



Geospatial mapping of groundwater potential zones in the Baitarani River Basin using entropy approach

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ABSTRACT

This study maps groundwater potential zones in the Baitarani River basin of Odisha using the Shannon entropy method. Ten thematic layers were prepared from satellite, terrain, geological, soil, rainfall and groundwater observation data. The layers included geomorphology, geology, rainfall, soil, land use and land cover, lineament density, drainage density, slope, elevation and topographic wetness index. Entropy weights were calculated from the relation between observation well distribution and thematic classes, and the weighted layers were overlaid in a geographic information system to prepare a groundwater potential map. The basin was classified into poor, moderate and good groundwater potential zones. The entropy result shows that the moderate zone covers 8836.14 km², which is 61.10 percent of the basin. The good zone covers 3045.33 km², which is 21.05 percent, while the poor zone covers 2579.82 km², which is 17.84 percent. Validation with fifty-six observation wells gave an overall accuracy of 60.7 percent. The study provides a basin-scale screening map for groundwater planning, while also showing that water quality, aquifer depth and local pumping conditions must be examined before site-level groundwater development.

Keywords: Baitarani River Basin, Geographic Information System, Groundwater Potential, Odisha, Remote Sensing

INTRODUCTION

Groundwater is one of the most vital sources of fresh water needed by humans, agriculture, industries, and ecosystems for survival. In India, where there is an abundance of population depending on agricultural activities, the availability of sustainable water resources is directly related to food security and rural livelihoods. The surface water sources are used for different purposes, which include rivers, ponds, lakes, and reservoirs. The availability of water from these sources is dependent on the season and the rainfall received by the area (Paul *et al.*, 2016).

The increasing population along with the increase in irrigated areas, industrialization, urbanization, and changes in the land use pattern has led to the increasing demand for water. Climate variability has led to changes in the natural recharge

of the aquifers. Unpredictable monsoon, extended dry periods, rise in temperature, and deterioration of surface water bodies can decrease the amount of infiltration and groundwater recharge (Rout *et al.*, 2016; Paramaguru *et al.*, 2022). Thus, the storage and water table levels of groundwater are affected, especially in those regions where there is heavy dependence on monsoon rainfall (Bai *et al.*, 2017). Occurrence of groundwater is not influenced by a single factor. It is the combined influence of climatic, geological, geomorphological, slope, soil and other hydrogeological factors (Rajaveni and Muniappan, 2023).

The Baitarani River basin is a significant basin in Odisha and contributes to agriculture, settlements, forests, mining operations, and industrialization. There are varied physio-geographical and geological conditions in the basin, which range from hard rock upland areas to the lower alluvial plain areas. There

are substantial areas of the basin that comprise lithified rocks such as limestones, dolomites, quartzites, volcanics, and semi-crystalline rocks. With varied geological conditions, the occurrence of groundwater varies widely from place to place. While one bore well can provide enough water in one place, another bore well in the vicinity could be unsuccessful due to lack of proper fracturing or weathering zones. Conventional groundwater exploration methods, including field investigation and geophysical surveys, provide useful information. However, these methods are often costly, time-consuming, and difficult to apply over large basin areas (Rout *et al.*, 2017; Khosravi *et al.*, 2018). Remote Sensing and Geographic Information System techniques offer an effective approach for studying groundwater potential over wide regions. These techniques allow the integration of different thematic layers, including geology, geomorphology, slope, drainage density, lineament density, rainfall, soil, elevation, and land use or land cover (Paul *et al.*, 2026). The analysis of these layers helps to identify the factors controlling groundwater recharge, storage, and movement. Remote sensing and GIS have been effectively used in earlier studies for mapping groundwater potential zones in different geological settings (Paramaguru *et al.*, 2019; Parida *et al.*, 2025). They also support the interpretation of geomorphological features, geological formations, and hydrological properties that influence groundwater occurrence.

Several decision-making and statistical methods have been applied for groundwater potential zone mapping. The Analytical Hierarchy Process is widely used because it incorporates expert knowledge while assigning weights to thematic layers. However, the assigned weights may vary according to the judgment of the researcher or expert (Pande *et al.*, 2021; Shinde *et al.*, 2024). Data-driven methods such as Shannon Entropy can reduce this subjectivity by assigning weights based on information content and spatial variation within the thematic layers. The entropy method evaluates the relative influence of each groundwater conditioning factor and gives higher importance to layers that provide more useful information for groundwater occurrence (Lv *et al.*, 2022). Therefore, it is suitable for studies where multiple hydrogeological factors need to be assessed objectively.

Although entropy-based groundwater potential mapping has been applied in different regions, its

application in the Baitarani River basin is important due to the basin's geological diversity and increasing groundwater stress. The upper and middle parts of the basin are mainly controlled by hard-rock aquifer systems, whereas the lower part is influenced by alluvial formations. These contrasting hydro-geological conditions require an integrated basin-scale approach. An entropy-based groundwater potential map prepared using geospatial technology can help classify areas into very high, high, moderate, low, and very low groundwater potential zones. The present study aims to delineate groundwater potential zones in the Baitarani River basin of Odisha using geospatial technology and the Shannon Entropy approach. The main objectives of the study are to prepare hydrogeological thematic maps of the Baitarani River basin, delineate groundwater potential zones using the Shannon Entropy model, and validate the prepared map with available well data. The outcome of this study can support groundwater planning, artificial recharge site selection, and sustainable water resource management in the basin.

MATERIALS AND METHODS

Description of the study area

The Baitarani River basin is located in eastern India and drains through Odisha before meeting the Bay of Bengal. The basin covers about 14,218 km². It lies situated between 20°35' N and 22°15' N latitude and 85°03' E to 87°03' E longitude. The river originates from the Gonasika and Guptaganga hills in Keonjhar district at an elevation of about 900 m above mean sea level. The river extends for about 360 km before draining into the Bay of Bengal. About 94.8 percent of the basin lies in Odisha, and the remaining upper catchment portion extends into Jharkhand. The basin passes through varied physiographic and geological settings. The upper and middle parts include hard-rock areas, hills, valleys and pediplains. The lower part includes alluvial and deltaic plains. Temperature ranges from about 6° in winter to 48.5° in summer. The main soils include loam, sandy clay loam and sandy loam. Fig. 1 gives the basin location and Fig. 2 presents the methodology of the study.

Data used and preprocessing

Ten thematic layers were used because groundwater occurrence in the basin is controlled by

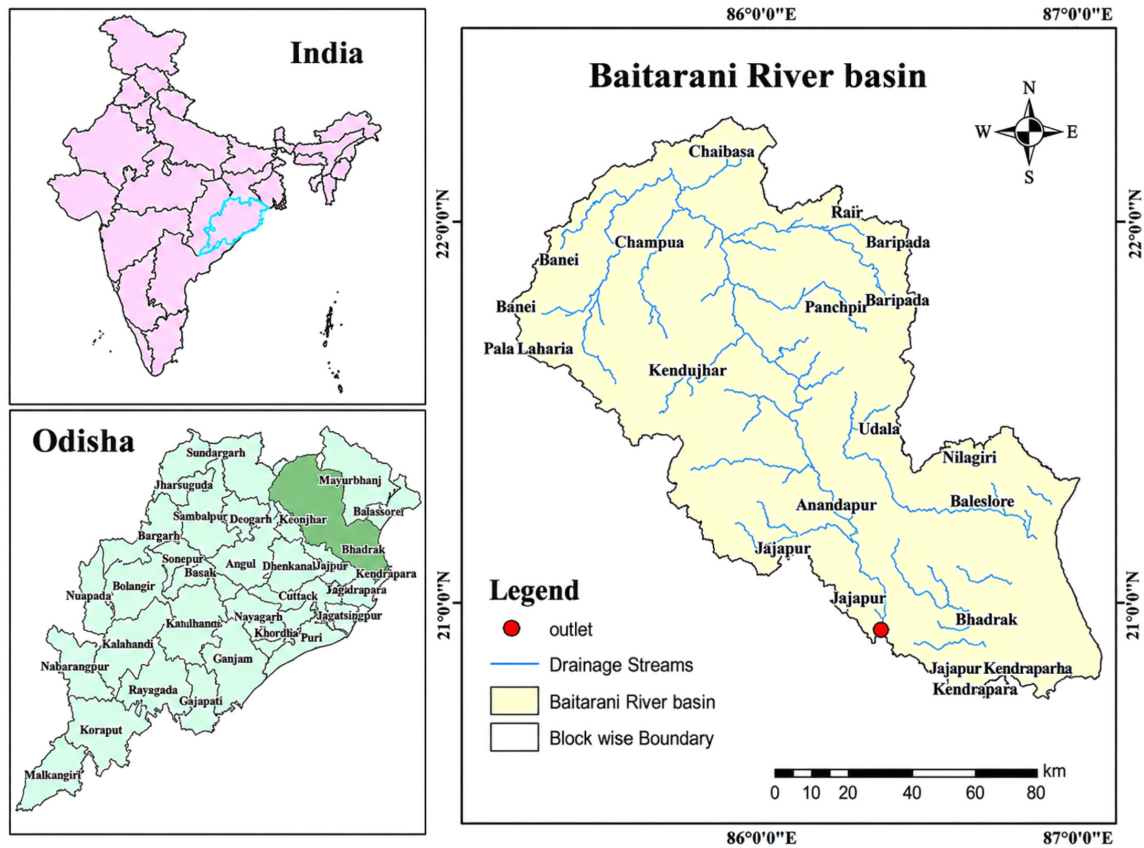


Fig. 1. Location map of the Baitarani River basin

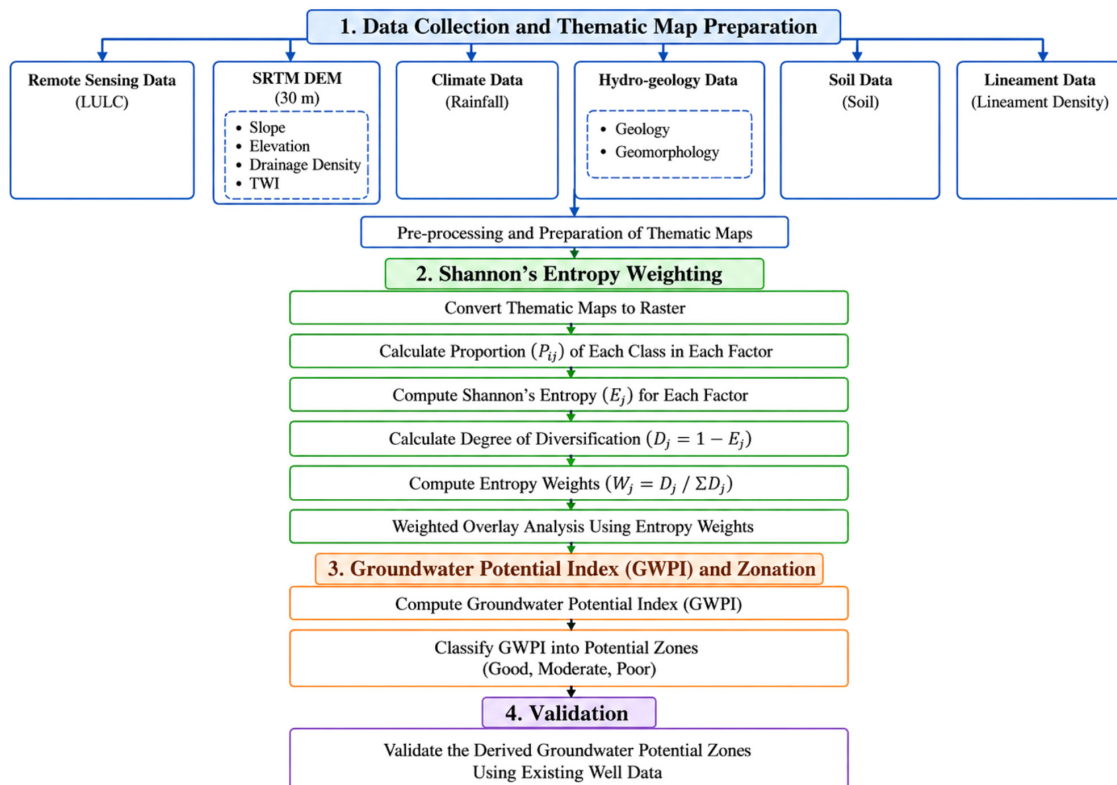


Fig. 2. Workflow adopted for Shannon entropy-based groundwater potential mapping.

Table 1. Data sources used for entropy-based mapping

Layer or data	Source	Scale or resolution
Digital elevation model	SRTM 30 m, USGS	30 m
Geology	Geological Survey of India	1:50,000
Geomorphology	NRSC Bhuvan	1:50,000
Lineament density	NRSC Bhuvan	1:50,000
Land use and land cover	ESRI LULC	10 m
Rainfall	India Meteorological Department, Pune	0.25p Gridded Data
Soil	FAO soil map	1:5,000,000
Groundwater validation	Central Ground Water Board	Point Data (56 observation wells)

terrain, geology, structure, drainage, land cover and rainfall. The layers were geomorphology, geology, rainfall, lineament density, slope, soil, land use and land cover, drainage density, elevation and topographic wetness index. ArcMap 10.8.2 was used for projection, raster conversion, reclassification and weighted overlay analysis. The thematic layers were projected to UTM zone 45 N and converted to a 30 m raster grid before overlay analysis. The data sources are summarized in Table 1.

Preparation of thematic layers

Each layer was clipped to the Baitarani basin boundary and the rasters were checked for spatial alignment before entropy-based overlay analysis. Geomorphology and geology were clipped and reclassified. The geomorphology classes were grouped into major landform classes such as alluvial plains, flood plains, deltaic plains, Padi plains and dissected hills. These classes were retained because they represent differences in recharge, runoff and groundwater storage. The geology layer was reclassified into major lithological groups to distinguish compact hard-rock formations from unconsolidated sedimentary formations. Rainfall data from 2020 to 2024 were processed by averaging the five-year values to obtain representative rainfall for the basin. The average rainfall points were interpolated using inverse distance weighting (IDW) in ArcMap. The interpolated rainfall surface was clipped to the basin boundary and reclassified into rainfall classes for the entropy model. The 2024 ESRI land use and land cover layer was clipped and reclassified into six classes. These were water bodies, forest, natural vegetation, agricultural land, built-up land and barren land. The soil layer was clipped to the basin boundary and reclassified using soil texture groups because texture controls infiltration and percolation. The SRTM digital elevation model (DEM) was used to prepare elevation, slope,

drainage density and topographic wetness index. The elevation raster was clipped and corrected using sink filling. Slope was derived from the corrected elevation model and then reclassified. Flow direction and flow accumulation were generated from the filled DEM. The stream network was extracted from the flow accumulation raster and used to prepare the drainage density layer. The topographic wetness index (TWI) was calculated from flow accumulation and slope. A small constant was included in the calculation to avoid division by zero in flat cells (Debnath *et al.*, 2023). The expression used was,

$$TWI = \ln \frac{a}{\tan(b)} + c$$

where 'a' is flow accumulation, 'b' is slope in radians and 'c' is the small constant. The output was reclassified into wetness classes. Lineament density was prepared by checking line geometry and applying the line density tool. The resulting density raster was reclassified into lineament density classes. After all layers were prepared, they were standardized into class ranks and used as inputs for Shannon entropy-based groundwater potential mapping.

Shannon entropy weighting

Shannon entropy was used to obtain the weights from the information theory of each thematic layer. The method gives more weight to a layer when the distribution of well points is uneven among its classes and when the layer provides more discrimination between groundwater conditions (Al-Abadi *et al.*, 2016; Saroughi *et al.*, 2024). It gives less weight to a layer when all classes have similar relations with wells or when the layer has a narrow spatial contrast. The method began with the frequency ratio for each class. The frequency ratio equals the percentage of observation wells in a class divided by the percentage of basin area occupied by that class. A ratio above one indicates that wells occur in that class more

often than expected from area alone. A ratio below one indicates weaker association. The ratio was then converted to probability density within each thematic layer. The final normalized entropy weight was calculated by dividing the raw weight of each thematic layer by the sum of all raw weights. In the weighted overlay, each raster cell received a class rank and a layer weight. The groundwater potential index was calculated as the sum of the products of layer weights and class ranks. Frequency ratio for class 'j' in layer 'i' (FR_{ij}) is given by,

$$FR_{ij} = \frac{\text{Percentage of Borewells in Class}}{\text{Percentage of Area in Class}}$$

Probability density (P_{ij}) for each class is then derived by normalizing the Frequency Ratio values,

$$P_{ij} = \frac{FR_{ij}}{\sum_{j=1}^m FR_{ij}}$$

Where, 'm' is the total number of classes within the specific thematic layer. The entropy value (H_i) for each thematic factor is computed as,

$$H_i = -\sum_{j=1}^m P_{ij} \log_2 P_{ij}$$

The maximum possible entropy ($H_{i,max}$) is calculated as,

$$H_{i,max} = \log_2 m$$

The information coefficient (I_i) measures the degree of certainty and is defined as,

$$I_i = \frac{H_{i,max} - H_i}{H_{i,max}}$$

The calculated weight value (V_i) for each thematic factor is then determined as,

$$V_i = I_i \times \sum_{j=1}^m FR_{ij}$$

Finally, the resultant weights were normalized to ascertain the percentage influence () of each thematic layer given as,

$$W_i = \frac{V_i}{\sum_{i=1}^n V_i}$$

The final Groundwater Potential Index was computed using,

$$GWPI = \sum_{i=1}^n W_i \times X_i$$

Where, ' X_i ' represents the reclassified rank of the features within the thematic layer. The continuous

Groundwater Potential Index raster was categorized into poor, moderate, and good zones.

Weighted overlay and classification

All thematic layers were standardized using class ranks from 1 to 9. A rank of 9 represented the most favorable groundwater condition and a rank of 1 represented the least favorable condition. Each standardized raster was multiplied by its normalized entropy weight. The weighted layers were summed to create the groundwater potential index raster. The final raster was classified into poor, moderate and good groundwater potential zones.

Validation

The entropy map was validated with fifty-six observation wells obtained from the Central Ground Water Board. The wells were classified into poor, moderate and good groundwater classes based the well yields, the validation points were classified into three categories: poor yield (<0.75 L/s), moderate yield (0.75 to 1.5 L/s), and good yield (>1.5 L/s). The mapped class at each well location was compared with the groundwater class derived from well observations. An error matrix was used to calculate producer accuracy, user accuracy and overall accuracy. Producer accuracy shows how well a ground class was mapped. User accuracy shows the reliability of a mapped class.

RESULTS

Spatial pattern of thematic layers

The thematic layers show that groundwater potential in the Baitarani basin is controlled by a combination of hard-rock terrain in the upper basin and more favorable lowland conditions in the lower basin. Undivided Precambrian rocks cover 70.48 percent of the basin, while Quaternary sediments cover 28.86 percent. This geological contrast is important because inter granular storage in alluvial materials can support more dependable shallow groundwater than compact rocks, unless the latter are weathered or fractured. Geomorphology (Fig. 3. (a)) shows a broad Pedi plain complex covering 46.46 percent of the basin. Alluvial, coastal, flood and deltaic plains together cover 28.67 percent. These plains are located mainly in the lower basin and form favorable recharge and storage environments. Dissected hills and valleys cover 22.09

percent and are less favorable where slope and runoff are greater. Rainfall (Fig. 3. (c)) varies from less than 1484 mm to more than 1629 mm based on the five-year average. The largest rainfall class covers 33.55 percent of the basin in the 1484 to 1532 mm range, followed by 26.72 percent in the 1532 to 1581 mm range. The rainfall range is not wide enough to dominate the entropy model by itself. Its groundwater role is expressed through its interaction with slope, land cover and geological storage. Lineament density is low over much of the basin (Fig. 3. (d)). About 83.72 percent of the area has lineament density less than 0.3 km/km². Higher lineament density classes occupy smaller areas but can be important in hard-rock zones where secondary porosity controls well success. The lineament result should be used with field checks because map-derived lineaments may include non-geological linear features. Slope and elevation results show why lower tracts are more favorable. About 58.97 percent of the basin has slope less than 3 degrees and lower slope favors infiltration and reduces rapid runoff (Fig. 3. (e)). Elevation ranges from below 150 m to 1183 m, with 35.18 percent below 150 m (Fig. 3. (i)). These low-elevation areas often correspond with valley, floodplain and alluvial environments. The land use and land cover map (Fig. 3. (g)) shows that agriculture occupies 49.30 percent of the basin. Forest and natural vegetation together cover 43.30 percent. Built-up land covers 5.34 percent, while water bodies and barren land occupy smaller areas. This layer is central to the entropy result because land cover reflects both recharge opportunity and water demand pressure. Drainage density is not interpreted in a single direction as shown in Fig. 3. (h). Low drainage density can favor infiltration where surface runoff is limited. Higher drainage density can indicate runoff

concentration and dissection, but in lowlands it may also mark moist and hydraulically connected floodplain areas. The basin has 37.26 percent area in the 1.1 to 1.4 km/km² drainage density class and 30.13 percent in the 0.7 to 1.1 class. Topographic wetness index values (Fig. 3. (j)) are mostly low. About 97.34 percent of the basin falls below 3, while higher values occupy small valley and lowland pockets. The spatial distribution of the ten thematic layers used in the entropy model is shown in Fig. 3.

Entropy weights

The normalized entropy weights, summarized in Table 2, show that land use and land cover is the most influential layer in this data set, with a weight of 37.29 percent. The topographic wetness index follows with 17.98 percent. Geology and lineament density receive 11.41 percent and 11.07 percent, while drainage density receives 8.14 percent and geomorphology receives 7.71 percent. Slope, rainfall, elevation and soil receive lower weights. Entropy gives a high weight only when a layer separates well observations among its classes. In this case, rainfall supports recharge but does not differentiate mapped groundwater classes as much as land cover and wetness. The highest entropy weight for land cover shows that the spatial relation between wells and land cover classes is strong. Agricultural land and water-related surfaces can support recharge during the monsoon. However, the same agricultural areas can become abstraction zones in the dry season. Thus, a high land cover weight should not be read only as recharge potential. It also identifies places where groundwater availability is strongly coupled with human land use. The class-level area, suitability rank and entropy weight used for weighted overlay are listed in Table 3.

Table 2. Shannon entropy values and normalized layer weights.

Layer	Entropy	Maximum entropy	Information coefficient	Raw weight	Normalized weight percent
LULC	1.42	2.58	0.447	0.788	37.29
TWI	0.90	2.32	0.610	0.380	17.98
Geology	0.99	1.58	0.370	0.241	11.41
Lineament density	1.95	2.32	0.155	0.234	11.07
Drainage density	1.77	2.32	0.235	0.172	8.14
Geomorphology	2.34	3.16	0.261	0.163	7.71
Slope	2.02	2.32	0.129	0.080	3.79
Rainfall	2.25	2.32	0.028	0.028	1.33
Elevation	2.27	2.32	0.019	0.015	0.71
Soil	1.56	1.58	0.012	0.012	0.57

Table 3. Class suitability ranks and entropy layer weights used in weighted overlay

Layer	Class	Area (%)	Suitability Rank	Entropy Weight (%)
Geology	Water body	0.67	9	11.41
	Quaternary sediments	28.86	7	11.41
	Undivided Precambrian rocks	70.48	3	11.41
Geomorphology	Water body	2.42	9	7.71
	Alluvial, coastal, flood and deltaic plains	28.67	8	7.71
	Piedplain complex	46.46	5	7.71
	Piedmont slope	0.04	3	7.71
	Dissected hills and valleys	22.09	2	7.71
	Quarry and mine dump	0.32	1	7.71
	Less than 1484 mm	19.26	1	1.33
Rainfall	1484 to 1532 mm	33.55	3	1.33
	1532 to 1581 mm	26.72	5	1.33
	1581 to 1629 mm	11.87	7	1.33
	More than 1629 mm	8.6	9	1.33
	Less than 0.3	83.72	2	11.07
Lineament density (in km/km ²)	0.3 to 0.6	8.45	4	11.07
	0.6 to 0.9	5.36	6	11.07
	0.9 to 1.2	2.18	7	11.07
	1.2 to 1.5	0.29	9	11.07
	Less than 3	58.97	9	3.79
Slope (in Degrees)	3 to 6	20.85	7	3.79
	6 to 9	6.56	5	3.79
	9 to 12	4.52	3	3.79
	More than 12	9.12	1	3.79
	Sandy loam	18.58	9	0.57
Soil	Sandy clay loam	39.54	5	0.57
	Loam	41.88	4	0.57
	Water bodies	1.92	9	37.29
Land use and land cover	Forest	31.1	8	37.29
	Natural vegetation	12.2	7	37.29
	Agricultural land	49.3	7	37.29
	Built-up land	5.34	1	37.29
	Barren land	0.14	3	37.29
	Less than 0.4	4.63	9	8.14
Drainage density (in km/km ²)	0.4 to 0.7	8.06	7	8.14
	0.7 to 1.1	30.13	6	8.14
	1.1 to 1.4	37.26	5	8.14
	More than 1.4	19.94	3	8.14
	Less than 150	35.18	9	0.71
Elevation (in meters)	150 to 345	13.67	7	0.71
	346 to 508	31.7	5	0.71
	509 to 729	12.5	3	0.71
	730 to 1183	6.95	2	0.71
	Less than 3	97.34	2	17.98
Topographic wetness index	3 to 6	1.96	4	17.98
	6 to 9	0.54	6	17.98
	9 to 12	0.13	7	17.98
	12 to 15	0.03	8	17.98

Groundwater potential zones from Shannon entropy

The Shannon entropy weighted overlay map divides the Baitarani basin into poor, moderate and good groundwater potential zones (Fig. 4). The moderate zone is the largest class, covering 8836.14

km² or 61.10 percent of the basin. The good zone covers 3045.33 km² or 21.05 percent. The poor zone covers 2579.82 km² or 17.84 percent. The moderate class dominates because large parts of the basin contain mixed conditions. Many areas have

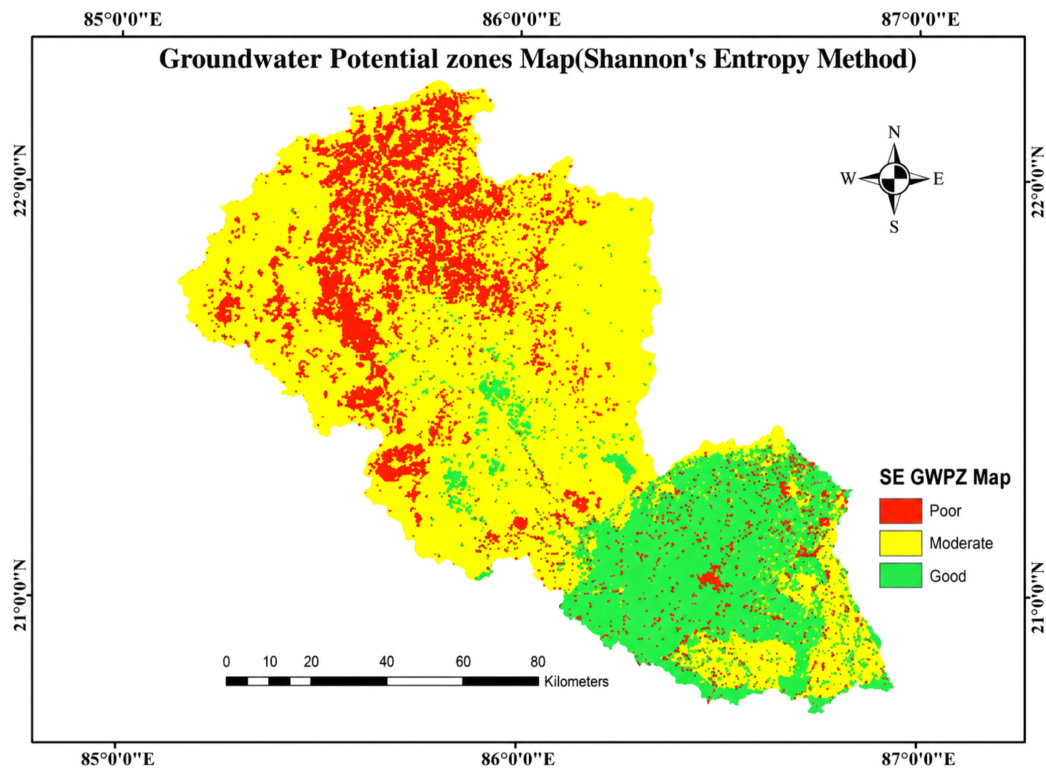


Fig. 4. Groundwater potential zone map using Shannon entropy

favorable slope or agricultural land but are underlain by hard rocks or have low lineament density. Other areas have good geomorphic position but may have higher drainage dissection or limited wetness. The good class is concentrated where favorable conditions overlap, especially low slope, lower elevation, alluvial or floodplain geomorphology, suitable land cover and better wetness conditions. The poor class occurs where steep slopes, hard rocks, low lineament density or less favorable land cover reduce recharge and storage potential. The entropy model maps 21.05 percent of the basin as good, while the analytical hierarchy method maps 28.97 percent as good. Entropy also maps a larger poor class than the analytical hierarchy result. This suggests that the data-driven method gives less

favorable status to areas where well distribution does not support the class ranks.

Validation of the Shannon entropy map

The validation used fifty-six Central Ground Water Board observation wells (Fig. 5). The entropy map produced an overall accuracy of 60.7% as depicted in Table 5. The moderate class had the highest producer accuracy, 77.7%, and a user accuracy of 65.6%. The poor class had a producer accuracy of 42.0% and a user accuracy of 61.5%. The good class had a producer accuracy of 50.0% and a user accuracy of 45.4%. The weaker good-class validation suggests that surface indicators alone do not always separate productive groundwater

Table 5. Error matrix for validation of the Shannon entropy groundwater potential map

Groundwater Potential Zones	Mapped Poor	Mapped Moderate	Mapped Good	Row Total
Observed Poor	8	8	3	19
Observed Moderate	3	21	3	27
Observed Good	2	3	5	10
Column Total	13	32	11	56
Producer Accuracy (%)	42.0	77.7	50.0	
User Accuracy (%)	61.5	65.6	45.4	
Overall Accuracy (%)	60.7			

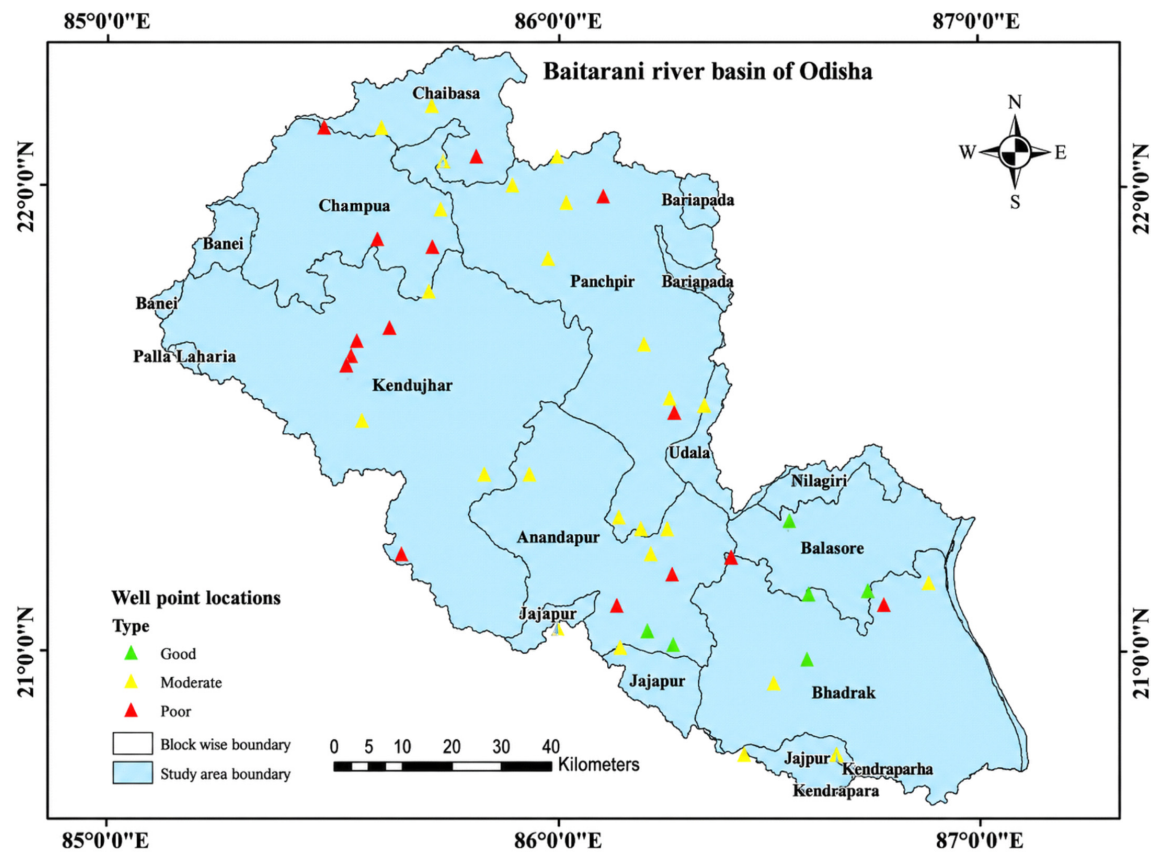


Fig. 5. Observation well locations used for validation

locations. Well depth, pumping rate, aquifer type, fracture connectivity and water quality may influence the observed well class.

DISCUSSION

The Shannon entropy result shows that the groundwater potential map is controlled mainly by land use and land cover, topographic wetness index, geology, lineament density and drainage density. This does not mean that rainfall, soil and elevation are hydrologically unimportant. It means that, in this dataset, their classes gave less contrast in relation to the observation wells. Rainfall remains a major recharge source in the Baitarani basin, but the mapped rainfall range is narrow, from 1484 to 1672 mm. Therefore, rainfall received a lower entropy weight because its classes were less able to separate poor, moderate and good groundwater conditions. In the lower Baitarani basin, alluvial and coastal transition areas may support productive shallow aquifers, but salinity and other water-quality risks can occur. Electrical conductivity, chloride, nitrate, fluoride and seasonal salinity checks are therefore needed before drinking water or irrigation

development, especially near the lower basin and coastal margin (Paul *et al.*, 2016). Agriculture also needs a balanced interpretation. Paddy fields and bunded lands can support recharge during the monsoon by slowing runoff and increasing percolation. During the rabi and summer seasons, the same areas may increase abstraction. Thus, agricultural good-potential zones should be managed through conjunctive use, micro-irrigation, recharge structures and water budgeting. The moderate accuracy of the entropy map is linked to hard-rock aquifer heterogeneity. Productive wells in such terrain often depend on weathered thickness, fracture aperture, fracture connectivity and depth to the water-bearing zone. These conditions are not fully represented by surface layers. Lineament density is useful, but all lineaments are not productive fractures (Embaby *et al.*, 2024; Jari *et al.*, 2023). The map should therefore be used for first-level screening and should be supported by resistivity survey, borehole data, pumping tests and local hydrogeological investigation before well-site selection. The validation result explains why the moderate class is more reliable than the good class. The moderate zone covers 61.10 percent of the basin and shows

the best agreement with observed wells. The good zone covers 21.05 percent, but only ten observed wells were available in the good dynamic groundwater class, making validation sensitive to a few points. Abstraction pressure, aquifer depth, aquifer type and water quality may also reduce agreement. Compared with the AHP study of Das *et al.* (2020) in the Mahanadi basin, this entropy-only study gives a data-driven interpretation for the full Baitarani basin. Its main contribution is its basin-scale application across hard-rock, agricultural, mining-influenced and lower alluvial transition zones.

CONCLUSIONS

This study prepared a Shannon entropy-based groundwater potential map for the Baitarani River basin using ten thematic layers and Central Ground Water Board observation wells. The entropy weights indicate that land use and land cover is the strongest layer, followed by topographic wetness index, geology, lineament density, drainage density and geomorphology. Rainfall receives a low entropy weight because its mapped range is relatively narrow and does not separate observed well classes as much as other layers. This result should be interpreted as information value within the model, not as the physical absence of rainfall control. The basin was classified into three groundwater potential zones. The moderate zone covers 8836.14 km² or 61.10%. The good zone covers 3045.33 km² or 21.05%. The poor zone covers 2579.82 km² or 17.84%. Validation with fifty-six observation wells gave an overall accuracy of 60.7 percent. The moderate class was validated better than the good class, which shows the role of aquifer heterogeneity, well depth, abstraction and local hydrogeological conditions. The main contribution of the study is a full-basin entropy-based groundwater potential map for a hard-rock to alluvial transition basin. The map can support planning of recharge structures, controlled groundwater development, field surveys and block-level water resource management. It should not be used as a stand-alone well-siting map. Future work should include independent validation wells, well yield, lithology, aquifer depth, seasonal time series, water quality data and geophysical surveys.

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