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Spatial and Seasonal variation of groundwater characteristics in Bankura Sadar Sub-division

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Abstract

In semi-arid locations, climate change and human activities have a significant impact on groundwater properties. Mastering the groundwater dynamic variation and giving scientific recommendations for the sensible exploitation and management of groundwater resources require analysing the change in groundwater level and measuring the contributions of influencing elements. For the Bankura Sadar sub-division in West Bengal's semi-arid climatic zones, an attempt was made to find probability distributions using seasonal (January, April, August, and November for 2019 to 2020) statistics on groundwater table. The study describes how a geostatistical method was used to improve an existing network of groundwater samples. Semivariogram analysis was performed to fit the best theoretical model with experimental model. The study shows that ordinary kriging provides the best answer, and that the error variance can be used to add more observation wells for the best groundwater level tracking network infrastructure. The exponential semivariogram model derived from conventional kriging provides the best fit model, according to spatial and seasonal evaluations. The results revealed that the groundwater level demonstrated amazing regularity with seasonal use throughout the year. Consequently, the interannual groundwater level continued to fall, resulting in the depression cone. For appropriate groundwater monitoring, these methods can be implemented for intra-district water level depth analysis.

Keywords: Groundwater, Geostatistics, Ordinary Krigging, Semivariogram, Water level depth, Seasonal variation

Introduction

Groundwater is a major cause of water supply in many places around the world, particularly in rural areas (Nas and Berkatay, 2010). It is one of the key sources of irrigation and ecosystem, in addition to drinking water. From all of the world's water resources, about 2.5 percent of water is increasing as freshwater. Humans have access to water in the form of rivers, lakes, reservoirs, and underground water sources (Ebrahimi et al., 2011). Groundwater irrigation accounts for around 53% of India's overall irrigation potential, and about half of the country's irrigated land is reliant on it (Central Water Commission 2006). India has been dealing with declining groundwater quality as a result of fast urbanisation and an exponentially growing population (Brindha et al. 2011). Periodic variations in groundwater quality are usually caused by changes in the source and composition of recharged water, as well as hydrological and human influences (Aghazadeh and Mogaddam 2010).

Overextraction has resulted in a 61 percent decrease in groundwater levels between 2007 and 2017, with up to 89 percent of the removed groundwater being used for agriculture. Groundwater accessibility in India is influenced by both anthropogenic and climate variability. Rainfall contributes 68 percent of India's annual renewable natural groundwater supplies, while irrigation return flows, canal seepage, and recharge from ponds, tanks, and water conservation buildings provide the remaining 32 percent (CGWB, 2020). According to the Central Ground Water Board (CGWB), which is part of the Ministry of Water Resources, excessive groundwater removal is to account for a 61 percent drop in groundwater levels in wells in India between 2007 and 2017. Groundwater, which provides 40% of the world's irrigation, is a key resource for food security. Quantifying the effects of groundwater depletion on agricultural output is especially important in India, the world's largest consumer of groundwater, where groundwater provides 60 percent of the country's irrigation supply (Dalin et al., 2017). Since the 1960s, tube well development in India has exploded, allowing farmers to enhance cropping intensity, or the number of seasons in which crops are planted in a given year, by expanding production into the generally dry winter and summer seasons (Gandhi and Namboodiri, 2009). Much of India's food production increases during the last 50 years can be attributed to this increase in cropping intensity.

Many studies employed a geostatistical approach to investigate geographical differences in groundwater properties. Polluted groundwater has a heterogeneous spatial distribution, and pollutant concentration estimates are rarely available for every potential location in a given area. For geographic groundwater quality analysis, many research have employed a combination of GIS and statistical approaches. The analytical hierarchy process (Rahmati et al., 2015), frequency ratio (Guru et al., 2017), weights-of-evidence (Al-Abadi, 2015), evidential belief function (Nampak et al., 2014), certainty factor (Razandi et al., 2015), logistic regression (Nguyen et al., 2020), and artificial neural networks have all been used in some studies to evaluate groundwater potential (Lee et al., 2018).

For decades, West Bengal has struggled with groundwater quality. In West Bengal, Bankura is part of the red lateritic zone (Nag and Kundu 2016). Due to the inadequate water holding capacity of the soil, high drainage, surface runoff, and substantial soil erosion, the area is extremely vulnerable to any shift in rainfall (Milly 1994). In addition, the yearly rainfall in this area is highly unpredictable, and droughts occur frequently (Roy et al. 2020). Water tainted with fluoride affects about 12% of the population in eight of the state's 23 districts. Contamination is more prevalent in the state's western regions, such as Purulia and Bankura (De et al., 2021). Due to severe water constraint, the Bankura area, which is home to almost 400 Santhals, is on the verge of being parched. The people, especially women, are forced to go up to four kilometres to gather water from the river due to a serious lack of drinking water (Nag and

Ghosh, 2013). The water problem intensifies as summer approaches, forcing communities to travel even longer distances in quest of drinking water.

As a result, the purpose of this study is to investigate the geographical and seasonal variability of groundwater in the Bankura sub-division. The findings of this study could be utilised to improve regional planning and management approaches aimed at ensuring the long-term viability of groundwater use.

Study area

Bankura is one of West Bengal's most prominent westernmost districts, and its location on the Tropic of Capricorn gives it climatological significance. Although it is a semi-arid region, it is very susceptible to drought. The research region lies on the Bankura sadar sub-groundwater division's management blocks, which have an uneven landscape and are underlain by Precambrian crystalline rocks. Between 22°59'8.845" and 23°38'12.242" North latitude and 86°47'52.828"E –87°23'11.231" East longitude is the Bankura Sadar sub-division located (Figure 1). Geographically, the Bankura Sadar sub-division comprises the far eastern aspect of the Ranchi Plateau, which is related with the Dwarakeswar–Gandheswari Rivers' depositional fluvial terraces as it goes east (Nag and Das, 2017). As the world's population grows, the yield gap for water grows wider every day. The people of these locations are threatened by both physical and economic water shortages. Because of this, the research region has been considered in order to better comprehend the current situation, as well as the local people's ability to adapt to it and their views on the problem.

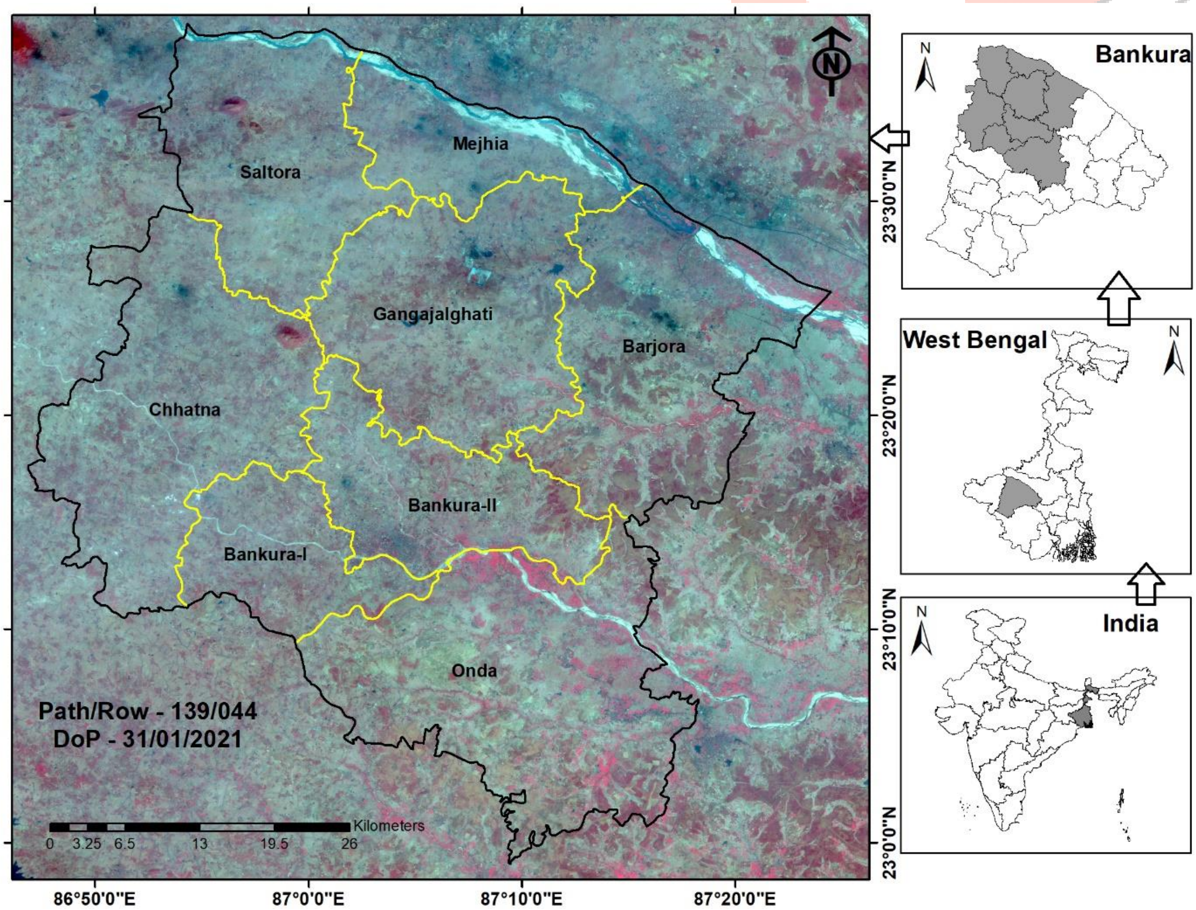

Figure 1: Location map of Bankura sadar sub-division (West Bengal, India)

Materials and Methods

Data collection and processing

Well inventory survey was carried out in Bankura Sadar sub-division with the help of global Positioning System (GPS) and details such as location of wells, types of well, diameter of the well, usage of well, depth of water table etc. Monthly groundwater level data were recorded from 49 wells for the period from April 2019 to January 2020, and was validated with the groundwater level data available between 2015-2016 with the Central Groundwater Level, Government of India. All of the theme layers were rasterized and projected into UTM Projection, WGS 84 Datum Zone 45, with a spatial resolution of 30 metres. Based on the geographic location, a point layer was generated on QGIS v2.0 platform.

Q-Q plot

Following data collecting, histograms and normal Quantile–Quantile (QQ) plots were used to evaluate for normality of the water table data (i.e., depth to the water table measured in metres). The data should have a normal distribution in a histogram or a normal QQ plot to fit the spatial map and produce a better prediction accuracy in the map. If the histogram reveals a skewed trend in the data, the data must be modified.

Semivariogram analysis

Semivariogram was used to assess global groundwater movements (i.e., a rising or deepening trend of the water table coupled with spatial directions). In geostatistics, the semivariogram (*h*) is the key tool for expressing the spatial variation between surrounding observations (Ahmadi and Sedghamiz 2008). It is equal to one-half of the variance of the difference in data points at all sites isolated by h in Eq1.

$$\gamma(h) = \frac{1}{2N(h)}\sum_{i=1}^{N}[z(x_i) - z\,x_i + h)]^2 \ldots\ldots\ldots\ldots\ldots Eq.1.$$

where *z(xi)* and *z(xi + h)* are the amplitudes of the parameter (e.g., depth to the water table evaluated from the ground surface in metres) at point x_i and a point *h* away from point x_i, respectively. The total number of feature pairs (i.e., well pairs) dispersed by the distance *h* is *N(h)*. Empirical semivariogram models for April, August, November, and January were created to examine and characterize spatial autocorrelation.

The nugget to sill ratio illustrates how spatially dependent variables are. Model explanation is divided into three categories: Strong spatial dependency is indicated by a ratio of less than 25%; moderate spatial dependence is indicated by a ratio of between 25 and 75 percent; and weak spatial dependence is indicated by a ratio of more than 75 percent.

Spatial interpolation

Kriging is the best sequential unbiased interpolation tool for calculating unknown spatial and temporal parameters with the smallest mean interpolation error (Chung et al., 2019). Ordinary, simple, universal, Poisson probability, and other types of kriging methods are accessible (Böhner and Bechtel 2017). The methodology adopted is determined on the qualities of the data available. The ordinary kriging (OK) approach asserts that the data sets are static and uses a semivariogram to obtain the best fit for the spatial connection model, which approximates the values without bias and with the least variation (Cressie 2015). The ordinary kriging approach was used in this investigation due to the precedent of ordinary kriging and the properties of the given data.

The root-mean-square error (RMSE) and average standard error (SE) estimations are included in the cross-validation statistics (Chung et al., 2019; Taye et al., 2018). The empirical semivariogram models anticipate a closer match between observed and forecast groundwater depths when the RMSE and SE are less. Furthermore, an RMSE score near to zero indicates an unbiased forecast.

Results

Groundwater level data and water quality factors can be used to make quick decisions utilising a decision - making framework like GIS. Because it is becoming progressively vital to comprehend the core ideas of depicting groundwater flow, an attempt has been made to develop maps to anticipate groundwater flow using water level data for the Bankura Sadar sub-division. In the month of April, depth of water level is varied between 1.71m/bgl and 14.41m/bgl with a mean value of 6.20 m/bgl±3.14. In August, water level depth is varied from 0.26 m/bgl to 10.23 m/bgl, with mean water level of 2.97 m/bgl and standard deviation of ±2.20 (Table 1). In November, water level depth is varied between 1.67m/bgl and 11.96 m/bgl (mean±standard deviation 5.14±2.20). In January, water level depth is varied from 2.2 m/bgl to 14.30m/bgl, with an estimated mean water level depth of 7.32 m./bgl±3.14. The results also showed positive skew for all the estimated months. The highest positive skew was observed in the month of August and lowest positive skewness value was recorded for January month. The results also showed high positive kurtosis value.

Table 1: Descriptive statistics of groundwater depth characteristics in the study area

Year	Minimum (m/bgl)	Maximum (m/bgl)	Mean (m/bgl)	Std. Deviation	Median	Skewness	Kurtosis	1st Quartile	3rd Quartile
April	1.71	14.41	6.20	3.14	5.93	0.895	3.66	3.72	7.89
August	0.26	10.23	2.97	2.20	2.52	1.194	4.26	1.44	3.79
November	1.67	11.96	5.14	2.20	4.77	1.17	4.22	3.54	6.11
January	2.2	14.3	7.32	3.14	6.7	0.62	2.69	5.24	8.64

To find the best match for the spatial relationship models, semivariogram modelling was used. To create the semivariogram curve, some values were grouped as per the separation distance (bin). The semivariogram model is shown in Figure 3 on data from the groundwater table for the months of April, August, November, and January. It shows that pairs of semivariogram values varied with the change of season. The highest mean value was recorded in the month of January (1.896) and the lowest mean value was recorded in the August (0.777). There is a directional distance is detected in different season.

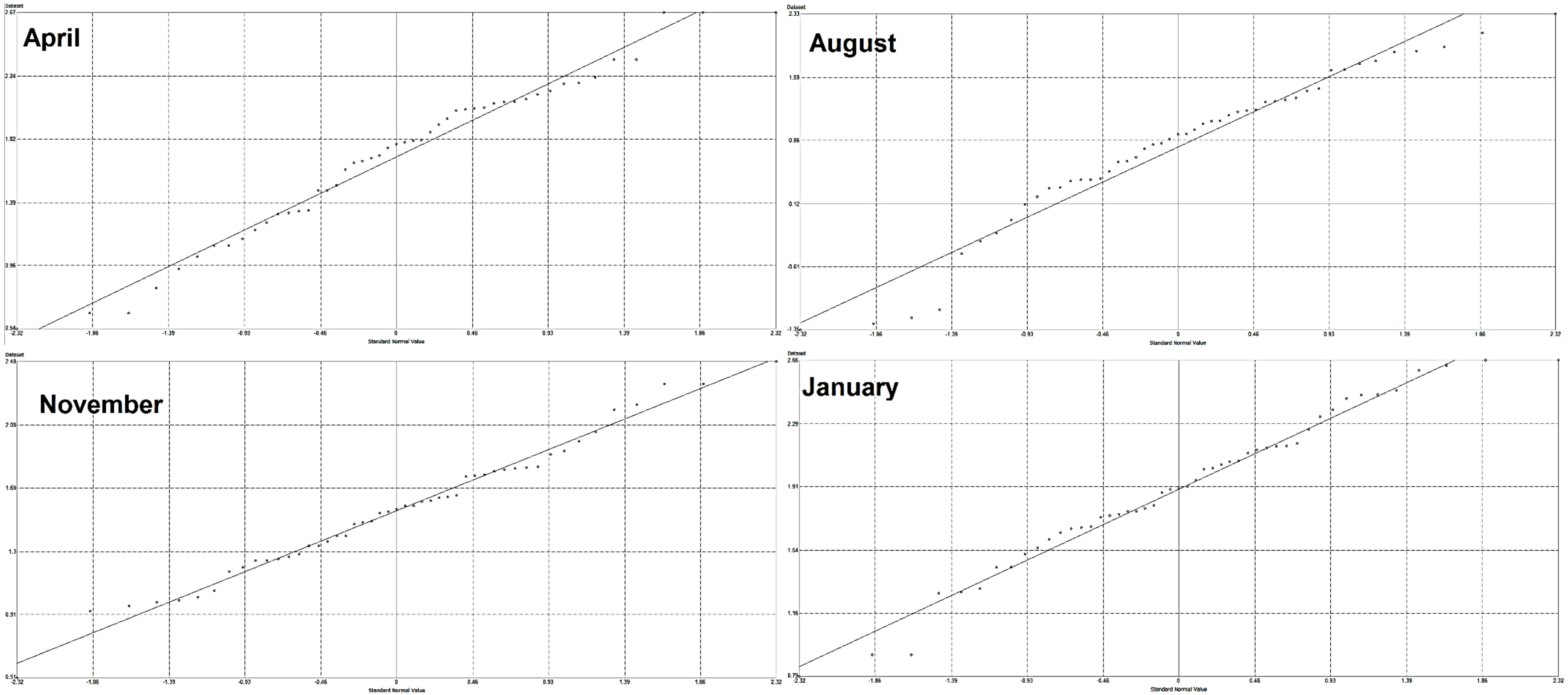

Figure 2: Q-Q plot of seasonal variation of groundwater characteristics

Consequently, at four different months, the values of the parameter's nugget, range, sill, and lag size were calculated (Table 2). The estimated partial sill was highest in month of August. The result of the analysis shows strong spatial dependence of the water level depth. The smaller value of lag size was calculated for each month which indicated more accurate estimate of the nugget for the semivariogram model.

Table 2: Model summary of semivariogram analysis of groundwater characteristics

Season	Mean	Range	Partial Sill	Nugget	Lag size	Nugget/Sill
April	1.694	0.1215	0.0652	0.9248	0.0202	14.18
August	0.777	0.0711	0.8503	0.2086	0.0099	0.25
November	1.553	0.9489	0.09	0.99025	0.079	11.00
January	1.896	0.9849	0.05	1.01688	0.079	20.34

After accounting for the impact of explanatory environmental factors, the geographical trend in the data is represented by a spatially-varying mean trend surface. The red dots represent the mean semivariance values between all pairs of villages with a separation distance within a discrete distance bin, with the dots on the x-axis being located at the midpoint of each bin. The fitted theoretical variogram model is represented by the blue solid line (Figure 3). The empirical variogram is primarily outside of this region, indicating that there is a substantial spatial trend in the data. After adjusting for the set of linear predictors of the water level depth covariate model, the residuals are fitted with the trend in semivariogram. When compared to the mean trend, the reduction in range parameter indicates that the water level depth variables account for some (but not all) of the observed geographic variation.

Figure 4 portrays the spatial and temporal variation of water level at different time periods. In the month of April, water level depth was less than 6m/bgl in the east and south-east of the study area. The maximum depth (>8.1 m/bgl) of water level was observed in the central part of the study area. During August, more than 70% of the study area having water level was estimated as less than 3m/bgl. The highest dept of water level was recorded in the small pockets of south-west, south-east and north of the study area. The month of November, the lowest water level depth is recorded east and north-west of the study area. The depth of water level is maximum in the south-west, north-west and north of the study area. In the month of January, more than 70% of the study area having the water level depth of 6m/bgl. The highest water level depth was recorded in the south-east, south-east and small pockets of central and north-east of the Bankura Sadar sub-division.

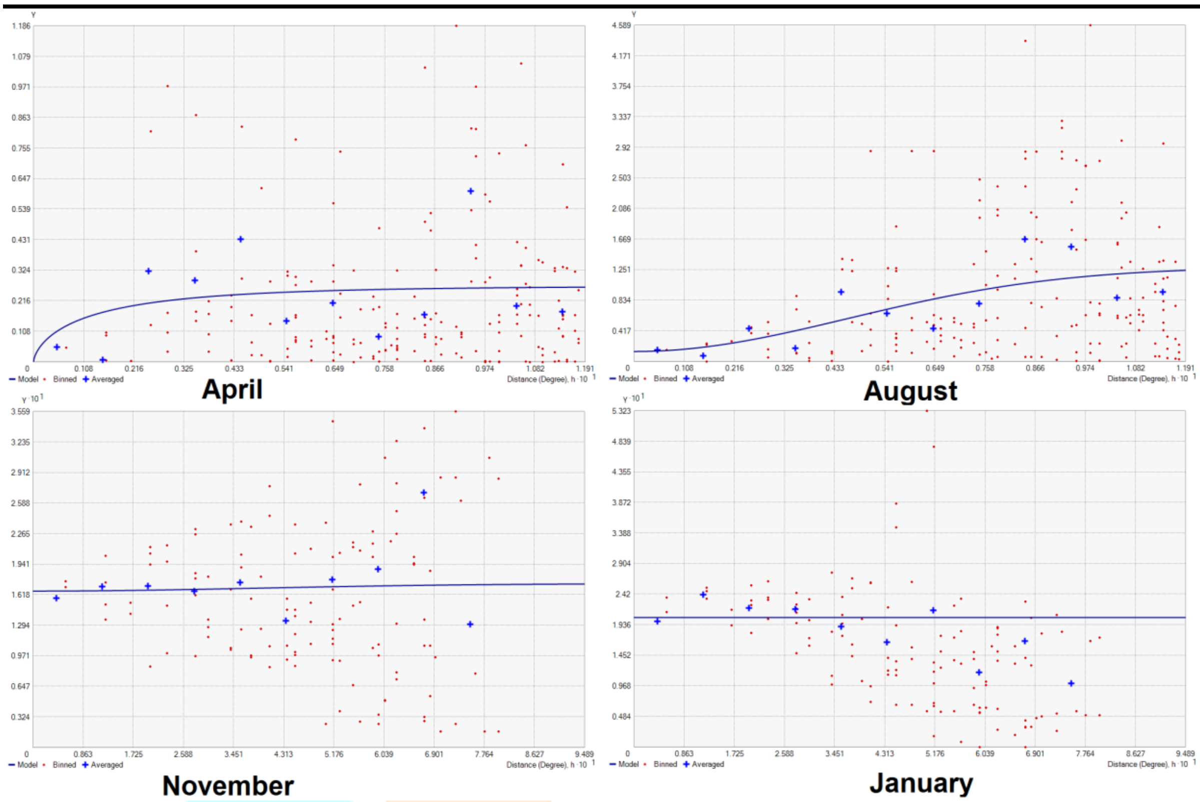

Figure 3: Semivariogram analysis of groundwater distribution in Bankura sadar sub-division

Before creating the prediction maps, the predictive models were subjected to cross-validation testing to determine their correctness. Both the RMSE and the average SE should be as little as possible, as previously indicated. Table 3 shows the results of the data checks for the water table. The highest value of RMSE was calculated for the month of January (3.644), followed by April (3.53) and the lowest value of RMSE was recorded for the month of August.

Table 3: Model summary of Inverse Distance weighting

Year	Average Standard Mean	RMSE	Regression function
April	0.062	3.53	0.020 * x + 5.96
August	0.010	2.31	0.052 * x + 2.652
November	0.002	2.593	-0.053 * x + 5.255
January	-0.062	3.644	-0.066 * x + 7.487

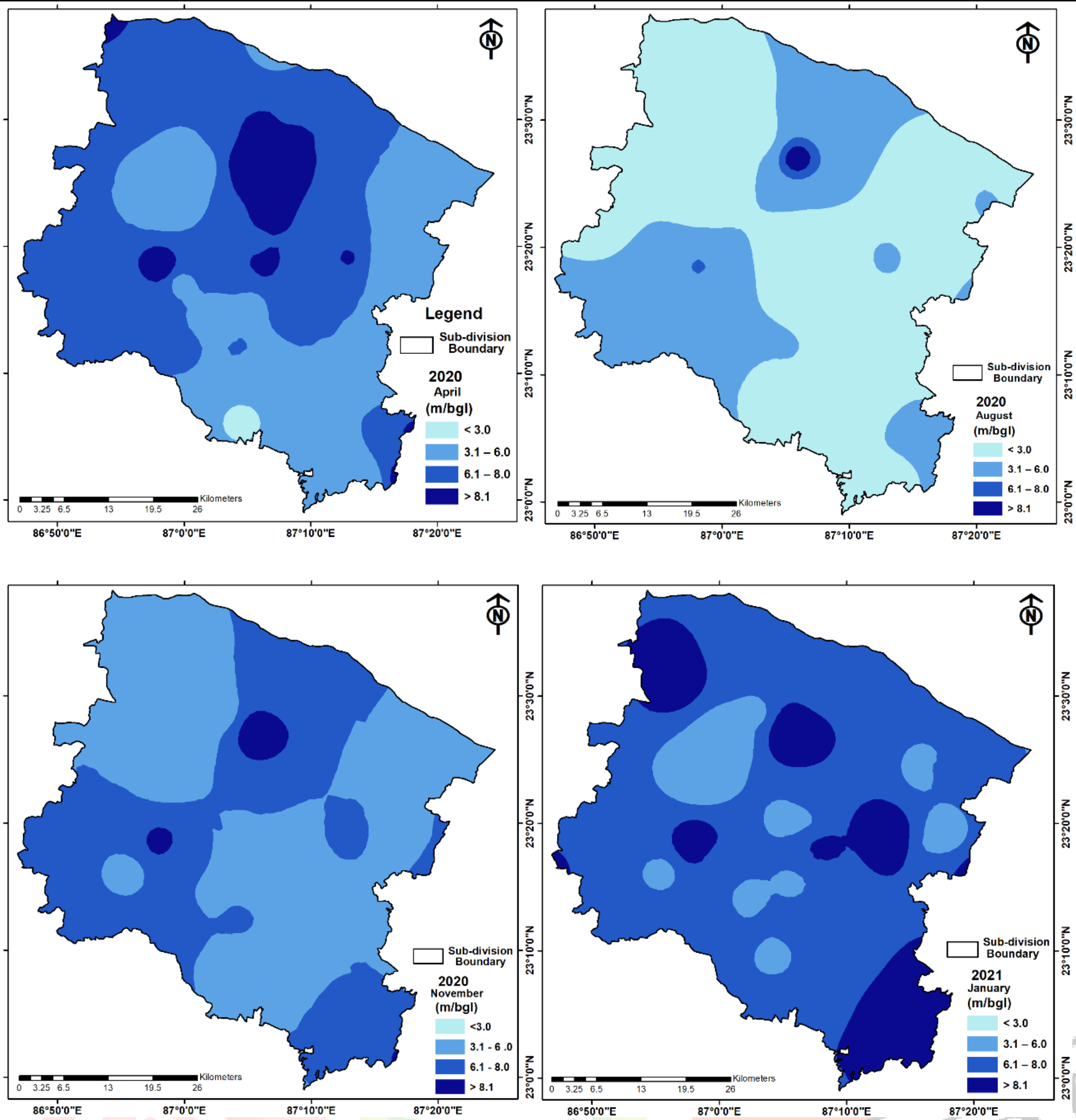

Figure 4: Spatial variation of groundwater distribution in Bankura sadar sub-division

Discussion

To understand the dynamic behaviour of the aquifer system in Bankura Sadar Sub-division, both season and geographical variability of water level were investigated together. Because the water level time varies and is indicated using the same network of observation wells at appropriate intervals, estimating it for all time periods becomes onerous, as does following all the processes of geostatistical estimation. To account for the periodic change in water level, however, it is feasible to group water levels for similar time periods and analyse them geostatistically for geographical variability (Halder et al., 2020). The level of groundwater exploitation is still modest, and the groundwater is only used for home purposes. After the conclusion of winter irrigation, the preceding year, the groundwater level begins to gently rise, reaching its maximum point of the year in March and then tending to be quite steady.

In the Bankura Sadar sub-division, the influence of human occupations on groundwater level fluctuations is represented by exploitation quantity, which is modified by changes in irrigated area, population, planting structure, and water-saving irrigation technology (Halder et al., 2020). Every year, in the months of April and March, this Darkeswar river basin experiences severe climatic, hydrological, and agricultural dryness, which can sometimes last into June due to the delayed onset of monsoon.

During the hot and humid summer season, well discharge does not reach a suitable level, and the majority of wells dry up (Dey et al., 2018). The mean value for all of the selected villages during August is considerably lower than other seasons (Table 2) in the current study, which is mostly due to high rainfall in the month, as well as previous months. While groundwater levels appear to be depleting in May, this could be due to water removal for irrigation, increased water absorption by plants, particularly deep-rooted plants, increased evapotranspiration due to high temperatures, poor or no rainfall in and around May, and other water-related activities.

From the results of the entire study, it is obvious that there has been a disparity in the changes in groundwater table depth between the villages and seasons studied. Farmers start large-scale cultivation and extract groundwater for seasonal crop irrigation (potato, sunflower, potato, wheat, vegetables, mustard). The groundwater level has dropped to its lowest point since April, with a decline range of 3.72-7.89 m/bgl. Due to the end of spring irrigation, groundwater withdrawal intensity is low. During this stage, the groundwater level steadily rises to 0.05 -.77 m/bgl. Crop growth, which necessitates a huge amount of groundwater to meet growth needs, occurs throughout this period, which lasts the longest (Vishwajith et al., 2015). The exploitation quantity accounts for more than 70% of the entire year, and the groundwater reaches its maximum intensity. In August, the groundwater level rapidly declines to its lowest point of the year, forming a regional cone of depression, with a decline amplitude of 1.44 – 3.79 m/bgl. The intensity of exploitation weekens as the summer irrigation season draws to a close. During this time, groundwater exploitation is at a minimum, and the groundwater level rises quickly to 5.24 – 8.64 b/bgl. Because of limited scale winter irrigation, the pace of growth in groundwater level fluctuates. However, the overall trend has continued to grow from November to December, with an intensity of 3.54 – 6.11 m/bgl.

Conclusion

Spatial and seasonal investigation was attempted to understand the mechanism of groundwater level fluctuations in Bankura Sadar sub-division, West Bengal (India). The maximum average water level depth s recorded in the month of April and the lowest average depth of water level is estimated for the month of August. In the south-east and small pockets of north and south-west part of the Bankura Sadar sub-division, water table is higher. However, groundwater fluctuation is minimum in the north part of the study area. Nonetheless, there are significant limitations to this study that will need to be addressed in future research. To begin, more data should be entered into the database. Seasonal or monthly data would be useful in determining the variation's finer features. Although a factor analysis will be performed to identify shared traits, the contribution of each variable to each of the three factors is yet undetermined. Domestic and environmental water demands, on the other hand, were linked to population growth and the expansion of human demand. As a result, we proposed that the depletion of groundwater should be attributed in part to population expansion. In geostatistical modelling groundwater table depth, this study also demonstrates that different probability distributions are suited for different locales. The probability of different groundwater table depths for subdivision at the micro level might be calculated using the probabilities and used for effective planning.

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