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Optimization of Groundwater Level Monitoring Network Using GIS-based Geostatistical Method and Multi-parameter Analysis: A Case Study in Wainganga Sub-basin, India

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Abstract: Groundwater is one of the most important resources, its monitoring and optimized management has now become the priority to satisfy the demand of rapidly increasing population. In many developing countries, optimized groundwater level monitoring networks are rarely designed to build up a strong groundwater level data base, and to reduce operation time and cost. The paper presents application of geostatistical method to optimize existing network of observation wells for 18 sub-watersheds within the Wainganga Sub-basin located in the central part of India. The average groundwater level fluctuation (GWLF) from 37 observation wells is compared with parameters like lineament density, recharge, density of irrigation wells, land use and hydrogeology (L_iRDLH) of Wainganga Sub-basin and analyzed stochastically in Geographic Information System (GIS) environment using simple, ordinary, disjunctive and universal kriging methods. Semivariogram analyses have been performed separately for all kriging methods to fit the best theoretical model with experimental model. Results from gaussian, spherical, exponential and circular theoretical models were compared with those of experimental models obtained from the groundwater level data. Spatial analyses conclude that the exponential semivariogram model obtained from ordinary kriging gives the best fit model. Study demonstrates that ordinary kriging gives the optimal solution and additional number of observation wells can be added utilizing the error variance for optimal design of groundwater level monitoring networks. This study describes the use of Geostatistics methods in GIS to predict the groundwater level and upgrade groundwater level monitoring networks from the randomly distributed observation wells considering multiple parameters such as GWLF and L_iRDLH. The method proposed in the present study is observed to be an efficient method for selecting observation well locations in a complex geological set up. The study concludes that minimum 82 wells are required for proper monitoring of groundwater level in the study area.

Keywords: observation wells; groundwater; kriging; semivariogram; Geographic Information System (GIS)

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1 Introduction

Observation wells are useful for monitoring groundwater quality and quantity within the space, time and different hydrogeological setups. Groundwater level monitoring through observation well is one of the essential part of groundwater management. It is not possible to install monitoring wells at every location, but for an effective groundwater management, it is prerequisite to know the status of groundwater at unmonitored location. To reduce the cost of construction and installation of additional observation wells in existing networks, iden-

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tification of most appropriate locations is needed. Planning for installation of monitoring wells can be based on the place, demand, local conditions and other socio-economic factors of a particular area (IGRAC, 2006).

Monitoring networks are based on the management and technical level objectives (Jousma and Roelofsen, 2004). Management level objectives include development of groundwater resources, exploitation and impacts of the environment while technical level objectives include factors such as climate, topography and hydrogeology, population density, economy *etc*. (WMO, 1989; UNESCO, 1998; Jousma and Roelofsen, 2004). There are different classifications of groundwater level monitoring networks; basic monitoring networks and specific monitoring networks are two main types among them (IGRAC, 2006). Basic groundwater level monitoring network involves monitoring of larger area (whole country wise or complete basin wise) where the observation wells are installed at comparatively larger distances and frequency of observation is low, considerably stretched for longer duration. Groundwater level monitoring is necessary to be studied at local and regional scale since most of the groundwater problems are related to local and regional level. Specific monitoring networks are designed on local level based on specific objectives, such as availability of groundwater resources for irrigation, domestic water supply, industries, natural conservation areas *etc*.

Geostatistical method is a class of statistics used to analyze and predict the values associated with the spatial and temporal phenomena (ESRI, 2013), which has been applied to groundwater studies by many researchers from time to time. Kambhammettu *et al.* (2011) applied universal kriging to create a continuous surface of water table elevation for Carslbad area with alluvial aquifer situated in the SE of New Mexico, USA. A generalized MATLAB code was developed to generate omni-directional and directional semivariogram. Application of geostatistical tool for optimum location of sites for monitoring groundwater levels were studied by Prakash and Singh (2000) using groundwater level data of 32 observation wells of the upper Kongal basin, Nalgonda District, Andhra Pradesh, India. Optimum design of groundwater level monitoring network was applied and demonstrated by Chao *et al.* (2011) using overlay tools. Ahmadi and Sedghamiz (2007) analyzed spatial and temporal changes of groundwater level variation in 39 piezometric wells for 12 years duration using geostatistical approach. The above researchers have predicted values at unsampled locations as well as measure of uncertainty for those predictions using only the groundwater level data.

Varouchakis and Hristopulos (2013) compared stochastic and deterministic methods for mapping groundwater levels in the sparsely monitored basin. In stochastic ordinary kriging, universal kriging and kriging with delaunay triangulation were used, while inverse distance weighting and minimum curvature for the deterministic method was used for analysis. The three parameter Spartan semivariogram models were applied for the first time to hydrological data and it yielded the optimal cross validation performance among the investigated models. Gundogdu and Guney (2007) studied spatial analyses of groundwater levels for Mustafakemalpasa left bank irrigation scheme using universal kriging method. Various empirical semivariogram models matched with the experimental models and it was found that the rational quadratic empirical semivariogram model was the best fitted model. Comparison of kriging and inverse square distance method was carried out (Kumar and Remadevi, 2006) to study groundwater level variations using 60 observation wells for Indira Gandhi Nahar Pariyojana (IGNP agriculture commanded area in part of Rajasthan, India). Júnez-Ferreira and Herrera (2013) presented a geostatistical method for optimal design of the space-time hydraulic head monitoring networks and its application to the Valle de Queretaro aquifer. Selection of space-time monitoring points was done using Kalman filter combined with a sequential optimization method. Spatial and temporal variation of groundwater level data has been attempted using ordinary, simple and universal kriging (Kumar *et al.*, 2005; Sun *et al.*, 2009). Outcome of comparative analysis of predicted values with observed values shows that the simple kriging was optimal method for Minqin oasis region located in North West China. Theodossiou and Latinopoulos (2006) applied kriging method to optimize the groundwater quality networks using groundwater level data of aquifer in Upper Anthemountas basin, Chalkidiki peninsula, Greece.

Thus, overall objective of groundwater level monitoring is to assess the quality; identify the variations in groundwater, storage, discharge and recharge, and; to detect effects of climate change on groundwater resources; to assess the impact of groundwater development; to assess the effectiveness of groundwater management and protection measures *etc*. (WMO, 1989; UNESCO, 1998; Jousma and Roelofsen, 2004). Impacts of intensive human activities on groundwater have unmitigated to the entire basin and integrated management of water resources needs regional information of groundwater level at basin scale (zhou *et al.*, 2013).

The objective of this study was to optimize the existing monitoring network of wells which focuses on the specific objective of availability of groundwater resources for irrigation and domestic water supply within 18 sub-watersheds of Wainganga basin. Wainganga basin was selected for study as it has less density of observation wells, lowering groundwater trends due to over exploitation and varied geological/aquifer setup. Many researchers have used geostatistical (kriging) methods and standard error (uncertainty) prediction map to optimize the groundwater level network using input as groundwater level data. Although it provides the initial basis for adding the observation well, analysis considering only ground water level is scientifically insufficient. Thus, the present study considers several parameters with groundwater level data such as land use change, usage of groundwater, precipitation-recharge, types of aquifer, hydrogeology and other local conditions *etc*. for detailed and effective design of the monitoring networks. Geographic Information System (GIS) based geostatistical methods such as ordinary, simple disjunctive and universal kriging have been applied and compared to create groundwater level fluctuation (GWLF) maps using pre/post groundwater level data of 37 observation wells. To optimize the existing network of observation wells, new observation wells were added in areas with maximum error variances to minimize the error. Additional parameters such as lineament density, recharge, density of irrigation wells, land use and hydrogeology (L_iRDLH) were analyzed along with GWLF to prioritize the suitable location of observation wells.

2 Materials and Methods

2.1 Study area

Wainganga basin in Nagpur District of Maharashtra, India is selected as the study area for the present study which stretches between latitudes of 20°35′N–21°44′N and longitudes of 78°15′E–9°40′E. The area falls in survey of India topo-sheets 55 K, O and P, with an elevation about 310 m above mean sea level (Singh and Katpatal, 2015). Kanhan and Pench are the main rivers flowing through the district. Major crops in entire district are jowar, cotton, wheat and pulses. Nagpur District has a semi-arid climate; winter starts from October to February months. The average day temperature is about 27℃ while that of night is about 14℃. From the month of March, temperature starts increasing. May is the hottest month with an average temperature of about 40℃. Nagpur District mainly receives precipitation from southwest monsoon during June to September. The western parts of the district receive an average precipitation of 800 to 900 mm and other parts of the District receive 1000 mm to 1200 mm annual precipitation. Nagpur District has varied geological setup with igneous, sedimentary and metamorphic rocks (GSI, 2009). Wainganga basin has 40 sub-watersheds within Nagpur District, out of which 18 sub-watersheds with geographical area of 3320 km^2 are selected for study based on different geologic formations (Fig. 1).

2.2 Data source

In this study, input data for creation of thematic maps were collected from various sources. Groundwater level data were obtained from central ground water board (CGWB) and groundwater surveys and development agency (GSDA) for 37 observation wells. Lineament and land use of the study area were derived on 1∶50 000 scale using IRS P6 LISS III satellite image (http://bhuvan.nrsc.gov.in/gis/thematic/index.php). The annual average precipitation data from 14 meteorology stations for the period 2004–2012 were procured from India meteorological department (IMD). Information related to sub-watershed wise density of irrigation wells in the area was obtained from annual report of CGWB and GSDA. Hydrogeology map of the area was obtained from the geological survey of India (GSI).

3 Methodology

In the present study, geostatistical approach and multiparameter analysis within GIS environment (Zhou *et al.*, 2013) were used to optimize the existing networks of wells. In geostatistical approach, simple kriging, ordinary kriging, disjunctive kriging and universal kriging

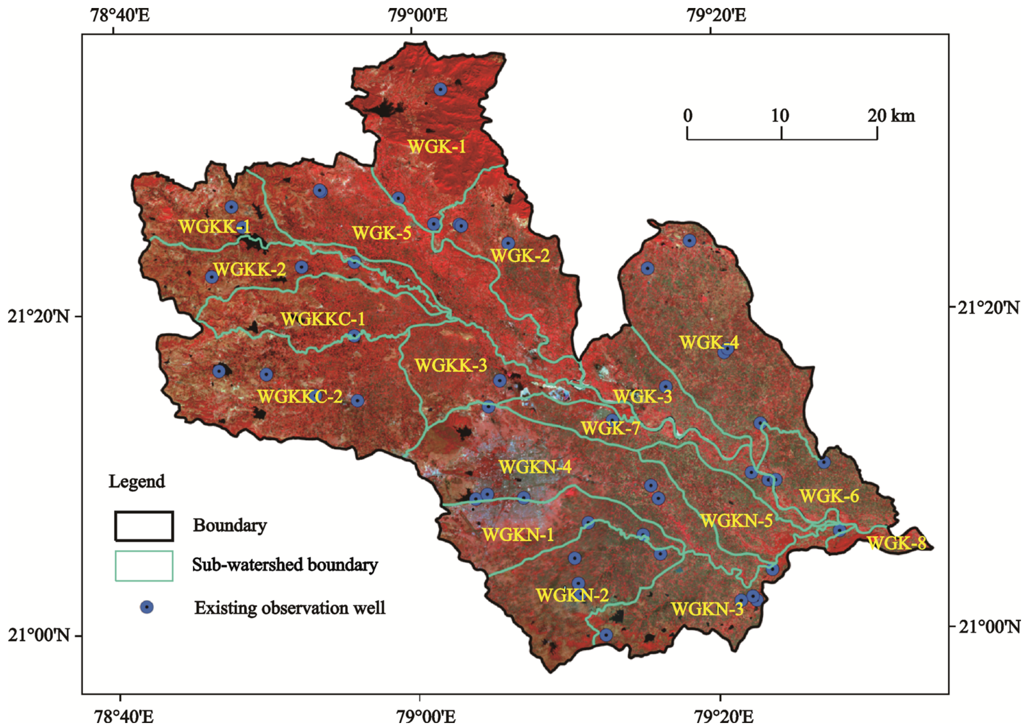


Fig. 1 Map of study area, depicting location of existing observation wells

interpolation methods were used. These geostatistical methods (kriging interpolation) is able to estimate the values at unsampled location as wells as it will predict the error at those unsampled location, i.e., uncertainty of prediction within the area under considerations. This uncertainty of prediction is considered as the basis for upgrading observation wells network. Other deterministic interpolation methods have not been used in the optimization process as it does not consider the uncertainty of the prediction. Parameters such as L_iRDLH were used in combination with geostatistical method to optimize the existing network of wells. The overall methodology to optimize the networks of wells was briefly summarized in flow chart (Fig. 2). The subsequent section describes the geostatistical methods, preparation of thematic maps of groundwater level fluctuation (GWLF) and L_iRDLH parameters from input data sets and overall procedure to optimize the existing networks of observation wells.

3.1 Geo-statistical method

Geostatistics is defined as the branch of statistical sciences that studies spatial/temporal phenomena and capitalizes on spatial relationships to model possible values of variables at unobserved and unsampled locations (Caers, 2005). As stated, geostatistics is a subset of statistics specialized in the analysis and interpretation of geographically referenced data (Goovaerts, 1997). Spatial statistics is a process of extracting data summaries from spatial data and comparing these to theoretical models that explain how spatial patterns originate and develop (Ripley, 2004).

Kriging is an interpolation technique based on the theory of regionalized variables (Matheron, 1965). It is a family of regionalized linear regression techniques in which the value of a property at an unsampled location is estimated from the values at neighboring locations. The basic tool of geostatistics is the semivariogram, which measures the spatial variability which increases as samples become more dissimilar (Emmanuel and Clayton, 2001). The semivariogram function $\gamma(h)$ was originally defined by Matheron (1965) as the half the averaged squared difference between points separated by distance 'h' (Equation (1)).

$$\gamma(h)=\frac{1}{2}E\{[z(s_i)-z(s_i+h)]^2\} \tag{1}$$

where, E is the statistical expectation operator, $z(s_i)$ is the value of a target variable at some sampled location and $z(s_i+h)$ is the value of the neighbor at distance s_i+h. Prior to geostatistical estimation, it is necessary to compute variogram model for any possible sampling interval (Ahmadi and Sedghamiz, 2007).

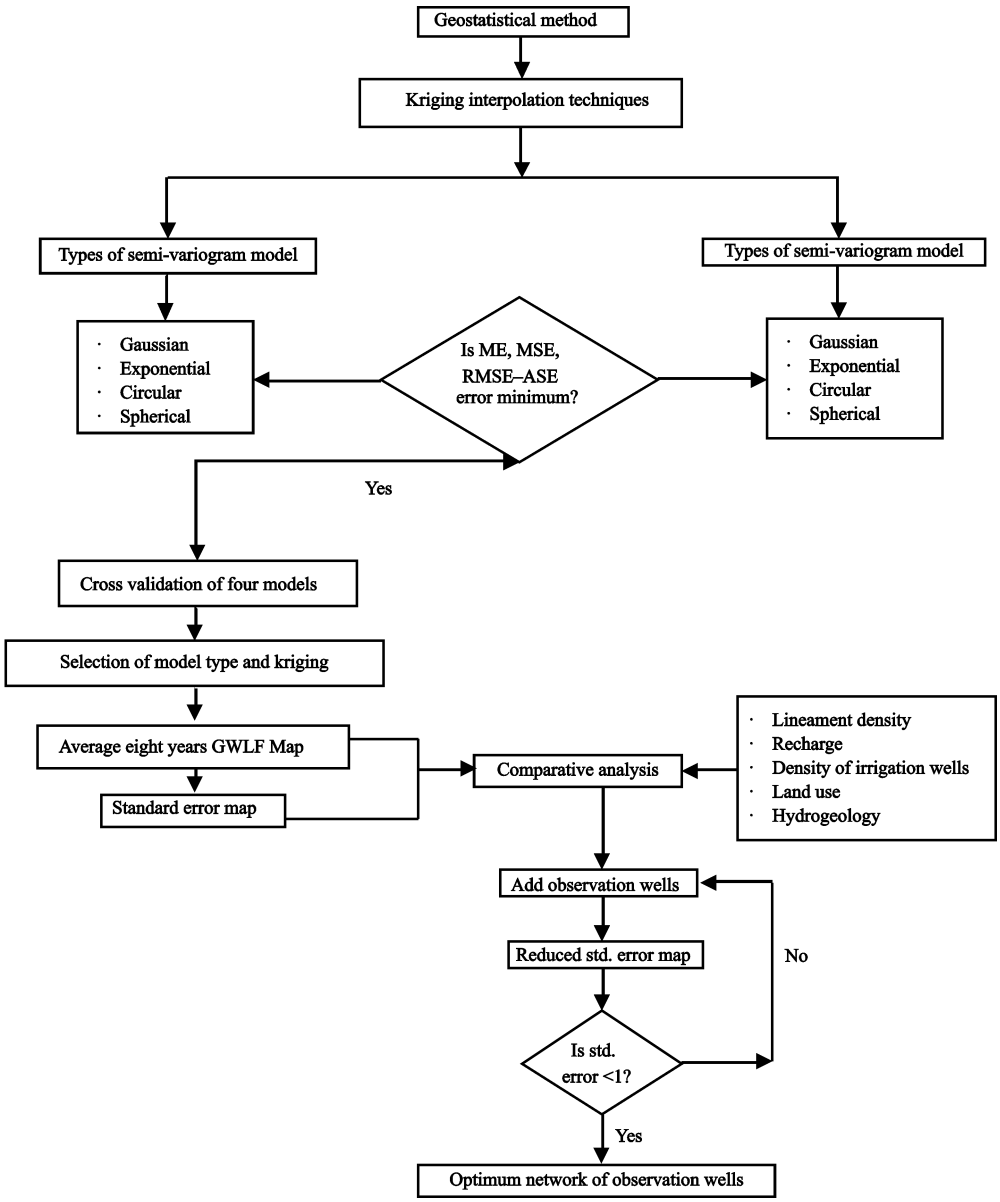


Fig. 2 Methodology for selection of observation wells. ME: mean error, MSE: mean square error, RMSE: root mean square error, ASE: average standard error, RMSE–ASE: arithmetic difference between RMSE and ASE

3.1.1 Ordinary kriging

In ordinary kriging, the mean of the regionalized variable is assumed to be constant throughout the area of interest. The general equation of kriging estimator can be written as:

$$\hat{Z}(x_0) = \sum_{i=1}^{n} \lambda_i Z(x_i) \tag{2}$$

where, $\hat{Z}(x_0)$ is the estimated variable at location x_0; λ_i is the kriging weight and $Z(x_i)$ is the observed variable at location x_i; n is the number of sample in the data set.

$$\sum_{i=1}^{n} \lambda_i = 1 \quad \text{and} \quad \sum_{i=1}^{n} \lambda_i \gamma(x_i, x_j) - \mu = \gamma(x_i, x) \tag{3}$$

where, $\gamma(x_i, x_j)$ are the modeled semivariogram at location x_i and x_j; μ is the Lagrange multiplier; $\gamma(x_i, x)$ are the modeled semivariogram at location x_i and predicted spatial location x.

Difference between predicted and the actual values should be zero; it is referred to as making the prediction unbiased. In order to ensure the predictor to be unbiased the sum of the weight λ_i must be equal to one and Equation (3) must be solved simultaneously to minimize the constraint. $\hat{Z}(x_0)$ is the unknown value to be calculated at location x_0, $Z(x_i)$ is the known value at location x_i, λ_i is the kriging weight calculated based on distance, semivariogram and spatial relationships among the measured values around the predicted locations, μ is the Lagrange multiplier, $\gamma(x_i, x_j)$ are the modeled semivariogram values estimated based on the distance between the sample of observations identified at ith and jth locations and $\gamma(x_i, x)$ are the modeled semivariogram values estimated based on the distance between the ith sample observation location and the predicted spatial location.

3.1.2 *Simple kriging*

Simple kriging, mathematically least complicated form of kriging, is based on the three assumptions: 1) the mean is known, 2) the random function is second order stationary, so the mean, spatial covariance and semivariance do not depend upon x, and 3) the observations are the partial realization of a random functions $Z(x)$, where x represents the spatial location (Davis, 2002). Mathematically simple kriging (Equation (4)) is expressed as:

$$\hat{Z}(x_0) = m + \sum_{i=1}^{n} \lambda_i [Z(x_i) - m] \tag{4}$$

where, m is the expected or mean value of $Z(x)$. In order to determine the kriging weights estimated variance should be minimum, $\mathrm{Var}\{\hat{Z}(x_0) - Z(x)\}$; also to ensure the unbiased nature of the estimator, $E\{\hat{Z}(x_0) - Z(x)\} = 0$.

3.1.3 *Disjunctive kriging*

Disjunctive kriging (DK) represents nonlinear form of kriging (i.e., results in a non linear estimator) which in general presents an expansion over linear kriging methods (Yates *et al.*, 1986). Disjunctive kriging is expressed as:

$$\hat{Z}(x_0) = \sum_{i=1}^{n} \lambda_i [Z(x_i)] = \sum_{i=1}^{n} \sum_{k=0}^{\infty} \lambda_{ik} H_k [Z(x_i)] \tag{5}$$

where, n is the number of samples, $\lambda_i[Z(x_i)]$ is a function to be determined and articulated on the right hand side of Equation (5) as series of Hermite polynomials, λ_{ik} is a constant depends on i and k. In order to ensure the unbiased nature of the estimator, $E\{\hat{Z}(x_0) - Z(x)\} = 0$ and $Var\{\hat{Z}(x_0) - Z(x)\} = \min$.

3.1.4 *Universal kriging*

Universal kriging (UK), mathematically complicated form of kriging. In the universal kriging model the spatial distribution of the target variable is described by the sum of a deterministic trend i.e., $m(x_i)$, modeled by a linear regression on covariates, and random component or function i.e., $Z(x_i)$. Mathematically UK is expressed as Equation (6) (Cressie, 1993).

$$\hat{Z}(x_0) = m(x_i) + Z(x_i) = \sum_{l=0}^{L} a_l f_l(x_i) + Z(x_i) \tag{6}$$

where, a_l is lth drift coefficient vector; f_l is the basic function of spatial coordinates; L is the number of sample in the data set.

3.2 Cross validation test

In order to ensure unbiasedness of the prediction, cross validation test has been performed; to select appropriate the kriging interpolation techniques and suitable semi-variogram model. GWLF values from 37 observation wells point data used as the input for cross validation test; this point data added into the base map and interpolated using kriging techniques. Four theoretical variogram models such as gaussian, exponential, circular and spherical were used. During the prediction phase, these four semivariogram models were plotted in order to select the best-fitted one and to assess the accuracy of the kriging interpolation methods.

The semi-variogram models were selected from a set of mathematical functions that describe spatial relationships such as gaussian, spherical, exponential and circular models. The performances of the fitted semi-variogram models were examined based upon cross validation technique. The observed values of mean error (ME), mean square error (MSE), root mean square error (RMSE) and average standard error (ASE) are estimated to verify the performance of the developed model. All these errors are expressed by Equations (7)–(10) below (Goovaerts, 1997). These procedures were repeated and applied to each ordinary, simple, universal, disjunctive kriging methods.

$$ME = \frac{1}{n} \sum_{i=1}^{n} [Z^*(x_i) - Z(x_i)] \tag{7}$$

$$MSE = \frac{1}{n} \sum_{i=1}^{n} \frac{Z^*(x_i) - Z(x_i)}{\sigma_v^2(x_i)} \tag{8}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}[Z^*(x_i) - Z(x_i)]^2} \quad (9)$$

$$ASE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\sigma_v^2(x_i)} \quad (10)$$

where, $\sigma^2_v(x_i)$ is the kriging variance for location (x_i), $Z^*(x_i)$ and $Z(x_i)$ are the estimated and the observed values of the parameter at the location (x_i), respectively.

If the predictions are unbiased, the ME should be close to zero. But because of its limitation due to its dependence upon the amount of the data and to its indifference to the wrongness of semivariogram, ME is generally standardized by the MSE, being ideally zero (Gorai and Kumar, 2013). Conversely, the difference between RMSE and ASE should be calculated to specify if the prediction errors were correctly assessed and it should be minimum and close to zero (Goovaerts, 1997). On the other hand, if the RMSE is less than the ASE, then the variability of the predictions is overestimated; and if the RMSE is greater than the ASE, then the variability of the predictions is underestimated. Once the best model is selected, it is used to create GWLF map that provides the spatial distribution of the parameter to be estimated.

3.3 Preparation of thematic maps of groundwater level fluctuation (GWLF) and L_iRDLH parameters

All the data sets were processed and analyzed in ArcGIS software for the generation of individual thematic layers of GWLF and L_iRDLH parameters. The procedure to create individual thematic maps is briefly described below.

Groundwater level fluctuation (GWLF) was estimated by subtracting average post monsoon groundwater level from pre monsoon groundwater level for the years 2004 to 2012. GWLF point data were processed and interpolated using geostatistical method to prepare GWLF map of the study area in GIS environment.

Lineament is considered as one of the important parameter as it is directly associated with the geological structures within the study area (Nag and Ghosh, 2012). Lineaments in the study area were interpreted directly from the IRS-P6 LISS III satellite image.

The precipitation data for the period 2004–2012 has been interpolated using the inverse distance weighting (IDW) interpolation technique to produce the mean precipitation (*P*) map of the study area. Groundwater recharge map with six recharge zones were created using Equation (11) proposed by Thomas *et al*. (2009).

$$R = 5.732(P - 89.7)^{0.51} \quad (11)$$

where, *R* is groundwater recharge from precipitation, and *P* is mean precipitation.

Density of irrigation wells for the study area were obtained from the CGWB and GSDA and this information were analyzed and compiled to prepare map of density of irrigation well watershed wise. Further, this map was compared with GWLF map and linear relationship between density of irrigation wells and groundwater level fluctuation has been estimated.

The different land use (LU) features found in Wainganga Sub-basin were mapped using the enhanced IRS-P6 LISS III satellite image. The LU map prepared was used and classified based on the character of each LU features that influence the usage of groundwater within the area of sub-basin.

The hydrogeology map of study area was prepared using district resource map of GSI (2009). Study area was categorized into three types of rocks: igneous rocks, consolidated and unconsolidated sedimentary rocks and metamorphic rocks; these types of rocks are further classified into eight sub categories.

3.4 Selection of optimum observation well locations

The present study estimates optimum number and location of observation wells using geostatistical method in GIS environment considering average GWLF and impact parameters such as lineament density, recharge density of irrigation wells, land use and hydrogeology (L_iRDLH). Cross validation technique was used to check the adequacy and validity of the developed model. After selecting appropriate kriging interpolation technique and suitable semi-variogram model, GWLF map was prepared. In succession, standard error map was prepared using input as average groundwater level fluctuation map for the year 2004–2012. Standard error (SE) measures the accuracy and bias of the predicted sample and it was estimated using Equation (12):

$$SE = \frac{\sigma}{\sqrt{n}}, \quad \sigma = \sqrt{\frac{\sum(a - \bar{a})^2}{n}} \quad (12)$$

where, σ is standard deviation, '*a*' indicates observed groundwater levels, $\bar{a}$ is mean of all values in the data set and '*n*' is the number of sample in the data set. Standard error map obtained from GWLF map and L_iRDLH parameters were compared and analyzed separately. The status of L_iRDLH parameters and the maximum SE values of GWLF were used to select the location of observation wells in the existing network of Wainganga Sub-basin. Initially, few observation wells were added considering GWLF (std. error map) and five parameters. After adding the additional number of observation wells, standard error was computed and this procedure was repeated until the std. error reduced to 1.

4 Results and Discussions

4.1 Groundwater level fluctuation (GWLF) cross validation results

Cross validation results for universal kriging, ordinary kriging, simple kriging and disjunctive kriging interpolation techniques were examined and computed separately for each four semi-variogram models. The values of ME, MSE, RMSE and ASE were estimated and results were summarized in Table 1. In order to ensure the predictions results to be unbiased, ME values should be close to zero. It was observed from the results that ME values are not close to zero; this may be due to its indifference and dissimilarity values of semivariogram model. Hence, ME values are standardized by the MSE, being ideally zero (Isaaks and Srivastava, 1989; Cressie, 1993; Goovaerts, 1997).

Based on the arithmetic difference between RMSE and ASE (i.e., RMSE–ASE) values, it has been observed that, when using gaussian model, simple kriging (0.1168) is better than the ordinary kriging (0.2576). Even for gaussian model, universal kriging (0.0423) is better than the ordinary kriging as well as simple kriging model. Also, when considering the circular model, universal kriging (0.0464) is found better among the others kriging method. There are some differences in the estimated values of MSE and RMSE–ASE resulting from different kriging and semi-variogram models. All the results of cross validation test are summarized in Table 1 which suggests that exponential model (ordinary kriging) provides the most accurate estimation as the ME (0.102), MSE (0.0339) and RMSE–ASE (0.0052) values are least among all the kriging methods and respective semi-variogram models. Since least values are obtained from ME, MSE and RMSE–ASE, therefore ordinary kriging with exponential semivariogram model yields the most accurate predictions for GWLF and it was selected for further predictive analysis and optimization process.

As discussed in section 3.1.1 and Table 1, ordinary kriging interpolation method was preferred over other kriging method as it yielded lower difference between

Table 1 Cross validation results for four different semi-variogram models using kriging interpolation techniques

Kriging	Semi-variogram model	ME	RMSE	MSE	ASE	RMSE–ASE
Simple kriging	Gaussian	0.1346	1.8804	0.0466	1.7636	0.1168
	Spherical	0.1401	1.8577	0.0491	1.7303	0.1274
	Exponential	0.1497	1.8486	0.0536	1.7492	0.0994
	Circular	0.1379	1.8704	0.0475	1.7385	0.1319
Ordinary kriging	Gaussian	0.1400	2.0012	0.0508	1.7436	0.2576
	Spherical	0.1110	1.9075	0.0383	1.8305	0.0770
	Exponential	0.1020	1.8882	0.0339	1.8830	0.0052
	Circular	0.1140	1.9356	0.0402	1.8087	0.1269
Universal kriging	Gaussian	0.1097	1.8878	0.0374	1.8455	0.0423
	Spherical	0.1118	1.9852	0.0381	1.8643	0.1209
	Exponential	0.1086	1.8734	0.0368	1.8554	0.0180
	Circular	0.1314	1.8775	0.0450	1.8311	0.0464
Disjunctive kriging	Gaussian	0.1346	1.8804	0.0466	1.7636	0.1168
	Spherical	0.1401	1.8577	0.0491	1.7303	0.1274
	Exponential	0.1497	1.8486	0.0536	1.7492	0.0994
	Circular	0.1379	1.8704	0.0475	1.7385	0.1319

Notes: ME: mean error, MSE: mean square error, RMSE: root mean square error, ASE: average standard error, RMSE–ASE: arithmetic difference between RMSE and ASE

(RMSE–ASE) and MSE (Table 1). GWLF map of the study area is divided into six zones ranging from 1.30 to 8.34 m below ground level (bgl) (Fig. 3). GWLF are observed to be high (5.00–8.34 m bgl) in sub-watersheds WGKK1, WGKK2, WGKKC1, WGKKC2, WGK8, and in some part of WGKN3, WGKN1, WGKN2, WGK2; moderate (3.6–5.0 m bgl) in sub- watersheds WGK2, WGK3, WGK4, WGK6, WGKN4, WGKN5, WGKK3 and low (1.3–3.6 m bgl) in sub-watersheds WGK1, WGK5, and in some parts of WGKKC2, WGKN1, WGKK2, WGKN4, WGKN5, WGK3 and WGK6.

4.2 Groundwater level fluctuation in reference to impact parameters

Many previous studies (Prakash and Singh, 2000; Ahmadi and Sedghamiz, 2008; Chao *et al*., 2011; Kambhammettu *et al*., 2011; Ibtissem *et al*., 2013) considered geostatistical method to select the observation well location. In geostatistical method, SE map were created using groundwater level data of pre/post monsoon season or difference between pre/post monsoon season data and its geographical location. In these studies, the location having high standard error value was considered as suitable site for additional observation wells. Practically, it has been observed that only SE (uncertainty) prediction map obtained from the groundwater data is insufficient as basis for selection of observation well location. There are several parameters other than groundwater data that can be considered in geostatistical analysis for selection of appropriate site for observation wells. For example, moderate to high values of SE obtained in the water bodies (river, lakes) as well as in forest areas which are not appropriate locations for addition of observation wells.

GWLF is considered as the most important parameters for optimization of existing observation wells as it reflects all the dynamics occurred due to recharge and extraction of groundwater for different purposes. Therefore, the selection of observation wells can be made including GWLF and other impact parameters which influence the selection of observation wells. In the present study lineament density, recharge, density of irrigation wells, land use and hydrogeology (L_iRDLH) are the selected impact parameters which can directly/indirectly affect the GWLF and these parameters were found to be suitable for selecting sites for additional observation wells. It was observed that L_iRDLH parameters are relating to GWLF of the study area and can be used for upgrading the existing network of observation wells. Selection of observation wells and relation between GWLF and L_iRDLH parameters is described in subsequent sections.

4.2.1 Groundwater level fluctuation and lineaments

Lineament density indicates the groundwater potential of the area since presence of lineaments generally represents a permeable zone and hence it is an important guide for groundwater exploration (Fenta, 2015). Lineament density plays a significant role in the occurrence and movement of groundwater resources in the crystalline rocks (Preeja *et al.*, 2011). The study area consists of major and minor lineaments which vary in length from a few meters to kilometers. Three major lineament trends, NW-SE, NE-SW and W-E have been identified within the study area. Lineament density was observed to be high in igneous rocks, moderate in metamorphic rocks and low in sedimentary rocks. In sub-watersheds WGKK1, WGKK2, WGKKC1, WGKKC2, WGKN3 and WGK8, the lineament density is high (Fig. 3) compared to other sub-watersheds within the study area. It may be observed in Fig. 3 that the GWLF is more in sub-watersheds with high lineament density. Although, the lineament densities are high in watersheds WGK1, WGKN1 and WGKN2, the GWLF shows less variation, due to presence of dense forest and dense built up areas where groundwater usage is negligible. The site and number of additional observation wells was decided by considering the variation in GWLF and lineament density within sub-watersheds. Hence, more additional observation wells were placed in the regions with high variation in GWLF as well as high lineament density.

4.2.2 Groundwater level fluctuation and recharge

Precipitation is the major factor responsible for groundwater recharge. The average annual precipitation of the study area is from 1000 to 1200 mm. The relationship between pre/post monsoon groundwater level and annual precipitation (2004–2012) is analyzed. The recharge through precipitation is directly proportional to groundwater potential of shallow unconfined aquifers. Pre and post monsoon groundwater level shows high correlation with preceding and current year's precipitation respectively (Fig. 4a). Recharge from the precipitation is an important parameter affecting the water level

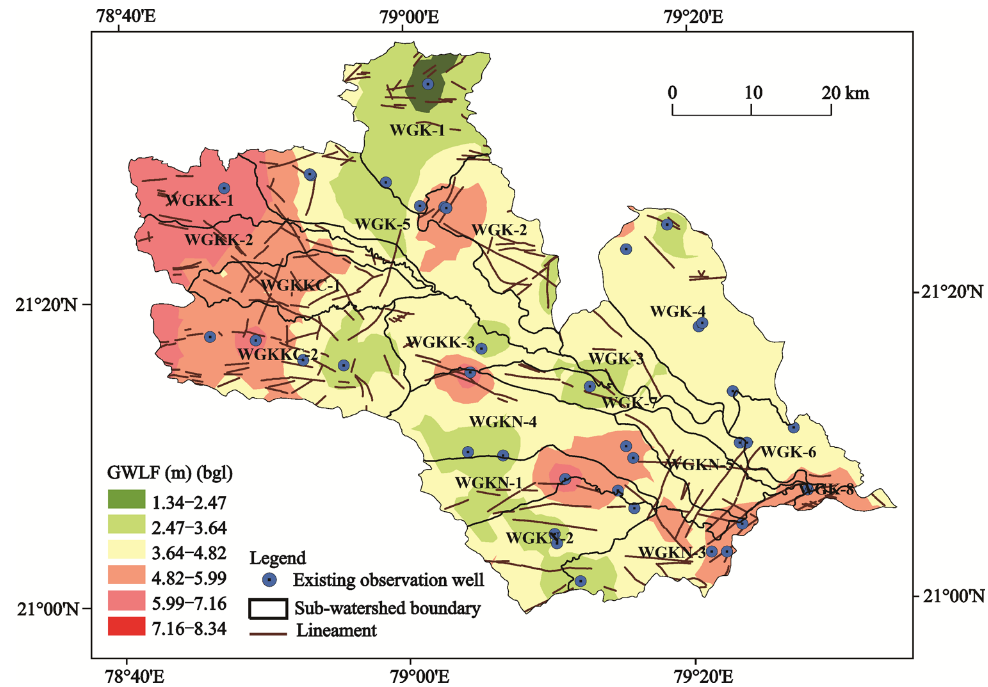


Fig. 3 Average Groundwater Level Fluctuation (GWLF) map during 2004 and 2012 and lineament map of study area

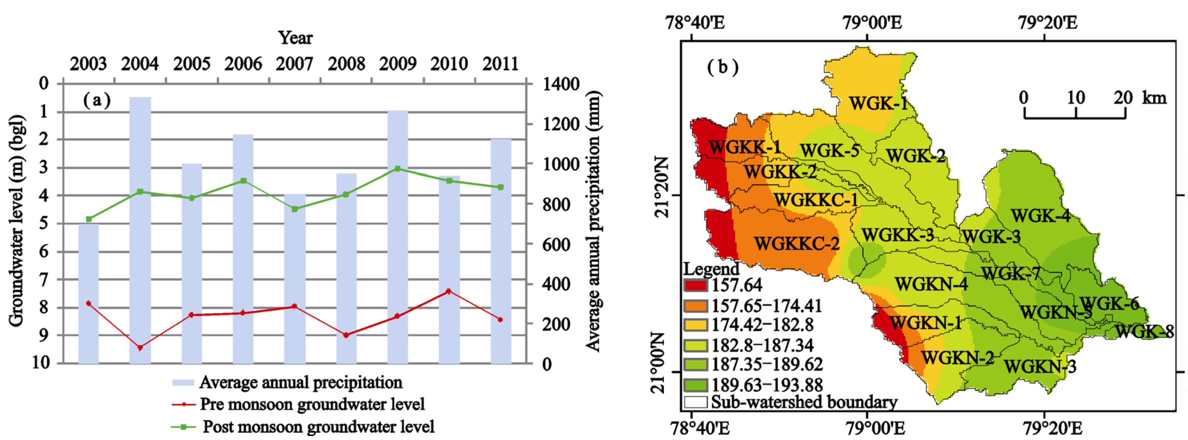


Fig. 4 Average post and pre monsoon groundwater level vs. average annual precipitation (2004–2012) (a) and groundwater recharge map of study area (b)

of the region and hence it is considered as one of the criteria for selecting location of observation wells in the present study (Fig. 4b).

It was observed that the groundwater recharge in NW region is less, moderate in central part and more in SE part of the study area. Comparing recharge map with GWLF, it was observed that GWLF is high in the lowest recharge zone and vice-versa. Zones showing high GWLF as well as low recharge were given high preference for locating additional observation wells. Thus, six sub-watersheds (WGKK1, WGKK2, WGKKC1, WGKKC2, WGKN1 and WGKN2) were preferred as location for placing additional observation wells.

4.2.3 Groundwater level fluctuation and density of irrigation wells

Groundwater is being extracted in the Wainganga Sub-basin region using electric pumps for agriculture and domestic purposes. The sub-watershed wise density of irrigation wells ranges from 2.8 to 16.8 wells/km^2 (GSDA and CGWB, 2014). It was observed that the density of irrigation wells are high (9.5–16.8 wells/km^2) in sub-watersheds WGKKC1, WGKKC2, WGK6, WGKK1, WGKK2, WGKN3 and WGKN5, moderate (5.5–6.8 wells/km^2) in sub-watersheds WGK4, WGK5, WGK7, WGK8 and low (2.8–5.5 wells/km^2) in sub-watersheds WGK1, WGK2, WGK3, WGKN1, WGKN2, WGKN4 and WGKK3. The average GWLF of the study area was compared with density of irrigation wells for each sub-watershed (Fig. 5a). GWLF and density of irrigation wells is linearly correlated. Thus, more numbers of additional observation wells were preferred in the sub-watersheds with high variation in GWLF as well as high density of irrigation wells.

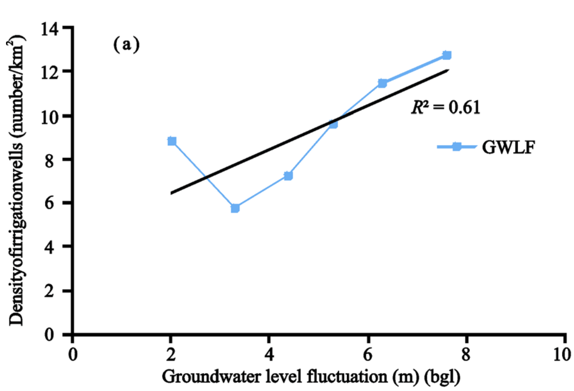
4.2.4 Groundwater level fluctuation and hydrogeology

Study area consists of three types of rocks: Igneous rocks (33.66%) which extend sideways from NW to SW region, consolidated and unconsolidated Sedimentary rocks (14.5%) located along main rivers in the central region of the basin and Metamorphic rocks (51.84%) present towards NE to SE region. Average groundwater level fluctuation (GWLF) shows direct correlation with types of rock formation (Fig. 5b). Average GWLF are high (4.5 to 7.0 m) for igneous rocks, moderate (3.0 to 4.5 m) for metamorphic rocks and low to moderate (3.3 to 4.5 m) for consolidated and unconsolidated sedimentary rocks. These three types of rocks are further classified into eight sub categories (Fig. 6). In Wainganga Sub-basin, the rocks become aquifers through development of weathering, fracturing and secondary porosity. Thus, the hydrogeological characteristic of the exposed rocks can be considered as a significant factor for locating the additional groundwater observation wells. Additional observation wells were added considering mutual relationship between average GWLF and types of rock as well as the sub-watershed boundary. Hence, while adding additional wells, igneous rocks were given higher priority, metamorphic rocks were given medium and sedimentary rocks were given low priority. Eleven additional wells were placed in sub-watersheds with igneous rocks having high GWLF (WGKKC1, WGKKC2, WGKK1 and WGKK2 with four existing wells) whereas six wells were added in sub-watersheds with high to moderate GWLF (WGKN1, WGKN2, WGKN3 and WGKN4). Thus, the total number of observation wells in igneous rock increased from 10 to 27.

In regions of consolidated and unconsolidated sedimentary rocks, GWLF is low to moderate and hence only 6 observation wells were added with seven existing wells. Although the average GWLF is moderate to low in metamorphic rocks, the region covered by this rock type is more (51.84%) in the study area. Four classes of metamorphic rocks present in the Wainganga Sub-basin is shown in Fig. 6 and andalusite-mica-schist (AMS), calc-gneiss-and-manganiferous-marble-with-manganese-ore-pockets (CGMMMO), unclassified-gneiss-tirodi-gneissic complex (UGTG) and amgaon-gneissic-complex-gneiss-migmatite (AGCGM) (GSI, 2009). The variation in GWLF is also not constant in these four classes; in North region (CGMMMO) GWLF is low (1.3–3.5 m) in sub-watershed WGK1 and in SE part (AMS) GWLF is high (4.5–6.0 m) in sub-watershed WGK8. The additional observation wells were located by considering these variations. In all, 22 observation wells were added in the metamorphic regions and hence the number of wells increased from 18 to 40.

4.2.5 Groundwater level fluctuation and land use

Study area comprises of five different land use classes namely agriculture (70%), built up (5%), forest (10%), wasteland (12%) and water body (3%) (Fig. 7). Forest



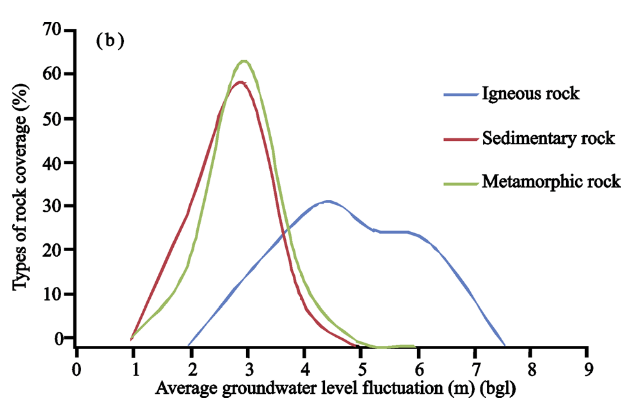


Fig. 5 Relationship between average GWLF and density of irrigation wells (a) and relationship between average GWLF and types of rock coverage in percentage during 2004 and 2012 (b)

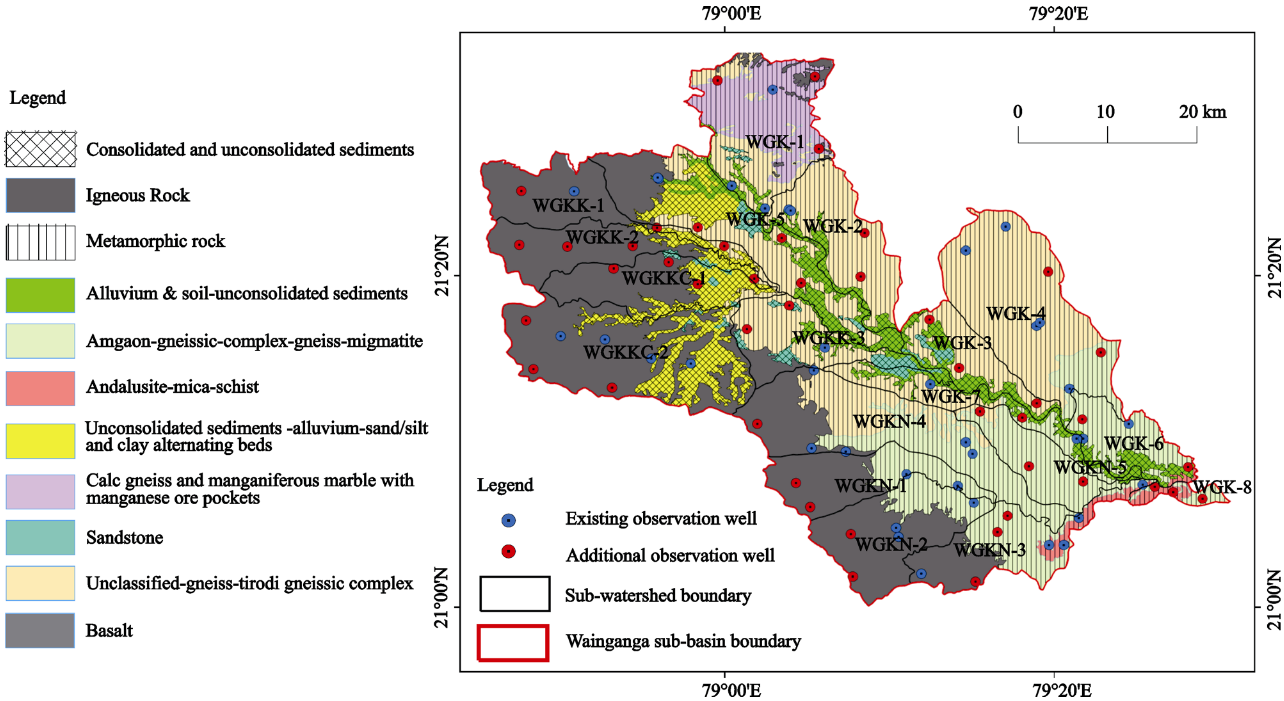


Fig. 6 Hydrogeology of study area

area is located mostly in the North, NW, Centre, and in SE of study area. Since the usage of groundwater in the forest area is negligible, it is not considered for installation of the additional observation wells.

In city areas where the built up is more, major source of water supply is from the surface water through piped network and hence the usage of groundwater is very less. In the outer periphery of the city area, pipe network is less and hence water demand in this area is met through the groundwater. Groundwater is the major source for irrigation and hence more additional observation wells are added in agricultural areas. Sites for locating observation wells near the water bodies are not preferred as it would not represent the actual groundwater scenario. GWLF is low in the built up area, forest area, high in the outer periphery of the city area and high to moderate in the agriculture areas. This indicates that land use classes of study area directly influence the usage of groundwater within the basin. Therefore, areas showing more groundwater usage and high GWLF are considered for locating additional observation wells in the study area.

4.3 Optimization of groundwater level network

Based on the SE map obtained from GWLF considering L_iRDLH parameters, additional numbers of observation wells were located. The SE map was generated with existing 37 observation wells, using only GWLF where maximum values of errors (1.2 to 2.2) were observed in NW, central and outer periphery of the study area (Fig. 8a). Now, nine consecutive scenarios were generated using GWLF and L_iRDLH parameters and in each of these scenarios, observation wells were added to minimize SE (Fig. 8b), the root mean square error (RMSE), and average standard error (ASE) (Table 2).

To optimize the existing network of observation wells, five wells were added to the existing network in each scenario by considering the location of maximum error in the SE map (Fig. 8a) as well as L_iRDLH parameters and the respective RMSE and ASE were verified. As the number of observation wells in existing network increases, a decrease in errors is noticed. ME, MSE, RMSE, and ASE were observed to be minimum after adding 45 additional observation wells (Table 2). The associated SE reduced from 2.20 to <1.00 (Fig. 8b), ME from 0.0800 to 0.0178, RMSE from 1.7549 to 1.2521, MSE from 0.0304 to 0.0115 and ASE from 1.7610 to 1.1819. Thus, from this analysis it is concluded that the optimum number of observation wells that can be added to the existing network is 45 in 18 sub-watersheds of the study area.

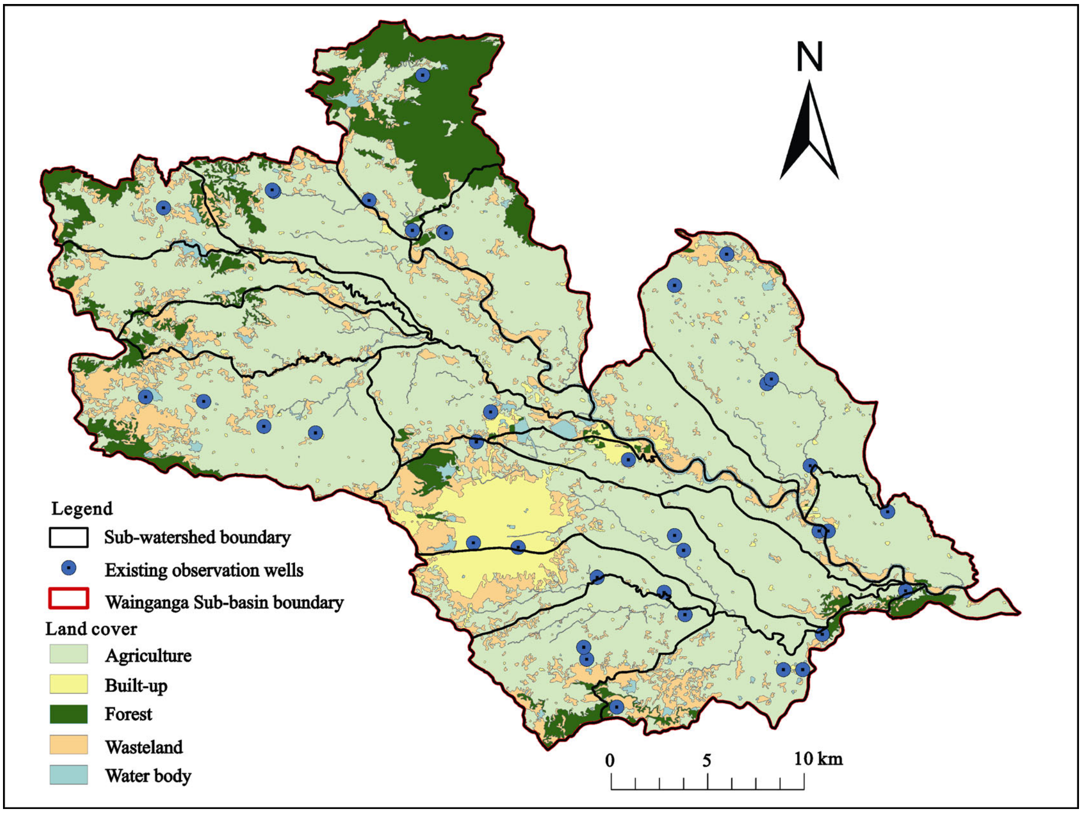


Fig. 7 Land use map of study area

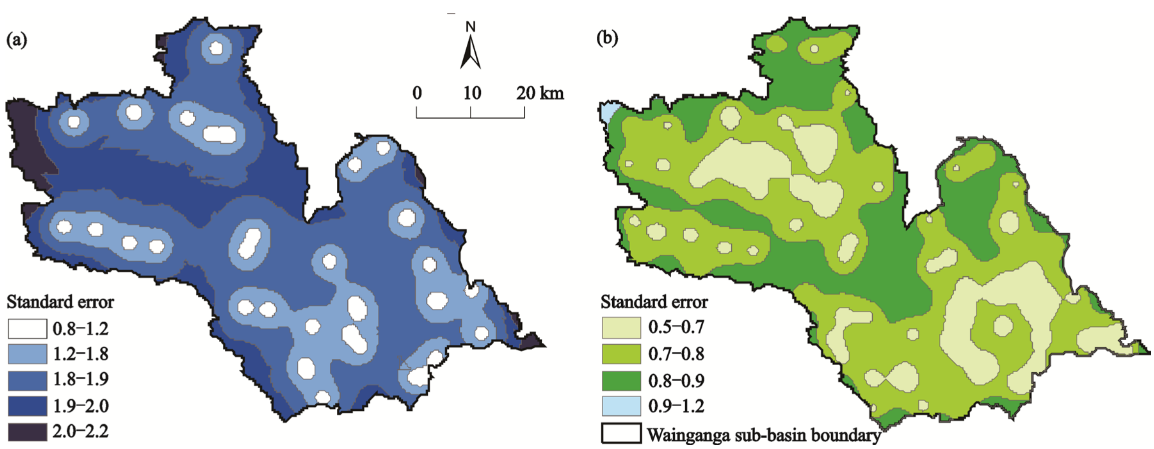


Fig. 8 Standard error map created using ordinary kriging (a) using only GWLF and (b) Reduced standard error map after optimization considering GWLF and L_iRDLH

Table 2 Cross validation results obtained for nine scenarios using exponential model of ordinary kriging due to addition of observation wells

Indices	OW5	OW10	OW15	OW20	OW25	OW30	OW35	OW40	OW45
ME	0.0800	0.0511	0.0535	0.0492	0.0504	0.0403	0.0276	0.0181	0.0178
RMSE	1.7549	1.6421	1.5975	1.5030	1.4477	1.4016	1.3413	1.2918	1.2521
MSE	0.0304	0.0189	0.0245	0.0243	0.0263	0.0216	0.0155	0.0111	0.0115
ASE	1.7610	1.6803	1.5452	1.4503	1.3775	1.3032	1.2565	1.2393	1.1819

Notes: OW: total number of added observation wells to existing network after each scenario, ME: mean error, MSE: mean square error, RMSE: root mean square error, ASE: average standard error

5 Conclusions

The study presents an application of geostatistical method in combination with multi-parameters that have influence on variations of groundwater levels, to optimize existing network of observation wells in area with heterogeneous aquifer system. Analysis carried out using only geostatistical method may not give satisfactory results; hence, the study also utilizes parameters like GWLF, lineament density, recharge, density of irrigation wells, land use and hydrogeology for better optimization of observation wells. The study was carried out for 18 sub-watersheds within the Wainganga Sub-basin located in the central part of India to find the optimum number and location of the observation wells using GIS based geostatistical methods. Geostatistical methods such as simple, ordinary, disjunctive and universal kriging were examined and compared to identify their applicability for prediction of groundwater monitoring wells of unmonitored locations within the study area.

The number and location of additional wells was based on the indicated groundwater influence parameters as it is observed that the GWLF is more in the region with high lineament density, low recharge, high density of irrigation wells, agricultural area, igneous rock and some parts of metamorphic rocks. The arbitrary addition of wells will reduce the standard error variance but it may not be a suitable representative location for observation wells. Cross validation test was performed to select appropriate method and semivariogram model for further predictive analysis and optimization process. Considering the least error variance, ordinary kriging with exponential theoretical variogram model was found to be more suitable for the present study with consideration of GWLF and L_iRDLH parameters. The error indices such as SE, ME, MSE, RMSE, and ASE were observed to be minimum after adding 45 additional observation wells of which 17, 22 and 6 were respectively added to igneous, metamorphic and sedimentary terrains. The error variances are observed to be more in the NW, central and outer periphery of the study area where observation wells are less. Hence, the study suggests that more number of observation wells is necessary in existing network in these locations.

Optimized monitoring network of wells obtained from the present study provides both statistical and scientific basis for upgrading the network of observation wells. The method adopted in the current study is observed to be an efficient method for selecting observation well locations in a region with varied geological setup. Similar methods can be applicable for area with more heterogeneous geological types. Location of wells can also be selected with other optimization techniques with these L_iRDLH parameters. All the analysis has been performed for shallow aquifer system and it is recommended that the proposed observation wells should pierce the full saturated thickness of aquifer.

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