A Hybrid Spatial–Analytical Network Process Model for Groundwater Inventory in a Semi-Arid Hard Rock Aquifer System—A Case Study

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Abstract: Growing agricultural, industrial, and residential needs have increased the demand for groundwater resources. Targeting groundwater has become a challenging endeavour because of the complex interplay between varying climatic, geological, hydrological, and physiographic elements. This study proposes a hybrid RS, GIS, and ANP method to delineate groundwater zones. The resource was evaluated using seven surface hydrological and six subsurface aquifer parameters. The analytic network process model was used to determine the global priority vectors of each subclass. Surface and subsurface groundwater potential maps were created by assigning the resulting weights and spatially integrating them. Later, an integrated potential map was used to determine the global priority vectors of each subclass. Surface and subsurface groundwater potential maps were created by assigning the resulting weights and spatially integrating them. Later, an integrated potential map was created by combining them. The validation of the obtained results using water level data demonstrates that the integrated map accurately predicted the zones. The area under study has 172.94 km$^2$ of good groundwater potential. An area of 393.01 km$^2$ is classified as having a moderate potential, and an area of 410 km$^2$ is classified as having low potential. These findings will be beneficial to regional policymaking and long-term groundwater management. The results show that an integrated approach using ANP can better determine the groundwater potential zones in semi-arid zones.

Keywords: analytical network process; aquifer parameters; geographic information system; remote sensing; groundwater potential zone

1. Introduction

The global water cycle has undergone significant changes over the last century (Milly et al., 2005 [1]). Urbanization and population growth have increased domestic, agricultural, and industrial water needs (Okello et al., 2015 [2]). The per capita actual and virtual water consumption has also significantly increased (Hoekstra and Chapagain, 2007 [3]). The present annual global water demand is around 4600 km$^3$, and it is projected to rise between 5500 and 6000 km$^3$ by 2050 (Wada et al., 2014 [4]; Boretti and Rosa, 2019 [5]). Increasing demand and poor water quality have made groundwater the only reliable source in many parts of the world. Consequently, extreme high groundwater extraction rates are witnessed in parts of America, Asia, Europe, and the Middle East. Especially in the Russian Federation, the water supply of more than 50% of the territory and population is based on groundwater, but now some territorial entities including the Murmansk, Kurgan, Omsk, Novgorod, and Yaroslavl regions, certain areas of the Arkhangelsk, Rostov, and Tyumen regions, the Republic of Kalmykia and the Stavropol Territory are experiencing significant water deficits (Pykhtin, 2019 [6]). Globally 30% of the world’s largest groundwater systems are in distress.
In India, too, one of the most urgent sustainability challenges is the rapid depletion of groundwater. Several aquifers are experiencing water stress (Gleeson et al., 2012 [7]). For the past 20 years, India has been the world’s most rapidly depleting region in terrestrial water storage (TWS), with a rate of 3–4 centimetres per year (World Bank, 2012 [8]). As reported by the Ministry of Jal Shakti, the annual per capita water availability has decreased from 1816 m$^3$ in 2001 to 1545 m$^3$ in 2001 and is projected to drop to 1367 cubic metres in 2031 (MoWR, 2021 [9]). Unsustainable irrigation pumping and changes in land use have depleted the groundwater (Srinivasan et al., 2015 [10]; Penny et al., 2018 [11]). Environment India predicts that by 2050, six states will be water scarce, and four will be water stressed (Grasso, 2021 [12]). The water table in the northwest region of India has dropped below 20 m and is continuing to fall at a rate of more than 1 m per year (MacDonald et al., 2016 [14]; Mishra et al., 2018 [15]).

Due to overexploitation, unsaturated shallow aquifer zones are expanding horizontally and vertically (Luo et al., 2019 [16]). Furthermore, future climate change will likely impact shallow unconfined aquifers (Russo and Lall, 2017 [17]). Therefore, it is essential to precisely target the deep groundwater potential zones to exploit the shallow groundwater rationally. However, due to diverse geological formations, intricate tectonic structures, climatic variations, and various hydrological conditions, groundwater behaviour is complex in deeper hard rock zones. Therefore, a large quantity of multidisciplinary data and a well-defined methodology are required to delineate the potential zone and model the groundwater.

Researchers have developed various direct and indirect methods to explore groundwater over the last few decades. The surface methods include geophysics (MacDonald et al., 2005 [18]; Porsani et al., 2005 [19]; Anomohanran et al., 2017 [20]), electromagnetic methods (Cook et al., 1989 [21]; Selvam and Sivaharan, 2012 [22]), and geology (Solomon and Quiel, 2006 [23]; Kudamnya et al., 2019 [24]). However, the investigations are costly, take considerable time, and require a skilled workforce.

Indirect methods, such as logistic regression (Ozdemir, 2011 [25]; Pourtaghi and Pourghasemi, 2014 [26]), decision trees (Chenini, 2010 [27]), artificial neural network models (Corsini et al., 2009 [28]), Shannon’s entropy (Naghibi et al., 2015 [29]), and machine learning techniques such as random forest and maximum entropy (Srivastava et al., 2017 [30]; Elbeltagi et al., 2021 [31]), and so on, have recently gained attention in demarcating resources. However, geographical information systems (GIS) and remote sensing are also powerful and cost-effective in demarcating the resources. Satellite data provide baseline information on groundwater influencing parameters, namely drainage, slope, land use, land cover, soil, geomorphology, lineament and lithology (Saraf and Choudhury, 1998 [32]; Thakur and Raghuvanshi, 2008 [33]; Dar et al., 2010 [34]; Oikonomidis et al., 2015 [35]; Magesh et al., 2012 [36]; Saravanan et al., 2020 [37]). GIS offers a structured framework for storing and integrating spatial and non-spatial datasets (Gumma and Pavelic, 2013 [38]; Senanayake et al., 2012 [39]), but it is important to understand that the parameters used to determine groundwater potential come from various sources. Further, the degree of influence of the parameters will also change over time and space. Such inappropriate geographic data integration from diverse sources might lead to erroneous spatial predictions. However, the analysis can minimise the unprecedented uncertainties by combining geostatistical techniques.

This study attempted to overcome this challenge by combining geographical data with a multicriteria decision-making (MCDM) tool to determine the groundwater potential zone. Multicriteria decision analysis (MCDA) offers a systematic way of evaluating multiple parameters (Kumar et al., 2014 [40]; Rahmati et al., 2015 [41]; Razandi et al., 2015 [42]; Jennifer and Jha, 2017 [43]). The easiest and most comprehensive MCDA technique is the simple additive weighting technique (SAW). Based on significance, weights are assigned qualitatively to each parameter (Kamaraju et al., 1996 [44]; Shaban et al., 2006 [45]). Other statistical methods commonly used to prospect groundwater include frequency ratio (Manap et al., 2013 [46]; Naghibi et al., 2015 [29]; Trabelsi et al., 2019 [47]), logistic regres-
sion (Pourtaghi and Pourghasemi, 2014 [26] and weights of evidence (Ozdemir, 2011 [25]). Subsequently, Saaty (1980) [48] proposed the analytical hierarchy approach (AHP). This semi-quantitative top-down decision model is used to predict weights based on the ideal relationship between the parameters through a pairwise comparison. However, all the parameters in the physical world are extremely interconnected. Thus the analytic network process (ANP), an AHP inheritor developed by Saaty (1980) [48], makes it possible to establish the complex interrelationships through a network model (Jenifer and Jha, 2017 [43]; Rajani et al., 2018 [49]; Siva et al., 2017 [50]; Sujatha, 2020 [51]; Gebru et al., 2020 [52]). Since the non-linear structure is much closer to reality, it produces better results. Although the model has extensive application in geo environments (Meade and Sarkis, 1998 [53], Sujatha and Sridhar, 2017 [54]; Sujatha, 2020 [51]), its use in groundwater studies is limited.

Tiruttani is a drought-prone zone faced with extreme water scarcity, which widely affects agricultural and drinking water uses. Besides in a few limited areas, the region’s surface water supply is inadequate to meet local requirements. Therefore, this study aims to create a groundwater prospecting model utilising the ANP approach. Furthermore, groundwater research frequently includes surface factors (Saraf et al., 2004 [55]), whereas the subsurface parameters are least investigated. In this study, an experiment was undertaken to identify prospective groundwater zones by ANP modelling using both surface and subsurface factors and perform a validation by comparing the results with field data.

2. Description of the Study Area

The areas between northern latitudes 12°56′30″ N and 13°18′30″ N and longitudes 79°30′30″ E and 79°47′ E in and around the Tiruttani block of Tamil Nadu were studied (Figure 1). The study comprises an area of 975 sq. km with typical massive rock shoots dissected by fractures. The area’s annual rainfall varies from 950 mm to 1150 mm under the influence of both northeast and southwest monsoons. The main rivers that flow within the study region are Nagari and Palar. Groundwater is found in the weathered mantle under phreatic conditions and in the fissured and fractured zones at deeper depths under semi-confined conditions. The weathered zone is between 2 and 12 m thick.

Figure 1. Map showing study area and geo-position of rain gauge stations, geophysical survey stations and pump test locations.
3. Material and Methods

In the present study, groundwater potential assessment in the Tituttani hard rock region was performed using seven surface and six subsurface parameters. The proposed method consists of four steps (Figure 2): (1) surface parameter-based groundwater prospecting, (2) subsurface parameter-based groundwater prospecting, (3) an integrated new method that considers both parameters, and (4) characterizing the distribution of groundwater potential and assessing the model efficiency.

![Flow chart showing methodology.](image)

**3.1. Constructing Thematic Layers**

The surface parameters used to identify the spatial distribution of various groundwater potential zones were extracted from multiple analogue and digital datasets such as topographical maps, satellite images and digital elevation models. The lithology map was derived from Tamil Nadu’s Geological and Mineral map published by the Geological Survey of India. After geo-rectifying and projecting, it was digitised and converted into a thematic layer using GIS software. The IRS 1D–LISS III geocoded (P142 R51, P143 R51 dated 15 December 2015) digital satellite data was processed using the supervised classification maximum likelihood method and the geomorphic units were mapped. Likewise, land use and land cover units were interpreted by adopting the NRSC level II classification system (NRSC manual, 2012 [56]). A digital elevation model (DEM) with a spatial resolution of 90 m × 90 m and an elevation accuracy of 3 m to 5 m was developed using Shuttle Radar Topographic Mission (SRTM) data. The spatial distribution of lineaments was extracted from satellite images and further updated using the DEM, and shaded relief outputs were produced from the SRTM data. Subsequently, the lineament density map was then generated by the inverse distance weighted (IDW) method. A drainage map was made by scanning, rectifying, and digitising the Survey of India topographical sheets (57O/8, 57O/11, 57O/12, 57O/16, 57P/9) of 1:50,000 scale, and a map on drainage density was then prepared as earlier. The soil map was reproduced from the soil resource map published by the soil survey and land use organisation (SSLU) of the Tamil Nadu agricultural department. The slope gradient was derived from the SRTM DEM. Ground truth verification was performed using a GPS survey. The interpreted geomorphology, land use, land cover and major lineaments were checked in the field.

A database of subsurface parameters influencing the occurrence and movement of groundwater was created. Geophysical resistivity surveys were performed at ten locations, and the aquifer thickness map was then prepared. A total of five bore wells, five dug cum bore wells, and 15 dug wells were selected for investigation. GPS was used to geotag the locations of the wells mentioned above, and their water levels were recorded. A pumping test was conducted, and parameters such as permeability, transmissivity, specific capacity
and storage coefficient were determined in the field. Later, they were spatially plotted, interpolated and classified using GIS software.

The analytical network process (ANP) model was employed in the study for delineating the groundwater potential zone (Figure 2). The ANP framework was constructed for surface and subsurface parameters separately using super decision software. Global priority vectors indicating the influence of each parameter compared with others of being a groundwater potential parameter were derived. Derived vector values were dully allocated and transformed into raster layers. By spatially adding the respective data sets, surface and sub–potential surface maps were created. In addition, an integrated groundwater potential map was also generated by combining the resulting outputs. The water level data were obtained at random intervals and classified into shallow, moderate, and deep based on their depth to validate the outcomes. Correlation coefficients were obtained by correlating them spatially with the potential surface, subsurface, and integrated groundwater maps.

3.2. Analytical Network Process Model

ANP is a multicriteria decision model that superset the well-known Saaty (1980) [48] developed analytic hierarchy process (AHP) model. ANP provides a broad framework for dealing with choices without assuming anything. ANP reduces a multicriteria complex problem to a non-linear network (Saaty, 1980 [48]; Sujatha and Sridhar, 2017 [54]; Sujatha, 2020 [51]). More importantly, the interdependence of network elements allows better modelling of complex problems since most real-life situations are non-linear. Thus, they are closer to reality and, as a result, yield more accurate results. This study developed two ANP models to target groundwater: one based on surface parameters and the other based on subsurface parameters.

There are four stages to the ANP modeling process.

Step-1. This step involves framing the network structure accordingly. The goal is to identify a potential groundwater zone. The thematic layers form the criteria group, while the categories in each theme include the sub-criteria group. The potential zones, namely high, moderate and poor, comprise the alternatives group.

Step-2. The pairwise comparison between the elements in each group are correlated with all other elements in the network by Saaty’s 1–9 scale (Table 1). Subsequently, local priority vectors are derived.

Table 1. Saaty’s scale of relative importance.

| Importance                  | Scale |
|-----------------------------|-------|
| Extreme importance          | 9     |
| Very, very strong           | 8     |
| Very strong importance      | 7     |
| Strong                      | 6     |
| Strong importance           | 5     |
| Moderate plus               | 4     |
| Moderate importance         | 3     |
| Weak                        | 2     |
| Equal importance            | 1     |

If both the sets of comparisons then prove inconsistent, a review is necessary. As a result, verifying that they are consistent is required before using comparison matrices for evaluation and analysis. The most well-known consistency index for the pairwise comparison matrices in the ANP is the consistency ratio by Saaty. The consistency index (CI) of the derived weights of each set of pairwise comparisons is calculated by:

\[ CI = (\lambda_{\text{max}} - n)/(n - 1) \]
where $n$ is the size of the pairwise matrix, and if $CI$ is less than 0.10, it is assumed that the judgments are consistent (Saaty, 1980 [48]). Similarly, the consistency of the entire pairwise comparison matrix is checked using the consistency ratio (CR):

$$CR = CI / RI$$

where $RI$ is a random consistency index computed for different $n$ values is given in Table 2.

**Table 2. Random consistency index.**

| n  | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   | 9   | 10  | 11  | 12  | 13  | 14  | 15  |
|----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| RI | 0   | 0   | 0.58| 0.90| 1.12| 1.24| 1.32| 1.41| 1.45| 1.49| 1.51| 1.53| 1.56| 1.57| 1.59|

For perfect consistency, the consistency measure $\lambda_{max}$ equals $n$; therefore, the consistency index $CI$ equates to zero, resulting in a CR of zero. However, this is not the case on many occasions, and the CR usually has a value greater than zero. Saaty recommends that CR be 0.1 or less, and the expert should revise the judgments if CR is significantly greater than 0.1.

Step-3. To obtain the overall priorities of the elements, a supermatrix is formed. The super matrix serves as a unifying framework, representing the overall relative dominance of one element over another in the network.

The diagram labeled “Figure 3” provides a description of the overall structure of the super matrix, where $W_{ij}$ is a block matrix consisting of priority weight vectors ($w$) of the influence of the elements in the $i$th cluster concerning the $j$th cluster, $e_{Nn}$ signifies the $n$th element in the $N$th cluster, and $CN$ signifies the $N$th cluster. In a situation where the $i$th cluster has no effect on the $i$th cluster, $W_{ij}$ is set to zero (a case of inner dependence). The super matrix created by completing this phase is referred to as the “initial supermatrix.”

![Figure 3. General structure of the super matrix.](image)

There are three different kinds of super matrices: (i) the limit super matrix, (ii) the weighted super matrix, and (iii) the unweighted super matrix. No cluster comparisons were made since the current ANP model has just two clusters. Therefore, the weighted and unweighted super matrix are identical. As a result, the values of the other two super matrices remain unknown.

Step-4. By computation, global priority vectors representing a numeric value between 0 and 1 are derived, which indicate the relative importance of each element.
4. Database on Factors Influencing Groundwater Potential

4.1. Surface Parameters

The earth’s surface morphology and its characteristics determine the rate of infiltration and indirectly influence the groundwater potential of the region. The surface groundwater influencing parameters such as drainage, slope, land use and land cover, soil, geomorphology, lineament and lithology were considered (Abdalla, 2012) [57].

4.1.1. Lithology

The six major lithological units in the study area are shown in Figure 4a. The largest are the hornblende fissile-biotite gneiss and epidote-hornblende gneiss (68.25 percent). Within the gneiss, basic dykes with an EW orientation are noted. Granite patches are observed in the central, fluvial deposits in the southern, and clay in the eastern parts of the study area. Deep and moderate weathering is observed in the gneissic and charnockitic formations, respectively. The thickness of the joint/fractured zone is considerable in gneissic formations and comparatively less in granite and charnockite. Gneiss was assigned high potential in groundwater, charnockite and sandstone as moderate potential, and granite with low potential (Krishnamoorthy et al., 2000 [58]). Pairwise comparisons are established in ANP accordingly.

4.1.2. Geomorphology

Geomorphology is a field that deals with groundwater accumulation and movement in a terrain (Kale and Gupta, 2001 [59]). The pediplain geomorphic unit comprises the max-
imum part of the study area (738.63 sq. km), followed by the alluvial plain (125.43 sq. km). Although denudational hills, floodplain, pediment, and structural hills only form a small portion (Figure 4b). Pediplains are characterised by a thick weathered zone and are moderately favourable for groundwater. The alluvial plain also signifies groundwater occurrence. Due to their closeness to streams and soil features, flood plains account for 3.45% of the study area and have the greatest potential for groundwater recharge [60–62].

4.1.3. Land Use and Land Cover

The potentiality of groundwater and the land surface characteristics are highly interrelated. Land use and land cover govern the degree of infiltration and runoff. Most of the study is dominated by cropland (598.74 sq. km), followed by water bodies (107.93 sq. km), fallow land (33.43 sq. km), and wasteland (22.97 sq. km). Smaller areas are covered by built-up land (31.70 sq. km), land with scrub (63.19 sq. km), land without scrub (33.56 sq. km), and plantation classes (78.69 sq. km) (Figure 4c). The croplands are irrigated and have a higher water holding capacity, allowing time for infiltration and are, thus, a more influential parameter in prospecting (Siva et al., 2017 [50]).

4.1.4. Lineament Density

Lineaments are the rectilinear or barely curvilinear structural components formed due to seismotectonic events. The remotely sensed data lineaments were mapped based on texture, relief, drainage, and tonal linearity. An isoline map was subsequently prepared and graded into high, medium, and low lineament density zones using the inverse distance weighted method (IDW) in ArcGIS (Figure 4d). The high-density region is approximately 460.25 sq. km. The medium-density region occupies 398.23 sq. km, and the low-density region is 117.43 sq. km. Increased secondary porosity enhances groundwater recharge in a highly faulted and fractured region (Yeh et al., 2016 [63]). Thus, the higher the lineament density, the more significant the groundwater potential.

4.1.5. Drainage Density

The drainage pattern is a reflection of the geological and topographical influences of the rocks that underlie it. The groundwater condition of an area can be inferred through its drainage pattern and density (Magesh et al., 2012 [36]). Dendritic, trellis and parallel patterns are prevalent in the study. In addition, rectangular, circular, and radial patterns are also observed. The drainage density was calculated, interpolated spatially, and categorised as high, medium and low drainage density (Figure 4e). The density areas with moderate to medium drainage would have higher surface infiltration and permeability.

4.1.6. Soil

The soil of the study area consists primarily of inceptisol (63%). The eastern portion also includes alfisol and entisol. Additionally, patches of vertisol are seen at four locations (Figure 4f). In large part, the recharge of aquifers is determined by soil infiltration and storage. Entisols are immature soils with little or no horizon and have the original parent material characteristics and, thus, have reasonable infiltration. Vertisol, alfisol, and inceptisol have the lowest infiltration rates due to texture and organic matter (Duiker et al., 2001 [64]).

4.1.7. Slope

The region’s slope map was divided into three classes based on the NRSA classification scheme. Most of the study region falls below the gentle slope category (0 to 1%), and medium slopes (1–5%) and steep slopes (>5%) are found in the north and northwest parts, respectively (Figure 4g). A higher slope suggests a higher potential for erosion, higher surface runoff and less infiltration (Rajaveni et al., 2017 [60]). In contrast, areas with gentle slopes have greater potential for groundwater recharge.
4.2. Subsurface Parameters

Aquifer properties are responsible for the percolation, transport and storage of water in hard rock terrain. A pumping test was performed in twenty-five wells to determine the hydraulic properties such as transmissivity (T), permeability (K), storage coefficient (S), and specific capacity (SC; Banton and Bangoy, 1996 [64]; Sanders, 1998 [65]; Hasan et al., 2020 [66]).

4.2.1. Water Level

Water level provides information on groundwater storativity and is, thus, a significant factor in determining potential regions. The study’s water levels range from 8.1 m below ground level (bgl) to 15.60 m. The levels were subsequently plotted, and isolines were generated using the ArcGIS IDW tool. They were then classified as high (11.31 and 15.60), medium (10.7 to 11.31), and low (10.7 to 11.31), and low (8.01 to 10.07 bgl). The map reveals that all three groups extend around the entire area of study (Figure 5a). The more favourable zone is the shallow water level accompanied by moderate and deep water (Suganthi et al., 2013 [67]).

![Figure 5. (a–f) Thematic layers on subsurface groundwater influencing parameters.](image-url)

4.2.2. Aquifer Thickness

For groundwater development, it is critical to have an adequate depth of aquifer since this provides a greater supply of resources. The formation’s resistivity was measured at ten locations up to 100 m in depth. Their actual resistivities were calculated based on the
observed apparent resistivity. An isoline aquifer thickness map was developed using the ArcGIS IDW tool, based on the depth at which bedrock was encountered (Figure 5b). The high aquifer thickness zone is located in the central portion (325.58 sq. km). In contrast, the medium zone is located in the southern and northern areas (325.57 sq.km). The study’s western and eastern parts (325.67 sq. km) are predominantly in the low zone. Deeper aquifers have a higher holding capacity and are, thus, more significant in identifying zones with higher potential for groundwater recharge.

4.2.3. Permeability

Permeability indicates the movement of water within the aquifer system. Permeability depends upon the nature of the rock’s porosity and interconnected pores. The study area’s permeability varies from 2.60 to 27.91 m$^3$/day. Based on these values, the study area was interpolated spatially and graded as low permeability zone (2.60 to 10.04 m$^3$/day), medium zone (10.04 to 12.82 m$^3$/day), and high zone (12.80 to 27.91 m$^3$/day). The spatial distribution of the low, medium and high permeability zones is 325.10, 325.50, and 325.16 sq. km (Figure 5c). High permeability values are favourable for a high groundwater potential zone (da Costa et al., 2019 [68]).

4.2.4. Transmissivity

Transmissivity refers to the amount of water transferred horizontally through the aquifer’s formation or its maximum saturation depth. The assessed transmissivity was between 7.79 m$^2$/day and 600.14 m$^2$/day. As before, these values were divided into high transmissivity zones (144.84 to 600.14 m$^2$/day), medium zones (70.51 to 144.84 m$^2$/day), and low transmissivity zones (7.79 to 70.51 m$^2$/day) (Figure 5d). Low and moderate transmissivity zones have a high potential to hold water, whereas high transmissivity implies low groundwater potential; thus, comparisons were made in the ANP model (Hassan et al., 2016 [69]).

4.2.5. Storage Coefficient

The storage coefficient in the study area varies from 0.0001 to 0.0009 and is further graded into high (0.0004 to 0.0009), medium (0.0002 to 0.0004) and low (0.0001 to 0.0002) storage coefficient zones (Figure 5e). A high storage coefficient indicates a good groundwater potential zone, a medium storage coefficient a moderate potential and a low storage coefficient a poor potential zone (Sridharan et al., 1995 [70]).

4.2.6. Specific Capacity

The yield per unit drawdown measures a specific capacity (Q/s). The tests found that the specific capacity ranges between 0.0042 and 0.522. As for the previous parameters, it was spatially divided into low (0.0042 to 0.160), medium (0.160 to 0.256), and high (0.256 to 0.0522) (Figure 5f). High specific capacity is considered a good potential groundwater zone, the moderate specific capacity area is considered medium and low has poor potential. The comparisons were based on the above relationship (Summers, 1972 [71]).

5. Results and Discussion

5.1. Mapping Potential Groundwater Zones

The complex ANP model was developed using super decisions software 2.8.0. Four clusters were primarily developed: goal, criteria, alternative, and potential. The potential groundwater zone was designated as a goal cluster. The parameters affecting the surface groundwater, i.e., drainage, slope, land use and land cover, soil, geomorphology, lineament and lithology, were grouped under the criteria cluster. The subclasses of the aforementioned parameters were grouped within the alternative cluster. A fourth cluster was created, namely potential, with good, moderate and poor nodes to extract the potential groundwater outcomes.
Then concerning the goal, each element (parameter) within the criteria cluster was compared to the other (inner dependency). For instance, concerning the goal (groundwater potential), geomorphology was correlated with drainage density, soil, slope, and within the same cluster. Similarly, their subclass elements in the alternative cluster were compared amongst themselves. For example, in addition to comparing it with its contemporaries such as pediment and alluvial plain, the flood plain of the subclass of geomorphology was also compared with subclasses of other parameters such as lineament density high, and forth and barren land in land use and land cover.

Then, the nodes (elements) of the criteria cluster were compared with all nodes in the alternative cluster (outer dependence). For example, concerning groundwater potential, the geomorphology in the alternative cluster was correlated with its subclass and the subclasses of other parameters. In the next step, each node in the alternative cluster was compared with elements in the potential cluster. For example, a pairwise analysis between the floodplain and high drainage density was established in good potential. Similarly, all subclasses in the cluster of criteria were compared concerning the potential cluster’s good, moderate, and poor elements. Likewise, a reverse comparison (feedback) was also made between the elements in various clusters.

A supermatrix was constructed by establishing 361 pairwise comparisons between nodes in the various clusters, and its resultant priority vectors are displayed in Table 3. The analytical output from ANP may be found in the Raw data column. The Normals column contains output data that has been normalized. The Ideals column contains numerical values representing the relative dominance of each parameter over the other within the network in terms of groundwater potentiality (Feibert et al., 2016 [72]). Groundwater occurrence, movement, and quality are all influenced by geological units. This area’s basement is made up of gneiss and charnockite (Figure 4a). These rocks have medium porosity and moderate groundwater potential zones (Hazell et al., 1992 [73]), earning 9 and 10 in the overall priority vector.

### Table 3. Ideal values and overall ranking of surface parameters derived through supermatrix computation.

| Sl.No | Alternatives       | Total   | Normal   | Ideal   | Ranking |
|-------|--------------------|---------|----------|---------|---------|
| 1     | Floodplain         | 0.0573  | 0.1311   | 1       | 1       |
| 2     | Cropland           | 0.0446  | 0.102    | 0.7782  | 2       |
| 3     | Pediplain          | 0.0423  | 0.0967   | 0.7377  | 3       |
| 4     | DD *—low           | 0.0321  | 0.0734   | 0.5599  | 4       |
| 5     | LD *—high          | 0.0312  | 0.0713   | 0.5441  | 5       |
| 6     | Water bodies       | 0.0298  | 0.0545   | 0.4154  | 6       |
| 7     | Gentle slope       | 0.0231  | 0.053    | 0.4038  | 7       |
| 8     | Entisols           | 0.0227  | 0.0519   | 0.3958  | 8       |
| 9     | Gneiss             | 0.0218  | 0.05     | 0.3812  | 9       |
| 10    | Charnokite         | 0.0148  | 0.0339   | 0.2586  | 10      |
| 11    | Pediment           | 0.0127  | 0.029    | 0.2211  | 11      |
| 12    | Fallow land        | 0.0126  | 0.0289   | 0.2205  | 12      |
| 13    | Vertisols          | 0.0121  | 0.0277   | 0.2114  | 13      |
| 14    | Medium slope       | 0.011   | 0.0251   | 0.1917  | 14      |
| 15    | LD medium          | 0.0092  | 0.0211   | 0.161   | 15      |
| 16    | Built-up land      | 0.0087  | 0.0198   | 0.1512  | 16      |
| 17    | DD medium          | 0.0084  | 0.0191   | 0.1459  | 17      |
| 18    | Sandstone          | 0.0056  | 0.0173   | 0.1322  | 18      |
| 19    | Alfisols           | 0.006   | 0.0137   | 0.1048  | 19      |
| 20    | Dyke               | 0.0053  | 0.0122   | 0.0934  | 20      |
| 21    | Wasteland          | 0.0053  | 0.0121   | 0.0921  | 21      |
| 22    | Inceptisols        | 0.0052  | 0.012    | 0.0916  | 22      |
| 23    | LD—low             | 0.0051  | 0.0116   | 0.0882  | 23      |
| 24    | Structural hill    | 0.0044  | 0.01     | 0.0766  | 24      |
| 25    | Granite            | 0.0033  | 0.0076   | 0.0578  | 25      |
| 26    | DD—high            | 0.0033  | 0.0075   | 0.057   | 26      |
| 27    | Steep slope        | 0.0032  | 0.0072   | 0.0553  | 27      |

*LD—lineament density; DD—drainage density.*
Sandstone has a value of 18 because of its poorly sorted and highly cemented character, making it a low groundwater potential zone (Chilton and Seiler, 2006 [74]). On the other hand, Granites and dykes have a lower porosity (Verma and Patel, 2021 [75]) and are ranked with values of 20 and 25, respectively, as low groundwater potential zones. Geomorphologically, floodplains (rank 1, Table 3) and pediplains (rank 3, Table 3) yield moderate to good groundwater (Thapa et al., 2017 [76]), earning them higher rankings. Pediment ranks 11 due to its moderate to poor groundwater potential. Because they are unfractured rock with limited infiltration, structural hill landforms (rank 24, Table 3) have very low groundwater potential (Ramaiah et al., 2012 [77]). Cropland (rank 2, Table 3) and water bodies (rank 6, Table 3) both allow for a large amount of infiltration and have a strong groundwater potential, and as a result, cropland and water bodies are awarded higher rankings in terms of land use and land cover (Varughese et al. 2012 [78], Rajaveni et al., 2017 [60]).

On the other hand, built-up land and wasteland have a limited infiltration capability (Das, 2017 [79]), earning them a grade of 16 and 21, respectively (Table 3). The slope significantly influences surface water infiltration from the ground. If the slope percentage is relatively low, surface water, mostly made up of precipitation, has a greater opportunity to percolate into the subsurface over a longer period. Runoff is more immediate on steep slopes, resulting in less time for water to remain on the ground surface and a significant loss in groundwater recharge potential (Jaafarzadeh et al., 2021 [80]). Rankings of 7, 14 and 27 were calculated for the gentle, moderate and steep slope classes, respectively (Table 3). As far as drainage density is concerned, a high drainage density stimulates high runoff while a low density promotes infiltration (Rashid et al., 2012 [81], Bagyaraj et al., 2013 [82]), whereas lineament density, the process is reversed, meaning that high density promotes infiltration and low density leads to runoff (Lentswe and Molwalefhe, 2020 [83]). The overall rankings derived from the above parameters also substantiate this (Table 3).

Subsequently, the values that were calculated as ideal were then integrated after being assigned to the appropriate variables (subclasses). The overall cumulative values range between 1.6809 and 6.5366 (Figure 6a). In order to make the results easier to understand, they were reorganized into three distinct categories: high (6.5366–4.8461), moderate (4.8461–3.2275) and low (3.2275–1.6809) potential zones (Figure 6a). High prospect zones covering 210.92 sq. km are located sporadically in the northwestern and western regions of the resulting surface groundwater potential map (Figure 6a). The moderate zones with an area of 341.2 sq. km to the west, surround the high zones mentioned above. The areas with low potential, with 423.84 sq. km, are mainly observed in the southern and eastern parts of the study area (Figure 6a).

Next, six subsurface parameters viz: storage coefficient, specific capacity, transmissivity, permeability, aquifer thickness and water level were grouped below the criteria cluster and their subclasses under the alternative cluster. The deeper the aquifer thickness, the greater the fracture density and storage potential. The overall ranking value confirmed this with a ranking of 1 for deep aquifer thickness (Table 4), 8 for moderate, and 15 for shallow aquifer thickness (Raji and Abdulkadir, 2020 [84]). The water level is a significant component in assessing the groundwater potential since it immediately offers evidence about the storativity of groundwater. A shallow water level suggests a greater potential for groundwater (Chatterjee and Dutta, 2022 [85]). Accordingly, the shallow water level category received score of 2 (Table 4), whereas the moderate and deep water level categories receive scores of 10 and 14, respectively. High permeability results in a high groundwater potential zone (Machiwal et al., 2015 [86]). The acquired rankings also confirm this with 6, 7 and 16 for high, moderate and low categories of transmissivity (Table 4). A high storage coefficient corresponds to a good groundwater potential zone (5), a medium storage coefficient area to a medium potential zone (11) and an area with a low storage coefficient to a poor potential zone (17). Similarly, a high specific
capacity (Kumar et al., 2017 [88]) is recognised as a good groundwater potential zone (4), moderate specific capacity area as medium (9) and an area possessing low specific capacity as a poor potential zone (13) (Table 4).

Figure 6. Groundwater potential zone maps based on (a) surface parameters, (b) subsurface parameters, and (c) amalgamated parameters along with geo-positions of inventory wells.

Table 4. Ideal values and the overall ranking of subsurface parameters derived through supermatrix computation.

| Sl.No. | Alternatives                  | Total  | Normal | Ideal  | Ranking |
|--------|-------------------------------|--------|--------|--------|---------|
| 1      | Aquifer thickness—deep        | 0.0887 | 0.2085 | 1      | 1       |
| 2      | Water level—shallow           | 0.0614 | 0.1444 | 0.6929 | 2       |
| 3      | Permeability—high             | 0.0486 | 0.1143 | 0.5484 | 3       |
| 4      | Specific capacity—high        | 0.0363 | 0.0853 | 0.4094 | 4       |
| 5      | Storage coefficient—high      | 0.032  | 0.0753 | 0.3612 | 5       |
| 6      | Transmissivity—high           | 0.0287 | 0.0675 | 0.3237 | 6       |
| 7      | Transmissivity—moderate       | 0.0193 | 0.0453 | 0.2175 | 7       |
| 8      | Aquifer thickness—moderate    | 0.0163 | 0.0383 | 0.1838 | 8       |
| 9      | Specific capacity—moderate    | 0.0156 | 0.0367 | 0.1761 | 9       |
| 10     | Water level—moderate          | 0.0141 | 0.0331 | 0.1586 | 10      |
| 11     | Storage coefficient—moderate  | 0.0129 | 0.0304 | 0.146  | 11      |
| 12     | Permeability—moderate         | 0.0116 | 0.0273 | 0.1308 | 12      |
| 13     | Specific capacity—low         | 0.0097 | 0.0228 | 0.1092 | 13      |
| 14     | Water level—deep              | 0.0084 | 0.0198 | 0.0951 | 14      |
| 15     | Aquifer thickness—shallow      | 0.0071 | 0.0167 | 0.0803 | 15      |
| 16     | Transmissivity—low            | 0.0051 | 0.0121 | 0.058  | 16      |
| 17     | Storage coefficient—low       | 0.0048 | 0.0113 | 0.0542 | 17      |
| 18     | Permeability—low              | 0.0046 | 0.0109 | 0.0521 | 18      |
Thus, the total rankings produced by various aquifer parameters using the ANP model corroborate the fundamental aquifer characteristics (Nsiah et al., 2018 [89]; Dhakate, 2020 [90]; Hasan et al., 2021 [91]; Masoud et al., 2022 [92]). Subsequently, the derived ideal values (Table 4) were substituted by the respective factors, and by integrating all, subsurface parameters-based groundwater potential maps were derived. The resulting cumulative value for pixels varies from 3.0285 to 0.6042. They were then reclassified as high (3.0285–2.214), moderate (2.214–1.4122), and low (1.4122–0.6041) potential zones (Figure 6b). The high potential zone seems to transact as a linear patch from the middle to the northwestern area and comprises 175.57 sq. km. The moderate potential region also has a similar linear pattern covering 431.16 sq. km. At the same time, the low potential region appears to occupy the northeastern, southeastern, and southern parts of the study area as isolated pockets spanning an area of 369.2 sq. km (Figure 6b).

Based on the surface (Figure 6a) and subsurface potential maps (Figure 6b), it is inferred that most of the area has significant groundwater prospects. In contrast, the Tirruttani block is designated by the Central Ground Water Board (CGWB, 2007 [93]) as overexploited. In addition, the above maps revealed an intricate pattern in the spatial distribution of potential regions. Hence, to contemplate the collective impact, both the unclassified surface and subsurface potential maps were combined spatially, integrated, and then an “integrated groundwater potential zone” map was prepared. The resultant pixel values range from 9.5850 to 2.2311 and were later classified into high (9.5850–7.1337), moderate (7.1337–4.6824), and low (4.6824–2.2311) potential zones (Figure 6c).

From the resultant integrated groundwater potential map, the eastern and southern parts seem to have high potential (Figure 6c). The visual correlation of the high potential zone with the surface (Figure 6a) and subsurface parameter maps (Figure 6b) prepared earlier shows that, spatially, the zone is characterized by pediplain, high lineament density, moderate drainage density, cropland, moderate water level, deep aquifer thickness, high permeability, moderate transmissivity, a moderate to high storage coefficient, and a high specific capacity. The central area was revealed as a low potential zone (Figure 6c). All the surface and subsurface parameters in this low-prospect region are less conducive to groundwater (Figures 4a–g and 5a–f). The spatial assessment shows that, despite the alluvial plain, the least desirable parameters, namely land with and without scrub, plantation and fallow land, low lineament density, moderate to high drainage density, gentle to moderate slope, moderate to deep water level, low to medium permeability, medium to high transmissivity, low to medium storage coefficient, and low to medium-specific capacity are observed in this zone. The eastern and northern parts are categorized as a moderate groundwater potential zone (Figure 6c). The spatial correlation shows moderate potential parameters in this region. Thus, the results obtained corroborate the general opinion offered by many earlier workers (Garewal et al., 2015 [94]; Owolabi et al., 2020 [95]; Singha et al., 2021 [96]).

5.2. Validation of Results

The results of the surface, subsurface and integrated groundwater potential maps were validated using water level data. The water level was collected from 35 locations and based on their depths to ground level, fourteen wells were categorized as shallow (2.40 to 10 m bgl), thirteen as moderate (12 to 18 m bgl), and eight as deep (24 to 90 m bgl). This data was then spatially correlated with the above maps (Figure 6a–c). The frequency ratio method is used as an indicator for validating the potential maps (Ozdemir, 2011 [8]; Naghibi et al., 2015 [12]). The frequency ratio is an approach to bivariate statistics that may be described as \( FR = (W/TW)/(CP/TP) \), where \( W \) is some pixels of well, i.e., good, in each category, and \( TW \) is the total of good pixels in the study area. \( TP \) is the total number of pixels in the study area, and \( CP \) is the number of pixels in each potential zone category.
5.2.1. Spatial Correlation between Water Level and Surface Parameters-Based Groundwater Potential Zones

The number of pixels comprising each potential zone category was first calculated. This shows that the overall study area consists of 1,070,566 (TP) pixels. From this total, 466,483 (CP) fall in the high potential zone category, 374,608 pixels in the moderate, and 229,475 pixels in the low potential category. Then, by dividing the number of pixels in each category by total pixels, the CP/TP ratio was calculated. For example, the ratio between pixels under the high potential zone category to overall pixels is 0.3636. Subsequently, the W/TW value was calculated by dividing the number of wells in each water level category (W) by the total number of wells (TW). For instance, 13 wells fall into the shallow water level category in the high groundwater potential zone. Thus, the W/TW ratio is 0.3714. Using these derived values, the frequency ratio was calculated. Accordingly, the frequency ratio was calculated for all the water level categories. The results show that the shallow water level falling within the high potential zone category among various correlations has a clear correlation (0.8542). In contrast, all the other categories exhibit only a poor correlation (Table 5).

Table 5. Frequency ratio between water level and surface parameter-based groundwater potential zones.

| Potential Zone Category | No. of Pixels | CP/TP   | No. of Wells | W/TW   | FR     |
|-------------------------|---------------|---------|--------------|--------|--------|
| Shallow water level     |               |         |              |        |        |
| High                    | 466,483       | 0.435734929 | 13           | 0.371429 | 0.852419 |
| Moderate                | 374,608       | 0.349915839 | 1            | 0.028571 | 0.081652 |
| Low                     | 229,475       | 0.214349232 | 0            |        |        |
| Moderate water level    |               |         |              |        |        |
| High                    | 466,483       | 0.435734929 | 5            | 0.142857 | 0.327853 |
| Moderate                | 374,608       | 0.349915839 | 7            | 0.2     | 0.571566 |
| Low                     | 229,475       | 0.214349232 | 1            | 0.028571 | 0.133294 |
| Deep water level        |               |         |              |        |        |
| High                    | 466,483       | 0.435734929 | 3            | 0.085714 | 0.196712 |
| Moderate                | 374,608       | 0.349915839 | 3            | 0.085714 | 0.244957 |
| Low                     | 229,475       | 0.214349232 | 2            | 0.057143 | 0.266588 |
| Total                   | 1,070,566     | 35      |              |        |        |

5.2.2. Spatial Correlation between Water Level and Subsurface Parameters-Based Groundwater Potential Zones

Similarly, the spatial correlation between groundwater level categories and subsurface parameters based on potential groundwater zones shows that eleven out of fourteen shallow wells fall in the high potential zone. Out of 13 moderate water level wells, five fall in the high potential zone, four in the moderate potential zone and four in the low potential zone. Two wells in the deep water level well category fall in the high potential zone, one in moderate and five in low potential zones.

Using frequency ratios, the coincidence between water level categories and subsurface parameter-based groundwater potential was calculated (Table 6). This shows a good correlation between shallow water level and high potential zone (0.820193) and between deep water level and low potential zone (0.78834). In contrast, the other parameters have very poor correlations.
Table 6. Frequency ratio between water level and subsurface parameter-based groundwater potential zones.

| Potential Zone Category | No. of Pixels | CP/TP  | No. of Wells | W/TW  | FR      |
|-------------------------|---------------|--------|--------------|-------|---------|
| Shallow water level     |               |        |              |       |         |
| High                    | 410,225       | 0.383185 | 11           | 0.314286 | 0.820193 |
| Moderate                | 466,341       | 0.435602 | 1            | 0.028571 | 0.065591 |
| Low                     | 194,000       | 0.181213 | 2            | 0.057143 | 0.313336 |
| Moderate water level    |               |        |              |       |         |
| High                    | 410,225       | 0.383185 | 5            | 0.142857 | 0.372815 |
| Moderate                | 466,341       | 0.435602 | 4            | 0.114286 | 0.262363 |
| Low                     | 194,000       | 0.181213 | 4            | 0.114286 | 0.630672 |
| Deep water level        |               |        |              |       |         |
| High                    | 410,225       | 0.383185 | 2            | 0.057143 | 0.149126 |
| Moderate                | 466,341       | 0.435602 | 1            | 0.028571 | 0.065591 |
| Low                     | 194,000       | 0.181213 | 5            | 0.142857 | 0.78834  |

Total 1,070,566 35

5.2.3. Spatial Correlation between Water Level and Integrated Groundwater Potential Zones

The spatial correlation between water level categories and integrated subsurface parameters shows that 13 shallow wells are in the high potential zone. One is in the moderate potential zone, which is similar to the results obtained from the correlation between water level and surface parameters. However, for the moderate category, out of 13 wells, 12 wells are in the moderate category, and one well is in the deep category. In the deep water level well category, all eight wells fall exactly in the low potential zone category.

The frequency ratio values between water level categories and integrated groundwater potential zone categories (Table 7) showed a very good correlation in all categories. The frequency ratio value between shallow water level and the high potential category is 1.021087. Similarly, the frequency ratio value between moderate water level and the moderate potential zone is 0.756871, thus indicating a correlation. Likewise, deep water level wells and low potential zones also exhibited a good correlation (1.247328).

Table 7. Frequency ratio between water level and amalgamated groundwater potential zones.

| Potential Zone Category | No. of Pixels | CP/TP  | No. of Wells | W/TW  | FR      |
|-------------------------|---------------|--------|--------------|-------|---------|
| Shallow water level     |               |        |              |       |         |
| High                    | 389,427       | 0.363758 | 13           | 0.371429 | 1.021087 |
| Moderate                | 484,959       | 0.452993 | 1            | 0.028571 | 0.063073 |
| Low                     | 196,180       | 0.183249 | 0            | 0   | 0       |
| Moderate water level    |               |        |              |       |         |
| High                    | 389,427       | 0.363758 | 0            | 0   | 0       |
| Moderate                | 484,959       | 0.452993 | 12           | 0.342857 | 0.756871 |
| Low                     | 196,180       | 0.183249 | 1            | 0.028571 | 0.155916 |
| Deep water level        |               |        |              |       |         |
| High                    | 389,427       | 0.363758 | 0            | 0   | 0       |
| Moderate                | 484,959       | 0.452993 | 0            | 0   | 0       |
| Low                     | 196,180       | 0.183249 | 8            | 0.228571 | 1.247328 |
| Total                   | 1,070,566     |        | 35           |       |         |

The water level and the surface potential map show a good correlation for the high potential category, whereas the other classes only show a weak correlation. However, the subsurface parameter strongly correlates between shallow water level and high potential
zone and between deep water level and low potential zone. The other parameters, however, showed a very weak correlation. Interestingly, the frequency ratio values obtained for the integrated groundwater potential zone show a precise correlation in all classes. Thus, from the above, it can be surmised that the integrated map comprising both surface and subsurface parameters yields better results, followed by subsurface and surface parameter-based potential maps.

6. Conclusions

The current study was undertaken to identify and classify groundwater potential zones in the Tiruttani region using the RS/GIS-based ANP model. Three groundwater potential maps were created using (1) surface parameters, (2) subsurface parameters, and (3) a combined map by integrating them. The validation with ground truth data reveals that the surface parameter-based output accurately predicted the shallow potential zones, whereas the subsurface-based model foresaw the deep zones. On the other hand, the integrated method successfully predicted the shallow, moderate, and deep potential zones. The findings suggest the need of an integrated approach, especially under the current global groundwater depletion scenario.

Considering the integrated map, the good groundwater potential region tends to cover only a small area of 172.94 sq.km (17.72%), indicating that the larger portion of the study area is experiencing severe groundwater scarcity. At the same time, moderate potential zones comprise 393.01 sq. km (40.27%) and the low potential zones are 410 sq. km (42.01%). As per the CGWB report, the water table is drastically depleting in and around the study area. Interestingly, the area receives 1104 mm of mean annual rainfall and has a very good aquifer thickness. By augmenting site-specific recharge mechanisms, the groundwater resource in the Tiruttani area could be enhanced.

Our findings demonstrate that the ANP-based GIS model is a cost-effective and dependable method for delineating groundwater potential zones in hard rock terrain. Though ANP is ideal for establishing complex interrelationships between real-world factors, it is recommended that relevant criteria and influencing factors be brainstormed and selected based on the hydrological conditions of the region. The results can be further improved by using appropriate high resolution satellite images and DEM. Incorporating sizable pump test data derived from various depths and across several thematic sub-classes can yield even better results. In terms of future methodology, developing techniques based on machine learning is an exciting prospect.

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