Modeling Short-Term Spatial and Temporal Variability of Groundwater Level using Geostatistics and GIS

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ABSTRACT

Continuous depletion of groundwater levels from deliberate and uncontrolled exploitation of groundwater resources lead to the severe problems in arid and semi-arid hard-rock regions of the world. Geostatistics and GIS have been proved as successful tools for efficient planning and management of the groundwater resources. The present study demonstrated applicability of geostatistics and GIS to understand spatial and temporal behavior of groundwater levels in a semi-arid hard-rock aquifer of Western India. Monthly groundwater levels of 50 sites in the study area for 36-month period (May 2006–June 2009; excluding three months) were analyzed to find spatial autocorrelation and variances in the groundwater levels. Experimental variogram of the observed groundwater levels was computed at 750 m lag distance interval and four most-widely used geostatistical models were fitted to the experimental variogram. The best-fit geostatistical model was selected by using two goodness-of-fit criteria, i.e., root mean square error (RMSE) and correlation coefficient (r). Then spatial maps of the groundwater levels were prepared through kriging technique by using the best-fit geostatistical model. Results of two spatial statistics (Geary's C and Moran's I) indicated a strong positive autocorrelation in the groundwater levels within 3 km lag distance. It is emphasized that the spatial statistics are promising tools for geostatistical modeling, which help choose appropriate values of model parameters. Nugget-sill ratio (<0.25) revealed that the groundwater levels have strong spatial dependence in the area. The statistical indicators (RMSE and r) suggested that any of the three geostatistical models, i.e., spherical, circular and exponential, can be selected as the best-fit model for reliable and accurate spatial interpolation. However, exponential model is used as the best-fit model in the present study. Selection of the exponential model as the best-fit was further supported by very high values of coefficient of determination (r^2 ranging from 0.927 to 0.994). Spatial distribution maps of groundwater levels indicated that the groundwater levels are strongly affected by surface topography and presence of surface water bodies in the study area. Temporal pattern of the groundwater levels is mainly controlled by the rainy-season recharge and amount of groundwater extraction. Furthermore, it was found that the kriging technique is helpful in identifying critical locations over the study area where water saving and groundwater augmentation techniques need to be implemented in order to protect depleting groundwater resources.

Keywords: Autocorrelation, Geary's C, Geostatistics, GIS, groundwater level, kriging, Moran's I, spatial and temporal variations.

1. INTRODUCTION

Groundwater is the largest freshwater source in arid and semi-arid regions across the world. Importance of groundwater is further enhanced when subsurface formations consist of hard-rock aquifers. The groundwater potentiality in such semi-arid hard-rock regions is largely limited to shallow weathered and fractured zones. In order to meet the continuously increasing demands of freshwater, there has been indiscriminate exploitation of groundwater resources. If pumping exceeds the total amount of recharge, groundwater mining occurs and the aquifer becomes no longer sustainable (Sophocleous, 2005). The mismanagement of groundwater resources leads to the depletion of the aquifer storage, declining groundwater levels and deterioration of groundwater quality in hard-rock aquifer (Voudouris, 2006).

Groundwater has been the mainstay for meeting the domestic needs of more than 80% of rural and 50% of urban population in India (Mall et al., 2006), besides 60% of irrigated food production depending on well irrigation (Shah et al., 2000). Groundwater extraction across northern India in response to the growing demand for water has recently been exceeding the replenishable groundwater, causing a steady lowering of the water table (Hoque et al., 2007; CGWB, 2006). The problem of decreasing groundwater availability and how future climate change might impact an already serious situation is well-recognized for northern India (Barnett et al., 2005; Kumar et al., 2005; Amarasinghe et al., 2007). Therefore, it is vital to prognosticate the behaviour of the groundwater levels in the hard-rock aquifers both on spatial and temporal scales in order to formulate strategies for efficient planning and management of the scarce groundwater resources.

Monitoring of groundwater levels provides discrete measurements in space and time, which are the pre-requisites for the quantitative assessment of groundwater resources. The geostatistical techniques are useful for analyzing inherent uncertainties of groundwater systems and can be used in groundwater estimation problems, including interpolation, integration and differentiation (ASCE Task Committee, 1990). Geostatistics was developed to deal with problems involved in estimating phenomena that have a spatial autocorrelation structure among observations (Matheron, 1963).

In addition, the geographic information system (GIS) has emerged as a powerful tool for handling spatial data and decision making in several areas including engineering and environmental fields (Stafford, 1991; Goodchild et al., 1993; Chen et al., 2004). The geostatistical analysis can efficiently be performed within GIS environment. Thus, an integrated application of geostatistics and GIS is a promising tool for the effective analysis of spatial and temporal hydrogeologic data. The geostatistics has been used by several researchers for optimizing a groundwater monitoring network, e.g. Sophocleous et al. (1982), Pucci and Murashige (1987), Prakash and Singh (2000), Cameron and Hunter (2002), and Theodossiou and Latinopoulos (2006). Ahmadi and Sedghamiz (2007, 2008) applied geostatistics for spatial and temporal analyses of the groundwater levels in Darab plain of Iran.

The hard-rock hilly terrains of Aravalli Range in Rajasthan (the largest and the driest state of India), suffers from frequent droughts due to poor and delayed monsoon, low rainfall, abnormally high summer-temperature and inadequate water resources (Bhuiyan et al., 2006). Among consecutive five drought years (1998-2002), the 2002 drought was one of the severest droughts in Rajasthan as well as in the history of India (Samra, 2004). In 2002, the deviation from the normal rainfall was as high as -33% in Udaipur district of Rajasthan (UNDP, 2002). Consequently, the groundwater level declined considerably in Ahar River basin (situated in the Aravalli Range). In fact, the groundwater level in Ahar River basin declines every year with the advancement of non-monsoon season, particularly during summers when surface water sources dry up and groundwater level lowers beyond the economic lift of pumping. Most dugwells, which constitute the main source of drinking water for rural communities, completely dry up during non-monsoon seasons. Thus, the study area is severely afflicted with water scarcity, which has direct impact on the livelihood, health and sanitation of the inhabitants. Unfortunately, no scientific study has been conducted to date in the study area to analyze variability of the groundwater levels. Therefore, in the present study, geostatistics and GIS techniques are integrated to model spatial and temporal variations of groundwater levels in order to understand the behavior of the hard-rock aquifer systems.

2. MATERIALS AND METHODS

2.1 Description of Study Area

The present study is carried out in Ahar River basin of Udaipur district, Rajasthan, India (Fig. 1). The Ahar River basin is part of Girwa and Badgaon blocks of Udaipur district encompassing an area of 348 km^2. The study area is bounded by longitude 73°36′51″E to 73°49′46″E and latitude 24°28′49″N to 24°42′56″N. The basin is characterized by sub-tropical and sub-humid to semi-arid climatic conditions. The study area consists of almost a continuous girdle of hills. The general slope of the area is from the northwest to the southeast direction. The average annual rainfall is 60.90 cm, about 90% of which is experienced during the rainy season (June to October). The geology consists of Aravalli and post-Aravalli systems consisting of the gneiss, schist, phyllite-schist and the combination of these rock formations.

The surface water resources in the study area are mostly available in rivers and lakes. Three major rivers of the area are Ahar, Kotra and Amarjok rivers; Ahar is the main river of the study area. All three rivers are seasonal rivers and therefore, there is a dearth of annual perennial flow. The area is drained by the Ahar river, which enters the basin from the northeast direction and flows toward the southeast up to Udaisagar lake. The lakes of the study area are Fatehsagar, Pichhola, Udaisagar, Lakhawali, Roopsagar and Goverdhansagar. Of the total six lakes, Fatehsagar, Pichhola and Udaisagar are relatively large in size. The lakes are artificial, and most of their storage capacity is filled up by the runoff water drained from the surrounding catchments. Hence, the water level of the lakes fluctuates greatly, and often, the lakes dry up entirely during drought seasons.

Groundwater in the study area mainly occurs in unconfined aquifers. About 90% pairs of among 50 groundwater monitoring sites showed moderate-to-highly significant correlations between groundwater levels, which suggests that the most of the monitoring sites are hydraulically connected (Machiwal et al., 2011). The groundwater is mainly extracted by means of dug wells, tubewells, handpumps and stepwells. Of the total groundwater-extracting mechanisms presently existing in the area, dug wells account for 68.52%, tubewells for 1.62%, handpumps for 29.35% and stepwells for 0.51% (Singh, 2002). The well density has been noticed relatively higher in the southeast part of the study area, while the northeast and central parts have lower densities of the wells (Singh, 2002). The higher number of wells in relation to area and population coincides together and is found in and around industrial area located in the southeast portion of the area.

2.2 Data Collection and GIS Analysis

The extent of the Ahar River basin was extracted by digitizing the boundaries of the basin from the geometrically rectified toposheets based on watershed approach. Thus, entire drainage lines extending up to Ahar River were bounded within the basin without intersecting any drainage line. In this study, GIS has been used for the preparation, handling, and processing of thematic layers of the monthly groundwater levels by using Integrated Land and Water Information System (ILWIS) software, version 3.2 (ILWIS, 2001). In GIS, Universal Transverse Mercator (UTM) projection system was used with Ellipsoid as Everest India 1956 and Datum as Indian (India Nepal). The delineated map of the Ahar River basin along with its location and groundwater monitoring sites is shown in Fig. 1.

This study involves use of monthly groundwater level data of 50 monitoring sites for 36-month period (May 2006 to July 2009); data for November 2006, February 2007 and October 2007 were missing. Accuracy of the groundwater level data was up to the nearest 1-mm, collected by means of TLC (temperature level conductivity) Meter made by Solinst, Canada. Latitude and longitude of the monitoring sites (Fig. 1) were recorded by means of Trimble-made Global Positioning System.

2.3 Checking Normality and Trends and Analysis of Rainfall-Groundwater Dynamics

A basic pre-requisite condition before applying geostatistical analysis is that groundwater levels should follow normal distribution and should be free from any kind of spatial trends. Hence, normality of the spatial groundwater levels was checked before geostatistical modeling by plotting histograms and by applying one of the most powerful statistical tests, i.e., Shapiro-Wilk test, for individual 11 months (August 2008 – June 2009) by using STATISTICA software. Significance of spatial trends in the groundwater levels was evaluated by regression analysis between monthly groundwater levels and geographical coordinates (i.e., latitude and longitude). The presence of the linear and second-order polynomial spatial trends was also checked following another approach used by several researchers worldwide, e.g., Ma et al. (1999), Wu et al. (2003), and Bruland and Richardson (2005). Both linear and second-order polynomial trend models are defined as follows:

$$\mathrm{GWL} = a\,X + b\,Y + c \tag{1}$$

$$\mathrm{GWL} = a\,X^2 + b\,Y^2 + c\,X + d\,Y + e \tag{2}$$

where GWL = groundwater level (m bgs); X and Y = longitude and latitude in UTM coordinate system (m), respectively; and a, b, c, d and e are coefficients determined for individual months. The goodness-of-fit of the calculated trend was measured by coefficient of determination (r^2).

To understand rainfall-groundwater dynamics in the study area, rainfall barcharts along with groundwater hydrographs for 50 monitoring sites were plotted.

2.4 Determination of Spatial Statistics of Groundwater Levels

Spatial autocorrelation and variance help to get an impression of the nature of point data before interpolation and find necessary parameters for kriging. Distance, up to which the spatial autocorrelation exists between point pairs of the groundwater levels, can be found out by plotting the autocorrelation values against the distance classes. This distance value can be used as the limiting distance in point interpolations through geostatistics. There are two widely used spatial statistics, i.e., Moran’s Interpretation (I) of statistical maps, and Geary’s

Contiguity ratio (C), which help in understanding spatial autocorrelation and variance among point pairs.

Moran's I Equation: Mathematically, the Moran's I is expressed as follows (Moran, 1948):

$$I = \frac{n}{\sum\sum W_{ij}} \quad \frac{\sum\sum W_{ij}(Z_i - \overline{Z})(Z_j - \overline{Z})}{\sum(Z_i - \overline{Z})^2} \tag{3}$$

Geary's C Equation: The Geary's C is expressed as (Geary, 1954):

$$C = \frac{n-1}{2\sum\sum W_{ij}} \quad \frac{\sum\sum W_{ij}(Z_i - Z_j)^2}{\sum(Z_i - \overline{Z})^2} \tag{4}$$

where $n =$ total number of points, $W_{ij} =$ weight of a point pair, $Z_i =$ value of point i, $Z_j =$ value of point j, and $\overline{Z} =$ average of all available points.

The interpretation of statistical maps (I) behaves like Pearson's correlation coefficient since its numerator consists of a sum of cross-products of centered values (which is a covariance term), comparing in turn the values found at all pairs of points in the given distance class (Waller and Gotway, 2004). The coefficient I is sensitive to extreme values, just like Pearson correlation coefficient. The contiguity ratio (C) is closely related to semi-variance function used to compute a variogram (Legendre and Fortin, 1989), but contrary to semi-variance function, it can be tested for significance. The Geary's C is a distance-type function since the numerator sums the squared differences between values found at various pairs of points being compared. The value of Geary's C ranges from 0 to 2.

In this study, spatial autocorrelation between point pairs of the groundwater levels in individual 11 months were determined by using Geary's C and Moran's I test-statistics. For all point pairs in a distance class, the values for Moran's I and Geary's C were obtained. Geary's C compared the squared differences of point pair values to the mean of all values. Moran's I related the product of differences of point pair values to the overall difference. The general interpretation of these two statistics is summarized in Table 1.

2.5 Modeling Spatial Variation of Groundwater Levels by GIS-based Geostatistical Technique

In the present study, spatial maps of groundwater levels were prepared based on point observations of the groundwater levels by using kriging technique in GIS environment. Firstly, four geostatistical models namely, spherical, circular, Gaussian and exponential, were fitted to the experimental variogram of the groundwater levels of individual 11 months. Thereafter, the best-fit geostatistical model was selected and used for the spatial interpolation of the groundwater levels.

The theoretical basis of geostatistics has been described in detail by several authors (Goovaerts, 1997; Issaks and Srivastava, 1989; Kitanidis, 1997). There exist several spatial interpolation techniques, e.g., kriging, inverse distance weighting, deterministic splines, etc. However, kriging, or best linear unbiased estimation (BLUE) given only the variogram, has found the most applications in mining, geology, and hydrology (Kitanidis, 1997). A major advantage of kriging is that it is more flexible than other interpolation methods (Kitanidis, 1997). The weights are not selected on the basis of some arbitrary rule that may be applicable in some cases but not in others, but depend on how the function varies in space. Data can be analyzed in a systematic, objective way and prior experience is used to derive a variogram that is then used to determine the appropriate weights. Depending upon the scale of variability, we may use equal or highly variable weights. Another advantage of kriging is that it provides the means to evaluate the magnitude of the estimation error (Kitanidis, 1997). The mean square error is a useful rational measure of the reliability of the estimate; it depends only on the variogram and the location of the measurements.

In case of interpolation, kriging is an "exact interpolator". That is, the contour surface of the estimate reproduces the measurements. If Z(x) represents any random function (e.g., transmissivity field in an aquifer) with values measured at n locations in space $z(x_i)$, i = 1, 2, … n and if the value of the function Z has to be estimated at the point x_0, which has not been measured, the kriging estimate is defined as (Journel and Hujibregts, 1978):

$$Z^*(x_0) = \sum_{i=1}^{n} \lambda_i \, z(x_i) \tag{5}$$

where $Z^*(x_0)$ = estimation of function $Z(x)$ at point x_0 and λ_i = weighting factors.

In order to achieve the unbiased and optimal estimations in ordinary kriging, the following set of conditions should be solved simultaneously.

$$\sum_{j=1}^{n} \lambda_j \, C(x_i, x_j) - \mu = C(x_i, x_0) \qquad i = 1, 2, \ldots n \tag{6}$$

$$\sum_{j=1}^{n} \lambda_j = 1 \tag{7}$$

where μ is the Lagrangian multiplier and $C(x_i, x_j)$ = value of covariance between two points x_i and x_j.

The variogram, also known as experimental variogram, is an erratic curve (Kitanidis, 1997, 1999). It is not possible to use this variogram in the estimation purpose. Therefore, the curve of the experimental variogram is approximated by another theoretical curve with a defined mathematical expression. This smooth curve fitted to the experimental variogram is known as theoretical variogram. The commonly used variogram models are spherical, circular, Gaussian, and exponential (Issaks and Srivastava, 1989; Kitanidis, 1997). The mathematical expressions for these theoretical variogram models are given below.

Spherical Model:

$$\gamma(h) = C_0 + C\left(\frac{3h}{2a} - \frac{h^3}{2a^3}\right) \qquad \text{For } 0 < h \leq a \qquad (8)$$

$$\gamma(h) = C_0 + C \qquad \text{For } h>a \qquad (9)$$

Circular Model:

$$\gamma(h) = C_0 + C\left[1 - \frac{2}{\pi}\arccos(h/a) + \frac{2h}{\pi a}\sqrt{1-(h/a)^2}\right] \qquad \text{For } 0< h\leq a \qquad (10)$$

$$\gamma(h) = C_0 + C \qquad \text{For } h>a \qquad (11)$$

Gaussian Model:

$$\gamma(h) = C_0 + C\left[1 - e^{-(h/a)^2}\right] \qquad (12)$$

Exponential Model:

$$\gamma(h) = C_0 + C\left(1 - e^{-h/a}\right) \tag{13}$$

where C_0+C is the sill, a is the range, and h is the separation vector or lag distance.

In this study, suitable lag interval for experimental variogram of individual months was chosen after making several trials by fitting theoretical variogram models to experimental variogram. It was observed that lag interval of 750 m appears to be appropriate for all the months. The lag interval beyond 750 m resulted in fewer points in the variogram, while shorter lag distances created clusters of the points, which make it difficult to fit the geostatistical models. All the geostatistical analyses were performed in GIS environment by means of ILWIS software (ILWIS, 2001).

2.6 Goodness-of-Fit Criteria for Selecting Best-Fit Geostatistical Model

In this study, two goodness-of-fit criteria, namely root mean square error (RMSE) and correlation coefficient (r) were employed to adjudge the performance of the four geostatistical models. These goodness-of-fit criteria have been used in various hydrological modeling studies.

The root mean square error (RMSE) is mathematically expressed as:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}\left[z(x_i) - z^*(x_i)\right]^2}{n}} \tag{14}$$

Mathematical expression of the correlation coefficient (r) is given as:

$$r = \frac{n\sum_{i=1}^{n}\left[z(x_i)\cdot z^*(x_i)\right] - \left[\sum_{i=1}^{n} z(x_i)\cdot \sum_{i=1}^{n} z^*(x_i)\right]}{\left[\sqrt{n\left\{\sum_{i=1}^{n}\left[z(x_i)^2\right]\right\} - \left\{z(x_i)\right\}^2}\right]\cdot\left[\sqrt{n\left\{\sum_{i=1}^{n}\left[z^*(x_i)^2\right]\right\} - \left\{z^*(x_i)\right\}^2}\right]} \tag{15}$$

2.7 Investigation of Short-Term Temporal Variability in Groundwater Levels

In this study, temporal variability of the groundwater levels was explored by plotting box and whisker plots two times: first by means of the groundwater level data for 50 sites and then by means of the groundwater levels for 36 months. A box plot summarizes median, 25^{th} and 75^{th} percentiles (boundaries of the box), whiskers (upper and lower), and outliers (Machiwal and Jha, 2012). The outliers/extremes in this study were detected using the STATISTICA software, which considers a data point to be an outlier if the data point is outside the 1.5 times box length range from the upper and lower values of the box. On the other hand, an extreme value is that which is outside the three times box length range from the upper and lower values of the box (Tukey, 1977). Moreover, temporal change in spatial distribution of the kriged groundwater levels was investigated for 11-month period.

3. RESULTS AND DISCUSSION

3.1 Rainfall-Groundwater Dynamics

The groundwater levels at most of the sites are revealed to be strongly affected by the seasonal rainfall; barcharts of the rainfall along with groundwater hydrographs for the six sites are shown in Fig. 2 as examples. It is observed that the temporal pattern of the groundwater levels is similar for a large number of sites in the area. Peaks in groundwater levels during July or August and troughs during May or June are attributed to the seasonal cycle of wet and dry periods (Fig. 2). It was found that the groundwater levels were the shallowest in the post-rainy season of 2006, which might be due to relatively high rainfall in this year compared to rest of the 2 years. Temporal patterns of some of the sites showed disperse nature of groundwater levels after 2007 because of the localized pumping effect and uneven distribution of rainfall. The groundwater levels in the study area respond fairly well to the rainfall events.

3.2 Results of Normality Test and Spatial Trend Test

Histograms of the groundwater levels for 11 months are shown in Figs. 3(a-k). It is apparent from Figs. 3(a-k) that the groundwater levels follow an approximately normal distribution in all the months. Results of the Shapiro-Wilk (S-W) test further confirm normality of the groundwater levels. Observed S-W test-statistics indicates that null hypothesis of the presence of normality in the groundwater levels can not be rejected at 1% significance level as p-value is greater than 0.01 for all the months [Figs. 3(a-k)]. Hence, the groundwater level data come from a normally distributed population and hence, the data were subsequently used for geostatistical modeling.

Regression analysis between monthly groundwater levels and geographical coordinates (i.e., latitude and longitude) demonstrated that no spatial trends exist in groundwater levels of all 11 months over the study area. Furthermore, r^2 values ranged from 0.019 to 0.048 for linear trend and from 0.021 to 0.054 in case of second-order polynomial trend. The very low and insignificant r^2 values indicate that no spatial trend is present in the time series of groundwater levels over the study area. The absence of spatial trends confirms the presence of stationarity in the monthly groundwater levels, and therefore, the monthly groundwater levels are adequate to be used for geostatistical modeling.

3.3 Spatial Autocorrelation and Variance of Groundwater Levels

The value of both the spatial statistics, i.e., Geary's C and Moran's I, was computed for groundwater levels over selected distances with 750 m lag interval using different point pairs of monitoring sites within a particular lag distance. Spatial autocorrelograms of 11 months plotted between the computed spatial statistics as ordinate and lag distances as abscissa are presented in Fig. 4. A good resemblance in plots of spatial statistics [Figs. 4(a-k)] suggests similar spatial pattern of the groundwater levels over 11 months. It is seen from Figs. 4(a-k) that the values of Geary's C range between 0 and 1 up to a lag distance of 3 km, and the values of Moran's I remains greater than 1 up to 3 km distance in all the months. Interpretation of C and I values from Table 1 indicates a strong positive autocorrelation among groundwater levels within 3 km. Therefore, the groundwater levels at unknown sites in the study area should be estimated by interpolating known groundwater levels within 3 km limiting distance from the unknown point. Thus, the limiting distance of 3 km was used in computing spatial groundwater levels over the area by using the best-fit geostatistical model. Beyond the distance of 3 km, the value of Geary's C exceeds 1 and the value of Moran's I becomes negative. A positive autocorrelation is also seen in the groundwater levels beyond the lag distance of 15 to 16 km. However, it is observed that number of point pairs used to compute spatial statistics (Moran I and Geary C) beyond the lag distance of 15 km are only 5, 6, 16, and 18, which are very less compared to the number of point pairs used within 15 km lag distance for a total 50 sites. Hence, the positive autocorrelation beyond the lag distance of 15-16 km may not be considered significant.

3.4 Best-fit Geostatistical Model and Model Parameters

Parameters of the four geostatistical models fitted to monthly groundwater levels of 11 months are shown in Table 2, and the corresponding values of two goodness-of-fit criteria are summarized in Table 3. It can be seen from Table 3 that three geostatistical models, viz., spherical, circular and exponential are the best-fit models based on the two goodness-of-fit criteria for estimating areal distribution of groundwater levels in all 11 months. However, the exponential model was selected as the best-fit model for computing areal distribution of monthly groundwater levels in the study area. The best-fitted exponential model variograms for two months, i.e., September 2008 and March 2009, are shown in Figs. 5(a,b) as an example. The accuracy of kriged values depends mostly on the variogram values at small lags (Isaaks and Srivastava, 1989). In general, the nugget-to-sill ratio can be used to classify the spatial dependence (Liu et al., 2006). A variable is considered to have strong spatial dependence if the ratio is less than 0.25, and has a moderate spatial dependence if the ratio is between 0.25 and 0.75; otherwise, the variable has a week spatial dependence (Liu et al., 2006). The nugget-sill ratio in the present study is found to be less than 0.25 for all the months. Therefore, the groundwater levels have strong spatial dependence in the study area.

The accuracy of the fitted variogram and selection of the best-fit geostatistical model, i.e., exponential, were verified by predicting the groundwater levels of the known points by kriging. The observed and predicted groundwater levels were plotted on 1:1 line and linear regression model was fitted. The accuracy of the exponential geostatistical model in groundwater level prediction was checked by using goodness-of-fit criterion, coefficient of determination (r^2). Results of the linear regression modeling along with 1:1 line are shown in Figs. 6(a-k). The r^2 values range between 0.927 (November 2008) and 0.994 (April and May 2009) for 11 months [Figs. 6(a-k)]. The very high r^2 values verify that the groundwater levels predictions are highly reliable, and selection of exponential model as the best-fit geostatistical model is adequate.

Nugget value for the exponential model shows semi-variance other than zero (ranging from 2 to 7 m^2) at zero lag distance (Table 2), which indicates either measurement errors or small-scale spatial variability of the groundwater levels even over small distances (Delhomme, 1978). Value of the sill parameter is observed to be the lowest (28 m^2) during rainy season (September and October months), and then the sill almost shows an increasing trend over different dry season months till it achieves the highest value of 78 m^2 in June (Table 2). The continuous increase in sill parameter over the entire dry season suggests constant increase in spatial variance (or reduction in autocorrelation) of the groundwater levels for corresponding range in different months. It is also revealed from Table 2 that value of the range parameter remains close to 3 km in almost all the months, which means that the groundwater levels show spatial autocorrelation up to 3 km separation distance in the study area. It is worth mentioning that the similar finding is obtained by interpreting the results of the Moran's I and the Geary's C in the previous section. Hence, the results of the best-fit geostatistical model support the interpretation of both the spatial statistics (I and C) that a strong positive autocorrelation among groundwater levels exists up to a lag distance of 3 km [Figs. 4(a-k)]. The similar findings also emphasize that range parameter of the geostatistical model resembles to the maximum lag distance up to which Moran's I statistics remains positive and Geary's C statistics ranges between 0 and 1. Based on the above discussion, both the spatial statistics, C and I, seem to be advantageous in choosing accurate value of the range parameter while fitting the theoretical geostatistical model to the experimental variogram. In general, parameters of the geostatistical models are chosen by trial and error while looking at visual fitting of the model. However, use of the C and I statistics may help reducing the subjectivity of choosing the model parameters. Therefore, it is emphasized that the spatial statistics (I and C) are promising tools for geostatistical modeling, which help in selecting appropriate values of model parameters.

3.5 Spatial Distribution of Groundwater Levels

The contour maps of 11-month (August 2008 - June 2009) groundwater levels were generated by ordinary kriging technique using best-fit exponential model. Classified contour maps of the kriged groundwater levels for 11 months are shown in Figs. 7(a-k). It is apparent from Figs. 7(a-k) that the groundwater levels remain relatively shallow (within a depth range of 2-5 m during August – December months, and 8-11 m during January – June months) in the central part of the study area in all the 11 months. There exist two major lakes, Fatehsagar and Picchola, in the central part of the study area (Fig. 1) with their gross water storage capacities of 12.08×10^9 and 13.67×10^9 litres, respectively, and it is likely that the water stored in the lakes is recharged into the aquifer in this part of the area because of longer infiltration opportunity time. The groundwater levels are relatively deep nearby boundaries of the study area, where topographic elevations are comparatively high (Fig. 1), and mostly structural hills are present. Furthermore, densities of irrigation-purpose wells are relatively higher in the southern and the northeast parts of the study area (Singh, 2002), which directly exert much pressure on the groundwater level. Therefore, the groundwater in the southern and the eastern portions is generally available at greater depths compared to that in the northeast and the central parts of the area.

The Ahar River enters the study area from the northwest direction and flows toward the southeast direction following the surface topography (Fig. 1) up to Udaisagar lake and exits the area from the southeast direction. Thus, this might be a good location for practicing water-harvesting systems for recharging freshwater into the underlying aquifer. However, the northeast and the southern parts of the area also require much attention and caution regarding exploitation of groundwater. The critical over-exploited aquifers in the study area can be recuperated by adopting suitable strategies to cope with depleting groundwater levels, e.g., changing cropping pattern and growing less water requiring crops, implementation of micro-irrigation methods such as sprinkler, drip, and alternate furrow irrigation.

3.6 Temporal Variation of Groundwater levels

The variation of observed monthly groundwater levels over the study area is shown with the help of box and whisker plots in Fig. 8. It is well discernible from Fig. 8 that the groundwater levels of sites W3 and W47 remains more or less stable over the year. The site W3 is located at downstream of the Lakhawali lake and the site W47 is very close to Ahar River (Fig. 1). Therefore, it is most-likely that water contained in surface water bodies gets recharged into the groundwater and maintains the invariable groundwater levels. On the contrary, considerable groundwater fluctuations take place at sites W19, W20, W28, W29, and W44 (Fig. 8). It can be seen from Fig. 1 that the site W44 exists in the southern part, and the sites W19 and W20 are situated near the northeast boundary of the study area where the huge quantities of the groundwater resource are extracted by relatively large density of irrigation-purpose wells (Singh, 2002). The depleted groundwater levels are generally recovered during rainy season, resulting in the large fluctuations of groundwater levels. However, the sites W28 and W29 are located close to two seasonal rivers, i.e. Amarjok and Kotra (Fig. 1), which flows during rainy season only. Hence, the groundwater levels, which are depleted during dry period of the year, are recuperated back during rainy season due to occurrence of groundwater recharge.

Furthermore, it is seen that values of the median groundwater level are more or less at the centre of the box for nine sites (site W7, W12, W15, W18, W27, W31, W35, W41 and W42), which indicates that the groundwater level time series at these sites precisely follows normal distribution. Outliers are seen in the groundwater levels of three sites, i.e. sites W6, W18 and W43 (Fig. 8). The outliers at sites W6 and W18 are caused by rapid rise of the monthly groundwater levels (rise of 6.45 and 8.10 m at the sites W6 and W18, respectively) due to groundwater recharge occurring during rainy season, whereas outlier at site W43 represents drastic decline of the monthly groundwater level (decline of 2.2 m) because of excessive pumping during dry period in the area.

Moreover, temporal variation of the groundwater levels during 36-month period over the study area is shown in Fig. 9. It is seen from Fig. 9 that the median groundwater levels are very shallow in September and October months in all the years. The median groundwater levels start declining after October month every year at the end of rainy season, and the groundwater levels continuously decline over the entire dry season. However, the rate of decline, which remains high at the beginning, starts decreasing with time, and the median groundwater levels remains stable during May and June months. Outliers can be seen in the groundwater levels of few of the months. The large spatial variation in groundwater level during the dry season is due to extraction of huge quantities of the groundwater at relatively higher rate to meet irrigation need of the crops. In contrast, the least spatial variation of groundwater levels is seen in rainy season. In September month, groundwater irrigation is generally not provided in the study area due to surplus availability of the surface water and the groundwater levels in the entire study area rise in response to rainy season recharge. The earlier discussed rainfall-groundwater dynamics support the above inferences.

Temporal variation in spatial distribution of the groundwater levels in the study area over 11-month period can be seen from Fig. 7(a-k). It is clear from Figs. 7(a-k) that the groundwater levels remain within 11 m from ground surface in 68% of the area in August 2008. However, almost 85% of the area was having groundwater level within 11 m bgs in September 2008. Thereafter, the area having groundwater level within 11 m bgs started decreasing continuously over time up to June 2009, when 11 m bgs groundwater level was present in 20% of the area. Simultaneously, the area having groundwater levels beyond 14 m bgs was the lowest (5%) in September month of the year 2008, and the area increased thereafter up to the highest of 71% in May month of the year 2009. This shows that there is a direct effect of rainy season recharge on the groundwater levels during rainy season months (June to September). However, the groundwater levels continuously decline during dry period months due to extensive extraction of the groundwater resource for providing irrigation to dry season crops. Therefore, water-saving techniques for instance, rainwater harvesting systems and micro-irrigation methods, i.e., drip and sprinkler, respectively, are very useful in efficient planning and management of the water resources in the area, especially in the northeast and the southern parts, which are very critical regions in the study area.

4. CONCLUSIONS

The application of geostatistics and GIS techniques in modeling spatial and temporal variations of groundwater levels has been demonstrated in this study using monthly groundwater-level data of 50 sites for the 36-month period (May 2006–June 2009) obtained from a semi-arid hard-rock groundwater basin of Western India. Histograms and Shapiro-Wilk test indicated presence of normality in the groundwater levels of all the sites. It is emphasized that two spatial statistics namely Moran’s I and Geary’s C are promising tools for geostatistical modeling, which help select appropriate values of model parameters. Both I and

C statistics indicated a strong positive autocorrelation in the groundwater levels within 3 km separation distance. Therefore, the groundwater levels at unknown points were determined through spatial interpolation of the known groundwater levels within 3 km limiting distance. Based on the goodness-of-fit criteria (RMSE and correlation coefficient), the exponential model was selected as the best-fit geostatistical model for ordinary kriging method. The suitability of the exponential model was further verified by regression analysis which indicated very high values of coefficient of determination (r^2>0.92). The nugget-to-sill ratio of <0.25 for the exponential model suggested that the groundwater levels of the study area have strong spatial dependence.

Spatial distribution of the groundwater levels is highly influenced by the topography and the presence of major surface water bodies in the study area. The groundwater levels were found to be relatively shallow in the central part of the study area, while the groundwater levels near the southern and the northeast boundaries of the study area are at relatively large depths. Both the southern and the northeast portions of the study area require appropriate strategies to maintain groundwater levels, which are currently being depleted by relatively dense network of wells used for irrigation. Furthermore, groundwater fluctuation was found to be comparatively large for the sites located nearby seasonal rivers, at higher topography and at hills. The rainy-season recharge and groundwater extraction for irrigation are major factors to control temporal pattern of groundwater levels in the study area.

Overall, the performance of kriging technique in spatial modeling of groundwater levels was found to be adequate in this study. The kriging technique helps in identifying critical areas (suffering from declining groundwater level) in a groundwater basin, which in turn addresses the urgent need to implement suitable water saving as well as groundwater augmentation techniques such as rainwater harvesting and groundwater recharge. The methodology and outcomes of this study are also useful to other hard-rock areas of India as well as in other semi-arid regions of the world. Finally, it is concluded that integrated geostatistics and GIS techniques are very reliable and helpful tools for sustainable management of groundwater resources.

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Table 1. Interpretation of Geary’s C and Moran’s I

Moran’s Interpretation (I) of Maps	**Interpretation**	**Geary’s Contiguity Ratio (C)**
I > 0	Strong positive autocorrelation	0 < C < 1
I < 0	Strong negative autocorrelation	C > 1
I = 0	Random distribution of values	C = 1

Table 2. Parameters of four geostatistical models for groundwater levels of 11-month period

S. No.	Month	Model Parameters	Spherical	Circular	Gaussian	Exponential
1	August 2008	Nugget (m^2)	7	7	10	7
		Sill (m^2)	35	35	33	35
		Range (m)	7000	6000	3000	3000
2	September 2008	Nugget (m^2)	5	5	6	2
		Sill (m^2)	26	26	26	28
		Range (m)	7000	6000	3000	3000
3	October 2008	Nugget (m^2)	7	7	9	4
		Sill (m^2)	29	29	28	28
		Range (m)	11000	10000	4000	3500
4	November 2008	Nugget (m^2)	9	9	11	6
		Sill (m^2)	46	46	48	50
		Range (m)	9000	8000	4000	4500
5	December 2008	Nugget (m^2)	16	16	19	4
		Sill (m^2)	54	55	54	54
		Range (m)	11000	10000	4500	3000
6	January 2009	Nugget (m^2)	5	7	10	3
		Sill (m^2)	55	55	56	57
		Range (m)	6500	6000	3500	2700
7	February 2009	Nugget (m^2)	6	4	11	2
		Sill (m^2)	60	59	59	59
		Range (m)	6000	5000	3000	2000
8	March 2009	Nugget (m^2)	4	5	9	3
		Sill (m^2)	59	59	59	60
		Range (m)	5000	5000	2500	2500
9	April 2009	Nugget (m^2)	8	5	10	2
		Sill (m^2)	58	58	58	58
		Range (m)	5500	5000	2800	2300
10	May 2009	Nugget (m^2)	3	3	5	2
		Sill (m^2)	59	59	59	62
		Range (m)	5000	5000	2700	2500
11	June 2009	Nugget (m^2)	4	3	10	2
		Sill (m^2)	74	75	77	78
		Range (m)	5000	5000	3000	2800

Table 3. Results of two goodness-of-fit criteria for four geostatistical models

Goodness-of-fit Criterion	**Spherical**	**Circular**	**Gaussian**	**Exponential**
(a) August 2008				
Root Mean Square Error (m)	1.80	1.81	2.46	1.63
Correlation Coefficient	0.960	0.958	0.912	0.972
(b) September 2008				
Root Mean Square Error (m)	1.43	1.44	1.80	0.69
Correlation Coefficient	0.971	0.970	0.945	0.993
(c) October 2008				
Root Mean Square Error (m)	2.29	2.35	2.75	1.36
Correlation Coefficient	0.937	0.933	0.883	0.979
(d) November 2008				
Root Mean Square Error (m)	2.76	2.81	3.67	2.06
Correlation Coefficient	0.926	0.924	0.831	0.963
(e) December 2008				
Root Mean Square Error (m)	3.46	3.51	4.12	1.30
Correlation Coefficient	0.903	0.900	0.824	0.987
(f) January 2009				
Root Mean Square Error (m)	1.69	2.07	3.27	1.06
Correlation Coefficient	0.976	0.964	0.892	0.991
(g) February 2009				
Root Mean Square Error (m)	1.67	1.36	3.00	0.68
Correlation Coefficient	0.978	0.985	0.917	0.997
(h) March 2009				
Root Mean Square Error (m)	1.24	1.50	2.62	0.95
Correlation Coefficient	0.988	0.982	0.938	0.993
(i) April 2009				
Root Mean Square Error (m)	1.78	1.43	2.75	0.65
Correlation Coefficient	0.98	0.98	0.93	1.00
(j) May 2009				
Root Mean Square Error (m)	0.95	1.04	2.21	0.64
Correlation Coefficient	0.993	0.991	0.955	0.997
(k) June 2009				
Root Mean Square Error (m)	1.21	1.14	2.97	0.77
Correlation Coefficient	0.991	0.992	0.936	0.996

Figure Captions

Fig. 1. Location map of the study area along with groundwater monitoring sites

Fig. 2. Rainfall barcharts along with groundwater hydrographs

Figs. 3(a-k). Histograms and Shapiro-Wilk test-statistics of monthly groundwater levels for 11 months

Figs. 4(a-k). Spatial autocorrelograms for monthly groundwater levels of 11 months

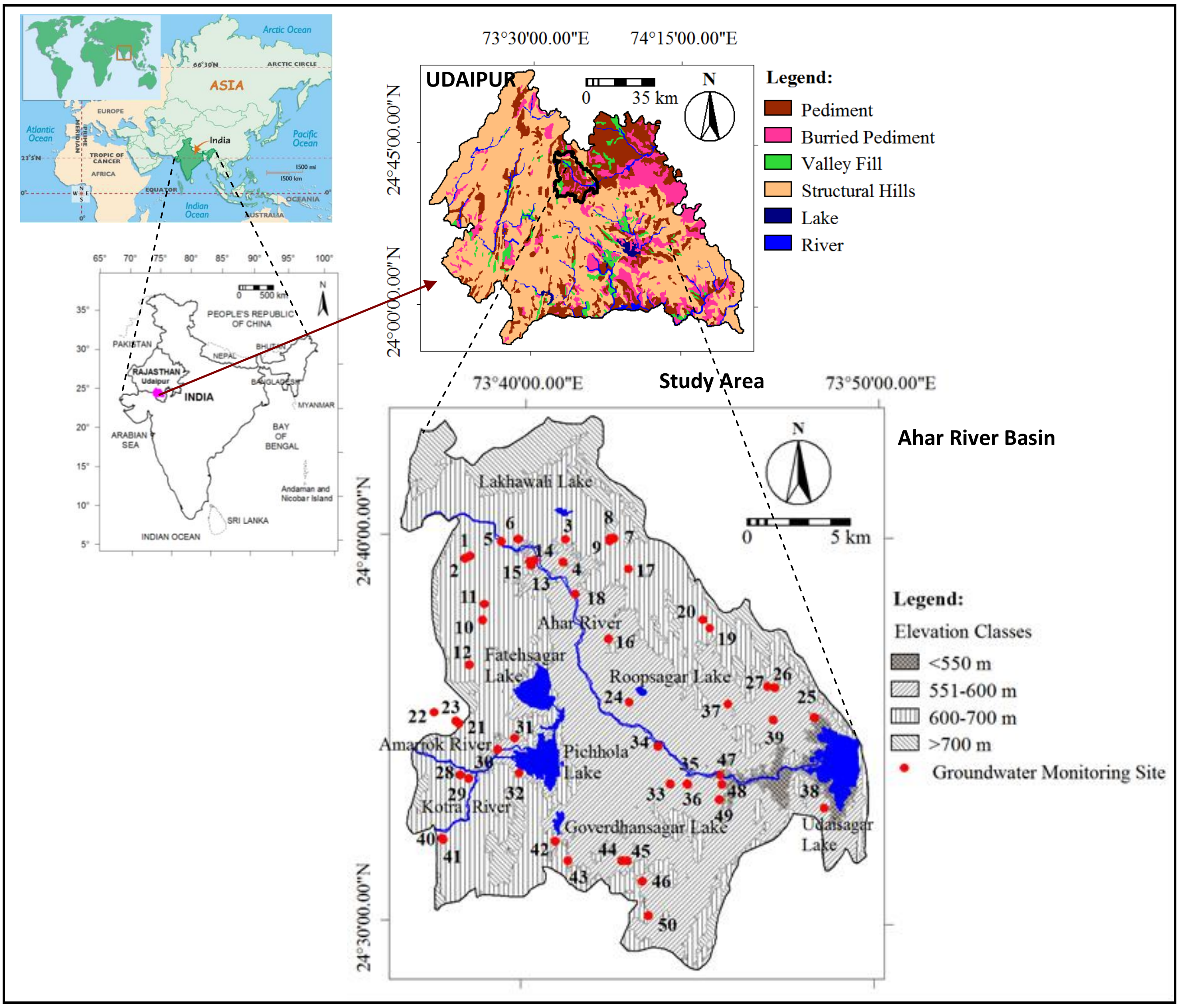
Fig. 5. Experimental variogram and fitted theoretical exponential geostatistical model for groundwater levels of (a) September 2008 and (b) March 2009

Figs. 6(a-k). The best-fitted regression model (*solid line*) between the observed and predicted (by exponential model) groundwater levels for 11 months and 1:1 line (*dashed line*)

Figs. 7(a-k). Spatial distribution maps of groundwater level for eleven months

Fig. 8. Box and whisker plots of the observed groundwater level across groundwater monitoring sites

Fig. 9. Box and whisker plots of the observed groundwater level over 36-month period



Arctic Ocean
ASIA
EUROPE
Atlantic Ocean
Pacific Ocean
AFRICA
Indian Ocean
India
OCEANIA
AUSTRALIA
PEOPLE'S REPUBLIC OF CHINA
PAKISTAN
NEPAL
BHUTAN
RAJASTHAN
Udaipur
INDIA
BANGLADESH
MYANMAR
ARABIAN SEA
BAY OF BENGAL
Andaman and Nicobar Island
SRI LANKA
INDIAN OCEAN
0 500 km
73°30'00.00"E
74°15'00.00"E
24°45'00.00"N
24°00'0.00"N
UDAIPUR
0 35 km
N
Legend:
Pediment
Burried Pediment
Valley Fill
Structural Hills
Lake
River
73°40'00.00"E
Study Area
73°50'00.00"E
Ahar River Basin
24°40'00.00"N
24°30'00.00"N
N
0 5 km
Lakhawali Lake
Ahar River
Fatehsagar Lake
Roopsagar Lake
Amarjok River
Pichhola Lake
Kotra River
Goverdhansagar Lake
Udaisagar Lake
Legend:
Elevation Classes
<550 m
551-600 m
600-700 m
>700 m
Groundwater Monitoring Site

Fig. 1

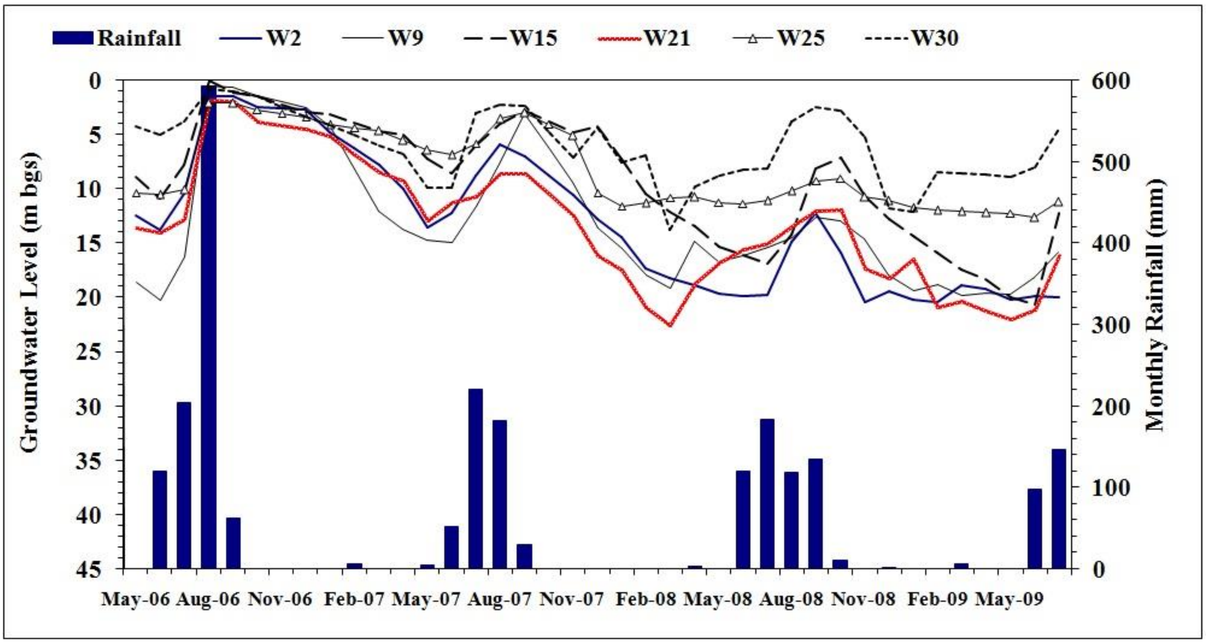

Rainfall
W2
W9
W15
W21
W25
W30
Groundwater Level (m bgs)
Monthly Rainfall (mm)
0
5
10
15
20
25
30
35
40
45
600
500
400
300
200
100
0
May-06 Aug-06 Nov-06 Feb-07 May-07 Aug-07 Nov-07 Feb-08 May-08 Aug-08 Nov-08 Feb-09 May-09

Fig. 2

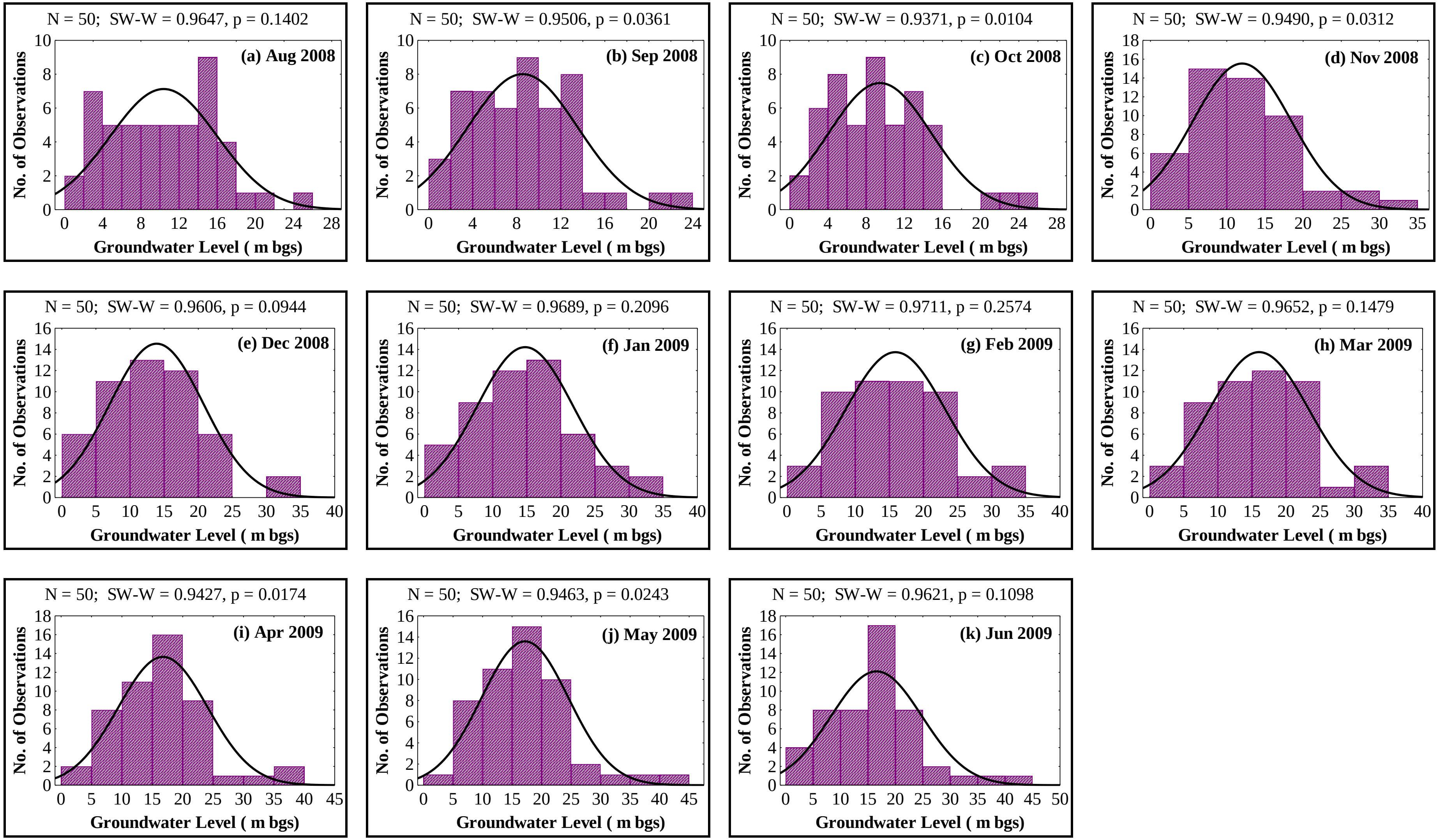
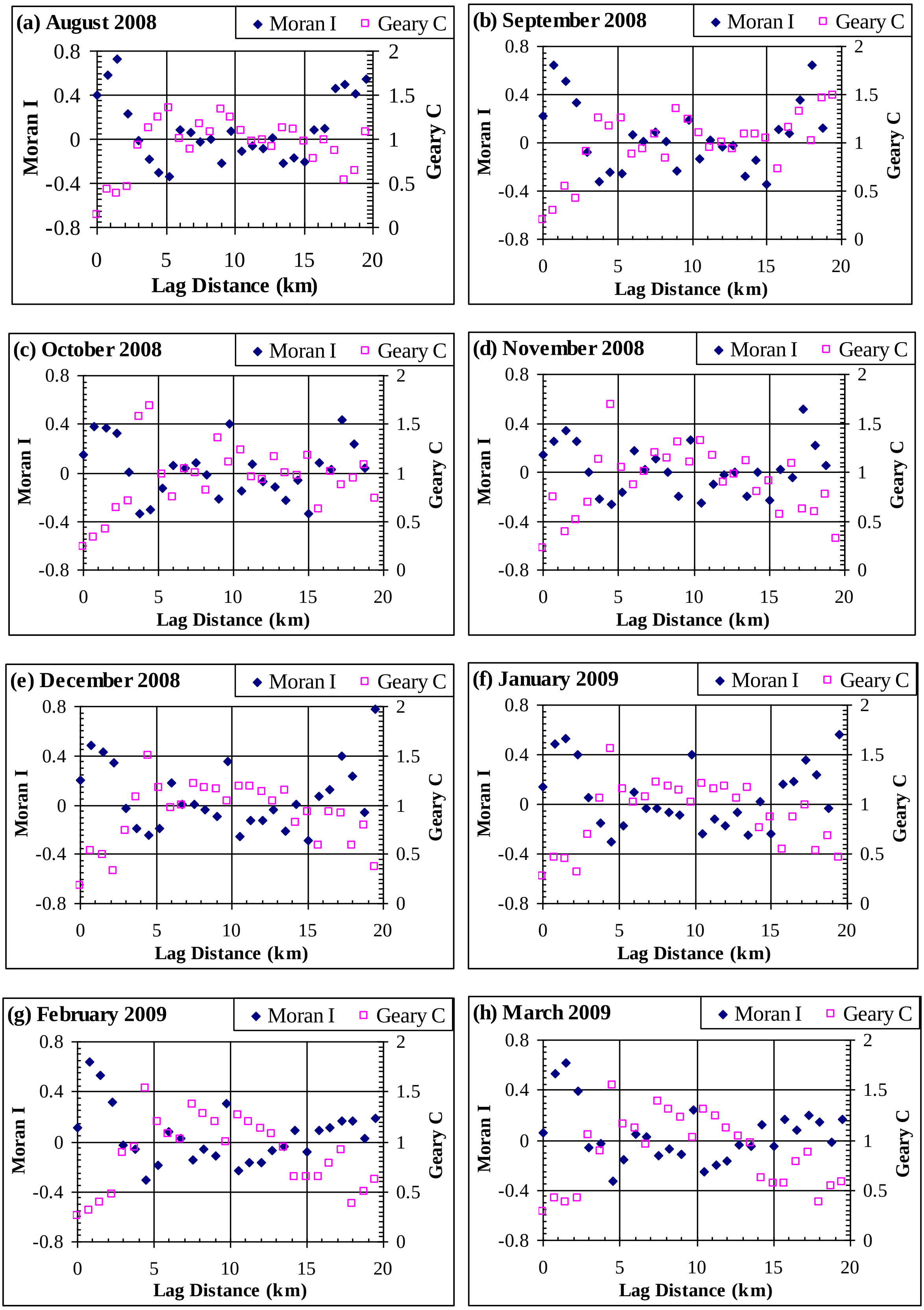
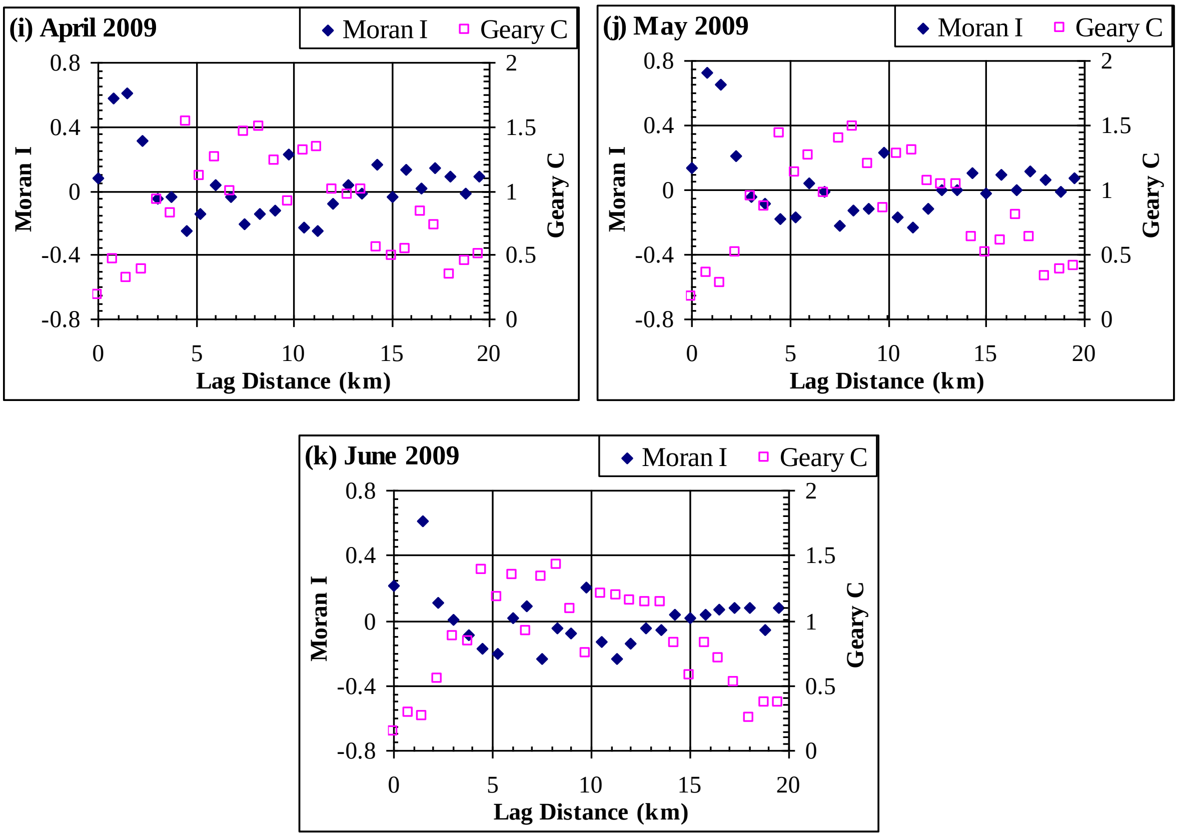

N = 50; SW-W = 0.9647, p = 0.1402
(a) Aug 2008
N = 50; SW-W = 0.9506, p = 0.0361
(b) Sep 2008
N = 50; SW-W = 0.9371, p = 0.0104
(c) Oct 2008
N = 50; SW-W = 0.9490, p = 0.0312
(d) Nov 2008
N = 50; SW-W = 0.9606, p = 0.0944
(e) Dec 2008
N = 50; SW-W = 0.9689, p = 0.2096
(f) Jan 2009
N = 50; SW-W = 0.9711, p = 0.2574
(g) Feb 2009
N = 50; SW-W = 0.9652, p = 0.1479
(h) Mar 2009
N = 50; SW-W = 0.9427, p = 0.0174
(i) Apr 2009
N = 50; SW-W = 0.9463, p = 0.0243
(j) May 2009
N = 50; SW-W = 0.9621, p = 0.1098
(k) Jun 2009
No. of Observations
Groundwater Level (m bgs)

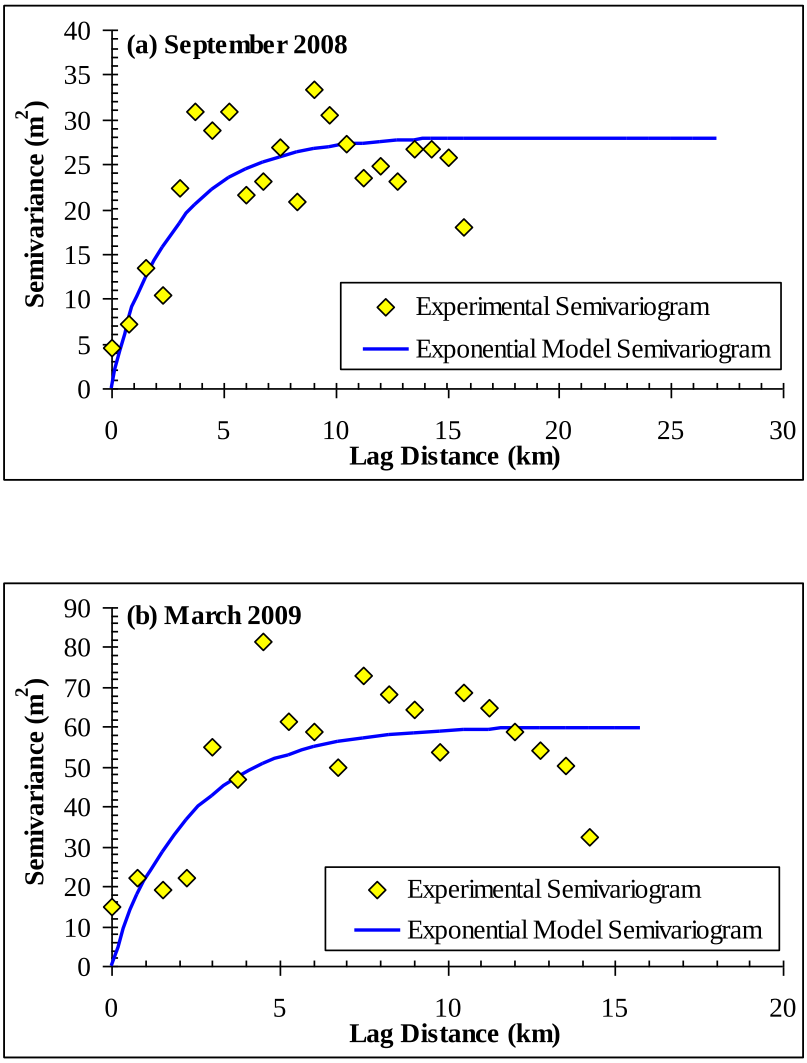
Fig. 3(a-k)



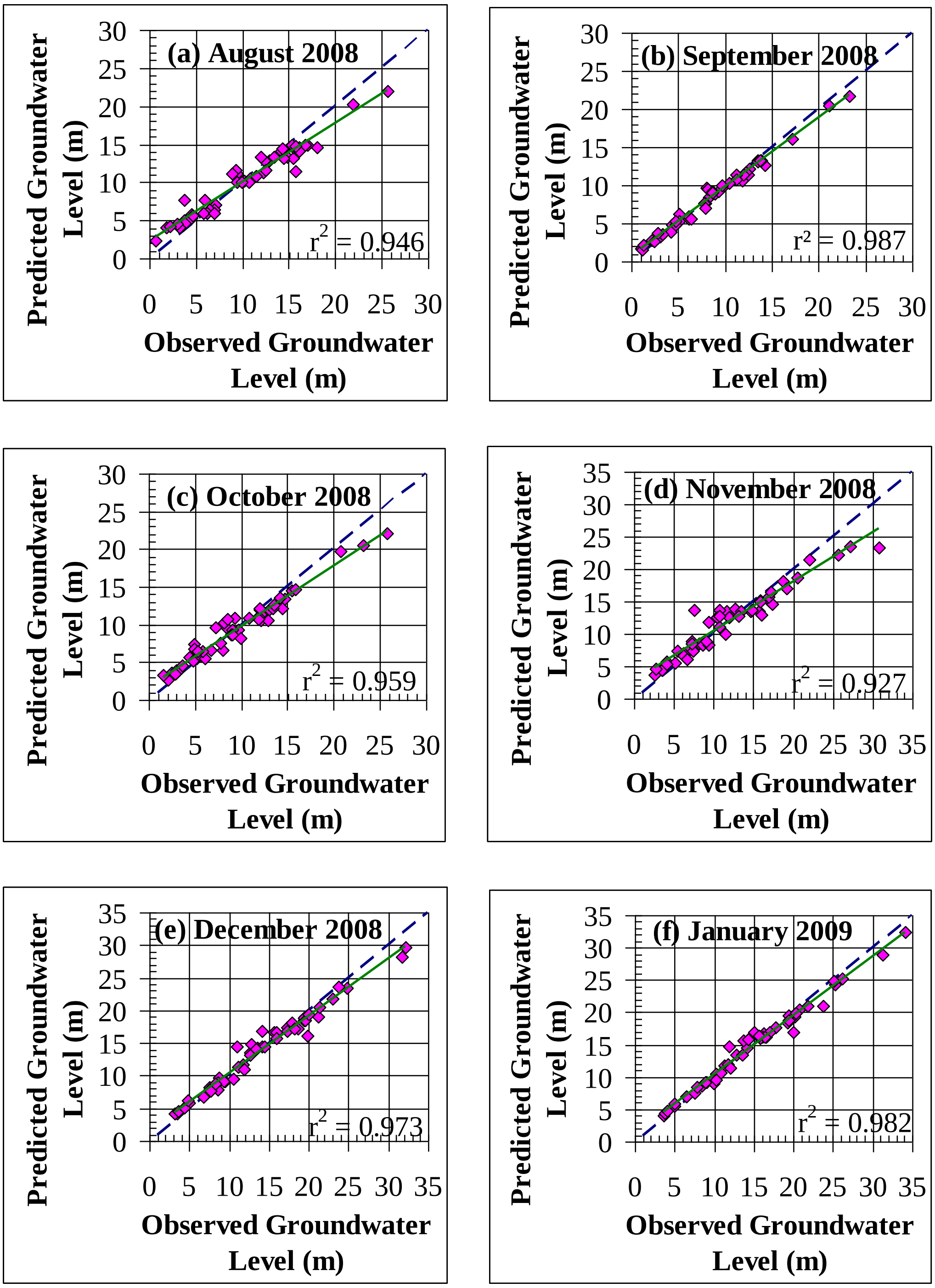
(a) August 2008
(b) September 2008
(c) October 2008
(d) November 2008
(e) December 2008
(f) January 2009
(g) February 2009
(h) March 2009
Moran I
Geary C
Lag Distance (km)
0.8
0.4
0
-0.4
-0.8
2
1.5
1
0.5
0
0
5
10
15
20

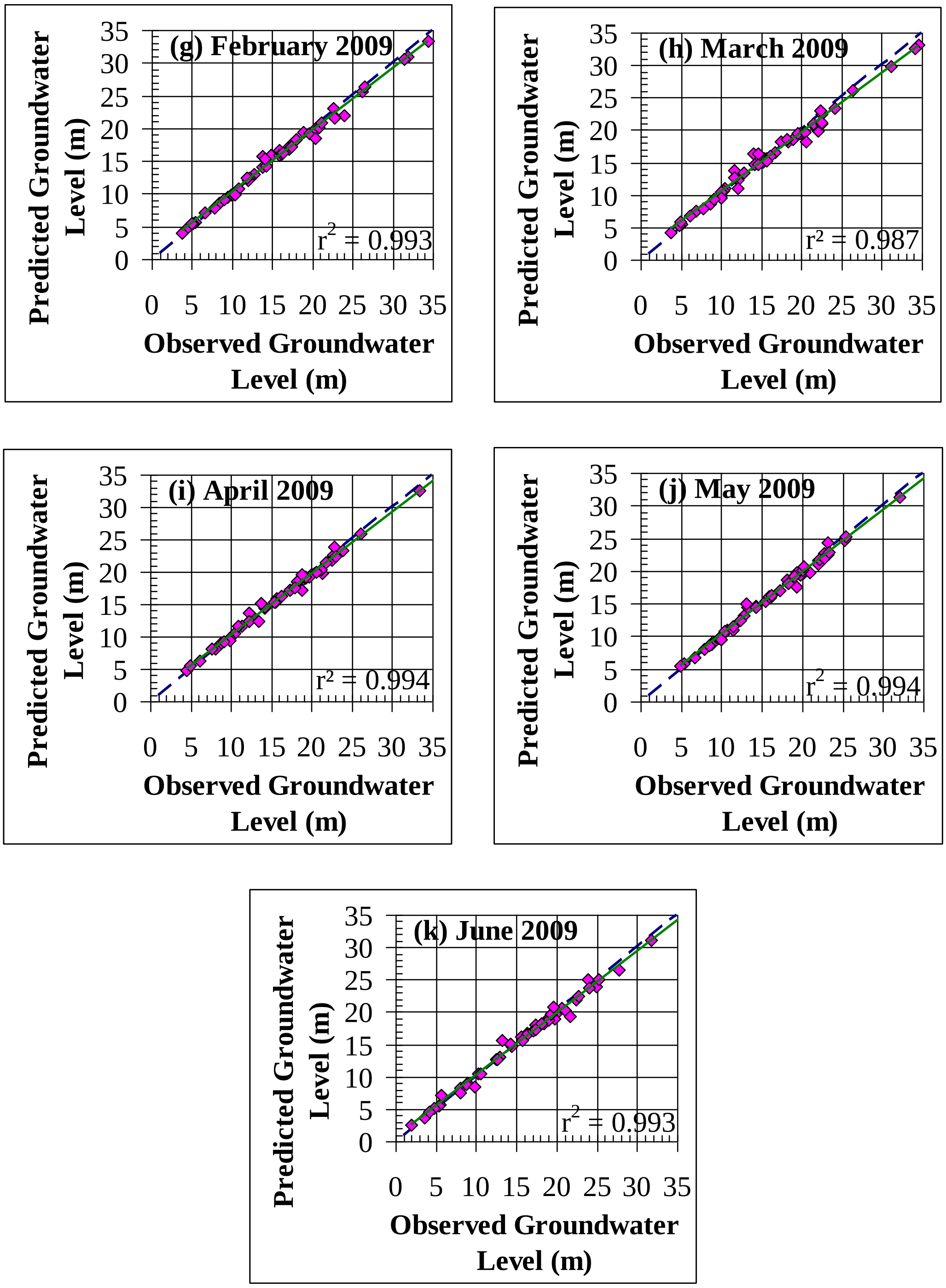

(i) April 2009
Moran I
Geary C
0.8
0.4
0
-0.4
-0.8
2
1.5
1
0.5
0
0
5
10
15
20
Lag Distance (km)
(j) May 2009
Moran I
Geary C
0.8
0.4
0
-0.4
-0.8
2
1.5
1
0.5
0
0
5
10
15
20
Lag Distance (km)
(k) June 2009
Moran I
Geary C
0.8
0.4
0
-0.4
-0.8
2
1.5
1
0.5
0
0
5
10
15
20
Lag Distance (km)

Figs. 4(a-k)

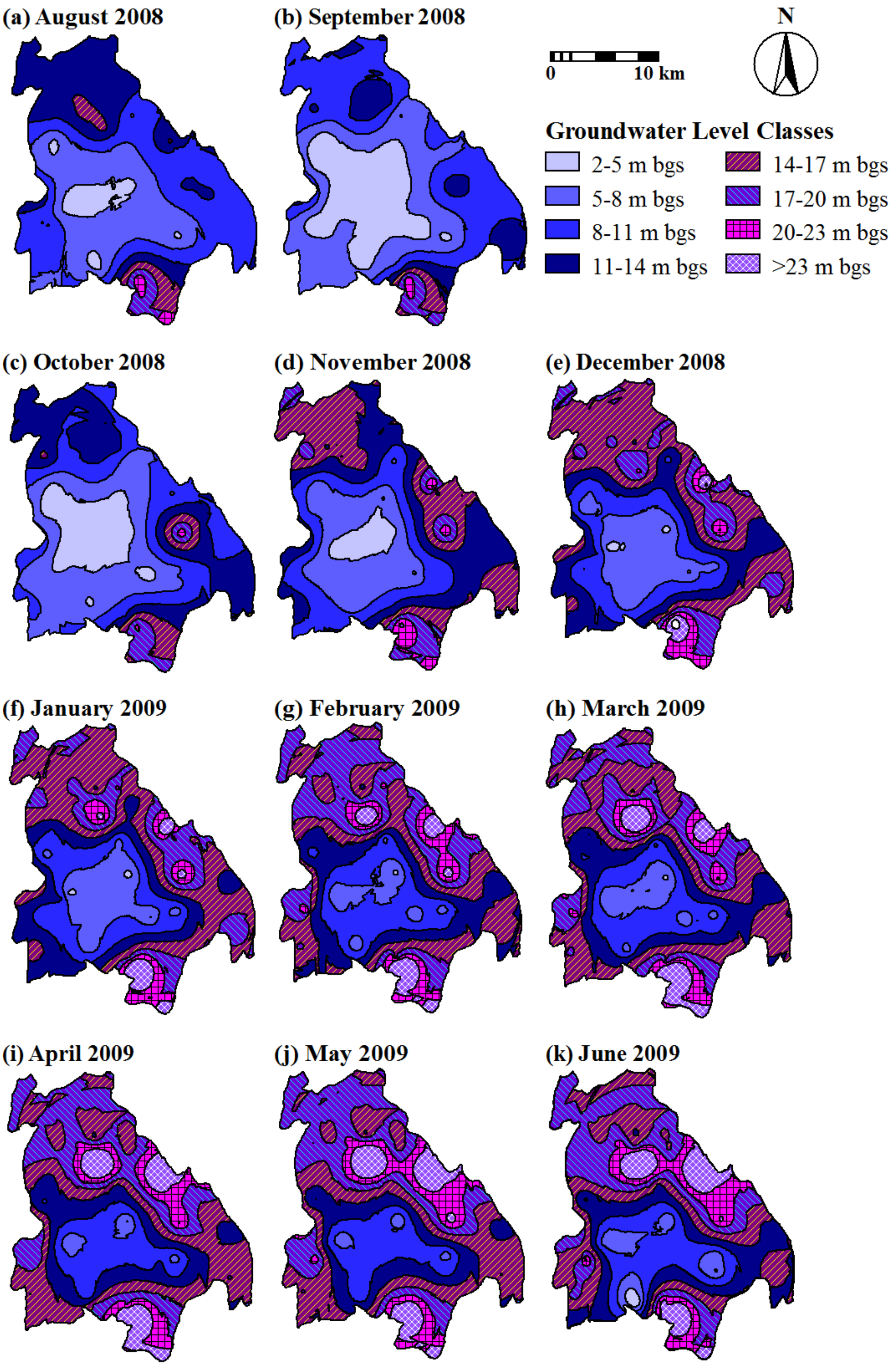

(a) September 2008
Semivariance (m²)
Lag Distance (km)
Experimental Semivariogram
Exponential Model Semivariogram
0 5 10 15 20 25 30 35 40
0 5 10 15 20 25 30
(b) March 2009
Semivariance (m²)
Lag Distance (km)
Experimental Semivariogram
Exponential Model Semivariogram
0 10 20 30 40 50 60 70 80 90
0 5 10 15 20

Figs. 5(a,b)


(a) August 2008
r2 = 0.946
(b) September 2008
r² = 0.987
(c) October 2008
r2 = 0.959
(d) November 2008
r2 = 0.927
(e) December 2008
r2 = 0.973
(f) January 2009
r2 = 0.982
Predicted Groundwater Level (m)
Observed Groundwater Level (m)


(g) February 2009
r² = 0.993
(h) March 2009
r² = 0.987
(i) April 2009
r² = 0.994
(j) May 2009
r² = 0.994
(k) June 2009
r² = 0.993
Predicted Groundwater Level (m)
Observed Groundwater Level (m)
0 5 10 15 20 25 30 35

Figs. 6(a-k)


(a) August 2008
(b) September 2008
N
0
10 km
Groundwater Level Classes
2-5 m bgs
5-8 m bgs
8-11 m bgs
11-14 m bgs
14-17 m bgs
17-20 m bgs
20-23 m bgs
>23 m bgs
(c) October 2008
(d) November 2008
(e) December 2008
(f) January 2009
(g) February 2009
(h) March 2009
(i) April 2009
(j) May 2009
(k) June 2009

Figs. 7(a-k)

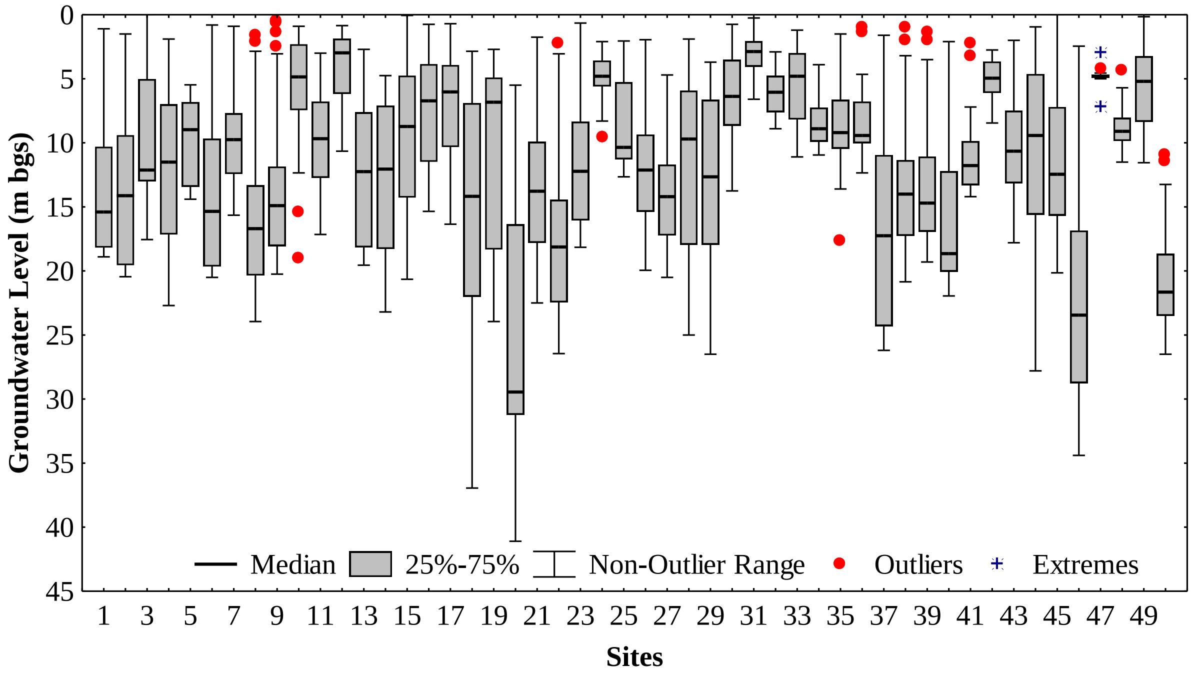

Groundwater Level (m bgs)
0
5
10
15
20
25
30
35
40
45
Median
25%-75%
Non-Outlier Range
Outliers
Extremes
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41 43 45 47 49
Sites

Fig. 8

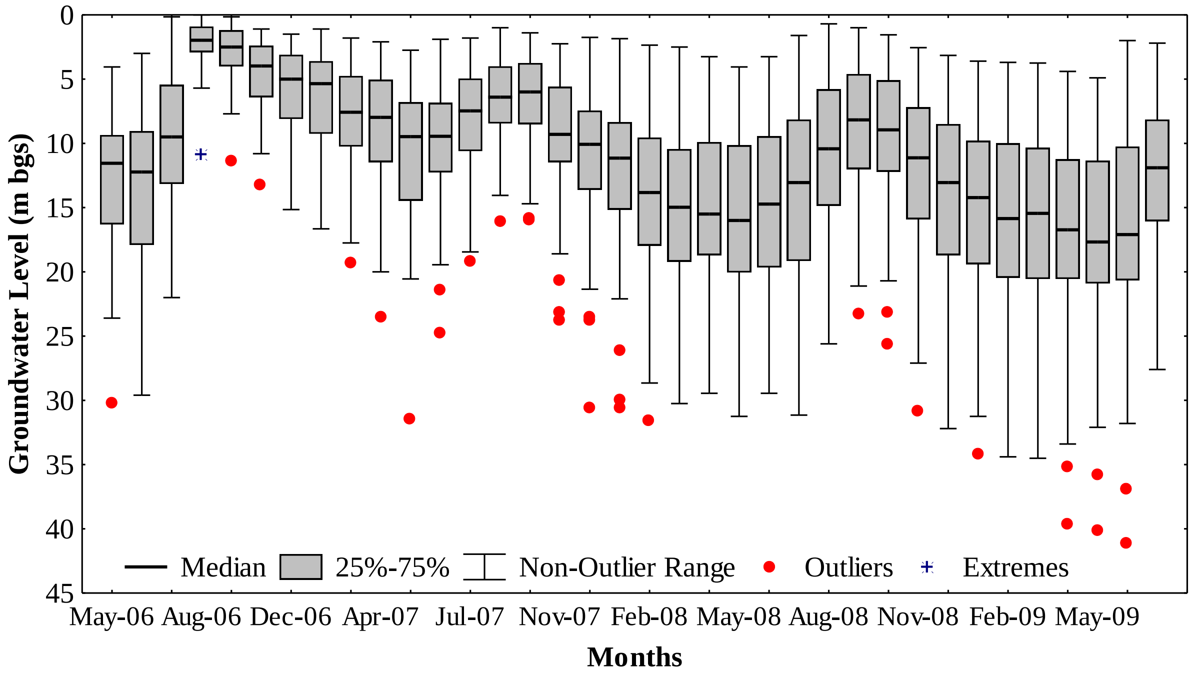

Groundwater Level (m bgs)
0
5
10
15
20
25
30
35
40
45
Median
25%-75%
Non-Outlier Range
Outliers
Extremes
May-06 Aug-06 Dec-06 Apr-07 Jul-07 Nov-07 Feb-08 May-08 Aug-08 Nov-08 Feb-09 May-09
Months

Fig. 9