An Appraisal of Water Quality using Geostatistics: A Case Study in Bankura Sub-division, West Bengal (India)

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Abstract

For irrigation purposes, groundwater quality should be regularly checked so that the danger of geochemical pollutants can be decreased using the suitable treatment procedure. As an outcome, the present work focused on shaping the suitability of groundwater collected from the Bankura sub-division in West Bengal, India, for irrigation purposes using several water quality indicators. To assess the groundwater quality, 59 samples were taken from various locations around the research region during the period between 2019 and 2020, and parameters such as pH, EC, TH, alkalinity (HCO_3^-), calcium (Ca+), magnesium (Mg+2), sodium (Na+), chloride (Cl−), and potassium (K) were assessed. The permeability index (PI), magnesium ratio (MR), Kelley's Index (KI), and sodium percentage (Na%) were calculated using the aforementioned factors. Geostatistical modelling (Empirical Bayesian Kriging) has been used to evaluate the geographical distribution of groundwater quality parameters. For the majority of the index's values, the exponential semivariogram model has been certified as the best-fitting model. Additionally, the water quality index (WQI) is used to represent total water quality in a single term and determine whether water is fit for human consumption or not. The study area's WQI values range from 14.6 to 46. 16.39% indicates good water, 20.54% indicates bad water, 51.17% indicates very poor water, and 11.90% indicates water unfit for agriculture. The current dataset revealed the use of water quality indices that could be useful to policymakers in terms of proper management, treatment, and long-term social progress.

Eine Bewertung der Wasserqualität mit Hilfe von Geostatistik: Eine Fallstudie im Unterbezirk Bankura, Westbengalen (Indien)

Zusammenfassung

Für Bewässerungszwecke sollte die Grundwasserqualität regelmäßig überprüft werden, damit die Gefahr geochemischer Schadstoffe durch geeignete Aufbereitungsverfahren verringert werden kann. Infolgedessen konzentrierte sich die vorliegende Arbeit darauf, die Eignung des im Bankura-Untergebiet in Westbengalen, Indien, gesammelten Grundwassers für Bewässerungszwecke anhand verschiedener Wasserqualitätsindikatoren zu bestimmen. Zur Beurteilung der Grundwasserqualität wurden im Zeitraum zwischen 2019 und 2020 59 Proben an verschiedenen Orten im Forschungsgebiet entnommen und Parameter wie pH-Wert, EC, TH, Alkalität (HCO3-), Calcium (Ca+), Magnesium (Mg+) ermittelt 2) wurden Natrium (Na+), Chlorid (Cl-) und Kalium (K) bewertet. Der Permeabilitätsindex (PI), das Magnesiumverhältnis (MR), der Kelley-Index (KI) und der Natriumanteil (Na%) wurden unter Verwendung der oben genannten Faktoren berechnet. Geostatistische Modellierung (Empirical Bayesian Kriging) wurde verwendet, um die geografische Verteilung von

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Grundwasserqualitätsparametern zu bewerten. Für die Mehrzahl der Indexwerte wurde das exponentielle Semivariagramm-Modell als das am besten passende Modell zertifiziert. Darüber hinaus wird der Wasserqualitätsindex (WQI) verwendet, um die Gesamtwasserqualität in einem einzigen Begriff darzustellen und zu bestimmen, ob Wasser für den menschlichen Verzehr

geeignet ist oder nicht. Die WQI-Werte des Untersuchungsgebiets liegen zwischen 14.6 und 46. 16.39 % weisen auf gutes Wasser hin, 20.54 % auf schlechtes Wasser, 51.17 % auf sehr schlechtes Wasser und 11.90 % auf Wasser, das für die Landwirtschaft ungeeignet ist. Der aktuelle Datensatz enthüllte die Verwendung von Wasserqualitätsindizes, die für politische Entscheidungsträger im Hinblick auf eine ordnungsgemäße Bewirtschaftung, Behandlung und langfristigen sozialen Fortschritt nützlich sein könnten.

1 Introduction

Water pollution is a serious issue that has grown in both developed and emerging countries, threatening both economic progress and the environmental and physical health of billions of people (Plessis 2022). Water quality is one of the most pressing issues facing nations in the twenty-first century, posing a threat to human health, restricting food production, diminishing ecological services, and impeding growth in the economy (Lin et al. 2022). Agriculture, which accounts for 70% of water abstractions worldwide, plays a major role in water pollution. Farms discharge large quantities of agrochemicals, organic matter, drug residues, sediments, and saline drainage into water bodies. The result ant water pollution poses demonstrated risks to aquatic ecosystems, human health, and productive activities (UNEP, 2016). Agricultural pollution has already surpassed pollution from towns and industries as the leading cause of inland and coastal water pollution in the majority of high-income countries and several developing markets (e.g. eutrophication). In the country's groundwater aquifers, nitrate from agriculture is the most frequent chemical pollutant (WWAP 2013). Massive volumes of untreated municipal and industrial wastewater are serious challenges in low-income countries and growing economies. However, agricultural contamination is becoming a problem, exacerbated by rising sediment runoff and groundwater eutrophication.

Groundwater quality is influenced by a variety of factors, including geology, the degree of chemical weathering of the prevalent lithology, recharge water quality, and inputs from sources other than water–rock interaction. Srinivasamoorthy et al. (2008) aimed to investigate the lithological influence and dominance of anthropogenic influences on groundwater chemistry in Salem district, Tamil Nadu, India. In the Indian state of Uttar Pradesh, Mohan et al. (2000) attempted to identify geochemical stratigraphic and demarcate areas unfit for human consumption. Rajmohan et al.

(2007) tried to demonstrate that nitrate pollution is closely related to land use pattern. Several studies on appraisal for domestic and industrial operations, as well as associated groundwater quality assessment, have been published (Vasanthavigar et al. 2010; Pritchard et al. 2008). The research region has lateritic uplands, valley cuttings, and terraced banks together with a gently to moderately dipping plain. Geographically, the area is the far eastern edge of the Ranchi Plateau and eventually integrates with the Dwarakeswar and Gandheswari Rivers' depositional fluvial ramps as it moves east. The Dwarakeswar River, which runs from north-west to south-east, is an example of the area south-easterly trend. The region's overall pattern of drainage is perpendicular to sub-parallel and is primarily governed by underlying structural features. Due to the poor ability of the soil to retain water, extensive drainage, surface runoff, and considerable soil erosion, the region is extremely vulnerable to any change in rainfall (Milly 1994). Additionally, this region experiences repeated droughts and has a highly unpredictable annual precipitation (Das et al. 2017; Roy et al. 2020). Due to the whims of the monsoon and a lack of surface water, India's water shortages have also become a major concern, especially in the dry and semi-arid regions (Bhunia et al. 2018).

Geographical Information System (GIS) has turned into a significant tool for storing, analysing, and displaying spatial data, which may be used for a variety of monitoring, planning, and resource management applications. GIS has developed as an important platform for resource management research due to its capacity to utilise geographical data according to desired objectives and in a variety of domains within an integrated environment (Bhunia et al. 2018; Zeilhofer et al. 2007). Its ability to address multidimensional resource management difficulties, such as water, is due to its efficiency in exploratory data processing, visualisation, and model building capacity. GIS is the most ideal multispectral spatial analysis tool, and it may be used in practically any situation (including real-time data analysis) where spatial data must be accessed and evaluated (Ali and Ahmad 2020). Geographical interpolation techniques in ArcGIS, such as deterministic and geostatistical interpolation, have been used to better explain the spatial and temporal distribution of natural resources, such as groundwater, and associated environmental challenges (Gunaalan et al. 2018). The research also attempts to emphasise the usefulness of geostatistical methodologies based on geographic information systems in measuring groundwater quality in the region and evaluating the vulnerability of water-borne diseases based on water

quality indices (Longley et al. 2005). Key benefits of EBK over standard kriging models include the following: (1) it enables for moderate local and large non-stationarity in the records; (2) it permits for differing measurement errors; (3) if necessary, the method can reshape the data to abide to a spatial Gaussian distribution indigenously using the Normal Score process; (4) in the case of large datasets, the input data can be separated into subsets of predetermined dimension that may or may not overlap; and 5) in each subset, the distribution of the various possible variograms is generated and predicted (Krivoruchko and Gribov 2014, 2019). Mirzaei and Sakizadeh (2016) compared three interpolation methods for estimating a water quality index and determined that EBK was the best.

In light of the foregoing, it is critical to determine the area's groundwater quality for irrigation reasons. The objective of this paper is to examine the feasibility of groundwater in the area for irrigation using a hydro-chemical approach and geospatial intelligence in Bankura sub-division in West Bengal (India).

2 Study Area

Figure 1 illustrates the geographical distribution of Bankura sub-division in West Bengal in India. Because the rivers in this area are perennial and there are no canal facilities, the area's economy is centred on agriculture, which is largely reliant on groundwater. As a result, the poor residents of Bankura rely heavily on groundwater for agricultural uses. A gentle to moderately undulating plain with lateritic uplands, valley cuttings, and graded banks characterises the study region (Nag and Das 2017). Geographically, the area forms the far eastern edge of the Ranchi Plateau, eventually merging with the depositional fluvial terraces of the Dwarakeswar and Gandheswari Rivers as it moves east. The Dwarakeswar River, which runs from north-west to south-east, is a good example of the area south-easterly slope. The overall drainage pattern of the area is parallel to sub-parallel, with geological structural features controlling the majority of it. Chotanagpur granite gneiss with meta-sedimentary remnants are the country rocks. The weathered overburden has a high porosity and contains a substantial amount of water hydrogeologically, but it has a limited permeability owing to its comparatively high clay concentration. Basement rock, on the other hand, is relatively young and regularly fractured, resulting in significant permeability (Krishnamurthy et al., 2007).

Owing to the low rainfall and scarcity of water resources during certain seasons of the year, the majority of surface water sources, including ponds and streams, entirely dry up (Nag 1998; Das et al. 2021). Communities in Bankura have been dealing with severe water shortages for some time now,

which has forced the local populace to alter how they utilise water. The majority of the sub-division, with the exception of the valley fills, is characterised by the existence of skeletal soil, which is occasionally lateritic as well (Nag and Ghosh 2013). The weathered overburden has a high porosity hydrogeologically and holds a lot of water, but it has a poor permeability because of its comparatively high clay concentration. On the contrary, the basement rock is regularly fragmented and so has high permeability since it is relatively young (Krishnamurthy et al., 2007).

3 Materials and Methods

From September through June in the year 2019–2020, 69 groundwater samples were taken from open hand-dug wells, boreholes, and springs to examine groundwater quality for irrigation usage. Samples were collected randomly within the study site. To assess the variance in the chemical quality of groundwater in the research region and the presence of harmful substances, water samples were taken from Groundwater Monitoring Wells (GWMWs). The coordinates of the sampling location of the water samples were obtained using a Garmin handheld GPS receiver with a precision of 5 m or better. 1-L vials or plastic bottles were used to acquire water samples (Das et al. 2021). During field prep, all vials were cleaned twice: once with tap water and then again with distil water. Finally, before sampling, the vials were rinsed with the sample water from a water body (Nag and Das 2017). To ensure that the sample was indicative of the surface water source, the vials were washed thoroughly with the sample water. Following the collection of water samples, the vials were appropriately labelled for recognition, put in a cooler box, and sent to the lab for laboratory analysis. Until the laboratory examination, water samples were preserved in a 4 °C refrigerator cooler (Gidey 2018).

In situ measurements of pH and EC were made using a pH metre (Model No. pH-5011) and an EC metre (Model No. COND5022). Under significant cations, Na^+ and K^+ were determined using a flame photometer (Model No. PEP 7 and PEP 7/C), whereas Ca^{2+} and Mg^{2+} were determined using a complexometric titration with $AgNO_3$ solution, as per usual technique (Kundu and Ara 2019). Some popular water quality indices usable for irrigation water quality monitoring, such as total hardness, sodium percentage (Na percent), sodium absorption ratio (SAR), Kelly's index (KI), permeability index (PI), and magnesium ratio (MR), were estimated using standard Eqs. (1–7) for the appraisal of usability of Bankura sub-division water in irrigation.

$$\text{Percentage sodium}(\%\text{Na}) = \frac{\left(Na^+ + K^+\right) * 100}{\left(Ca^{2+} + Mg^{2+} + Na^+ + K^+\right)},$$
(1)

$$SAR = \frac{Na^+}{\frac{([Ca^{2+}+Mg^{2+}])^{0.5}}{2}}, \qquad (2)$$

$$TH = \left[2 * \left(\frac{Ca^{2+}}{40}\right) + \left(2 * \left(\frac{Mg^{2+}}{24}\right)\right)\right] * 50, \qquad (3)$$

$$KI = \frac{Na^+}{(Ca^{2+} + Mg^{2+})}. \qquad (4)$$

$$MH = \frac{(Mg^{2+})}{(Ca^{2+} + Mg^{2+})} * 100, \qquad (5)$$

$$PI = \frac{\left(Na^+ + \sqrt{HCO_3^-}\right)}{(Ca^{2+} + Mg^{2+} + Na^+)} * 100 \qquad (6)$$

The GW's physicochemical characteristics were mapped spatially using the EBK method. In order to account for the uncertainty in semivariogram estimation, EBK offers a distribution of semivariogram models. Due to its reliance on constrained maximum likelihood estimate, the EBK is more practical and superior to other geostatistical modelling techniques currently in use (Senoro et al. 2022). Empirical Bayesian Kriging (EBK) differs from other traditional kriging techniques in that the parameters are dynamically tuned using multiple semivariogram models rather than a single semivariogram. Due to its reliance on constrained maximum likelihood estimate, the EBK is more realistic and superior to other existing geostatistical modelling methods (Senoro et al. 2022). When compared to other traditional kriging techniques, EBK has a number of major advantages, including a reduced need for interactive modelling, more accurate prediction of standard error and projection for small datasets, and exact prediction of considerably non-static data. In EBK, the following steps are used: (1) Using available information, a semivariogram model is evaluated. (2) Using the semivariogram model, a new value is replicated for each input data point. (3) A new semivariogram model is generated using the simulated data. The strength of the new semivariogram model is then calculated using Bayes' rule. The semivariogram computed in step 1 is used to replicate a new set of values at the input sites by repeating steps 2 and 3 (Krivoruchko and Gribov 2014).

Cross-validation is an ArcGIS feature that compares anticipated and observed values using the appropriate facts and figures:

$$ME = \frac{1}{n} \sum_{i=1}^{n} (y_i - x_i),$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - x_i)^2},$$

$$ASE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \sigma^2(y_i)},$$

$$MSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} [\frac{(y_i - x_i)}{\sigma(y_i)}]^2}.$$

The best method among the various interpolation strategies was determined using cross-validation (Yao et al. 2014). Cross-validation was determined using the root-mean-square error (RMSE), mean error (ME), mean standardised error (MSE), root-mean-square standardised error (RMSSE), and average standard error (AS) validation/prediction using Arc GIS interpolation strategies comparison between the predicted and measured values. The simulated value is y_i, the observed value is x_i, and the standard deviation is σ in these equations. Each observation is extracted one at a time, and the remaining data are used to forecast them. Once it is projected that the next data point will be extracted, each data point is restored. It is critical to estimate the predictability of outcomes appropriately.

The water quality index (WQI) approach is effective for evaluating water quality deterioration (Ayers and Westcot, 1985). WQI aids in the monitoring of water quality issues and the effectiveness of shielding actions. It is a crucial criterion for determining whether or not water is suitable for irrigation. The WQI was calculated by assigning weights (w_i) for every chemical parameter based on its relative significance for irrigation. Water quality factors such as pH, EC, sodium, total hardness (TH), SAR, MR, KI, and PI were given a weight of 1 to 5 based on their importance in terms of water quality. The relative weight (Wi) is calculated (Table 3) using the following equation:

$$W_i = \frac{W_i}{\sum_{i=1}^{N} W_i},$$

where W_i denotes relative weight, w_i denotes parametric weight, and n denotes the set of variables.

According to Pillai and Khan (2016), a quality rating scale (q_i) for each parameter is allocated by dividing its concentration in each water sample by its respective standard and multiply that number by 100:

$$q_i = \frac{C_i}{S_i} x 100,$$

where q_i denotes the quality index, and according to the BIS (1998) recommendations, C_i is the concentration of each chemical parameter in each water sample in milligrammes per litre, and Si is the irrigation water standard for each chemical parameter in milligrammes per litre. To calculate the WQI, first find the SI for each chemical parameter (Table 1), which is then utilised to calculate the WQI using the equation below:

$$Sl_i = W_i x q_i,$$

$$WQI = \sum Sl_i,$$

where SI is the ith parameter's sub-index, q_i is the rating based on i^{th} parameter's strength, and n is the number of parameters.

4 Results

Table 2 presents a summary of the Bankura division's general hydrochemistry. Ratanpur village in Onda block had the lowest pH of 7.2, while Indpur village in Indpur block had the highest pH of 8.2. All sampling stations in Bankura division have electrical conductivity (EC) ranging from 150 $\mu S \bullet cm^{-1}$ in Tantirbandh village of Taldangra block to 4550 $\mu S \bullet cm^{-1}$ in Gouripur village of Chhatna block. Nandanpur village in Mejia block had the lowest calcium concentration at 8.00 mg/L, while Gouripur village in Chhatna block had the highest at 16.67 mg/L. Khirpai village in Indpur block had the highest magnesium concentration of 73 mg/L, while Fakirdanga village in Taldangra block had the lowest value of 2.0 mg/L. Because Mg salts are more soluble in water than Ca^{2+} salts, dissolved magnesium concentrations in most natural streams are lower than dissolved calcium concentrations (Ramesh and Anbu 1996). Low EC values showed rapid ion exchange between soil and water, as well as insoluble geologic rocks and mineral formations and little solute dissolution. The Ca^{2+} concentration in the collected samples ranged from 8.0 mg/L (Nandanpur village, Mejhia) to 312 mg/L (Gouripur village, Chhatna), indicating that it is the dominant cation, followed by Na^+, which ranged from 16 mg/L (Radhanagar, Onda block) to 55.0 mg/L (Gouripur, Chhatna block), indicating that it is the second most dominant cation (Fig. 1).

The concentration of SO^{4-} in the water varied from 5 mg/L (Tarasingh Bridge, Barjora) to 245 mg/L (Gouripur, Chhatna block), indicating that it was the major anion. Cl^- concentrations varied from 36 mg/L (Ratanpur, Onda block) to 715 mg/L (Gouripur, Chhatna block), with a mean of 188.76 mg/L, and were within FAO's irrigation guidelines (0.0–1050.0 mg/L) (Ayers and Westcot, 1985). Water quality characteristics that primarily affect crop output must be

Table 1 Weightage for irrigation water-quality index

Parameters	Sub-classes	Weightage
pH	<7.60	4
	7.61–7.70	3
	7.71–7.80	2
	>7.80	1
EC	<710	4
	711–1200	3
	1201–1600	2
	>1601	1
%Na	<30	4
	31–40	3
	41–60	2
	>61	1
SAR	<21.17	4
	21.18–27.23	3
	27.24–32.55	2
	>32.56	1
TH	<214.06	4
	214.07–322.66	3
	322.67–438.19	2
	>438.20	1
KI	<0.27	4
	0.28–0.60	3
	0.61–1.00	2
	>1.01	1
MR	<23.32	4
	23.33–25.08	3
	25.09–27.11	2
	>27.12	1
PI	<9.14	4
	9.15–12.95	3
	12.96–18.72	2
	>18.73	1

investigated in order to assess the Bankura division's appropriateness for irrigation use. Irrigation water is divided into four categories based on its pH value. Figure 2 depicts a visual fit of empirical semivariance values (blue crosses) to the semivariogram spectrum obtained by the EBK model. Figure 3 depicts the interpolated versus observed water quality characteristics. Figure 3 uses normal Q–Q plots to examine the distribution of interpolation mistakes. Univariate normality is indicated by normal Q–Q plots. The points will depart from the line if the data are asymmetric (i.e. not normal). For each groundwater quality metric, a histogram and normal Q–Q plot analysis were used, and it was revealed that only the pH, MR, KI, and SAR variables had a normal distribution. Electrical conductivity, sodium, and TH concentrations were shown to have non-normal distributions. This may be attributed to geographical, geological,

**Table 2** Descriptive statistics of water quality parameters in the study area

Water Quality parameters	Minimum	Maximum	Mean	Std. Dev	Skewness	Kurtosis	1st Quartile	3rd Quartile
pH	7.2	8.2	7.76	0.223	− 0.213	2.136	7.55	7.9
EC (mg/L)	150	4550	1108.3	950.04	1.83	6.32	503	1388.5
Sodium (%)	22.15	81.33	60.46	13.62	− 1.13	3.85	55.84	70.14
SAR (meq/L)	4.20	60.19	27.78	14.46	0.26	2.14	13.76	38.42
TH (mg/L)	37	1001	254.07	218.25	1.52	4.89	94.5	360.5
KI (meq/L)	0.276	4.33	1.726	0.868	0.663	3.763	1.155	2.305
MR (meq/L)	7.143	35.29	25.24	7.069	− 0.738	2.751	20.455	30.517
PI (meq/L)	4.12	40.213	11.38	6.60	2.296	10.07	7.176	14.053

and demographic challenges in the study area. Although the subsurface is the greatest reservoir of drinking water and is less contaminated than surface water, the growing inorganic trashes in current circumstances have the potential to pollute both surface and groundwater. A log transformation was used to get the dispersion nearer to normal for those values. Interpolation errors were regularly distributed ($p > 0.05$) and the best fit line through the interpolated vs observed water levels had a slope close to 1. These data support the EBK model's absence of systematic bias.

A geospatial intelligence is a specific tool that is used to construct spatial distribution maps based on water quality metrics, identifying acceptable and unsuitable zones. pH, EC, percent Na, TH, SAR, KI, MR, and PI all had spatial distribution maps created in this study. The water quality values were interpolated using the EBK model.
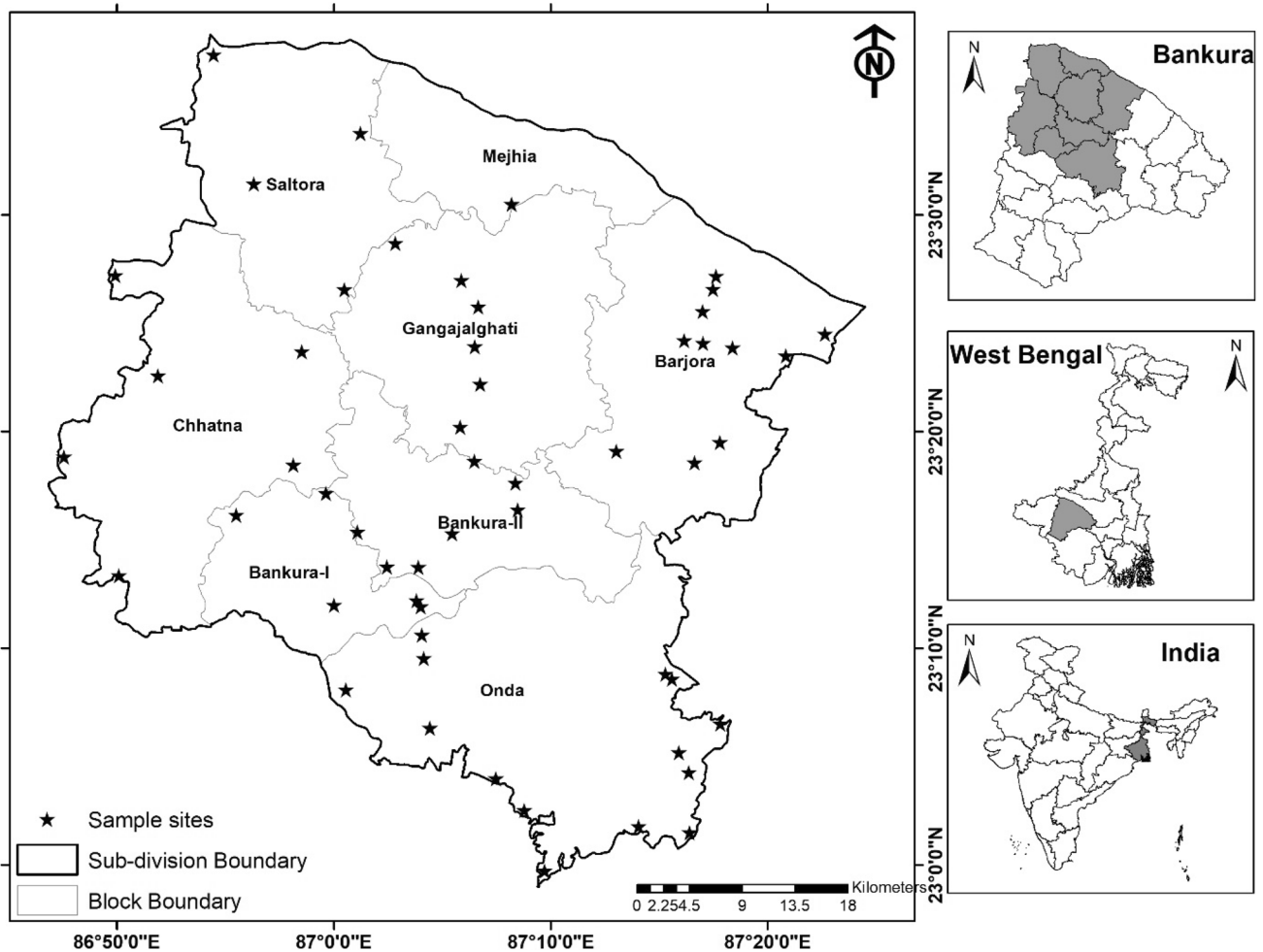
Fig. 1 Location map of the Bankura sub-division in West Bengal, India
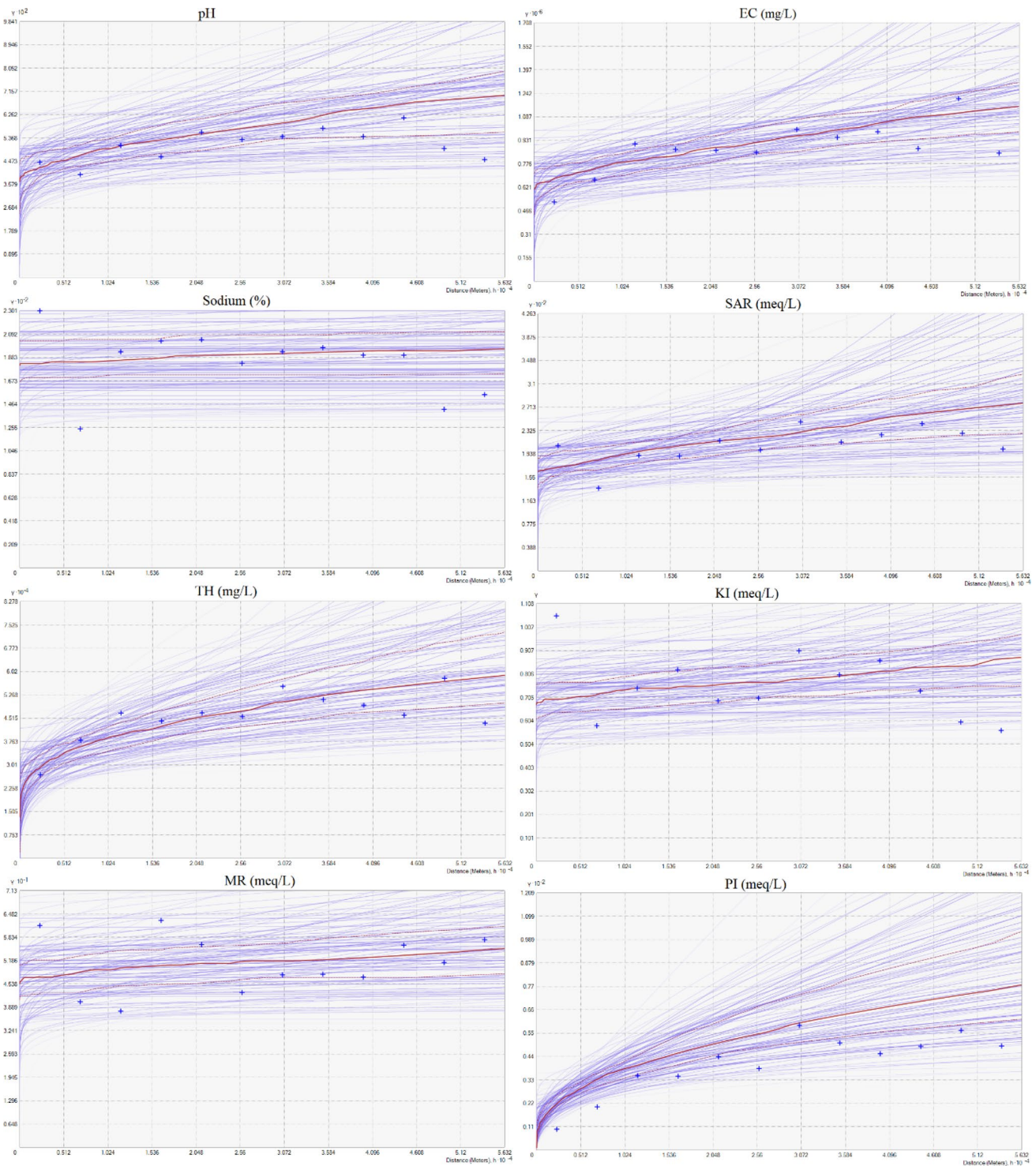
Fig. 2 Semivariogram analysis of water quality data in Bankura division

Cross-validation was used to find the best-fitting theoretical EBK model to test model accuracy and bias in relation to observed water levels each year. The EBK modelling method is ideally suited to data that is substantially non-Gaussian. K-Bessel was the theoretical model. The number of iterations was set to 100 and the transformation was set to empirical. The subset size was 100 and the overlap factor was 1. With a smoothing value of 0.2 and a search radius of 1.65 km, the Search Neighbourhood option was set to smooth circular.
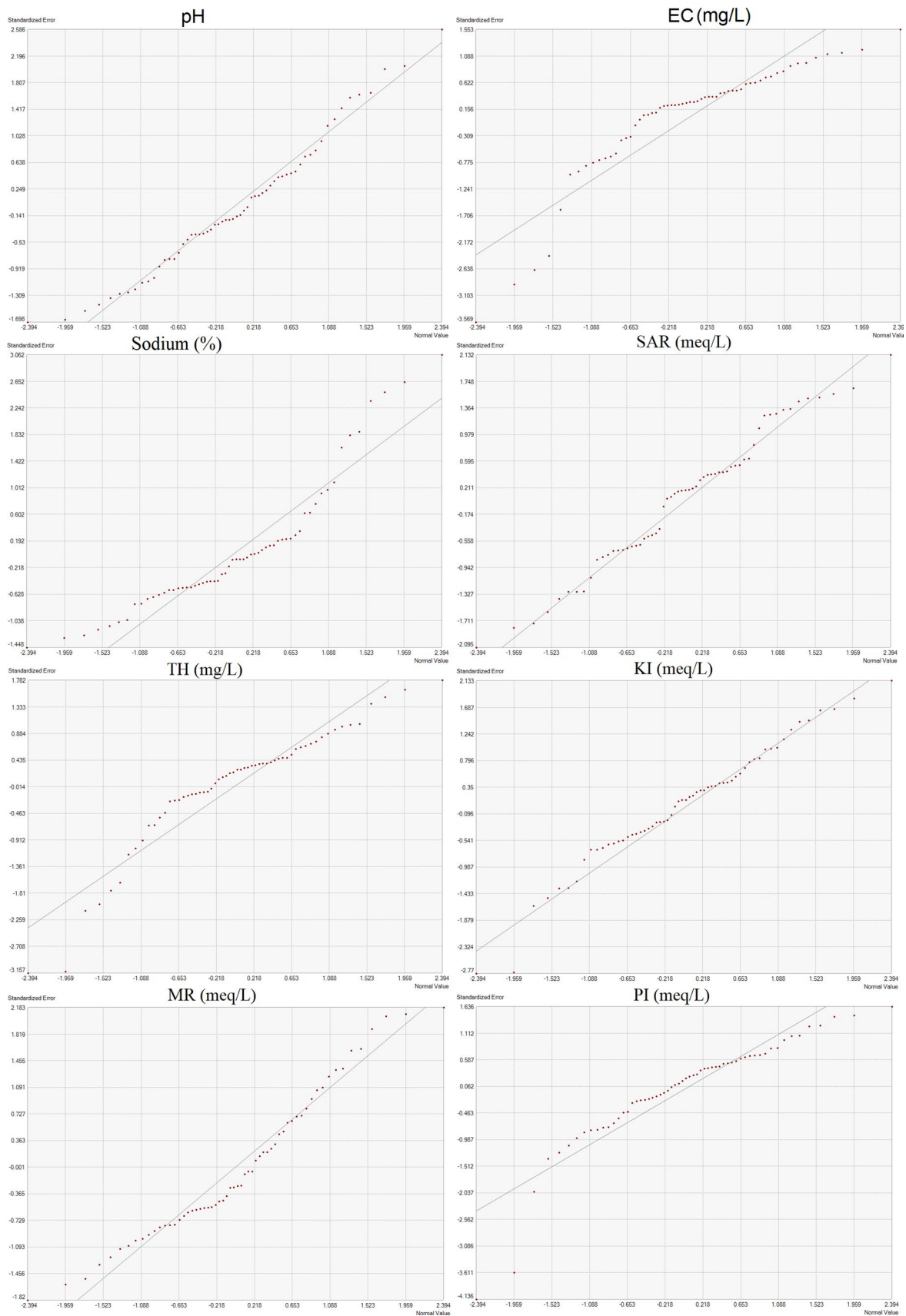
Fig. 3 Q-Q plot of water quality index s in the Bankura sub-division

Table 3 Areal and percent-wise distribution of water quality parameters in Bankura sub-division

Parameters	Sub-classes	No. of Pixel	Area (in Sq km)	Percent	Remarks**
pH	< 7.60	1990	148.7	5.67	Suitable
	7.61–7.70	8549	647.4	24.67	Suitable
	7.71–7.80	12,567	947.68	36.11	Not suitable
	> 7.80	11,272	880.61	33.55	Not suitable
EC (mg/L)	< 710	2774	215.71	8.22	Good
	711–1200	15,806	1199.96	45.72	Permissible
	1201–1600	6949	529.67	20.18	Doubtful
	> 1601	8849	679.02	25.87	Unsuitable
%Na	< 30	11,397	867.57	33.06	Good
	31–40	9562	729.12	27.78	Permissible
	41–60	7418	567.75	21.63	Permissible
	> 61	6001	459.93	17.53	Doubtful
SAR	< 21.17	4924	378.89	14.44	Crops grown and water used
	21.18–27.23	6650	507.94	19.36	Sensitive crops are not taken
	27.24–32.55	13,087	997.58	38.01	Problems on most soil. Good salt tolerant plants can grow
	> 32.56	9717	739.85	28.19	Water is not used for crop
TH	< 214.06	12,987	988.48	37.67	Good
	214.07–322.66	9016	686.77	26.17	Permissible
	322.67–438.19	7564	578.81	22.06	Doubtful
	> 438.20	4811	370.33	14.11	Not suitable
KI	< 0.27	1396	112.72	4.29	Good
	0.28–0.60	12,605	958.56	36.52	Permissible
	0.61–1.00	10,920	833.95	31.78	Doubtful
	> 1.01	9457	719.16	27.4	Unsuitable
MR	< 23.32	6592	504.2	19.21	Good
	23.33–25.08	8039	612.78	23.35	Permissible
	25.09–27.11	12,513	952.59	36.3	Doubtful
	> 27.12	7234	554.82	21.14	Unsuitable
PI	< 9.14	11,767	898.1	34.22	Good
	9.15–12.95	10,627	808.77	30.82	Unsuitable
	12.96–18.72	8327	635.59	24.22	Doubtful
	> 18.73	3657	281.94	10.74	Not suitable

**Source: Permissible limits of water used for irrigation have been analysed based on published literature from various sources (Ramesh et al. 2020; Banderi et al. 2012), followed by Bureau of Indian Standards (1987)

The pH value varied from 7.2 to 8.2 when most forms of groundwater were in direct contact with the atmosphere, indicating that the groundwater samples were neutral to strongly alkaline. Based on the pH value, the study area is divided into four major categories (i) < 7.60, (ii) 7.60–7.70, (iii) 7.71–7.80, and (iv) > 7.81 (Table 3; Fig. 4). The highest pH concentration value (> 7.81) is observed in the south-west and east of the Bankura sub-division. The lowest pH value (< 7.60) is observed in the north and south-east of the sub-division (Fig. 5). The medium concentration of pH value is observed in the central and north-east of the study area.

Except in extreme cases, water pH has no direct impact on crops. In drip and micro-spray irrigation systems, pH > 8.2 with high HCO^{3-} has a substantial impact on crop productivity and can cause blockage. Furthermore, high pH water might cause salts to precipitate, reducing pesticide efficacy.

Groundwater samples had EC values ranging from 150 mg/L (Tantirbandh village, Taldangra block) to 4550 mg/L (Gouripur village, Chhatna block), with an average of 1108 mg/L. This fluctuation in EC values can be explained by lithology (Zenget al. 2016), evaporation rate (Aragüéset al. 2015), weathering, and recharge quantity (Sulieman et al. 2016). In other words, salts dissolved from soil and aquifer materials, as well as salts leached through irrigation, can alter groundwater salinity (Deshpande and Aher 2012). Based on the geographical

Fig. 4 Areal and percent-wise distribution of water quality parameters in the study area

distribution of EC, the study area is divided into four classes, namely, (i) <710 mg/L, (ii) 711–1200 mg/L, (iii) 1201–1600 mg/L, and (iv) >1601 mg/L (Fig. 6 and Table 3). 45.72% (1199.96 sq km) of the study area covered with EC values of 711–1200 mg/L and only 8.22% of the study area having EC values <711 mg/L (215.71 sq km). Results shows maximum concentration is observed in the west and south-west of the Bankura sub-division. The lowest concentration of EC is recorded from south-east of the study area. North

and east of the study area having the EC concentration of 711–1200 mg/L (Fig. 6).

The Na% has also been employed in the classification of water for irrigation. Na + is an important characteristic that aids in the classification of any water source for irrigation purposes. The water transport capacity of Na^+ is reduced due to chemical interaction with the soil. While the reactions of Na^+ and CO_3^{2-} form alkaline soils, the reactions of Na^+ and chloride generate saline soils. Crop growth is slowed by sodium soil (alkaline/saline) (Todd and Mays 2004). If the
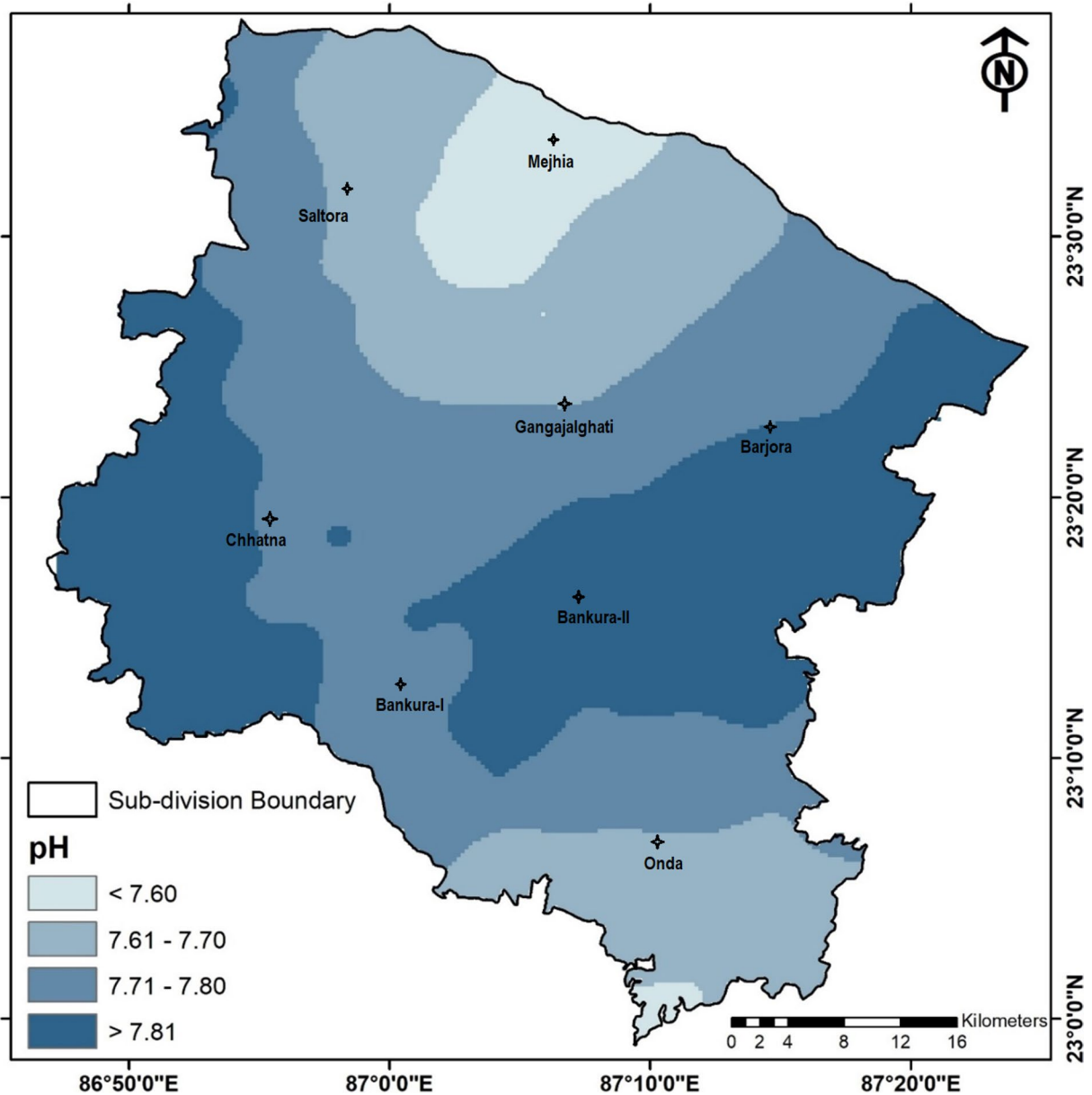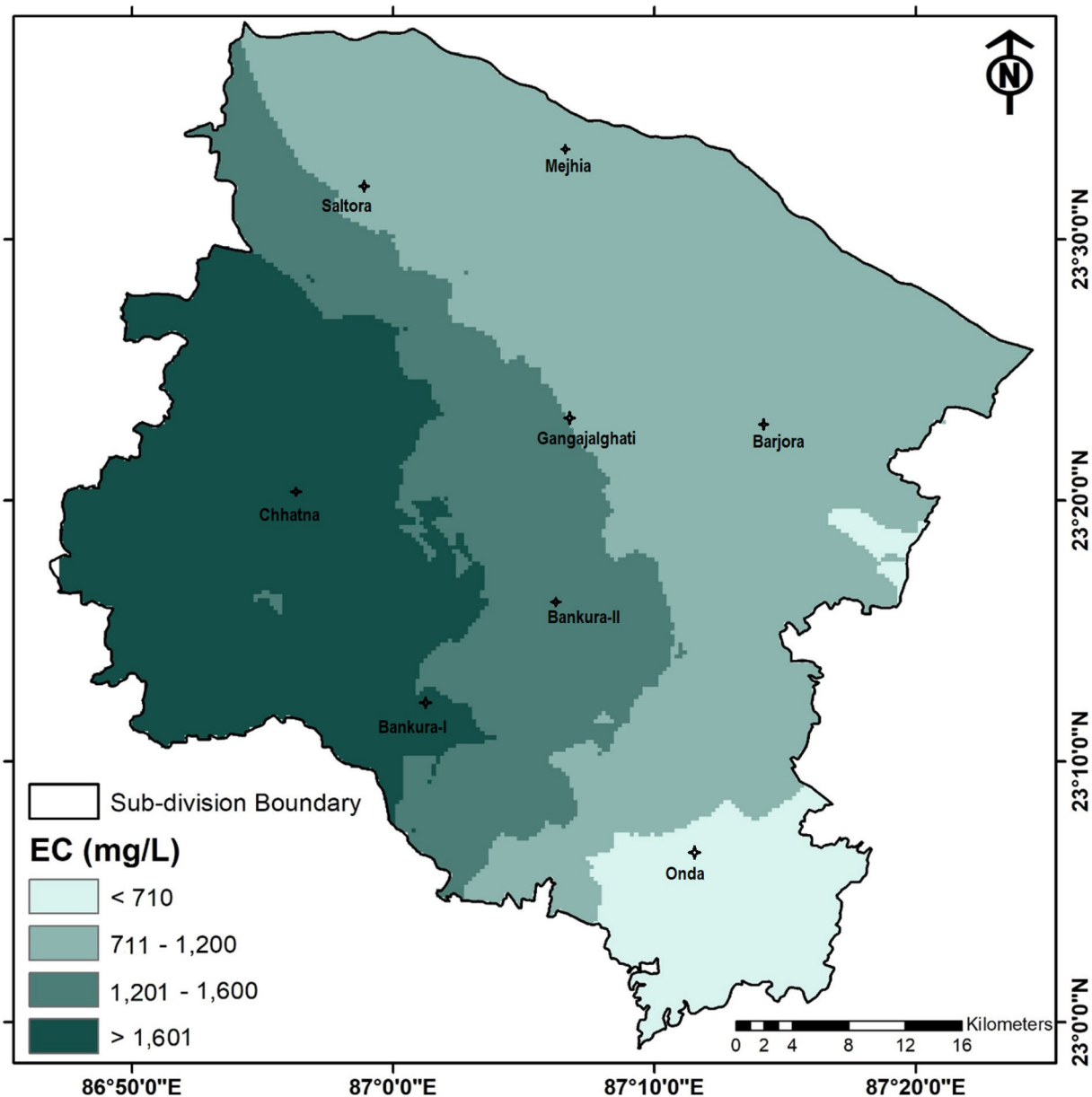
Fig. 5 Geographical distribution of pH in Bankura sub-division

concentration of Na + in irrigation water is high, the ions will gravitate towards the clay, eliminating Ca^{2+} and Mg^{2+} ions in the process (Khodapanah et al. 2009). Water and air cannot travel easily or freely during wet conditions in this position, and such grounds have become rigid when dry. Excellent (less than 30%), good (31–40%), permissible (41–60%), and unsuitable (more than 61%) are the classifications for water depending on %Na^+ (Fig. 7). Results showed 33.06% of the study area having less than 30%Na^+ (867.57 sq km), followed by 31–40% of Na^+ in 27.78% (729.12 sq km) and 17.53% of the study area covered by more than 61% of Na^+ (Table 3; Fig. 4).

The SAR is a useful index for determining the adequacy of irrigated water for sodium hazard, and it is more strongly linked to the proportions of exchangeable sodium in the soil. Suarez et al. (2006) discovered that as SAR values decline, hydraulic conductivity and aggregated stability decrease, as well as clay dispersion, compressible clay swelling, surface crusting, and reduced tillage. The primary issue with high sodium concentrations is their influence on soil permeability, water infiltration, and total salinity, which is hazardous to agricultural plants. In the study area, the maximum percent of SAR value is observed in the central and west of the Bankura sub-division. The minimum percent of SAR value
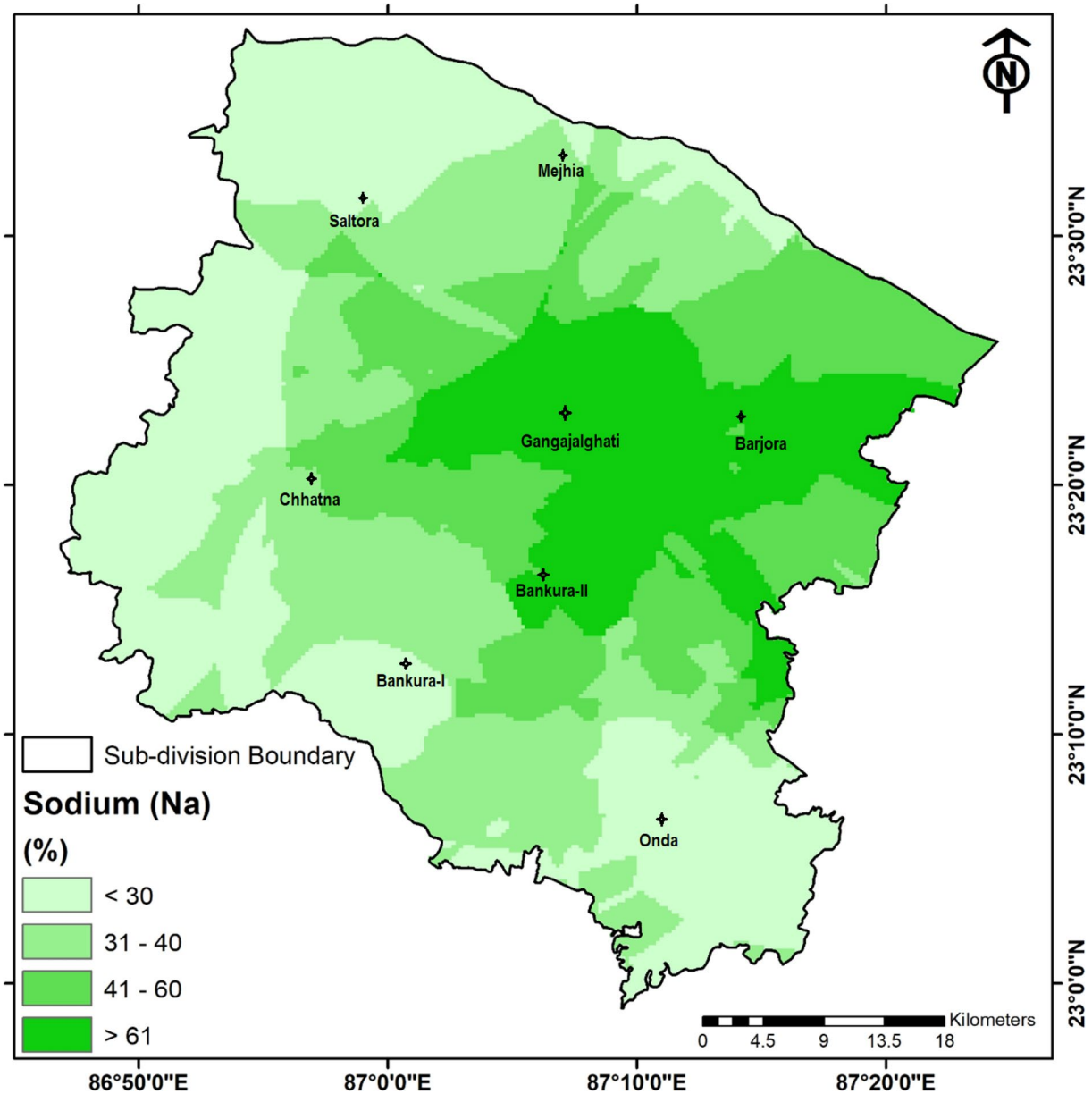
Fig. 6 Geographical distribution of EC in Bankura sub-division

is observed in the south-east and extreme north-west of the sub-division.

As a result, 14.44% (378.89 Sq km) of groundwater samples are extremely good and can be considered for all soil types without harmful sodium consequences, 19.36% of groundwater samples are good (Table 3), 38.01% (997.58 sq km) of groundwater samples are fair, and 28.19% (739.85 sq km) of groundwater samples are of poor quality for irrigation (Table 3; Fig. 8).

The presence of divalent metallic cations (Ca^{2+} and Mg^{2+}) causes water hardness, which can be calculated as the sum of Ca^{2+} and Mg^{2+} concentrations in meq/l corresponding to CaCO3 (Todd & Mays 2004). The TH value

is categorised as soft (214.06 mg/l), moderately hard (214.07–322.66 mg/l), hard (322.67–438.19 mg/l), and extremely hard (> 438.20 mg/l) in the Bankura sub-division (Fig. 9). Geographically, the maximum estimated TH value was observed in the west and south-west of the sub-division. The minimum estimated TH value was found in the east, north, and south-east part of the study area. Results also showed 37.67% (988.48 sq km) of the study area having TH value of less than 214.06 mg/L, followed by 26.17% (686.77 sq km) of the study area having TH value between 214.07 and 322.66 mg/L and only 14.11% of the study area having TH value of > 438.20 mg/L (370.33 sq km).

Fig. 7 Geographical distribution of %Na in Bankura sub-division

Kelly devised a method for determining the quality and classification of irrigation water based on the ratio of Na^+ to Ca^{2+} and Mg^{2+}. A KI of greater than one indicates an overabundance of Na + in the water (Fig. 10). As a result, water with a KI ≤ 1 has been recommended for irrigation, whereas water with a KI ≥ 1 has been ruled out due to too much sodium in water for irrigation (Ramesh and Elango 2012). In the study area, the maximum value of KI was observed in the east of the sub-division and the minimum KI calculated value is observed in the north-west and south-west of the sub-division (Fig. 10). The medium value of KI was found in the central part of the sub-division.

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In groundwater, alkaline soil (Ca^{2+} and Mg^{2+}) is in a condition of balance. Both Ca^{2+} and Mg^{2+} ions have been
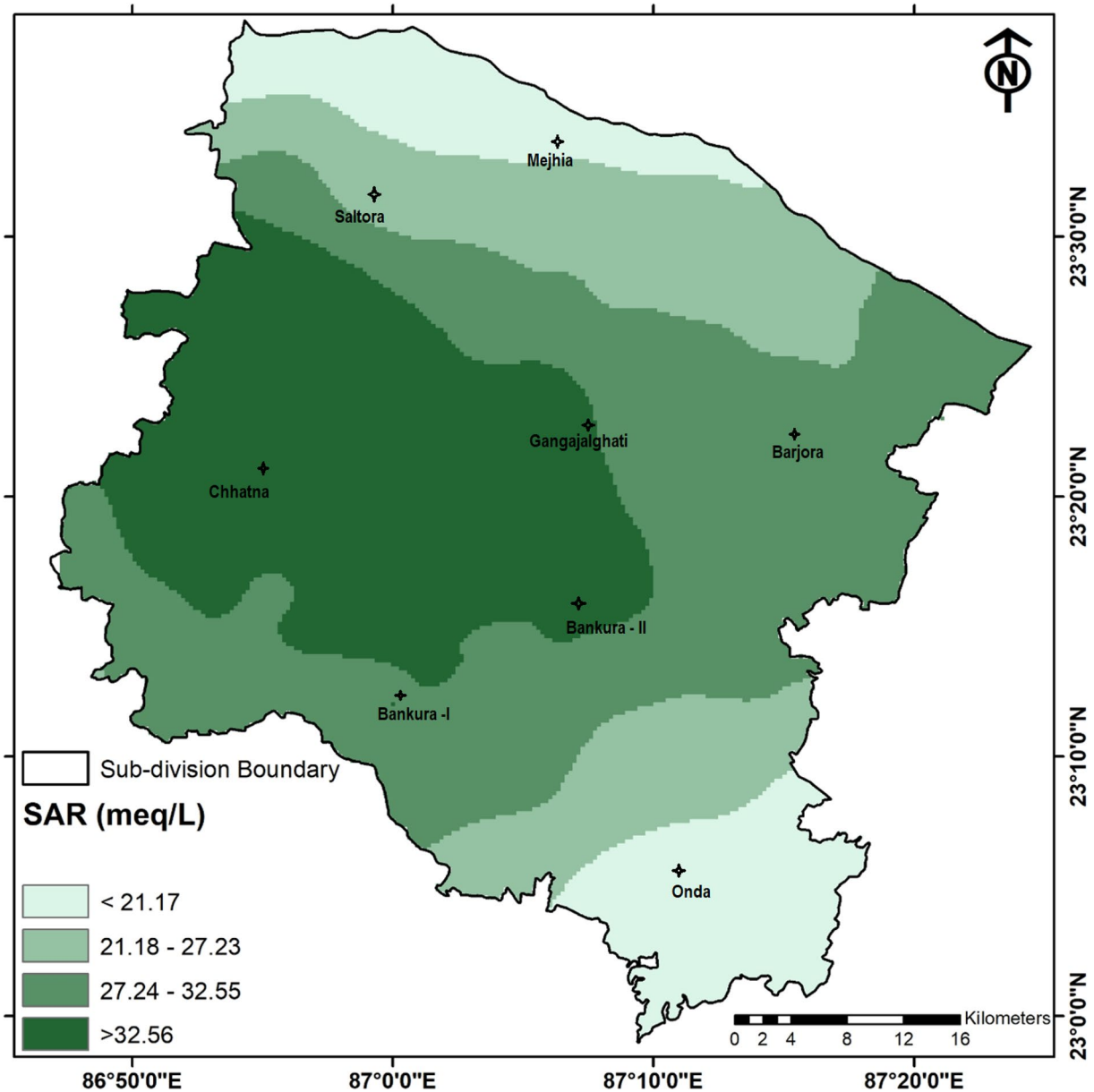
Fig. 8 Spatial distribution of SAR in the study area

linked to soil friability and aggregation, and both are essential nutrients for crop growth. Significant Ca^{2+} and Mg^{2+} concentrations in water can raise soil pH, turning the soil to a saline environment (Fig. 11). MR > 27 has not been found to be suitable for irrigation (Khodapanah et al. 2009). Based on the estimated MR value, the study area is categorised into four classes: (i) < 23.32 meq/L, (ii) 23.33–25.08 meq/L, (iii) 25.09–27.11 meq/L, and (iv) > 27.12 meq/L (Fig. 11). Geographically, the maximum value of MR is observed in the north-west of the sub-division and the minimum estimated value was distributed in the south-west and southeast of the study area. In the research area, 21.14% of the groundwater samples are dangerous (MR value > 27 meq/L),

with the remaining 36.30% in the acceptable region and the remaining 42.56% suitable for irrigation. According to MR calculations, more than 55% of groundwater samples are unfit for irrigation (Table 3).

The Permeability Index (PI) is frequently used to analyse the irrigated water's suitability, which is altered by long-term exposure to irrigation water containing high levels of Na^+, Ca^{2+}, Mg^{2+}, and alkalinity ions. Class I (> 18.73 meq/L, acceptable), class II (12.96–18.72 meq/L, good), class III (9.15–12.95 meq/L), and class III (9.16 meq/L, unsuitable) are the four levels of PI. Irrigation water of class I and class II has been considered (Fig. 12). With an average value of 11.38 meq/L, the PI values range from 4.120 meq/L
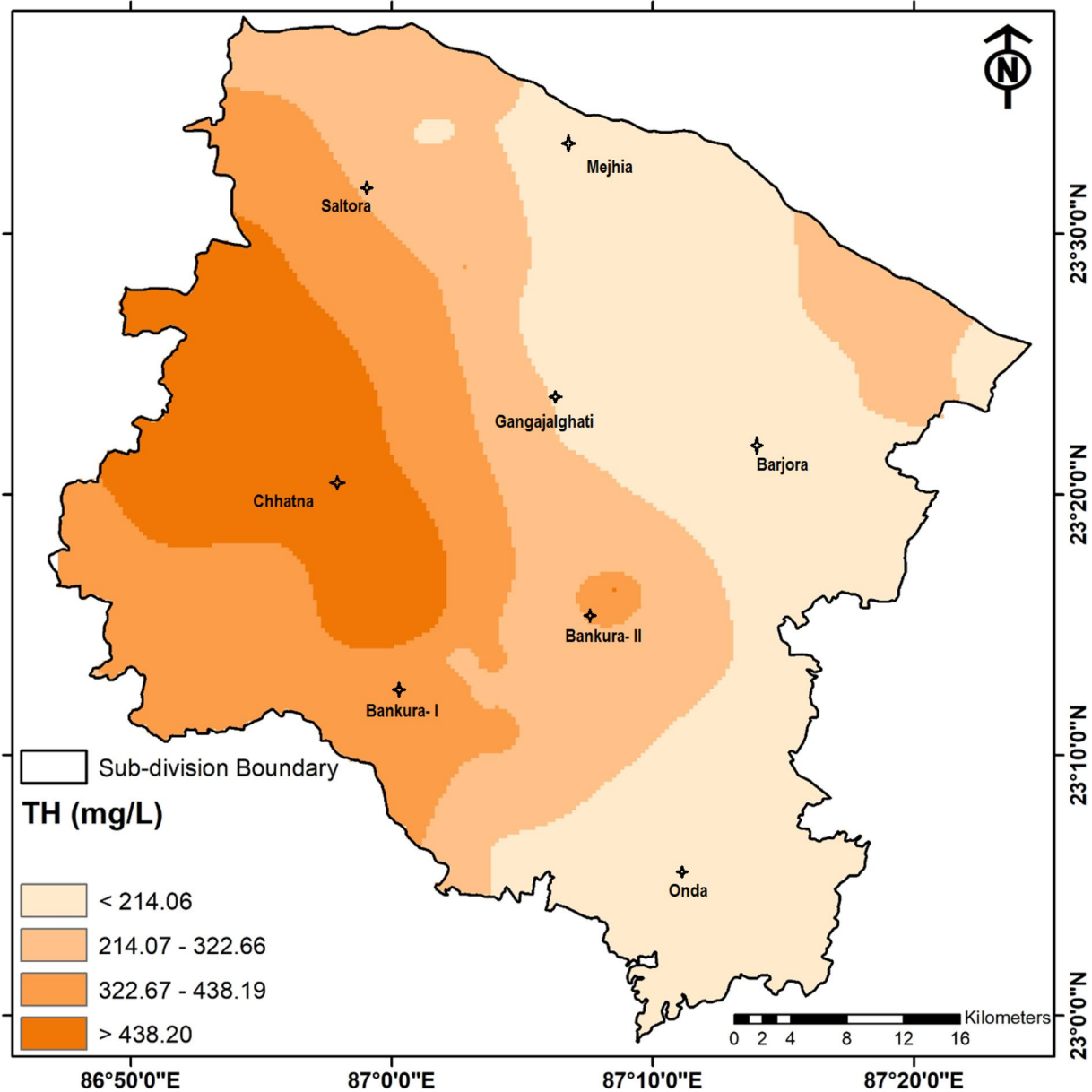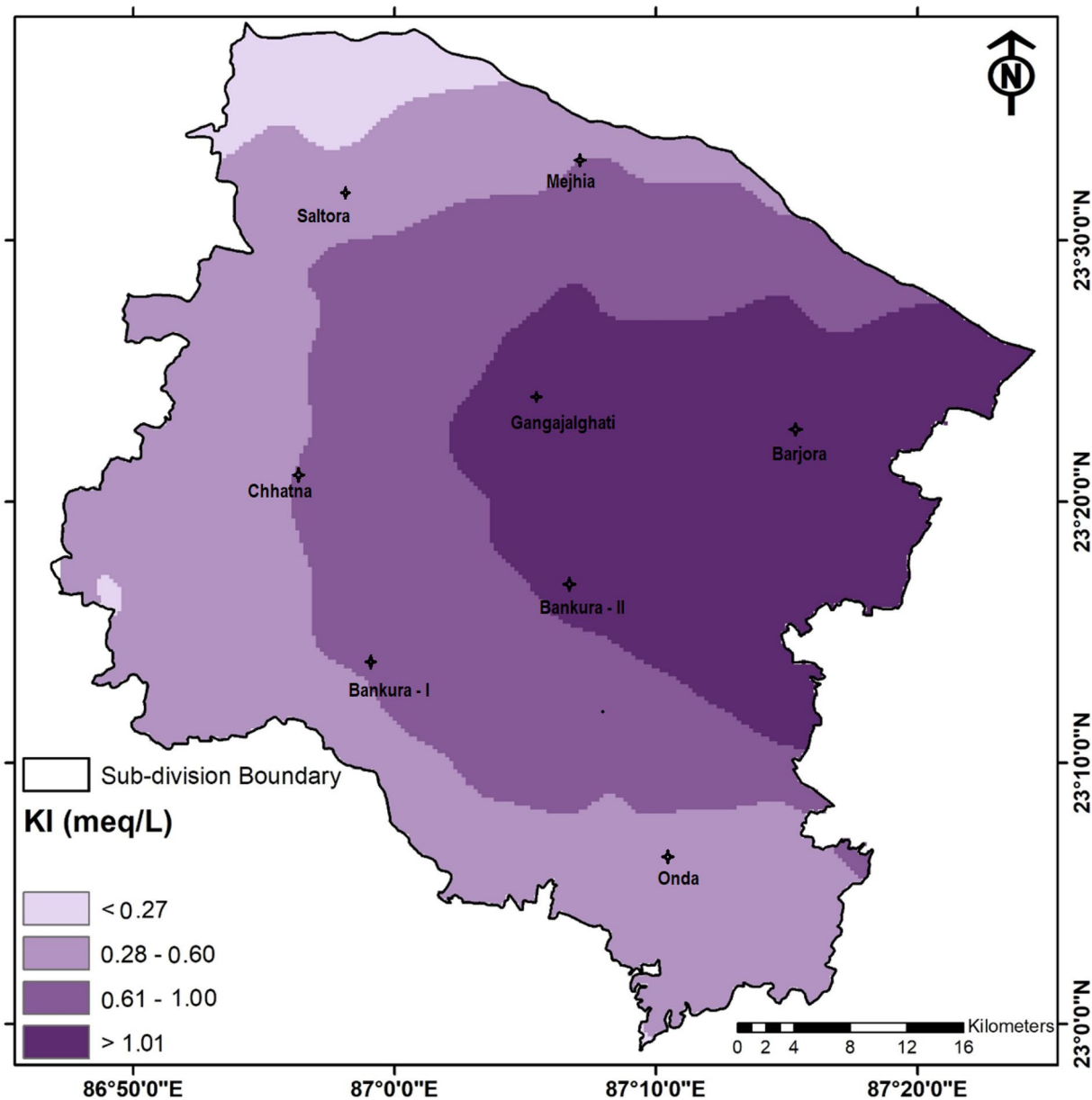
Fig. 9 Spatial distribution of TH in Bankura sub-division

(Shalbani village, Bankura II) to 40.212 meq/L (Nandan-pur village, Mejia block). The highest estimated PI value was found in the north and north-west of the Bankura sub-division and the lowest estimated PI value was found in the west and south-west of the study area. The study region is classified into four primary classes based on the estimated value of PI: I 9.14 meq/L, (ii) 9.15–12.95 meq/L, (iii) 12.96–18.72 meq/L, and (iv) 18.73 meq/L. According to the data, about 34.22% and 30.82% of the water samples analysed are classified as good and suitable for irrigation in the first and second categories, respectively (Table 3).

To examine the variability of predictions and evaluate the performance (under or over-estimation) of the EBK model,

various errors from cross-validation were analysed using the methods indicated in Table 4. ME and MSE values around zero, convergent RMSE and ASE values, and RMSSE values near unity are all proof of this. However, this statistic has a number of significant flaws: it is scale dependent and insensitive to variogram inaccuracies. As a result, the MSE is frequently used to standardise the ME, with an ideal value of zero, implying that a correct model would have an MSE near to zero. The prediction errors have been accurately assessed if the RMSE is near to the ASE. The variability of the forecasts is overstated if the RMSE is lower than the ASE; conversely, the variability of the predictions is under-estimated if the RMSE is higher than the ASE. The RMSSE

Fig. 10 Spatial distribution of Kelly index in Bankura sub-division

metric yielded the same result (Table 4). It should be in the neighbourhood of one. If the RMSSE is greater than one, the variability of the forecasts has been underestimated; conversely, if it is less than one, the variability of the predictions has been exaggerated (Gharbia et al. 2016).

Excellent irrigation water quality (> 31), good water quality (26–30), poor water quality (21–25), and water unsuitable (> 20) for irrigation purpose are the WQI ranges and classes of water quality region (Table 5; Fig. 13). The study area's WQI values range from 14.6 to 46. 16.39% indicates good water, 20.54% indicates bad water, 51.17% indicates very poor water, and 11.90% indicates water unfit for agriculture. This could be due to excessive ion leaching,

over-exploitation of groundwater, direct runoff discharge, or agricultural influence. The magnitudes of nitrate, total dissolved solids, hardness, bicarbonate, and manganese in the groundwater at particular areas have been discovered to be the main cause of the high WQI.

5 Discussion

The purpose of this research is to show how to describe groundwater quality in the Bankura sub-division of West Bengal using an integrated method that comprises irrigation water indices and geostatistical modelling (India). In order
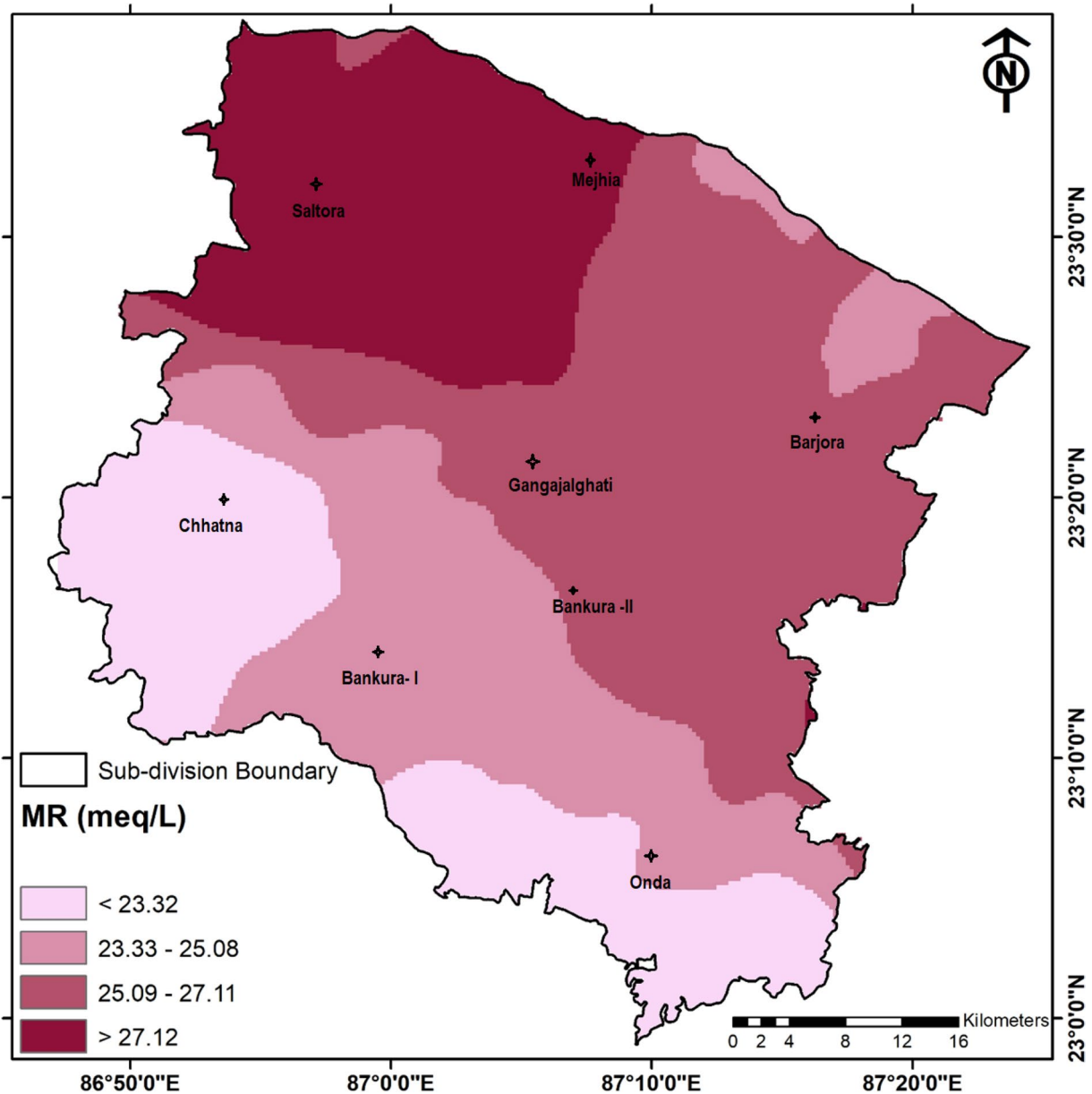
Fig. 11 Spatial distribution of Magnesium Ratio (MR) in Bankura sub-division

to assist urbanisation and land reclamation, it is required to assess and map accessible groundwater resources for various purposes in certain isolated places. Various academicians have attempted to build a wide range of WQIs for assessing groundwater quality; the index used relies on the groundwater input characteristics and the desired outcomes (Tiwari et al. 2014). For the assessment of groundwater quality and quantity around the world, a variety of statistical models and strategies have been applied. In many parts of the world, multivariate statistical tools aid in the identification of possible factors/sources that influence water systems and provide a dependable instrument for trustworthy water resource

management as well as a speedy solution to pollution issues (Bhuiyan et al. 2015; Molla et al. 2015; Bodrud-Doza et al., 2016). As a result, groundwater quality metrics that generate enormous datasets necessitate the interpretation of complicated data matrices, as well as a deeper understanding of water quality and interrelationships across characteristics and sample sites.

Groundwater physicochemical analyses revealed that the pH and EC in the studied area have changed significantly. To the east, west, and north-east of the sub-division, the underground aquifer system buffers the alkaline pH. However, as the northern reaches amass, the pH levels gradually
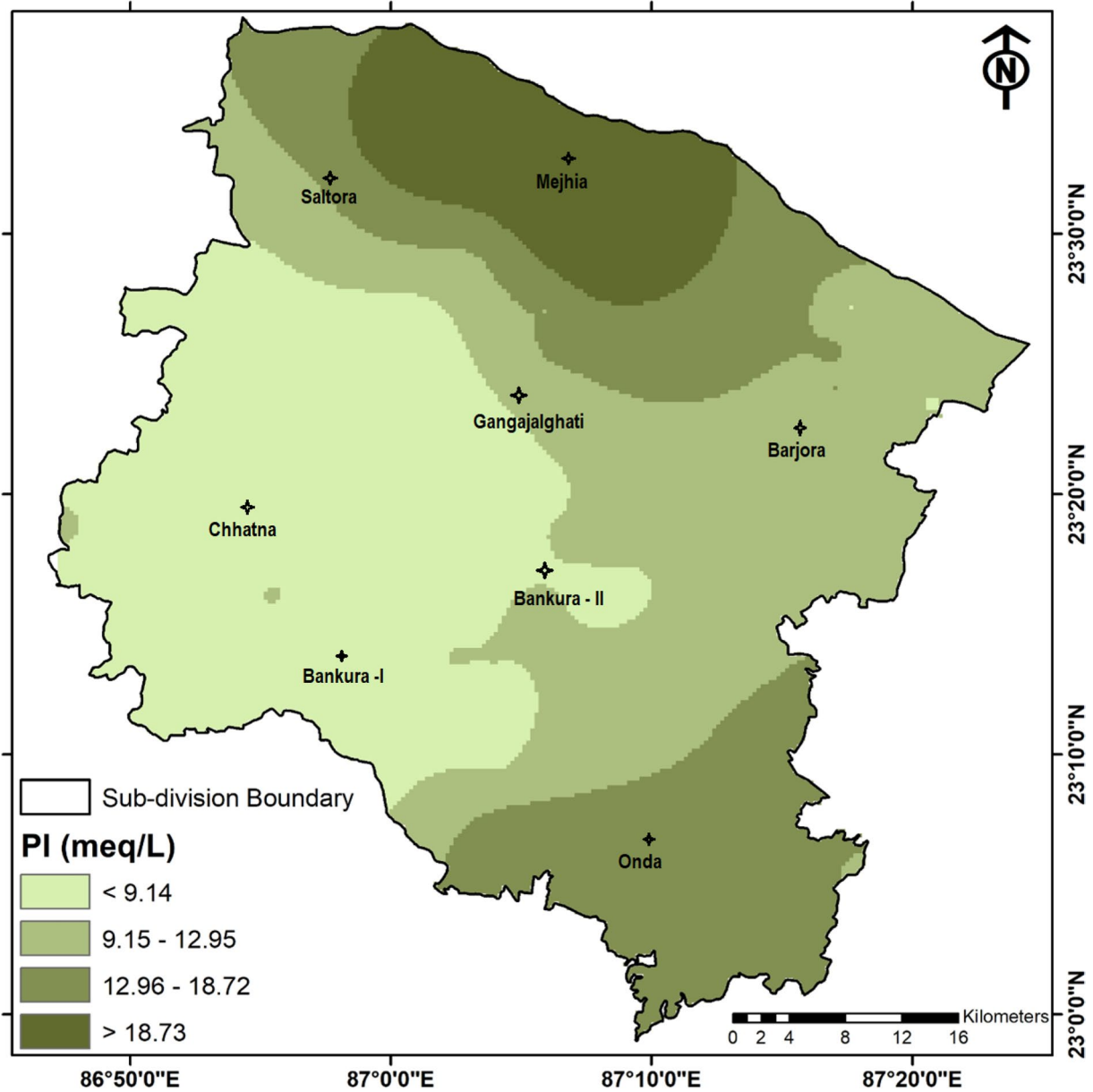
**Fig. 12** Spatial distribution of Permeability Index (PI) in Bankura sub-division

Table 4 Model validation parameters

Water Quality parameters	Mean Error	RMS	Mean Standardized	RMSES	ASE
pH	− 0.00769	0.22374	− 0.02407	0.97581	0.22904
EC (mg/L)	24.3773	901.635	0.02646	0.99046	904.543
Sodium (%)	0.65361	14.1309	0.045443	0.99053	14.2724
SAR (meq/L)	0.141421	13.76501	0.010231	0.96285	14.39448
TH (mg/L)	4.29179	196.43117	0.021216	0.99322	196.8618
KI (meq/L)	0.043326	0.872124	0.047708	0.98629	0.88772
MR (meq/L)	− 0.140497	7.154941	− 0.01936	0.98268	7.290362
PI (meq/L)	0.000853	6.315361	− 0.001044	1.03310	5.81764

Table 5 Irrigation water quality classification in Bankura sub-division

Water Quality Index	No. of Pixel	Area (sq km)	Percent
< 20	4043	312.32	11.90
21–25	17,670	1342.9	51.17
26–30	7011	538.93	20.54
> 30	5654	430.25	16.39

rise. Furthermore, variations in EC values imply very saline water in the research area's south-west corner. Chemical weathering of primary silicates in basaltic lithology confers calcium ions, while evaporation predominance leads to calcrete deposition and calcium in groundwater due to widespread semi-arid environments. The bulk of $Ca2+$ and $Mg2+$ samples came from a variety of sources, including carbonate minerals as well as other minerals. Major anions such as HCO3 are produced by the weathering of major silicates such as olivine, plagioclase, and pyroxene, and SO^4 is derived from human sources, while Cl penetrates the subsurface aqueous system as a result of groundwater salinization. Furthermore, NO^3 enters the groundwater system as a part of
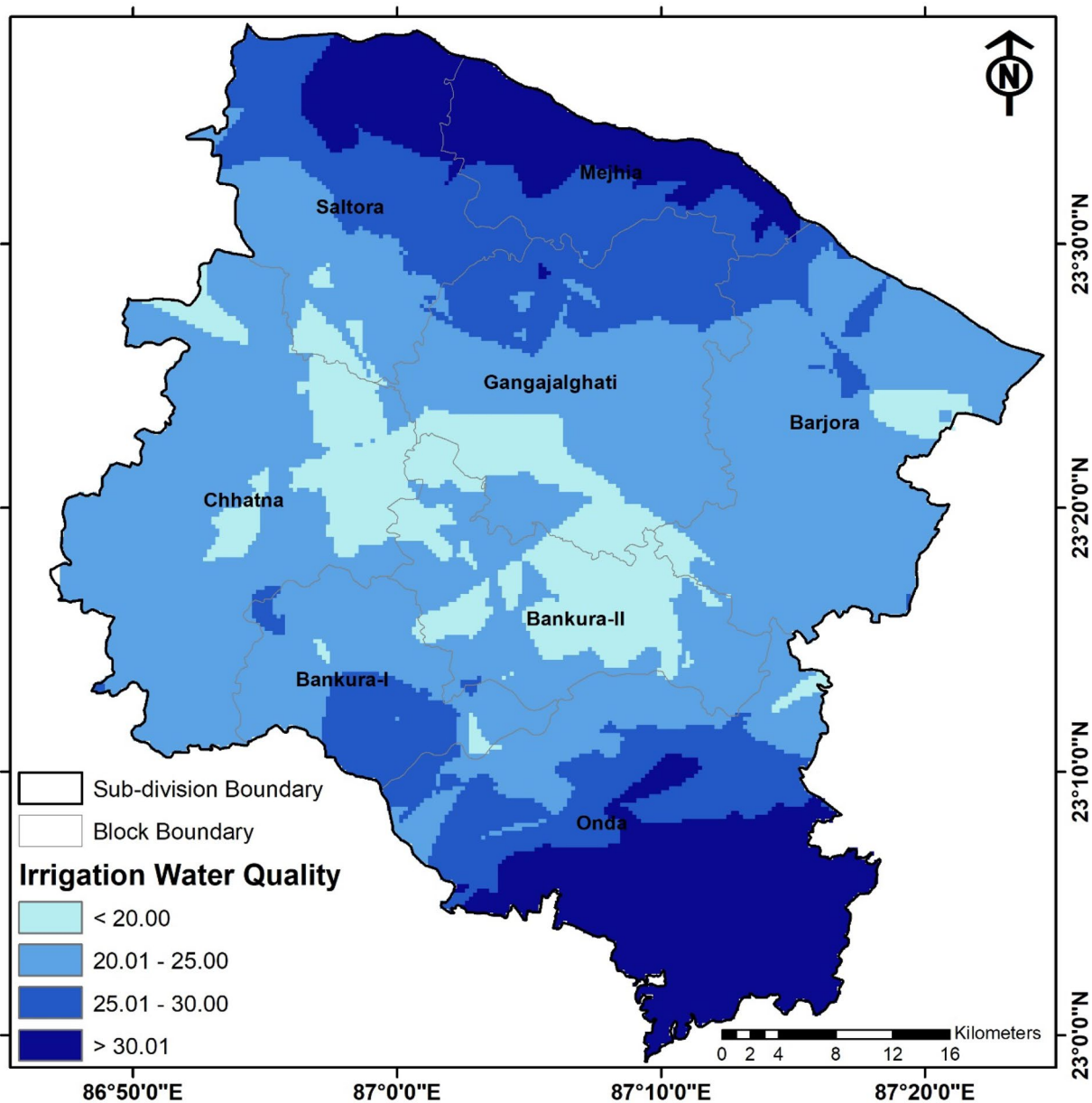
Fig. 13 Groundwater irrigation suitability analysis of Bankura sub-division

anthropogenic sources from farming activities (nitrogenous fertilisers).

The groundwater samples were classified based on their irrigation usage, resulting in descriptive data for irrigation indices and categorization. When dissolved ions are in abundance, a soil property reduces its vitality and impairs the soil's fertility. The growth of plants or crops is hampered by soil infertility. The osmotic pressure in the root zone is altered when there is too much salt in the water. The growth of plants or crops is halted as a result of the reduced absorption of water. The classification of groundwater quality based on irrigation indices, according to the aforesaid analysis, was as follows: SAR indicates good suitability, %Na indicates uncertain variability, KI indicates not recommended for irrigation due to alkali damage, PI indicates class I, category that is suitable, MR indicates good, EC indicates unsuitability, and TH indicates hard water for irrigation. In general, irrigation indices indicate that the groundwater quality is high saline, alkali-harmful, and highly hard, implying that it is unsuitable for irrigation.

As a result, groundwater quality metrics that generate enormous datasets necessitate the interpretation of complicated data matrices, as well as a deeper understanding of water quality and interrelationships across characteristics and sample sites. For the geographic fluctuation of water quality measures, geostatistical modelling is examined. The variability of pollutants in groundwater is revealed by their spatial distribution (Masoud 2014). In the literature, numerous geostatistical interpolation methods have been published (Webster and Oliver 2001). The EBK interpolation method is utilised in this work to make a preliminary conclusion about the geographic variation of groundwater quality metrics. As a result of the cross-validation results, the EBK approach can more effectively anticipate spatial variability for the research area. Data aggregation for GW quality assessment includes the use of in situ and hybrid machine learning—geostatistical methodologies. Contamination of GW in an island province has posed a health risk, particularly when GW is used as the principal source of household, agricultural, and industrial water. Kriging methods are the best way for Gaussian distribution data, and there are several interpolation techniques accessible in the literature. The expected squared difference between paired data values is affected by the distance by which sites have diverged, and lastly, prediction, when using the Kriging technique with semivariogram model.

6 Conclusion

The quality of the groundwater and its appropriateness for drinking and agricultural applications were assessed geographically and hydrochemically using the available wells.

Various geostatistical techniques were used to observe the groundwater quality characteristics and their spatial distribution. The concentrations of EC, sodium, and hardness were found to have non-normal distributions. Each parameter dataset was examined with the semivariogram models EBK interpolation techniques. Cross-validation was used to evaluate prediction accuracy.

The current situation suggests that groundwater in the Bankura sub-division will deteriorate unless immediate action is made to safeguard Quaternary groundwater aquifers and reduce pollution risk. As a result, the study suggests that well depths in the area should not be less than 120 m to prevent filthy water from percolating, as well as limiting the use of agrochemicals on agricultural fields and managing the use of harmful fertilisers and pesticides. To fulfil the Sustainable Development Goals (SDGs), information collecting for GW quality monitoring may be guided by this research. To provide us a better grasp of the possible health repercussions, regular monitoring is also necessary. A health risk evaluation based on GW quality should also be carried out. Preliminary treatments on GW quality control are also required.

Declarations

Conflict of interest There is no conflict of interest.

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