European Economic Letters
ISSN 2323-5233
Vol 14, Issue 4 (2024)
http://eelet.org.uk

THE ECOLOGICAL IMPACT OF A CERTAIN PLACE AREAS BY USING GEO-SPATIAL TECHNIQUES

[1]Mankari Sapana Sadashiv
[1]Research Scholar, Department of Computer Science, Mansarovar Global University, Billkisganj, Sehore, Madhya Pradesh-466001
[2]Dr. Manisha Yadav
[2]Research Guide, Department of Computer Science, Mansarovar Global University, Billkisganj, Sehore, Madhya Pradesh-466001

ABSTRACT
This article presents the most popular methods for processing remotely sensed data, with an emphasis on image processing techniques and the possibilities of GIS technology for their applications using GIS and remote sensing, many control management programs may be quickly designed. Another point to note is that several research have addressed developmental planning concerns by combining remote sensing with GIS. In addition to providing a solid foundation for developing baseline information on natural resources a need for planning, implementing, and monitoring any developmental program remote sensing also offers this service.

Keywords: Internet of Things, soil moisture, Information, and visualization.

INTRODUCTION
Internet of Things (IoT) connected devices and devices placed strategically throughout ground water locations is the backbone of this breakthrough. Among the many pieces of information gathered by these sensors are readings of the surrounding environment, including things like air quality, soil moisture, humidity, and temperature. By continuously collecting this attributed data, we can not only assess the groundwater situation in real-time, but we can also analyze trends and use predictive modelling to plan for future resource management.
The data collected from different sensors is easily incorporated into spatial databases, which enables the visualization and analysis of information with a geographic reference. In order to create spatially explicit databases that measure and map the distribution, condition, and dynamics of ground water, Geographic Information Systems (GIS) are crucial in organizing this data. Through the use of this spatial dimension, stakeholders are better able to understand the geographical connections between various resource metrics and to spot any patterns or correlations.
In addition, a more complete picture of the relationship between groundwater is shown by superimposing ascribed IoT data onto geographical datasets. Thanks to this cooperation, trouble spots, outliers, or crucial zones in the ecosystem may be located. To illustrate the idea, sensors connected the IoT might allow for the real-time monitoring of water quality in various bodies of water. This data, when plotted on a map, can identify where pollution is coming from or what needs fixing right away.
Any information that makes reference, either explicitly or implicitly, to a physical place is considered spatial data. Geographic information systems (GISes) are the most frequent tools for processing and analysing this data. GISes help users in many different sectors grasp the spatial context, patterns, and connections in order to make better decisions, communicate more effectively, and conduct additional analyses.
Spatial data, sometimes known as geospatial data or geographic information, is numerical information that often uses a geographic coordinate system to depict a real-world object, whether it be natural or man-made. Cartesian, often called "x" and "y" coordinates, are two-dimensional (2D) geographic references used by the system. Having said that, spatial data encompasses a lot more than just the locations shown on a two-dimensional map. Images shown as rasters (a grid of pixels) and descriptions of specific geographic features are further examples of spatial information. Lines and polygons are also examples of geometric forms.

LITERATURE REVIEW
Aderemi, Banjo Ayoade et.al. (2021). an ecosystem's sustainability and human resilience to climate change and unpredictability are both impacted by groundwater, the world's greatest dispersed reservoir of freshwater. Nevertheless, groundwater supplies are not static; they may shift due to land use, abstraction, and climatic fluctuations. Many traditional approaches, including specific numerical methods for groundwater modelling, have been put forth to address these issues. The widespread use of IoT devices has promoted better data collection practices for groundwater resource management. Also, data on availability and changes to groundwater resources is crucial for data-driven groundwater resource management to work properly. Currently, there are research indicates that managers of groundwater do not possess the essential data due to the absence of an efficient and up-to-date framework for managing this resource. Research also shows that present methods of data collecting are inefficient compared to the demands of computational models and management objectives.
Singh, Manmeet et.al. (2020). Every single living thing on Earth needs water. The urgency of water resource conservation is rising in tandem with the exponential rise in the global population. The problem of water management

has been the subject of several expensive and energy-intensive proposals in the past. The smart water management system is becoming more and more of a priority as the IoT takes root. Prior to doing a comprehensive review of all existing water management systems that rely on the internet of things, this research thoroughly examines the architecture and different components of such a system. Additionally, a number of measuring metrics, including some of the metrics used by water management systems include salinity, water level, pH, and turbidity. that have been suggested in the literature. These parameters have also been used to compare different systems. Lastly, the survey is used to compile qualities that are crucial to these systems that need to be included in future designs.

Senozetnik, Matej et.al. (2018). Effective management of groundwater is crucial for any metropolitan system. As a result, different stakeholders and decision-makers require data that may be requested. For a variety of uses, this article lays forth a conceptual and practical framework for gathering, analysing, and distributing groundwater data. Continuously gathered from many sources and converted into a standard format, it enables regulated access to the data. This method ensures that both current and historical data are accessible at all times, allowing for real-time queries and further analysis. Additional data gathering domains may be added to the proposed system down the road.

RESEARCH METHODOLOGY

Two distinct types of data products are used to assess the effects of a section of the Penna River on a small number of environmental variables. "Spatial data" refers to the topographical and thematic data, while "attribute data" describes the field data and collateral data.

Data products can be either spatial or non-spatial/attribute. The geographic information system includes features such as hydrogeology, drainage, physiography, base information, slope, and a map of possible groundwater. Social and economic factors, soil quality indicators, and metrics for groundwater quality make up the non-spatial or attribute data.

Spatial information

Toposheets from the Survey of India and data collected by satellite sensing systems make up the spatial data. With the LISS-III sensors of the IRS-ID satellite, the satellite's sensors are panchromatic. A toposheet of India was surveyed at a scale of 1:50,000.

Attribute information

There were a number of prime water quality measures tested after sample collection, including Elements such as magnesium, sulfate, chloride, nitrate, total hardness, alkalinity, and pH. The following soil quality metrics were measured in the samples: organic matter, bulk density, soil moisture, carbon, pH, electrolyte concentration, calcium, magnesium, nitrate, and potassium.

GIS Information Sources

We used four separate sources to get all of the data we needed for our water quality model study.

(i) Satellite image
(ii) Toposheets (SOI)
(iii) Collateral information
(iv) Field data

CREATION OF SPATIAL DATABASE

Thematic layers

In order to prepare thematic layers, one must use digitize outdated maps, extract crucial data from digital image processing RS, from field data. Based on several types of maps, including topographical, existent, field, and RS data, ArcGIS software was used to construct thematic maps that pinpointed the locations of GWPZ inside the study area. Monsoon, slope, and vadose zone layers were comprised of these sets of maps, together with geology, geomorphology, LULC, DD, soil types, and WLF before and after. (Shekhar and Pandey, 2014). The maps were created at a scale of 1:50,000. the SRTM

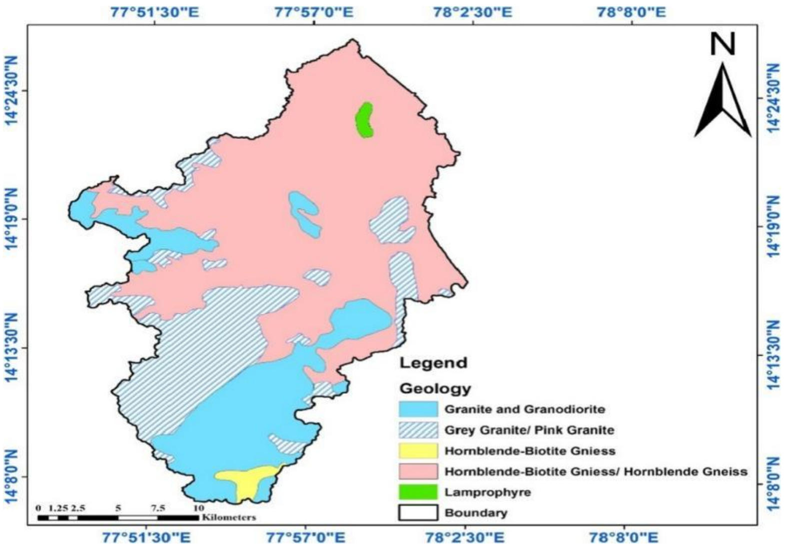

Fig. 1. Geology.

Assignment of weights and weights normalization

The AHP of a constructible option, in which the issue is partitioned into several restrictions, merged in a multi-level structure, judgements about the overall significance of component groups are made, as well as conflicting results (Saaty, 1999). The AHP relies on expert opinion to determine priority weights and is based on the idea of measurement by pairwise comparison matrix (PCM). Using weightages ranging from 1 to 9, the PCM is computed, revealing the relative frequency of each map's significance (Saaty 1980, 1990, 2004, 2008). Thematic strata' PCMs are compared using a scale based on factors including slope features, DD, WLF both before and after the monsoon, VZ, soil types, LULC, and geomorphology.

We classified the restrictions according to PCM and used the relative weight matrix and normalised main eigen value to get the impact % of the thematic layers. The fact that there are more than five classes in each theme tier suggests that the interdependencies among them are too complicated. That is why AHP is used to establish the link between these seven theme maps, which are accomplished via various classes. Implementing AHP in the context of theme layers and comparison classes independently incorporates the corresponding advancements (Saaty, 1980, 2004).

Pair wise comparison matrix (PCM)

In the 8 × 8 pairwise matrix that is currently being created, the eight thematic layers—The abbreviations GM, GE, LULC, DD, soil, WLF, VZ, and soil all stand for different fields of study: geomorphology, geology, land use/landcover, drainage density, soil types, water level fluctuations, vadose zone, and slope—are integrated based on the correlations and relative importance of these layers. the main component matrix (PCM) and normalized values and eigenvectors, respectively, based on the relative significance.

As stated in previous studies, If the Consistency Ratio (CR) is less than or equal to 0.1, it means the reciprocal matrix is suitable; if it's larger than 0.1, it means the PCM has to be modified. This is the basic premise for assessing the order of comparison.

$$\mathrm{CR} = \frac{CI}{RI}$$

CI: Index of Consistency; RI: It is the Random Consistency Index.

$$\mathrm{CI} = \frac{\lambda max - n}{n-1}$$

"n" is the number of comparisons, while "λmax" is the principal eigen value. A high degree of consistency is shown by the results of Λmax = 9.8997, n = 8, RI = 1.41, CI = 0.1124, and CR = 0.08 are the values used for the consistency check of the theme layers.

Table 1 AHP scale (Saaty, 2008).

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

Table 2. Pair-wise comparison matrix for the AHP process.

Thematic map	GM	GE	LULC	DD	WLF	Soil	Slope	VZ
GM	1.00	0.50	0.33	5.00	5.00	0.50	1.00	1.00
GE	5.00	1.00	0.25	4.00	1.00	0.50	0.50	3.00
LULC	3.00	4.00	1.00	5.00	2.00	0.33	3.00	0.25
DD	0.20	0.25	0.20	1.00	0.33	0.25	0.20	0.33
WLF	0.20	1.00	0.50	3.00	1.00	0.33	2.00	1.00
Soil	2.00	0.50	3.00	4.00	3.00	1.00	3.00	2.00
Slope	1.00	2.00	0.33	5.00	0.50	0.33	1.00	0.20
VZ	7.00	0.33	4.00	3.00	1.00	0.50	5.00	1.00

Table 3 Standardized pair-wise comparison matrix and theme parameter weights

Thematic map	GM	GE	LULC	DD	WLF	Soil	Slope	VZ	Normalized weight	CR
GM	0.052	0.052	0.035	0.167	0.361	0.133	0.064	0.114	0.12	0.08
GE	0.258	0.104	0.026	0.133	0.072	0.133	0.032	0.342	0.14	
LULC	0.155	0.418	0.104	0.167	0.145	0.089	0.191	0.028	0.16	
DD	0.010	0.026	0.021	0.033	0.024	0.067	0.013	0.038	0.03	
WLF	0.010	0.104	0.052	0.100	0.072	0.089	0.127	0.114	0.09	
Soil	0.103	0.052	0.312	0.133	0.217	0.267	0.191	0.228	0.19	
Slope	0.052	0.209	0.035	0.167	0.036	0.089	0.064	0.023	0.08	

Table 4. Assigned and normalized weights.

Theme	%area	AHP weight	Fuzzy membership	Class
Geology	56.75	14	0.96	Hornblende-biotite gneiss/hornblende gneiss
	20.59		0.75	Granite and granodiorite
	0.44		0.65	Lamprophyre

	21.10		0.45	Grey granite/pink granite
	1.12		0.85	Hornblende-biotite gneiss
Geomorphology	54.05	12	0.98	Denudational origin-pediment-Pedi plain complex
	3.01		0.03	Denudational origin-low dissected hills and valleys
	2.70		0.38	Waterbodies
	1.92		0.48	Structural origin-low dissected hills and valleys
	38.33		0.38	Denudational origin-moderately dissected hills and valleys
Landuse/landcover	21.98	16	1.91	Forest, evergreen/semievergreen
	38.01		1.39	Agriculture, cropland/plantation
	11.56		0.24	Agriculture, fallow land
	6.01		0.86	Barren/uncultivable/wastelands, scrubland
	4.18		0.00	Wetlands/waterbodies
	10.48		0.94	Dense forest
	7.79		0.00	Built-upland
Drainage density	11.49	3	0.57	0–2.06km/km^2
	23.11		0.89	2.06–3.60km/km^2
	26.44		1.00	3.60–5.37km/km^2
	25.98		1.89	5.37–8.21km/km^2
	12.97		1.28	8.21–15.06km/km^2
Soils	58.01	19	1.45	Loamy-skeletal, mixed (Calcareous)
	0.40		0.00	Fine, Montmorillonite (Calcareous)
	3.57		0.54	Rocklands & clayey-skeletal, mixed
	38.02		0.71	Rocklands &loamy-skeletal, mixed
Slope	49.61	8	1.39	0–5
	26.02		0.67	05–10
	12.35		0.20	10–25
	7.78		0.00	25–45
	4.25		0.75	N45
Water level fluctuations	5.49	9	0.75	0.0–3.3
	3.73		0.80	3.3–5.8
	31.48		1.33	5.8–8.1
	44.12		0.98	8.1–10.2
	15.19		1.12	10.2–14.4
Vadose zone	18.18	19	0.80	1.9–8.8
	20.09		1.33	8.8–16.1
	47.27		0.98	16.1–22.4
	9.51		1.12	22.4–30.7
	4.95		0.00	30.7–41.3

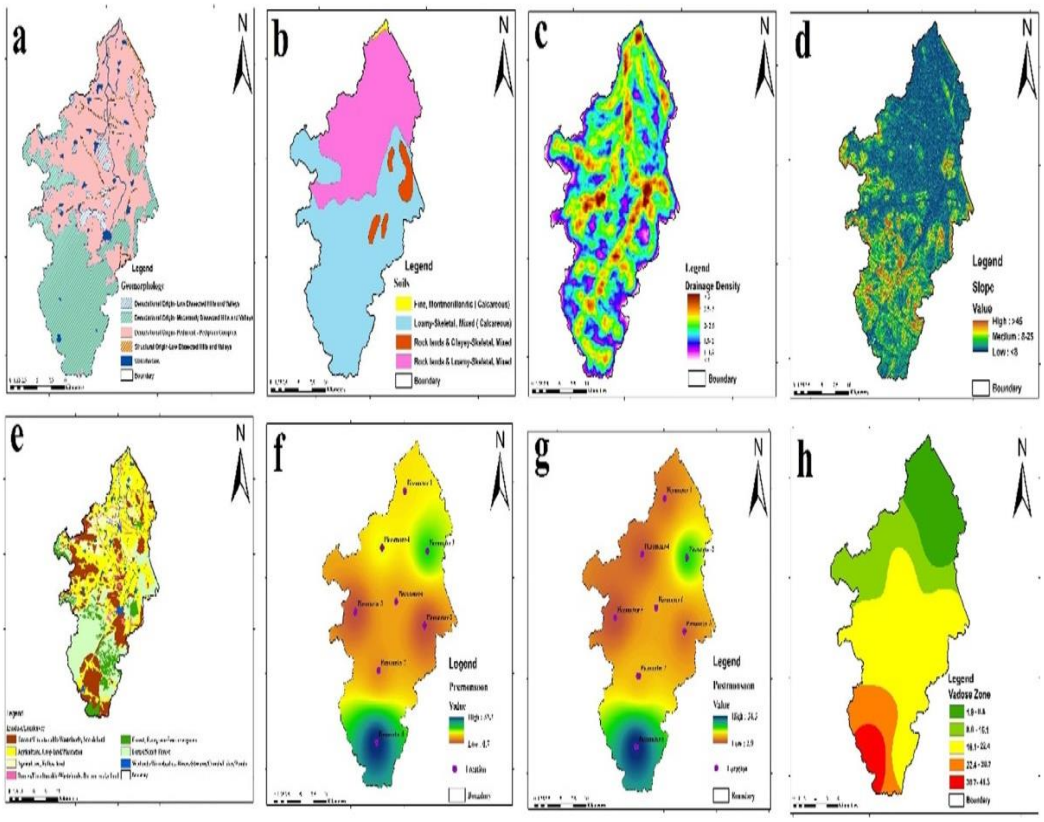

Fig.2.a Geographical feature, b Soil types, c Density of drainage, d Slope, e Land use/cover, and f Changes in water levels before the monsoon and after the rains Vadose Zone, Fluctuations.

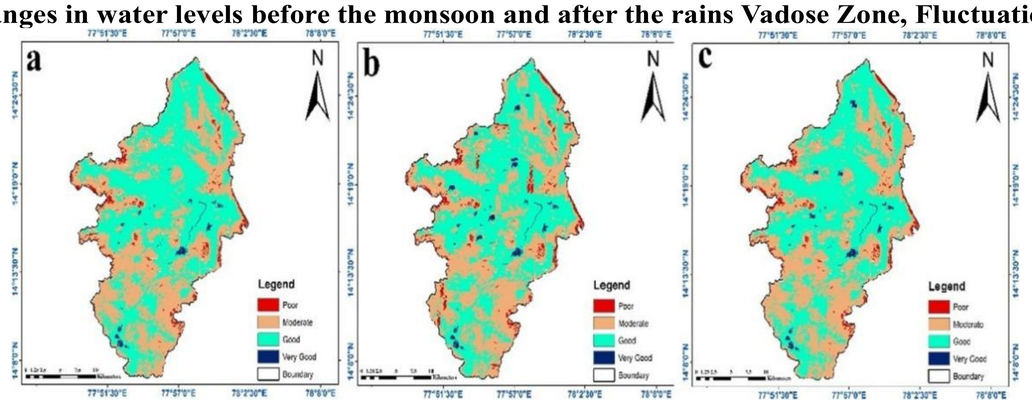

Fig.3.Integrated AHP-Fuzzy, a Zone of Groundwater Potential, b Zone of Fuzzy Logic, c Zone of Slope.

Table5 Ground water Potential Zones through AHP.

Ground water potential zone	% area	Area (km^2)
Poor	2.36	11.47
Moderate	44.68	217.56
Good	52.09	253.67
Very good	0.87	4.24

Thematic maps' relative effect is determined by ranking parameters including lithology, grade, LULC, soil type, depth, vertical zone, and slope, using a similar procedure. Table 4. shows how important each component is in determining the probability of GWPZ, which were based on a PCM among the parameters. The following are the criteria for each: lithology, LD, LULC, soil types, DD, VZ, rainfall, and slope.

CONCLUSION

The dire state of the region's water supply is due to both climatic and geomorphic factors. The expansion of agricultural operations is thus being hindered by this. They may also be used as resources with the right management, according to the extensive research on the geomorphic state.

REFERENCES

1. Aderemi, Banjo Ayoade & Olwal, Thomas & Ndambuki, Jm & Rwanga, Sophia. (2021). A Review of Groundwater Management Models with a Focus on IoT-Based Systems. 10.20944/preprints202107. 0227.v3.
2. Singh, Manmeet & Ahmed, Suhaib. (2020). IoT based smart water management systems: A systematic review. Materials Today: Proceedings. 46. 5211-5218. 10.1016/j.matpr.2020.08.588.
3. Senozetnik, Matej &Herga, Zala & Šubic, Tine &Bradeško, Luka & Kenda, Klemen & Klemen, Kristina &Pergar, Petra &Mladenić, Dunja. (2018). IoT Middleware for Water Management. Proceedings. 2. 696. 10.3390/proceedings2110696.
4. Shit, Pravat & Shit, Pravat & Brahma, Soumen. (2022). GIScience application for groundwater resources management and decision support. 10.1016/B978-0-323-99963-2.00014-6.
5. Singh, Ajay. (2014). Groundwater resources management through the applications of simulation modeling: A review. Science of The Total Environment. 499. 10.1016/j.scitotenv.2014.05.048.
6. Kadham, Shaymaa & Ahmed, Mohammed & Abbass, Nisreen &Karupusamy, Sathishkumar. (2022). IoT and artificial intelligence–based fuzzy-integral N-transform for sustainable groundwater management. Applied Geomatics. 10.1007/s12518-022-00479-3.
7. Ilie, Codrina& Gogu, Radu. (2019). Current trends in the management of groundwater specific geospatial information. E3S Web of Conferences. 85. 07020. 10.1051/e3sconf/20198507020.
8. Nampak, Haleh & Pradhan, Biswajeet &abdmanap, Mohamad. (2014). Application of GIS based data driven evidential belief function model to predict groundwater potential zonation. Journal of Hydrology. 513. 283–300. 10.1016/j.jhydrol.2014.02.053.
9. Abdelkareem, Mohamed & Abdalla, Fathy. (2021). Revealing potential areas for water resources using integrated remote-sensing data and GIS-based Analytical Hierarchy Process. Geocarto International. 37. 1-19. 10.1080/10106049.2021.2005155.
10. Chonattu, Jaseela& Prabhakar, Kavya & Harikumar, P S. (2016). Geospatial and Statistical Assessment of Groundwater Contamination Due to Landfill Leachate—A Case Study. Journal of Water Resource and Protection. 08. 121-134. 10.4236/jwarp.2016.82010.
11. Rao, Xiaokang& Ma, Rui & Zhang, Li & Liu, Jia. (2022). Research and design of a digital twin-driven smart river basin platform. Metaverse. 3. 11. 10.54517/met.v3i2.1815.