Examining the groundwater level in a semi-arid district of eastern India: spatiotemporal trends, determinants, and future prospects

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Abstract

The present study aims to examine the spatio-temporal and seasonal fluctuation of groundwater levels in an eastern Indian semi-arid region. Also, it attempted to investigate the involvement of different significant groundwater usage factors in causing such variations and trends. Furthermore, by evaluating temporal patterns and the influence of the crucial drivers, generate meaningful predictions for raising community awareness about the future. A combination of statistical, spatial analysis, and machine learning techniques were used to fulfill the objectives. Overall, the findings revealed that the south-eastern corner (consisting of Bundwan and Barabazar Blocks), the far western region (especially Jhalda I and II Blocks), and some of the eastern Blocks are most vulnerable to groundwater scarcity. The monitoring stations in this region are typically suffering a significant declining trend in groundwater level, with a substantial amount of Sen's Slope. In contrast, the centrally positioned Blocks have lesser susceptibility. The MLR analysis and spatial thematic maps demonstrate a strong association between this spatial pattern of declining groundwater table and the groundwater drivers in consideration. Thus, it is acceptable to suggest that drivers from the human world must be included in the groundwater management planning of the Purulia district. Finally, the predictions from the time series confirm that if no interventions are implemented, the average groundwater level will decline by 2.5 meters by 2030. Therefore, Purulia urgently requires a realistic plan to prevent future generations from becoming refugees in their own land.

1. Introduction

Groundwater is an essential renewable resource on the earth that can be replenished. The dependence of the global economic (agricultural and industrial) and domestic sectors on groundwater sources exemplifies its significance (Giordano, 2009). However, as a resource, groundwater is becoming increasingly vulnerable as a consequence of the fast-expanding population, changes in food consumption habits, quality of life, and alterations in land use land cover patterns. Scientists from throughout the world are worried about the related emerging challenges. (Das et al., 2021; Sishodia et al., 2016). Although it is a renewable resource, the storage of genuinely useable freshwater is limited. Studies have seen that the characteristics of groundwater are also changing as demand and developmental activity-related pressure started increasing (D’Odorico et al., 2018; Wheida & Verhoeven, 2007). Specifically, in the semi-arid regions in developing countries, water is becoming more overexploited, polluted, and unsuitable for human consumption (Gleick, 1998; Kadam et al., 2020).

India is one of the most populous nations, with more than 1.35 billion population and approx. 500 million livestock population (Gunthe & Patra, 2020; Hegde, 2019). It is also the global highest consumer of groundwater. It uses more than 230 km^3 of groundwater each year, which is higher than one-fourth of the total global consumption (AQUASTAT, 2010). In this total water use, being an agriculture-dominated country, groundwater use for irrigation purposes has the largest share (78%), followed by the domestic sector (6%) and industrial sector (5%) (Siebert et al., 2010). Furthermore, due to insecure and limited municipal water supplies, urban populations have become increasingly reliant on groundwater during the

last three decades (Foster & Chilton, 2003; Furlong & Kooy, 2017). In India, monsoon rains are the primary source of groundwater replenishment. This seasonal rainfall provides around 58 percent of the yearly groundwater supply (CGWB, 2014). However, rising climatic variability has increased the uncertainty of monsoon rainfall, and due to a shortage of storage areas to store monsoon rain, monsoon rainfall recharge is fast diminishing (Dangar et al., 2021; Lal, 2001). Particularly in dry, semi-arid, and drought-prone areas, shallow aquifers' rapid depletion and water shortage are becoming an increasingly severe problem (Gebru et al., 2021; Kundu & Nag, 2018). Therefore, to secure the population with a sustainable and well-managed groundwater system, it is high time to develop some sustainable policy measures. However, before going for any recommendation, identifying the actual problem from the spatial and temporal viewpoint and understanding the factors behind such issues is very important (Conant et al., 2019; Ladi et al., 2021). Studying the spatio-temporal trend of the groundwater level (GWL) and its relationship with various important influencing drivers is crucial in this regard. It helps in understanding the nature of groundwater in a particular region by answering questions like how the GWL is changing spatially and in what way it is reacting to the changing socio-economic and physical environments.

Along with the physical factors, there are different anthropogenic factors, which are responsible for the diverse spatio-temporal variability of groundwater in terms of quantity and quality. However, after the green revolution and the introduction of HYV (High Yield Varieties) seeds in India, irrigation has become one of the major forces that stimulate the daily increase in depth of the subsurface water table (Das et al., 2021; Kashyap & Agarwal, 2021). Apart from irrigation, land use intensification, massive population growth, rapid urbanization, industrialization, etc., also shaped groundwater overexploitation in India (Paria et al., 2021). Scholars have employed a variety of statistical, mathematical, and geospatial tools to explain the changing nature of the subsurface groundwater table while researching these various components and their influence on groundwater depletion(Ashtekar & Mohammed-Aslam, 2019; Das et al., 2021; Sishodia et al., 2016). Among them, remote sensing and geographic information system coupled with meaningful statistical methods are the most powerful and readily available. It is because, an integrated GIS technique allows one to combine space and time under one umbrella and visualize the location-wise change of any event over a period of timescales, which is extremely useful for area-specific, cost-effective, and sustainable policymaking. (Bhunia et al., 2021).

Purulia district falls under the dryland area of the Chhotanagpur plateau fringe arid zone (Haldar & Saha, 2015). Long and hot summer generates a significant amount of evapotranspiration, which causes riverbeds to dry up (Acharya & Nag, 2013; Kar et al., 2020). On the other hand, during monsoon rains, the rough and slopy surface causes more surface runoff, resulting in a groundwater crisis in the district (Das et al., 2019; Gupta & Patel, 2021). Apart from that, the geological settings of this region also limit the recharge of groundwater. Besides these physical factors, several anthropogenic activities affect the groundwater system of this district. In their article, Bera and Das (2021) argued that more than one-third of the total population in the Purulia district manages their livelihood through irrigation-based agricultural practices, and the majority of irrigation water is sourced from shallow aquifers, which causes fast aquifer drying. Furthermore, water contamination, negligence, and leakage intensify the water deficit almost

throughout the year. Therefore, adequate groundwater evaluation, planning, and management are essential for this region in a time-bound manner.

Against the above background, the objectives of the present paper are–

1) To understand the nature of GWL disparities and the changing trend of GWL of different stations distributed throughout the semi-arid Purulia District.

2) Highlight how the groundwater table behavior is related to several concerning drivers like total groundwater draft, stages of groundwater development, the area under irrigation, and agricultural yield.

3) And put light on the future status of the GWL by considering the changing trend and differential impacts of the multiple drivers.

Assessment of the trend of subsurface groundwater level and understanding the determinants behind such variation of the water table from the viewpoint of both space and time are the first step toward formulating cost-effective recommendations. For the Purulia district (dry zone of eastern India), there is rarely a study that integrates all these investigation elements so far. Thus, the findings of this study will bridge the gap, and the predictions for the future will serve to promote awareness among current and future generations and create a sense of sustainable groundwater use. Overall, research like this helps policymakers, economists, and groundwater planners in developing appropriate and long-term strategies by successful identification of the regions of groundwater sensitivity and future vulnerabilities.

2. Sources For Data And Methods

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2.1. The study area

Purulia district was formed when the erstwhile Manbhum District of the then Bihar was disintegrated and amalgamated with the state of West Bengal, an eastern state in India (Fig. 1) (Rana, 1994). The district is currently bounded on three sides by Jharkhand, with the districts of Hazaribagh and Dhanbad to the north, Singbhum to the south, and Ranchi to the west. While the districts of West Bengal, notably Bankura, Burdwan, and Midnapore, encircle the eastern edge. Except for a tiny segment in the northeastern portion of the district, where sediments of the Gondwana age prevail, the geological formation of the region is dominated by pre-Cambrian metamorphic rocks (Haldar & Saha, 2015). The most prevalent rock types are Granites and granite gneisses, while recent and sub-Recent unconsolidated sediments are limited to small river channels and valleys (Fig. 2).

Figure 1 (Near Here)

According to (CGWB, 2006), in Purulia, groundwater is found mostly in (1) Weathered zones, (2) Saprolite zones, (3) Fractured hard rock zones, and (4) Narrow zones of unconsolidated sediments along river valleys.

The weathered zone might be up to 25 meters thick, and groundwater occurs under water table conditions. The dug wells may produce up to 2.75 lps of water.

In granitic terrain, **the saprolite zone** is situated between the weathered mantle and new rock mass. This zone ranges in depth from 10 to 30 mbgl, with an average thickness of 4m. Groundwater occurs in a semi-confined environment with a yield of up to 2.5 lps.

In the hard rock groundwater, exploration has been conducted down to 198 mgbl. The occurrences of saturated fractures are generally restricted to 50 to 110 mbgl. However, in Gondwana sediments, drilling down to 103 m reveals the existence of fractures within the depth of 24– 36 mbgl that are capable of yielding 3.3–5.5 lps.

The unconsolidated sediment zone in river valleys is of modest thickness, ranging from 5 to 13 mbgl, with an area of not more than 1–2 > 5.5 m. Open wells and shallow tube wells can produce up to 20 m3/hr during scary situations.

Figure 2 **(Near Here)**

2.2. Sources of Data

This study is primarily based on secondary databases collected from conventional sources. The groundwater level (GWL) data for 52 stations in the Purulia district was acquired from the India-WRIS (https://indiawris.gov.in/wris/#/groundWater) portal by filtering agencies as CGWB from 2000 to 2019. The CGWB collects information from 113 stations located throughout the district. However, we have only included those stations with complete data to avoid data inconsistencies. Aside from that, the India-WRIS portal was also used to gather groundwater draft and stages of groundwater development information of different timescapes for all of the community development Blocks. The databases for the parameters like total area under groundwater irrigation and agricultural yield for each Block were obtained from the Department of Planning and Statistics, Government of West Bengal published District statistical handbook of various years. In addition, the geological pattern map of the Purulia District was created using the Geological Survey of India (GSI) published 1:250,000 District Resource Map (https://www.gsi.gov.in/webcenter). The digitization of the scanned district resource map was performed in the ArcGIS 10.8 software environment.

2.3. Methods used

The flowchart displaying step-by-step methodologies for this research is shown in Figure (3). However, the essential techniques used in this study have been discussed separately.

Figure 3 **(Near Here)**

2.3.1. The nature of groundwater level (GWL)

The nature of obtained GWL data was analyzed using some simple statistical techniques. Such as, to determine the pattern and station-by-station change in GWL over time, LOWESS (Locally Weighted Scatterplot Smoothing) was used. LOWESS aims to identify the best-fitting curve without presuming that the data must fit into a specific distribution shape or be linear (Roystont & Altman, 1994). Since the GWLs at various sites rarely follow a normal distribution, LOWESS is the best option when plotting the best fit line in a time series. In this work, SPSS v22 was used to create LOWESS scattered plots for both the post-monsoon and pre-monsoon seasons.

The variance of GWL data in different geological facies (Fig. 2) was shown using another statistical technique, Boxplot analysis. Here, we attempted to understand GWL fluctuation on diverse geological facies because numerous studies have indicated that complex rock settings are the primary cause of drilling failure and groundwater dearth. The Boxplot depicts the upper and lower limits, median, and inter-quartile range of the data, which are the most important statistical measures for identifying the unique nature of the data (Zheng & Keleş, 2020). Further, boxplot modeling also helps in finding the distinct data values and outliers of the dataset. In this study, the GWL databases of the considered two decades (2000–2019) were arranged according to the available geological class to perform the Boxplot analysis.

2.3.2. Statistical trend analysis

The statistical Mann-Kendall test was used to determine the significance of changes in GWLs during the previous 20 years (2000–2019). It is rank-based in nature and is one of the best non-parametric tests that are significantly powerful if the data structure is not normally distributed (Pathak & Dodamani, 2019; Sishodia et al., 2016). The MK test may also be used for a time series with missing data. As a result, it is regarded as the best-fit trend test for the pre-and post-monsoon seasons when assessing trends in GWL data (mainly non-normal type). In the present study, the pre-and post-monsoon GWLs were separately examined because groundwater levels in a monsoon rain-fed area are normally deepest in the month of May (pre-monsoon) and shallowest in October (post-monsoon).

To be more specific, the MK test is a non-parametric regression technique that is used to evaluate whether the observed data increases or falls with time. The computation of the Kendall statistics S is done by comparing later measured values and earlier measured values. In this way, a total of n (n -1)/2 potential data pairs should be examined for n number of observations. Mathematically the equation is

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} Sign(x_j - x_k)$$

Where -

$$Sign(x_j - x_k) = 1 \text{ if } (x_j - x_k) > 0$$
$$= 0 \text{ if } (x_j - x_k) = 0$$
$$= -1 \text{ if } (x_j - x_k) < 0$$

The output with more significant positive S values indicates an upward trend, whereas larger negative values depict a downward trend. Trends were assessed at a significance threshold of 95% ($\alpha = 0.05$).

Furthermore, the MK test was usually used in conjunction with Sen's slope to determine the steepness of the trend (Li et al., 2021). Sen's Slope is the median of the slopes obtained by all of the data pairs that have been compared, and it is determined using the formula:

Sen's Slope = Median $\{\frac{x_j - x_k}{x_j - x_k} : k < j\}$

Where, j = (1 to n), k = {1 to (n – 1)}, and n is the total number of observations.

To perform the MK test and Sen's slope measurement in R Studio software version 4.1.0, the package "*trend*" written in R was installed in the R environment.

2.3.3. Relationship between parameters and spatio-temporal GWL

To find out how the varying water table depth is influenced by the existing factors of the research region, in other words, to relate the spatially variable GWL and its changing trend with the influencing factors, some influencing drivers are taken into consideration. The concerned drivers are – a) total annual groundwater draft, b) stages of groundwater development, c) the total area under groundwater irrigation, and d) agricultural yields.

The multiple linear regression method has been applied in this study to measure the correlation between the concerning drivers and the spatial GWL variability. It is because when several independent variables linearly influence one dependent variable, it is the best fitting tool to measure the association. The basic assumption of the MLR model is that the dataset must be correlated linearly, and there should not be any autocorrelation and multicollinearity within the dataset (Hanley, 2016). However, before selecting the MLR model to analyze how multiple independent variables are working behind one response variable, one should test the linearity of the data as well as the trend line. In the present study, to check the linearity of

the data, a correlation matrix has been prepared. A correlation matrix based on linear regression is the best statistical technique to identify linearity (Li et al., 2018).

Further, the Durbin Watson test has been performed to check the autocorrelation (Zeisel, 1989). If the Durbin Watson test result is close to or equal to 2, it indicates that there is no autocorrelation, 0–2 indicates a positive autocorrelation, and 2–4 indicates a negative autocorrelation between the variables. Also, to determine the presence of multicollinearity between the predictor and subordinate variables, collinearity tests have been conducted to get the VIF values. The variance inflation factor (VIF) is the ratio of the total model variance to the variance of a model with only one independent variable (Alin, 2010). A high VIF indicates a significant degree of multicollinearity between the linked independent variable and the other variables.

The MLR model for examining the association between the GWL variability and multiple concerning drivers can be written as-

$$Y_{(GWL)} = \beta_0 + \beta^1 * \text{total groundwater Draft} + \beta^2 * \text{stages of groundwater development} + \beta^3 * \text{area under groundwater irrigation} + \beta^4 * \text{agricultural yield} + \mu$$

Where $Y_{(GWL)}$ represents the dependent variable, 'β' is the regression coefficient; the 'β_0' and 'μ' are regression constant and error terms of the model, respectively.

2.3.4. Preparation of thematic maps and future prediction of groundwater level

Along with the relationship analysis (discussed in the previous section) to spatially visualize the association, thematic layers for all the considered determinant factors were prepared using the widely used IDW (Inverse Distance Weighting) method from the spatial analyst toolbox in ArcGIS 10.8 software environment (Bronowicka-Mielniczuk et al., 2019; Chen & Liu, 2012).

Further, utilizing time-series data with a relevant and appropriate simulation model to anticipate the future status of an event can aid in successful and long-term policy planning (Banerjee et al., 2009; Das et al., 2021). In the current study, on the basis of 20 years trend of the pre-monsoon and post-monsoon GWL for each station, the next 11 years (up to 2030) GWL has been predicted. The prediction was made using the Artificial Neural Network (ANN) algorithm in the R Studio environment (Kulisz et al., 2021). The package "nnfor" and "forecast" written in R were utilized to run the ANN algorithm. Unlike the MLR model, before running the ANN algorithm "Ljung-Box" test was carried out to check the autocorrelation between the water level data. Being passed the test, the datasets are fitted in ANN-based time series using suitable R code. After that, the multilayer perceptions (mlp) neural network was applied. It automatically finds the hidden nodes and autoregression after processing the time series. Finally, after developing the mlp-based neural network, to get the forecast or predicted result mlp.frc (multilayer perceptions. forecast) code has been used in the R Studio v4.1.0 software. Finally, based on the forecasted GWL information, spatial

maps have been prepared using the IDW technique from ArcGIS 10.8 software for both pre-and post-monsoon seasons of 2030.

3. Results

3.1. Dynamics of groundwater level in Purulia District

In this study, several statistical approaches were employed to evaluate how the GWL is evolving geographically (station by station) and the nature of the datasets. Climatologically, the study area is located in a monsoonal rainfed zone (Ghosh et al., 2016). Rainfall occurs mostly from May to September (monsoon season), and rainfall is the principal source of groundwater recharge, as previously noted. Hence, the region has the highest GWL depth during pre-monsoon (May-June) and the lowest GWL depth during post-monsoon (October). Thus, to make the study more logical, we have considered pre-and post-monsoon seasonal GWL for analysis.

First, to identify station-wise changes in groundwater depth patterns during pre-monsoon and post-monsoon seasons, the two LOWESS-based scatterplots and regression lines have been plotted (Figs. 4a and b). The highly fluctuating stations are the points (representing 20 years average GWL of pre-and post-monsoon seasons) that are more deviated from the locally weighted regression line. During pre-monsoon Bandoan (Bundwan)[1], Hura (Hura), Jhargo (Jhalda-I), Manbazar (Manbazar-I), Suisa (Bagmundi), and Bhangabandh (Barabazar) are showing very high positive fluctuations. While Chakaltore and Tamna from Puruliya - I C.D. Block showed high negative fluctuations from the regression line. This means the Blocks Bundwan, Hura, Jhalda, Bagmundi, Barabazar, and Manbazar face a significant increase in depth in the pre-monsoon season. In contrast, Hura (Hura), Jhargo, Dungridi (Baghmundi), and Bagmundi (Bagmundi) are the high positive fluctuation stations in the post-monsoon season. Moreover, from the LOWESS, it is clear that the groundwater level fluctuation in Purulia follows a similar pattern in pre-and post-monsoon seasons. In the pre-monsoon season, the stations with higher groundwater levels tend to have higher GWL depth during post-monsoon with varying intensity.

Figure 4 **(Near Here)**

To understand how the GWL fluctuation is controlled by the geological structure over 20 years (2000–2019), a simple statistical tool boxplot has been utilized in the present study. It is a well-known fact that geology is a very important parameter in groundwater study because it is the factor that mainly decides the recharge of the groundwater (Arya et al., 2020). Figures (5a and b) depict the boxplot analysis output of both pre-and post-monsoon seasons. In the pre-monsoon season, the region with intrusive granite has the highest fluctuation. However, the mica-schist shows high fluctuations with the highest median value. In contrast, the shale sandstone has the lowest fluctuation.

In the post-monsoon season, the highest groundwater level fluctuation with the highest median value is found in the biotic gneiss geologic structure. The mica-schist structure is next to it. At the same time, the

shale sandstone group and calc-limestone group have the lowest variability with a lower GWL.

Figure 5 **(Near Here)**

3.2. Trends in groundwater level

The station-wise trend of all the selected stations (52) of CGWB (Central Ground Water Board) has been calculated using the MK trend test and Sen's Slope. The results from the test show that 61.46 percent of total stations in the pre-monsoon season have a statistically significant ($\alpha = 0.05$) positive trend means increasing the depth of GWL with Sen's Slope ranging from 0.04 to 0.31 m/yr^{-1} (Table 1). The test also found that 13 percent of stations (7 in number) have a negative trend with a statistically significant "Kendall S." The rate of decline for these measuring stations ranged from − 0.07 to -0.16. Among 52 stations, 13 stations have no significant trend in the pre-monsoon season. However, 47 percent of the station with an insignificant trend has declined to range from 0.003 to 0.08.

Table 1 **(Near Here)**

In the post-monsoon season, the trend analysis has found that the GWL of 56 percent of the total 52 stations is declining means depth is increasing significantly at 95 percent significance (Table 2). The rate of decline in such cases distributes from 0.05 to 0.48 m/yr^{-1}. Only two stations are found with a significant rising trend (Sen's Slope = -0.06 to -0.10 m/yr^{-1}). At the same time, 21 stations of 52 total stations have no such significant trend. However, 18 among 21 have a positive trend (increasing depth) ranging from 0.0005 to 0.08 m/yr^{-1}.

Table 2 **(Near Here)**

When the focus has been given to the spatial distribution of the significant declining and rising trends of both seasons, the analysis found some exciting results. The stations, namely Joypur (Joypur), Kotshila (Jhalda-II), Sarbori (Neturia), Balitora (Santuri), Bandoan (Bundwan), depict a significant rising in GWL in the pre-monsoon season. Whereas, post-monsoon season, not a single station shows a statistically significant rising in water level. Only Jhalda (Jhalda-I Block) shows a meaningful rising trend (-0.06 m/yr^{-1}) though it is not statistically significant. When we went to the identification of declining GWL trend, then stations, namely Arsha (Arsha), Neturia (Neturia), Bhangabandh (Barabazar), Suisa (Baghmundi), and some other stations are found to have a rapid rate of decline. Figures (6a and b) depict the spatial structure of station wise rate of change in GWL in the Purulia District. The motive behind spatially plotting the calculated trend is to help the policy planner identify specific zone for implementing groundwater management practices.

Figure 6 **(Near Here)**

3.3. Association between spatio-temporal GWL and multiple concerning drivers

In finding the causes behind the GWL variability throughout the study area, the present study incorporated several concerning drivers that significantly affect the depth of GWL. Studies in groundwater science mostly talked about the physical factors and their importance in groundwater occurrence. Studies in this region have already discussed the potential groundwater zones using physical factors (Das et al., 2019; Maity & Mandal, 2019). However, as we are trying to understand the declining GWL trend in this study, the most critical drivers are associated with groundwater use. Therefore, the four most important factors, such as – total groundwater draft (domestic + irrigation), stages of groundwater development, the area under groundwater irrigation (irrigation water use), and agricultural yield, were considered. Further, to identify the influences of these factors quantitively, the multiple linear regression (MLR) model was used. For the MLR analysis, the GWL station-wise data are arranged in a Block-wise manner, and by taking an average of all the respective years (2000 to 2019), the GWL values are organized. Similarly, the databases for all the other factors were organized by averaging the annual database of different years. However, because of data inconsistency, 11-year Block-level datasets (2000, 2002, 2005, 2009, 2010, 2011, 2013, 2014, 2016, 2017, and 2018) were used for averaging the agricultural yield and area under groundwater irrigation in the Purulia district.

Before running the MLR model in SPSS to test of linearity of the data, a correlation matrix has been developed for all the considered variables and presented with scatter plots (Fig. 8). The matrix clearly indicates the linearity of the relationships between every individual factor. Table (3) depicts the model summary output of the MLR, with r = 0.934 (highly positive correlation between the variables) and a standard error estimate of 0.33. The Durbin-Watson test result depicts no autocorrelation between the variables. The VIF statistics confirmed no multicollinearity problems in the dataset, as all the VIF values are under 3.0 (in the ideal condition). The ANOVA table (Table 4) very clearly depicts that the model is significant at < 0.0001 level with an F value of 25.810. Therefore, the null hypothesis is rejected.

The coefficient table (Table 5) is another crucial table that shows how and which dimension each variable influences the response variable (GWL). By considering all these values, scholars can easily predict the trend of future groundwater levels. Here all the "**β**" values or coefficient values depict a positive dimension of the equation. The equation of MLR by putting all the "**β**" values will be –

$$Y_{(GWL)} = 2.87(\beta_0) + 0.003*\text{total groundwater Draft} + 0.014*\text{stages of groundwater development} + 0.006*\text{area under groundwater irrigation} + 0.004*\text{agricultural yield} + 0.3283$$

Now, with this equation, we can easily calculate Y (GWL) for any values of the predictors, viz. total groundwater draft, stages of groundwater development, the area under groundwater irrigation, and agricultural yield.

Table 3 **(Near Here)**

Table 4 **(Near Here)**

Table 5 **(Near Here)**

3.4. Spatial mapping and relationship of GWL and concerned predators

Figure (7) shows the spatial pattern of all five variables of relational analysis. The average GWL map displays that the south-eastern and the western bordered part of the study area has a very high to high groundwater depth. The Bundwan C.D. Block represents the most depth of GWL with a depth of 8.13m. When we relate the GWL spatiality with the geological pattern of the study area, the region with mica-schist and biotic gneiss has the highest groundwater level mainly because of minimal infiltration capacity and unavailability of water in the shallow aquifer. However, it explains one side of the coin. Thus, we need to focus on the groundwater use parameters.

Figure 7 **(Near Here)**

From the correlation matrix (Fig. 8), it is clear that all the variables considered in the MLR have a positive and moderate to a strong association with each other. While discussing how strongly each groundwater use parameter is associated with the GWL spatially, the study found that the groundwater draft has a very strong positive correlation with the average groundwater level (GWL) ($r = 0.92$). From the map (Figs. 7a and b), it can be interpreted that the spatial pattern of the groundwater draft is highly matching with the spatial pattern of GWL. The region with a higher draft has the higher GWL. In the case of the area under irrigation, the correlation value with groundwater level is 0.86. Similarly, for all the selected variables, there was a good matching with the groundwater level patterns (see the correlation matrix and the maps in Figs. 7 and 8).

Figure 8 **(Near Here)**

3.5. Future prediction and mapping using the simulation model

At the end of the analysis, to see how the groundwater level will behave in the near future (in the year 2030), the artificial neural network (ANN) model has been used to predict the future. The whole process of future prediction was processed in open-source R Studio software. First, mlp-based forecasts were made for each individual C.D. Block, and the spatial maps for both pre-monsoon and post-monsoon seasons were prepared by considering the predicted value for the year 2030 (Figs. 9a and b). The expected map for pre-monsoon season 2030 reveals that the C.D. Block Bundwan will have the most rapid decline, followed by Kashipur and Jhalda-II C.D. Blocks. While in the post-monsoon season, the highest depth of the Burdwan C.D. Block will be followed by the Barabazar C.D. Block. At the same time, both the maps represent a relative rising in groundwater level at Balarampur and Santuri C.D. Block. The most exciting fact is that the Kashipur C.D. Block, which has a moderate depth in the present average GWL map (Fig. 7a), may be vulnerable in the near future because of a significant decline in the water table. The reason behind such decline is discussed in the discussion section.

Figure 9 **(Near Here)**

Apart from the predicted spatial GWL maps, to understand the future groundwater level of the Purulia district, a separate ANN model has been developed for the entire district. However, the mean annual groundwater level data for two decades (2000–2019) have been considered in the present case of the entire district. Figures (10) indicates the predicted graph of the groundwater level at a 99 percent significance level ($p = < 0.001$). The prediction revealed that the average groundwater level depth for the year 2030 would be 8.2m which is 2.42m higher than the present average groundwater level.

Figure 10 **(Near Here)**

4. Discussion

The current study excellently integrates the nature of changing groundwater levels with critical concerning drivers in both time and space. The findings clearly indicate that most of the monitoring stations in the study area are suffering a considerable decline in groundwater level, with a large amount of Sen's Slope. If the current trend continues, the average groundwater level will drop by around 2.5 meters by 2030. The study also found that groundwater usage drivers had a considerable positive impact on groundwater levels. Therefore, it is reasonable to state that, in addition to the rough hard rock structure and geology (most famous among scholars), the drivers from the human world must be included in groundwater management studies in the present study area.

Based on our research objectives, the present study can be divided into three parts. In the first part, the station-wise and geological class-wise behavior of the groundwater level of the Purulia district were examined. It was discovered that the south-eastern corner (specifically Bundwan, Manbazar, and Barabazar Blocks) and the far western end of the study district (Jhalda I, II, Joypur) suffered the most positive water level fluctuations from the local average (Gupta & Patel, 2021). This is mainly attributed to the limited infiltration capability of mica-schist and biotic gneiss geology(GEC, 2015; Haldar & Saha, 2015) and the fast-increasing manmade land-use change driven groundwater demand (Census of India, 2011). The boxplot analysis also supports the statement that the groundwater fluctuation is higher in the biotic gneiss and mica schist structure. However, the measuring stations in Blocks such as Purulia II, Para, Santuri, Balarampur, and some others, on the other hand, show lesser variations due to lower drafts (Fig. 7b) and less groundwater consumption (Gupta & Patel, 2021).

Aside from the fluctuations, the station-by-station trend analysis revealed several intriguing facts. Like despite the fact that water level fluctuations are more significant, the stations from Blocks such as Jhalda-II, Joypur, Bundwan, Neturia, and Jhalda-I indicate a growing trend in groundwater level (decreasing depth). While, the stations from the Blocks, namely Arsha, Bagmundi, Purulia I, II, Hura, and Puncha, show a rapid diminishing trend (increasing depth). This is due to the differential stages of groundwater development (Fig. 7d). If the stages of groundwater development are high, that means the draft is high, but there is a good balance between stakeholder interests and ecological needs (Villholth, 2016). Another interesting observation from the trend analysis that must be mentioned here is that several stations (Bundwan, Neturia, Santuri, Joypur, etc.) exhibit a growing trend in the pre-monsoon

season but a dropping trend in the post-monsoon season (Minea et al., 2020). The findings from the relational analysis with the concerning driver explain the reason behind such characteristics. The Joypur and Bundwan Blocks are in the higher stage of groundwater management, and the Blocks like Neturia and Santuri have the lower groundwater-based irrigation area and groundwater draft. Further, Gupta & Patel (2021), in their study, found that the usage of groundwater is less in the northern and southwestern parts of the study area. However, in the post-monsoon season, most stations have shown a decline in GWL because of increasing climatic irritancies and frequent drought over the study area (Ghosh, 2009; Haldar & Saha, 2015).

Scholars in the Purulia district consistently highlighted the physical aspect of the relevant drivers whenever they discussed the groundwater system (Acharya & Nag, 2013; Chakraborty & Paul, 2004; Das et al., 2019; Gupta & Patel, 2021; Kundu & Nag, 2018). However, the results of the second part of our research have demonstrated the significance of the reverse side of the coin. It observed a similar finding to what other studies in the Gangetic basin been discovered (Das et al., 2021; Sahu et al., 2015; Dijk et al., 2020). The area under groundwater irrigation, total groundwater drafts, stages of groundwater development, and agricultural production patterns (the drivers of human water use and management) all have significant impacts on the geographical variation of groundwater levels. Halder et al., (2020), in the Silabati river basin (which is overlapped with the present study area), found that 60 percent of wells are located near agricultural land and where groundwater drafting from submersible wells is extensive, showing a significant declining trend, particularly in post-monsoon seasons.

The third section of the current study focuses on ANN-based future groundwater level prediction (Das et al., 2021; Malakar et al., 2020). The expected spatial pattern of the groundwater level for the year 2030 depicts several fascinating pieces of information. In the western bordered region of the district, while having a rising pre-monsoon trend (but a declining trend in post-monsoon) and higher stage groundwater development, groundwater depth will be more prominent by 2030. It might be due to the ongoing large-scale urbanization and massive groundwater draft in this region (Ghosh & Chakma, 2014). Apart from that, for the Kashipur Block, which has a moderate groundwater depth level, depth will rapidly increase by 2030. The higher agricultural yield (higher groundwater consumption) (Fig. 7e), the growing numbers of census towns (Census of India, 2011), and significant groundwater draft (Fig. 7b) might be the controlling components behind such decline.

Overall, the southern section of the research area, except the Balarampur C.D. Block, is highly susceptible in terms of groundwater supply in the near future, followed by the eastern Blocks of Manbazar I, II, Hura, and Kashipur. At the same time, despite the fact that the entire region is threatened by acute groundwater scarcity, the central and western C.D. Blocks (excluding Jhalda I and II) are appreciably less susceptible. Therefore, based on the study findings and facts, water harvesting structures must be developed as soon as possible in Jhalda-II, Bundwan, Manbazar, and Jhalda-I C.D. Blocks. The same may be done in the Kashipur, Hura, and Raghunathpur-I C.D. Blocks after that. Finally, places like Purulia-II, Arsha, and Joypur might be considered. Lineament junction zones, in combination with other morphological characteristics, can be used to decide where these dug wells can be built. Falling water levels are also significantly visible

in much of the region, notably in Blocks like Bundwan, Jhalda-II, Baghmundi, Manbazar-II, Raghunathpur-II, and Kashipur during the post-monsoon season. Therefore, groundwater drafting regulations are very much essential from the administrative side. Lastly, one of the shortcomings of the present study is the absence of a continuous annual dataset for the parameters that are used in the relational analysis. Hence, further study is required that integrates all physical, hydrologic, and groundwater usage factors to capture the more extensive features of groundwater behaviors and offer more precise, long-term suggestions.

5. Conclusion

Water is one of the most valuable and abandoned resources on the earth. However, due to increased urbanization and economic growth, freshwater (water intended for human use) is reducing radically (FAO, 2007). The situation is particularly acute in semi-arid regions, where pumped groundwater meets the majority of domestic and economic demands (Misra, 2014). Purulia district is one such example of a critical semi-arid region, where inhabitants rely on aquifer water for their everyday needs as well as for farm activities. According to some researchers, water shortage in the Purulia district may be ascribed not only to insufficient surface and groundwater but also to the economic incapacity of the inhabitants to invest in infrastructure to extract water from aquifers or other water sources to meet their demand (Gupta & Patel, 2021; Haldar & Saha, 2015).

Therefore, Purulia must plan its groundwater future as soon as possible to prevent future generations from becoming climate refugees in their own land. The current study may serve as a starting point for developing appropriate policies for managing groundwater. The results will help the policymakers in the successful identification of the region of groundwater sensitivity and future vulnerabilities. It will also be helpful in understanding how the groundwater usage parameters relate to the groundwater scenario of the Purulia district. Further, based on the suggestions, the hydrologists, geologists, environmentalists, and legislators may make appropriate groundwater management planning. This prospective research will also serve to promote awareness among current and future generations and create a sense of sustainable groundwater use.

Declarations

1. **Competing Interest:** We would like to declare that we have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.
2. **Availability of data and materials**: All the utilized data sources of this research are very clearly written under ***2.2. Sources of Data*** section of the article.
3. **Consent for Publication**: This paper has not yet been published and is not currently being considered for publication. If accepted, it will not be published anywhere in the same manner, in English or any other language, even electronically, without the copyright holder's express agreement.
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6. **Credit Statement:** The first author (Tarun Goswami) conceived the idea, designed the study, collected information from different sources, standardized the datasets, drafted the work, and revised it critically for important intellectual content. The second author (Somnath Ghosal) reviewed the manuscript and approved the version to be published.

Data availability statement

All the utilized data sources of this research are very clearly written under ***2.2. Sources of Data*** section of the article.

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Footnote

[1] The text enclosed in parentheses refers to the C.D. Blocks where the stations are situated.

Tables

Table 1: Mann-Kendall trend test - results for pre-monsoon season

Stations	Z	p-value	Score (S)	var	Kendall's tau	Sen's Slope
Aharrah	2.38	0.01	74	945	0.39	0.05
Anara	1.56	0.11	49	936	0.25	0.04
Arsha	2.01	0.02	63	947	0.4	0.08
Bagda	0.03	0.97	2	950	0.01	0.003
Baghmundi	-0.64	0.51	-21	949	-0.11	-0.02
Balitora	-2.01	0.04	-63	949	-0.33	-0.07
Bandoan	-2.85	0.004	-69	949	-0.34	-0.07
Barabazar	2.16	0.01	71	949	0.39	0.08
Baraurma	-0.68	0.49	-22	950	-0.11	-0.002
Bero	2.32	0.02	69	949	0.38	0.05
Bhangabandh	2.43	0.01	76	950	0.4	0.14
Bishpuria	1.97	0.05	66	949	0.32	0.06
Chakaltore	0.74	0.45	24	948	0.12	0.04
Chinpina	2.21	0.02	65	948	0.35	0.09
Deuli	4.28	0.000	133	949	0.7	0.12
Dhabani	4.22	0.000	131	949	0.69	0.22
Dubra	0.68	0.49	22	950	0.11	0.04
Gaurandih	3.63	0.0002	113	949	0.59	0.14
Gobag	-2.21	0.03	-69	949	-0.36	-0.1
Hariharpur	1.39	0.16	44	948	0.23	0.08
Hura	1.99	0.04	68	950	0.49	0.1
Indrabil	-1.89	0.06	-58	949	-0.34	-0.09
Jhalda	2.45	0.0084	75	949	0.38	0.13
Jhapra	-0.064	0.94	-3	947	-0.01	-0.0003
Jhargo	3.05	0.002	95	949	0.5	0.09
Joypur	-3.21	0.001	-100	950	-0.52	-0.16
Kantadihi	3.11	0.001	97	949	0.51	0.14
Chakdah	3.05	0.002	95	949	0.05	0.13

Keshargarh	-0.45	0.64	-15	949	-0.07	-0.0002
Korenge	-0.19	0.84	-7	947	-0.03	-0.002
Kotshila	3.53	0.0004	-81	950	-0.47	-0.09
Kustar	2.56	0.01	80	950	0.42	0.097
Asanbani	1.99	0.05	68	950	0.37	0.08
Manbazar	2.55	0.004	72	949	0.4	0.09
Mathbura	2.95	0.003	92	948	0.48	0.18
Naduara	1.96	0.05	61	949	0.36	0.15
Napara	2.75	0.005	86	950	0.45	0.14
Narayanpur	-4.47	0.000	-139	949	-0.73	-0.14
Neturia	3.63	0.0002	113	949	0.59	0.31
Palashkhola	2.05	0.04	58	948	0.37	0.07
Panara	0.35	0.72	12	950	0.06	0.02
Para	2.66	0.007	83	949	0.43	0.1
Podalaroad	1.98	0.05	57	949	0.35	0.04
Purulia	2.06	0.04	60	949	0.4	0.08
Santaldih	2.49	0.01	78	950	0.41	0.108
Sarbori	-1.97	0.05	-56	950	-0.29	-0.15
Simla	-1.78	0.05	-60	950	-0.32	-0.08
Sindri	2.02	0.047	63	950	0.37	0.09
Suisa	2.17	0.02	68	950	0.35	0.16
Dungridi	1.99	0.05	57	950	0.33	0.18
Takariya	3.34	0.0008	104	950	0.54	0.24
Tamna	3.41	0.0006	106	948	0.56	0.07

Table 2: Mann-Kendall trend test - results for post-monsoon season

Stations	Z	p-value	Score (S)	Var	Kendall's tau	Sen's Slope
Aharrah	1.99	0.05	61	950	0.32	0.07
Anara	2.05	0.04	63	950	0.36	0.09
Arsha	2.33	0.01	73	949	0.39	0.15
Bagda	1.46	0.14	46	948	0.24	0.067
Baghmundi	0	1	1	949	0.005	0.0005
Balitora	1.76	0.007	55	949	0.29	0.03
Bandoan	2.15	0.02	59	950	0.38	0.06
Barabazar	0.71	0.47	23	949	0.12	0.03
Baraurma	1.07	0.2	34	950	0.17	0.04
Bero	2.63	0.008	82	948	0.43	0.14
Bhangabandh	4.48	0.000007	139	949	0.73	0.48
Bishpuria	1.98	0.05	59	950	0.29	0.07
Chakaltore	0.58	0.55	19	947	0.1	0.009
Chinpina	2.88	0.003	90	950	0.47	0.07
Deuli	3.53	0.0004	110	950	0.58	0.24
Dhabani	4.93	0.000	153	949	0.81	0.44
Dubra	2.22	0.002	68	950	0.4	0.05
Gaurandih	2.5	0.01	78	950	0.41	0.07
Gobag	0.97	0.33	31	949	0.16	0.03
Hariharpur	2.17	0.028	87	950	0.39	0.06
Hura	0.68	0.49	22	950	0.11	0.03
Indrabil	0.71	0.47	23	944	0.12	0.016
Jhalda	-2.4	0.01	-75	949	-0.39	-0.06
Jhapra	-0.35	0.72	-12	950	-0.06	-0.019
Jhargo	2.48	0.002	83	950	0.46	0.11
Joypur	1.68	0.09	53	949	0.28	0.08
Kantadihi	1.16	0.25	37	949	0.2	0.06
Chakdah	1.96	0.05	61	949	0.32	0.09

Keshargarh	1.97	0.05	61	949	0.32	0.06
Korenge	1.97	0.05	59	949	0.31	0.06
Kotshila	3.92	0.000	122	950	0.64	0.19
Kustar	1.68	0.09	53	949	0.28	0.06
Asanbani	1.13	0.26	36	950	0.18	0.03
Manbazar	2.16	0.02	69	950	0.36	0.09
Mathbura	2.27	0.02	71	949	0.37	0.23
Naduara	1.46	0.144	46	950	0.24	0.06
Napara	-0.32	0.7455	-11	949	-0.058	-0.008
Narayanpur	-1.97	0.05	-62	950	-0.33	-0.1
Neturia	3.21	0.001	100	950	0.52	0.22
Palashkhola	3.05	0.002	95	949	0.5	0.09
Panara	0.9	0.36	29	949	0.15	0.02
Para	2.37	0.01	74	948	0.39	0.09
Podalaroad	1.62	0.1	51	949	0.26	0.05
Purulia	1.10	0.26	35	949	0.18	0.06
Santaldih	2.75	0.005	86	950	0.45	0.07
Sarbori	1.98	0.05	62	950	0.33	0.07
Simla	-0.94	0.34	-30	950	-0.16	-0.08
Sindri	1.46	0.1443	46	950	0.24	0.07
Suisa	1.96	0.05	60	950	0.32	0.17
Dungridi	2.4	0.01	78	949	0.37	0.11
Takariya	2.11	0.03	66	948	0.34	0.08
Tamna	2.14	0.03	67	949	0.35	0.06

Table 3: Summary results of Multiple Linear Regression (MLR)

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	0.934	0.873	0.839	0.32830	1.636
Predictors: (Constant), Agri_Yield, GW_Stage, GW_Draft, GW_Irrigation					
Dependent Variable: GWL					

Table 4: ANOVA table of MLR model

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	16.378	4	4.094	25.810	0.000[b]
	Residual	2.380	15	0.159		
	Total	18.757	19			
df - degree of freedom						

Table 5: Coefficients of MLR model and collinearity statistics

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	2.874	0.551		5.215	0.000		
	GW_Irrigation	0.003	0.006	0.747	3.496	0.025	0.216	2.983
	GW_Draft	0.014	0.002	0.563	2.300	0.036	0.281	2.667
	GW_Stage	0.006	0.019	0.668	3.282	0.030	0.246	1.975
	Agri_Yield	0.004	0.011	0.885	4.746	0.017	0.237	2.305
VIF = Variance inflation factor								

Figures

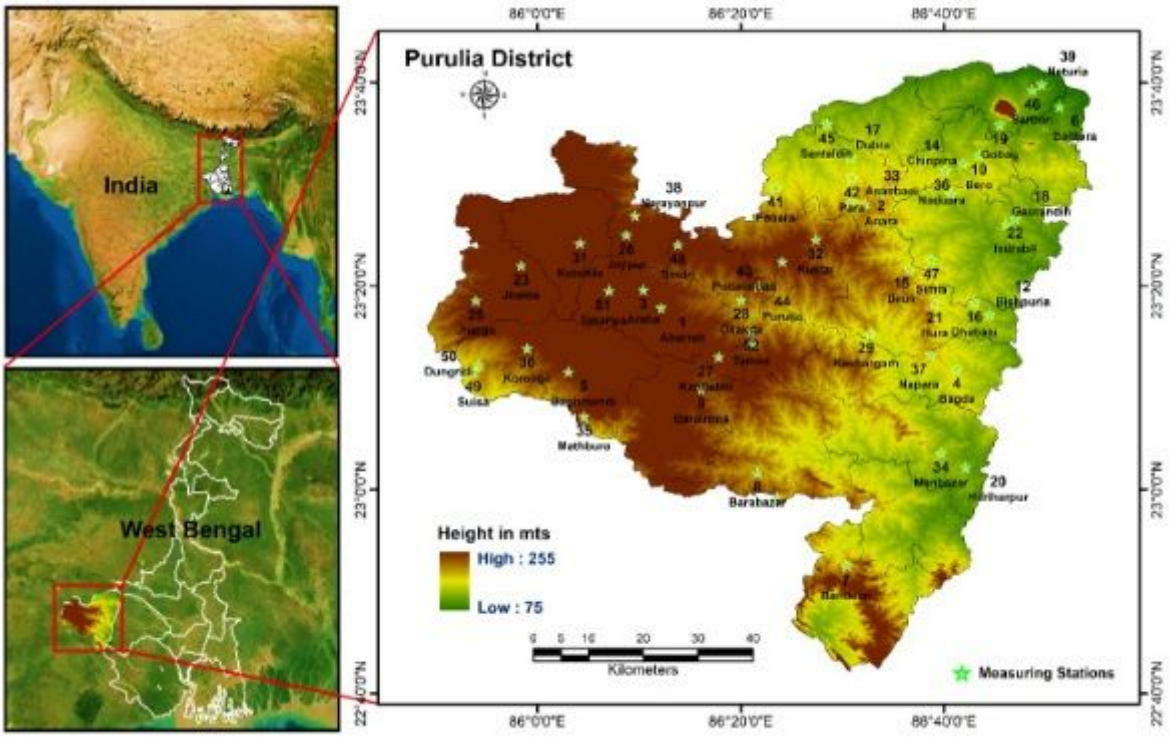

Figure 1

The area under research (Location Map)

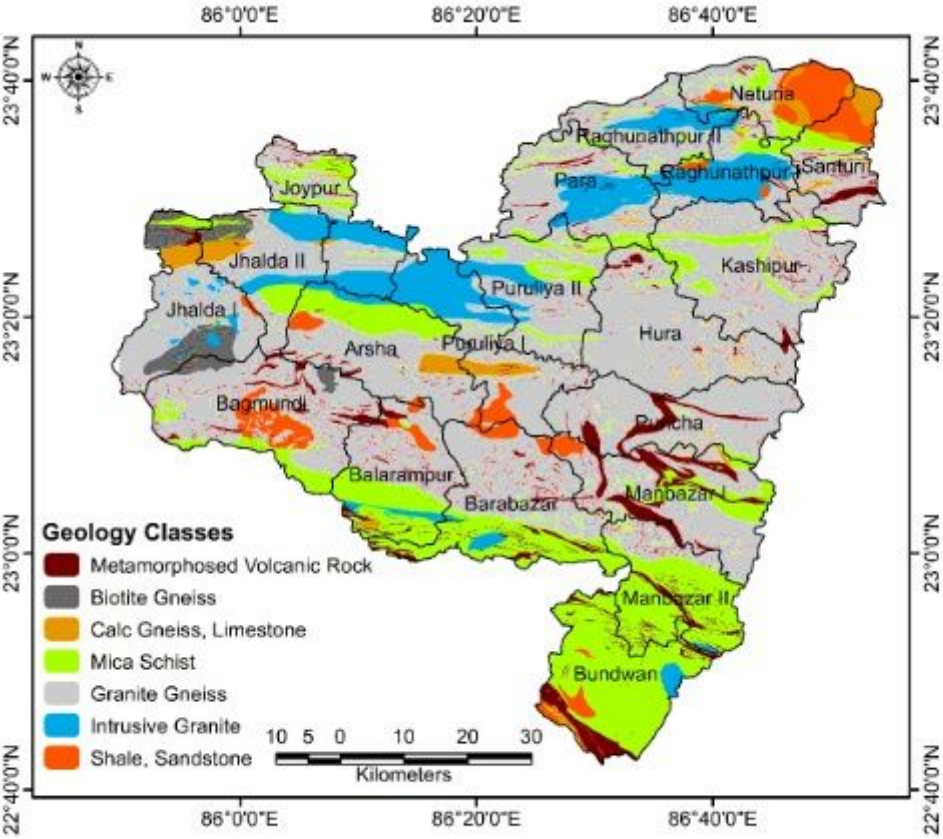

Figure 2

Geological pattern of Purulia District

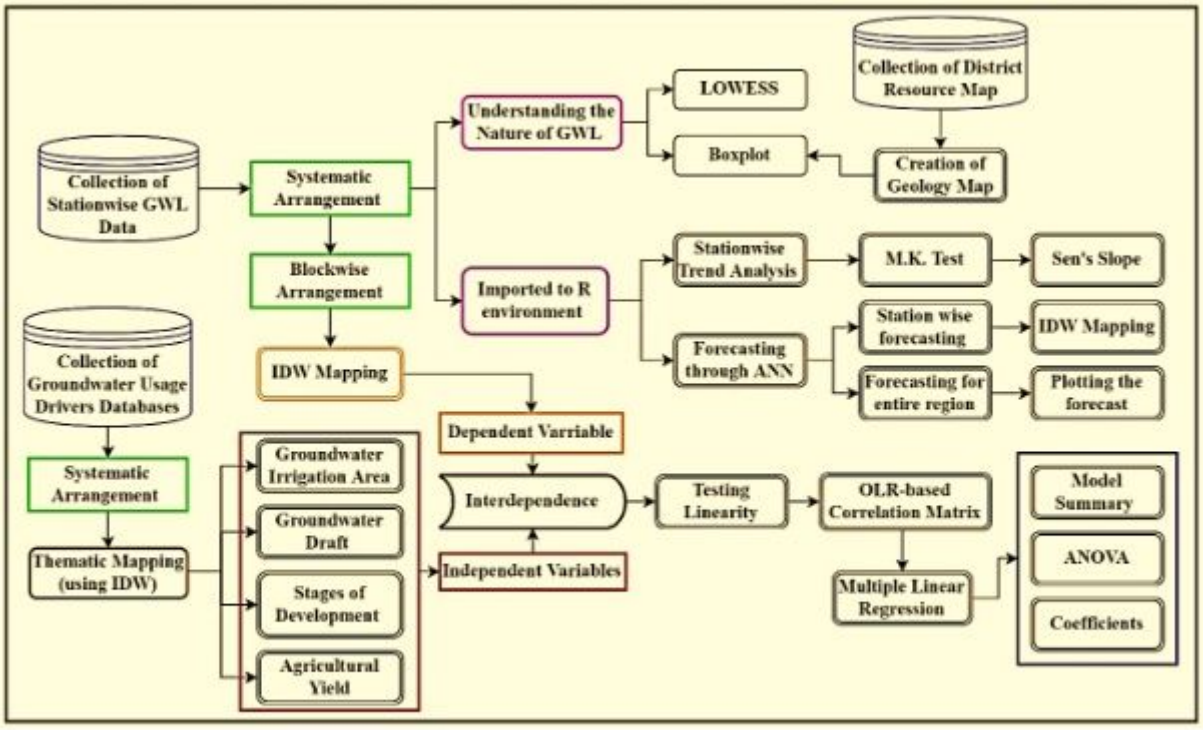

Figure 3

Study design flow chart

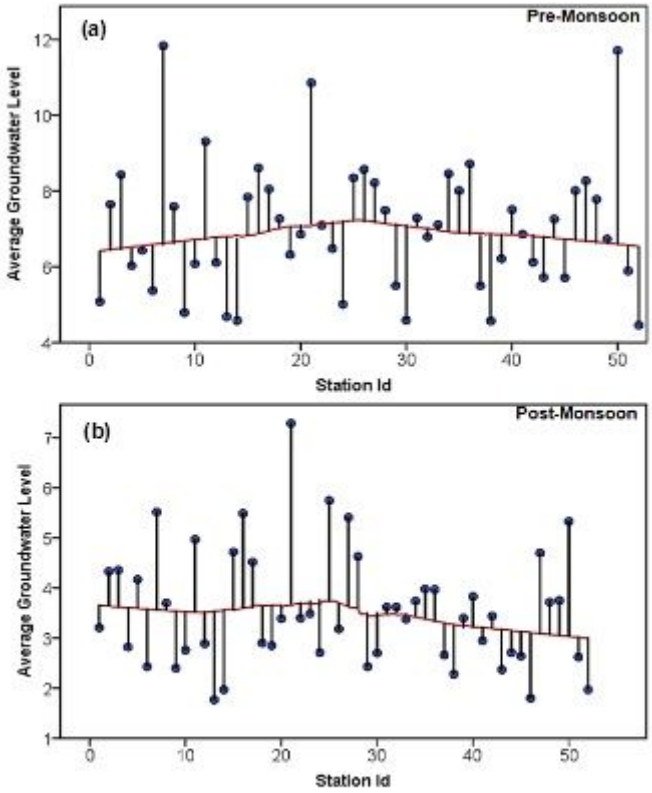

Figure 4

Locally weighted regression and scatterplot for pre- and post-monsoon groundwater level

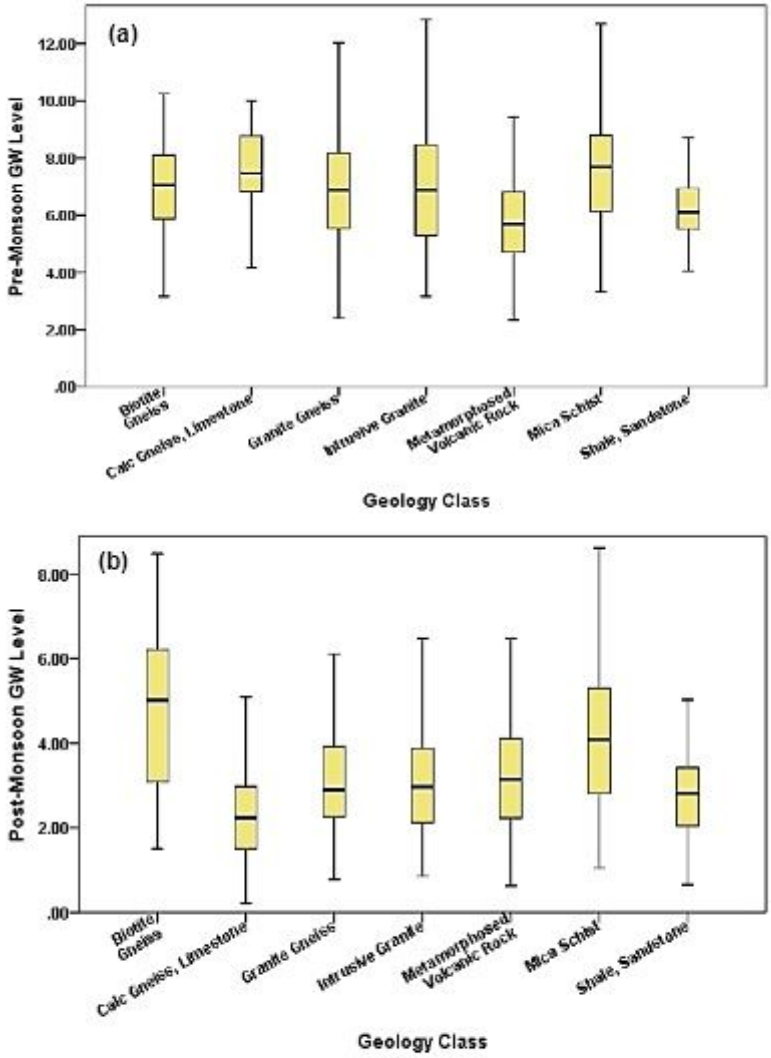

Figure 5

Boxplots showing fluctuation of groundwater level in different geological facies during pre- and post-monsoon season

Figure 6

Station-wise changing trend of groundwater level with Sen's slope

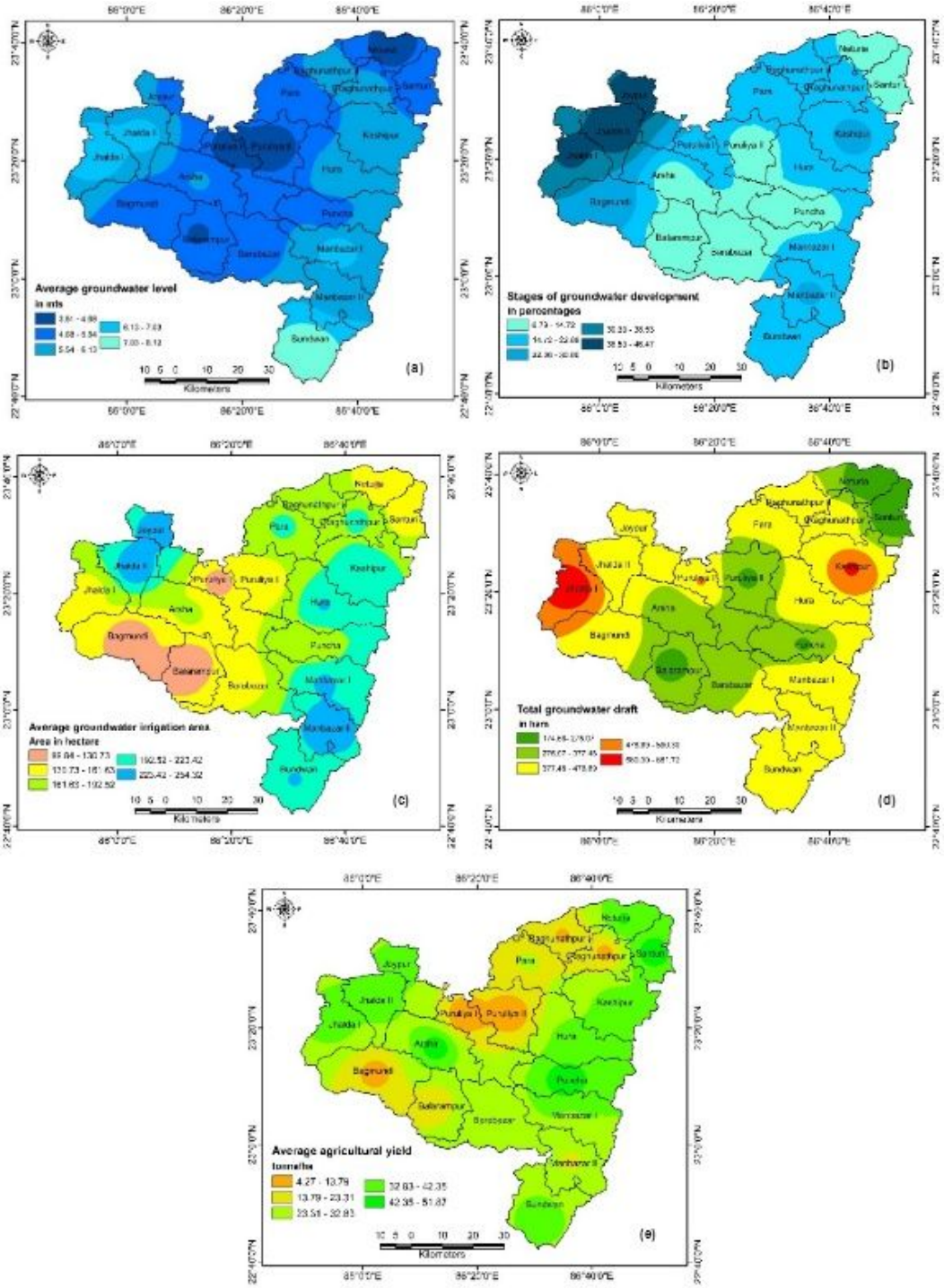

Figure 7

Thematic IDW-based maps of the multiple concerning drivers

Figure 8

Correlation matrix diagram for testing the linearity

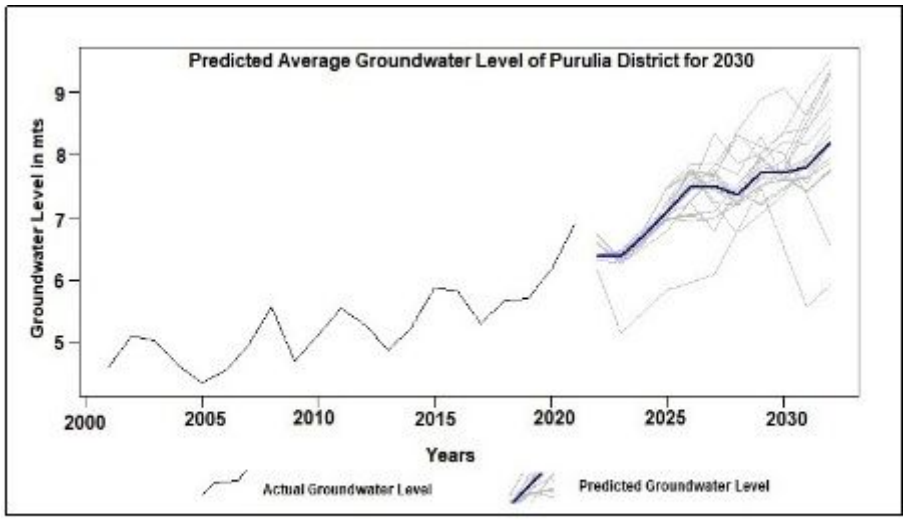

Figure 9

Spatial pattern of pre- and post-monsoon groundwater level in the year 2030

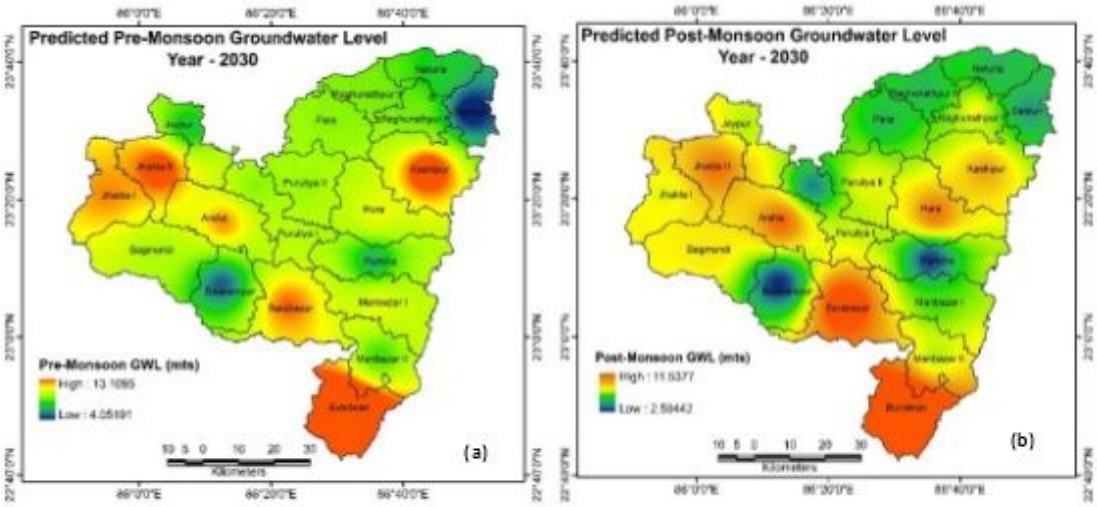

Figure 10

Changing groundwater level of Purulia District (2000 - 2030)