of the Kimberley Region, Western Australia. edited by DAFWA. Perth: Western Australia Agriculture Authority.

Petheram, R. J., B. Kok, and E. Bartlett-Torr. 2003. *Plants of the Kimberley region of Western Australia*. Rev. ed. Perth, W.A.: University of Western Australia Press.

Pigram, C. 2009. SRTM2-DSM Cover Letter. Canberra: Geoscience Australia.

Pike, R. J. 1993. A bibliography of Geomorphometry, the quantitative representation of topography - suppliment 1.0. edited by U.S. Department of the Interior. Menlo Park, California U.S. Geological Survey.

Pike, R. J., Evans, I.S. and Hengl, T. 2009. "Geomorphometry: A Brief Guide." In *Geomorphometry. Concepts, Software, Applications*, edited by T. and Reuter Hengl, H.I., 3-30. Oxford, UK: Elsevier.

Porwal, A., Carranza, E.J.M., and Hale, M., . 2003. "Knowledge-driven and data-driven fuzzy models for predictive mineral potential mapping." *Natural Resource Research* 12 (1).

Porwal, A., Deb Das, R., Chaudhary, B., Gonzalez-Alvarez, I., and Kreuzer, O. 2015. "Fuzzy Inference systems for prospectivity modeling of mineral systems and a case-study for prospectivity mapping of surficial Uranium in Yeelirrie Area, Western Australia." *Ore Geology Reviews* 71:839-852.

Prince, B. 2009. Managing the East Kimberley rangelands. edited by Department of Land and Water. Kununura: Australian Government.

Qui, F., Chastain, B., Zhou, Y., Zhang, C., and Sridharan, H., . 2014. "Modeling land suitablility/capability using fuzzy evaluation." *GeoJournal* 79:167-182.

Rhoads, B. L., and C. E. Thorn. 1993. "Geomorphology as Science - the Role of Theory." *Geomorphology* 6 (4):287-307.

Rios-Pena, L., Kneib, T., Cadarso-Suarez, C., and Marey-Perez, M.,. 2017. "Predicting the occurrence of wildfires with binary structured additive regression models." *Journal of Environmental Management* 187:154-165.

Robinson, T. P., Novelly, P., Corner, R., Thomas, P., and Russell-Brown, A., . 2012. Pastoral lease assessment using geospatial analysis. Department of Food and Agriculture, Western Australia.

Rogness, J. and Nykamp, D.Q., . 2016. "Quadric surfaces." http://mathinsight.org/quadric_surfaces.

Rowe, W.D. 1994. "Understanding Uncertainty." *Risk Analysis* 14 (5).

RuleQuest Research. 2015. "Data Mining Tools See5 and C5.0." accessed February 2. www.rulequest.com/see5-info.html.

Russell, P.J. 2007. "Assessing Long-Term Change in Rangeland Ecological Health using the Western Australian Rangeland Monitoring System."Doctorate, Muresk Institute, Centre for the Mangement of Arid Environments, Curtin University of Technology.

Ryan, K., Huey, A-M., Fletcher, M. 2015. Assessing rangeland conditions. edited by Department of Agriculture and Food: Government of Western Australia.

Saaty, T.L. 1977. "A scaling method for priorities in Hierarchical Structures." *Journal of Mathematical Psychology* 15:234-281.

Sayles, R.S. and Thomas, T.R., . 1978. "Surface topography as a nonstationary random process." *Nature* 271:431-434. doi: 10. 1038/271431a0.

Schoknecht, N. 2003. Land unit mapping for the Ord and Keep River catchments. edited by Department of Agriculture. Perth, WA: Department of Agriculture.

Schoknecht, N., Tille, P and Purdie, B. 2004. Soil-Landscape Mapping in the South-Western Australia. edited by Department of Agriculture. Perth: Department of Agriculture.

Sen, S., Areedran, G., and Singh, C.K. 2017. Snow leopard habitat modeling using neuro-fuzzy technique and a comparitive analysis between traditional overlay and neuro-fuzzy technique - A case study of Chamoli and Pithorgarh District of Uttarahand. *Environment and Earth Observation*: 247-263.

Speck, N.H., Bradley, J., Lazarides, M., Patterson, R.A., Slatyer, R.O., Stewart, G.A., and Twindle, C.R.,. 1960. The lands and pastoral resources of the North Kimberley area, WA. In *Land Research Series*. Melbourne, Victoria.

Speck, N.H., Lazarides, M., Fitzgerald, K., Perry, R.A., and Thomas, F., . 1964. General report on lands of the West Kimberley Area, WA. In *Land Research Series*, edited by CSIRO: Commonwealth Scientific and Industrial Research Organisation.

Speight, J.G. 1990. *Landform. In Australia Soil and Land Survey Field Handbook*. Hopkins, Melbourne, Victoria: Inkarta Press.

Speight, J.G. 2009a. "Landforms." In *Australian Soil and Land Survey Field Handbook*, edited by The National Committee on Soil and Terrain, 15-72. Canberra, Australia: CSIRO Publishing.

Speight, J.G., and McDonald,R.C., . 2009b. "The site concept." In *Australian Soil and Land Survey Field Handbook*, edited by The National Commitee on Soil and Terrain, 5. Collingwood, Victoria: CSIRO publishing.

Stewart, G.A. 1970. Lands of the Ord-Victoria area, Western Australia and Northern Territory. In *Land Research Series*, edited by CSIRO. Melbourne, Victoria.

Strahler, A.N. 1968. "Slope analysis." In *Geomorphology*, 998-1002. Springer Berlin Heidelberg.

Strahler, A.N. 1992. "Quantitative/dynamic geomorphology at Columbia 1945-60: a retrospective." *Progress in Physical Geography* 16 (1):65-84.

Survey, United States Geological. 2005. "Proposal for Geospatial Positioning Accuracy Standards, Part 3: National Standard for Spatial Data Accuracy." USA.gov, accessed March, 14. http://www.fgdc.gov/standards/projects/FGDC-standards-projects/accuracy/part3/progpas3.

Survey, United States Geological. 2018. "Landsat missions." http://landsat.usgs.gov.

Tape, T.G. 1993. "Likelihood ratios; Interpreting diagnostic tests." http://gim.unmc.edu/dxtests/Default.htm.

Theobald, D.M., Harrison-Atlas, D., Monahan, W.B., and Albano, C.M., . 2015. "Ecologially-relevant maps of landforms and physiographic diversity for climate adaptation planning." *PLOS one*:17. doi: 10.1371.

Thompson, J. A., J. C. Bell, and C. A. Butler. 2001. "Digital elevation model resolution: effects on terrain attribute calculation and quantitative soil-landscape modeling." *Geoderma* 100 (1-2):67-89.

Tyler, I. 2000. *Geology and Landforms of the Kimberley*. Kensington, Perth, WA: Department of Conservation and Land Management. Original edition, 1996.

United States Geological Survey. 2011. "EarthExplorer." USA.gov, accessed Jan 2011. http://edcsns17.cr.usgs.gov/EarthExplorer/

Van Gool, D., Tille, P., and Moore, G. . 2005. Land Evaluation Standards for Land Resource Mapping. edited by Department of Agriculture. Perth: State of Western Australia.

Van Vreeswyk, S., and Thomas, P. 2008. Annual Pastoral Land Condition Report; 2006/2007 Financial Year. edited by Western Australia Department of Food and Agriculture. Perth, WA: Department of Food and Agriculture, Western Australia.

Wardrop, M. 2009. "Aborginal Art Online." Aboriginal Art Online Pty Ltd.

Wegener, M. 2000. "Spatial Models and GIS." In *Spatial Models and GIS: New Potential and New Models*, edited by A.S. Fotheringham, and Wegener, M., . USA and Canada: Taylor & Francis Inc.

Western Australia Land Information Authority. 2011. "Landgate." The Government of Western Australian http://www.landgate.wa.gov.au/corporate.nsf.

Wood, J. 2007. Modelling Surfaces. In *Geographic Information Science*. City University London.

Wood, J. 2009a. "Geomorphometry in Landserf." In *Geomorphometry; Concepts, Software and Applications*, edited by T. and Reuter Hengl, H.I. Oxford, UK: Elsevier.

Wood, J. 2009b. "Landserf 2.3 Tutorial." Last Modified April 20, 2009, accessed Sept 23, 2010. http://www.soi.city.ac.uk/~jwo/landserf/landserf230/doc/tutorial/index.html.

Wood, J. 2009c. The LandSerf Manual.

Wood, J. 2009d. "Overview of Software Packages Used in Geomorphometry." In *Geomorphometry: Concepts, Software, Applications*, edited by T. and Reuter Hengl, H.I. Oxford, UK.: Elsevier.

Wood, J.D. 1996. "The geomorphological characterisitics of digital elevation models."Doctorate, University of Leicester.

XD, Definiens Developer. 2009. Definiens eCognition Developer 8 - User Guide. Trappentreustr. 1 D-80339 Munchen, Germany: Definiens AG.

Zadeh, L.A. 1965. "Fuzzy sets." *Elsevier* 8 (3):338-353.

Zhang, J., and Goodchild, M., . 2002. *Uncertainty in Geographic Information*. Edited by P. Fisher, and Raper, J., , *Research Monographs in Geographic Information Systems*. Great Britain, UK: Taylor & Francis Group.

Zonneveld, I.S. 1989. "The land unit - A fundamental concept in lnadscape ecology, and its application." *Landscape Ecology* 3 (2):67-86.

APPENDICES

Appendix 1 – Technical Bulletin land unit tables.

A. Antrim land system

B. Wickham land system

C. O'Donnell land system

*These tables have been altered slightly from the original DAFWA "Technical Bulletin – Land Systems of the Kimberley Region, Western Australia". The table has been divided to include Geology as a separate field. Pasture Type has been omitted.

A. Antrim land system

Percentage (%)	Landform	Soil	Vegetation	Geology
50	Mesas and buttes with steeply sloping margins	Mostly rock outcrops with basalt boulders and pockets of red clayey soils.	Bloodwood-southern box sparse low woodland (Corymbia opaca) with arid short grass (Enneapogon spp.) or upland tall grass (Sorghum stipoideum); snappy gum sparse low woodland (Eucalyptus brevifolia) with hard spinifex (Triodia wiseana, T. inutilis, T. intermedia) or arid short grass (Enneapogon spp.)	Rocky outcrops with basalt boulders. Mesas and Buttes
40	Crests and slopes of rounded hills		As for unit 1 Also tussock grasses such as Sehima nervosum	
5	Moderate to gentle slopes	Frayne - brown loam merging into dark red clay, generally stony on surface	Bloodwood-southern box sparse low woodland (Corymbia opaca, E. limitaris, E. tephrodes), silver-leaved box sparse low woodland (E. pruinosa), or snappy gum sparse low woodland (E. brevifolia), all with arid short grass (Enneapogon spp.)	
2	Gentle lower slopes and flat areas	Cununurra, Argyle, Barkly - grey and brown crackling heavy clays.	Mitchell and other mid-height grasses (Astrebla pectinata, Aristida latifolia).	
2	Flats bordering drainage lines	Variable light to medium textured alluvial soils	Frontage woodland (C. opaca, C. bella) with arid short grass (Enneapogon spp.) or frontage tall grasses.	
1	Stream channels		Fringing communities	

B. Wickham land system

Percentage (%)	**Landform**	**Soil**	**Vegetation**	**Pasture Type**
20	Structural plateaux of sandstone or quartzite with deep V-shaped gorges	Rock outcrop and shallow sandy skeletal soil	Snappy gum sparse low woodland (Eucalyptus brevifolia) with soft spinifex (Triodia pungens, T. bitextura)	CAHP 90, HSHP 10
20	Structural plateaux with benches, formed on interbedded limestone, shale and sandstone	As for unit 1	As for unit 1	CAHP 90, HSHP 10
10	Mesas, capped by hard sandstone overlying soft shales	As for unit 1	As for unit 1	CAHP 90, HSHP 10
20	Cuestas formed on interbedded hard sandstone over shales	As for unit 1	As for unit 1	CAHP 90, HSHP 10
20	Hogbacks and ridges	As for unit 1	As for unit 1	CAHP 90, HSHP 10
4	Lower gentle slopes	Elliot - grey loam merging into	Bloodwood - southern box sparse low woodland (Corymbia opaca, E. limitaris, E. tephrodes, C. confertiflora) or silver-leaved box (E.	TAPP 50, CSPP 50

		yellow clay; some Tobermorey - shallow calcareous loamy soils	pruinosa) sparse low woodland, both with threeawn mid-height grass (Aristida pruinosa, A. browniana, Chrysopogon fallax) or arid short grass (Enneapogon spp., Aristida spp.)	
3	Gentle slopes adjacent to streamlines	Elliot and miscellaneous alluvial soils	As for unit 6	TAPP 50, CSPP 50
3	Stream channels		Fringing communities	FRIP

C. O'Donnell land system

Percentage (%)	Landform	Soil	Vegetation	Pasture Type
12	Hills and ridges: less than 60 m high; benched slopes up to 70%, locally vertical, and basal scree slopes up to 35%	Outcrop with limited areas of reddish, shallow, gravelly skeletal soil (24)	Open snappy gum woodland with Triodia bitextura. Eucalyptus brevifolia community (1d)	CAHP
12	Hill-footslopes: concave, up to 10%, and less than 400 m long; oputcrop and cobble debris in upper parts, colluvial mantles in lower parts	OUtcrop with reddish skeletal soil (24) some shallow red sands: Cockatoo family (7)	Mixed grasslands with scattered trees and shrubs. Local bare patches. Chrysopogon spp. Dichanthium fecundum and Enneapogon spp. Communities (48, 61)	RGRP 50, ASGP 50
51	Interfluves: flat or gently sloping crests up to 1% and 1.6km wide, with marginal slopes up to 2%; cobble mantles and local outcrop	Outcrop, with reddish sandy and loamy skeletal soils (24) with shallow brownish sands and loams over red clay: Moonah family (17)	Very open grassy woodland with Enneapogon spp. And other short grasses. E. brevifolia community (1f)	ASGP

6	Crackling clay plains: less than 1% and 3.2km wide; hummocky surfaces	Dark brown self-mulching clays: Wonardo family (14)	Mitchell grass and ribbon grass-bluegrass grasslands with sparse trees and shrubs. Astrebla spp. And Chrysopogon spp., Dichantium fecundum and Chrysopogon spp. Communites (47, 48, 49)	MGAP 50, RAPP 50
10	Alluvial drainage floors: up to 400 m wide with gradients 1 in 100 to 1 in 400; sandy surfaces with pebble patches	Complex of greyish to brownish sands and loams over tough domed clays: Jurgurra family (19). Mottled yellowish sandy to loamy soils: Elliott family (6). Clayey alluvial soils: Fitzroy family (22)	Mixed grasslands as in unit 2	RGRP 50, ASGP 50
9	Channels: up to 90 m wide and 4.5m deep	Channels, bed-loads range from deep sand to cobbles. Banks, brownish loamy alluvial soils: Robinson family (21)	Open woodland fringing community with patches of frontage grasses. E. camaldulensis community (40)	FRIP 50, FRGP 50

Appendix 2 - Ord-Bonaparte Program land unit tables.

A. Antrim land system

B. Wickham land system

C. O'Donnell land system

A. Antrim land system

Land unit	Summary Description	Landform	Geology	Soil	Vegetation	Name
317An_4	Low hills, mesas and associated upper slopes with much rock outcrop on basalt. Mostly rock outcrop with basalt boulders; pockets of red loamy and clayey soils.	Low hills, mesas and associated upper slopes with much rock outcrop	basalt	Mostly rock outcrop with basalt boulders; pockets of red loamy and clayey soils	Sparse Corymbia terminalis and Eucalyptus argillacea woodlands with arid short grasses or E. brevifolia woodlands with hard spinifex	Antrim hill and mesa subsystem
317An_5	Gently to moderately sloping lower footslopes and very low rises on basalt. Brown or red stony loams merging to clay.	Gently to moderately sloping lower footslopes and very low rises	basalt	Brown or red stony loams merging to clay	Corymbia terminalis, Eucalyptus argillacea or E. brevifolia sparse woodland with arid short grasses	Antrim footslope subsystem
317An_6	Gentle lower slopes and level plains on basalt. Grey and brown cracking clay soils.	Gentle lower slopes and level plains	basalt	Grey and brown cracking clay soils	Grasslands of Astrebla spp., Dichanthium fecundum and Chrysopogon fallax with occasional small bauhinia and terminalia trees	Antrim plains subsystem
317An_8	Narrow drainage floors and channels on basaltic alluvium. Variable red alluvial soils including red sandy earths and red loamy earths.	Narrow drainage floors and channels	basaltic alluvium	Variable red alluvial soils including red sandy earths and red loamy earths	Eucalypt woodlands and perennial grasses Chrysopogon fallax and Dichanthium fecundum and fringing woodlands with coarse perennial grasses and sedges	Antrim drainage floor subsystem

B. Wickham land system

Land unit	Summary Description	Landform	Geology	Soil	Vegetation	Name
316Wk_3	High hills ridges and plateaux and associated steep slopes and benches on sandstone and shale. Much rock outcrop and pockets of shallow sandy skeletal soils.	High hills ridges and plateaux and associated steep slopes and benches	sandstone and shale	Much rock outcrop and pockets of shallow sandy skeletal soils	Sparse low woodlands of Eucalyptus brevifolia and Corymbia species with Triodia bitextura and annual sorghum	Wickham high hills subsystem
316Wk_4	Low undulating to steep hills and ridges on sandstone. Shallow sands and loams and loamy earths.	Low undulating to steep hills and ridges	sandstone	Shallow sands and loams and loamy earths	Sparse low woodlands of Eucalyptus brevifolia and Corymbia species with Triodia bitextura and annual sorghum	Wickham low hills subsystem
317Wk_3	High hills ridges and plateaux and associated steep slopes and benches on sandstone and shale. Much rock outcrop and pockets of shallow sandy skeletal soils.	High hills ridges and plateaux and associated steep slopes and benches	sandstone and shale	Much rock outcrop and pockets of shallow sandy skeletal soils	Sparse low woodlands of Eucalyptus brevifolia and Corymbia species with Triodia bitextura and annual sorghum	Wickham high hills subsystem
317Wk_4	Low undulating to steep hills and ridges on sandstone. Shallow sands and loams and loamy earths.	Low undulating to steep hills and ridges	sandstone	Shallow sands and loams and loamy earths	Sparse low woodlands of Eucalyptus brevifolia and Corymbia species with Triodia bitextura and annual sorghum	Wickham low hills subsystem
317Wk_5	Gentle lower slopes on sandstone. Shallow sands and loams and loamy earths.	Gentle lower slopes	sandstone	Shallow sands and loams and loamy earths	Sparse woodlands of Corymbia terminalis, Eucalytpus argillacea, E. pruinosa with perennial grasses	Wickham lower slope subsystem

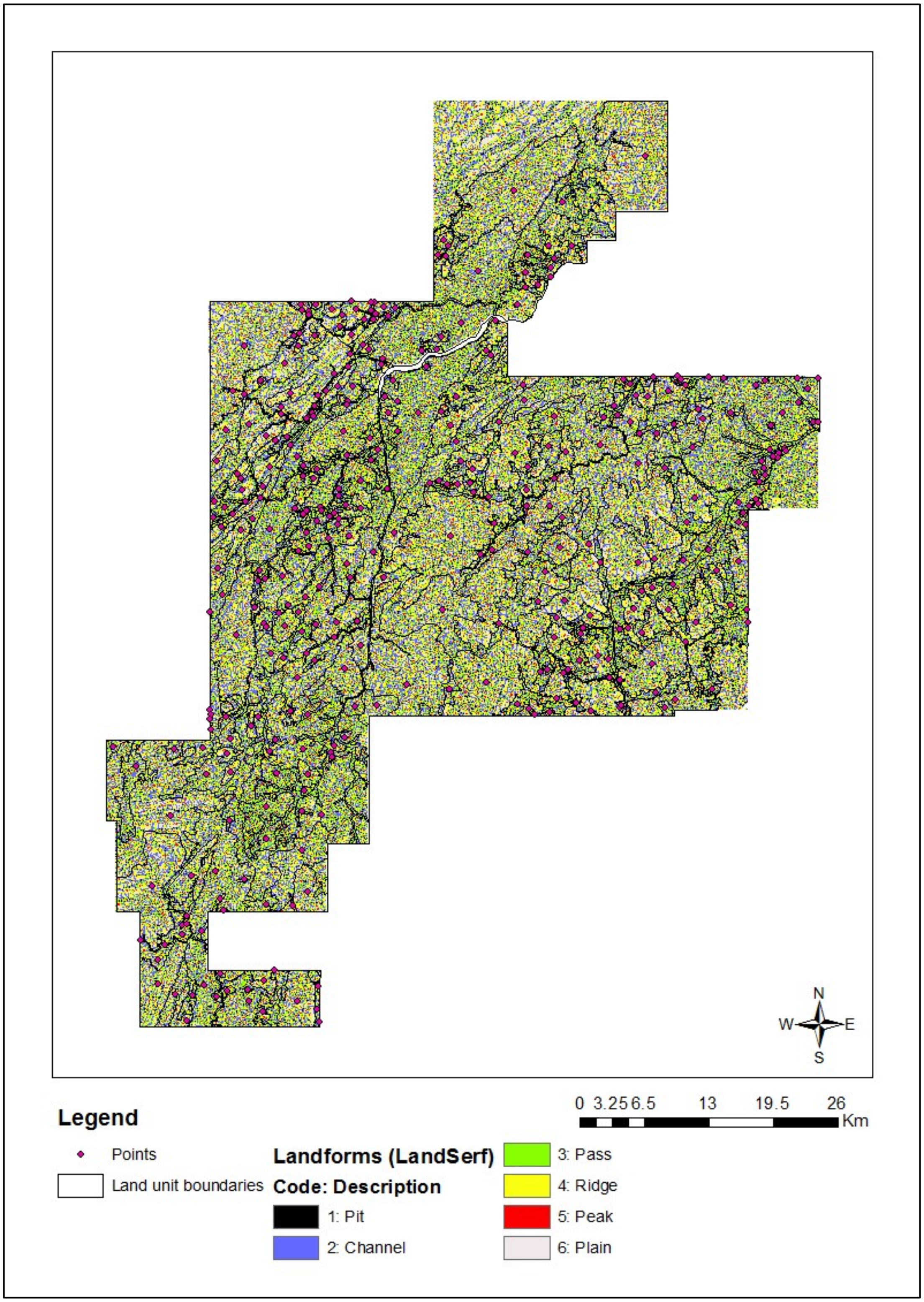
					Aristida spp. Chrysopogon fallax, Triodia bitextura	
317Wk_8	Narrow drainage floors, gentle slopes and streamlines on alluvium from sandstone and quartzite and minor sandstone outcrop. Yellow and brown sands of variable depth, often cobbly in streamlines.	Narrow drainage floors, gentle slopes and streamlines	alluvium from sandstone and quartzite and minor sandstone outcrop	Yellow and brown sands of variable depth, often cobbly in streamlines	Eucalypt woodlands with Aristida spp. mid-height grasses and Chrysopogon fallax. Also, eucalypt, terminalia and melaleuca grassy fringing woodlands	Wickham drainage subsystem
344Wk_3	High hills ridges and plateaux and associated steep slopes and benches on sandstone and shale. Much rock outcrop and pockets of shallow sandy skeletal soils.	High hills ridges and plateaux and associated steep slopes and benches	sandstone and shale	Much rock outcrop and pockets of shallow sandy skeletal soils	Sparse low woodlands of Eucalyptus brevifolia and Corymbia species with Triodia bitextura and annual sorghum	Wickham high hills subsystem
344Wk_8	Narrow drainage floors, gentle slopes and streamlines on alluvium from sandstone and quartzite and minor sandstone outcrop. Yellow and brown sands of variable depth, often cobbly in streamlines.	Narrow drainage floors, gentle slopes and streamlines	alluvium from sandstone and quartzite and minor sandstone outcrop	Yellow and brown sands of variable depth, often cobbly in streamlines	Eucalypt woodlands with Aristida spp. mid-height grasses and Chrysopogon fallax. Also, eucalypt, terminalia and melaleuca grassy fringing woodlands	Wickham drainage subsystem

C. O'Donnell land system

Land unit	Summary Description	Landform	Geology	Soil	Vegetation	Name
312Od_5	Gently undulating to rolling rises on granite. Red or brown sandy duplexes with minor stony soils and occasional outcrop.	Gently undulating to rolling rises	granite	Red or brown sandy duplexes with minor stony soils and occasional outcrop	Open woodland of Eucalyptus brevifolia and Corymbia dichromophloia with occasional Bauhina cunninghamii and Carissa lanceolata	O'Donnell granitic rises subsystem
312Od_6	Level to undulating low plains on granite. Red or brown shallow loamy or sandy duplexes and red sandy or loamy earths.	Level to undulating low plains	granite	Red or brown shallow loamy or sandy suplexes and red sandy or loamy earths	Woodland of Corymbia dichromophloia and Eucalyptus brevifolia with other trees and shrubs such as Terminalia arostrata and Carissa lanceolata and an	O'Donnell granitic plains subsystem
312Od_7	Level to undulating gilgai plains on alluvium. cracking clays with or without self-mulching surfaces with gilgai micro-relief.	Level to undulating gilgai plains	alluvium	cracking clays with or without self-mulching surfaces with gilgai micro-relief	Grasslands of Chrysopogon fallax, Dichanthium fecundum and Aristida latifolia with scattered trees of Terminalia arostrata and Bauhinia cunninghamii	O'Donnell gilgai rises subsystem
312Od_8	Drainage floors and channels on alluvium. Alluvial soils.	Drainage floors and channels	alluvium	Alluvial soils	Woodland of mixed Eucalyptus pruinosa and E. spp with Carissa lanceolata common and an understorey of tussock grasses	O'Donnell drainage floor subsystem

					including Themeda triandra,	

Appendix 3 - 100 Random points for landform classification accuracy analysis.


N
W
E
S
0 3.25 6.5 13 19.5 26
Km
Legend
Points
Land unit boundaries
Landforms (LandSerf)
Code: Description
1: Pit
2: Channel
3: Pass
4: Ridge
5: Peak
6: Plain

Appendix 4 - Comparison between field data and land unit descriptions (including photos).

Waypoint	Field Description	Field Photos	Land unit	Land unit landform description	Agree/Disagree
021	Plain – high ground, long grasses.		312Od_8	Drainage floors and channels	Disagree
024	Plain – sparse cypress and eucalyptus, perennial grasses.		312Od_7	Level to undulating gilgai plains	Agree
022	Pit – Boab trees¸ cypress trees and some wild plums, surrounded by granite covered boulder hills.		312Od_7	Level to undulating gilgai plains	Disagree
002	Drainage (Creek bed) – granite, eucalyptus trees in drainage, perennial grass.		312Od_6	Level to undulating low plains	Disagree
020	Drainage – Boab trees, marshy.		312Od_6	Level to undulating low plains	Disagree
025	Drainage – 'Sandy Creek', surrounded by scrub vegetation (various).		312Od_8	Drainage floors and channels	Agree
026	Plain – two Boab trees.		312Od_8	Drainage floors and channels	Disagree

003	Drainage – Eucalyptus, reeds, tall grasses, granite float, surrounded by rolling hills.		312Od_6	Level to undulating low plains	Disagree
019	Pass – granite boulders and float, sparse eucalyptus.		312Od_6	Level to undulating low plains	Agree
004	Pass – approx. 500-1km wide, perennial grass, sparse eucalyptus.		312Od_6	Level to undulating low plains	Agree

018	Slope – granite boulders.		312Od_6	Level to undulating low plains	Agree
005	Pass – approx. 500 m wide, sparse eucalyptus, perennial grass.		312Od_6	Level to undulating low plains	Agree
006	Plain – dry long grasses, very sparse (various) trees, alluvial cover, granite float.		312Od_6	Level to undulating low plains	Agree

017	Pass/Plain – high ground, rolling small hills.		312Od_6	Level to undulating low plains	Agree
007	Plain – dry long grasses, very sparse (various) trees, alluvial cover, granite and quartz float.		312Od_6	Level to undulating low plains	Agree
008	Slope – Gneiss outcrop, edge of plain, rolling hills, very weathered and eroded.		312Od_8	Drainage floors and channels	Disagree
009	Drainage – reeds, medium eucalyptus.		312Od_8	Drainage floors and channels	Agree
010	Drainage – granite outcrop and float.		312Od_8	Drainage floors and channels	Agree

011	Pass/Plain		312Od_6	Level to undulating low plains	Agree
016	Drainage – granite boulders, various trees including wild plums.		312Od_6	Level to undulating low plains	Disagree
012	Plain, small rolling hills, sparse eucalyptus, spinifex and termite mounds.		312Od_6	Level to undulating low plains	Agree
015	Plain		312Od_6	Level to undulating low plains	Agree
013	Drainage – Big Mable River		312Od_6	Level to undulating low plains	Disagree
014	Plain – Baula Wah community		312Od_6	Level to undulating low plains	Agree
032	Drainage		312Ri_6	Level to undulating plains	Disagree

031	Plain – perennial grass, mostly sparse Twin-Leaf Bloodwood.		316Pp8A	Channels and banks of major rivers and creeks	Disagree

Appendix 5 - Subjective conditional probabilities (%).

A. Antrim land system

B. Wickham land system

C. O'Donnell land system

A. Antrim land system subjective probabilities (%).

Landforms						
	Pit	Channel	Pass	Ridge	Peak	Plain
alu1	1	1	1	50	50	50
alu2	1	1	1	60	80	1
alu3	1	1	1	40	1	1
alu4	1	5	70	1	1	80
alu5	50	90	20	1	1	1
alu6	50	100	1	1	1	1

Vegetation				
	Durack Ranges_738	Kimberley Foothills_808	Kimberley Foothills_811	Bow River Hills_77
alu1	1	1	100	1
alu2	1	80	1	1
alu3	5	1	90	1
alu4	1	20	1	80
alu5	10	1	1	20
alu6	5	5	5	5

Geology				
	Sp; Sandstone, basalt	d3d; Dolerite, gabbro, and ultrabasic intrusions	g3b; Granite	Kb1; Sandstone
alu1	1	90	1	1
alu2	1	90	1	1
alu3	1	90	10	1
alu4	1	40	5	1
alu5	5	40	5	5
alu6	5	5	5	5

Relief			
	Channel, plain	Pass, plain, low hills, moderate hills	Moderate hills, high hills, pass, plains
alu1	1	1	100
alu2	1	50	50
alu3	1	90	1
alu4	50	50	1
alu5	100	30	1
alu6	100	1	1

Elevation (m)			
	500	400	300
alu1	80	80	50
alu2	50	50	50
alu3	20	50	50
alu4	5	5	70
alu5	1	1	80
alu6	1	1	100

B. Wickham land system subjective probabilities (%).

Landforms						
	Pit	Channel	Pass	Ridge	Peak	Plain
wlu1	20	30	5	30	50	50
wlu2	5	5	5	50	50	50
wlu3	1	5	5	60	70	50
wlu4	1	5	5	80	50	1
wlu5	1	5	10	90	10	1
wlu6	1	50	80	1	1	1
wlu7	1	80	50	1	1	50
wlu8	5	100	50	1	1	1

Vegetation								
	VB_812	VB_810	VB_808	DR_738	KF_808	KF_811	BRH_77	BRH 842
wlu1	5	5	80	40	80	20	40	20
wlu2	5	5	80	40	80	20	40	20
wlu3	5	5	80	40	80	20	40	20
wlu4	5	5	80	40	80	20	40	20
wlu5	5	5	80	40	80	20	40	20
wlu6	10	1	1	10	1	5	5	10
wlu7	10	1	1	10	1	5	5	10
wlu8	10	1	1	10	1	5	1	10
* VB – Victoria Bonaparte, DR – Durack Ranges, KF – Kimberley Foothills, BRH – Bow River Hills								

Geology						
	Sp; Sandstone, basalt	d3d; Dolerite, gabbro, and ultrabasic intrusions	g3b; Granite	Kb1; Sandstone	f3b; Acid volcanic rocks	d3b; Dolerite, gabbro, and ultrabasics
wlu1	40	10	1	80	1	10
wlu2	40	10	1	80	40	10
wlu3	40	10	1	80	40	10
wlu4	40	10	1	80	5	10
wlu5	40	10	1	80	1	10
wlu6	40	10	1	80	20	10
wlu7	40	10	1	50	20	10
wlu8	10	5	1	40	1	5

Relief			
	channel, plain	pass, plain, low hills, moderate hills	moderate hills, high hills, pass, plains
wlu1	10	50	80
wlu2	10	50	80
wlu3	10	50	80
wlu4	10	50	80
wlu5	10	50	80
wlu6	20	80	50
wlu7	50	50	1
wlu8	80	20	1

Elevation (m)				
	500	400	300	200
wlu1	50	50	50	50
wlu2	50	50	50	50
wlu3	50	50	50	50
wlu4	50	50	50	50
wlu5	50	50	50	50
wlu6	10	10	50	80
wlu7	10	10	10	50
wlu8	5	5	10	30

C. O'Donnell land system subjective probabilities (%).

Landforms						
	Pit	Channel	Pass	Ridge	Peak	Plain
olu1	1	1	1	80	70	10
olu2	10	1	10	10	1	10
olu3	1	20	50	30	1	50
olu4	10	20	50	1	1	100
olu5	50	100	10	1	1	1
olu6	50	100	10	1	1	1

Vegetation					
	Bow River Hills 808	Ord Plains 833	Bow River Hills 837	Bow River Hills 834	Bow River Hills 77
olu1	50	1	1	1	50
olu2	1	70	70	1	1
olu3	1	1	1	1	100
olu4	1	1	1	100	1
olu5	1	100	70	1	1
olu6	50	1	1	1	1

Geology					
	g3b; Granite	f3b; Acid volcanic rocks	s3b; Sedimentary rocks	g3c; Granite	d3c; Dolerite, gabbro, and ultrabasic
olu1	50	1	1	50	50
olu2	50	50	1	50	1
olu3	50	50	1	50	1
olu4	50	1	50	50	1
olu5	1	1	50	1	1
olu6	1	1	50	1	1

Relief			
	channel, plain	pass, plain, low hills, moderate hills	moderate hills, high hills, pass, plains
olu1	1	1	100
olu2	1	100	50
olu3	1	100	20
olu4	80	80	1
olu5	80	20	1
olu6	100	1	1

Elevation				
	500	400	200	100
olu1	80	1	1	1
olu2	80	1	1	1
olu3	80	1	1	1
olu4	1	70	80	100
olu5	1	70	80	100
olu6	1	70	80	100

Appendix 6 – Binary Weighted Overlay (BWO) probability tables.

A. Antrim land system

B. Wickham land system

C. O'Donnell land system

A. Antrim land system BWO probability tables.

Landforms						
	Pit	Channel	Pass	Ridge	Peak	Plain
alu1	0	0	0	1	1	1
alu2	0	0	0	0	1	0
alu3	0	0	0	1	0	0
alu4	0	0	0	0	0	1
alu5	0	1	0	0	0	0
alu6	0	1	0	0	0	0

Relief			
	channel, plain	pass, plain, low hills, moderate hills	moderate hills, high hills, pass, plains
alu1	0	0	1
alu2	0	1	1
alu3	0	1	0
alu4	1	1	0
alu5	1	0	0
alu6	1	0	0

Geology				
	Sp; Sandstone, basalt	d3d; Dolerite, gabbro, and ultrabasic intrusions	g3b; Granite	Kb1; Sandstone
alu1	0	1	0	0
alu2	0	1	0	0
alu3	0	1	0	0
alu4	0	1	0	0
alu5	0	1	0	0
alu6	1	1	1	1

Vegetation				
	Durack Ranges_738	Kimberley Foothills_808	Kimberley Foothills_811	Bow River Hills_77
alu1	0	0	1	0
alu2	0	1	0	0
alu3	0	0	1	0
alu4	0	0	0	1
alu5	0	0	0	1
alu6	1	1	1	1

Elevation (m)			
	500	400	300
alu1	1	1	0
alu2	1	1	1
alu3	0	1	1
alu4	0	0	1
alu5	0	0	1
alu6	0	0	1

B. Wickham land system BWO probability tables.

Landforms						
	Pit	Channel	Pass	Ridge	Peak	Plain
wlu1	0	0	0	0	1	1
wlu2	0	0	0	1	1	1
wlu3	0	0	0	1	1	1
wlu4	0	0	0	1	1	0
wlu5	0	0	0	1	0	0
wlu6	0	1	1	0	0	0
wlu7	0	1	1	0	0	1
wlu8	0	1	1	0	0	0

Vegetation								
	VB_812	VB_810	VB_808	DR_738	KF_808	KF_811	BRH_77	BRH_842
wlu1	0	0	1	0	1	0	0	0
wlu2	0	0	1	0	1	0	0	0
wlu3	0	0	1	0	1	0	0	0
wlu4	0	0	1	0	1	0	0	0
wlu5	0	0	1	0	1	0	0	0
wlu6	0	0	0	0	0	0	0	0
wlu7	0	0	0	0	0	0	0	0
wlu8	0	0	0	0	0	0	0	0
* VB – Victoria Bonaparte, DR – Durack Ranges, KF – Kimberley Foothills, BRH – Bow River Hills								

Geology						
	Sp; Sandstone, basalt	d3d; Dolerite, gabbro, and ultrabasic intrusions (inc. basalt)	g3b; Granite	Kb1; Sandstone	f3b; Acid volcanic rocks	d3b; Dolerite, gabbro, and ultrabasics
wlu1	0	0	0	1	0	0
wlu2	0	0	0	1	0	0
wlu3	0	0	0	1	0	0
wlu4	0	0	0	1	0	0
wlu5	0	0	0	1	0	0
wlu6	0	0	0	1	0	0
wlu7	0	0	0	1	0	0
wlu8	0	0	0	0	0	0

Relief			
	channel, plain	pass, plain, low hills, moderate hills	moderate hills, high hills, pass, plains
wlu1	0	1	1
wlu2	0	1	1
wlu3	0	1	1
wlu4	0	1	1
wlu5	0	1	1
wlu6	0	1	1
wlu7	1	1	0
wlu8	1	0	0

Elevation (m)				
	500	400	300	200
wlu1	1	1	1	1
wlu2	1	1	1	1
wlu3	1	1	1	1
wlu4	1	1	1	1
wlu5	1	1	1	1
wlu6	0	0	1	1
wlu7	0	0	0	1
wlu8	0	0	0	0

C. O’Donnell land system BWO probability tables.

Landforms						
	Pit	Channel	Pass	Ridge	Peak	Plain
olu1	0	0	0	1	1	0
olu2	1	0	1	1	0	1
olu3	0	0	1	0	0	1
olu4	0	0	1	0	0	1
olu5	1	1	0	0	0	0
olu6	1	1	0	0	0	0

Vegetation					
	Bow River Hills 808	Ord Plains 833	Bow River Hills 837	Bow River Hills 834	Bow River Hills 77
olu1	1	0	0	0	1
olu2	0	1	1	0	0
olu3	0	0	0	0	1
olu4	0	0	0	1	0
olu5	0	1	1	0	0
olu6	1	0	0	0	0

Geology					
	g3b; Granite	f3b; Acid volcanic rocks	s3b; Sedimentary rocks	g3c; Granite	d3c; Dolerite, gabbro, and ultrabasic
olu1	1	0	0	1	1
olu2	1	1	0	1	0
olu3	1	1	0	1	0
olu4	1	0	1	1	0
olu5	0	0	1	0	0
olu6	0	0	1	0	0

Relative relief			
	channel, plain	pass, plain, low hills, moderate hills	moderate hills, high hills, pass, plains
olu1	0	0	1
olu2	0	1	1
olu3	0	1	1
olu4	1	1	0
olu5	1	0	0
olu6	1	0	0

Elevation (m)				
	500	400	200	100
olu1	1	0	0	0
olu2	1	0	0	0
olu3	1	0	0	0
olu4	0	1	1	1
olu5	0	1	1	1
olu6	0	1	1	1

Appendix 7 - Fuzzy Weighted Overlay (FWO) fuzzy membership tables.

A. Antrim land system

B. Wickham land system

C. O'Donnell land system

A. Antrim land system FWO probability tables

Landforms						
	Pit	Channel	Pass	Ridge	Peak	Plain
alu1	0.01	0.01	0.01	0.33	0.33	0.33
alu2	0.01	0.01	0.01	0.42	0.56	0.01
alu3	0.02	0.02	0.02	0.89	0.02	0.02
alu4	0.01	0.03	0.44	0.01	0.01	0.51
alu5	0.31	0.55	0.12	0.01	0.01	0.01
alu6	0.32	0.65	0.01	0.01	0.01	0.01

Vegetation				
	Durack Ranges_738	Kimberley Foothills_808	Kimberley Foothills_811	Bow River Hills_77
alu1	0.01	0.01	0.97	0.01
alu2	0.01	0.96	0.01	0.01
alu3	0.05	0.01	0.93	0.01
alu4	0.01	0.20	0.01	0.78
alu5	0.31	0.03	0.03	0.63
alu6	0.25	0.25	0.25	0.25

Geology				
	Sp; Sandstone, basalt	d3d; Dolerite, gabbro, and ultrabasic intrusions (incl. basalt)	g3b; Granite	Kb1; Sandstone
alu1	0.01	0.97	0.01	0.01
alu2	0.01	0.97	0.01	0.01
alu3	0.01	0.88	0.10	0.01
alu4	0.02	0.85	0.11	0.02
alu5	0.09	0.73	0.09	0.09
alu6	0.25	0.25	0.25	0.25

Relief			
	channel, plain	pass, plain, low hills, moderate hills	moderate hills, high hills, pass, plains
alu1	0.01	0.01	0.98
alu2	0.01	0.50	0.50
alu3	0.01	0.98	0.01
alu4	0.50	0.50	0.01
alu5	0.76	0.23	0.01
alu6	0.98	0.01	0.01

Elevation (m)			
	500	400	300
alu1	0.38	0.38	0.24
alu2	0.33	0.33	0.33
alu3	0.17	0.42	0.42
alu4	0.06	0.06	0.88
alu5	0.01	0.01	0.98
alu6	0.01	0.01	0.98

B. Wickham land system FWO probability tables.

Landforms						
	Pit	Channel	Pass	Ridge	Peak	Plain
wlu1	0.11	0.16	0.03	0.16	0.27	0.27
wlu2	0.03	0.03	0.03	0.30	0.30	0.30
wlu3	0.01	0.03	0.03	0.31	0.37	0.26
wlu4	0.01	0.04	0.04	0.56	0.35	0.01
wlu5	0.01	0.04	0.09	0.77	0.09	0.01
wlu6	0.01	0.37	0.60	0.01	0.01	0.01
wlu7	0.01	0.44	0.27	0.01	0.01	0.27
wlu8	0.03	0.63	0.32	0.01	0.01	0.01

Vegetation								
	VB_812	VB_810	VB_808	DR_738	KF_808	KF_811	BRH_77	BRH_842
wlu1	0.02	0.02	0.28	0.14	0.28	0.07	0.14	0.07
wlu2	0.02	0.02	0.28	0.14	0.28	0.07	0.14	0.07
wlu3	0.02	0.02	0.28	0.14	0.28	0.07	0.14	0.07
wlu4	0.02	0.02	0.28	0.14	0.28	0.07	0.14	0.07
wlu5	0.02	0.02	0.28	0.14	0.28	0.07	0.14	0.07
wlu6	0.23	0.02	0.02	0.23	0.02	0.12	0.12	0.23
wlu7	0.23	0.02	0.02	0.23	0.02	0.12	0.12	0.23
wlu8	0.26	0.03	0.03	0.26	0.03	0.13	0.03	0.26
* VB – Victoria Bonaparte, DR – Durack Ranges, KF – Kimberley Foothills, BRH – Bow River Hills								

Geology						
	Sp; Sandstone, basalt	d3d; Dolerite, gabbro, and ultrabasic intrusions	g3b; Granite	Kb1; Sandstone	f3b; Acid volcanic rocks	d3b; Dolerite, gabbro, and ultrabasics
wlu1	0.28	0.07	0.01	0.56	0.01	0.07
wlu2	0.22	0.06	0.01	0.44	0.22	0.06
wlu3	0.22	0.06	0.01	0.44	0.22	0.06
wlu4	0.27	0.07	0.01	0.55	0.03	0.07
wlu5	0.28	0.07	0.01	0.56	0.01	0.07
wlu6	0.25	0.06	0.01	0.50	0.12	0.06
wlu7	0.31	0.08	0.01	0.38	0.15	0.08
wlu8	0.16	0.08	0.02	0.65	0.02	0.08

Relief			
	channel, plain	pass, plain, low hills, moderate hills	moderate hills, high hills, pass, plains
wlu1	0.07	0.36	0.57
wlu2	0.07	0.36	0.57
wlu3	0.07	0.36	0.57
wlu4	0.07	0.36	0.57
wlu5	0.07	0.36	0.57
wlu6	0.13	0.53	0.33
wlu7	0.50	0.50	0.01
wlu8	0.79	0.20	0.01

Elevation (m)				
	500	400	300	200
wlu1	0.25	0.25	0.25	0.25
wlu2	0.25	0.25	0.25	0.25
wlu3	0.25	0.25	0.25	0.25
wlu4	0.25	0.25	0.25	0.25
wlu5	0.25	0.25	0.25	0.25
wlu6	0.07	0.07	0.33	0.53
wlu7	0.13	0.13	0.13	0.63
wlu8	0.10	0.10	0.20	0.60

C. O'Donnell land system FWO probability tables.

Landforms						
	Pit	Channel	Pass	Ridge	Peak	Plain
olu1	0.01	0.01	0.01	0.49	0.43	0.06
olu2	0.24	0.02	0.24	0.24	0.02	0.24
olu3	0.01	0.13	0.33	0.20	0.01	0.33
olu4	0.05	0.11	0.27	0.01	0.01	0.55
olu5	0.31	0.61	0.06	0.01	0.01	0.01
olu6	0.31	0.61	0.06	0.01	0.01	0.01

Vegetation					
	Bow River Hills 808	Ord Plains 833	Bow River Hills 837	Bow River Hills 834	Bow River Hills 77
olu1	0.49	0.01	0.01	0.01	0.49
olu2	0.01	0.49	0.49	0.01	0.01
olu3	0.01	0.01	0.01	0.01	0.96
olu4	0.01	0.01	0.01	0.96	0.01
olu5	0.01	0.58	0.40	0.01	0.01
olu6	0.93	0.02	0.02	0.02	0.02

Geology					
	g3b; Granite	f3b; Acid volcanic rocks	s3b; Sedimentary rocks	g3c; Granite	d3c; Dolerite, gabbro, and ultrabasic
olu1	0.33	0.01	0.01	0.33	0.33
olu2	0.33	0.33	0.01	0.33	0.01
olu3	0.33	0.33	0.01	0.33	0.01
olu4	0.33	0.01	0.33	0.33	0.01
olu5	0.02	0.02	0.93	0.02	0.02
olu6	0.02	0.02	0.93	0.02	0.02

Relative relief			
	channel, plain	pass, plain, low hills, moderate hills	moderate hills, high hills, pass, plains
olu1	0.01	0.01	0.98
olu2	0.01	0.66	0.33
olu3	0.01	0.83	0.17
olu4	0.50	0.50	0.01
olu5	0.79	0.20	0.01
olu6	0.98	0.01	0.01

Elevation (m)				
	500	400	200	100
olu1	0.96	0.01	0.01	0.01
olu2	0.96	0.01	0.01	0.01
olu3	0.96	0.01	0.01	0.01
olu4	0.00	0.28	0.32	0.40
olu5	0.00	0.28	0.32	0.40
olu6	0.00	0.28	0.32	0.40

Appendix 8 – Positive Weights of Evidence (PWofE)

Sufficiency ratio tables.

A. Antrim land system

B. Wickham land system

C. O'Donnell land system

A. Antrim land system Sufficiency ratio tables.

Landforms						
	alu1	alu2	alu3	alu4	alu5	alu6
Pit	0.001	0.002	0.040	0.028	2.440	5.430
Channel	0.003	0.004	0.109	0.391	11.775	32.041
Pass	0.003	0.004	0.114	20.094	1.891	0.161
Ridge	0.140	0.240	6.621	0.055	0.053	0.112
Peak	0.045	0.154	0.020	0.014	0.014	0.029
Plain	0.193	0.003	0.084	11.099	0.057	0.121

Vegetation						
	alu1	alu2	alu3	alu4	alu5	alu6
DURACK RANGES_738	0.016	0.024	1.610	0.778	46.030	63.462
KIMBERLEY FOOTHILLS_808	0.007	2.880	0.131	7.778	1.028	20.455
KIMBERLEY FOOTHILLS_811	0.789	0.007	13.913	0.224	0.677	12.692
BOW RIVER HILLS_77	0.006	0.009	0.113	42.000	29.123	17.188

Geology						
	alu1	alu2	alu3	alu4	alu5	alu6
Sp; Sandstone, basalt	0.029	0.029	0.027	0.060	0.313	1.816
d3d; Dolerite, gabbro, and ultrabasic intrusions	0.257	0.257	0.229	0.219	0.182	0.056
g3b; Granite	0.020	0.020	0.217	0.240	0.199	0.820
Kb1; Sandstone	0.017	0.017	0.016	0.035	0.183	1.061

Relative relief						
	alu1	alu2	alu3	alu4	alu5	alu6
Low	0.004	0.007	0.084	24.662	37.225	27.966
Moderate	0.005	0.434	14.896	5.635	0.221	28.613
High	1.815	0.735	0.126	0.325	0.325	0.656

Elevation (m)						
	alu1	alu2	alu3	alu4	alu5	alu6
500	0.655	0.786	4.089	3.267	0.516	1.042
400	0.458	0.563	10.101	2.557	0.408	0.825
300	0.067	0.141	2.340	14.617	16.849	34.042

B. Wickham land system Sufficiency ratio tables.

Landforms								
	wlu1	wlu2	wlu3	wlu4	wlu5	wlu6	wlu7	wlu8
Pit	4.00	0.63	0.43	0.19	0.19	1.14	1.54	5.11
Channel	0.41	0.07	0.16	0.09	0.09	6.48	10.94	18.35
Pass	0.09	0.09	0.20	0.12	0.27	17.78	7.66	9.49
Ridge	0.32	0.66	1.53	1.43	2.26	0.11	0.15	0.15
Peak	0.95	1.08	3.20	1.32	0.27	0.17	0.23	0.23
Plain	1.24	1.43	2.66	0.04	0.04	0.21	10.03	0.29

Vegetation								
	wlu1	wlu2	wlu3	wlu4	wlu5	wlu6	wlu7	wlu8
VICTORIA BONAPARTE_812	0.10	0.10	0.23	0.10	0.10	9.36	12.60	15.01
VICTORIA BONAPARTE_810	0.53	0.53	1.20	0.53	0.53	3.20	4.31	6.93
VICTORIA BONAPARTE_808	0.94	0.94	2.12	0.94	0.94	0.33	0.45	0.67
DURACK RANGES_738	0.44	0.44	0.98	0.44	0.44	4.64	6.25	7.25
KIMBERLEY FOOTHILLS_808	0.94	0.94	2.12	0.94	0.94	0.33	0.45	0.67
KIMBERLEY FOOTHILLS_811	0.43	0.43	0.97	0.43	0.43	4.80	6.47	7.12
BOW RIVER HILLS_77	0.67	0.67	1.52	0.67	0.67	3.39	4.56	1.03
BOW RIVER HILLS_842	0.28	0.28	0.63	0.28	0.28	6.57	8.85	10.38

Geology								
	wlu1	wlu2	wlu3	wlu4	wlu5	wlu6	wlu7	wlu8
Sp; Sandstone, basalt	0.65	0.50	1.12	0.63	0.65	3.45	5.97	2.83
d3d; Dolerite, gabbro, and ultrabasic intrusions	0.58	0.49	1.10	0.58	0.58	2.94	5.50	5.50
g3b; Granite	0.50	0.50	1.13	0.50	0.50	3.00	4.04	9.24
Kb1; Sandstone	0.64	0.48	1.09	0.62	0.64	3.35	3.32	6.13
f3b; Acid volcanic rocks	0.05	1.57	3.54	0.16	0.05	4.36	7.70	0.85
d3b; Dolerite, gabbro, and ultrabasic intrusions	0.58	0.49	1.10	0.58	0.58	2.94	5.50	5.50

Relative relief								
	wlu1	wlu2	wlu3	wlu4	wlu5	wlu6	wlu7	wlu8
Low	0.16	0.16	0.37	0.16	0.16	1.90	12.73	26.06
Moderate	0.54	0.54	1.21	0.54	0.54	5.09	6.39	2.29
High	0.87	0.87	1.95	0.87	0.87	2.76	0.10	0.10

Elevation (m)								
	wlu1	wlu2	wlu3	wlu4	wlu5	wlu6	wlu7	wlu8
500	0.77	0.77	1.73	0.77	0.77	1.14	2.96	2.23
400	0.77	0.77	1.73	0.77	0.77	1.14	2.96	2.23
300	0.60	0.60	1.36	0.60	0.60	5.01	2.36	3.78
200	0.36	0.36	0.82	0.36	0.36	5.13	8.56	8.05

C. O’Donnell land system Sufficiency ratio tables.

Landforms						
	olu1	olu2	olu3	olu4	olu5	olu6
Pit	0.007	0.350	0.007	0.064	0.501	0.501
Channel	0.004	0.016	0.096	0.079	0.693	0.693
Pass	0.006	0.325	0.513	0.395	0.067	0.067
Ridge	1.083	0.337	0.264	0.006	0.007	0.007
Peak	8.918	0.052	0.014	0.012	0.013	0.013
Plain	0.054	0.250	0.382	0.858	0.005	0.005

Vegetation						
	olu1	olu2	olu3	olu4	olu5	olu6
BOW RIVER HILLS_808	3.72	0.04	0.01	0.11	0.04	18.09
ORD PLAINS_833	0.06	5.74	0.01	0.14	9.69	0.17
BOW RIVER HILLS_837	0.08	7.94	0.01	0.16	6.78	0.20
BOW RIVER HILLS_834	0.07	0.05	0.01	297.62	0.05	0.19
BOW RIVER HILLS_77	3.55	0.03	1.76	0.10	0.04	0.13

Geology						
	olu1	olu2	olu3	olu4	olu5	olu6
g3b; Granite	2.36	2.36	0.31	5.03	0.12	0.14
f3b; Acid volcanic rocks	0.07	6.36	0.83	0.15	0.24	0.27
s3b; Sedimentary rocks	0.02	0.02	0.003	2.75	6.54	7.35
g3c; Granite	2.36	2.36	0.31	5.03	0.12	0.14
d3c; Dolerite, gabbro, and ultrabasic intrusions	42.49	0.13	0.02	0.27	0.45	0.51

Relative relief						
	olu1	olu2	olu3	olu4	olu5	olu6
Low	0.03	0.02	0.003	4.33	4.75	7.55
Moderate	0.03	3.15	0.58	4.56	0.89	0.05
High	13.67	2.07	0.12	0.10	0.06	0.07

Elevation (m)						
	olu1	olu2	olu3	olu4	olu5	olu6
500	3.64	3.64	0.48	0.02	0.01	0.01
400	0.10	0.10	0.01	7.36	4.23	4.75
200	0.09	0.09	0.01	7.41	4.26	4.78
100	0.07	0.07	0.01	7.49	4.30	4.84

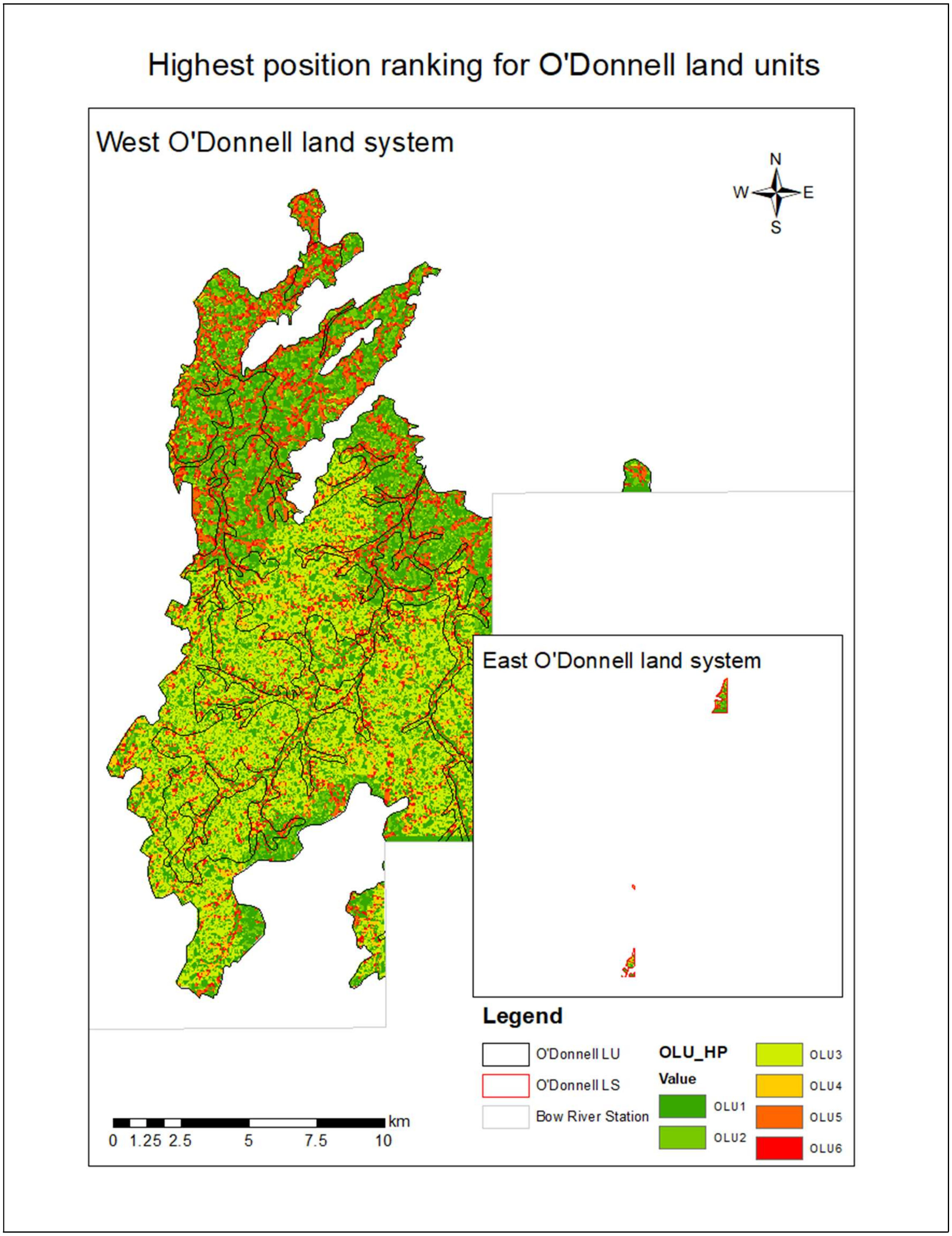
Appendix 9 – O'Donnell highest position results.

A. BWO 'most likely' land units

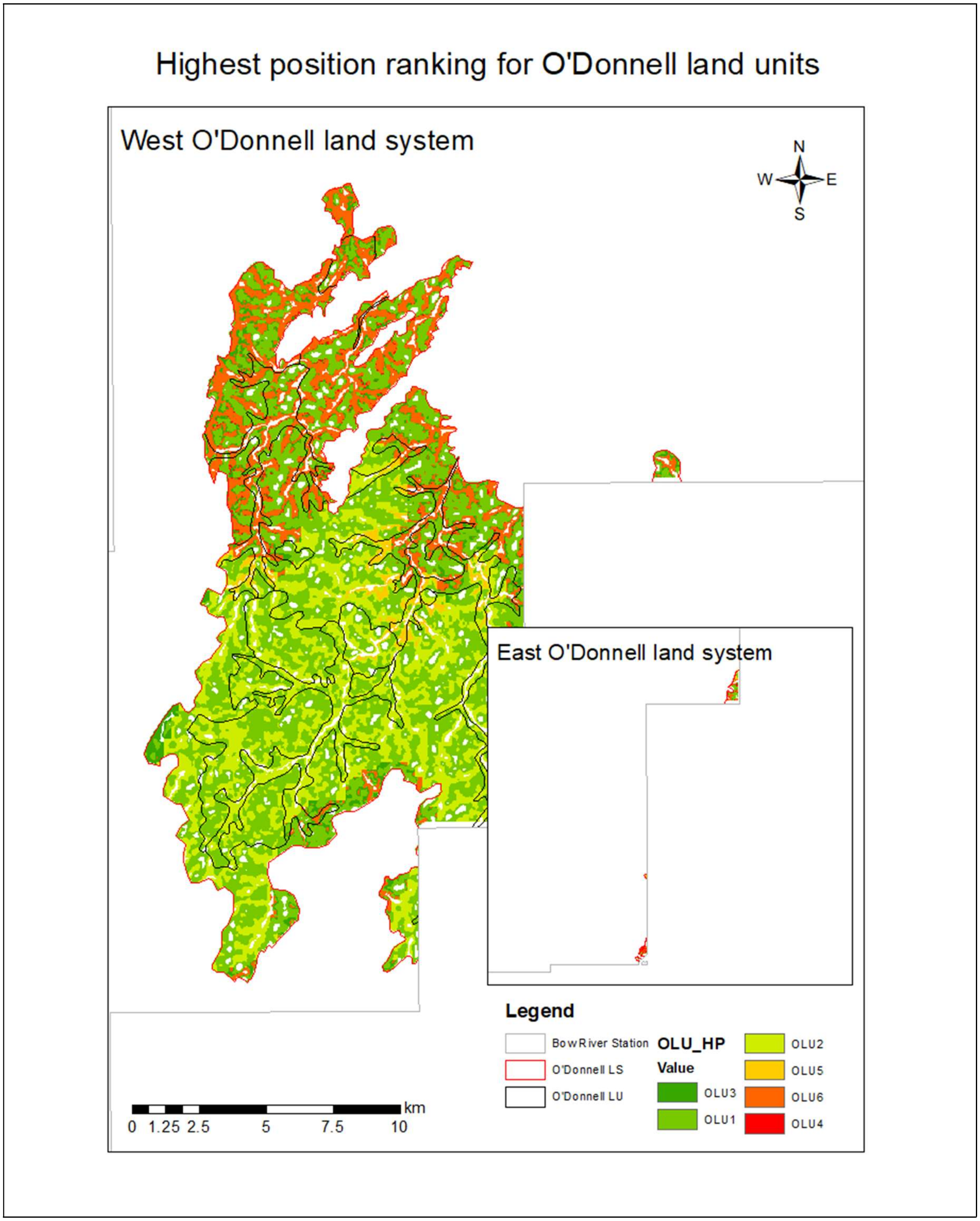
B. FWO 'most likely' land units

C. PWofE 'most likely' land units

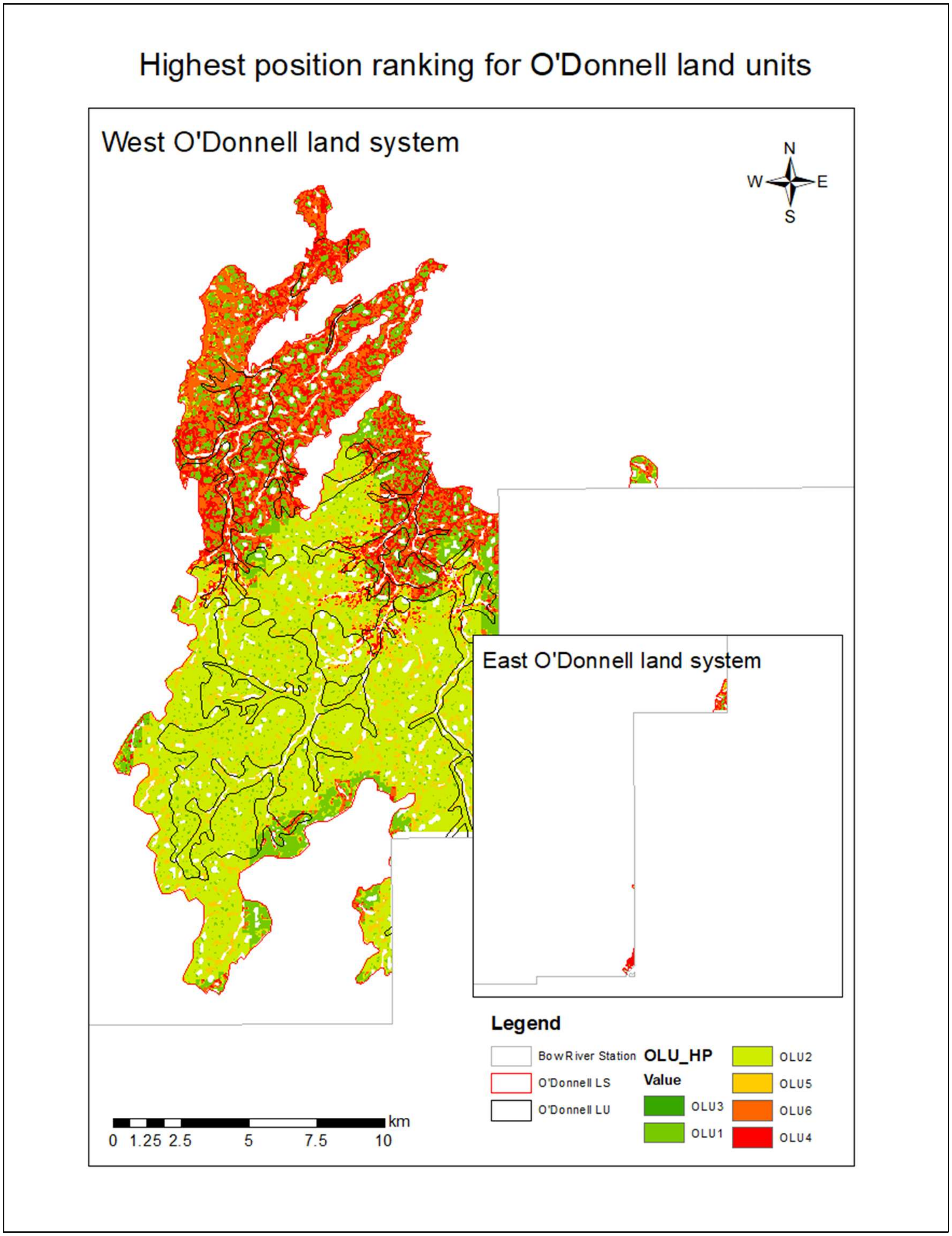
A. O’Donnell land system BWO highest position results.



B. O’Donnell land system FWO highest position results.



C. O’Donnell land system PWofE highest position results.



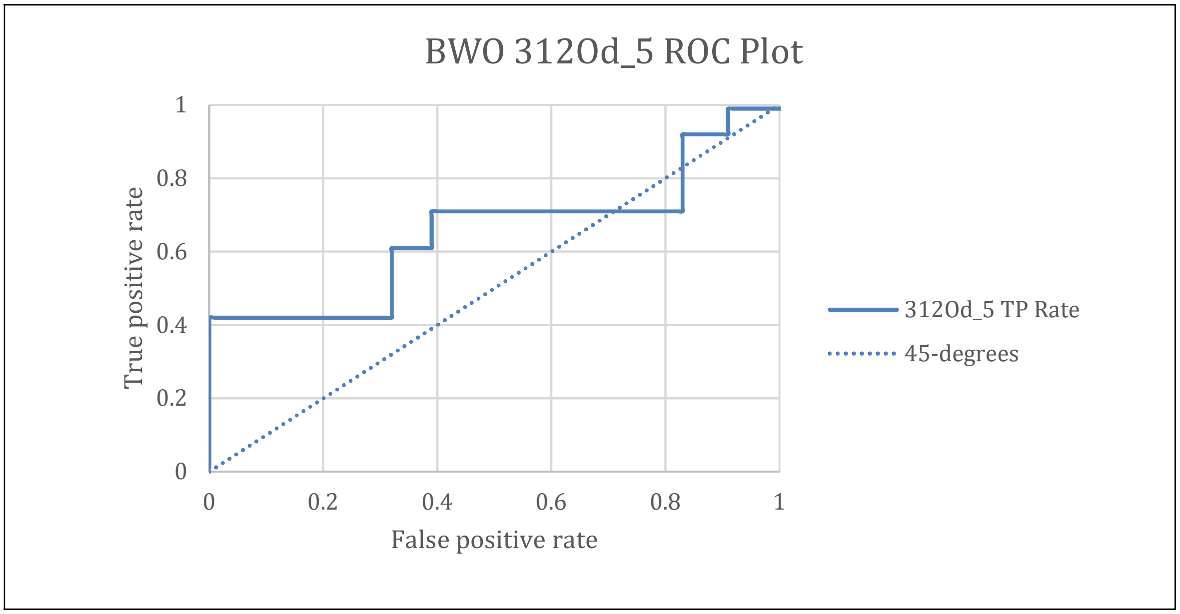
Appendix 10 – O'Donnell 312Od_5 ROC plots.

A. BWO prediction model

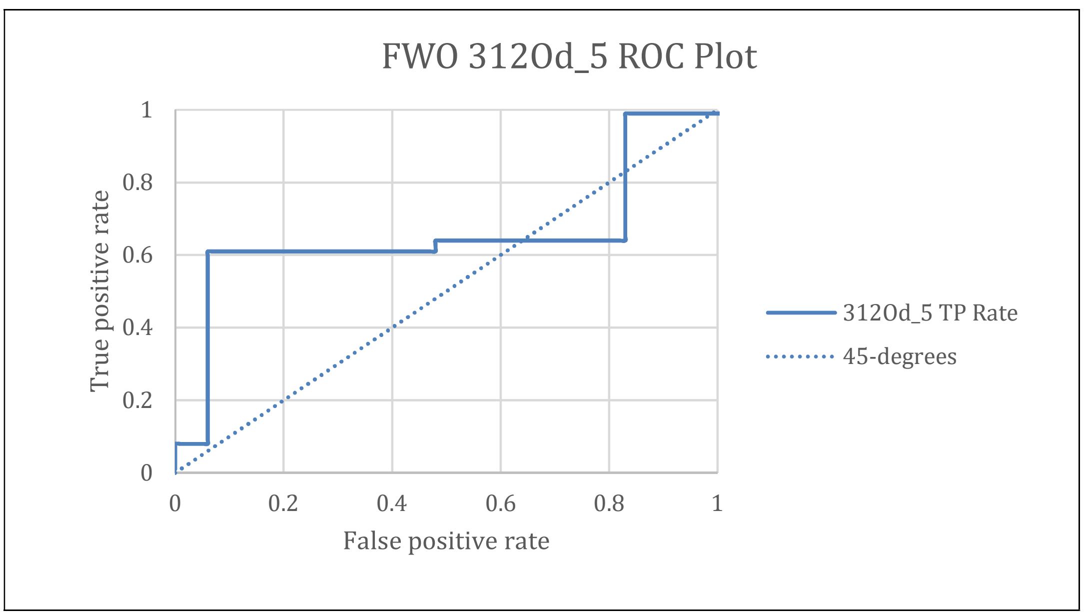
B. FWO prediction model

C. PWofE prediction model

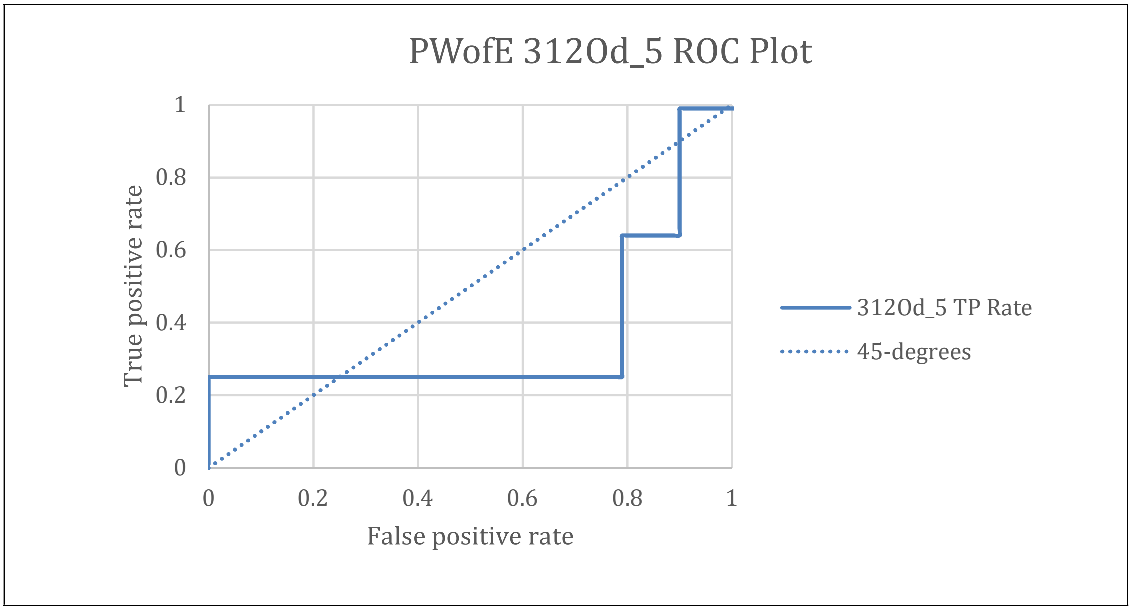
A. ROC plot for O'Donnell land unit 312Od_5 using the BWO prediction model.



B. ROC plot for O'Donnell land unit 312Od_5 using the FWO prediction model.



C. ROC plot for O'Donnell land unit 312Od_5 using the PWofE prediction model.



Appendix 11 – O’Donnell contingency tables.

A. FWO prediction model

B. PWofE prediction model

A. Contingency table for the O'Donnell FWO prediction model.

	OLU1, OLU2 (HP2, HP3)	OLU3 (HP1)	OLU4, OLU5 (HP6, HP4)	OLU6 (HP5)	Total
312Od_5	11533	1529	595	7844	21501
312Od_6	109999	8421	2957	18435	139812
312Od_7	29181	396	66	1168	30811
312Od_8	22371	1930	2315	7992	34608
Total	173084	12276	5933	35439	226732
Correctly predicted %	7	69	1	23	0.124

B. Contingency table for the O'Donnell PWofE prediction model.

	OLU1, OLU2 (HP2, HP3)	OLU3 (HP1)	OLU4, OLU5 (HP6, HP4)	OLU6 (HP5)	Total
312Od_5	8070	0	6775	6656	21501
312Od_6	94831	62	26849	18070	139812
312Od_7	26797	0	3206	808	30811
312Od_8	17793	0	10543	6212	34548
Total	147491	62	47373	31746	226672
Correctly predicted %	5	100	7	20	0.077

Appendix 12 – Comparison between field descriptions and O'Donnell land unit results.

A. FWO model field comparison

B. PWofE model field comparison

A. FWO model and field data comparison.

O'Donnell land units – FWO model vs field data					
Waypoint	**Field Description**	**Elevation**	**Highest position result**	**Technical Bulletin land unit**	**Match**
025	Drainage - 'Sandy Creek', various scrub vegetation	519	3	OLU2	No
026	Plain - Boab trees	519	2	OLU1	No
027	Plain	527	2	OLU1	No
028		530	3	OLU2	
029		530	2	OLU1	
030		529	2	OLU1	
031	Plain - perennial grasses, sparse bloodwood trees	467	2	OLU1	No
032	Drainage	509	4	OLU5	Yes
033	Drainage	498	5	OLU6	Yes
034		501	2	OLU1	
035	Plain	512	5	OLU6	Yes
036	Lower slope	513	5	OLU6	No
037	Peak	519	2	OLU1	Yes
038	Mid slope	520	2	OLU1	Yes
039	Plain	513	2	OLU1	No
040		511	3	OLU2	
041	Plain	527	2	OLU1	No
042	Plain	522	2	OLU1	No
043	Plain	529	3	OLU2	No
044	Plain	519	2	OLU1	No
045		530	1	OLU3	
046	Plain	542	0		
047	Plain	538	2	OLU1	No
048	Plain	535	3	OLU2	No
049	Drainage	525	3	OLU2	No
050	Drainage	527	3	OLU2	No
					Agreement total = 26%

B. PWofE model and field data comparison.

O'Donnell land units – PWofE model vs field data					
Waypoint	**Landform**	**Elevation**	**Highest position**	**'most likely' land unit**	**Agreement**
25	Drainage	519	3	OLU2	No
26	Plain	519	3	OLU2	No
27	Plain	527	3	OLU2	No
28		530	4	OLU5	
29		530	3	OLU2	
30		529	3	OLU2	
31	Plain	467	3	OLU2	No
32	Drainage	509	4	OLU5	Yes
33	Drainage	498	5	OLU6	Yes
34		501	2	OLU1	
35	Plain	512	5	OLU6	No
36	Lower slope	513	6	OLU4	No
37	Peak	519	2	OLU1	Yes
38	Mid slope	520	2	OLU1	Yes
39	Plain	513	2	OLU1	No
40		511	3	OLU2	
41	Plain	527	3	OLU2	No
42	Plain	522	3	OLU2	No
43	Plain	529	3	OLU2	No
44	Plain	519	3	OLU2	No
45		530	3	OLU2	
46	Plain	542	No data		
47	Plain	538	3	OLU2	No
48	Plain	535	3	OLU2	No
49	Drainage	525	3	OLU2	No
50	Drainage	527	4	OLU5	No
					Agreement total = 21%