Groundwater for Sustainable Development

Evaluation of non-uniform groundwater level data using spatiotemporal modeling

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Abstract:	Groundwater is one of the main sources of freshwater. To ensure its sustainability, it is important to know its current status and changing pattern over time, through the essential groundwater monitoring program conducted by water management planners, groundwater modelers and urban developers. However, uniformly distributed data is hardly available in most catchments. In this study, the Spatiotemporal Regression Kriging method (Rkriging) was adopted to derive a spatiotemporal pattern for Harvey River Catchment in Western Australia, using the limited groundwater data in the catchment. The accuracy of the estimation was investigated using the Leave-One-Out Cross-Validation approach. Time-series analysis (i.e., auto-correlation and cross-correlation) was then employed to provide a better understanding of the estimated groundwater level change (∆GWL) over time. To gain insight into the change of groundwater levels, the correlation between groundwater level (GWL) and precipitation pattern with possible time-lag was explored. The results showed that the Rkriging method is satisfactory and the findings were consistent with the previously published results in literature in the area. The estimated decreasing GWL trend matched the precipitation pattern in the catchment. Such shallow groundwater levels in Harvey Catchment resulted in a short time-lag between the precipitation and GWL time-series. The proposed method should be applied to other catchments with limited groundwater data and can be a useful approach for catchments with irregular temporal and spatial data.
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Highlights:

- Spatiotemporal kriging model is constructed to estimate groundwater level from non-uniformly distributed data
- The model performance is assessed using Leave-One-Out Cross validation
- The association between groundwater level change and rainfall is explored
- The framework is applicable to any other catchments, particularly, catchments in data-scarce regions

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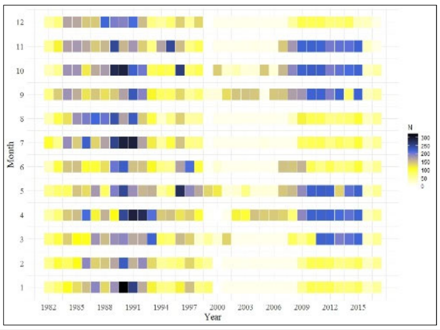

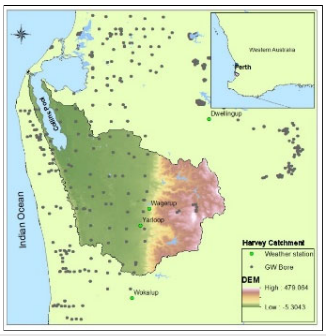

Input: Non-uniform spatial and temporal groundwater level (GWL) data, Harvey Catchment, AU

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Regression kriging method

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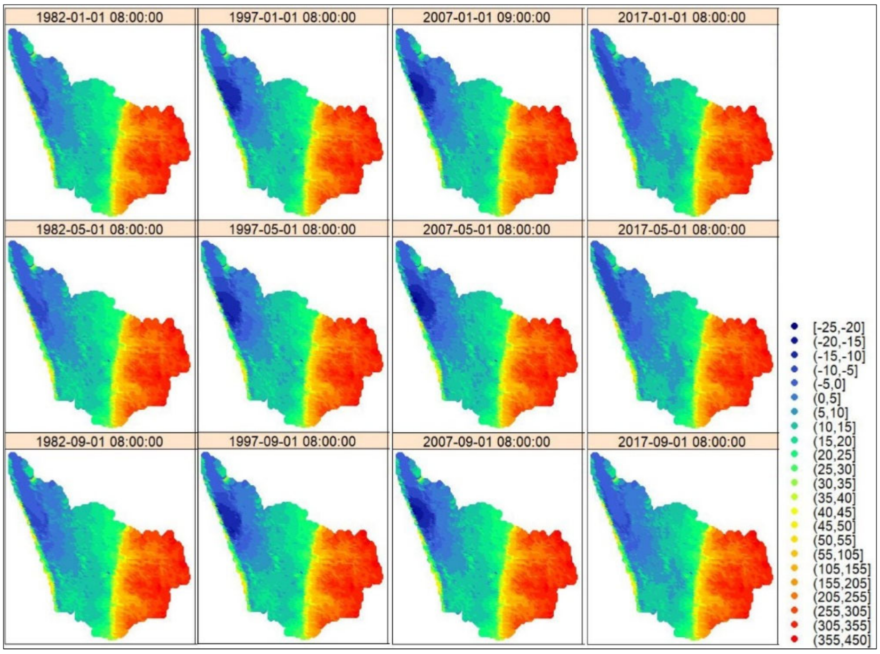

Output: Monthly GWL data and associated maps for the study period (1982-2018)

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Time-series analysis

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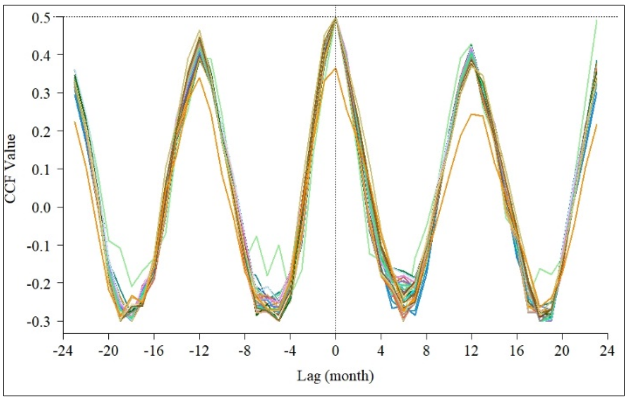

Short time-lag is detected between ΔGWL and Precipitation

Evaluation of non-uniform groundwater level data using spatiotemporal modeling

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Abstract

Groundwater is one of the main sources of freshwater. To ensure its sustainability, it is important to know its current status and changing pattern over time, through the essential groundwater monitoring program conducted by water management planners, groundwater modelers and urban developers. However, uniformly distributed data is hardly available in most catchments. In this study, the Spatiotemporal Regression Kriging method (Rkriging) was adopted to derive a spatiotemporal pattern for Harvey River Catchment in Western Australia, using the limited groundwater data in the catchment. The accuracy of the estimation was investigated using the Leave-One-Out Cross-Validation approach. Time-series analysis (i.e., auto-correlation and cross-correlation) was then employed to provide a better understanding of the estimated groundwater level change (ΔGWL) over time. To gain insight into the change of groundwater levels, the correlation between groundwater level (GWL) and precipitation pattern with possible time-lag was explored. The results showed that the Rkriging method is satisfactory and the findings were consistent with the previously published results in literature in the area. The estimated decreasing GWL trend matched the precipitation pattern in the catchment. Such shallow groundwater levels in Harvey Catchment resulted in a short time-lag between the precipitation and GWL time-series. The proposed method should be applied to other catchments with limited groundwater data and can be a useful approach for catchments with irregular temporal and spatial data.

Keywords

Spatiotemporal Regression Kriging; Non-uniformly distributed data; Groundwater level; Leave-One-Out Cross-Validation; Time-series analysis; Data-scarce catchments

1 Introduction

Groundwater produces almost 30% of known freshwater resources worldwide and almost 96% of non-solid freshwater (Green et al., 2011). As groundwater is less sensitive to the immediate climate variation, it is a great water source to overcome droughts and mitigate climate change impacts on limited freshwater resources. However, excessive groundwater discharge and lack of enough recharge threaten the existence of these precious freshwater systems (Green et al., 2011). Regular monitoring program is usually conducted to understand the changing pattern of groundwater and help proposing effective groundwater management and decision-making plans. However, due to the costs and accessibility, only limited sites are monitored, resulting in sparse data series over the catchments, discontinuous sites and missing observations within sites. The lack of regular measurements, which results in spatiotemporal data gaps, can disturb our understanding of the catchment (Ruybal et al., 2019; Varouchakis & Hristopulos, 2013). To better understand the status and changing patterns of groundwater levels (GWL) for both management and research purposes, uniformly distributed GWL are necessary. This, only, can be achieved by filling the gaps (that is, estimating the missing values in space and time) through interpolation methods (Varouchakis & Hristopulos, 2013), which have been widely used in many research areas; for instance, rainfall pattern prediction (Goovaerts, 2000), climate parameters estimation (Haylock et al., 2008), spatial analysis of groundwater quantity and quality (Dash et al., 2010) and spatial variability of GWL (Varouchakis & Hristopulos, 2013; Yao et al., 2014). Most of these studies, however, explored either spatial or temporal aspect of the subjects and not the interplay between time and space; while due to the changing environment, geohydrological parameters, such as groundwater, are subject to change in time and space (Varouchakis & Hristopulos, 2019). To accurately take account of these changes, the employed method should consider the interdependency between temporal and spatial aspects of the parameters. From modelling perspectives, simultaneously considering both the irregularly sampled spatial and temporal data can best use the available information. One of the popular interpolation methods is spatiotemporal regression kriging (Rkriging) which has been applied to variables in different catchments and will be used for this purpose. The Rkriging uses spatial and temporal correlations between observed (sampled) points to estimate the un-sampled spatiotemporal locations (Hu et al., 2017; Adigi 2019). The model, unlike most interpolation methods, performs well for un-sampled locations or where uniform data is not available (Hu et al., 2017; Adigi 2019). The Rkriging, unlike techniques such as spline interpolation, can interpret the geostatistical aspect of the parameter (Hengle et al., 2012) where the variability of the parameter in space and time is modeled by adding the temporal element to the spatial domain. Hu et al (2017) used spatiotemporal regression kriging (Rkriging) to predict precipitation trend in Uygur region, where the station data is sparse and unevenly distributed. They chose Normalized Difference Vegetation Index (NDVI), Digital Elevation Model (DEM) and a temporal index as the model's regressors. The model was able to successfully detect a pattern in precipitation, and successfully reveal the correlation between precipitation and altitude (Hu et al., 2017). In another interesting research, Ruybal et al (2019) used Rkriging to predict groundwater level at ungauged locations in Arapahoe aquifer and showed that the Rkriging method is a competent approach to estimate the GWL. The model was able to produce realistic values and Rkriging showed to be superior to the traditional kriging method (Ruybal et al., 2019).

The spatial and temporal dependency of the studied parameter (here, GWL) is called empirical variogram. The interpolation models, including kriging, fit a surface to the empirical variograms and produce modeled variograms (here after called variograms). Fitting the optimal variograms is the first and most important step for conducting an accurate spatiotemporal analysis. Adding temporal domain to the spatial interpolation, usually, results in a more accurate and realistic modeling, however it can increase the complexity of the model. For instance, the temporal and spatial structure of the variogram are not necessary the same. The spatial and temporal variograms can follow different covariance functions and patterns (Graler et al., 2016; Voss et al., 2016). Earlier spatiotemporal variograms (STvariogram) were built of separate spatial and temporal domains. These domains werelater added or multiplied together, to form the final spatiotemporal variogram. These variograms, called separable, are simpler but based on unrealistic assumptions (Varouchakis & Hristopulos, 2019); therefore, non-separable variograms have been developed and were applied in many fields, including hydrogeology. For instance, Guo et al (2014) applied three non-separable spatiotemporal variogram models (i.e., Cressie–Huang model, Gneiting model and product-sum model) to predict the green gas emission over China, during 2009-2012. They compared these variogram models with the empirical variogram surface, and showed that the product-sum model predicts slightly better than the rest. However, the three models were almost equally capable of generating column-averaged carbon dioxide dry air mole fractions (Xco^2) concentration maps (Guo et al., 2014).

In the current research, spatiotemporal regression kriging (Rkriging) method is adopted to investigate GWL, in the highly important Harvey Catchment in Western Australia, where the historical observed data were spatially and temporally irregular. The catchment is one of the main water sources for the Perth metropolitan (Al-Safi et al., 2020). It is home to a vast range of groundwater-dependent biodiversity, and its wetlands and lakes are in the list of wetlands of international importance (Environmental Protection Authority, 2008). The proposed method produces spatiotemporal maps for the catchment to track the groundwater change during the study period of 1982-2017. To choose the best spatiotemporal variogram, for a given sample set, several variograms are compared; to find the optimum number of spatial and temporal observations, different spatiotemporal sampling sizes are investigated. The whole catchment is divided into fine grids and for each grid a monthly timetable is provided to overcome non-uniformity due to the temporal and spatial gap in the observed data.

As the catchment information (such as location and elevation) can be highly corrected, direct use of this data may make the model too sensitive. Correlated covariates can affect the significance of the variables, and their interdependence can make the estimation sensitive to minor changes which might introduce imprecise regression coefficients and accordingly higher errors to the model. Therefore, Principal Component Analysis (PCA) is performed to prevent multi-collinearity in the covariates and to avoid information overlapping. The PCA is a common method that transforms the covariates into orthogonal and uncorrelated components. It reduces the original variables to a limited number of integrated variables, which explain most of the variance (Ruybal et al., 2019). The stepwise regression algorithm is, also, used to select the most significant regressors. The accuracy of the Rkriging method is examined by the Leave-One-Out-Cross validation technique.

After studying groundwater change in the catchment, it is interesting to explore the possible reason behind the change. Although precipitation is one of the main factors affecting GWL, its impact on GWL is not fully understood (Kotchoni et al., 2019), mainly due to lack of enough GWL information and complicated structure of groundwater. Time-series analysis (i.e., cross-correlation and auto-correlation) is a common approach to investigate correlation between hydrological time-series (Cai & Ofterdinger, 2016; Duvert et al., 2015; John & John, 2019; Kim & Lee, 2017; Lee et al., 2006; Lehmann & Rode, 2001; Shi et al., 2019). The cross-correlation analysis provides useful information regarding the significance and the first response of the groundwater resources to precipitation. Auto-correlation analysis, on the other hand, reveals structure of the time-series and impact of memory effect. In this paper, the correlation between the estimated groundwater and observed precipitation time-series with possible lags is examined at a randomly selected number of points, to investigate the interdependency between GWL and precipitation time-series, and detect any possible time-lag.

The paper is organized as follows. The study area and data set are described in Section 2, followed by the methodology. The results and model assessment in relation to the data set are given in section 4. In section 5, conclusions and a discussion are drawn from this study.

2 Study area and data

Harvey River Catchment with size of 1041 km^2 is located at 130 km south of Perth city in Western Australia. The Harvey River is one of the most important water sources for Perth metropolitan area. The catchment, as a part of the bigger Peel-Harvey basin, is internationally recognized as the main water-birds place in south west of Australia (Kelsey et al., 2010; Ruibal-Conti, 2014). It has a Mediterranean climate with hot-dry summers and cold-wet winters. Harvey catchment has experienced one of the fastest development and urbanization in Western Australia, especially in the coastal areas (Kazemi et al., 2019; Kelsey et al., 2010).

Almost all climate scenarios (GCMs) predicted hotter and drier climate for south Western Australia, for the next decades (Ali et al., 2012; CSIRO, 2009). Direct impacts of hotter and drier climate on GWL is variation of streamflow and precipitation, and accordingly, decreasing groundwater recharge. Climate change can also affect GWL indirectly, by reshaping groundwater users' daily routine (Taylor et al., 2013). Three main recharge mechanisms affecting groundwater system are direct recharge (e.g., infiltration resulted from precipitation), indirect recharge (e.g., infiltration from surface water), and localized recharge (e.g., concentrated surface water such as lakes and agricultural area) (De Vries & Simmers, 2002). In the case of Harvey catchment, where studies show the precipitation has decreased during the last decades, sandy soil structure of the area makes precipitation infiltration the only reliable means to replenish the water table. Groundwater consumption routine, on the other hand, has changed dramatically, from a very limited percentage during the 1960s to almost equal as surface water in 1985. Nowadays, more than 75% of water originates from groundwater in the area. Excessive water withdrawal for domestic, agricultural and industrial purposes, has affected the GWL, and therefore, has manipulated the dependent ecosystem (Ali et al., 2012; CSIRO, 2009).

The required groundwater and climate data are available on the Bureau of Meteorology (BOM) of Australia's website (BoM, 2020). The groundwater data were collected from monitoring wells for the period of 1982 to 2017, where the reference point is the mean sea level. The temporal and spatial availability of the data is highly non-uniform in the catchment. As presented in Figure 1 monitoring wells are unevenly scattered through the catchment. In the south-eastern part of the catchment, for instance, there are very few wells available.

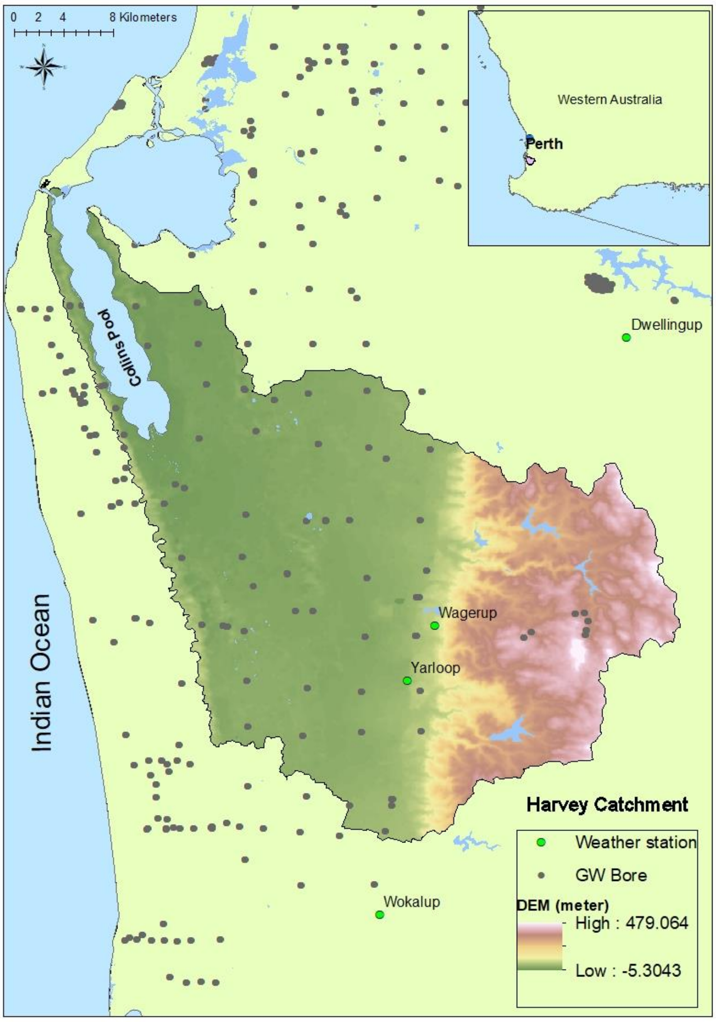


Fig.1 Locations of groundwater wells and weather stations in Harvey Catchment

The temporal distribution of the data is also not uniform. Many wells were operating only for limited years, some of the wells provide annual data and some monthly data (Fig.2). As presented in Fig.2, very few information is available in some years (e.g., 2000-2008). In this study, it is assumed that the temporal trend within the study period continues and is not affected by dramatic human-induced changes.

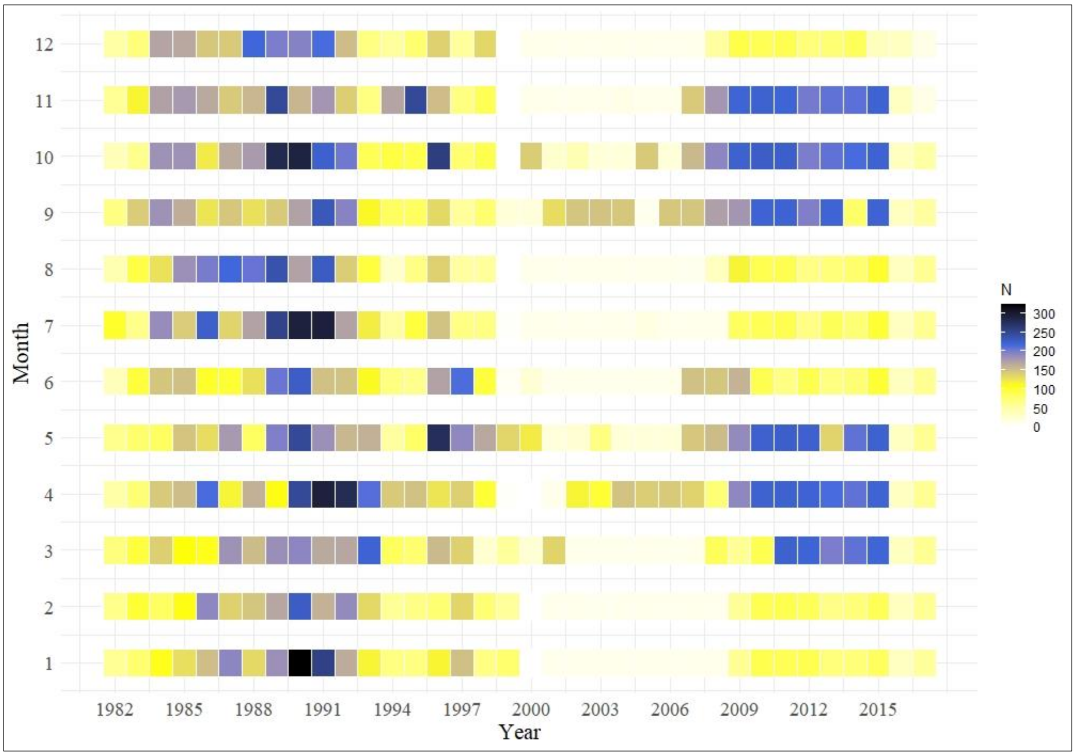


Fig.2 Heatmap of the available data showing non-uniform temporal distribution of the GWL information in the Harvey Catchment. N is number of available data in a month.

3 Methodology

Spatiotemporal Regression Kriging (Rkriging) predicts the spatial and temporal links between observed values. In this method, the regression (deterministic) and residual (stochastic) parts of the model are analyzed separately (Eq. (1)).

$$Z(s,t) = m(s,t) + \varepsilon(s,t) + r \tag{1}$$

where Z(s, t) is the observed GWL at space (s) and time (t), m(s, t) is the trend (deterministic) component, ε(s, t) is residual (stochastic) component of the model, which is the spatiotemporally auto-correlated residual for every $(s, t) \in S \times T$ where $S \subset R^2$ is the spatial domain and $T \subset R$ is the temporal domain (Varouchakis & Hristopulos, 2019), and r is the uncorrelated noise (Hu et al., 2017; Ruybal et al., 2019). The regression method is applied to predict the values on a fine grid. This part of the analysis, which called trend analysis, gives a rough estimation for each grid. Then, the residuals are extracted by deducting the trend from the observed data. For the residual part, the best spatiotemporal variogram (STvariogram) is fitted and the interpolated residuals for all grid values are calculated. Finally, the two components (trend and residual) are added back, to provide the final estimation of the GWL

(Hu et al., 2017). All of the analysis and codes are developed and performed in Rstudio platform.

3.1 RKriging of the residuals

The sample spatiotemporal semi-variogram (which is half the empirical STvariogram) is produced using the residuals as follow (Hu et al., 2017):

$$\gamma(h,u) = \frac{1}{2N(h,u)} \sum_{i=1}^{N(h,u)} [\varepsilon(s,t)_i - \varepsilon((s+ht)_i,(h+u))]^2 \tag{2}$$

where h is the separation distance for points in space, u is the separation in time, and $N(h, u)$ is the number of paired observations of z separated by lag (h, u). A model is fitted after the sample STvariogram is determined. Among the several models to estimate STvariogram, separable, Product-sum, and sumMetric models are the most common (Hu et al., 2017; Ruybal et al., 2019; Varouchakis & Hristopulos, 2019). The separable model, belongs to the separable covariance models, assumes that space and time domains of the variogram are separate and treats them independently, while product-sum and sumMetric models, belong to the non-separable covariance models, consider the interaction between space and time components. The advantages of the separable models are computationally fast with few parametrization, however these models cannot fully grasp the complicated interaction between the spatial and temporal components (Hengl et al., 2012; Geniaux, 2017; Varouchakis & Hristopulos, 2019). Therefore, in the current study, models from both separable and non-separable groups are selected and the results are compared to choose the best fit for the sample (empirical) spatiotemporal variogram.

3.2 Leave-One-Out Cross-Validation (LOOC)

To investigate the accuracy of the regression kriging, the Leave-One-Out Cross-Validation (LOOC) method is applied. A code is written in R to perform the spatiotemporal cross validation. During this process, for each space-time data is removed once, the remaining data are used to calibrate the model which is used to predict the value of the removed point. This process is repeated for all values in the data pool. Finally, the predicted values and observed values are compared to examine the accuracy of the prediction (Learning E.o.M, 2010).

3.3 Principal Component Analysis (PCA)

In this study, the built-in R functions prcomp() is used to perform the PCA. This function determines rotation and shift of the original data to a new coordinate system, in which the covariates are independent. For the current work, the two groups of covariates for PCA analysis are Harvey digital elevation model (DEM) and the extended boundary of the catchment (i.e., Longitude and Latitude of the catchment), as suggested by (Ruybal et al., 2019).

3.4 Time-series Analysis

Time-series analysis is carried out, for forty randomly selected grid points, to better understand interrelationship between estimated GWL and groundwater level change (ΔGWL), and precipitation time-series. The Cross-Correlation function (CCF) provides time-lag between the input and output, which suggests the response time of the output time-series. Equations 3 and 4 represent the mathematical expression of the CCF (Cai & Ofterdinger, 2016; Shi et al., 2019).

$$C_{xy}(k) = \frac{1}{n}\sum_{t=1}^{n-k}(x_t - \bar{x})(y_{t+k} - \bar{y}) \qquad (3)$$

$$\Gamma_{xy}(k) = \frac{C_{xy}(k)}{\sigma_x \sigma_y} \qquad (4)$$

where *Cxy(k)* is the cross-covariance between x_t (input time-series) and y_t (output time-series), k and n are the time-lag and the length of the time-series, respectively, and σ is the standard deviation of x and y.

The Auto-Correlation Function (ACF), on the other hand, is cross-correlation of the time-series with itself, at different time-lags. This parameter provides the "memory effect" of the dataset, which shows interdependency of the time-series to its historical values. For an uncorrelated time-series, the ACF shows sharp decrease within a short period, while a gradual decline shows strong interdependency and a long memory effect (Cai & Ofterdinger, 2016; Larocque et al., 1998).

4 Results

The study area is divided into 450×450 meter grids. For each grid a monthly temporal data-frame is provided to produce a uniform spatiotemporal structure and cover the temporal and spatial gaps in the observed data.

4.1 PCA calculation

As presented in Table 1, the PCA conversion of the original covariates (i.e., longitude, latitude and elevation) explained more than 96% of the variance with two components (i.e. PCA1 and PCA2).

Table 1 PCA conversion of the original covariates longitude, latitude and elevation explaining 96% of the variance

Parameters	PCA1	PCA2	PCA3
Standard deviation	1.375	0.9998	0.332
Proportion of Variance	0.63	0.33	0.04
Cumulative Proportion	0.63	0.96	1

As the difference between the variables' ranges and magnitudes might introduce bias to the analysis, all the values were scaled before being projected to the new coordinate system (i.e., PCA provided coordinates). A stepwise regression analysis was performed to provide the subset of optimum regressors, which best describe the trend component. The stepwise regression showed that among the various combinations of the potential predictors (i.e., PCA1, PCA2, latitude (Lat), longitude (Long), Elevation (Elev), Year the measurement was taken, and Month the measurement was taken), PCA1 and Long give the optimum combination. Hence, the trend component of GWL in the Harvey catchment has only the spatial dimension (Eq. (5)):

$$m(s) = -4.227 \times Long + 2.398 \times PCA1 + 1740.142 \tag{5}$$

Augmented Dickey-Fuller test for stationarity was used to check the stationarity of the input times-series. The test showed that before the trending decomposition the data was non-stationary with p-value = 0.3 and after decomposing and trend deduction, the residual became stationary with the p-value = 0.01.

4.2 Spatiotemporal variogram (STvariogram) model for residuals

Each component of the STvariogram can be described by a model such as spherical, exponential, Gaussian or Wave models. Different configuration of these models were tested for three widely used STvariograms (i.e., Separable, Product-sum and sumMetric), to determine the best model. Based on the least mean square value, the combination of the Exponential and Gaussian models were chosen for spatial and temporal components of the

STvariograms, respectively. For the joint component of the sumMetric STvariogram, the Exponential model was the best option (table 2). The initial values of sill, range and nugget were chosen based on the sample spatial and temporal variograms and then adjusted to minimize the mean square error between the sample and modeled STvariogram. In this case study, the directional sample variogram did not show strong anisotropic behavior, therefore the value of anisotropy (k) is set to minimum.

Table 2 Parameters of the fitted models and comparison of the goodness of fit to choose the best STvariogram

Variogram components	Model	Sill (km)	Range (km/day)	Nugget (km^2)	MSE (mean square error)		
					Separable	Product-sum	sumMetric
Spatial	Exponential	60	10	0	231	212	209
Temporal	Gaussian	50	1000	0			
Joint (only for sumMetric)	Exponential	80	20	40			

Fit.StVariogram function in the gstat package was used to fit the model against the empirical variogram from sample. The embedded L- BFGS- B algorithm was used to minimize the error between the model and the sample. The aforementioned algorithm is an extension of the Limited-memory BFGS optimization algorithm which belongs to Quasi-Newton methods. It is one of the most popular and efficient algorithms for fitting kriging models which allows to impose simple box constraints on the variables for numerical optimizations (Guitton, 2004).

The optimum number of spatiotemporal observations was determined by trial and error method. Comparing the STvariograms with the empirical variogram surface showed that both spatial closeness and number of available data in individual wells, play important roles in accuracy of the variograms. Congested number of wells in one location causes overfitting and scattered temporal data leads to unrealistic variogram. Finally, 641 wells, with at least 10 available temporal data, were selected, for this study.

As suggested in Table 2, the two non-separable models perform better than the separable model implying importance of the link between the spatial and temporal domains of the variogram. Among the three employed models, the sumMetric model outperforms the other STvariograms with lower Mean Square Error Value (MSE). The sumMetric model is a combination of sum and metric models (Eq.6) (Derakhshan & Leuangthong, 2006; Dimitrakopoulos & Luo, 1994; Rouhani & Hall, 1989).

$$\gamma_{ST}(s,t) = \gamma_S(h) + \gamma_T(u) + \gamma_J\left(\sqrt{h^2 + (ku)^2}\right) \quad (6)$$

where κ is the spatio-temporal ratio of anisotropy, which combines spatial distances with temporal distances, and $\gamma_S, \gamma_T, \gamma_J$ are the spatial, temporal, and joint components of the STvariograms, with separate nugget effects.

Figure 3 compares the empirical surface variogram and the best fitted STvariograms (i.e., sumMetric estimated STvariogram). The general increasing tendency of gamma-ST (γ_{ST}) with distance suggest that the correlation between the residuals decreases as the distance between the wells increases. The value of γ_{ST}, however, shows less sensitivity to time-lag.

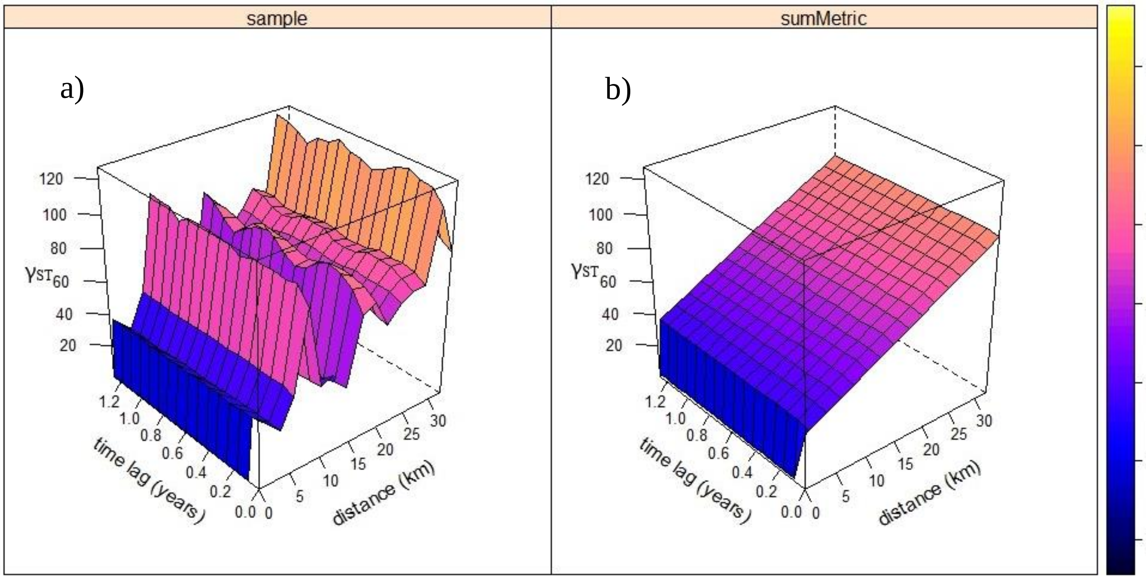


Fig.3 a) the empirical surface of the GWL residuals after trend removal and b) the fitted spatiotemporal variogram of the residuals using sumMetric model

4.3 Spatiotemporal Kriging Predicted Groundwater Levels

The trend (determinist component) and residual (stochastic component) together provide the final estimation of the GWL at any grid points in each month, based on which monthly GWL maps can be produced for the study years (i.e., 1982-2017). For the sake of presentation, Figure 4 presents only the maps for selected months of January, May and September in the selected years of 1982, 1997, 2007 and 2017. As expected, the deeper water table is located in south-eastern part of the catchment and shallower water table (the dark blue color) is in the coastal area (i.e., the north-western part, where the catchment meets the sea). It is also shown that GWL follows the same trend over the years although the actual GWL at each grid vary from year to year.

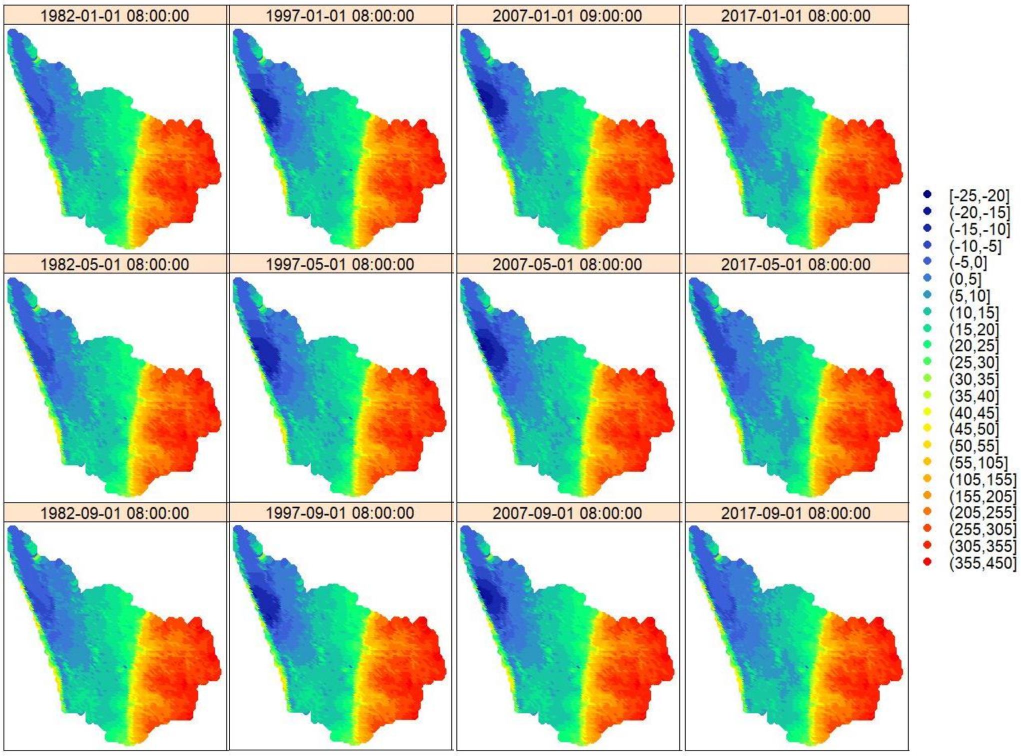


Fig.4 Created maps of estimated Harvey catchment GWL (m) for selected months of the study period (1982-2018) where hot and cold colors representing deeper and shallower groundwater level, respectivly

4.4 Cross-validation

The "Leave- one- out" cross- validation was carried out for almost 44000 spatiotemporal data points to compare the estimated values with the observed values (Figure 5). These spatiotemporal points are the observed GWL data from the wells, during the 36 years of study period. Non-uniformity of the observed data can also be observed from the figure where there is a lack of information within some ranges of elevation. The diagram suggests the Rkriging method is well capable of estimating GWL in the catchment, with the R-square value very close to 1 (i.e., 0.99).

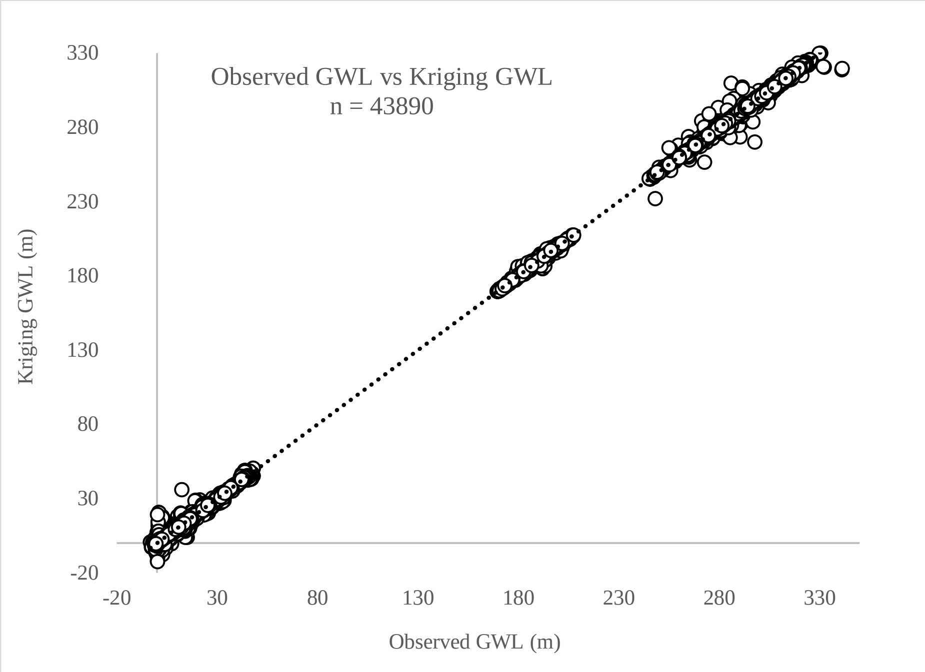
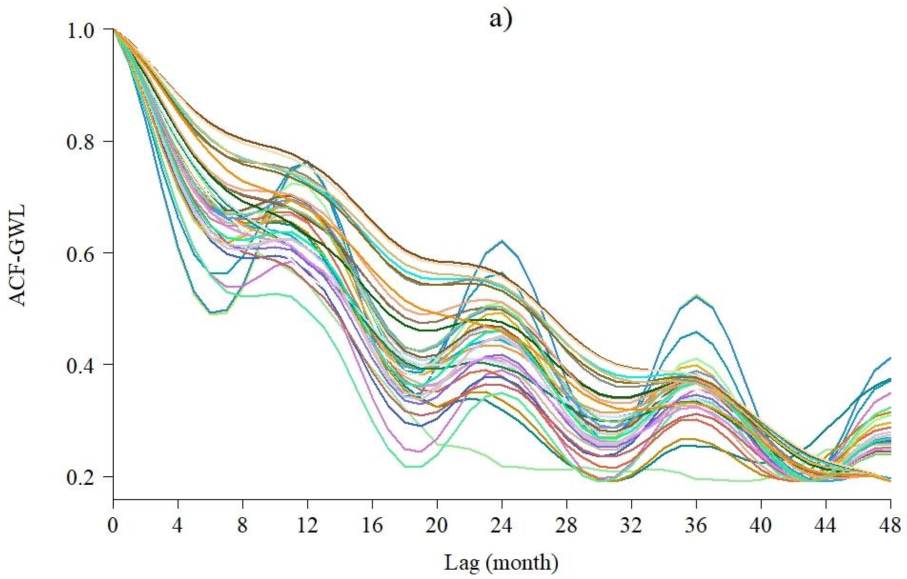


Fig.5 Leave–One-Out Cross Validation result showing the goodness of fit between Rkriging predicted GWL and observed GWL information from the 641 wells in the Harvey Catchment.

4.5 Time-series Analysis

Forty randomly selected samples (as hypothetical wells) were chosen to perform the auto-correlation and cross-correlation analysis. The samples are almost uniformly distributed in the catchment and cover all of the elevation classes. Figure 6 shows the values of auto-correlation function for GWL and ΔGWL. The gradual decline in the ground water level indicates the autocorrelation can last for at least four years (ACF above 0.2). Those samples which show sinusoidal, yet gradually decreasing patterns, are mainly located on the Collins Pool or very close to the pool. The ACF for ΔGWL shows completely different behavior and decreases rapidly which implies the effect of historical data naturally declines over time. For most of the cases, the ACF graphs for ΔGWL does not decrease with increasing lag and follow a sinusoidal pattern with 12 month circle, however, the seasonality and correlation are negligible. The aforementioned samples, located on or close to the Collins pool, perform higher seasonal auto-correlation values, indicating stronger impact of historical values and memory effect. As the pool is connected to the ocean (Figure 1), the unusual trend (i.e., stronger seasonal interdependency) of these samples can be because of the influence of ocean water.



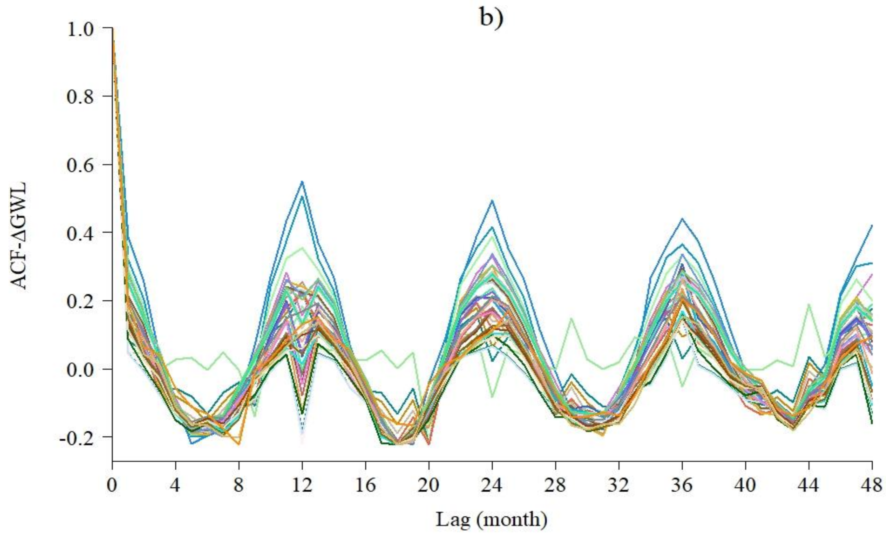


Fig.6 a) Auto Correlation Function (ACF) for GWL and b) ΔGWL in 48 months showing the autocorrelation values between the time-series

In Fig.7 the cross-correlation analysis between ΔGWL and average precipitation in the catchment is presented which suggests that the highest correlation happens at lag zero which indicates the time-lag between ΔGWL and precipitation is less than a month, meaning that precipitation needs less than a month to affect ΔGWL in the catchment. The short delay (lag-time) between precipitation and ΔGWL significantly depends on the catchment characteristics such as soil type, porosity, conductivity, land use, etc. and might be different for other locations, however it can provide straightforward, yet easy to implement information about the hydro(geo)logical system.

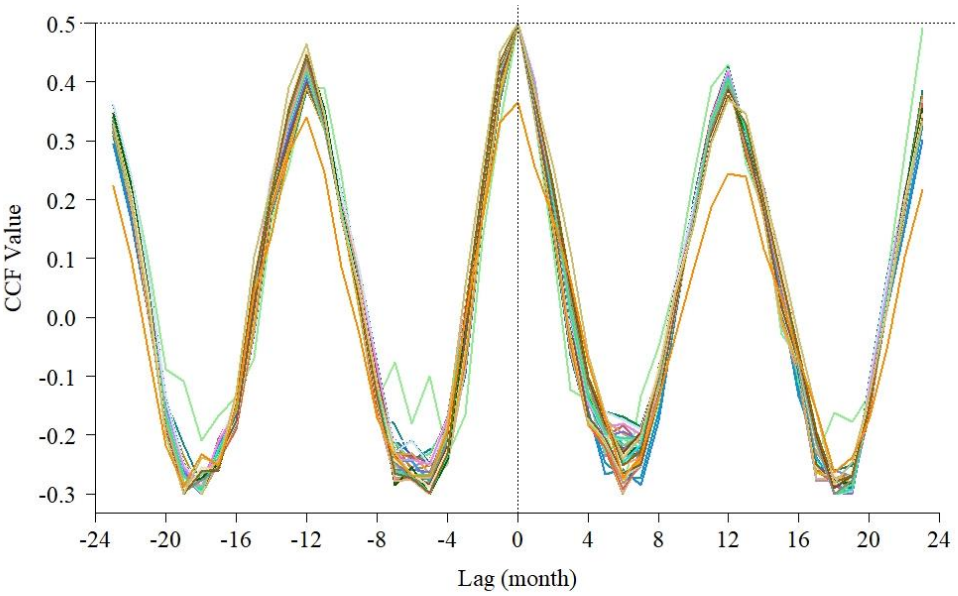


Fig.7 Cross-correlation between ΔGWL values and Precipitation (P) values showing time-lag between ΔGWL and precipitation is less than a month (the dashed lines show lag month during which the highest CCF value occurs between the two time-series)

5 Discussion

According to Figure 8 the mean monthly GWL has increased during 1988-1993 and decreased afterward (the trend line). The previous studies for the Harvey region reported decrease in GWL since 1980s (Ali et al., 2012; CSIRO, 2009; Kelsey et al., 2010) mainly due to extensive agricultural activities, urban development, and rainfall reduction. The current research confirmed these findings, showing that GWL in the catchment has decreased after a short period of increasing.

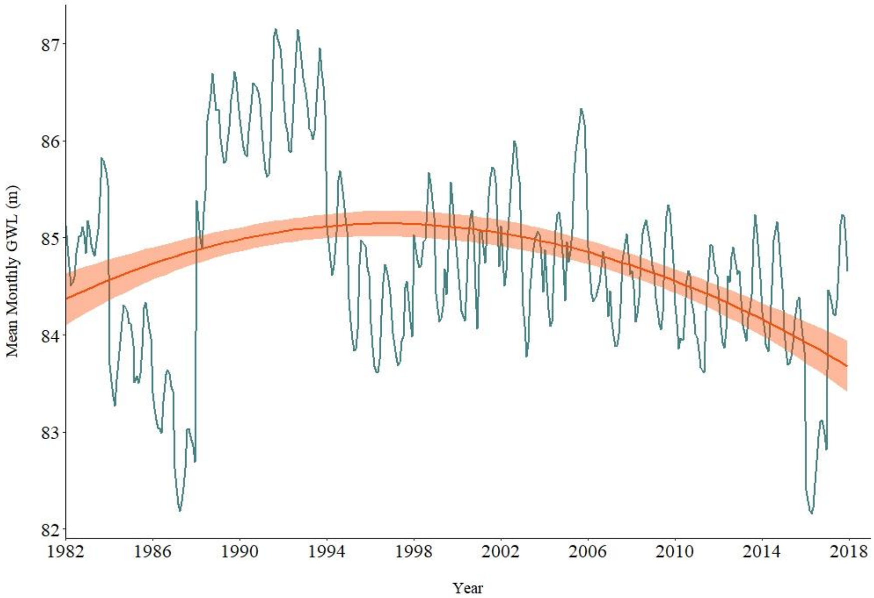
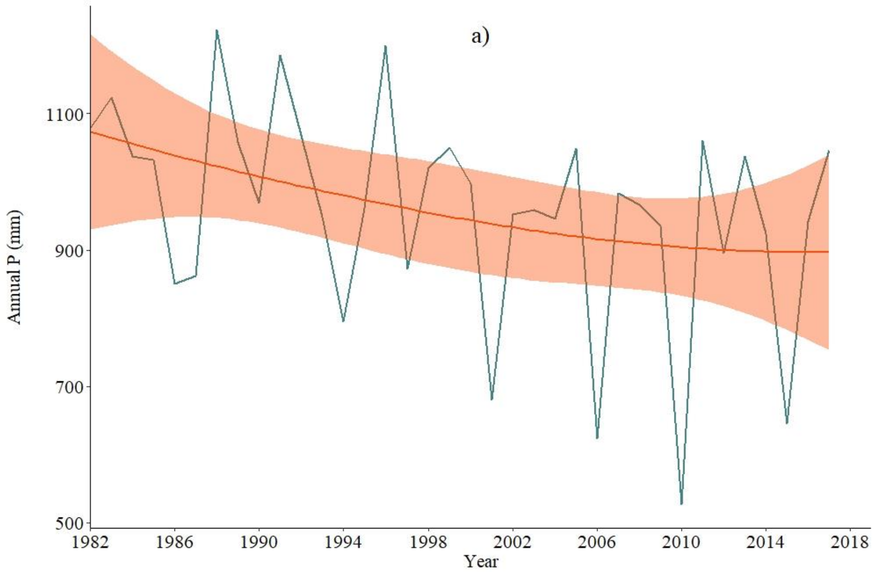


Fig.8 Mean Monthly trend of GWL during the study period

Figure 9 provides more detailed information. Although precipitation follows a decreasing trend (the red line), the annual precipitation during 1988 – 1993 is significantly above the average which coincides with those years in which GWL experienced a brief increase. The smooth bar around the trend lines for Figures 8 and 9 shows 95% level of confidence for the mean.



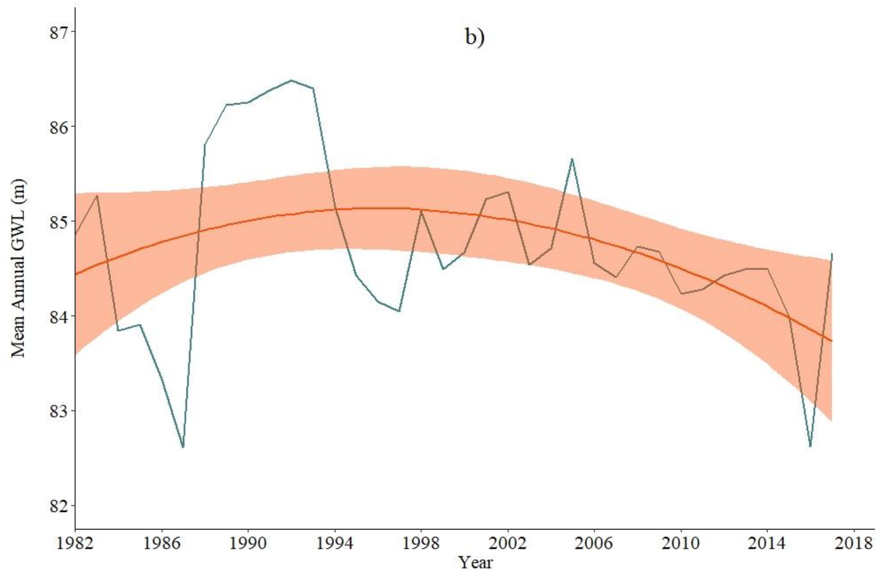


Fig.9 a) Annual Precipitation and b) Mean annual GWL trends during the study period

The Harvey Catchment, specifically in the coastal area, is reported to have a shallow water table. By deducting earth elevation from estimated GWL at each grid point, it was confirmed that the catchment is shallow, and water level almost stands within 10 meters below the earth surface. The deepest water table is located in the southeastern part of the catchment (Figure 4), where water level stands between 10 to 16 meters from the surface. Shallow catchments, especially in cases like Harvey, where the precipitation is highly seasonal, rejects recharging, after being full during winter time. Therefore the catchment is more vulnerable to water loss. On the other hand, rapid and extensive development in the study area causes higher rate of discharge than recharge, and hence results in more water loss. Decreasing water level increases the risk of ocean water intrusion, and deteriorates water quality (Ali et al., 2012). Because of the shallow groundwater, high permeability (i.e., high hydraulic gradient) and sandy soil of the catchment, a short time-lag between precipitation and ΔGWL was expected. The cross-correlation analysis showed the time-lag between the two time-series is less than a month. However, because of the chosen monthly time step in this study, it was not possible to detect the exact response time of ΔGWL time-series. In future studies, with a finer temporal grid (e.g., daily scale), it might be possible to track the possible weekly or daily time-lag. Although, due to the extensive computational process, probably, a shorter time period should be adopted.

The Rkriging method is a beneficial, yet, computationally extensive task. The model should perform the inversion covariance matrix, which makes the calculation process massive. Unlike spatial or temporal kriging, the method considers the time and space dependency of the variables by building a correlation between the parameters so that even when some of the spatial or/and temporal points are missing the uniform spatiotemporal estimation is carried on (Varouchakis & Hristopulos, 2019).

The proposed method showed that GWL has decreased in the catchment, during the study period. The estimated GWL provides valuable information about hydrogeological condition of the catchment, and hence can be useful for predicting future change and distinguishing potential environmental threats to the catchment (Ferdowsian & Pannell, 2009). Furthermore, the GWL information is important to accurately quantify water extraction capacity and amount of discharge and recharge to the groundwater system, which in return, is essential for proposing sustainable water supply plan (John & John, 2019; Kotchoni et al., 2019). Therefore, the outcome of this study is, also, useful for policymakers and water resources manager in developing sustainable plans and sustainable groundwater management. The present research is part of a more extensive study on the impact of climate change and human activities on water resources. For the next phase of the study, outcome of the current research will be applied to investigate water resources variations in the Harvey Catchment, during 1982-2017. In the absence of hydrological modelling and complex dataset, this method can provide valuable information. Moreover, the Rkriging method is a competent approach for cases with sparse non-uniform data, in fields such as hydrology, pollution tracking or other environmental studies.

6 Conclusion

As uniformly distributed groundwater data is not available, this study successfully applies Rkriging method to investigate groundwater change in the Harvey Catchment, Western Australia. The method displayed spatiotemporal interpolation between the non-uniform observed groundwater data. To overcome the temporal and spatial gap in the data, a uniform spatiotemporal grid was produced and accordingly monthly maps of the groundwater level for the catchment were created. The proposed method confirmed the reported decreasing groundwater level status in the catchment. In order to further investigate this reduction and its correlation with temporal precipitation change, time-series analysis was performed. The results showed there is a short time-lag between the precipitation and ΔGWL time-series (less than a month), which is expected considering Harvey Catchment has relatively shallow groundwater table. The proposed method can be used for other catchments where limited groundwater data is available. It increases the spatiotemporal understanding of the studied parameters where irregular temporal and spatial data is the only available information.

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The hydrological data (including groundwater and precipitation) were acquired from the website of Bureau of Meteorology (BOM) of Australia (http://www.bom.gov.au/waterdata/). All the code writing and modeling was done in Rstudio software, using the gstat, sp, spacetime and ggplot2 packages.

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Conflict of Interest Statement

The authors declare no conflicts of interest.

7 References

Adigi, J. A. (2019). Spatio-temporal regression kriging for predicting rainfall from sparse precipitation data in Ghana, University of Twente.

Al-Safi, H. I. J., Kazemi, H., & Sarukkalige, P. R. (2020). Comparative study of conceptual versus distributed hydrologic modelling to evaluate the impact of climate change on future runoff in unregulated catchments. Journal of Water and Climate Change, 11(2), 341-366.

Ali, R., McFarlane, D., Varma, S., Dawes, W., Emelyanova, I., Hodgson, G., & Charles, S. (2012). Potential climate change impacts on groundwater resources of south-western Australia. Journal of Hydrology, 475, 456-472.

Australian Bureau of Meteorology. Climate Data Online. Retrieved January 20, 2020, from http://www.bom.gov.au/climate/data/index.shtml

Environmental Protection Authority (2008). Water Quality Improvement Plan for the Rivers and Estuary of the Peel-Harvey System - Phophorus Management, Environmental Protection Authority, Perth, Western Australia.

Cai, Z., & Ofterdinger, U. (2016). Analysis of groundwater-level response to rainfall and estimation of annual recharge in fractured hard rock aquifers, NW Ireland. Journal of Hydrology, 535, 71-84.

CSIRO (2009) Groundwater yields in south-west Western Australia. A report to the Australian Government from the CSIRO South-WestWestern Australia Sustainable Yields Project. CSIRO Water for a Healthy Country Flagship, Australia.

CSIRO. (2009). Water yields and demands in south- west Western Australia. A report to the Australian Government from the CSIRO South- West Western Australia Sustainable Yields Project.

Dash, J., Sarangi, A., & Singh, D. (2010). Spatial variability of groundwater depth and quality parameters in the national capital territory of Delhi. Environmental Management, 45(3), 640-650.

De Vries, J. J., & Simmers, I. (2002). Groundwater recharge: an overview of processes and challenges. Hydrogeology Journal, 10(1), 5-17.

Derakhshan, H., & Leuangthong, O. (2006). A Review of Separable Spatiotemporal Models of Regionalization.

Dimitrakopoulos, R., & Luo, X. (1994). Spatiotemporal modelling: covariances and ordinary kriging systems. In Geostatistics for the next century (pp. 88-93): Springer.

Duvert, C., Jourde, H., Raiber, M., & Cox, M. E. (2015). Correlation and spectral analyses to assess the response of a shallow aquifer to low and high frequency rainfall fluctuations. Journal of Hydrology, 527, 894-907.

Ferdowsian, R., & Pannell, D. (2009). Explaining long-term trends in groundwater hydrographs. Paper presented at the Proceedings of the 18th World IMACS/MODSIM Congress, Cairns, Australia.

Geniaux, G. (2017). Analyzing spatio-temporal data with R: everything you always wanted to know-but were afraid to ask. Journal de la Société Française de Statistique, 158(3), 124-158.

Goovaerts, P. (2000). Geostatistical approaches for incorporating elevation into the spatial interpolation of rainfall. Journal of Hydrology, 228(1-2), 113-129.

Graler, B., Pebesma, E., & Heuvelink, G. (2016). Spatio-temporal interpolation using gstat. RFID Journal, 8(1), 204-218.

Green, T. R., Taniguchi, M., Kooi, H., Gurdak, J. J., Allen, D. M., Hiscock, K. M., . . . Aureli, A. (2011). Beneath the surface of global change: Impacts of climate change on groundwater. Journal of Hydrology, 405(3-4), 532-560.

Guitton, A. (2004). Bound constrained optimization: Application to the dip estimation problem. Stanford Exploration Project. Retrieved from http://sepwww.stanford.edu/data/media/public/docs/sep117/antoine1/paper_html/node6.html

Guo, L., Lei, L., Zeng, Z.-C., Zou, P., Liu, D., & Zhang, B. (2014). Evaluation of spatio-temporal variogram models for mapping Xco 2 using satellite observations: A case study in China. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 8(1), 376-385.

Haylock, M., Hofstra, N., Klein Tank, A., Klok, E., Jones, P., & New, M. (2008). A European daily high- resolution gridded data set of surface temperature and precipitation for 1950–2006. Journal of Geophysical Research: Atmospheres, 113(D20).

Hengl, T., Heuvelink, G. B., Tadić, M. P., & Pebesma, E. J. (2012). Spatio-temporal prediction of daily temperatures using time-series of MODIS LST images. Theoretical and applied climatology, 107(1), 265-277.

Hu, D., Shu, H., Hu, H., & Xu, J. (2017). Spatiotemporal regression Kriging to predict precipitation using time-series MODIS data. Cluster Computing, 20(1), 347-357.

John, R., & John, M. (2019). Adaptation of the visibility graph algorithm for detecting time lag between rainfall and water level fluctuations in Lake Okeechobee. Advances in Water Resources, 134, 103429.

Kazemi, H., Sarukkalige, R., & Badrzadeh, H. (2019). Evaluation of streamflow changes due to climate variation and human activities using the Budyko approach. Environmental Earth Sciences, 78(24), 713. doi:10.1007/s12665-019-8735-9

Kelsey, P., Hall, J., Kretschmer, P., Quinton, B., & Shakya, D. (2010). Hydrological and nutrient modelling of the Peel-Harvey catchment. In: Water Science Technical Series, Report.

Kim, J.-M., & Lee, J. (2017). Time series analysis for evaluating hydrological responses of pore-water pressure to rainfall in a slope. Hydrological Sciences Journal, 62(9), 1412-1421.

Kotchoni, D. V., Vouillamoz, J.-M., Lawson, F. M., Adjomayi, P., Boukari, M., & Taylor, R. G. (2019). Relationships between rainfall and groundwater recharge in seasonally humid Benin: a comparative analysis of long-term hydrographs in sedimentary and crystalline aquifers. Hydrogeology Journal, 27(2), 447-457.

Larocque, M., Mangin, A., Razack, M., & Banton, O. (1998). Contribution of correlation and spectral analyses to the regional study of a large karst aquifer (Charente, France). Journal of Hydrology, 205(3-4), 217-231.

Learning, E. o. M. (2010). Leave-One-Out Cross-Validation. In C. Sammut & G. I. Webb (Eds.), Encyclopedia of Machine Learning (pp. 600-601). Boston, MA: Springer US.

Lee, L., Lawrence, D., & Price, M. (2006). Analysis of water-level response to rainfall and implications for recharge pathways in the Chalk aquifer, SE England. Journal of Hydrology, 330(3-4), 604-620.

Lehmann, A., & Rode, M. (2001). Long-term behaviour and cross-correlation water quality analysis of the river Elbe, Germany. Water Research, 35(9), 2153-2160.

Pebesma, E. J. (2004). Multivariable geostatistics in S: The gstat package. Computers & Geosciences, 30(7), 683–691. https://doi.org/10.1016/j.cageo.2004.03.012

Rouhani, S., & Hall, T. J. (1989). Space-time kriging of groundwater data. In Geostatistics (pp. 639-650): Springer.

Ruibal-Conti, A. L. (2014). Connecting Land to the Ocean: A Restrospective Analysis of Nutrient Flux Pathways Within the Peel-Harvey Catchment-estuary System. University of Western Australia,

Ruybal, C. J., Hogue, T. S., & McCray, J. E. (2019). Evaluation of groundwater Levels in the Arapahoe Aquifer using Spatiotemporal regression kriging. Water Resources Research, 55(4), 2820-2837.

Shi, L., Zhang, B., Wang, H.-x., Zhang, H.-j., Peng, Z.-h., & Li, J.-y. (2019). Investigation on the causes of abnormal increase of water inflow in underground water-sealed storage system. Tunnelling and Underground Space Technology, 87, 174-186.

Taylor, R. G., Scanlon, B., Döll, P., Rodell, M., Van Beek, R., Wada, Y., . . . Edmunds, M. (2013). Ground water and climate change. Nature Climate Change, 3(4), 322-329.

Varouchakis, E. A., & Hristopulos, D. T. (2019). Comparison of spatiotemporal variogram functions based on a sparse dataset of groundwater level variations. Spatial Statistics, 34, 100245.

Varouchakis, E., & Hristopulos, D. (2013). Comparison of stochastic and deterministic methods for mapping groundwater level spatial variability in sparsely monitored basins. Environmental monitoring and assessment, 185(1), 1-19.

Voss, S., Zimmermann, B., & Zimmermann, A. (2016). Detecting spatial structures in throughfall data: The effect of extent, sample size, sampling design, and variogram estimation method. Journal of Hydrology, 540, 527-537.

Yao, L., Huo, Z., Feng, S., Mao, X., Kang, S., Chen, J., . . . Steenhuis, T. S. (2014). Evaluation of spatial interpolation methods for groundwater level in an arid inland oasis, northwest China. Environmental Earth Sciences, 71(4), 1911-1924.

Conflict of Interest Statement

The authors declare no conflicts of interest.

The Authors certify that all authors have seen and approved the final version of the manuscript and warrant that the article is the authors' original work, hasn't received prior publication and isn't under consideration for publication elsewhere.