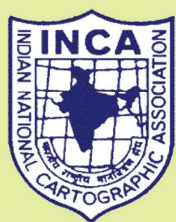
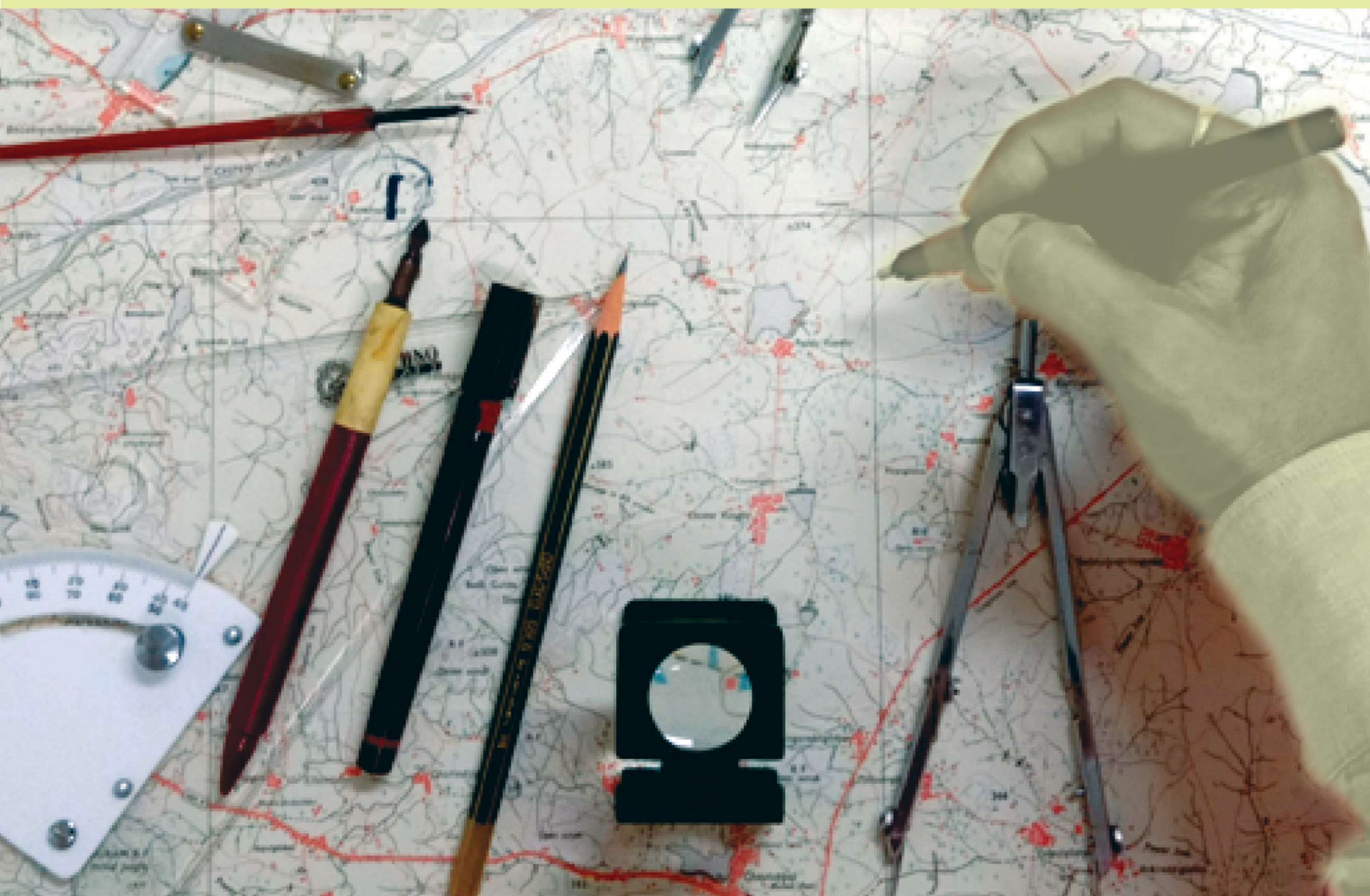


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Headquarters: Survey of India, Uppal, Room No. 234, APGDC Block
Hyderabad – 500 039 (Telangana, India)

Email: secretarygeneralinca935@gmail.com / editorinca.journal@gmail.com

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Regression-Based Integration of ICESat-2, GEDI and SRTM Data for DEM Generation

K. R. Remitha*, Hina Pande and Poonam Seth Tiwari

Indian Institute of Remote Sensing (IIRS), 4 Kalidas Road, Dehradun (India)

**Corresponding Author's Email: remitha10042001@gmail.com*

Abstract

Large-scale accurate DEMs are important topographic data for a variety of applications from environmental management and hazard assessment to urban planning and infrastructure development. DEMs have inherent errors due to their different acquisition process, and these errors are also related to terrain features. Additionally, global SRTM data is shown to have a large uncertainty, especially among areas with large canopy coverage and uneven topography. Studies on enhancement of DEM accuracy have been carried out in many researches. Current study involves in generation of improved DEM using Ice, Cloud, and land Elevation Satellite-2 (ICESat-2), Global Ecosystem Dynamics Investigation (GEDI) and Shuttle Radar Topography Mission (SRTM) data of Delhi with multiple regression techniques. It is a synergistic framework approach enabling to combine current multiple space-based terrain data sources for large-scale DEM generation. The ICESat-2 ATL08 terrain dataset is taken as the reference observations, while the GEDI Level 2A terrain data and the SRTM DEM are used as predictor variables. ICESat-2 and GEDI points were filtered to remove non-viable points based on defined criteria. Different regression models applied for integrating data to determine their performance and identify the most robust one. Random sampling points were extracted from generated DEMs for testing its accuracy. A visual comparison of the generated DEMs revealing unlike the SRTM DEM, containing many noisy artifacts, the DEMs produced in this study are notably smooth and free from these disruptive noise elements. RMSE of Delhi DEM generated using Random Forest Regression (RFR), Support Vector regression (SVR) and Artificial Neural Network (ANN) were 15.97, 15.23, 8.67. MAE of DEM's were 13.95, 14.62 and 6.77.

The present study emphasizes the advantages of integrating various space-based altimeter data and underscores the need for comprehensive data integration models. Nevertheless, the applicability and efficiency of the suggested workflow for creating global or regional DEM require further exploration in larger and more varied landscapes.

Keywords: Regression, ANN, DEM, ICESat-2, GEDI, SRTM.

Introduction

Digital elevation models are the digital representation of elevation of earth surface (Huang *et al.*, 2024), which serve as a critical data source for various engineering, science and environmental applications. Precise elevation data has significance in multiple domains, such as

hydrological watershed delineation, urban planning, drainage modelling and topographic analysis, where decision making and precise modelling is essential (Goud & Bhardwaj, 2021). However, ensuring their accuracy remains a significant challenge, as errors inherent in data acquisition and processing caused by factors like

collection techniques, terrain complexities and processing methods (Papasaika *et al.*, 2009), leading researchers to focus on improving DEM accuracies.

Numerous open source DEMs are available, which are generated by different techniques such as contour interpolation, SAR interferometry, Photogrammetry and LiDAR (Light Detection and Ranging) (Narin & Gullu, 2023). LiDAR is a technology which utilizes laser pulses to measure precise elevation data directly, it also has the high potentiality to penetrate the partial forest cover and hence allows in generating more accurate DEMs even in densely vegetated regions (Huang *et al.*, 2024). Unlike airborne and terrestrial LiDAR, space borne LiDAR enables in capturing continuous, consistent and extensive coverage of terrain features. There are many satellite-based LiDAR missions including, ICESat-1 and 2, CALIPSO, EnMAP, GEDI and so on. Among them ICESat-2 and GEDI datasets are used in the current study for its extensive data availability and coverage enabling them for elevation analysis. ICESat-2 and GEDI utilize similar ranging concept providing geolocated elevation data (Liu *et al.*, 2021). GEDI employing full wave form, multibeam laser system capturing reflected waveforms, L2 products of the GEDI are which contains processed valid surface returns, few quality flags are provided to filter out waveforms of poor quality due to poor geolocation, signal quality, cloud or terrain conditions. GEDI L2A is the specific product providing height measurements computed corresponding to the elevation of lowest detected return representing ground elevation (Dubayah *et al.*, 2020). Similarly, ICESat-2 ATL08 product provides elevation measurements utilizing surface finding algorithm, in which medium and high confidence ATL03 photons along with noise removed photons through DRAGANN technique and by ground finding median filters ground and top of canopy is flagged, with flag 1 depicting ground surface. ICESat -2 has been demonstrated in extracting high accuracy bare earth elevation (Shang *et al.*, 2022) for its photon counting technique, it gives good vertical precision (Yong *et al.*, 2023). Thus, both ICESat-2 and GEDI have capability in generating high precision DEMs.

Leveraging the high precision and extensive coverage of GEDI and ICESat -2 data, many researchers

have integrated these datasets with other global DEMs to improve their accuracy. To attain this, various regression techniques are employed by researchers, enabling effectively reducing the discrepancies and enhancing overall reliability of the DEM. Regression technique establish statistical relationship between input variables and generate output based on the relationship built, this helps in refining the DEM in order reduce the inconsistency in the values of elevation. Various regression models include RFR, MLR (Multiple Linear Regression), SVR, ANN and so on.

Studies like (Narin *et al.*, 2024) used different machine learning regression techniques in improving the DEM's accuracy, also (Pancholi *et al.*, 2023) simulated ICESat-2 DEM with several regressions and MLP regressor resulted in giving good results. In the regions of Lacchiwal Reserve Forest and Bhadra wildlife sanctuary performance of MERIT DEM is accessed with ICESat-2 as reference data, this resulted in confirming the accuracy specifications of MERIT DEM are within limit (Giribabu *et al.*, 2023). (Tian & Shan, 2024) integrated multiple spaceborne DEMs with many regression methods exhibited reduction in DEM errors. These findings prove that integration of LiDAR with global DEM's, improves the accuracy of the DEM.

Thus, the current study involves in generation of DEM by various regression techniques such as RFR, SVR and ANN by integrating ICESat-2 and GEDI data with SRTM DEM. This is a statistical approach in generating continuous DEM, on having ICESAT-2 as the reference and other two as the predictor variable.

Study Area

Delhi, the capital territory of India, is geographically situated between 76.50° to 77.20° E longitude and 28.24° to 28.53° N latitude, encompassing an area of approximately 1483 km² (Fig. 1). Bounded by Haryana and Uttar Pradesh, this region is a dynamic confluence of physiographic units and urban density. According to the 2011 Census of India, about 75% of its area is urbanized, with a population exceeding 16.78 million (Economic Survey of Delhi, 2022). Delhi's terrain is influenced by diverse geomorphological features, being a transitional zone between two major river plains, the

Ganga-Yamuna plain in the east and the Satluj-Ravi plain in the north, while also encompassing the terminal ridge of the Aravalli hill ranges. This diverse topography, coupled with extensive human-induced land cover changes, makes Delhi a compelling case for evaluating

elevation modelling accuracy in urban and semi-natural settings. Additionally, elevation data here is crucial for urban planning, flood risk management, and infrastructure development.

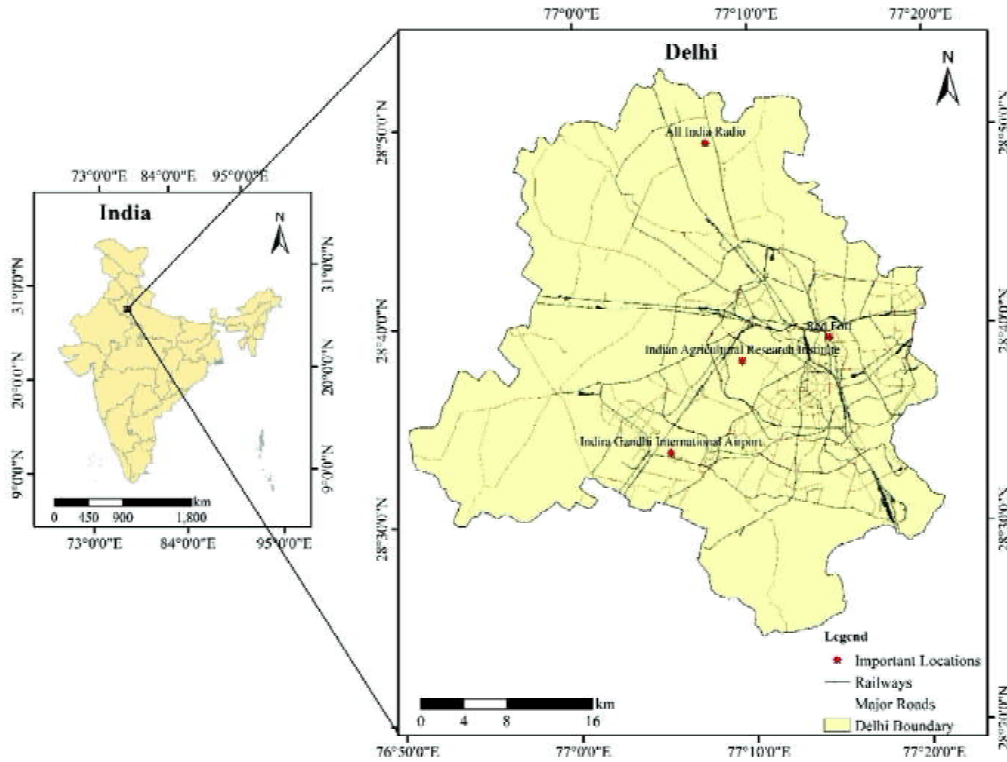


Fig. 1 : Location Map of the Study Area

Data Base

The study incorporates multiple spatial layers to support elevation modelling and validation across the selected regions. These datasets were used for tasks including

model training, prediction, and accuracy assessment. Care was taken to ensure spatial consistency, relevance to the study objectives, and suitability for machine learning integration. A summary of the datasets used and their roles is presented in Table 1.

Table 1: Data and their sources

Data	Product/ Date	Source
ICESat 2	ATL08 /27-10-2018 to 16-11-2023	https://openaltimetry.earthdatacloud.nasa.gov/data/icesat2/
GEDI	L2A_V002 /09-01-2019 to 16-11-2023	https://lpdaac.usgs.gov/products/gedi02_av002/
SRTM DEM	1-Arc second Global	https://earthexplorer.usgs.gov/

ICESat 2

Advanced Topographic Laser Altimeter System (ATLAS) is the photon counting instrument used in ICESat-2 (Neuenschwander *et al.*, 2022). It uses multibeam laser operating at 532nm of electromagnetic spectrum to

determine the reflected photon's X, Y, Z positions and six beams pairing 3 as per transmitting energy as strong and weak. These beams are named as ground track left and right along with number of pair such as 1, 2 and 3. Each strong or weak beam is separated by 3 km across track. Within each pair left/right spots are separated by 90 m

across track and 2.5 km along the track (Neumann *et al.*, 2023). ATL08 is a product of ICESat 2 providing terrain height, canopy height and canopy cover. Terrain surface elevation is given along track at fixed 100 m segment size (Neuenschwander *et al.*, 2022) *h_{te}_best_fit* parameter of ATL08 is used to generate Dem (Narin & Gullu, 2023). For this study ATL08 data from October 2018 to November 2023 are downloaded in csv format from openaltimetry (Khalsa *et al.*, 2020).

GEDI

GEDI is a full waveform Lidar system sending 3 laser pulses of near infrared wavelength. These pulses are split into 8 beams each separated 600 m apart across track with Footprint of 25m, of spacing 60 m along track. Level 2 product of GEDI contains geolocated information of return waveforms. Ground elevation, relative return

energy metrics and canopy top height are included in GEDIL02_A product (Dubayah *et al.*, 2020).

Methodology

The methodology adopted in this study involves a systematic workflow for generating high-resolution Digital Elevation Models (DEMs) using machine learning and deep learning approaches. The process is structured into key stages including data preprocessing, model training, hyperparameter optimization, prediction, and validation. Three modelling techniques, RFR, SVR, and ANN, were implemented to assess their capability in predicting surface elevation by learning from spatial and elevation-based input features. The workflow ensures comparability of model outputs by maintaining consistent input parameters and evaluation metrics. An overview of the entire process is illustrated in Fig. 2.

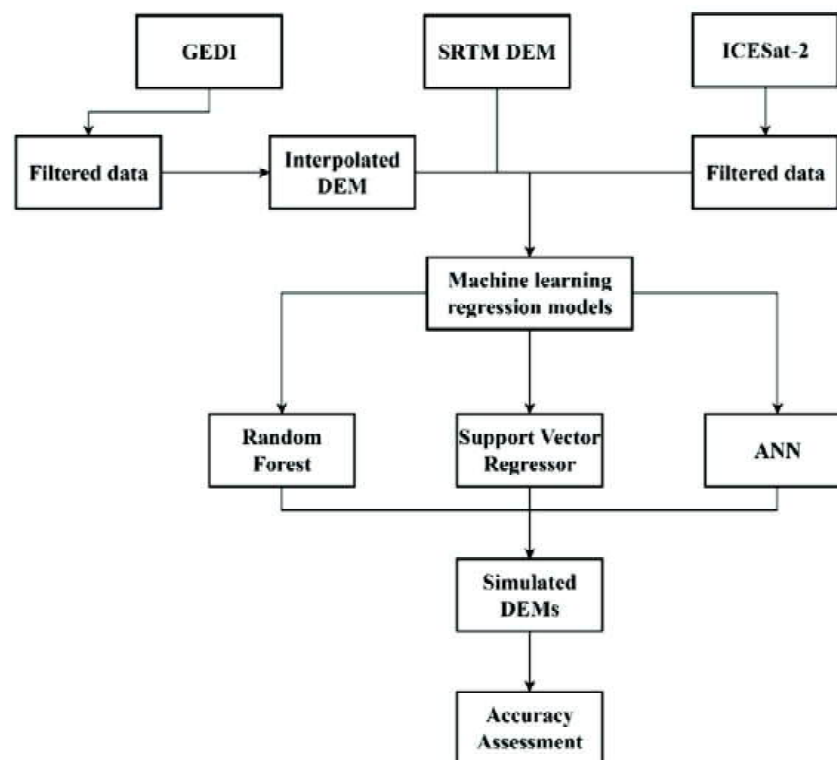


Fig. 2: Flow Chart of Methodology

Data filtering

For current study GEDIL02_A products are queried for the study area which are processed and extracted to shape

file using python script of GEDI subsetter (Browse LP DAAC Data User Resources / GEDI-Subsetter - Earthdata Source Code Repository, n.d.), and the footprints are filtered. Filtering of GEDI data helps in

obtaining good results. Filtering techniques are adapted as per the quality guidelines of GEDIL02A user guide including, quality_flag=1 for simplifying selection of most of useful data, surface_flag to be 0 or 1 which indicates the elevation center of lowest mode within 300m of DEM, sensitivity indicating maximum cover of canopy that can be penetrated to be greater than 0.9 in case of dense tree cover threshold can be increased, solar elevation to be less than zero indicating day time data to remove the negative impact of background solar

illumination and filtering out coverage beams as it cannot penetrate canopy covers, so usage of power beams returns gave better results (Dubayah *et al.*, 2020; Narin *et al.*, 2024). Also, ICESat-2 data is filtered for its data procured at night to avoid the impact of solar illumination also strong beams are mostly preferred, although weak beams with less error also considered. The filtered footprints of ICESat-2 and GEDIL02_A data in the study area is presented in Fig. 3.

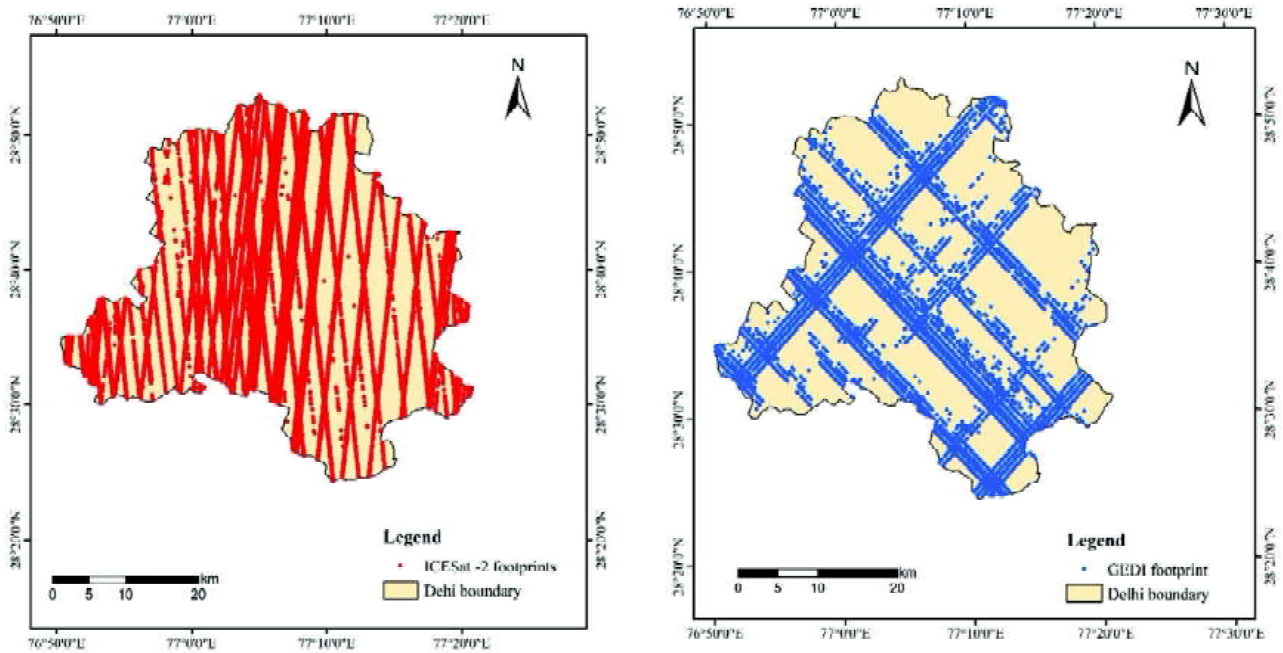


Fig. 3 : Filtered Footprints of ICESat-2 and GEDIL02_A data

Vertical Datum Correction

The GEDI and ICESat-2 elevation datasets are referenced to the WGS 84 ellipsoidal vertical datum, whereas the SRTM DEM is provided in the EGM96 orthometric datum. To ensure vertical consistency and enable accurate comparison across datasets, the SRTM elevations were converted to the WGS 84 datum using the gdalwarp utility (*Convert between Orthometric and Ellipsoidal Elevations Using GDAL – Spatial Thoughts*, n.d.). This transformation is essential for maintaining precision in elevation analysis and model validation.

Data Preparation

Input data for the model were prepared on extracting values of the SRTM elevation and GEDI. The pre-processed data of GEDI is interpolated in order to feed it as the input for the regression models, kriging technique was used, and the values of it are extracted with respect to ICESat-2 target variable. Similarly, value of SRTM is also extracted.

DEM Generation

DEM is generated using different machine learning techniques such as Random Forest regressor, Support

vector regressor and deep learning technique ANN, following sections describes about it.

Random Forest Regressor

Random Forest (RF) is a robust ensemble machine learning algorithm designed to improve predictive accuracy and reduce the risk of overfitting by aggregating the results of multiple decision trees (Breiman, 2001). The principal objective of this technique is to establish heterogeneity among the individual trees, on utilizing two primary mechanisms like bootstrap aggregation (bagging) and feature randomness. While training the datasets, multiple subsets of them are created by bootstrap sampling, on sampling them randomly with replacement. Thus, each decision trees are trained on different bootstrap sample, this results in learning various patterns and aspects of the data. Further at each split random subset of features is considered, preventing trees being similar and explore different decision boundaries. Out-of-Bag (OOB) data is important aspect of RF, in which particular portion of the training data is excluded from given bootstrap sampling and serve as in- built validation set in estimating the model's generalization errors, this eliminates the need for separate dataset for validation (Liaw & Wiener, 2002). Thus, performance of prediction will be unbiased on evaluating the respective OOB samples of each tree. Predictions are made by aggregating the individual decision tree's output, mostly averaging is carried out for regression tasks. This approach reduces the variance associated with each decision trees, enabling more accurate and stable predictions. The characteristic of RF such as resistance to overfitting, in-built interpretability and capability to handle high-dimensional data, enables its wider usability in remote sensing, geospatial analysis and environmental modelling (Pancholi *et al.*, 2023).

Support Vector Regressor

SVR derived from Support Vector Machine's (SVM) principles, which is similar to that of Kernel Ridge Regression, where kernel trick is used to handle nonlinear relationship by mapping input features into high dimensional feature space, enabling SVR to model

nonlinear and complex patterns with high accuracy (Smola & Schölkopf, 2004). It enables the flexibility in using different kernel functions such as radial basis function (RBF), polynomial, or linear kernels, that it applies to diverse regression tasks. The use of ϵ -insensitive loss function of SVR plays a key feature in tolerating the specified level of error within the training data, that it ignores small deviations and fits with overall trend. The optimization framework of soft margin enables potential outliers to fall outside the ϵ -tube, and with regularization parameter model's complexity is balanced and accuracy of prediction is bettered. Thus, robustness of SVR to noisy outliers, make it more generalized and stable in predictive performance of wide variety of applications like remote sensing, where underlying relationships are mostly nonlinear and affected by noises (Drucker *et al.*, 1997; Tian & Shan, 2024).

Artificial Neural Network

ANN are computational models, consisting of interconnected layers with neurons, inspired from structure and functioning of human brains, to understand the complex relationship, in handling problems of nonlinear relation and non- parametric, where traditional parametric models fail (Pancholi *et al.*, 2023). ANN involves in serving input data through an input layer and one or more hidden layers which enables in capturing complexity within the data using activation functions and produce the output.

The iterative learning procedure of the model by minimizing the error between predicted and actual outputs on adjusting the weights systematically between neurons, this technique is called as gradient-based optimization with backpropagation (Kim *et al.*, 2020). Universal approximation capability of ANN, is the powerful feature it can model any continuous function with sufficient data and complex network (Hornik, 1991). Thus, solving complex and high dimensional problems can be employed by ANN, especially in geospatial applications and reconstruction of continuous elevation surface like DEM, as it can learn complex terrain and its auxiliary characteristics (Girohi & Bhardwaj, 2022).

Hyper Parameters

Hyperparameter tuning was performed to ensure the ideal performance and generalization of machine learning models. On careful selection of hyperparameters, model's prediction accuracy increases on preventing over and underfitting.

For RFR, the tuning process focused on critical hyperparameters such as bootstrap (determining whether bootstrap samples are used when building trees), max_depth (maximum depth of the trees), min_samples_leaf (minimum number of samples required to be at a leaf node), min_samples_split (minimum number of samples required to split an internal node), and n_estimators (number of decision trees in the ensemble). Grid Search CV utility a grid search technique employed to evaluate various combinations of hyperparameters, where search space consisted of 162 candidates, with 2-fold cross validation, resulted to 324 model fits. This helped in identifying the set of parameters which had minimum prediction error and more stability across validation folds.

For SVR, hyperparameters, C (regularization parameter controlling the trade-off between smooth decision boundary and classifying training points correctly), epsilon (defining the epsilon-tube within which no penalty is given to errors), and gamma (kernel

coefficient for 'rbf', 'poly', and 'sigmoid' kernels) were explored. The grid search was applied with 8 candidate configuration, over 2-fold cross validation resulted to 16 model fits. With error-based evaluation where best configuration yielding least error, best model was selected.

For ANN, a random search strategy with Keras-Tuner, hyperparameter optimization was conducted efficiently, the included hyperparameters for tuning are number of hidden layers, number of neurons per layer, activation functions (ReLU, tanh, sigmoid), optimizer algorithms (e.g., Nadam), number of training epochs, and the number of trials. The primary objective function which is used for optimization was MSE (Mean Squared Error), with additional evaluation metrics such as Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) utilized to validate model robustness. Multiple configurations were tested and final tuned model employed with Nadam as optimizer, showed superior convergence behaviour and prediction accuracy.

A comprehensive summary of selected parameters for each model is presented in Table 2, while flow of methodology is illustrated in Fig. 2. This hyperparameter tuning ensured in identification of most effective model configuration, which in turn improved the reliability of predictions.

Table 2: Hyperparameters of each model

Model	Parameter	Range
Random Forest	n_estimator	100, 200, 300
	Max_depth	10, 20, 30
	Min_samples_split	2,5,10
	Min_samples_leaf	1,2,4
	Bootstrap	True, False
Support Vector Regressor	Kernel	rbf
	C	0.1,1
	Epsilon	0.01,0.1
	Gamma	Scale, 0.1
ANN	Learning Rate	0.01 to 0.0001
	Number of hidden layers	2 to 3
	Number of neurons	10 to 150
	Activation Function	TanH, sigmoid, ReLu
	Optimizer	Nadam
	Epochs	20

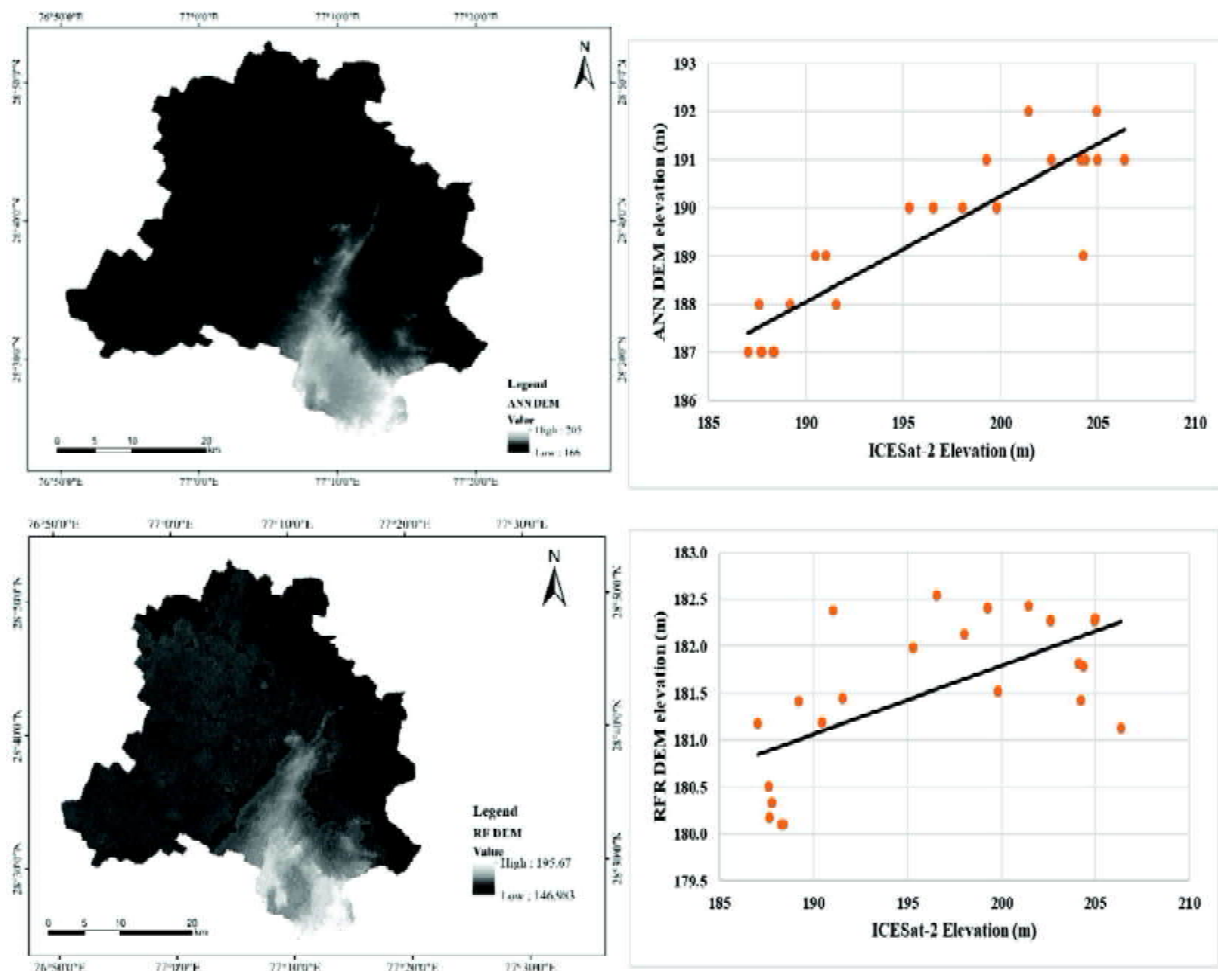
Results and Discussion

Following the extensive hyperparameter tuning and model training, RFR, SVR and ANN were evaluated for their ability to generate accurate DEMs across the selected study area. The performance of each model was assessed using reference elevation points extracted from the ICESat-2 dataset. RMSE and MAE are employed as primary evaluation metrics to ensure consistency and reliability in comparative analysis.

The Delhi region exhibiting considerable complexity of terrain due to its urbanized landscape, the ANN model achieved highest prediction accuracy among all other algorithms. ANN model was configured with an architecture of one input layer as SRTM DEM, two hidden layers with 80 and 135 neurons respectively and a single output neuron structured as a 1-80-135-1 network with tanh activation functions in the hidden layers and ReLU in the output layer. This configuration resulted in RMSE of 8.67 m and an MAE of 6.77 m, highlights the capability

of ANN to capture complicated elevation patterns and nonlinear relationships present in the terrain data.

The SVR model tuned with a C value of 1, epsilon of 0.01 and gamma set to 'scale', revealed moderately accurate predictions, resulting in an RMSE of 15.23 m and an MAE of 13.95 m, Whereas RFR, with hyperparameters set to bootstrap as True, max_depth as 30, min_samples_leaf as 2, min_samples_split as 2 and n_estimators as 300, produced an RMSE of 15.97 m and MAE of 14.62 m. SVR and RF captured broader elevation trends and their performance was relatively lower compared to ANN, especially in areas with abrupt terrain features or with limited training samples. **Fig.4** representing the generated DEMs and the scatter plots between the ICESat-2 and generated DEMs at vertical datum of WGS84, indicates better linear relation. Also, the tighter cluster is found around the ANN model predicted DEM with the ICESat-2, which underscores the superiority of the model.



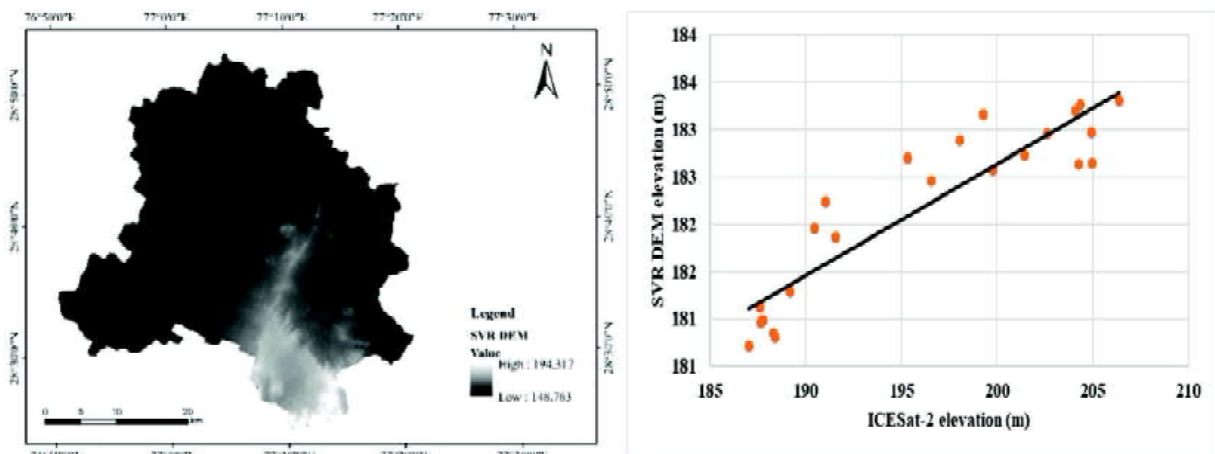


Fig. 4 : DEMs generated for the study area Delhi with its scatter plots with respect to ICESat-2 elevations
(a) Random Forest Generated DEM, (b) Support Vector Regressor Generated DEM, (c) ANN generated DEM

Conclusion

Current study explored the integration of spaceborne LiDAR data and global DEM through different regression techniques, to generate high resolution DEMs. On evaluating the resulting DEMs from three regression models, such as RFR, SVR and ANN, performance of ANN was found to be superior in complex, nonlinear elevation pattern.

This reinforces the importance of selection of appropriate model, based on complexity of terrain and data availability. RFR offers better prediction with less complex data, SVR captures the non-linearity effectively

with good amount of training dataset, while ANN captures complex relationships, with sufficient tuning.

Overall, the potentiality of spaceborne LiDAR integrated DEM, with regression techniques, is underscored. This technique enables in generation of accurate and timely elevation products. Such methods can support a wide range of geospatial applications, including urban planning, environmental monitoring and archaeological mapping. Future studies should aim to incorporate larger training datasets, multi-source inputs and advanced ensemble or hybrid modelling frameworks to improve the quality of DEM.

References

- Breiman, L. (2001). Random Forests. *Machine Learning*, 45, 5–32. classification, regression, ensemble
- Browse LP DAAC Data User Resources / GEDI-subsetter - Earth data Source Code Repository. (n.d.). Retrieved July 17, 2025, from <https://git.earthdata.nasa.gov/projects/LPDUR/repos/gedi-subsetter/browse>
- Convert between Orthometric and Ellipsoidal Elevations using GDAL – Spatial Thoughts. (n.d.). Retrieved July 17, 2025, from <https://spatialthoughts.com/2019/10/26/convert-between-orthometric-and-ellipsoidal-elevations-using-gdal/>
- Drucker, H., Burges, C. J. C., Kaufman, L., Smola, A., Vapoik, V., Long, W., & Nj, B. (1997). *Support Vector Regression Machines w) tw, . I.*
- Dubayah, R., Hofton, M., Blair, J. ., Armston, J., Tang, H., & Luthcke, S. (2020). *GLOBAL Ecosystem Dynamics Investigation (GEDI) Level 02 User Guide For SDPS PGVersion 1 (P001) of GEDI L2A Data and SDPS PGVersion 1 (P001) of GEDI L2B Data.*
- Economic Survey of Delhi. (2022). https://delhiplanning.delhi.gov.in/sites/default/files/Planning/ch._19_demographic_profile.pdf
- Giribabu, D., Hari, R., Sharma, J., Sharma, A., Ghosh, K., Kumar Bera, A., & Kumar Srivastav, S. (2023). Prerequisite Condition of Diffuse Attenuation Coefficient K_d (490) for Detecting Seafloor from ICESat-2 Geolocated Photons During Shallow Water Bathymetry. *Hydrology*, 11(1), 11. <https://doi.org/10.11648/j.hyd.20231101.12>

- Girohi, P., & Bhardwaj, A. (2022). A Neural Network-Based Fusion Approach for Improvement of SAR Interferometry-Based Digital Elevation Models in Plain and Hilly Regions of India. *AI (Switzerland)*, 3(4), 820–843. <https://doi.org/10.3390/ai3040050>
- Goud, G. P. S., & Bhardwaj, A. (2021). Estimation of Building Heights and DEM Accuracy Assessment Using ICESat-2 Data Products †. *Engineering Proceedings*, 10(1). <https://doi.org/10.3390/ecsa-8-11442>
- Hornik, K. (1991). Approximation capabilities of multilayer feedforward networks. *Neural Networks*, 4(2), 251–257. [https://doi.org/10.1016/0893-6080\(91\)90009-T](https://doi.org/10.1016/0893-6080(91)90009-T)
- Huang, J., Yang, Y., Yu, Y., & Zhang, Y. (2024). Vertical accuracy of open-source remote sensing data (AW3D30, TanDEM-X, ATLAS) for understory terrain estimation. *Geocarto International*, 39(1). <https://doi.org/10.1080/10106049.2024.2356855>
- Khalsa, S. J. S., Borsa, A., Viswanath, N., Minh, P., Kai, L., Christopher, C., Helen, F., Chaitan, B., & Luis, L. (2020). OpenAltimetry - rapid analysis and visualization of Spaceborne altimeter data. *Earth Science Informatics*, 1471–1480. <https://doi.org/10.1007/s12145-020-00520-2/Published>
- Kim, D. E., Liong, S. Y., Gourbesville, P., Andres, L., & Liu, J. (2020). Simple-Yet-Effective SRTM DEM improvement scheme for dense urban cities using ANN and remote sensing data: Application to flood modeling. *Water (Switzerland)*, 12(3). <https://doi.org/10.3390/w12030816>
- Liaw, A., & Wiener, M. (2002). Classification and Regression by randomForest. *R News*, 2(3).
- Liu, A., Cheng, X., & Chen, Z. (2021). Performance evaluation of GEDI and ICESat-2 laser altimeter data for terrain and canopy height retrievals. *Remote Sensing of Environment*, 264. <https://doi.org/10.1016/j.rse.2021.112571>
- Narin, O. G., Abdikan, S., Gullu, M., Lindenbergh, R., Balik Sanli, F., & Yilmaz, I. (2024). Improving global digital elevation models using space-borne GEDI and ICESat-2 LiDAR altimetry data. *International Journal of Digital Earth*, 17(1). <https://doi.org/10.1080/17538947.2024.2316113>
- Narin, O. G., & Gullu, M. (2023). A comparison of vertical accuracy of global DEMs and DEMs produced by GEDI, ICESat-2. *Earth Science Informatics*, 16(3), 2693–2707. <https://doi.org/10.1007/s12145-023-01060-1>
- Neuenschwander, A., Pitts, K., Jelley, B., Robbins, J., Markel, J., Popescu, S., Nelson, R., Harding, D., Pederson, D., Klotz, B., & Sheridan, R. (2022). *Ice, Cloud, and Land 26 Elevation Satellite (ICESat-2) Project Algorithm Theoretical Basis Document (ATBD) for 27 Land - Vegetation Along-Track Products (ATL08)*.
- Neumann, T. A., Brenner, A., Hancock, D. W., Robbins, J., Gibbons, A., Lee, J., Harbeck, K., & Saba, J. (2023). *ATLAS/ICESat-2 L2A Global Geolocated Photon Data*. <https://doi.org/10.5067/ATLAS/ATL03.006>
- Pancholi, S., Maithani, S., & Bhardwaj, A. (2023). Simulation of DEM based on ICESat-2 data using openly accessible topographic datasets †. *Environ. Sci. Proc*, 2023. <https://doi.org/10.3390/xxxxx>
- Papasaika, H., Poli, D., & Baltasvias, E. (2009). Fusion of digital elevation models from various data sources. *Proceedings of the International Conference on Advanced Geographic Information Systems and Web Services, GEOWS 2009*, 117–122. <https://doi.org/10.1109/GEOWS.2009.22>
- Shang, D., Zhang, Y., Chenguang, D., Qifang, M., & Ziquan, W. (2022). Extraction Strategy for ICESat-2 Elevation Control Points Based on ATL08 Product. *IEEE Transactions on Geoscience and Remote Sensing*, 06.
- Smola, A. J., & Schölkopf, B. (2004). A Tutorial on Support Vector Regression. Statistics and Computing archive. *Statistics and Computing*, 14.
- Tian, X., & Shan, J. (2024). ICESat-2 Controlled Integration of GEDI and SRTM Data for Large-Scale Digital Elevation Model Generation. *IEEE Transactions on Geoscience and Remote Sensing*, 62, 1–14. <https://doi.org/10.1109/TGRS.2024.3389821>
- Yong, F., Li, Z., Bincai, C., Li, G., & Haiyan, H. (2023). Spaceborne LiDAR Surveying and Mapping. In *GIS and Spatial Analysis*. <https://doi.org/DOI: http://dx.doi.org/10.5772/intechopen.108177>



Assessment of Forest Cover Change using MODIS Vegetation Continuous Fields Data

Niraj Priyadarshi^{1*}, Suparn Pathak¹, C. Sudhakar Reddy² and Srishti Mehta³

¹ Regional Remote Sensing Centre - East, NRSC/ISRO, Kolkata (India)

² National Remote Sensing Centre (NRSC), ISRO, Hyderabad (India)

³ TERI School of Advanced Studies, New Delhi (India)

**Corresponding Author's Email: nirajpriyadarshi@yahoo.com*

Abstract

Monitoring and evaluation of forest cover and disturbances is essential for achieving sustainable forest management. Land use change, especially deforestation is major factor contributing to greenhouse gas emissions. The Vegetation Continuous Fields (VCF) data of Moderate Resolution Imaging Spectro-radiometer (MODIS) was used to analyze spatiotemporal changes for two decades (2001-2020) in Jharkhand state, India. Each pixel of MODIS VCF product gives a percentage of tree cover (PTC), which contains the total canopy cover of trees 5 meters in height or more. The study found a significant decline in tree canopy cover from 2001 to 2009, mainly in the Hazaribagh, Latehar, Palamu, and Paschim Singhbhum districts. Spatial analysis also indicated the increase in percentage of tree cover from 2010 to 2020, mainly in Latehar, Chatra, and Paschim Singhbhum districts. The findings are in tune with the reporting of an increase in the extent of forest cover of the Jharkhand by Forest Survey India (2001 and 2015). This work demonstrates successful application of MODIS VCF data to assess and monitor forest cover at the regional scale. It is also recommending the use of time series VCF data for informed decision-making and management effectiveness at regional scale.

Keywords: Vegetation continuous fields, percentage of tree cover, forest cover, time series.

Introduction

Declining forest cover is a significant concern that can accelerate CO₂ emissions influencing climate change and exacerbating global warming. In India, the forest cover was 23.68% (768,436 sq. km) in 2001, which has come down to 21.71% (713,789 sq. km) by 2021 (SFR, 2001; SFR, 2015; Choubey, 2023). The forests provide habitat for millions of plant species & animals and are one of the central carbon sinks, which store around 650 billion tonnes of carbon (Global Forest Resources Assessment

2010). Anthropogenic factors are significant causes of India's decline in forest cover. The anthropogenic factors are encroachment in forest areas, shifting cultivation, logging trees, settlement expansion, infrastructure development, mining, forest fires, and overexploitation, whereas natural factors are insect infestations and landslides (Global Forest Resources Assessment 2010). Deforestation monitoring in South Asia is crucial due to the region's diverse and biologically rich ecosystems, including tropical rainforests, tropical deciduous forests, mangroves, and montane forests (Reddy *et al.*, 2018).

Deforestation is an environmental challenge that hurts the resilience and distribution of forests. Therefore, forest restoration is necessary due to its essential role in sustainable development.

The state of Jharkhand is rich in mineral and forest resources, and significant changes have occurred in the last two decades. The forest cover has increased from 28.40% (22,637 sq. km) in 2001 to 29.76% (23,721 sq. km) in 2021 (Sarif *et al.*, 2017; Choubey, 2023). It is reported that dense forest cover is decreasing daily, and the open forests are increasing over time in Jharkhand (Sarif *et al.*, 2017; Reddy *et al.*, 2016). Growing population and food demand have a direct negative impact and increase pressure, leading to significant forest degradation. There is a limited comprehensive study for the entire Jharkhand state by the researchers to analyze and assess forest cover change. Jharkhand has experienced significant forest disturbances, but continuous, region-specific monitoring of forest cover is limited, leaving a critical gap in understanding local forest dynamics. Hence, there is a requirement to assess forest cover change using satellite data. The remote sensing data is a state-of-the-art tool for evaluating forest cover and addresses the issues by providing accurate information about the study area.

As forest cover change is a significant challenge to assess and quantify, remote sensing data helps assess crucial insights and their impact. A standard method for change detection is comparing two or more images of different dates to detect changes. However, these approaches are unsuited for forest cover change because of harvest or replantation during that period (Priyadarshi *et al.*, 2020; Hansen *et al.*, 2010). Various studies have been carried out on the change in forest cover by researchers, including Firoz & Laxmi (2017), who explored the grid-based analysis for forest cover change; Yan & Margaret 2020 used lidar data to identify logging and forest fires, and so on. Despite various studies, there is a need for further exploration to assess forest cover change. In this direction, this study assesses forest cover by analyzing spatiotemporal profiles using tree cover information derived from vegetation continuous fields from 2001 to 2020 in Jharkhand state.

Study Area

The state of Jharkhand constitutes a total geographical area of 79,714 km² and is spread from 21°58'–25°30' N latitude and 83°21'–87°57' E longitude (Fig. 1). Jharkhand has rich biodiversity, which consists of about 30% (23,605 km²) of the forest area of Jharkhand, known as 'The Land of Forests', and about 40% of India's mineral resources (Sarif *et al.*, 2017; FSI, 2019; IUCN, 2021; Priyadarshi *et al.*, 2023). The forest types include tropical dry deciduous (51.3%), tropical moist deciduous (28.5%), and sal forests (20.2%) (Reddy *et al.* 2015; Roy *et al.*, 2015; FSI, 2019; FAO, 2022). It has diverse ecosystems and supports the livelihoods of people dependent on the forests for various ecosystem services (Kumar *et al.*, 2019; Firoz & Laxmi, 2017). The resources of Jharkhand directly influence land use, and the past study reported a direct relationship between forest conservation and mineral extraction activities (Sarkar & Chaudhuri, 2018; Bhattacharya *et al.*, 2020).

Data Base

Moderate Resolution Imaging Spectro-radiometer (MODIS) Vegetation Continuous Fields (VCF) data, which have a spatial resolution of 250m, were used to analyze spatio-temporal dynamics of the study area during 2001–2020. MODIS VCF product MOD44B provides the percentage of tree cover (PTC) pixel-wise, which comprises the total canopy cover of trees 5 meters in height or more (Carroll *et al.*, 2010; Townshend *et al.*, 2011). This MODIS VCF data is widely used to estimate forest cover changes, forest biomass, etc, in past studies for comparisons with available global published datasets (Carroll *et al.*, 2010; Townshend *et al.*, 2011; Sarif *et al.*, 2017). Past studies reveal that MODIS VCF has an advantage in that it is more effective because of its enhanced noise reduction capabilities and ability to address mixing issues in dense herbaceous vegetation (Sharma & Raj, 2024; Sarif *et al.*, 2017). Therefore, the current study used MODIS VCF data for the estimation of forest cover change during 2001 to 2020 over the study area.

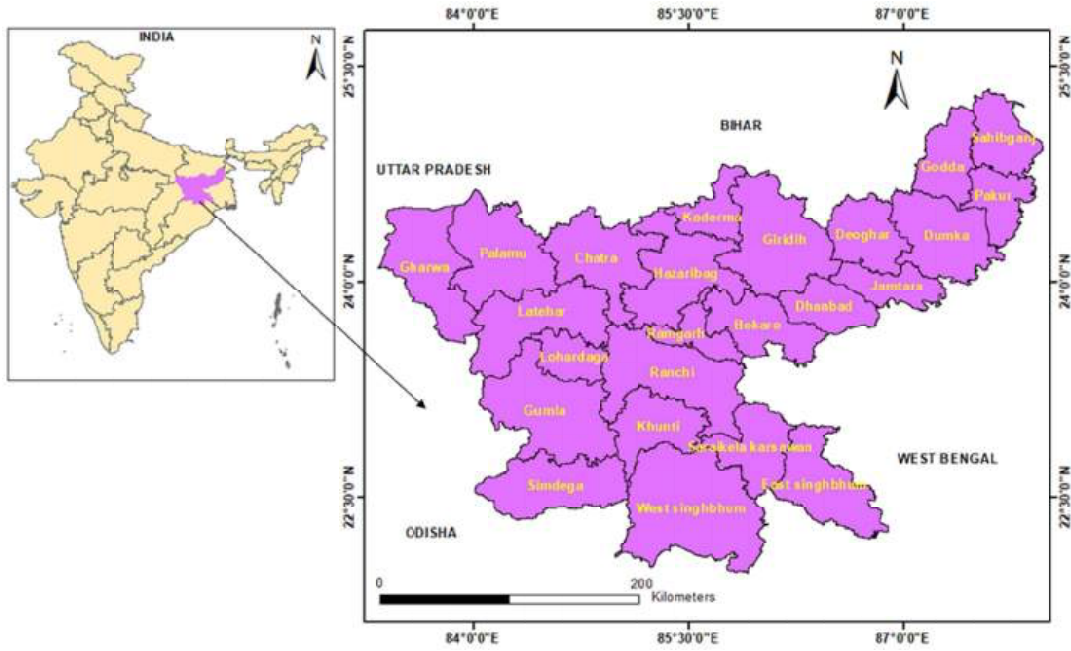


Fig. 1: Study Area Map of Jharkhand

Methodology

This study has used the MODIS VCF data to detect forest cover change from 2001 to 2020 over Jharkhand state. Since each MODIS VCF data may contain abnormalities, this study used a segmentation-based approach to compute the mean of three years of data to ensure consistency and reliability. The study analyzed the segmentation-based approach pixel-wise to quantify changes in forest cover. In this study, the MODIS VCF dataset was downloaded using Google Earth Engine, and the Forest mask (1:10K) received from NRSC, ISRO, Hyderabad, was used to extract data for the forest areas of Jharkhand state. The change analysis was carried out within the forest area of Jharkhand. The study conducted calculates the mean of three-year time period segments for analysis from 2001-2003(T1), 2007-2009 (T2), 2013-2015 (T3), and 2018-2020 (T4) (Sarif et al., 2017). Finally, forest cover change was computed using the mean of MODIS VCF changes between different segments, which include T1 and T2, T2 and T3, and T2 and T4 time periods (Equation 1-4).

$$\begin{cases} M = T2 - T1 \\ N = T3 - T2 \\ O = T4 - T2 \end{cases} \quad (1)$$

$$M = \frac{\sum_{k=2007}^{2009} VCF_k}{3} - \frac{\sum_{k=2001}^{2003} VCF_k}{3} \quad (2)$$

$$N = \frac{\sum_{k=2013}^{2015} VCF_k}{3} - \frac{\sum_{k=2007}^{2009} VCF_k}{3} \quad (3)$$

$$O = \frac{\sum_{k=2018}^{2020} VCF_k}{3} - \frac{\sum_{k=2007}^{2009} VCF_k}{3} \quad (4)$$

Results and Discussions

Forest cover change analysis of this study shows the temporal and spatial variability across the state of Jharkhand by estimating the mean of three years of MODIS VCF data for the time period of 2001-2003, 2007-2009, 2013-2015, and 2018-2020 segments. Results highlighted changes between four time periods, which include first (M) between time period 1 (2001-2003) and time period 2 (2007-2009) (Fig. 2); second (N) between time period 2 (2007-2009) and time period 3 (2013-2015) (Fig. 3) and third (O) between time period 3 (2007-2009) and time period 4 (2018-2020) (Fig. 4). Fig. 2 shows forest loss from 2001 to 2009 due to deforestation, which is evident in the southern and northwestern regions of Jharkhand state. The analysis revealed a significant decrease in forest cover / canopy from 2001 to 2009, mainly in the Hazaribagh, Latehar, Palamu, and Paschim Singhbhum districts, where tree cover loss is about 20% (Table 1). These regions have forest loss, possibly due to land conversion, mining, agriculture, and urban growth. The forest loss in most regions includes a 20% loss in some areas, indicating deforestation in the study area. In

some places, tree cover has not changed much, and in some areas, slightly increased tree cover was observed, possibly due to conservation measures before or during

natural succession. Jharkhand's forest cover decreased from 2001 to 2009 (Fig. 2).

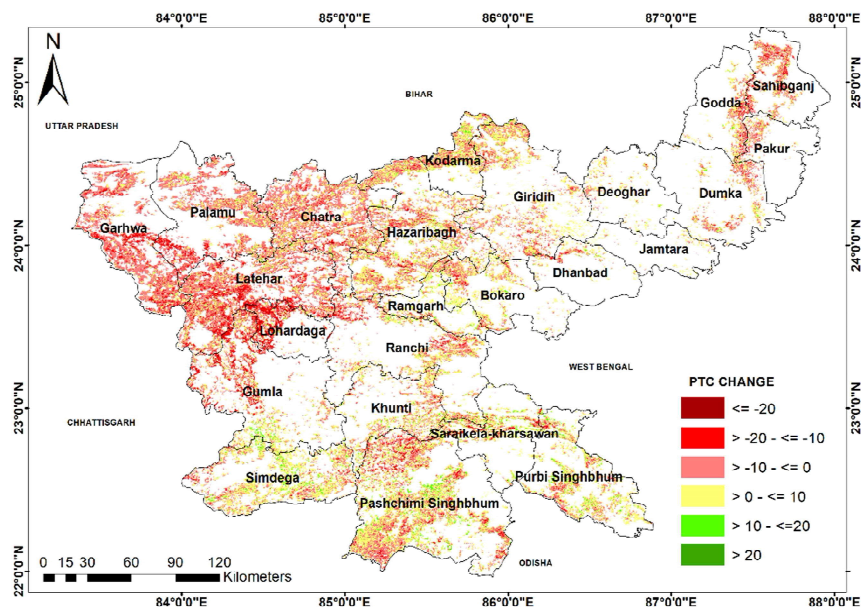


Fig. 2 : Spatial distribution of PTC change during 2001–2003 and 2007–2009

Fig. 3 reveals an increase in forest cover from 2007 to 2015 (N), where many regions significantly gained tree cover. In several districts, there is an increase in forest cover ranging between 20% and 30% in such districts as Latehar, Chatra, Paschim Singhbhum, etc (Fig. 3) (Table 1). During this period, the significant factors in increasing forest cover due to efforts in afforestation or natural

regeneration were more effective. There are several factors for an overall increase in the forest, which include (i) changes in forest management and conservation policies, (ii) socio-economic factors, (iii) natural regeneration, and other factors. Government policies played a vital role in increasing afforestation. There may be a reduction in agricultural areas, and a shift in economic

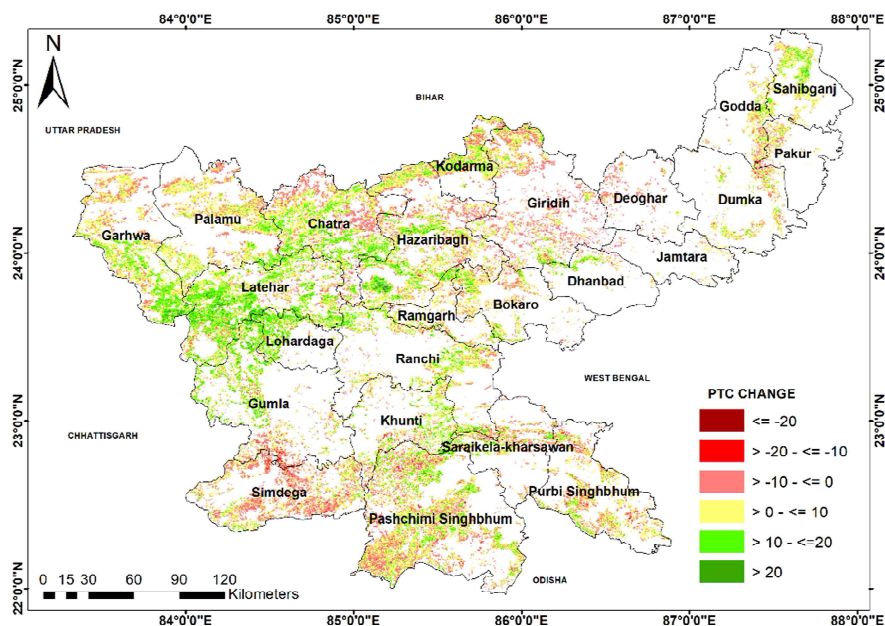


Fig. 3 : Spatial distribution of PTC change during 2007–2009 and 2013–2015

activities could reduce the pressure on forested areas. Finally, natural regeneration, afforestation, favourable climate conditions, and fewer disturbances could be reasons for positive changes in the forested regions. However, Forest Survey India (2001 and 2015) reported a reduction in dense forests and an increase in open forest areas. The changes during the 2007-2015 period show improved forest regeneration and plantations, which helped achieve comprehensive forest conservation.

The analysis reveals that the first time period, M, is negative (Fig. 2), indicating tree cover loss due to deforestation. Meanwhile, the second time period N was characterized as positive (Fig. 3), indicating a gain in tree cover due to afforestation efforts and natural growth (Table 1). Similarly, the third period, O (Fig. 4), was characterized as positive, indicating a gain in tree cover, except in a few places, like the northern region, showing a loss in tree cover. Forest cover change in different study

area locations was validated using high-resolution Google Earth images (Fig. 5). Figures 5a–c represent forest cover negative change between the years 2012 and 2020 for location near GUA village, geographically located at latitude 22°10′ 43.38″ N and longitude 85°2′ 1.54″ E. Figures 5d–f represents forest cover positive change between the years 2012 and 2023 for location near Nuia village, geographically located at latitude 22°14′ 42.15″ N and longitude 85°22′ 32.88″ E. Conservation policies, natural influences, and human interventions helped to shift from deforestation to reforestation in Jharkhand. The map of the spatial distribution of tree cover helped a deeper understanding of the process that drove these negative to positive shifts, influencing climate and the local ecosystem. This study helps in understanding these dynamics, which help implement the preservation and management of forest resources.

Table 1: Distribution of area (in km²) under 06 (six) change classes extracted from percentage of tree cover (PTC) change images during time periods M,N, and O of Jharkhand state

Time Period	<-20 (Area in km ²)	(-20 to -10)	(-10 to 0)	0 to 10	10 to 20	>20
M (2001-2003 & 2007-2009)	76.54	2,009.86	12,519.32	10,310.86	665.86	6.51
N (2013-2015 & 2007-2009)	0.46	188.78	7,128.57	13,367.60	4,587.32	436.14
O (2018-2020 & 2007-2009)	15.20	556.82	6,439.80	12,845.70	2,122.72	133.49

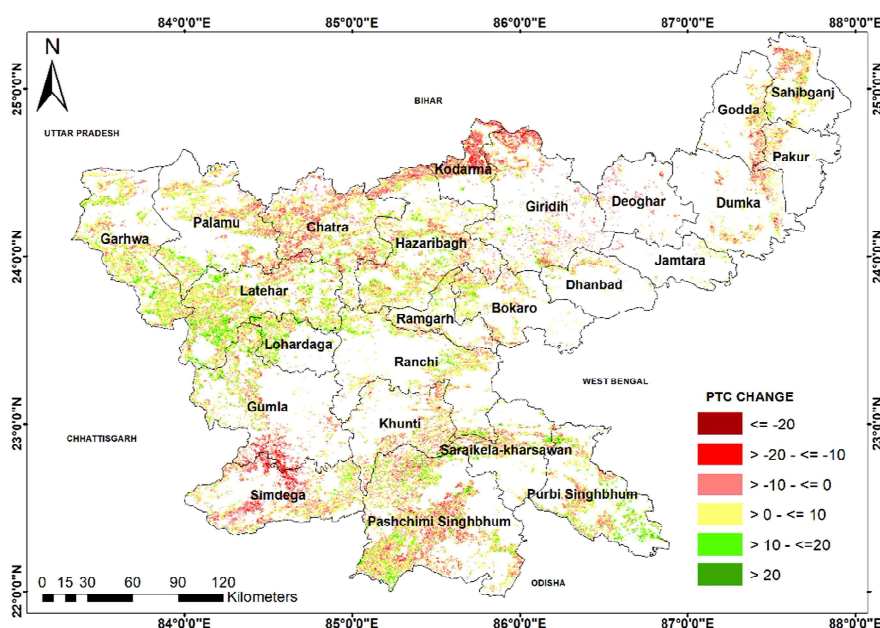


Fig. 4 : Spatial distribution of PTC change during 2007–2009 and 2018–2020

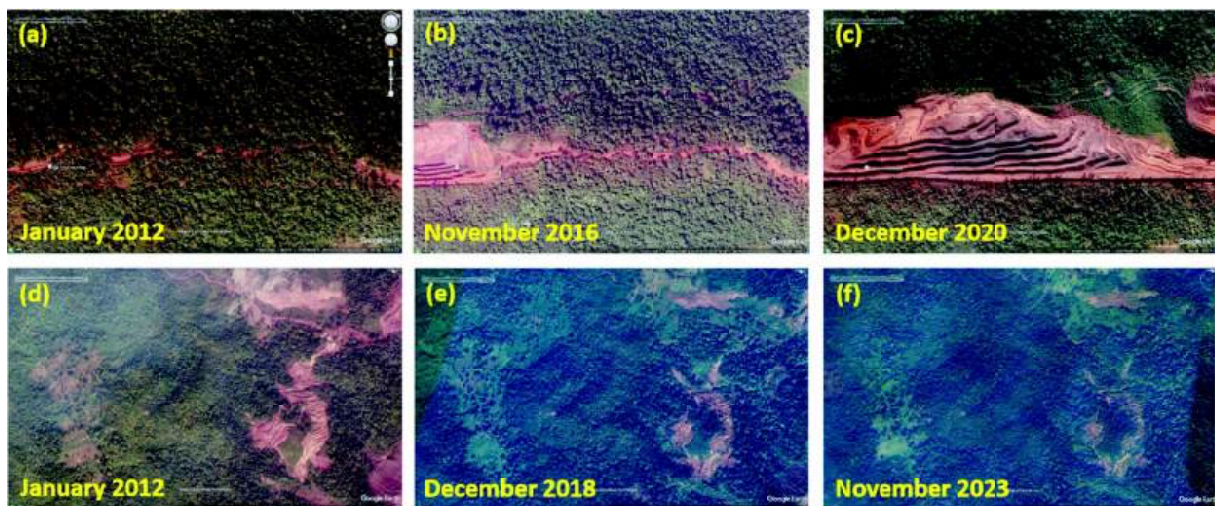


Fig. 5 : illustrates changes in vegetation, as evidenced by multi-temporal Google Images (a) Jan, 2012; (b) Nov, 2016 & (c) Dec, 2020 represents negative change; and (d) Jan, 2012; (e) Dec, 2018 & (f) Nov, 2023 represents positive change.

The decline in forest cover between 2001 and 2009, especially in southern and north-western Jharkhand, is linked to mining expansion, agricultural encroachment, and infrastructure growth (FSI, 2003; MoEF, 2006). In contrast, recovery during 2010–2020 corresponds with interventions such as the National Afforestation Programme (NAP, 2000), CAMPA (2009), stricter enforcement of the Forest Conservation Act, and community-driven Joint Forest Management (JFM). Socio-economic factors contributed to rural outmigration and natural regeneration on abandoned lands (FSI, 2015; 2019). These linkages strengthen the explanation of spatial patterns by connecting observed changes to concrete policy measures and socio-economic processes.

Conclusion

The current study provides an effective method to understand better the dynamics of forest cover long-term changes during 2001-2020 using MODIS VCF data at the pixel level over Jharkhand. Each pixel of the VCF product gives a percentage of tree cover (PTC), which contains the total canopy cover of trees 5 meters in height or more. The study revealed a significant decrease in forest

cover/ canopy from 2001 to 2009 (Hazaribagh, Latehar, Palamu, and Paschim Singhbhum districts) and an increase in forest cover from 2010 to 2020, mainly in Latehar, Chatra, and Paschim Singhbhum districts and most of Jharkhand state's forest area. After years of deforestation in the region, the results observed a shift towards reforestation, which will produce sound ecological effects. The results are in tune with the reporting of an increase in the forest cover of the Jharkhand state by Forest Survey India (2001 and 2015). The significant factors of overall growth in forest cover are changes in forest management and conservation policies, socio-economic factors, natural regeneration, and other factors. This study demonstrated the successful utilization of time series MODIS VCF data, which has captured abrupt and gradual change, to continuously monitor forest cover at the regional scale.

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References

- Bhattacharya, P., Sarkar, A., & Chaudhuri, S. (2020). Forest degradation and its impact on ecosystem services in Jharkhand: A case study. *Journal of Environmental Management*, 262, 110326.
- Choubey, A. K. (2023). *Forest coverage in the country*. Delhi: Press Information Bureau.
- Compensatory Afforestation Fund Management and Planning Authority (CAMPA) (2009). Ministry of Environment and Forests. Government of India.

- Forest Survey of India (FSI). (2019). State Forest Report 2019. Dehradun: Forest Survey of India.
- Forest Survey of India (FSI). (2015). State Forest Report 2015. Dehradun: Forest Survey of India.
- Forest Survey of India (FSI). (2003). State Forest Report 2003. Dehradun: Forest Survey of India.
- Food and Agriculture Organization (FAO). (2022). Forest degradation. Retrieved from www.fao.org
- Firoz, A., & Laxmi, G. (2017). Long-term deforestation assessment in Jharkhand state, India. *Biological Forum – An International Journal*, 7.
- IUCN (International Union for Conservation of Nature). (2021). Deforestation and forest degradation. Gland: IUCN. Retrieved from <https://www.iucn.org/resources/issues-briefs/deforestation-and-forest-degradation>.
- Global Forest Resources Assessment 2010. (2010). Rome: FAO.
- Hansen, M.C., Stehman, S.V., Potapov, P.V. (2010). Quantification of global gross forest cover loss. *Proc Natl Acad Sci* 107(19):8650–8655
- Kumar, M., Roy, P. S., & Joshi, P. K. (2019). The role of indigenous communities in forest conservation in Jharkhand. *Ecological Economics*, 156, 189-197.
- Ministry of Environment and Forests (MoEF) (2006). Report of the National Forest Commission. New Delhi, Government of India.
- National Afforestation Programme (NAP) (2000). Ministry of Environment and Forests. Government of India.
- Priyadarshi, N., Pathak, S., Chakraborty, D., Chowdary, V.M., Srivastav, S.K., Chandrasekar, K., Jeganathan, C., & Bandyopadhyay, S. (2023). Estimation of natural vegetation phenology metrics using time series EVI over Jharkhand state, India. *Journal of Spatial Science*, DOI: 10.1080/14498596.2023.2281926.
- Priyadarshi, N., Chowdary, V. M., Das, I.C., Jeganathan, C., Srivastava, Y. K., Rao, G.S., Raj, U., and Jha, C.S. (2020). Wavelet and non-parametric statistical based approach for long term land cover trend analysis using time series EVI data. *Geocarto International*, 35:5, 512-534, DOI:10.1080/10106049.2018.1520925.
- Reddy, C.S., Jha, C.S., Diwakar, P.G. & Dadhwal, V.K. (2015). Nationwide classification of forest types of India using remote sensing and GIS. *Environmental Monitoring and Assessment* 187(12): 777. DOI: 10.1007/s10661-015-4990-8.
- Reddy, C.S., Rakesh, F., Jha, C.S., Athira, K., Singh, S., Alekhya, V.V.L.P., Rajashekar, G., Diwakar, P.G. & Dadhwal, V.K. (2016). Geospatial assessment of long-term changes in carbon stocks and fluxes in forests of India (1930-2013). *Global and Planetary Change* 143: 50-65.
- Reddy, C.S., Saranya, K.R.L., Pasha, S.V., Satish, K.V., Jha, C.S., Diwakar, P.G., Dadhwal, V.K., Rao, P.V.N. & Krishna Murthy, Y.V.N. (2018). Assessment and Monitoring of Deforestation and Forest fragmentation in South Asia since the 1930s. *Global and Planetary Change* 161: 132-148.
- Roy, P.S., Behera, M.D., Murthy, M.S.R., Roy, A., Singh, S., Kushwaha, S.P.S., Jha, C.S., Sudhakar, S., Joshi, P.K., Reddy, C.S. et al. (2015). New vegetation type map of India prepared using satellite remote sensing: Comparison with global vegetation maps and utilities. *International Journal of Applied Earth Observation and Geoinformation* 39: 142-159.
- Sarkar, A., & Chaudhuri, S. (2018). Impacts of mining on forest and biodiversity: A study in Jharkhand, India. *Journal of Environmental Science and Technology*, 12(4), 179-191.
- Sarif, M.O., Jeganathan, C., and Saptarshi, M. (2017). MODIS-VCF Based Forest Change Analysis in the State of Jharkhand. *Proc. Natl. Acad. Sci., India, Sect. A Phys. Sci.* <https://doi.org/10.1007/s40010-017-0446-6>.
- SFR (2001) State of the Forest Reports of Jharkhand, Forest Survey of India (FSI), Ministry of Environment and Forests, Government of India, Dehradun, India. <http://fsi.nic.in>.
- SFR (2015) State of the Forest Reports of Jharkhand, Forest Survey of India (FSI), Ministry of Environment and Forests, Government of India, Dehradun, India. <http://fsi.nic.in>.
- Sharma, L.K., & Raj, A. (2024). Spatiotemporal forest health assessment for ecosystem conservation using MODIS data. In S. Mondal, & M. Dalai (Eds.), *Advances in Remote Sensing for Natural Resource Monitoring* (pp. 25-39). Springer.



Precise Positioning using GNSS Virtual Reference Stations (VRS) Data for Airborne LiDAR Applications

T.E. Rani*, J. Narendran, N. Madhusudhan Reddy, S. Muralikrishnan and R. Rambabu

National Remote Sensing Center (ISRO), Balanagar, Hyderabad (India)

**Corresponding Author's Email: rani_te@nrsc.gov.in*

Abstract

Airborne LiDAR technology provides a dense point cloud for generating high-resolution digital elevation models (DEMs) and digital surface models (DSMs). These models have various applications, including flood inundation modeling, storm surge studies, canopy height modeling (CHM) and power line assessment. During LiDAR data acquisition, Global Navigation Satellite System (GNSS) reference stations within 50 km of the study area are required to achieve precise geo-referenced point clouds. However, establishing GNSS reference stations can be time-consuming, costly and challenging, especially in disaster-affected or inaccessible areas. The Survey of India (SOI) has established a network of GNSS Continuous Operating Reference Stations (CORS) across the country, spaced approximately 60-70 km apart, which may not always meet the reference distance requirements. The paper explores the use of Virtual Reference Stations (VRS) service provided by the Survey of India (SOI) as an alternative to physical GNSS reference stations for generating geo-referenced LiDAR point cloud. VRS creates a virtual GNSS reference station at the desired location, offering dual-frequency (L1/L2) GNSS data without the need for users to set up physical GNSS reference stations. The study focuses on the Ramganga river basin, approximately covering 200 km length in Uttar Pradesh. Two GNSS reference stations were established by NRSC within the area of interest, with a base distance of about 50 km. Two VRS were also generated at the same locations as the NRSC reference stations. The geo-referenced LiDAR point cloud data were produced using both the NRSC reference stations and VRS data, and their vertical accuracy was compared. A variation of 15-25 cm was observed. Additionally, the accuracy of VRS was assessed in static mode by generating VRS data at known ground control points (GCPs) and compared the coordinates. The results showed a match within 5-10 cm horizontally and 10-20 cm vertically. This evaluation suggests that the GNSS VRS data is viable option for the generation of contours of 1 meter and above from LiDAR data. This study also highlights potential improvement in VRS service.

Keywords: GNSS, UAV, DTM/DSM, VRS, CORS, GCP.

Introduction

LiDAR, or Light Detection and Ranging, is an active remote sensing system that provides a dense point cloud, used to generate high-resolution Digital Elevation Models (DEMs) and Digital Surface Models (DSMs). These models serve a wide range of applications including flood

inundation modeling, storm surge studies, canopy height modeling (CHM), and power line assessments. During LiDAR data acquisition, Global Navigation Satellite System (GNSS) reference stations within 50 km of the study area provide essential correction data to ensure precise, geo-referenced point clouds.

A GNSS reference station is a fixed GNSS station with known coordinates that supplies correction data for a mobile GNSS rover, which collects positional data during LiDAR data acquisition. Both the base station and rover station record GNSS signals, and the data from the base station is used to correct the rover's positional errors through differential GNSS (DGNSS). These corrections are then applied to the point cloud, aligning it with accurate real-world coordinates in a specified coordinate system (International Terrestrial Reference Frame, ITRF), thus ensuring that the 3D model accurately represents the physical environment.

However, establishing GNSS reference stations can be time-consuming, costly and challenging, especially in disaster-affected or inaccessible areas. The Survey of India (SOI) has established a network of GNSS Continuous Operating Reference Stations (CORS) across the country, spaced approximately 60-70 km apart, which may not always meet the reference distance requirements. This paper explores the use of the Virtual Reference Station (VRS) service provided by the Survey of India (SOI) as an alternative to physical GNSS reference stations for generating geo-referenced LiDAR point clouds (Zhao, K et.al, 2017).

The Survey of India has operationalized a National CORS Network of 1018 stations, providing a continuous stream of satellite observations to a central server. VRS technology allows users to create virtual reference stations at desired locations by interpolating data from the existing CORS network. The VRS setup supports two services:

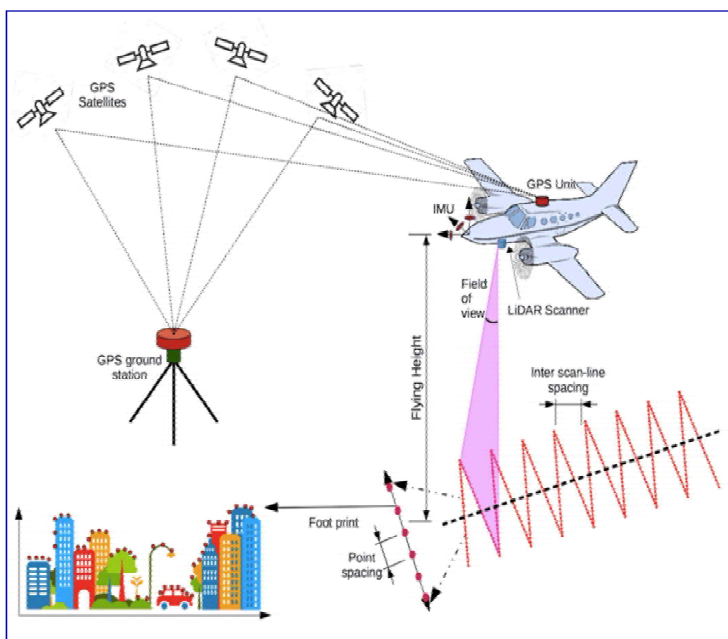


Fig. 1: GNSS assisted LiDAR data acquisition

(1) real-time kinematic (RTK) corrections, which offer centimeter-level accuracy essential for precise applications, and (2) dual-frequency (L1/L2) GNSS raw data and this can serve as reference data for the DGNSS process to generate geo-referenced data products (Survey of India, 2022). However, there are challenges associated with implementing and using VRS networks, such as the need for a robust communication infrastructure since the system relies on real-time data exchange between the rover and the reference stations. The accuracy of the system also depends on the quality and density of the reference station network, with more stations generally leading to better error modelling and overall accuracy.

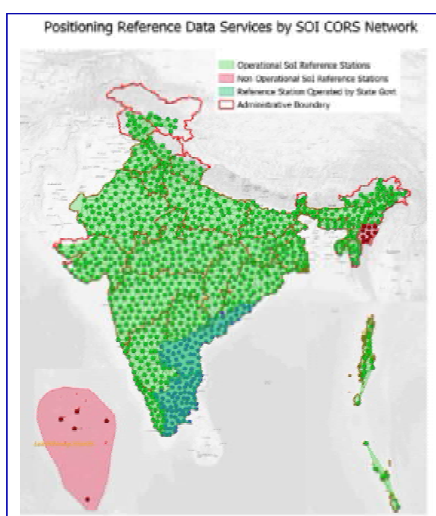


Fig. 2 : SOI CORS Network

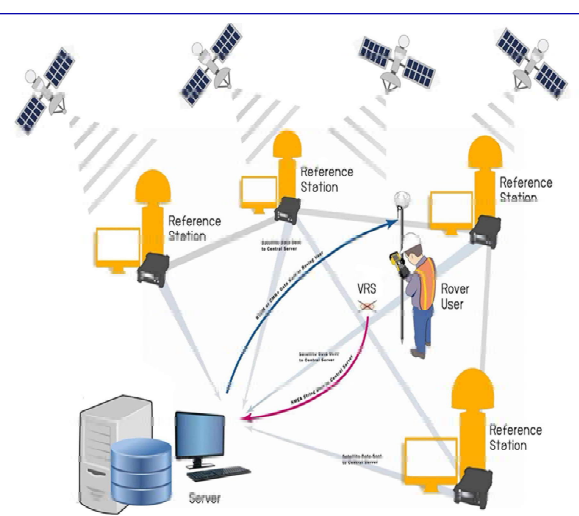


Fig. 3: VRS Technology

Objectives

(i) To explore the use of Virtual Reference Stations (VRS) as an alternative to physical GNSS reference stations for generating geo-referenced LiDAR point cloud.

(ii) To explore the VRS base in static mode for ground control surveys to generate Ground Control Points (GCPs).

The Study Area

This study focuses on the Ramganga river, a tributary of the Ganga in Uttar Pradesh. The project area spans for

15,180 sq. km and is divided into five 100 km blocks for efficient flight operations. GNSS base stations were placed near each block center. Two of these blocks were selected for this study, with LiDAR data acquisition conducted on April 15, 20 and April 21, 2023. During LiDAR data acquisition, GNSS base stations data was acquired in the two blocks (Base-1 and Base-2). VRS data from SOI's service was downloaded for the same base station locations.

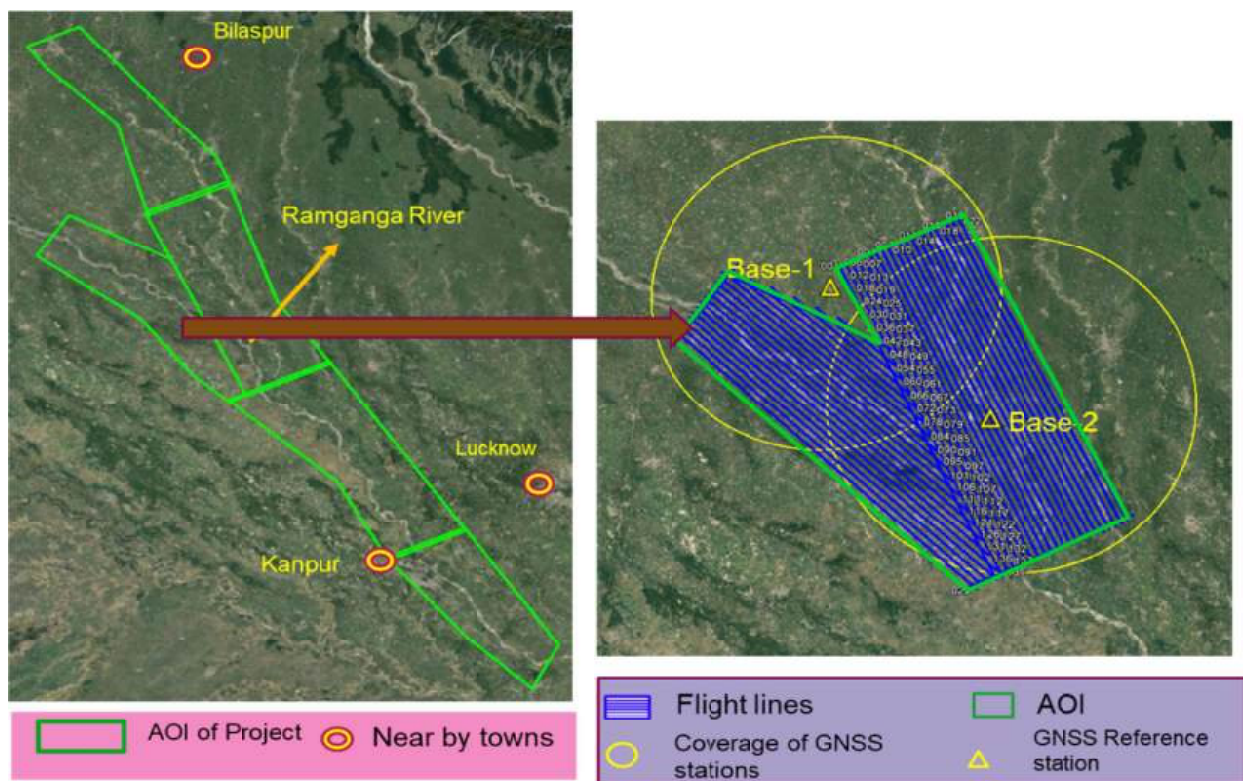


Fig. 4 : The study area Ramganga river, Uttar Pradesh

Methodology

The methodology for processing LiDAR data from acquisition to point cloud generation is outlined below as a flow chart (Fig. 5).

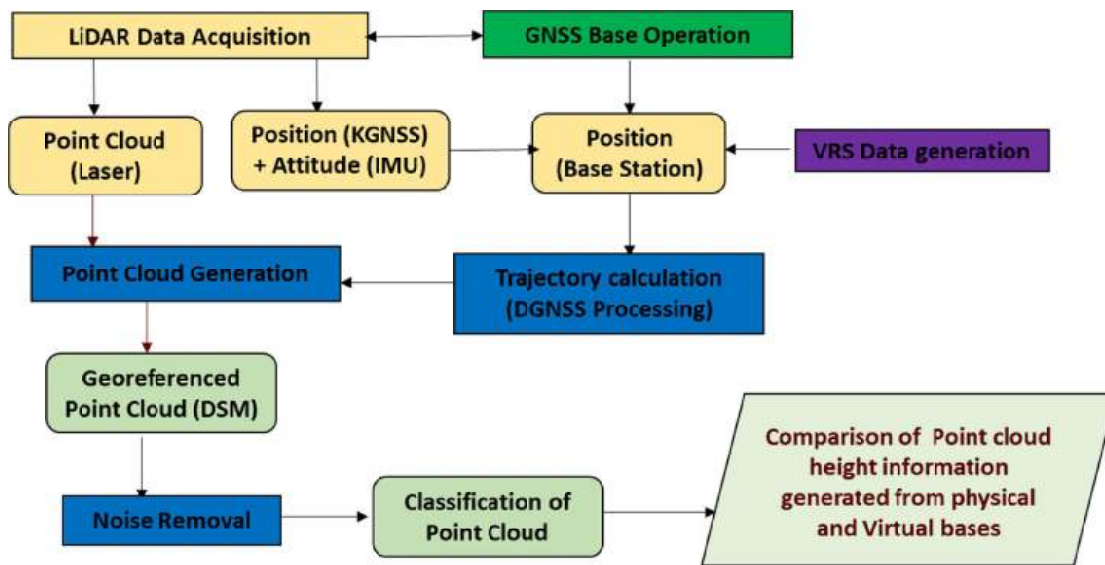


Fig. 5: Flow Chart of the study

a. Components of LiDAR Data Acquisition:

- **Acquisition of Point cloud using LiDAR Sensor:** A LiDAR sensor emits laser pulses towards the ground and records the time it takes for them to return, and provided the distance measurements.
- **GNSS rover data:** The GNSS receiver installed on the aircraft platform collects real-time positional data from GNSS satellites to accurately determine the LiDAR trajectory information.
- **IMU (Inertial Measurement Unit) data:** The IMU measures the sensor's motion and orientation, and provides attitude data, roll pitch and yaw.

b. GNSS Base operation and VRS data generation:

- **Base Station Data:** GNSS base station were operated at the locations Base1 and Base 2 (refer Fig. 4) during the LiDAR survey. The precise co-ordinates of base station were derived using Bernese processing software by networking with International GNSS Service (IGS). The base station data was used to correct positional errors in the GNSS data collected by the LiDAR sensor, improving the accuracy of the sensor's position using Differential GNSS technique.

- **VRS Data:** VRS data, sampled every second, was generated via the SOI CORS network at the physical GNSS base station location.

c. Trajectory Calculation and point cloud generation:

- **Sensor Path Calculation:** Corrected GNSS and IMU data are used to establish the trajectory of the LiDAR sensor. This defines the exact path the sensor followed during the survey, ensuring that the LiDAR points are positioned accurately in space.

d. Geo-referencing point cloud (DSM) and Noise removal:

- **Alignment with GNSS Data:** The corrected GNSS data and IMU data are applied to the point cloud, ensuring it is geo-referenced with real-world coordinates. This represents the digital surface model (DSM)
- **Noise and Outlier Removal:** Unwanted points (e.g., noise from water bodies, buildings, or sensor errors) are removed to improve the accuracy of the point cloud.

e. Classification of Point Cloud:

- **Ground vs. Non-ground Points:** The point cloud is classified into different categories (e.g., ground, vegetation, buildings) based on elevation and other attributes.
- f. Comparison of Point cloud height information generated from physical and Virtual GNSS bases:
- The LiDAR point cloud was generated using physical GNSS reference station data and VRS GNSS data, with results compared the both LiDAR point clouds

Results and Discussion

Quality of the VRS GNSS data:

VRS service uses GPS, GLONASS, GALELIO and BeiDou constellation to provide coordinate in ITRF2008. The data is downloadable in different sample intervals from 1 to 60 seconds. The VRS data is downloaded with 1-second sample to match with sample interval of rover GNSS data. The quality of GNSS VRS data is compared with physical GNSS data and observed few cycle slips in the GNSS data of VRS. These observations highlight areas for potential improvement in data quality.

Trajectory Parameter Derivation:

The combined processing of GNSS data from the reference station, rover station, and IMU data was performed using tightly coupled technology. This

approach estimates the position and orientation of the aircraft platform by integrating IMU data over time (El-Sheimy, N et. al, 2016). The resulting trajectory parameters, also called Exterior Orientation (EO) parameters, include:

- **Position:** Obtaining the final trajectory in terms of latitude, longitude, and altitude.
- **Velocity:** Calculating velocity as the derivative of position over time.
- **Acceleration:** Deriving acceleration from changes in velocity.
- **Orientation:** Using quaternion or Euler angles to represent the orientation of the object (roll, pitch, yaw) based on IMU data.

The accuracy of the derived trajectory parameters was assessed using the standard deviation of the final solution. The trajectory parameters were calculated using both physical reference station data and Virtual Reference Station (VRS) data.

As shown in the Fig. 6, the VRS-derived trajectory initially had gaps when processed with GNSS data alone but became continuous after combining with IMU data (Fig.7). The IMU operates at 200 Hz (200 samples per second), so its high data rate minimizes the impact of slips in the GNSS data on trajectory quality. Trajectory positions derived from physical and virtual GNSS data were compared. For the flight on 20-04-2023, the standard deviation difference (SD) for trajectory data using the physical base was up to 10 cm, while it was up to 30 cm with VRS data.

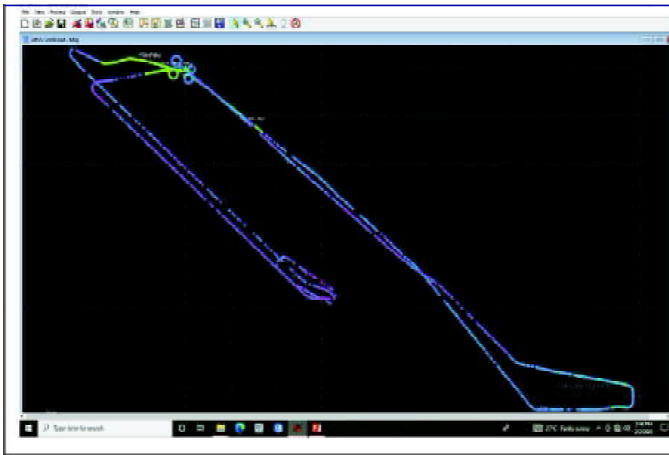


Fig. 6 : Trajectory with VRS GNSS data on 20-04-2023



Fig. 7 : Trajectory after combined data processing VRS GNSS data on 20-04-2023

Comparison of Trajectories

Comparative analysis of physical and virtual base-derived trajectories revealed variations of 0.5 to 1.0 meters in X, Y, and Z coordinates across three observation days and shown in Fig. 8, 9 and 10.

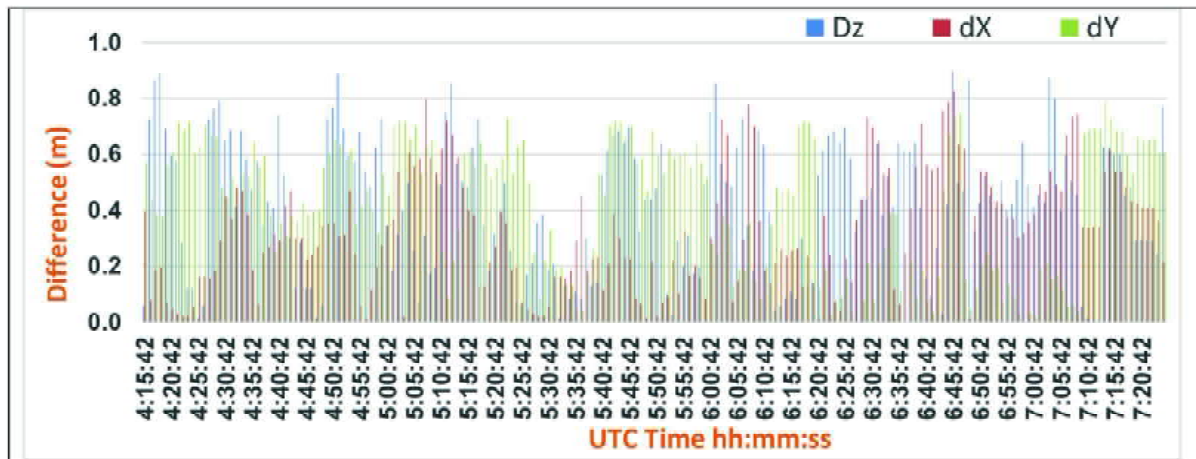


Fig. 8: Variation in X,Y,Z at trajectory level - 15-04-2023

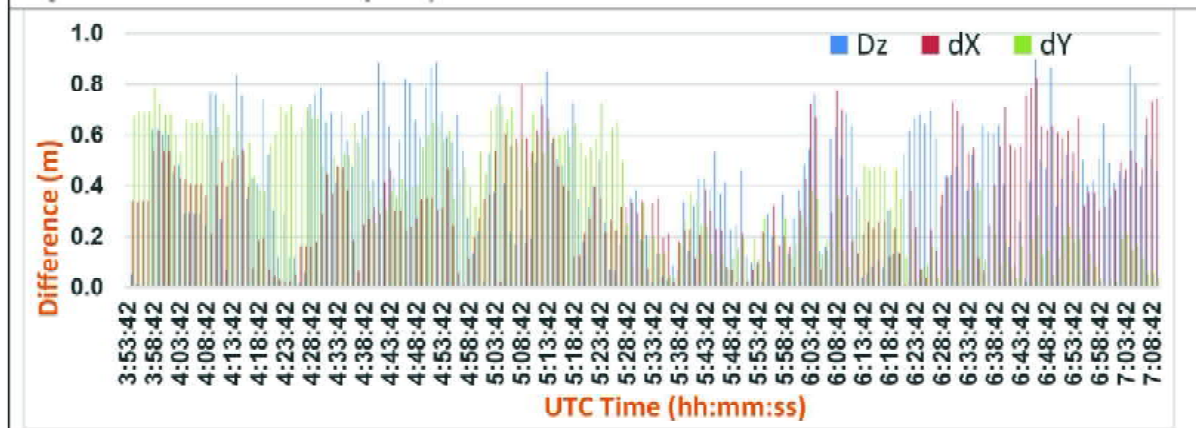


Fig. 9: Variation in X,Y,Z at trajectory level - 20-04-2023

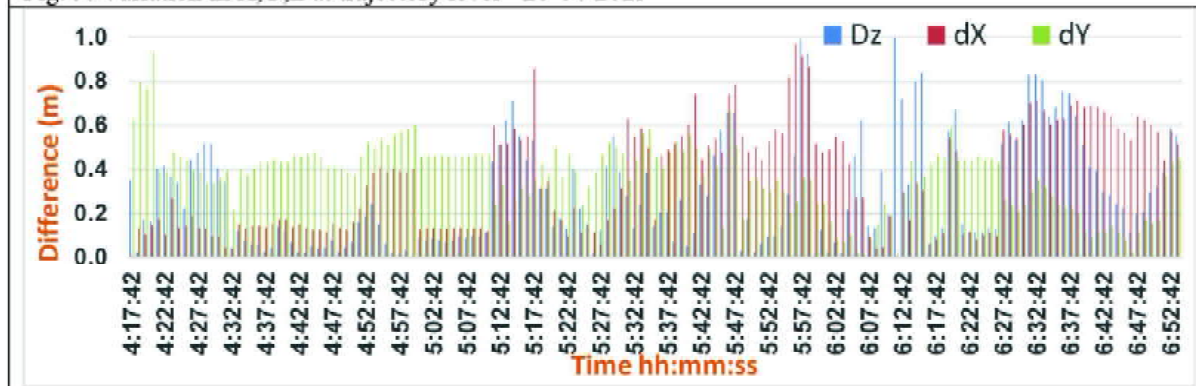


Fig. 10: Variation in X,Y,Z at trajectory level - 21-04-2023

Surface-Level LiDAR Evaluation

As described in Methodology, the geo-referenced LiDAR point cloud data were produced using physical and virtual

GNSS bases. Generated LiDAR point cloud at surface level using classification techniques and their vertical accuracy was compared. A variation of 15-25 cm was observed. The results are shown in Fig. 11, 12 and 13.

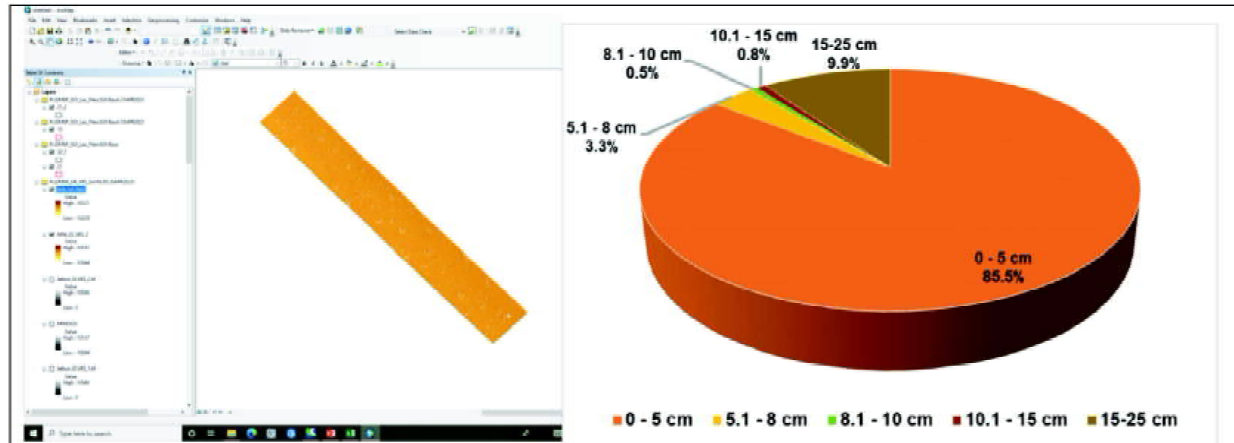


Fig. 11: Surface level LiDAR point cloud comparison results of 15-04-2023

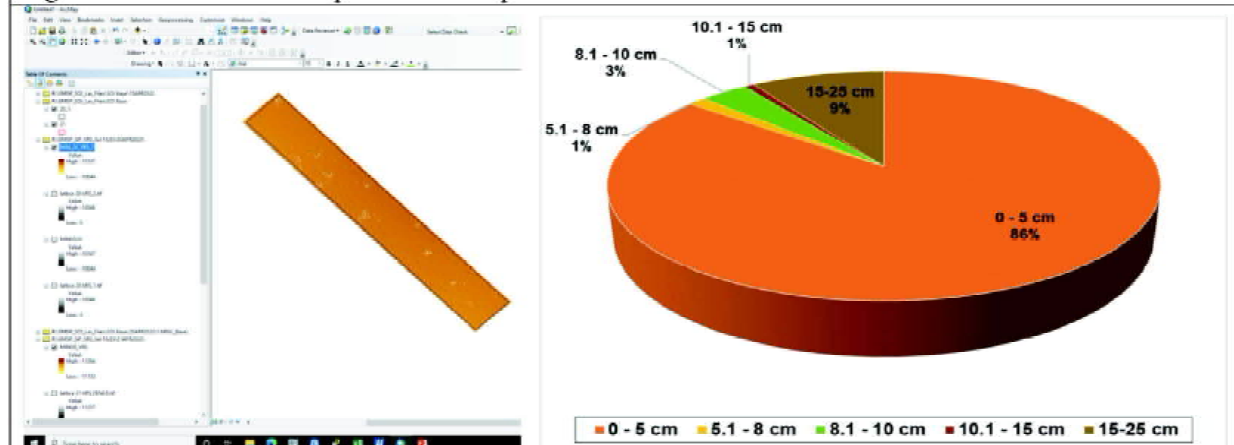


Fig. 12: Surface level LiDAR point cloud comparison results of 20-04-2023

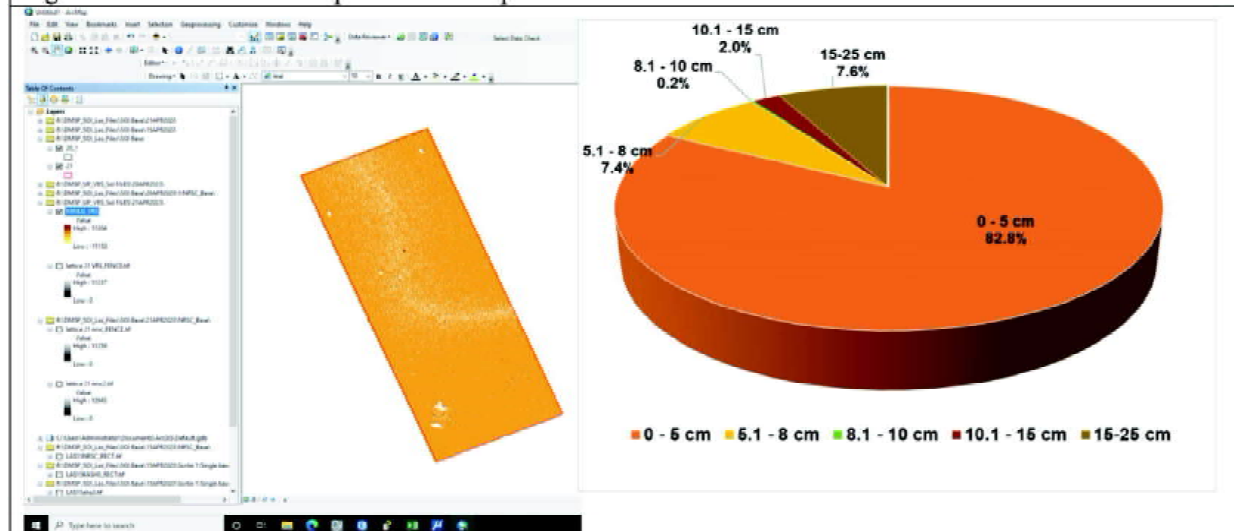


Fig. 13: Surface level LiDAR point cloud comparison results of 21-04-2023

Assessment of the GCPs accuracy generated with VRS data (Static mode)

Ground Control Points (GCPs) provide known, accurately measured coordinates essential for correcting spatial data to align with real-world geographic locations. Precise GCPs are required for the geo-referencing of aerial or satellite data products. These GCPs are typically derived using GNSS control surveys, where a base station plays a critical role by networking with the GCPs. GNSS surveys in network mode offer more accurate, reliable data across a large area, reducing errors and improving

overall survey quality. (Ritchie, J.C et.al, 2016). Operating a base station during a control survey, however, is time-consuming and costly. To mitigate this, Virtual Reference Station (VRS) data at base stations is validated, reducing the need for extensive fieldwork. Fig. 14 illustrates a typical control survey network.

The GCPs (rovers) generated in different areas using physical GNSS data were compared with those generated using virtual GNSS data. The results showed a variation within 5–10 cm horizontally and 10–20 cm vertically. The results are shown in Fig. 15.

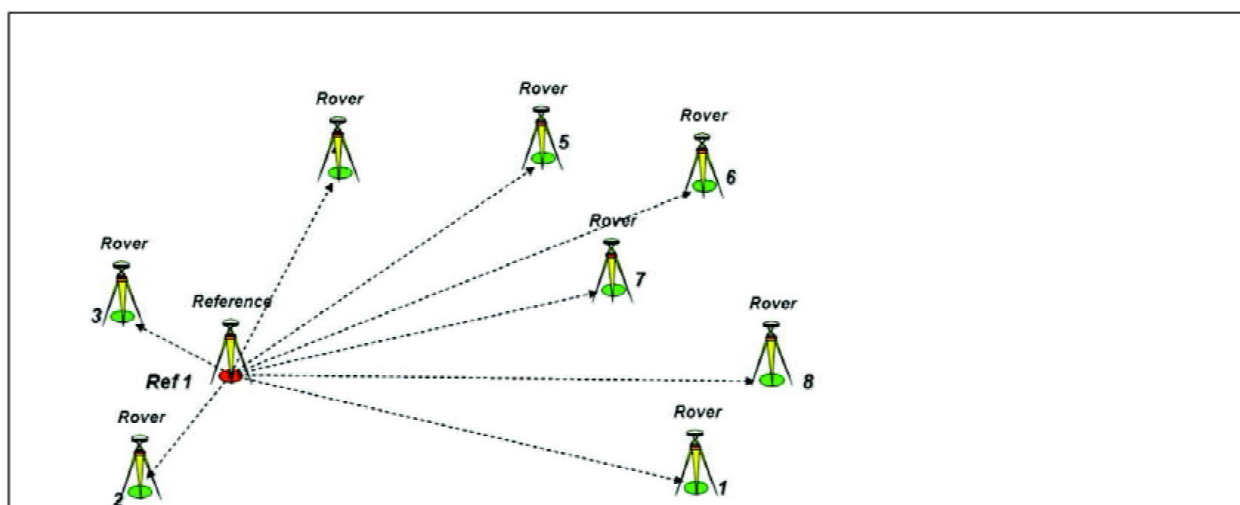


Fig. 14: Typical Control survey network

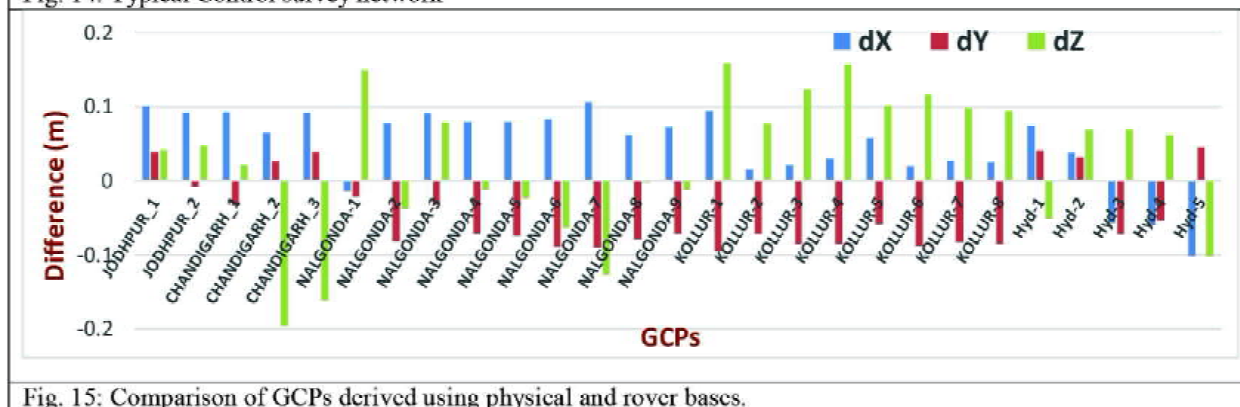


Fig. 15: Comparison of GCPs derived using physical and rover bases.

Conclusion

For kinematic accuracy studies, LiDAR data acquired over three days was analyzed. The trajectory for each day was derived using both physical and virtual bases and then compared. Variations ranging from 50 cm to 1 meter were observed in the easting, northing, and height components. The trajectory was derived at the flying

height. At the surface (ground) level comparison, the LiDAR data for the same three days was analyzed. VRS data produced vertical accuracy variations of up to 15 cm for 90% of the points and 15–25 cm for the remaining 10%, making it suitable for generating 1-meter contours. For static applications, VRS data accuracy at ground control points (GCPs) matched within 5–10 cm

horizontally and 10–20 cm vertically, making it appropriate for map generation at a 1:1,000 scale. These findings support the viability of VRS data for LiDAR data product generation. Accuracy is expected to improve further as VRS technology advances and cycle slips in the data are minimized.

Acknowledgements

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References

- El-Sheimy, N. & J. F. (2016). A new approach for GNSS and IMU integration in airborne mapping applications. *Journal of Navigation*, 69(2), 287-302. <https://doi.org/10.1017/S0373463315000718>.
- Ritchie, J.C. & Zabel, R. (2016). The use of ground control points for satellite imagery validation. *ISPRS Journal of Photogrammetry and Remote Sensing*, 117, 184-191. <https://doi.org/10.1016/j.isprsjprs.2016.05.017>.
- Survey of India. (2022). VRS data processing. *Survey of India Publications*. <https://surveyofindia.gov.in/webroot/UserFiles/files/SoP%20for%20VRS%20Data%20downloading.pdf>.
- Survey of India. (2022). <http://103.205.244.106/> for downloading VRS data.
- Zhao, K. & Chen, J. (2017). Evaluating the performance of Virtual Reference Station (VRS) technology. *Journal of Geodesy*, 91(3), 347-359. <https://doi.org/10.1007/s00190-016-0972-3>.



Spatial Analysis of Rural and Urban Development in Selected Blocks of Murshidabad District of West Bengal, India

Debjani Roy^{1*}, S.K. Mahidul² and Manab Ghosh³

¹ Department of Geography, Nirmala College, Ranchi, Jharkhand (India)

² Department of Geography, University of Gour Banga, Malda, West Bengal (India)

³ Department of Geography, Berhampore College, Murshidabad, West Bengal (India)

**Corresponding Author's Email: debjaniroy696@gmail.com*

Abstract

The spatial analysis of rural and urban development is crucial for understanding regional disparities in socio-economic conditions, especially in diverse country like India. India still continues to face significant challenges in achieving a balanced development between its urban and rural areas. Murshidabad district in West Bengal with a population density of 1,334 persons per km² (Census of India, 2011) faces severe shortages in healthcare and educational services, which have negatively impacted human capital development. This study seeks to analyze the overall development indices of health and education across Murshidabad district at block level, and to examine how these factors interact with population density and growth. Using statistical methods like development index, dimension index and z-score the study highlights the disparities in infrastructure and services and aims to provide insights into the broader challenges of regional development and their impact on quality of life.

Keywords: Regional disparities, balanced development, development indices, infrastructure services.

Introduction

The spatial analysis of rural and urban development is essential for understanding regional disparities in socio-economic conditions across India. Despite notable progress since independence, India continues to struggle with achieving balanced growth between its urban and rural areas. Unequal distribution of resources, uneven infrastructural development, and wide variations in literacy, health and employment opportunities have deepened these disparities.

Murshidabad district of West Bengal exemplifies these imbalances. With a population density of 1,334

persons per km² (Census of India, 2011), the district faces acute challenges in providing adequate healthcare, educational facilities and employment opportunities. The coexistence of densely populated urban centers and underdeveloped rural hinterlands highlights sharp contrasts in living standards and access to basic amenities. Persistent issues such as inadequate infrastructure, high population pressure and low levels of industrialization have hindered the district's human capital formation. The problem is further intensified by the district's geographical complexity - as divided into the Rarh and Barind tracts by the Bhagirathi river — which influences patterns of settlement, agricultural productivity and accessibility to

essential services. Therefore, an integrated spatial analysis of rural and urban development in Murshidabad is vital to identify intra-district disparities and to frame targeted policies aimed at achieving equitable regional development.

Literature Review

The spatial dynamics of rural and urban development have been a subject of extensive research, especially in regions with high population pressure and socio-economic diversity, such as Murshidabad district in West Bengal. Studies indicate that population distribution, infrastructure availability and service delivery are interlinked and significantly influence the quality of life in both rural and urban areas.

In this context, Ghosh (2024) examined the spatial distribution of health infrastructure and its relationship with quality of living across Murshidabad. Using GIS-based analysis, the study highlighted significant disparities in healthcare accessibility between densely populated urban-influenced blocks and rural hinterlands. The research underscored that while high-density areas often benefit from better health services, infrastructure often lags behind population growth, creating localized challenges.

Population growth and urbanization trends in Murshidabad have also been analyzed in detail. Halder (2018) reported that rapid population expansion, especially in blocks such as Samserganj and Farakka, is influenced by industrial activities, trade and transportation connectivity. This growth has intensified pressure on infrastructure, creating gaps in health, education and development services. Roy (2024) expanded this perspective by examining urban household living conditions across India, emphasizing that spatial heterogeneity and uneven service distribution in smaller urban centers, like census towns in Murshidabad, contribute to disparities in human development indicators. Further, Tarafder (2016b) specifically addressed disparities in health infrastructure within rural blocks of Murshidabad, illustrating how geographic isolation,

riverbank erosion, and inadequate planning hinder equitable access to essential services.

These studies collectively indicate that Murshidabad exhibits pronounced spatial variation in development. High-density urbanized blocks often have better educational and health services, but face infrastructural stress due to rapid population growth. In contrast, low-density rural blocks suffer from limited access to healthcare and educational facilities, despite occasionally having better overall development of infrastructure. This literature underscores the importance of an integrated spatial analysis approach that considers population density, health, education and overall infrastructure in evaluating rural and urban development in Murshidabad district.

Study area

Murshidabad district (**23°43' 30" N to 24°50' 30" N latitudes and 87°49' 17" E to 88°46' 00" E longitudes**) is a district of West Bengal in eastern India, which lies at the Indo-Bangladesh border (Fig. 1). This district's border area consists of ten community development blocks (CD Block), viz. Farakka, Samserganj, Suti-I, Suti-II, Raghunathganj, Lalgola, Bhagawangola-I, Bhagawangola-II, Raninagar-II and Jalangi. They are mostly located on the bank of the Padma river and physically, Bhagirathi river divided into two parts from east to west. C.D Blocks of the western part of the river locally are known as *Rarh*, which are characterized by an undulating surface, some hillocks, hard soil and a dry climate. C.D Blocks of the eastern part of Bhagirathi are known as *Bagri*, as characterized by a low-lying alluvial surface with a humid climate and fertile soil.

Objectives of the Study

- (i) To analyze spatial disparities in development and infrastructure using GIS and statistical methods to identify distribution patterns and their effectiveness.
- (ii) To assess the impact of population density on infrastructure quality and availability, highlighting areas of deficit for targeted policy interventions.

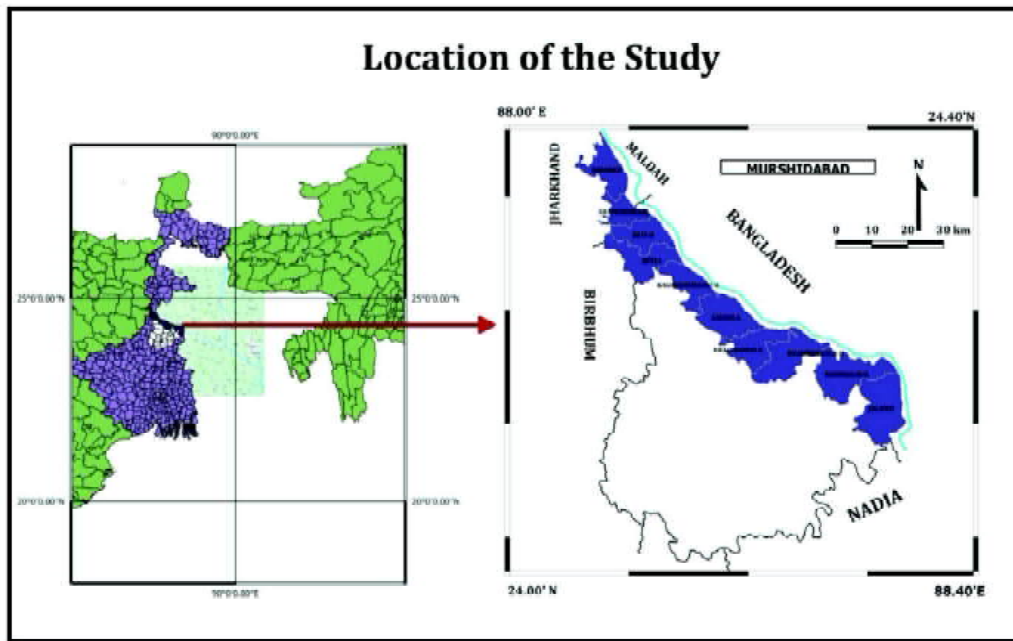


Fig. 1: Location of the Study Area

Database and Methodology

Variables for evaluating health infrastructure, education and development have been selected to assess societal progress. Health data were provided by the CMOH (Chief Medical Officer of Health), while education and development data came from primary surveys and the Department of Planning and Statistics.

1. Development Index (DI) = $1 - \frac{\sum I_{ij}}{n}$
Where, I_{ij} (individual normalized value) = $(Max - X_{ij}) / (Max_i - Min_i)$
Measure deprivation across variables (Riddersta *et al.*, 2014).

2. Health Infrastructure Index:

3. Dimension Index = $(Actual\ value - Min\ value) / (Max\ value - Min\ Val)$

and Health Index = $\frac{1}{12} \times (x_1 + x_2 + \dots + x_{12})$
(OECD, 2020).

4. Education Infrastructure (Z-Score Method):

$$Z_i = \frac{x_i - Mean}{Standard\ deviation}$$

Composite Z-score is summed across variables for infrastructure assessment (UNESCO, 2020).

5. Quality of Living Index

$$Xid = (OB\ val - MIN\ val) / (MAX\ val - MIN\ val)$$

Normalization for consistent scaling (World Bank, 2019).

6. Principal Component Analysis (PCA):
Weightage of variables based on first principal componentscore (Jolliffe, 2002).
7. Composite Development Indicator or Quality of Living (QoL)- $(HCI + HI + PCI + FCI / 4)$
Where HCI (Human capital Index), HI (Housing Index), PCI (Physical Capital Index), and FCI (Financial Capital Index) are calculated by $\sum(SCc \times SDv) / N$ (National Health Profile, 2020).

Results and Discussion

Cause Analysis of Population Density Variation

The population density pattern in the study area reveals substantial spatial variability, reflecting the diverse socio-economic and geographical characteristics of the region. Farakka and Samsarganj record the highest population densities in the district, with 2,489 and 4,459 persons per square kilometer, respectively. Farakka's high density is largely associated with its urban influence and the concentration of economic activities around the Farakka

Barrage project, while Samserganj's exceptionally high-density stems from its proximity to major transportation

routes, flourishing bidi industry, and rapid population growth.

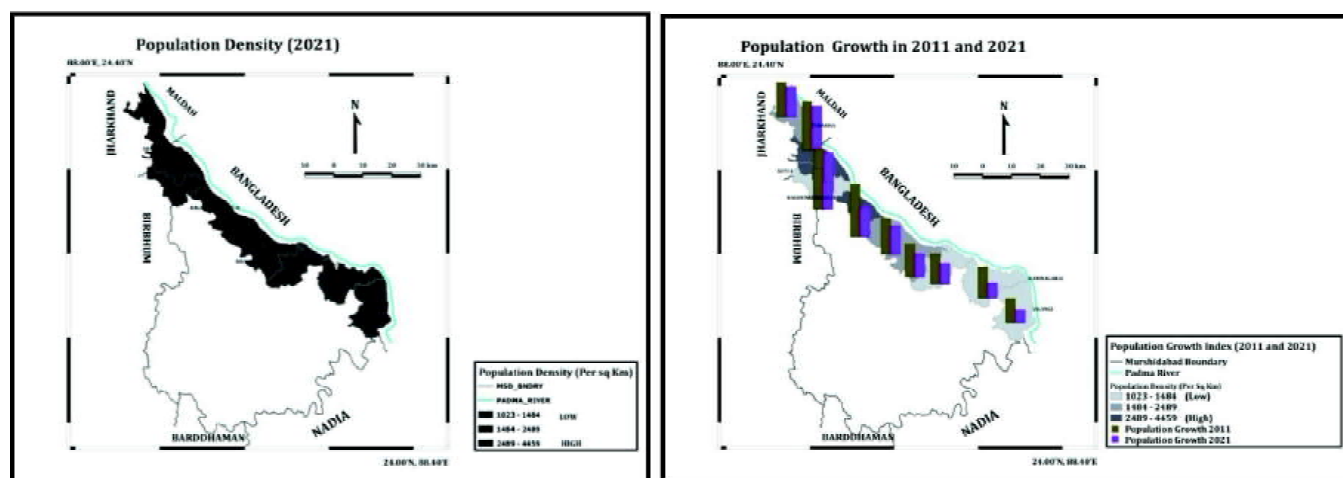


Fig. 2 & Fig. 3: Population density and population growth during 2011 and 2021 in the study area

The population density pattern in the study area reveals substantial spatial variability, reflecting the diverse socio-economic and geographical characteristics of the region. Farakka and Samserganj record the highest population densities in the district, with 2,489 and 4,459 persons per km² respectively. Farakka's high density is largely associated with its urban influence and the concentration of economic activities around the Farakka Barrage project, while Samserganj's exceptionally high density stems from its proximity to major transportation routes, flourishing bidi industry, and rapid population growth.

Blocks such as Suti-II and Raghunathganj-II also exhibit relatively high population densities, primarily due to strong urban influence from nearby towns like Raghunathganj, which serve as regional commercial hubs. Lalgola and Bhagawangola-I represent areas of moderate population density, indicating a transitional character between rural and semi-urban settings. Suti-I, being more rural and agrarian in nature, shows a moderate but lower density compared to its counterpart Suti-II (Fig. 2 & 3).

In contrast, Jalangi exhibits moderate population density influenced by geographical constraints, particularly recurrent riverbank erosion along the Padma river, which limits stable settlement expansion.

Bhagawangola-II and Raninagar-II record the lowest population densities, primarily due to their peripheral location and poor infrastructural development aggravated by riverbank erosion and flood-prone conditions along the Indo-Bangladesh border.

Relationship Analysis between Population Density and Health Infrastructure Index

The interrelationship between population density and the health infrastructure index across in the study area reveals an important insight into the adequacy and effectiveness of healthcare services in the region.

For instance, *Samserganj*, with its exceptionally high population density, boasts a health infrastructure index of 0.690, indicating well-developed healthcare facilities driven by the demand from its dense population. In contrast, Farakka, despite having a high population density, has a moderate health infrastructure index of 0.537, suggesting that its healthcare services may not fully meet the needs of its large population. The situation is almost similar in Suti II (Fig. 4).

Lalgola, with a moderate population density and a health infrastructure index of 0.482, reflects a more balanced scenario. However, Raghunathganj-II exhibits a stark contrast with high population density, yet a low

health infrastructure index of 0.204, highlighting inadequacies in healthcare services despite population pressure. Similarly, Bhagawangola-I shows a moderate

population density, but a lower health infrastructure index of 0.344, indicating underdeveloped healthcare services.

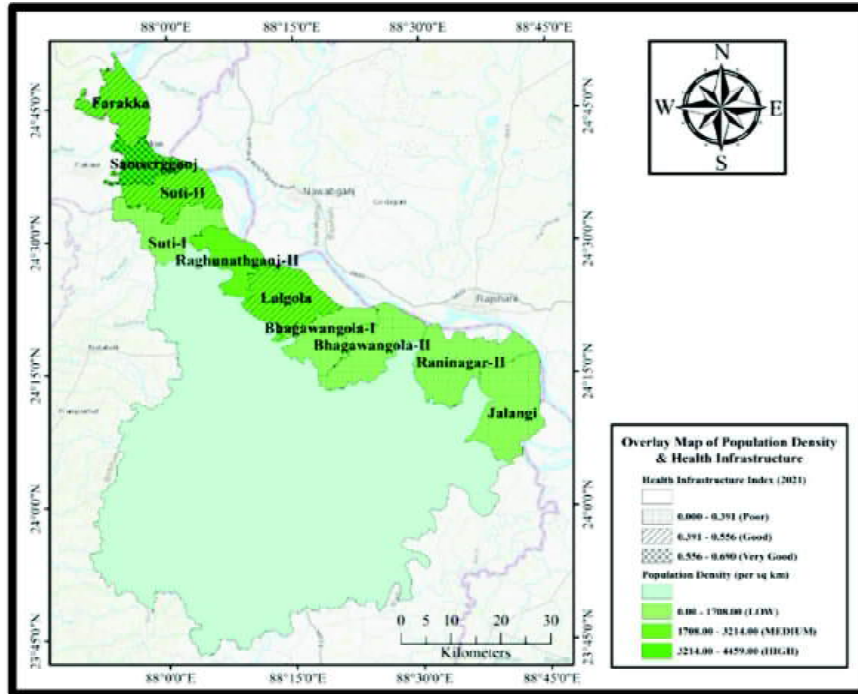


Fig. 4: Overlay map of population density and health infrastructure

Bhagawangola-II, characterized by low population density and a health infrastructure index of 0.328, exemplifies a rural area with limited healthcare services. Raninagar-II also struggles to provide adequate healthcare due to its low density. Finally, Jalangi, with a low health infrastructure index of 0.279, faces severe limitations, suggesting that low population density combined with inadequate infrastructure results in significant challenges in healthcare provision.

Thus, this relationship underscores significant disparities across the study area. High-density areas often benefit from better healthcare facilities, but challenges arise when infrastructure does not keep pace with population growth.

Relationship Analysis between Population Density and School Infrastructure Index (Primary and Higher Secondary)

The analysis of population density in relation to the infrastructure indices for primary and higher secondary

schools across various blocks in the study area reveals a nuanced picture of educational resource allocation and its adequacy relative to population needs. In Samsarganj, for example, the exceptionally high population density of 4459 persons per km² is matched by robust infrastructure indices for both primary and higher secondary schools at 10.13 and 10.92 respectively.

Farakka, with a population density of 2489 per km² also displays a strong educational infrastructure, particularly at the higher secondary level, where its index reaches 12.48. Suti-II, on the other hand, presents a scenario where high population density is accompanied by moderate infrastructure indices for both primary and higher secondary education at 8.61 and 10.38 respectively. Lalgola offers a more balanced picture, with a moderate population density and strong indices for both primary and higher secondary schools at 10.06 and 11.78, respectively. In contrast, Raghunathganj-II, despite its high population density shows moderate to high infrastructure indices with 8.89 for primary schools and 10.78 for higher secondary schools (Fig. 5 & 6).

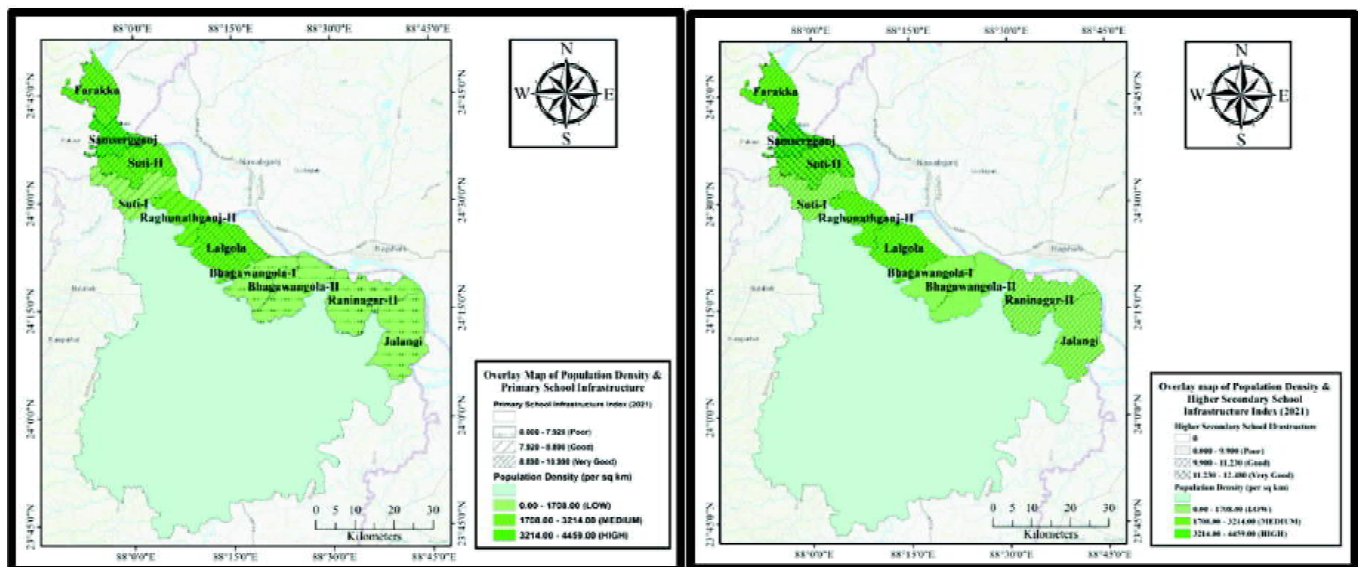


Fig. 5 & 6: Overlay map of population density with primary and higher secondary school infrastructure

Suti-I, with a lower population density stands out for its high educational infrastructure indices at 10.99 for primary schools and 11.23 for higher secondary schools. Bhagawangola-I, however, presents a different challenge. With a moderate population density it has lower infrastructure indices at 7.92 for primary schools and 9.90 for higher secondary schools.

Thus, the relationship between population density and school infrastructure in Murshidabad district shows that while high-density areas often have better educational resources, significant disparities remain, particularly in primary education. Blocks with lower density tend to have less developed primary school facilities, though secondary education may be better.

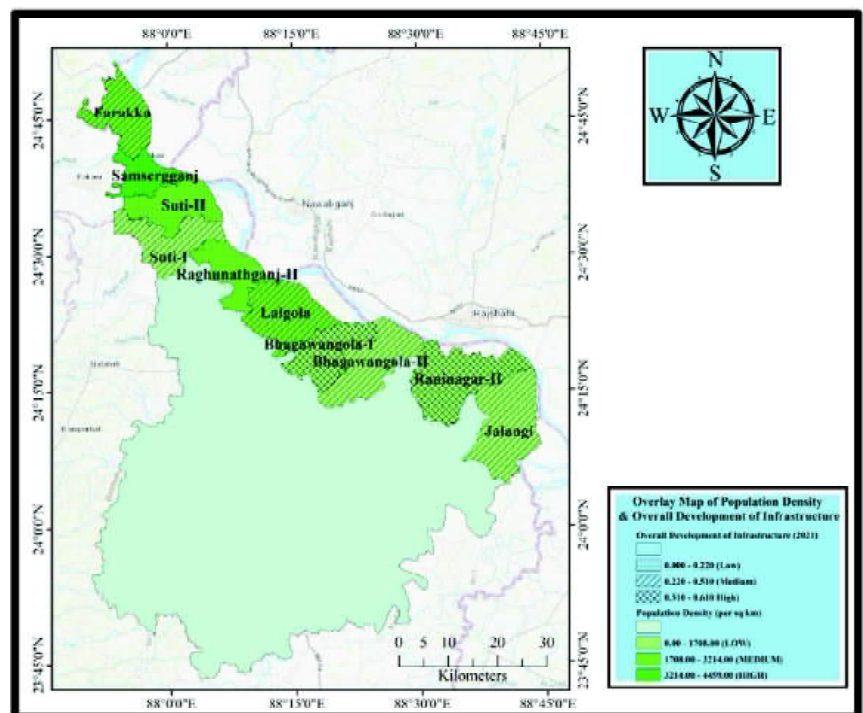


Fig. 7: Overlay map of population density and overall development of Infrastructure

Relationship Analysis between Population Density and Overall development

Overall development infrastructure analysis reveals that high-density blocks frequently struggle to match infrastructure growth with population needs. For instance, Samserganj has high density but a moderate infrastructure index of 0.38, while Farakka faces a mismatch with a

low index of 0.20. In contrast, Suti-II shows a healthier index of 0.47, indicating better planning.

Bhagawangola-I and Bhagawangola-II demonstrate that moderate and lower population density blocks can maintain high infrastructure indices of 0.61 and 0.50 respectively. Jalangi also benefits from a high index of 0.51 despite its lower density (Fig. 7).

Overall, areas with high population density often struggle with infrastructure development, while those with lower density enjoy better services. Addressing these disparities will require targeted efforts to improve infrastructure in high-density areas, ensuring that investments meet the needs of all blocks.

Analysis of Quality of Living in Relation to Health, Education and Overall Infrastructure Development

Analyzing the quality of living in the context of health, education and overall development of infrastructure across various blocks offers a nuanced view of how these factors collectively influence residents' well-being (Table 1). Samserganj stands out with high indices in health and education infrastructure, yet it struggles with a moderate overall infrastructure development index. Despite the robust health and educational services, the quality of living remains moderate, likely due to gaps in development infrastructure that could affect

transportation, sanitation and housing, thus limiting the overall benefits of good health and education.

Farakka presents a case where moderate health and education indices are coupled with a low overall infrastructure development index. This imbalance leads to a lower quality of living, indicating that even with relatively strong educational facilities, inadequate infrastructure, such as poor transportation and sanitation, significantly detracts from the residents' quality of life.

Lalgola, with its high education infrastructure, faces challenges similar to those of Samserganj. The block's low health infrastructure and overall development index contribute to a relatively low quality of living, despite the advantages offered by its strong educational services (Fig. 8).

In Raghunathganj-II, the scenario is different. Despite a low health infrastructure index, the block manages to maintain a decent quality of living due to its relatively better development and education infrastructure.

Table 1: Quality of Living in Relation to Health, Education and Overall Development Infrastructure, 2021

C.D. Blocks	Population Density (Persons per sq km)	Health Infrastructure Index (2021)	Primary School Infrastructure Index (2021)	Higher Secondary School Infrastructure Index (2021)	Overall Development Infrastructure (2021)	Level of Quality of Living (2021)
Farakka	2489	0.537	10.13	10.92	0.38	0.0793
Samserganj	4459	0.690	9.81	12.48	0.2	0.0646
Suti-I	1484	0.391	8.61	10.38	0.47	0.0588
Suti-II	3214	0.556	10.06	11.78	0.15	0.0618
Raghunathganj-II	2616	0.204	8.89	10.78	0.22	0.0902
Lalgola	2166	0.482	10.99	11.23	0.43	0.0716
Bhagawangola-I	1708	0.344	7.92	9.90	0.61	0.0503
Bhagawangola-II	1023	0.328	7.73	9.08	0.5	0.0503
Raninagar-II	1189	0.343	7.67	11.18	0.56	0.0518
Jalangi	1286	0.279	6.99	10.42	0.51	0.0986
Source- Computed by the authors.						

Bhagawangola-I and Bhagawangola-II both exhibit high overall development of infrastructure but lower indices in health and education. This results in a lower quality of living, illustrating that while high infrastructure development is crucial, its benefits are limited when health and education services are lacking. The situation in Raninagar-II echoes this situation. Despite better education and development of infrastructure, the block's

low health services contribute to only a modest quality of living underscoring the need for comprehensive improvements across all sectors.

Jalangi emerges as a block with lower health and education infrastructure, but good overall development of infrastructure. This combination results in the highest quality of living among the blocks are analyzed.

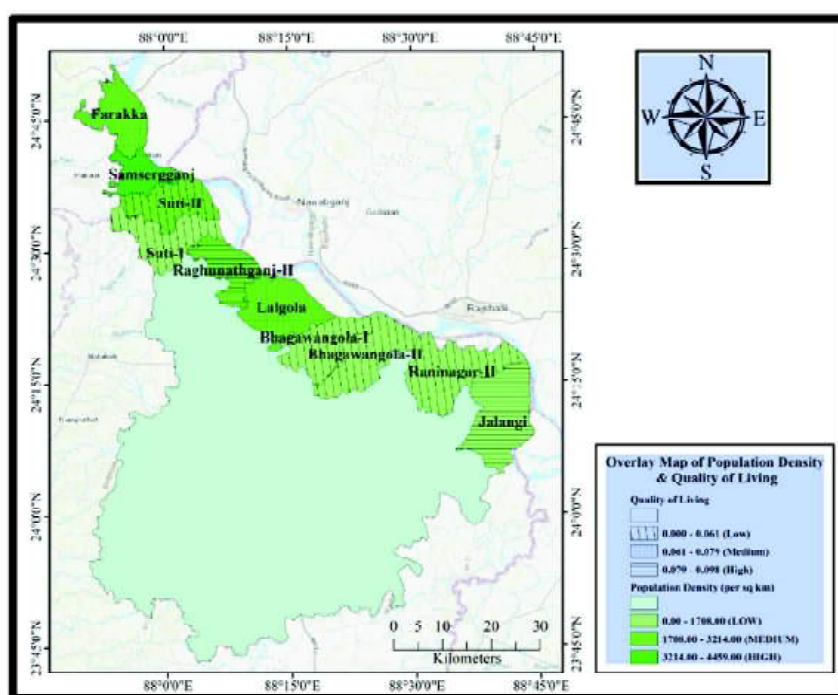


Fig. 8: Overlay map of population density and quality of living

Conclusion

The spatial analysis of rural and urban development across selected blocks of Murshidabad district reveals a pronounced disparities in population density, health infrastructure, educational facilities and overall development. High-density urban-influenced blocks such as Samsarganj, Farakka and Suti-II experience significant pressure on infrastructure and services. While educational and health facilities in some of these blocks are relatively strong, gaps in overall development infrastructure limit improvements in residents' quality of living.

Moderately dense blocks, including Lalgola and Suti-I, demonstrate transitional characteristics between rural and semi-urban areas. Despite adequate educational infrastructure, shortcomings in healthcare and development infrastructure restrict optimal living conditions. Low-density blocks such as Bhagawangola-

I, Bhagawangola-II, Raninagar-II and Jalangi face unique challenges linked to geographical constraints like riverbank erosion and limited accessibility. Interestingly, some of these lower-density blocks, particularly Jalangi, achieve higher quality of living due to balanced development of infrastructure and lower population pressure.

Overall, the study underscores that population density interacts closely with infrastructure availability and service delivery to shape living conditions. High-density alone does not guarantee better development, rather the adequacy and integration of health, education and overall infrastructure determine the quality of life. Hence, the findings highlight the need for targeted, region-specific interventions to bridge infrastructural gaps, ensure equitable service provision, and promote sustainable rural and urban development across the study area.

References

- Ghosh, M. (2024). *Spatial analysis of health infrastructure and quality of living using GIS: A case study of Murshidabad district, West Bengal*. Retrieved from https://obrieniph.ucalgary.ca/sites/default/files/teams/23/GIS%20Day%202024/Abstracts/Manab%20Ghosh-Health_GIS_Abstarct.pdf.
- Halder, S. (2018). *Pattern of population growth in Murshidabad district, West Bengal*. *Review of Research*, 7(7). Retrieved from <https://oldror.lbp.world/UploadedData/9932.pdf>.

- Jolliffe, I. T. (2002). *Principal component analysis* (2nd ed.). New York, NY: Springer. <https://doi.org/10.1007/b98835>.
- Ministry of Education, Government of India. (2020). *Unified District Information System for Education Plus (UDISE+) 2019–2020*. New Delhi: Ministry of Education, Government of India. Retrieved from <https://www.udiseplus.gov.in>. Accessed on March 10, 2024.
- Ministry of Health and Family Welfare, Government of India. (2020). *National Health Profile 2020*. New Delhi: Ministry of Health and Family Welfare, Government of India. Retrieved from <https://www.cbhidghs.nic.in>. Accessed on March 10, 2024.
- Organisation for Economic Co-operation and Development (OECD). (2020). *Health at a glance 2020: OECD indicators*. Paris: OECD Publishing. <https://doi.org/10.1787/4dd50c09-en>. Accessed on March 10, 2024.
- Roy, S. (2024). *Spatial heterogeneity in the urban household living conditions: A GIS-based analysis across 146 urban centers in India*. *Journal of Urban Affairs*, 46(2), 123–145. <https://doi.org/10.1080/19475683.2024.2304194>.
- Ridderstaat, J., Croes, R., & Nijkamp, P. (2014). A two-way causal chain between tourism development and quality of life in a small island destination: An empirical analysis. *Journal of Sustainable Tourism*, 22(7), 1080–1099. <https://doi.org/10.1080/09669582.2013.873445>.
- Tarafder, M. S. (2016). *Disparities in health infrastructure development in rural areas of Murshidabad district, West Bengal*. *Social Science Journal*, 6(1), 45–59. Retrieved from <https://journal.sijss.com/index.php/home/article/view/173>.
- United Nations Development Programme (UNDP). (2020). *Human development report 2020: The next frontier – Human development and the Anthropocene*. New York, NY: United Nations Development Programme. Retrieved from <https://hdr.undp.org>. Accessed on March 10, 2024.
- United Nations Educational, Scientific and Cultural Organization (UNESCO). (2020). *Global education monitoring report 2020: Inclusion and education – All means all*. Paris: UNESCO Publishing. Retrieved from <https://www.unesco.org/gem-report>. Accessed on March 10, 2024.
- World Bank. (2019). *World development report 2019: The changing nature of work*. Washington, DC: The World Bank. <https://doi.org/10.1596/978-1-4648-1328-3>. Accessed on March 10, 2024.



Patterns of Disparity in Social and Infrastructure Development and Associated Spatial Relationship in Manipur

M. A. Hakim* and Bimal Kumar Kar

Department of Geography, Gauhati University, Guwahati (India)

**Corresponding Author's Email: mahakim227@gmail.com*

Abstract

This study analyses the spatial patterns of social and infrastructural development across the state of Manipur at district level using a multi-dimensional index based on secondary data for mostly 2011. A pronounced core-periphery model is confirmed, having consistent with Myrdal's cumulative causation framework, where the Imphal valley districts (Imphal West and Imphal East) form a high-development core through the agglomeration of essential infrastructure and services. Conversely, peripheral hill districts, such as Senapati and Tengnoupal, are trapped in the lowest developmental stages, exhibiting a severe developmental disparity compared to the core. Critical outlier as identified through quadrant analysis, notably Senapati (High ISI–Low SDI), is indicating a significant decoupling between physical infrastructure and social outcomes. This finding highlights that infrastructure alone is insufficient without complementary investments in human capital and effective governance. Balanced regional development requires structural, equity-oriented interventions focusing on decentralized planning and targeted social infrastructure improvements in the hill regions.

Keywords: Regional Disparity, Social Development Index (SDI), Infrastructure Services Index (ISI), Quadrant Analysis, Regional Development.

Introduction

Development is a comprehensive process involving economic growth, social improvement and infrastructure development aimed at enhancing human well-being. However, regional inequalities persist as this progress concentrates in certain areas while other regions are left behind. Various studies on India have documented persistent and widening regional disparities across among the states. Inter-state economic and social disparities have been increasing despite various governmental measures to develop backward areas, with growing differences evident in demographic indicators, literacy rates, state domestic product, and poverty levels (Kurian, 2000).

Regional disparity in economic and human development across Indian states shows that inter-state disparities in per capita income and social indicators increased during the post-reform period despite overall economic growth (Dholakia, 2003). Analysis of spatial inequality demonstrates that development benefits remain concentrated in metropolitan areas and economically advanced regions, while rural and peripheral areas continue to lag behind (Ghosh, 2006). Investigation of development disparities reveals strong persistence in regional inequalities over decades, with patterns influenced by initial conditions, geographic factors, and

institutional capabilities (Banerjee & Kuri, 2015). District-level analysis across India confirms spatial clustering patterns in socio-economic development that are consistent with core-periphery dynamics, with prosperous districts concentrated in certain regions while backward districts cluster in others (Ohlan, 2013). Evidence from states and union territories documents significant regional disparities in social development indicators including education, health, and living standards (Kumar & Rani, 2019).

Infrastructure investment shapes regional economic outcomes and spatial disparities. Empirical evidence demonstrates that public expenditure on infrastructure, particularly core infrastructure like roads and highways, is highly productive and contributes significantly to aggregate economic output (Aschauer, 1989). Analysis of China's regional development finds that differences in infrastructure provision, especially transportation infrastructure, significantly explain regional disparities in economic performance across provinces (Démurger, 2001). Access to transportation networks has positive causal effects on regional per capita GDP growth, with benefits concentrated in areas near the infrastructure, though the magnitude of effects depends on complementary factors including human capital and institutional quality (Banerjee *et al.*, 2020).

Research on North-East India reveals distinctive development challenges stemming from geographic isolation, ethnic diversity, and infrastructure deficits. Analysis of north-eastern states from a policy perspective documents significant differences among the states including Manipur in income levels, poverty rates, investment flows, and per capita net state domestic product (Singh, 2018). The demographic profile of North-East India, with particular reference to Manipur, shows how recent population growth has placed considerable pressure on economic development, resource allocation, and planning priorities in the region (Singh & Sharma, 2010).

Studies on Manipur reveal how ethnic, geographic, and institutional factors intersect to shape development outcomes. Assertion of ethnic identity and accompanying political tensions in Manipur are rooted in fears among minority groups of losing their historical and culturally

acquired identities, with ethnic divisions contributing to development challenges that particularly affect hill districts (Shimray, 2001). Investigation of poverty patterns documents sharp contrasts between valley and hill regions of Manipur, with persistent and severe poverty in hill areas driven by poor economic performance, inadequate poverty alleviation programs, and limited implementation of land reforms (Singh, 2007). Comprehensive analysis examines how infrastructure deficits in Manipur and North-East India, shaped by factors including corruption, armed conflict, and political marginalization, have profound effects on social, economic, and ecological outcomes in the region (Ziipao, 2020).

In the light of the above, the present paper attempts primarily to examine regional inequalities in social and infrastructural development in Manipur through spatial and comparative analysis at the district level applying multi-dimensional approach.

Geographical Context of the Study Area

The state of Manipur lies in India's north-eastern part, stretching between 23°50' N to 25°41' N latitude and 93°2' E to 94°47' E longitude. The state has 854 km long boundary, with 352 km bordering Myanmar to the east and the remaining 502 km forming borders with Nagaland in the north, Mizoram in the south and south-west, and Assam to the west. Administrative reforms of the state in 2016 led to the formation of seven additional districts—Jiribam, Kakching, Kamjong, Kangpokpi, Pherzawl, Noney, and Tengenoupal—raising the total from nine to sixteen (Government of Manipur, 2016). Geographically, ten districts occupy the hilly terrain, while six are confined to the plains (Fig.1).

Covering an area of 22,327 km² the state accounts for 0.7 per cent of India's total area, characterized by a landscape where hills dominate 90 per cent of the territory and valleys constitute the remaining merely 10 per cent (Economic Survey, 2020–21). Census data for 2011 revealed a population of approximately 2.86 million inhabitants, reflecting a decadal increase of 24.5 per cent during 2001–2011 and a gender composition of 985 females per 1,000 males. Educational indicators during 2001–2011 and a gender composition of 985 females per 1,000 males. Educational indicators showed an overall

literacy rate of 76.90 per cent, with distinct differences between rural population (73.4 %) and urban residents (85.38%). Such a geographical framework helps

understand the prevailing spatial patterns of social and infrastructure development of Manipur in proper perspective.

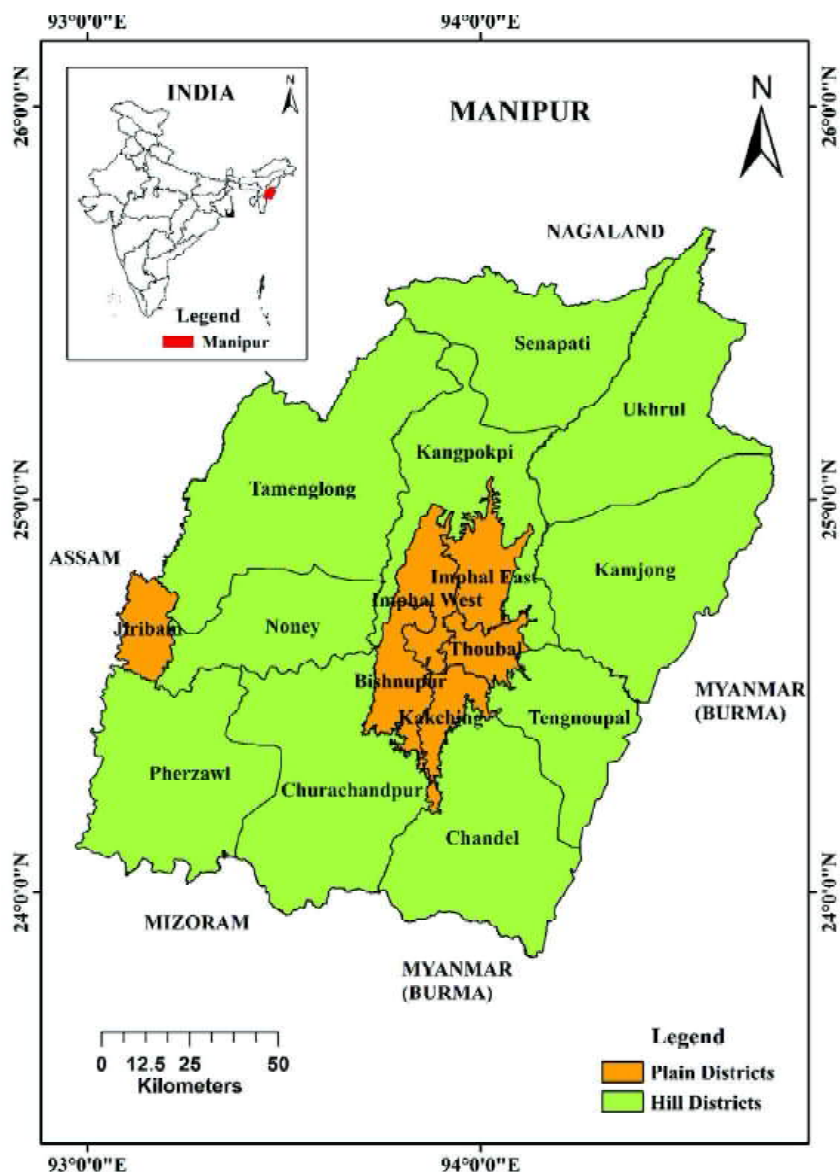


Fig. 1: Location map of the study area

Database and Methodology

The study is based on secondary data from different government publications and databases. Population and demographic data have been taken from the *Census of India, 2011*. Economic information has been drawn from the *Economic Survey of Manipur, 2020–21* published by the Directorate of Economics and Statistics, Government

of Manipur. Health data have been obtained from the *Rural Health Statistics, 2021–22* of the Ministry of Health and Family Welfare. Educational data have been sourced from the *All-India Survey on Higher Education (AISHE)* and *UDISE+ 2023* reports. Banking and financial data have been collected from the *Database on the Indian Economy (DBIE)* of the Reserve Bank of India for the period 2005–2022. These datasets form the basis for

assessing the spatial pattern of social and infrastructural development across the state of Manipur at district level.

Choice of Indicators

The selection of appropriate indicators is crucial for thoroughly assessing the various aspects of social and infrastructure development. These indicators of development reflect demographic characteristics, educational levels, participation in the workforce, access to essential amenities, financial and technological access, and the availability of basic infrastructure. Together, they help in understanding the living conditions, opportunities, and overall well-being of the population across the state.

Following the methodological approaches of Ohlan (2013) and Kumar & Rani (2019), multiple indicators are employed in this study to evaluate socio-infrastructural development in Manipur, comprising the following indicators.

Social Development Indicators

1. Sex Ratio
2. Percentage of Population Aged 0–6 (considered as a negative indicator)
3. Literacy Rate
4. Female Literacy Rate
5. Work Participation Rate
6. Female Work Participation Rate
7. Percentage of Households with Permanent Housing
8. Percentage of Households with Tap Water from Treated Sources
9. Percentage of Households with Electricity
10. Percentage of Households with Sanitary Toilets (Flush/Pour)
11. Percentage of Households with Drainage for Wastewater Disposal
12. Percentage of Households with a Kitchen
13. Percentage of Households Using LPG/PNG for Cooking
14. Percentage of Households Using Banking Services
15. Percentage of Households with a Computer

Infrastructural Facilities

1. Number of Banks in Rural Areas
2. Number of Banks in Urban Areas
3. Primary and Upper Primary Schools (Classes I–VIII)
4. Secondary Schools (Classes I–X)
5. Higher Secondary Schools (Classes VI–XII)

Data Analysis Techniques

This study employs the Wroclaw Taxonomic Method to construct the Social Development Index (SDI), the Infrastructural Services Index (ISI), and the Socio-Infrastructural Development Index (SIDI). Developed in the 1950s by Polish mathematicians at the University of Wroclaw, this method is based on the concept of an ideal unit, which refers to a unit that has the most desirable value for each indicator within the data set (Florek et al., 1952). Techniques for variable selection in social indicator studies aim to derive reduced sets of indicators while retaining the critical information about developmental dimensions (Hellwig, 1974). The method has been applied for ranking and comparing developmental progress across regions. Studies including Ohlan (2013) and Kumar & Rani (2019) have used this approach in constructing composite development indices for analysing regional disparities. Taxonomic methods provide foundational approaches for classification and grouping of regions based on multiple characteristics. The application of this method to measure social development and infrastructural services allows analysis of regional disparities and developmental patterns in Manipur.

In this study, data collection was done in the beginning for all the 16 districts including the recently established districts represented as the matrix $[X_{ij}]$. Each row i corresponds to a district, with i ranging from 1 to n , representing the total number of districts, and each column j corresponds to an indicator, with j ranging from 1 to k , signifying the number of indicators. Each district is conceived as a vector in a k -dimensional space.

Since the variables under consideration are measured in non-uniform units, data transformation was performed for comprehensive analysis. This

transformation results in the creation of a matrix of standardized indicators, denoted as $[Z_{ij}]$, using the following formula:

$$[Z_{ij}] = \frac{X_{ij} - \bar{X}_j}{\sigma_j} \quad \#(1)$$

Where,

$$\bar{X}_j = \frac{\sum_{i=1}^N X_{ij}}{N} \text{ and } \sigma_j = \left(\sum_{i=1}^N (X_{ij} - \bar{X}_j)^2 \right)^{1/2}$$

From the standardized indicator matrix $[Z_{ij}]$, identification of the optimal value for each indicator denoted as Z_{oj} was done. The optimal value can take the form of either the maximum or minimum value of the indicator, depending on the directional impact of the indicator on the level of development. To derive the pattern of development (C_i) for each district (i), at first the square of the deviation between the individual value of a transformed variable and its optimal value was done. This is mathematically expressed as:

$$P_{ij} = (Z_{ij} - Z_{oj})^2 \quad \#(2)$$

Pattern of development for each i and j is computed by using the following formula:

$$C_i = \left[\sum_{j=1}^N P_{ij} / (cv_j) \right]^{1/2} \quad \#(3)$$

where, cv_j is the coefficient of variation of the j^{th} indicator in X_{ij} .

To create a composite index that quantifies development (D_i) for each district (i), the following formula is employed:

$$D_i = \frac{C_i}{C} \quad \#(4)$$

where, $C = \bar{C} + 3\sigma C_i$;

where, $\bar{C} = \frac{\sum_{i=1}^N C_i}{N}$ and $\sigma C_i = \left(\sum_{i=1}^N (C_i - \bar{C})^2 \right)^{1/2}$

The closeness of the computed D_i to 0 indicates a higher level of development for the district, while values closer to unity suggest lower development. In the majority of cases, the resulting D_i falls within the range of $0 < D_i < 1$, which enables to evaluate and compare the development levels across the district effectively.

At the end of the analysis, districts were plotted in an orthogonal space diagram with SDI on the X-axis and ISI on the Y-axis. Median values of SDI and ISI divided the space into four quadrants, representing different stages of development. Population distribution within each quadrant was examined to analyse demographic patterns relative to development outcomes.

Categorization of various Developmental Phases

A ranking of districts based on composite indices has been undertaken for a meaningful characterization of various stages of development. Ranking has been done using mean and standard deviation of the composite indices. Stages of development has been classified as:

- i. High (Stage IV) = Composite Index $\geq$ (Mean + 1 SD);
- ii. High Middle (Stage III) = Mean > Composite Index > Mean + 1 SD;
- iii. Low Middle (Stage II) = Mean < Composite Index < Mean + 1 SD;
- iv. Low (Stage I) = Composite Index $\leq$ (Mean + 1 SD).

Results of Analysis and Discussion

Social Development Pattern

The SDI demonstrates a clear core and periphery pattern of development across Manipur (Table 1). The Imphal Valley districts of Imphal West (0.21) and Imphal East (0.24) record the highest development levels, serving as the state's developmental core. This concentration stems from the agglomeration of educational institutions, healthcare infrastructure and administrative services in urban centres, aligning with Myrdal's cumulative causation framework (1957).

It is observed from the analysis of relevant data that geographical location influences development outcomes substantially, though the relationship is not absolute. While most hill districts occupy lower development stages, Churachandpur (0.28) attains Stage IV (High) status despite its hill location, indicating that factors beyond topography determine developmental

trajectories. Conversely, Thoubal (0.58) falls into Stage II (Low middle) despite its location in the plain, showing that proximity to core areas do not guarantee higher development. Senapati (0.88) records the lowest development level, with an index value considerably higher than the next lowest district. This deficit reflects acute shortages in social infrastructure and service

delivery in geographically isolated regions. The gap between Senapati and the Imphal districts exceeds 0.60 index points, representing a severe disparity in developmental status.

Table 1: District-level Social Development Performance in Manipur, 2011

District	SDI	Rank	Stages of Development
Imphal West	0.21	1	IV (High)
Imphal East	0.24	2	
Churachandpur	0.28	3	
Ukhrul	0.30	4	III (High Middle)
Kamjong	0.35	5	
Pherzawl	0.36	6	
Bishnupur	0.44	7	
Kangpokpi	0.46	10	
Kakching	0.46	9	
Chandel	0.46	8	
Tamenglong	0.56	11	II (Low Middle)
Thoubal	0.58	12	
Noney	0.61	13	
Jiribam	0.62	14	
Tengnoupal	0.65	15	I (Low)
Senapati	0.88	16	

Source: Computed by the authors.

It is observed from the analysis of relevant data that geographical location influences development outcomes substantially, though the relationship is not absolute. While most hill districts occupy lower development stages, Churachandpur (0.28) attains Stage IV (High) status despite its hill location, indicating that factors beyond topography determine developmental trajectories. Conversely, Thoubal (0.58) falls into Stage II (Low middle) despite its location in the plain, showing that proximity to core areas do not guarantee higher development. Senapati (0.88) records the lowest development level, with an index value considerably higher than the next lowest district. This deficit reflects acute shortages in social infrastructure and service

delivery in geographically isolated regions. The gap between Senapati and the Imphal districts exceeds 0.60 index points, representing a severe disparity in developmental status.

Fig. 2 shows the spatial distribution of social development performance among the districts across Manipur, with higher development concentrated in the Imphal Valley and lower performance in the peripheral hill districts. This finding corresponds with Friedmann's core and periphery model (1966), wherein initial advantages in core regions attract resources and skilled personnel, reinforcing spatial inequalities. The districts closer to the Imphal Valley generally exhibit better social indicators, while peripheral hill districts experience resource outflows and limited investment. This pattern represents systemic underdevelopment rather than isolated deficiencies, necessitating structural interventions to address entrenched regional disparities.

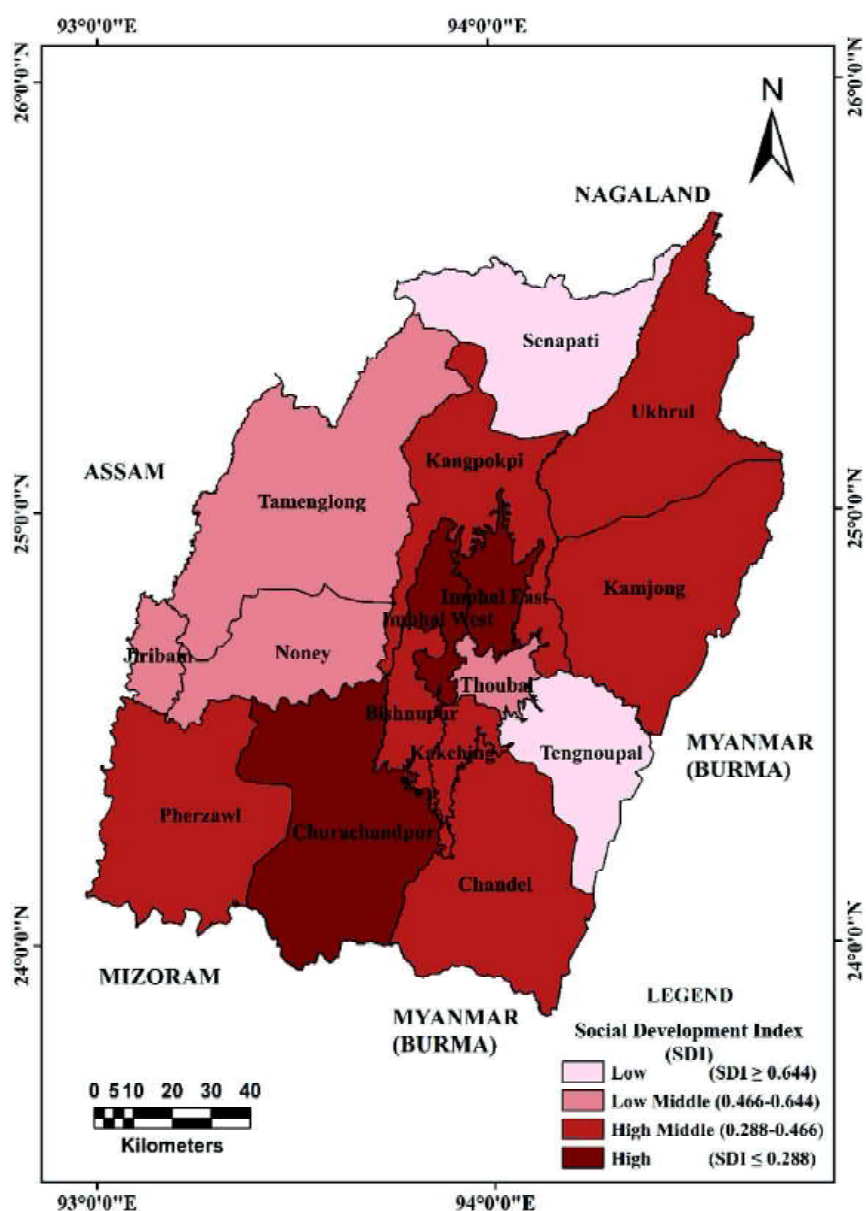


Fig. 2: Spatial variations in social development at the district level in Manipur, 2011

Infrastructural Development Pattern

Although infrastructure constitutes the foundational determinant of economic productivity and social welfare in Manipur, the distribution of infrastructure shows clear spatial disparities that deepen regional inequalities instead of reducing them. The ISI demonstrates substantial variation across among the districts in the state (Table 2). Imphal West (0.25) records the highest infrastructural

development, while Jiribam (0.74), Tengnoupal (0.71), and Noney (0.70) occupy the lowest development tier. This distribution exemplifies Myrdal's cumulative causation mechanism (1957), wherein established growth centres attract successive rounds of investment, progressively strengthening their infrastructural base while peripheral regions experience somewhat systematic neglect.

Table 2: District-level Infrastructural Development in Manipur, 2021-23

Districts	ISI	Rank	Stages of Development
Imphal West	0.25	1	IV (High)
Imphal East	0.36	2	
Thoubal	0.46	3	III (High Middle)
Churachandpur	0.51	4	
Senapati	0.52	5	
Bishnupur	0.53	6	
Kangpokpi	0.56	7	
Ukhrul	0.64	8	II (Low Middle)
Kakching	0.65	9	
Chandel	0.66	10	
Tamenglong	0.67	11	
Kamjong	0.7	14	
Pherzawl	0.7	13	
Noney	0.7	12	
Tengnoupal	0.71	15	
Jiribam	0.74	16	I (Low)

Source: Computed by the authors.

The spatial pattern of infrastructural services (Fig. 3) follows similar core and periphery dynamics, with Imphal West and Imphal East recording substantially higher infrastructure indices compared to geographically isolated hill districts. The infrastructural deficit in the hill districts extends not only to quantitative shortfalls but also to qualitative gaps in essential services. These deficiencies constrain participation in formal economic activities and perpetuate exclusion from main stream development processes. Hill districts thereby face barriers in accessing markets, healthcare services and educational opportunities, limiting economic diversification and livelihood options.

Comparing infrastructural and social development indices reveals overlapping patterns of deprivation. Districts with poor infrastructural endowments consistently exhibit lower social development outcomes, confirming the interdependence of these dimensions. However, notable exceptions exist in this respect. For instance, Senapati ranks fifth in infrastructural development (0.52) yet registers the lowest social development level (0.88), indicating that infrastructure provision alone does not guarantee improved social outcomes without complementary investments in human capital and service delivery.

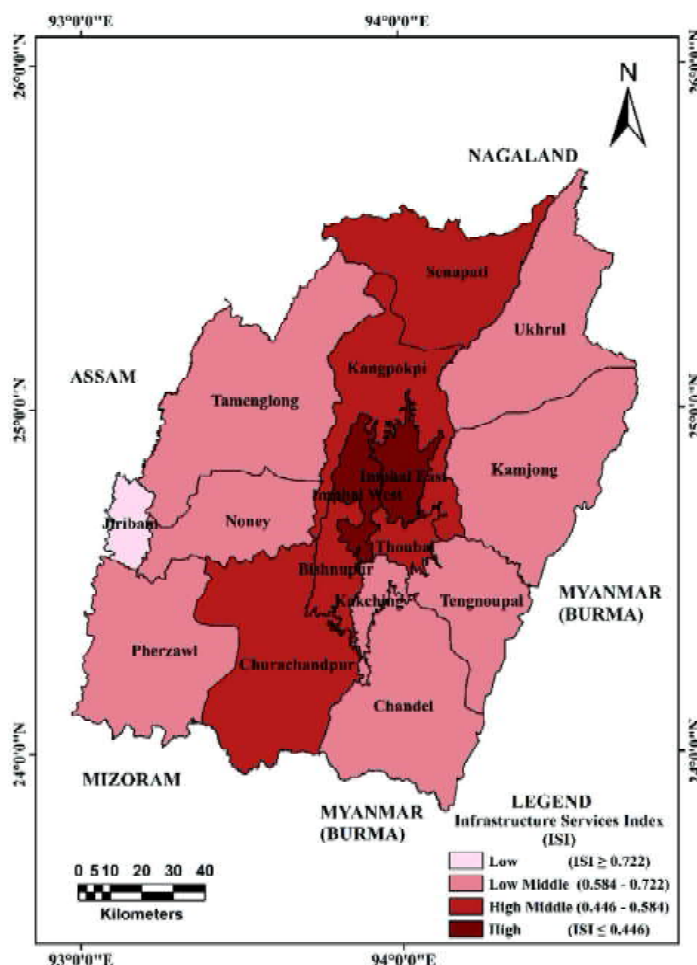


Fig. 3: Spatial patterns of infrastructural development at the district level in Manipur

Perroux's Growth Pole Theory (1950) elucidates this pattern through the concept of forward and backward linkages emanating from core growth poles. Mishra's Growth Foci Model (1971) explains the intermediate position of certain hill districts that benefit from partial spillover effects due to proximity to core areas, while remote districts remain excluded from development circuits. These theoretical frameworks underscore the spatially concentrated nature of infrastructure and its limited diffusion to peripheral regions, necessitating deliberate policy interventions to counteract market driven agglomeration tendencies.

Socio-infrastructural development pattern

The SIDI combining both social and infrastructural indicators, shows a clear disparity between the hill and plain districts of Manipur (Table 3). The plain districts such as Imphal West (0.24) and Imphal East (0.29) occupy the top ranks, reflecting their better progress in both social and physical infrastructure. Greater access to amenities has contributed to their higher stage of development, falling under Stage IV (High) and Stage III (High Middle). The presence of urban centres like Imphal has further supported growth by attracting trade, investment and population from the surrounding regions.

Table 3: Development levels derived from social and infrastructural indices

District	SIDI	Rank	Stage of Development
Imphal West	0.24	1	IV (High)
Imphal East	0.29	2	
Churachandpur	0.38	3	
Ukhrul	0.45	4	III (High Middle)
Bishnupur	0.49	5	
Kamjong	0.50	6	
Pherzawl	0.51	7	
Kangpokpi	0.52	8	
Kakching	0.55	9	II (Low Middle)
Chandel	0.55	10	
Thoubal	0.58	11	
Tamenglong	0.62	12	
Noney	0.67	13	
Jiribam	0.69	14	I (Low)
Tengnoupal	0.70	15	
Senapati	0.84	16	

Source: Computed by the authors.

In contrast, the hill districts such as Senapati (0.84), Tengnoupal (0.70) and Tamenglong (0.62) remain in the lower stages of development, indicating persistent infrastructural and social gaps.

Fig. 4 presents the composite development index, combining both social and infrastructural dimensions, which confirms the pronounced developmental disparity between valley districts and hill districts across Manipur. Sparse settlements, difficult terrain, limited connectivity and inadequate public facilities have slowed down progress in these areas. The prevailing wide gap between the hills and plains reflects an uneven pattern of regional

development within the state. While the plains enjoy the benefits of concentrated growth and administrative focus, the hill areas continue to face social and infrastructural neglect. To ensure balanced regional development, greater emphasis is needed on strengthening social infrastructure and improving access to essential services in the hill districts.

Looking at the demographic and spatial pattern of development, Manipur shows clear regional disparities (Table 4). The plain districts, especially those in the Imphal Valley, occupy about 10 per cent of the total area but hold over 40 per cent of the population and fall under

the high and high-middle stages of social and infrastructural development. In contrast, the hill districts, which cover nearly two-thirds of the state's area, remain mostly in the low and low-middle stages with a smaller

population share. This uneven distribution of people and resources indicates that development has been concentrated mainly in certain limited area.

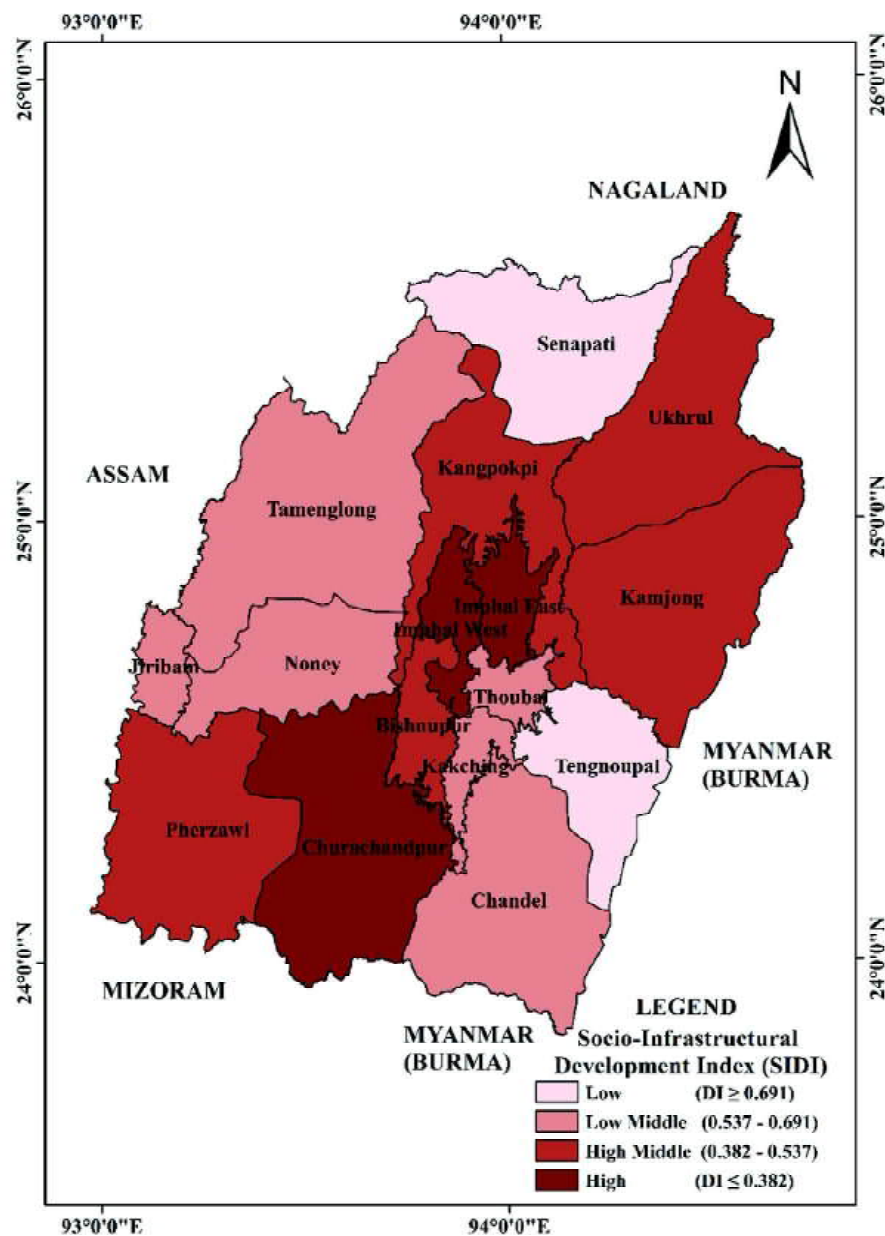


Fig. 4: District-level variations in social and infrastructural development in Manipur

Table 4: Stages of development by number of districts, area and population

Attributes	Stage of Development	Number of Districts	Area (%)	Population (%)
Social Development Index (SDI)	High ($SDI \leq 0.288$)	3	14.99	40.52
	High Middle ($0.288-0.466$)	7	49.66	30.92
	Low Middle ($0.466-0.644$)	4	22.38	16.50
	Low ($S.D.I. \geq 0.644$)	2	12.98	12.06
Infrastructure Services Index (ISI)	High ($ISI \leq 0.446$)	2	3.99	32.57
	High Middle ($0.446-0.584$)	5	29.49	43.07
	Low Middle ($0.584-0.722$)	8	65.04	22.82
	Low ($ISI \geq 0.722$)	1	1.48	1.54
Socio-Infrastructural Development Index (SIDI)	High ($SIDI \leq 0.382$)	3	14.99	40.52
	High Middle ($0.382-0.537$)	5	38.80	23.19
	Low Middle ($0.537-0.691$)	6	33.24	24.22
	Low ($SIDI \geq 0.691$)	2	12.98	12.06

Source: Computed by the authors.

Spatial Pattern of Relationship between Social Development and Infrastructure Development

The quadrant analysis reveals four distinct zones of development across Manipur, each reflecting a different degree of balance between social and infrastructural progress (Fig. 5).

Quadrant I (*High ISI–High SDI*) comprises Imphal West, Imphal East, Bishnupur, Churachandpur, Ukhrul, and Kangpokpi, representing the most advanced cluster. Nearly half of the state's population resides in these districts, showing a strong concentration of both

infrastructure and social facilities. The coexistence of high ISI and SDI values indicates that infrastructural expansion has been effectively converted into improvements in education, health, and living standards, creating a reinforcing cycle of growth. Quadrant II (*Low ISI–High SDI*) includes Kamjong, Pherzawl, Kakching, and Chandel, where social progress has outpaced physical infrastructure. Together these districts hold less than 10 per cent of the population, reflecting adaptive social mechanisms and strong community support systems that help overcome infrastructural constraints.

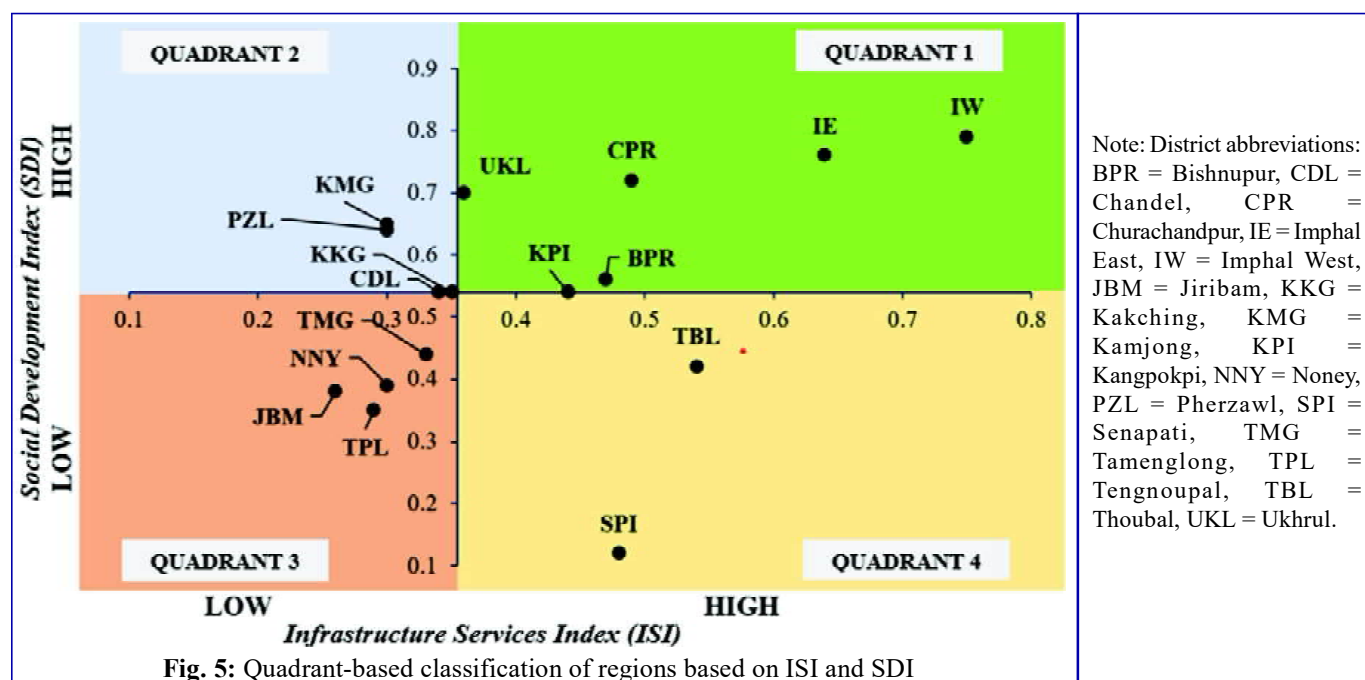


Fig. 5: Quadrant-based classification of regions based on ISI and SDI

In contrast, Quadrant III (*Low ISI–Low SDI*) comprising Noney, Jiribam, Tamenglong, and Tengnoupal, with about 9 per cent of the population which marks the least developed zone. Limited connectivity, poor accessibility, and weak institutional presence have produced a continuing cycle of underdevelopment, demanding focused regional planning and policy support. Quadrant IV (*High ISI–Low SDI*) includes Senapati and Thoubal, where infrastructural growth has not been matched by social progress. This shows that physical infrastructure alone does not ensure better social conditions. Despite visible improvements in infrastructure, uneven access to services and gaps in administration have limited social outcomes. These districts account for about 20 per cent of the population, indicating that a significant number of people remain underserved. Improving governance and ensuring equitable delivery of services are essential to translate infrastructure into real human development.

The correlation results reinforce these spatial patterns (Table 5). The relationship between ISI and SDI ($r = 0.394527$) indicates a moderate positive association, implying that infrastructural improvement supports but does not uniformly ensure social progress. The ISI–Population correlation ($r = 0.990378$) shows a very strong link, revealing that infrastructure is heavily concentrated in densely populated districts such as Imphal West, Imphal East, and Thoubal, where urbanization drives investment. The SDI–Population correlation ($r = 0.334229$), though weaker, remains positive, showing that social development depends more on institutional effectiveness than on population size. Overall, the pattern suggests that population density attracts infrastructural investment, while the quality of governance and equitable distribution of services determine the extent to which infrastructure translates into real social progress across Manipur.

Table 5: Correlation coefficients showing the relationship between SDI, ISI and Population

Factors	SDI	ISI	Population
SDI	1		
ISI	0.394527	1	
Population	0.334229	0.990378	1

Conclusion

The comprehensive analysis of SDI, ISI and SIDI demonstrates a fundamental imbalance in regional resource allocation, establishing a classic core-periphery structure, where the integration of social and infrastructural progress is systematically disjointed in peripheral districts.

This spatial inequality is rooted in the Imphal Valley, anchored by Imphal West and Imphal East, forming a high development core (Stage IV). This core benefits from agglomeration effects, validating Myrdal's and Friedmann's frameworks, creating a powerful virtuous cycle through the concentration of administrative and social infrastructure. Conversely, the majority of the state's hill districts, including Senapati and Tengnoupal, are stuck in the low stages (I and II), facing systemic underdevelopment and cumulative disadvantage. The resulting developmental gap, which exceeds 0.60 index

points between the best and worst performing districts, highlights a fundamental structural fault in regional planning.

Analysing the relationship between SDI and ISI through the quadrant analysis introduces some essential detail. While core districts exhibit mutually reinforcing growth, the most critical finding relates to the outliers in Quadrant IV (High ISI - Low SDI), specifically Senapati and Thoubal. Senapati, notably ranks fifth in infrastructure but records the state's lowest social development score. This powerful decoupling confirms that infrastructure is a necessary but profoundly insufficient condition for human development. Physical investments fail to yield improved social outcomes when pervasive governance gaps, non-equitable access, and utilization deficiencies persist. The counter evidence of districts like Churachandpur (Stage IV social development in a hill location) suggests that community strength can partially mitigate infrastructural constraints,

demonstrating that geography is not an absolute determinant of progress.

To address these persistent structural inequalities, an approach purely focused on economic or infrastructural metrics is inadequate. The solution requires a multi-dimensional, equity-oriented policy paradigm designed to transform the periphery. The policy interventions in this respect must prioritize strengthening human capital specifically through quality female education and decentralized, accessible healthcare services alongside

mandating the decentralization of financial power and empowering local authorities for context specific planning. Furthermore, infrastructural planning in the hill region should focus on improving the quality of basic services and facilities to promote balanced regional growth. Balanced development in Manipur hinges on interventions that deliberately counteract the pull of the core, focusing instead on converting every investment into guaranteed social access and human capital gains.

References

- Aschauer, D. A. (1989). Is public expenditure productive? *Journal of monetary economics*, 23(2), 177-200. [https://doi.org/10.1016/0304-3932\(89\)90047-0](https://doi.org/10.1016/0304-3932(89)90047-0)
- Banerjee, A., & Kuri, P. K. (2015). Development disparities in India: An enquiry into convergence. *Springer India*. <https://doi.org/10.1007/978-81-322-2331-3>
- Banerjee, A., Duflo, E., & Qian, N. (2020). On the road: Access to transportation infrastructure and economic growth in China. *Journal of Development Economics*, 145, 102442. <https://doi.org/10.1016/j.jdeveco.2020.102442>
- Census of India. (2011). *Primary Census Abstract: Manipur*. Office of the Registrar General & Census Commissioner, Ministry of Home Affairs, Government of India. Retrieved from <https://censusindia.gov.in/census.website/data/census-tables>
- Démurger, S. (2001). Infrastructure development and economic growth: an explanation for regional disparities in China? *Journal of Comparative economics*, 29(1), 95-117. <https://doi.org/10.1006/jcec.2000.1693>
- Dholakia, R. H. (2003). Regional disparity in economic and human development in India. *Economic and Political Weekly*, 38(39), 4166–4172. <https://www.jstor.org/stable/4414081>
- Directorate of Economics & Statistics, Government of Manipur. (2020-2021). *Economic Survey of Manipur*. Lamphelpat.
- Florek, K., Łukaszewicz, J., Perkal, J., Steinhaus, H. I., & Zubrzycki, S. (1952). Taksonomia. Wrocławska. *Przegląd Antropologiczny*, 17.
- Friedmann, J. (1966). *Regional development policy: A case study of Venezuela*. MIT Press.
- Ghosh, B. (2006). Spatial inequality and development: Theories, models and concepts. In B. Ghosh & P. K. De (Eds.), *Urban development and planning* (pp. 73–91). Concept Publishing Company.
- Government of Manipur. (December, 2016). Title: Governor of Manipur is pleased to order creation of 7 new districts by bifurcating the following districts (*Gazette Number: 408*).
- Hellwig, Z. (1974). A method for the selection of a “compact” set of variables. *Reports and papers in social sciences. Social Indicators: Problems of Definition and of Selection*, 30, 11-20.
- Kumar, N., & Rani, R. (2019). Regional disparities in social development: Evidence from states and union territories of India. *South Asian Survey*, 26(1), 1–27. <https://doi.org/10.1177/0971523118825388>
- Kurian, N. J. (2000). Widening regional disparities in India: Some indicators. *Economic and Political Weekly*, 35(7), 538–550. <https://www.jstor.org/stable/4408933>
- Ministry of Education, Department of Higher Education, Government of India. (August, 2025). *All India Survey on Higher Education (AISHE) portal*. Retrieved from <https://dashboard.aishe.gov.in/hedirectory/#/hedirectory>
- Ministry of Health and Family Welfare, Government of India. (2022). *Rural Health Statistics 2021–22*. Statistics Division, National Health Mission. Retrieved from https://mohfw.gov.in/sites/default/files/RHS%202021-22_2.pdf
- Misra, R. P., Prakas Rao, V. L. S., & Sundaram, K. V. (1971). *Growth poles and growth centres in regional planning and development in India (Vol. 3)*. United Nations Research Institute for Social Development.
- Myrdal, G., & Sitohang, P. (1957). *Economic theory and under-developed regions*.

- Ohlan, R. (2013). Pattern of regional disparities in socio-economic development in India: District level analysis. *Social Indicators Research*, 114, 841–873. <https://doi.org/10.1007/s11205-012-0176-8>
- Perroux, F. (1950). Economic space: theory and applications. *The quarterly journal of economics*, 64(1), 89-104. <https://doi.org/10.2307/1881960>
- Reserve Bank of India (RBI). (2022). *District, bank, and population group-wise number of offices opened by commercial banks (30 June 2005–31 December 2022)*. *Database on Indian Economy*. Retrieved from <https://cimsdbie.rbi.org.in/#/dbie/publications>
- Shimray, U. A. (2001). Ethnicity and socio-political assertion: The Manipur experience. *Economic and Political Weekly*, 3674-3677. <https://www.jstor.org/stable/4411161>
- Singh, R., & Sharma, A. R. (2010). Demographic Profile of North East India with Special Reference to Manipur. In B. J. Deb (Ed.), *Population and Development in North East India* (pp. 365-367). Concept Publishing.
- Singh, S.N. (2018). Regional Disparity and Sustainable Development in North Eastern States of India: A Policy Perspective. *Socio Economic Challenges*, 2(2), 41-48. https://essuir.sumdu.edu.ua/bitstream-download/123456789/68125/1/Singh_Regional_Disparity.pdf
- Singh, T. B. (2007). Poverty in Manipur. *Economic and Political Weekly*, 251-254. <https://www.jstor.org/stable/pdf/4419165.pdf>
- Unified District Information System for Education Plus (UDISE+). (2023, August 25). *Number of schools by school management and school category (Report ID: 1003)*. Retrieved from <https://dashboard.udiseplus.gov.in/>
- Ziipao, R. R. (2020). *Infrastructure of injustice: State and politics in Manipur and Northeast India*. Routledge India. <https://doi.org/10.4324/9781003045892>.



Groundwater Depletion in Birbhum District of West Bengal: Analyzing Trends and Identifying Depression Pockets

Subhasish Sutradhar

National Atlas and Thematic Mapping Organisation
Department of Science & Technology, Government of India, Kolkata (India)

**Corresponding Author's E-mail: subhasish.s95@natmo.gov.in*

Abstract

To fulfil the need of growing population and industrial operations, groundwater depletion has emerged as a major geophysical problem. The fast depletion of groundwater level is mainly caused by two main factors: excessive groundwater extraction, especially for industrial and agricultural purposes, and climate change, which impacts the natural cycles of water replenishment. The depletion of groundwater in Birbhum district of West Bengal has become an acute and urgent issue. The over-exploitation of groundwater, particularly for agricultural uses, has led to a major depletion of this indispensable resource. Birbhum district relies heavily on groundwater for irrigation, particularly in the eastern part characterised by high agricultural production as supported by fertile alluvial soil. However, owing to such a highly intensive agricultural activity the groundwater table is dropping at an alarming rate. The major aims of this study are twofold: first, to examine the changes in the groundwater table over a substantial period, and second, to anticipate the sites of groundwater depression pockets, where the groundwater level has drastically dropped. Groundwater data for the period 2014-2023 shows a significant decline in groundwater level throughout the district, with the eastern part experiencing the most severe depletion. The findings of this study also highlight the crucial need for more effective and long-term solutions to groundwater depletion in Birbhum district and other similar areas across the country. The accelerating decline of groundwater level has emerged as a serious problem, and if not solved, it might result in severe water shortages, endangering both agricultural and local residents' livelihood. Under this backdrop, the present study based on geospatial technology advocates for immediate action to improve groundwater management practices, encourage water conservation, and minimize reliance on groundwater resources in order to ensure long-term sustainability.

Keywords: Groundwater depletion, ground water management, geospatial technology, Birbhum district.

Introduction

As a vital supply of freshwater, groundwater serves the residential requirements of almost half of the world's population. Groundwater supplies around 38% of the

world's consumptive irrigation water needs (Dangar, Asoka, and Mishra 2021; Siebert et al. 2010). As the global population continues to rise, the need for potable water has created a new problem of groundwater depletion (Anand et al. 2020; Gibrilla, Anornu, and Adomako 2018;

Halder, Roy, and Roy 2020; Rahman et al. 2016). India has the largest proportion of irrigated land, which is supplied by groundwater (Siebert et al. 2010). On the other side, a significant proportion of the country's area is characterised by intensive agricultural practices primarily relying on groundwater for irrigation.

The variation of groundwater level was observed to have insight into several aspects, including recharge estimation, groundwater quality testing, regional groundwater modelling, surface water interactions, and rainfall-recharge relationships (Abijith et al. 2020; Balamurugan 2020; Chaudhary and Satheesh kumar 2018; Eyankware et al. 2020; Lu et al. 2014; Minea, Boicu, and Chelariu 2020; Prasad 2018; Sahoo et al. 2021; Sahoo and Jha 2013; Tao et al. 2022; Veeranna and Jeet 2021; Wakode et al. 2018). Current scientific study suggests a novel statistical and graphical method for detecting the trends ground water availability. Furthermore, computer-based GIS technology facilitates the identification of optimal groundwater recharge regions worldwide. It also enables the integration of groundwater table with other physical and socio-economic factors and the creation of prediction maps for future

estimation of groundwater level (Das et al. 2021).

Description of the Study Area

Covering an area of around 4,545 km², with 19 Community Development blocks, Birbhum district is situated in the western part of West Bengal. The topography of the district ranges from the undulating landscape of the western part to the alluvial plains in the east, which shape the dynamics of groundwater. The area is well-known for its varied landscape, which includes many rivers including the Ajay, Mayurakshi and Dwarka, lateritic soil and undulating terrain. With distinct wet and dry seasons and monsoon-dominated rainfall, the area has a tropical climate. The district's groundwater supplies are extensively replenished during the monsoon season. However, the excessive withdrawal of water, along with decreased penetration caused by changes in land use, has resulted in significant depletion. The primary goal of the study is to identify the areas under groundwater risk and to suggest sustainable water management techniques by examining the patterns during 2014-2023.

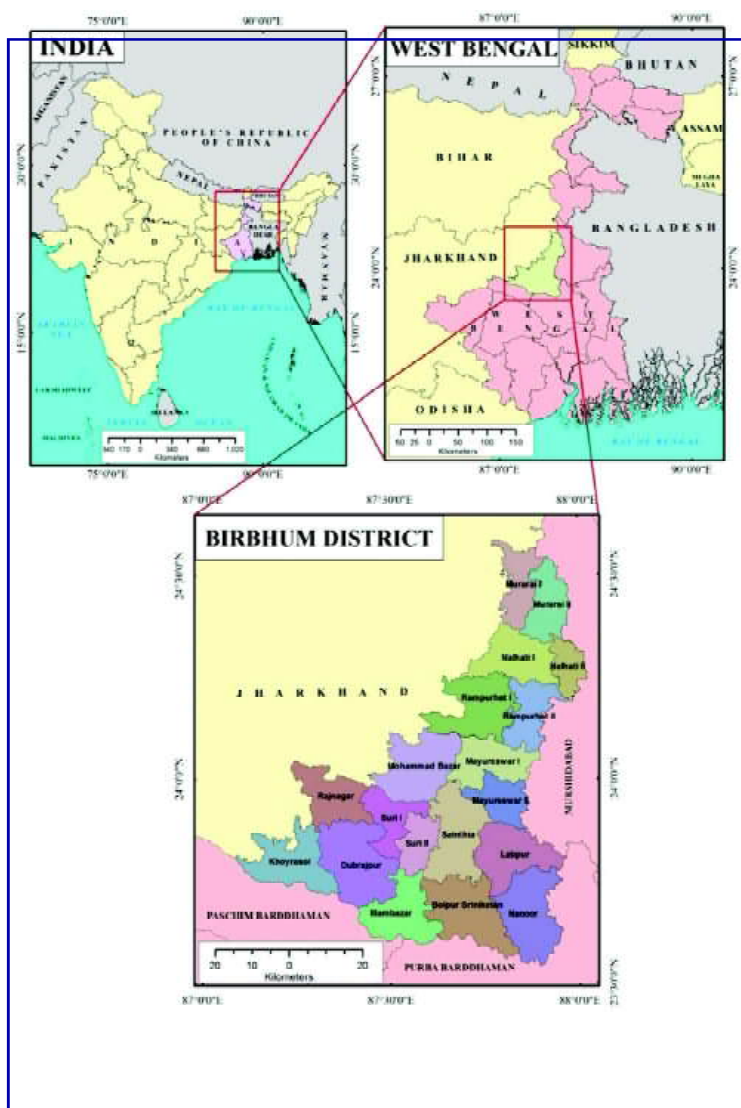


Fig. 1: Location Map of the Study Area

Materials and Methods

To analyze groundwater level fluctuation in Birbhum district, some important influencing factors are taken into account, like geology, aquifer, thickness, rainfall, drainage density, soil texture, groundwater draft, elevation, slope, NDVI, NDBI and NDWI along with groundwater level for spatial analysis. Table 1 demonstrates the used data

and their sources. Groundwater level data are analyzed by using Inverse Distance Weighting or IDW method is applied by using spatial analyst tool in ArcGIS software. Satellite imagery-based layers like NDVI, NDBI and NDWI are created from LANDSAT 8 OLI through the Google Earth Engine platform. Besides, elevation and slope layers are extracted from SRTM DEM through the same platform.

Table 1: Sources of Materials used in the study

Data Type		Description	Sources	Extracted Layer	Final Output
Conventional Data	Geology	District Resource Map, Birbhum 1:250,000	Geological Survey of India, Kolkata	Geology	Geological Map
	Aquifer Thickness	Thickness in Meters	http://indiawris.gov.in/wris/#/ India WRIS WebGIS Portal	Aquifer Thickness	Aquifer Thickness map
	Rainfall	CHIRPS	https://developers.google.com/earth-engine/datasets/catalog/UCSB-CHG_CHIRPS_PENTAD#description	Rainfall	Rainfall map
	Drainage	Topographical Sheets 1:50,000	Survey of India	Drainage	Drainage Density map
	Soil Texture	-	http://www.birbhum.gov.in/ Birbhum District Portal	Soil Texture	Soil Texture Map
	Groundwater Level	Groundwater Level, 2014 Groundwater Level, 2023	http://indiawris.gov.in/wris/#/ India WRIS WebGIS Portal	Groundwater Level	Groundwater Level Map
	Groundwater Draft	Groundwater Draft, 2013 Groundwater Draft, 2023		Groundwater Draft	Groundwater Draft Map
Remotely Sensed Data	Digital Elevation Model	SRTM DEM	https://earthexplorer.usgs.gov/ USGS EarthExplorer	Elevation	Elevation map Slope map
	Satellite Imagery	LANDSAT 8 OLI		NDVI NDWI NDBI	NDVI Map NDWI Map NDBI Map

To represent groundwater level fluctuations, groundwater level maps for the year 2014 and 2023 were considered and a groundwater level change map has been calculated between these two years. Beside this, 12 factors

that may influence groundwater level are considered. Pearson's correlation coefficient is calculated to identify the groundwater fluctuating factors. The entire methodology is depicted in the Fig. 2.

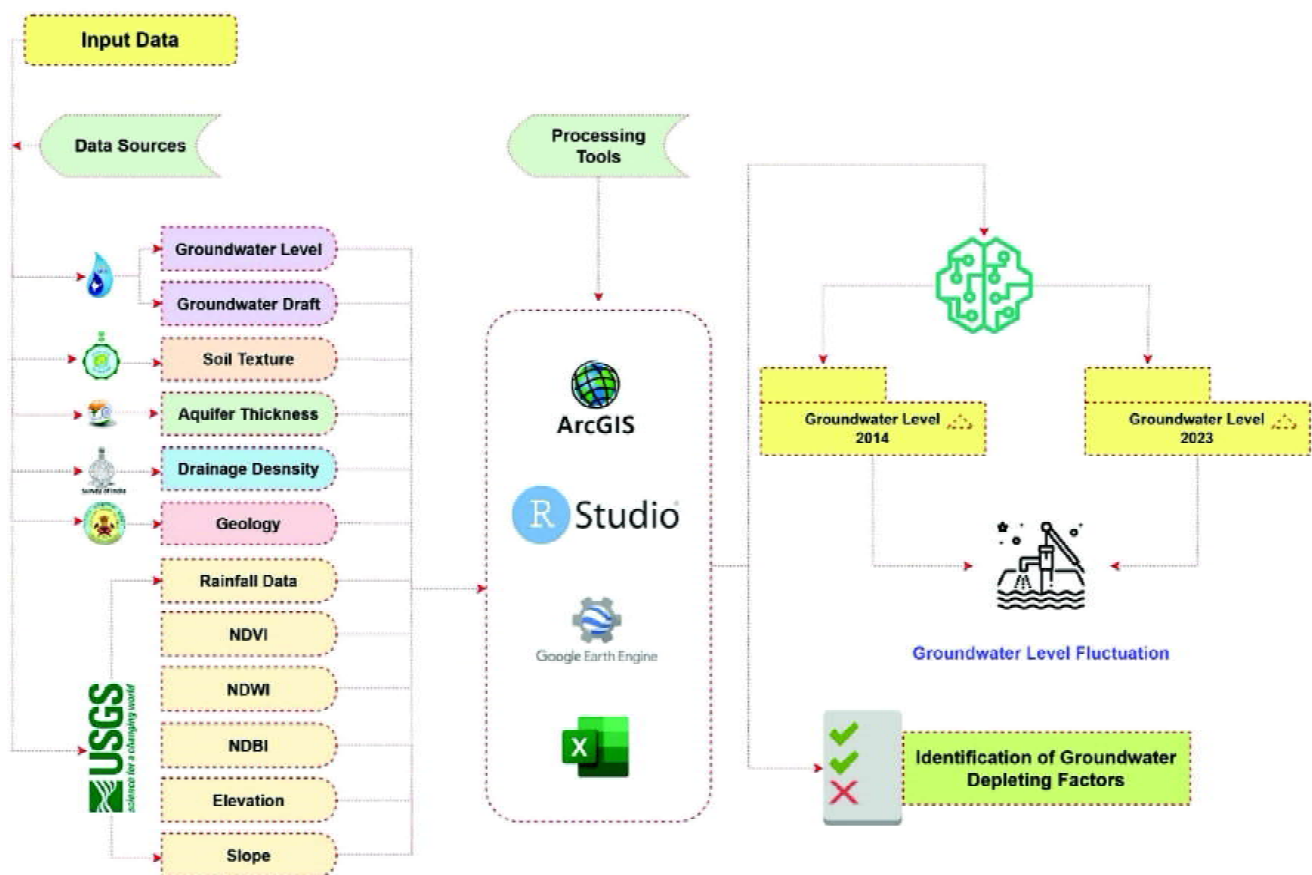


Fig. 2: Flowchart of the methodology

Results

Groundwater Level of 2014 and 2023

Spatial analysis of groundwater level has been done for the year 2014 and 2023. From this analysis it is found that part of Sainthia, Mayureswar-II and Labpur C.D. Blocks are worst affected by groundwater depletion in both the year. However, the groundwater depletion increased at alarming rate during 2014-2023 in these three blocks. In the Fig. 4, there is clear indication of increase of area under higher groundwater level in 2023 as compared to 2014.

The eastern part of the district faces a more critical situation regarding groundwater depletion, while the western side of the district located on the fringe of the Jharkhand plateau, and composed of granitic gneiss, sandstone, and Rajmahal trap rocks, it has low porosity. However, secondary fractures like lineaments allow limited water percolation to shallow depths. Additionally, a hard rock aquiclude is found near the surface, and the extraction of water in this region is minimal due to the difficulty of drilling. In contrast, the eastern part dominated by alluvial soils, witnesses intensive agricultural activity and significant groundwater extraction, leading to a more rapid decline in water level (Das et al. 2021).

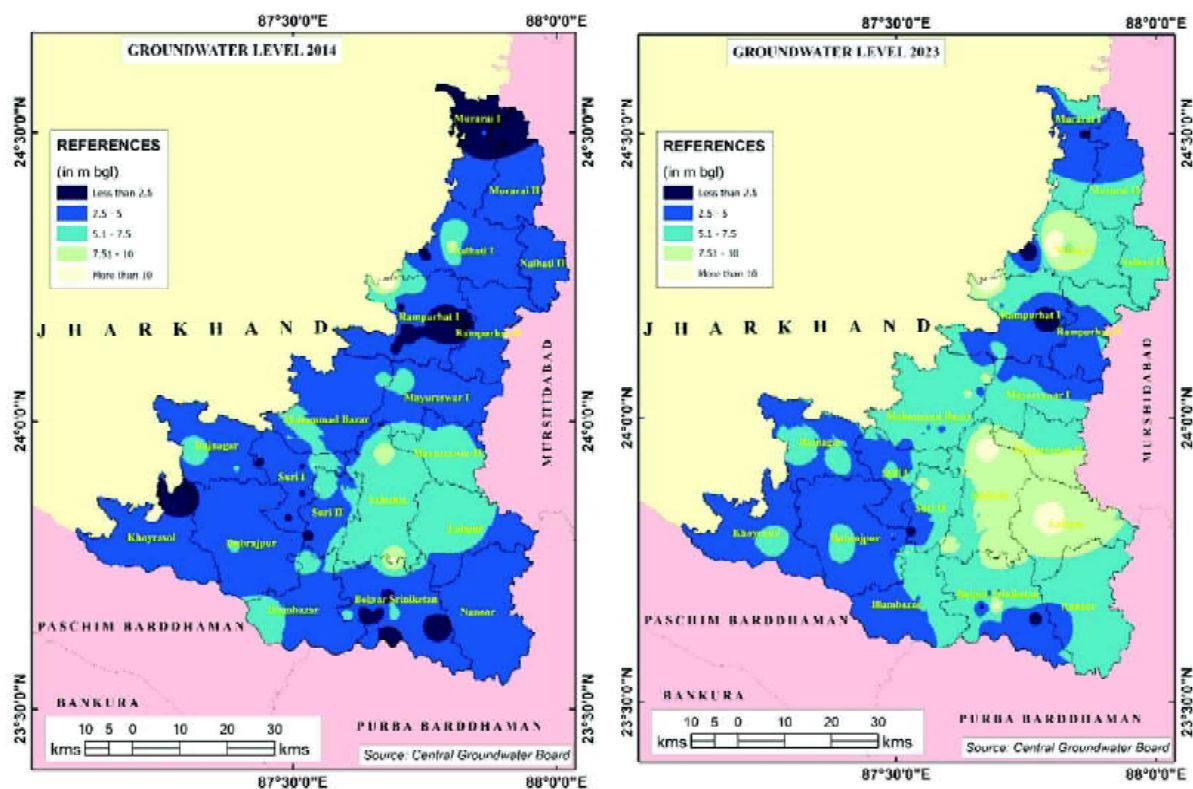


Fig. 3: Groundwater Level of 2014 and 2023

Distribution of Area Under Different Groundwater Level in Birbhum District, 2014 & 2023

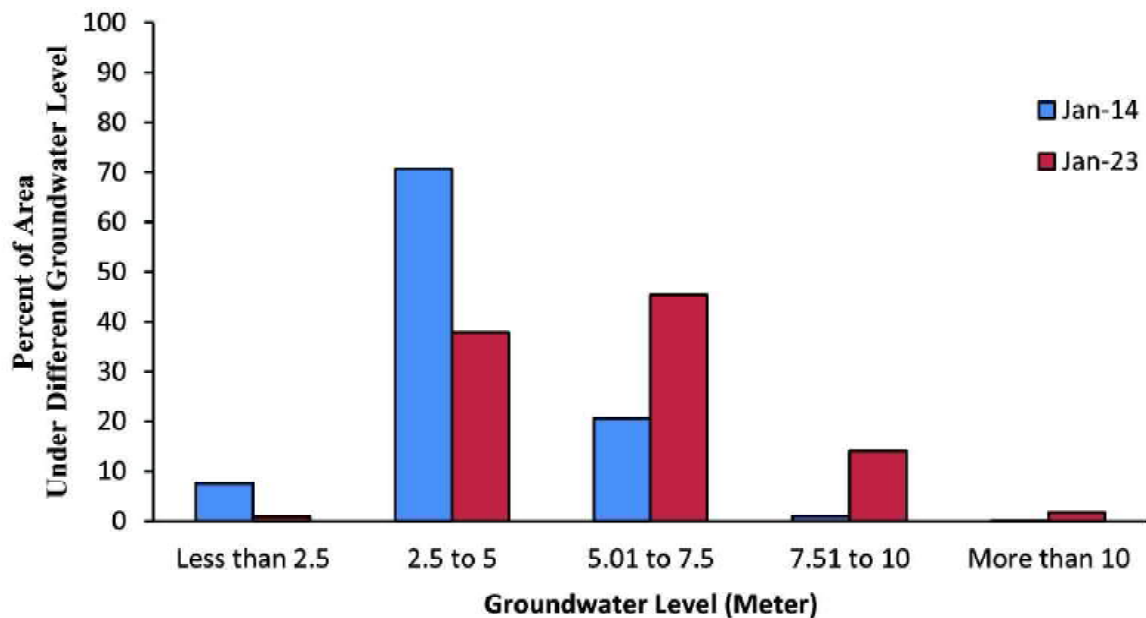


Fig. 4: Comparison of Area under Different Groundwater Level of 2014 and 2023

Change in Groundwater Level during 2014-2023

Fig. 5 and Fig. 6 reflect the marked depletion of groundwater as observed in Murarai I and Nalhathi I blocks, where the groundwater levels have decreased respectively by 2.32% and 2.29% of the total area. Furthermore, a notable 75% of the Labpur C.D. block has experienced a groundwater level drop between 3.1 mand 6m, indicating a substantial depletion. Similarly, Nalhathi I has experienced 38% of its area affected by this depletion process, followed by Murarai I with 19% and Bolpur-Sriniketan with 10%.

In contrast to these areas of significant depletion, the remaining areas within the study area show moderate to insignificant changes in groundwater level over the period under review. Interestingly, in some localized areas, there has been an increase in groundwater level when compared to the baseline data from 2014, suggesting a complex spatial variability in groundwater recharge and extraction patterns.

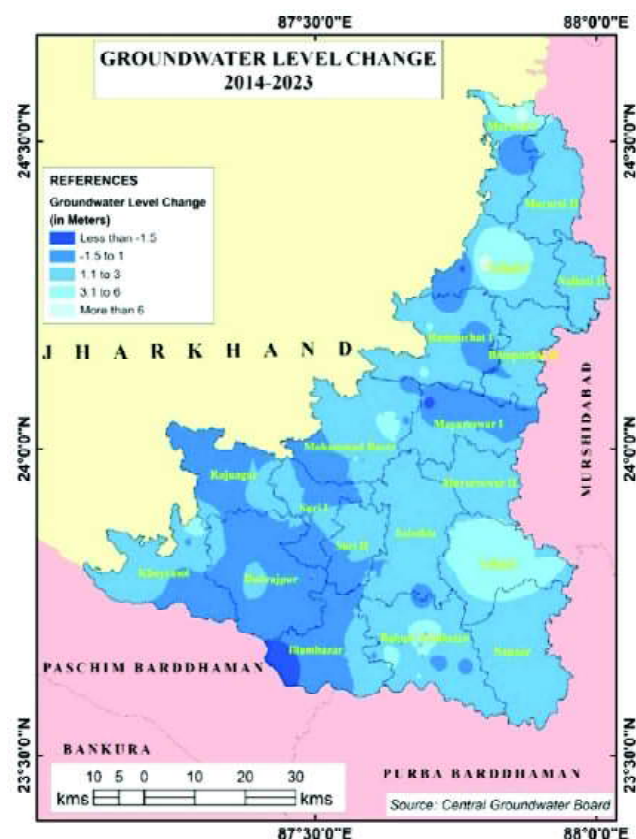


Fig. 5 : Groundwater Level Change of Birbhum District, 2014 - 2023

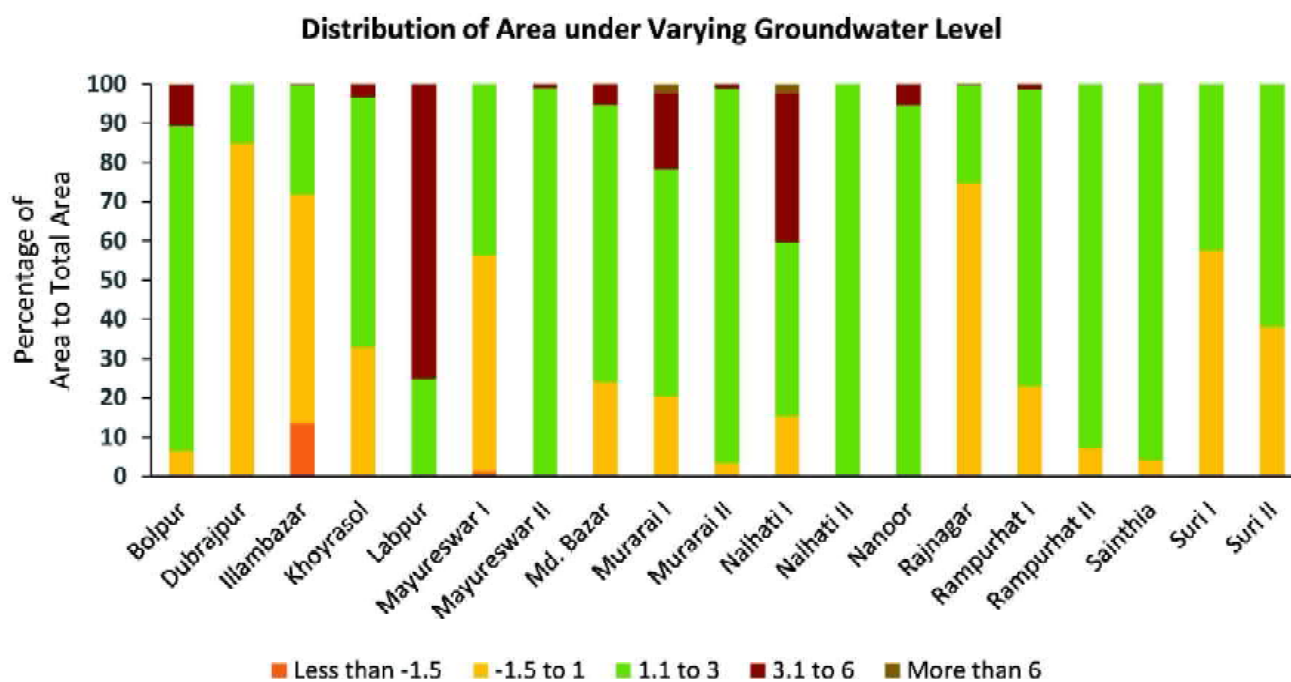


Fig. 6: Percentage Distribution of Area under Different Groundwater Level

Factors Influencing Groundwater Level

Groundwater level is influenced by a complex interplay of natural and human factors. Geological characteristics determine the type of aquifer, which affects water storage and flow. Thicker and more permeable aquifers allow higher groundwater levels, while soil texture influences infiltration, with sandy soils promoting recharge more than clayey soils. Rainfall is a major source of recharge, but drainage density affects how much rainwater infiltrates or runs off. Elevation and slope further control

recharge patterns, as steep slopes cause more runoff. Groundwater draft (extraction) lowers the level when over-exploited, while land cover changes, indicated by NDVI, NDBI, and NDWI, impact infiltration. NDVI reflects vegetation that aids recharge, NDBI highlights urban areas that reduce it, and NDWI shows surface water, which supports recharge. Hence, altogether these factors determine the availability and sustainability of groundwater (Fig. 7a to Fig. 7p)

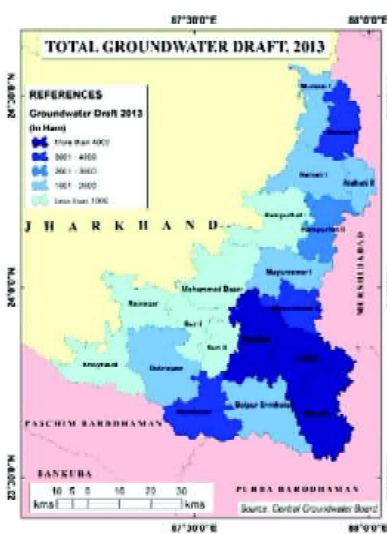


Fig. 7a

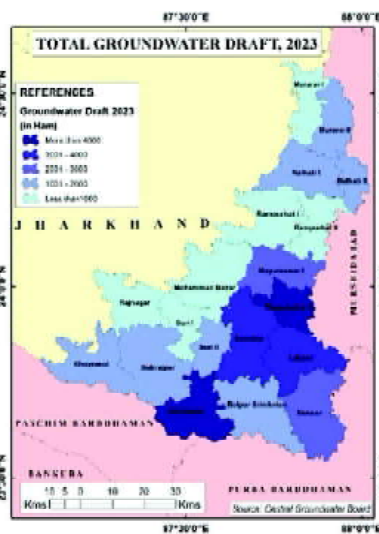


Fig. 7b

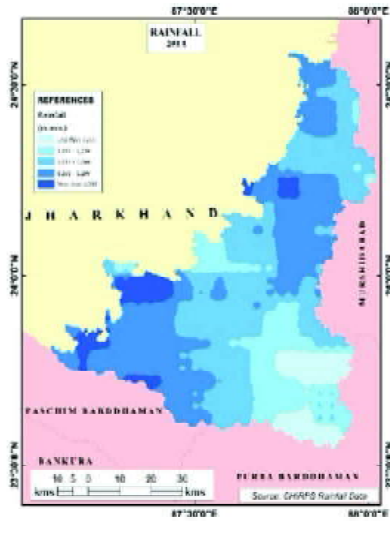


Fig. 7c

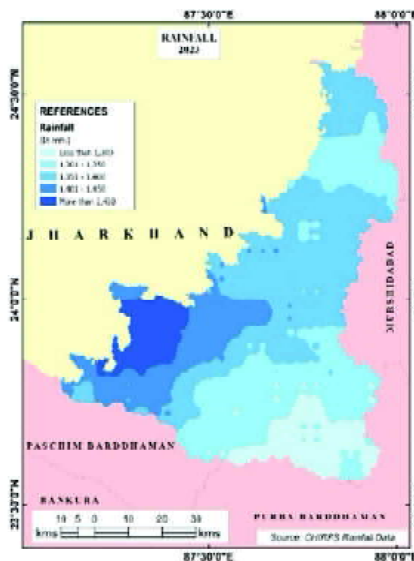


Fig. 7d

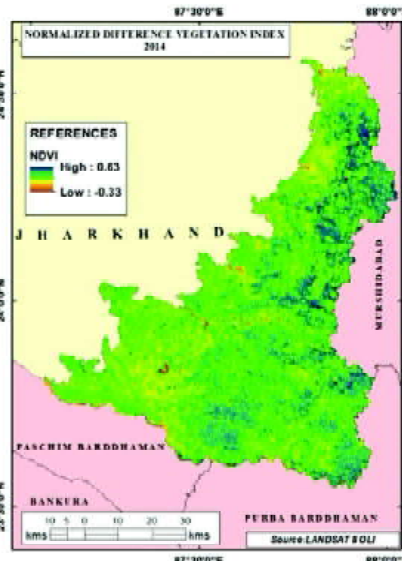


Fig. 7e

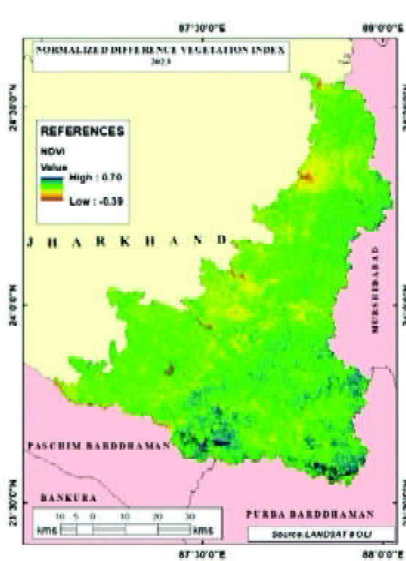


Fig. 7f

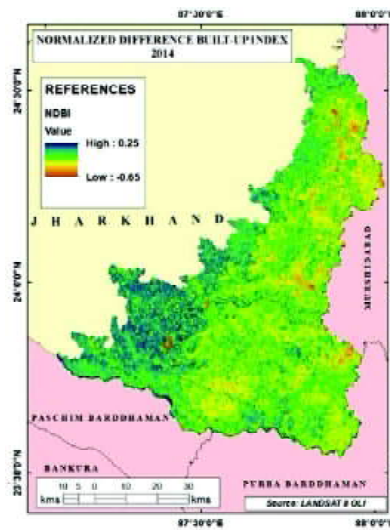


Fig. 7g

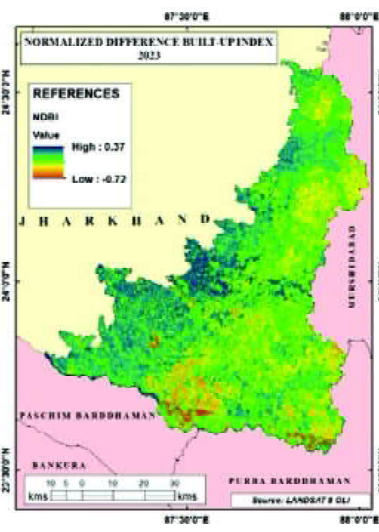


Fig. 7h

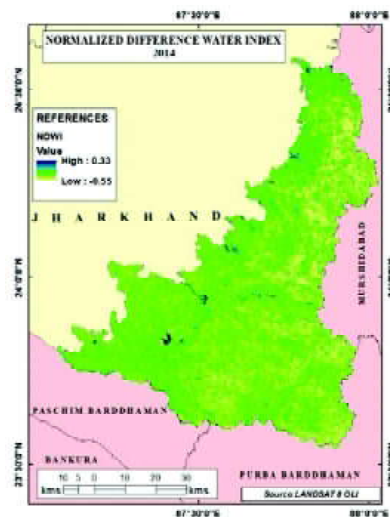


Fig. 7i

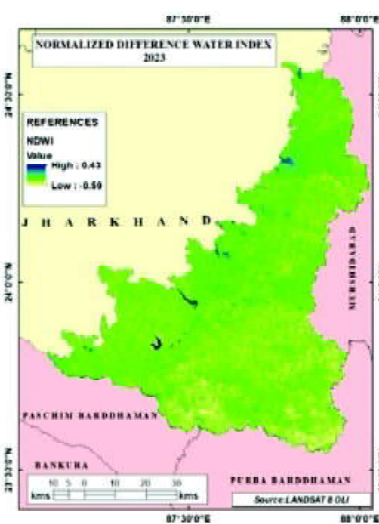


Fig. 7j

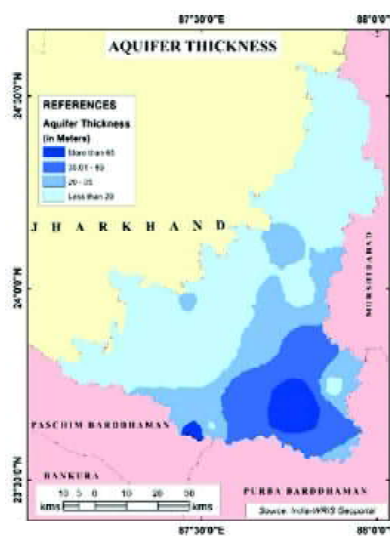


Fig. 7k

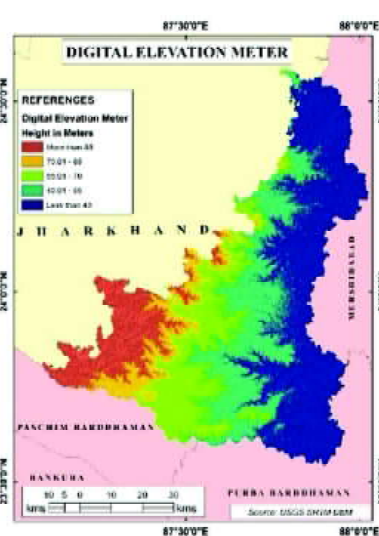


Fig. 7l

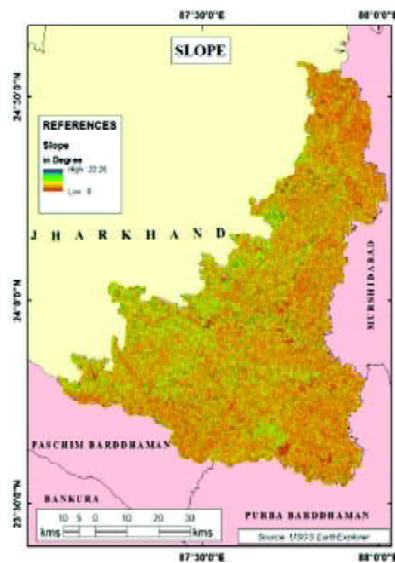


Fig. 7m

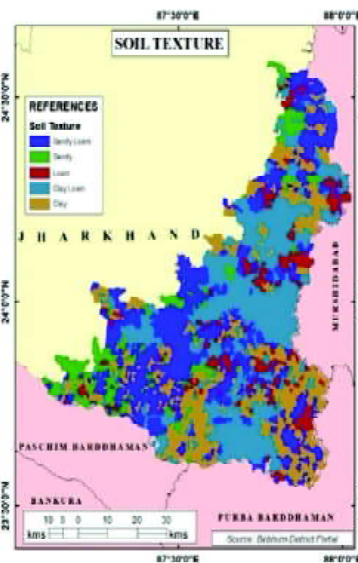


Fig. 7n

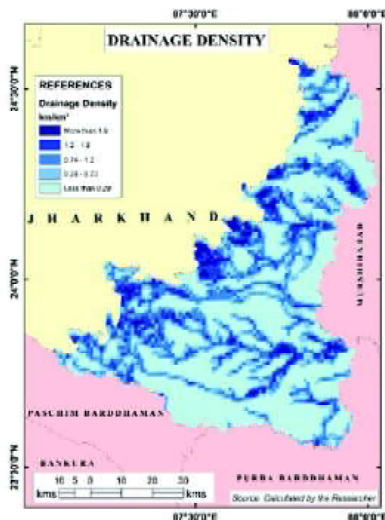


Fig. 7o

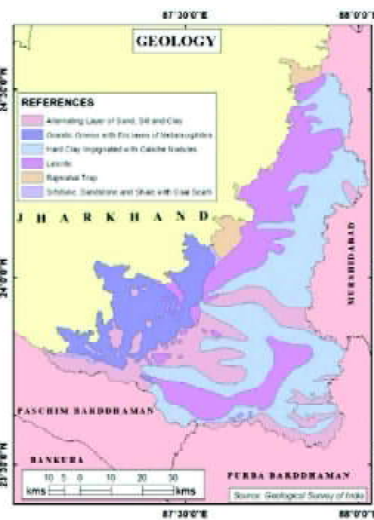


Fig. 7p

Fig. 7 (a to p): Groundwater Level Influencing Factors

Discussion

The results clearly indicate that groundwater depletion is predominantly observed in the eastern part of the study area. The correlation matrix further reveals that groundwater draft has the greatest influence on groundwater depletion during both the years (Fig. 8). Among all the influencing factors, it is evident that the eastern part of the district, where Mayureswar I, Mayureswar II, Sainthia, Labpur, Nanoor, and Illambazar blocks are located, is more favorable for

groundwater-based irrigation. This is primarily due to the presence of alluvial soil, which facilitates higher groundwater extraction and consequently, greater depletion level.

Conversely, in the western part of the district, which is characterized by hard rock geology, groundwater drainage is significantly less effective. The challenging drilling conditions in this region contribute to the lower groundwater draft, resulting in minimal depletion when compared to the alluvial soil regions in the east.



Fig. 8: Correlation Matrix of Groundwater Level and Its Influencing Factors for 2014 and 2023

Conclusion

The study reveals that the nature of groundwater depletion in Birbhum district during 2014-2023 is found to be mostly confined to the eastern part, which is distinguished by alluvial soils and extensive agricultural activity. The correlation analysis shows that groundwater draft is the most important element driving this depletion. Groundwater levels in blocks such as Labpur, Sainthia, and Mayureswar-II have fallen at alarming rates, with Labpur witnessing the worst hit. In contrast, the western part of the district, which is dominated by hard rock geology, has low groundwater depletion as a result of limited extraction and geographical limits.

The results highlight the complicated link between geological factors and groundwater depletion patterns. While the western part's hard rock aquifers limit water extraction, the eastern part's alluvial soils, which are more favourable to groundwater-based irrigation, have resulted in unsustainable water level owing to over-extraction. This regional heterogeneity necessitates focused groundwater management techniques, particularly in the eastern blocks,

to maintain the long-term sustainability of this critical resource.

By mapping these patterns, the study successfully highlights the places most at danger underlining the critical need for sustainable water management techniques. Such measures are critical for mitigating fast depletion and ensuring a balanced approach to groundwater use in the district.

In order to effectively arrest the ongoing groundwater depletion, integrated and location-specific sustainable management strategies need be implemented. Artificial recharge techniques such as percolation tanks, check dams, recharge trenches, and rooftop rainwater harvesting can significantly enhance groundwater replenishment, especially in the eastern alluvial zones. Crop diversification toward less water-intensive varieties will help reduce pressure on aquifers. Community-based water budgeting, conjunctive use of surface and groundwater, and adoption of geospatial monitoring tools for real-time water assessment can further ensure sustainable groundwater governance.

References

- Abijith, Devanatham, Subbarayan Saravanan, Leelambar Singh, Jesudasan Jacinth Jennifer, Thiagarajan Saranya, and K. S. S. Parthasarathy. 2020. "GIS-Based Multi-Criteria Analysis for Identification of Potential Groundwater Recharge Zones - a Case Study from Ponnaniyaru Watershed, Tamil Nadu, India." *HydroResearch* 3:1-14.

- Anand, B., D. Karunanidhi, T. Subramani, K. Srinivasamoorthy, and M. Suresh. 2020. "Long-Term Trend Detection and Spatiotemporal Analysis of Groundwater Levels Using GIS Techniques in Lower Bhavani River Basin, Tamil Nadu, India." *Environment, Development and Sustainability* 22(4):2779–2800.
- Balamurugan, P. 2020. "Assessment of Groundwater Quality in Salem District Using Gis Techniques (Doctoral Thesis)." Anna University.
- Chaudhary, Veena and S. Satheeshkumar. 2018. "Assessment of Groundwater Quality for Drinking and Irrigation Purposes in Arid Areas of Rajasthan, India." *Applied Water Science* 8(8):1–17.
- Dangar, Swarup, Akarsh Asoka, and Vimal Mishra. 2021. "Causes and Implications of Groundwater Depletion in India: A Review." *Journal of Hydrology* 596(August 2020):126103.
- Das, Niladri, Subhasish Sutradhar, Ranajit Ghosh, Prolay Mondal, and Sadikul Islam. 2021. "The Response of Groundwater to Multiple Concerning Drivers and Its Future: A Study on Birbhum District, West Bengal, India." *Applied Water Science* 11(4):1–22.
- Eyankware, M. O., C. G. Aleke, A. O. I. Selemono, and P. N. Nnabo. 2020. "Groundwater for Sustainable Development Hydrogeochemical Studies and Suitability Assessment of Groundwater Quality for Irrigation at Warri and Environs., Niger Delta Basin, Nigeria." *Groundwater for Sustainable Development* 10(August 2019):100293.
- Gibrilla, Abass, Geophrey Anornu, and Dickson Adomako. 2018. "Trend Analysis and ARIMA Modelling of Recent Groundwater Levels in the White Volta River Basin of Ghana." *Groundwater for Sustainable Development* 6:150–63.
- Halder, Sudipa, Malabika Biswas Roy, and Pankaj Kumar Roy. 2020. "Analysis of Groundwater Level Trend and Groundwater Drought Using Standard Groundwater Level Index: A Case Study of an Eastern River Basin of West Bengal, India." *SN Applied Sciences* 2(3):1–24.
- Lu, Wen Xi, Ying Zhao, Hai Bo Chu, and Lei Lei Yang. 2014. "The Analysis of Groundwater Levels Influenced by Dual Factors in Western Jilin Province by Using Time Series Analysis Method." *Applied Water Science* 4(3):251–60.
- Minea, Ionuț, Daniel Boicu, and Oana Elena Chelariu. 2020. "Detection of Groundwater Levels Trends Using Innovative Trend Analysis Method in Temperate Climatic Conditions." *Water (Switzerland)* 12(8).
- Prasad, R. 2018. "Groundwater Depletion Alarming in Northwest, Central India." *The Hindu*.
- Rahman, A. T. M. Sakiur, Md. Kamruzzaman, Chowdhury Sarwar Jahan, Quamrul Hasan Mazumder, and Ahammad Hossain. 2016. "Evaluation of Spatio-Temporal Dynamics of Water Table in NW Bangladesh: An Integrated Approach of GIS and Statistics." *Sustainable Water Resources Management* 2(3):297–312.
- Sahoo, Sasmita and Madan K. Jha. 2013. "Groundwater-Level Prediction Using Multiple Linear Regression and Artificial Neural Network Techniques: A Comparative Assessment." *Hydrogeology Journal* 21(8):1865–87.
- Sahoo, Satiprasad, Subha Chakraborty, Quoc Bao Pham, Ehsan Sharifi, Saad Sh Sammen, Matej Vojtek, Jana Vojteková, Ismail Elkhachy, Romulus Costache, and Nguyen Thi Thuy Linh. 2021. "Recognition of District-Wise Groundwater Stress Zones Using the GLDAS-2 Catchment Land Surface Model during Lean Season in the Indian State of West Bengal." *Acta Geophysica* 69(1):175–98.
- Siebert, S., J. Burke, J. M. Faures, K. Frenken, J. Hoogeveen, P. Döll, and F. T. Portmann. 2010. "Groundwater Use for Irrigation - A Global Inventory." *Hydrology and Earth System Sciences* 14(10):1863–80.
- Tao, Hai, Mohammed Majeed Hameed, Haydar Abdulameer Marhoon, Mohammad Zounemat-Kermani, Salim Heddad, Kim Sungwon, Sadeq Oleiwi Sulaiman, Mou Leong Tan, Zulfaqr Sa'adi, Ali Danandeh Mehr, Mohammed Falah Allawi, S. I. Abba, Jasni Mohamad Zain, Mayadah W. Falah, Mehdi Jamei, Neeraj Dhanraj Bokde, Maryam Bayatvarkeshi, Mustafa Al-Mukhtar, Suraj Kumar Bhagat, Tiyyasha Tiyyasha, Khaled Mohamed Khedher, Nadhir Al-Ansari, Shamsuddin Shahid, and Zaher Mundher Yaseen. 2022. "Groundwater Level Prediction Using Machine Learning Models: A Comprehensive Review." *Neurocomputing* 489:271–308.
- Veeranna, Jatoth and Pawan Jeet. 2021. "Groundwater Recharges Technology for Water Resource Management: A Case Study." *Groundwater Management and Resources* (October).
- Wakode, Hemant Balwant, Klaus Baier, Ramakar Jha, and Rafiq Azzam. 2018. "Impact of Urbanization on Groundwater Recharge and Urban Water Balance for the City of Hyderabad, India." *International Soil and Water Conservation Research* 6(1):51–62.



Religious and Socio-Economic Determinants of Fertility Pattern in India: An Intersectional Analysis

Fateh Singh and Govind Singh*

Department of Geography, JNV University, Jodhpur, Rajasthan (India)

**Corresponding Author's Email: govind5550@gmail.com*

Abstract

The Total Fertility Rate (TFR) measures the average anticipated number of children that a woman is likely to bear throughout her reproductive lifetime. This study examines the interplay of religious and socio-economic factors in shaping TFR across India, employing an inter-sectional analytical framework. Utilizing the data from NFHS, the paper examines how religious affiliation and socio-economic factors — such as income, education, occupation, and urban or rural residence — affect fertility outcomes. The analysis reveals a significant variation in TFR across religious communities, with socio-economic factors mediating these differences. Higher education and urban living are correlated with lower TFR for all groups, but the effect differs by religion due to cultural and institutional factors.

Keywords: TFR, NFHS, replacement level, demographically threatened.

Introduction

According to data from NFHS-5, India's TFR fell beneath the replacement level of 2.1 during 2019–21. Higher fertility in India is attributed to universality of marriage, low literacy, unmet need for contraception and traditional religious beliefs discouraging family planning (Mandal, et al., 2007). While the overall trend shows progress toward population stabilization, it conceals notable differences across regions, religious groups, and socio-economic categories. Educational attainment has a dominant effect on women's fertility, with higher levels of schooling linked to lower Total Fertility Rates (TFR), delayed marriage and increased use of contraceptive

(Sharma et al., 2020). The National Population Policy 2000 seeks to achieve long-term population stabilization by 2045. However, recent studies question the feasibility of achieving this goal within the set timeframe. Analysis of socio-economic and demographic data by religion from multiple sources indicates that the variations in fertility rates and family planning acceptance between Hindus and Muslims are minimal (Shariff, 1995). Fertility in a culturally and economically diverse country depends on a broad understanding of various factors. Religion, as a major cultural identity, influences reproductive behaviour, family size preferences, and healthcare access in complex ways. NFHS data reveal that the Muslims have the fertility rates higher than the Hindus, Christians, Sikhs and Jains.

This study takes an inter-sectional approach to gain deeper insights into India's fertility trends and their health policy implications.

Review of Literature

Alagarajan & Kulkarni (2008) identified a convergence of fertility rates among different religious communities. However, the Muslim fertility rates persist at relatively higher level compared to those of the Hindus and Christians. Mandal et al. (2007) observed that Muslim mothers in rural West Bengal had significantly higher average pregnancies (2.8) than Hindu mothers (1.68), attributing these disparities to social and religious norms that discourage contraception and encourage early marriage. Sharma et al. (2020), analyzing NFHS-4 data from Empowered Action Group (EAG) states, reaffirmed that religious affiliation remains a strong predictor of fertility differences. Their findings indicate that Muslim fertility continues to exceed replacement level (TFR = 2.61) compared to Hindus (2.13), even after accounting for socio-economic factors. These results are consistent with Shariff, (1995), who suggested that religious and cultural practices can pose constraints on family planning adoption and perpetuate demographic disparities. Arokiasamy (2009) demonstrated that increased educational attainment among women correlates with delayed marriage, greater contraceptive use, and a preference for smaller families. Similarly, Das & Mohanty (2012) reported a strong negative correlation between female literacy and total fertility rate (TFR) at the district level in Uttar Pradesh and Bihar. Mandal et al. (2007) found that overall female literacy exerted limited influence on fertility, they noted through stratified analysis that education lowered fertility among the Hindu women, but had minimal impact among the Muslims, indicating that religious norms may mediate educational effects. Ghosh (2018) further confirmed that districts characterized by higher literacy rates and urbanization consistently exhibit lower fertility across religious groups (Mandal et al., 2007). Both Alagarajan and Kulkarni (2008) and Arokiasamy (2009) emphasized that increase

in income, urbanization and access to health services contribute to fertility reduction, although these outcomes are moderated by cultural factors. Nonetheless, in less developed northern states, fertility rates remain elevated among low-income groups despite ongoing policy interventions (Das & Mohanty, 2012).

Study Area

India, located in the southern part of Asia, has an area of 3.28 million sq. km, making up 2.4% of the world's landmass and ranking as the seventh-largest country globally. The country is geographically bounded by China, Bangladesh, Pakistan, Bhutan, Afghanistan, Nepal and Myanmar. It shares sea borders with Maldives and Sri Lanka. India's diverse climate ranging from tropical in the south to alpine in the Himalayan region, extending from 8°4' N to 37°6' N latitude and from 68°7' E to 97°25' E longitude Fig. 1. The country is characterized by significant diversity in climate, culture and economic development. Its geography varies from the Himalayas and Indo-Gangetic plains to the Thar desert and coastal areas along the Arabian Sea and Bay of Bengal. According to the 2011 Census, the population of the country was 1,210,854,977, with a density of 382 people per sq. km. Uttar Pradesh ranks the most populous state, followed by Maharashtra, Bihar, and West Bengal. About 68.8% of the population lives in rural areas, while 31.16% in the urban areas. India's population is highly heterogeneous. Major religious communities include Hindus (79.8%), Muslims (14.2%), Christians (2.3%), Sikhs (1.7%), Buddhists (0.7%), and Jains (0.4%). The overall literacy rate is 74.04%, including 82.14% for male and 65.46% for female. The study covers all 28 states and 8 union territories of the nation.

Objectives

- (i) To analyse the patterns in the total fertility rate among the major religious groups in India.
- (ii) To examine the influence of female literacy on total fertility rates (TFR).
- (iii) To examine the regional variation between TFR in relation to wealth.

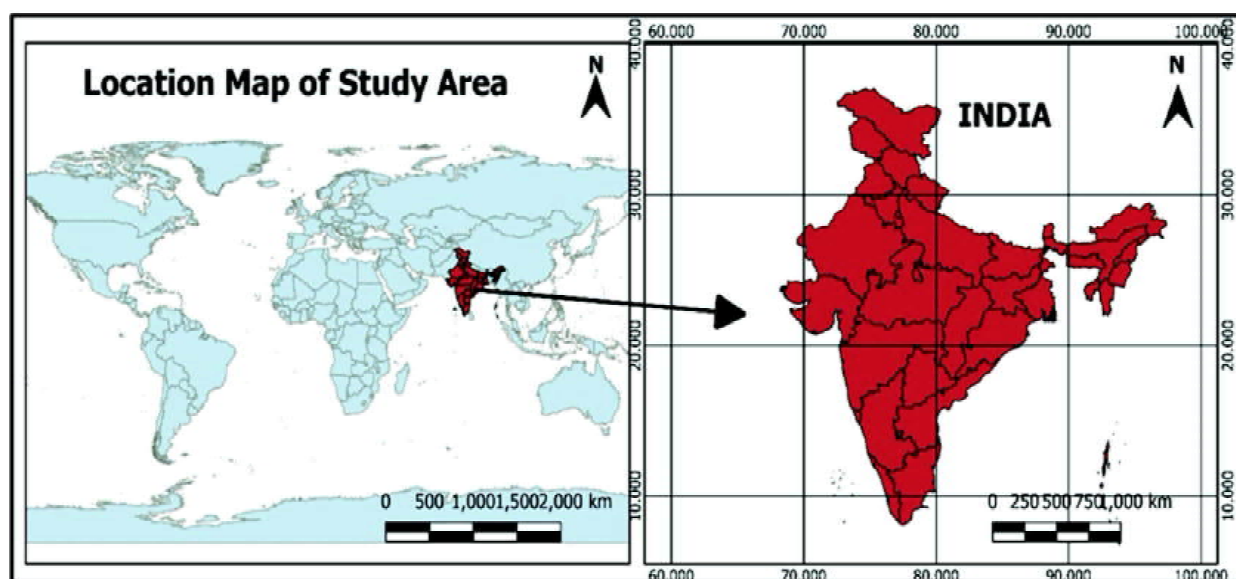


Fig. 1: Location Map of the Study Area

Database and Methodology

This study is primarily based on secondary data sourced from NFHS (IIPS, Ministry of Health & Family Welfare, Government of India). In particular, NFHS-5 (2019–21) forms the core dataset, with earlier rounds (NFHS-1 to NFHS-4) incorporated for comprehensive historical trend analysis. The study employs a quantitative analytical approach, integrating descriptive statistics, bivariate correlations, regression modeling, and intersectional analysis. Descriptive statistics has been employed to display TFR data by religion, state, wealth group, and across different periods (NFHS-1 to NFHS-5) to illustrate fertility trends. The Pearson correlation coefficient assessed the relationship between female literacy rate and TFR among the states. The data are systematically tabulated using Microsoft Excel and QGIS software is used for preparation of maps. The following simple linear regression equation is used:

$$Y = \alpha + \beta X$$

Where,

Y = Dependent variable (Total Fertility Rate)

X = Independent variable (Female Literacy Rate %)

α / alpha = Intercept of the regression line (value of Y when X=0)

β / beta = Slope coefficient (change in Y per unit change in X).

The formula used for Pearson's correlation coefficient is

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}}$$

r = Pearson correlation coefficient

X_i = value of independent variable

(Female Literacy Rate)

Y_i = value of dependent variable (TFR)

$\bar{x}$ = mean of X values $\bar{y}$ = mean of Y values

Σ = summation overall observations

Results and Discussion

This study investigates the intersection of religion, literacy and wealth with TFR across Indian states, and religious communities using NFHS-5 data (2019–21). It highlights how religious identity and socio-economic indicators such as female literacy and wealth play a significant role in shaping fertility behaviour in India. A critical determinant of TFR is female education, especially among women of childbearing age (15–49 years). In India, where demographic diversity is stark, understanding how education is shaping fertility behaviour is essential for targeted interventions. This paper utilizes recent NFHS-5 data to examine the association between state-level female literacy rates and total fertility rate (TFR), analysing the strength of this relationship and predicting fertility outcomes using regression analysis. India's total fertility rate (TFR) stands at 2.0 children per woman, marginally below the replacement level of 2.1 children per woman. Rural women record a TFR of 2.1, in contrast

to the 1.6 observed among the women living in urban areas.

Influence of Female Literacy on TFR

A correlation coefficient value of -0.425 shows a moderate negative relationship between female literacy and total fertility rate. As the independent variable (female literacy) increases, the dependent variable (TFR) tends to decrease, but the relationship is not very strong. A critical

determinant of TFR is female education, especially among women of child bearing age (15–49 years). The Table 1 consists of TFR, female literacy and estimated TFR (based on regression model). According to the regression equation, a 1% increase in literacy is associated with an approximate decrease of 0.0165 in the predicted total fertility rate (TFR). Kerala, with a high literacy rate at 98.3%, has a TFR of 1.79, which is 0.32 points above the expected value. This variance may be attributable to recent migration patterns or a potential rebound in fertility rates.

Table 1: Total fertility rate and female (15-49 year) literacy rate

States / UT	TFR	Female Literacy in % (15-49 y)	Estimated TFR
Andhra Pradesh	1.68	68.6	1.96
Arunachal Pradesh	1.8	71.3	1.92
Assam	1.87	77.2	1.82
Bihar	2.98	57.8	2.14
Delhi	1.62	83.7	1.71
Goa	1.3	93	1.56
Gujarat	1.86	76.5	1.83
Haryana	1.91	79.7	1.78
Himachal Pradesh	1.66	91.7	1.58
Jammu and Kashmir	1.41	77.3	1.82
Karnataka	1.67	76.7	1.83
Kerala	1.79	98.3	1.47
Madhya Pradesh	1.99	65.4	2.01
Maharashtra	1.71	84.6	1.70
Manipur	2.17	87.6	1.65
Meghalaya	2.91	88.2	1.64
Mizoram	1.87	94.4	1.54
Nagaland	1.72	85.8	1.68
Odisha	1.82	69.5	1.95
Punjab	1.63	79.4	1.78
Rajasthan	2.01	64.7	2.03
Sikkim	1.05	88.9	1.63
Tamil Nadu	1.76	84	1.71
Tripura	1.7	80.6	1.76
Uttar Pradesh	2.35	66.1	2.00
West Bengal	1.64	76.1	1.84
Chhattisgarh	1.82	72.5	1.90
Jharkhand	2.26	61.7	2.07
Uttarakhand	1.85	79.8	1.78
Telangana	1.75	66.6	1.99
Andaman Nicobar	1.28	86	1.67
Chandigarh (UT)	1.4	78.7	1.80
Dadra and Nagar H	1.84	77.3	1.82
Lakshadweep (UT)	1.42	96.5	1.50
Puducherry (UT)	1.49	89.7	1.61
Ladakh (UT)	1.31	76.8	1.83

Source: Prepared by Authors based on data from NFHS 5 (2019-21).

Regression Residual Analysis (Actual TFR - Predicted TFR)

Regression residuals indicate how much actual TFR deviates from the model's predicted value. Higher positive residuals states have higher fertility than expected based on their literacy levels. The higher negative residuals demonstrate that these regions report significantly lower fertility than predicted (Table 2).

Meghalaya records the highest positive residual at 1.27, which may be due to matrilineal traditions and tribal norms which prefer bigger families. Bihar stands at 0.84 and Uttar Pradesh at 0.35 with moderately high positive, probably reflecting the traditional way of life and poor implementation of family planning measures. Manipur is at 0.52 and Mizoram is at 0.33 with slightly higher fertility rates, more influenced by tribal practices and low levels of urbanization. Kerala surprises with its very high literacy rate with a positive residual of 0.32, which may be attributed to cultural conservatism or migration factors that promote higher fertility than otherwise expected from

such education levels. Low positive residuals are found in Jharkhand (0.19), Haryana (0.13), Himachal Pradesh (0.08) and Uttarakhand (0.07) due to factors such as son preference and low women's empowerment. Sikkim witnesses a moderately high negative residual (-0.58), because there exists high degree of health awareness and healthcare services. The areas like Ladakh (-0.52) and Jammu and Kashmir (-0.41) also witness considerably low TFR as compared to their female literacy rates. But the picture of Chandigarh (-0.40) appears to be slightly better largely due to urban impact and prevailing family planning awareness. Andaman & Nicobar (-0.39) records its lower birth rate as influenced by remoteness, migration and environmental constraints. The picture as observed with respect to lower TFR in the southern and coastal states like Andhra Pradesh (-0.28), Telangana (-0.24), Karnataka (-0.16), Goa (-0.26) and West Bengal (-0.20) might be associated with considerably encouraging education, urbanization and economic development.

Table 2: Top 10 Highest Positive and Negative Residuals showing states

State	Residual	State	Residual
Meghalaya	1.27	Sikkim	- 0.58
Bihar	0.84	Ladakh (UT)	- 0.52
Manipur	0.52	Jammu and Kashmir	- 0.41
Uttar Pradesh	0.35	Chandigarh (UT)	- 0.40
Mizoram	0.33	Andaman & Nicobar	- 0.39
Kerala	0.32	Andhra Pradesh	- 0.28
Jharkhand	0.19	Goa	- 0.26
Haryana	0.13	Telangana	- 0.24
Himachal Pradesh	0.08	West Bengal	- 0.20
Uttarakhand	0.07	Karnataka	- 0.16

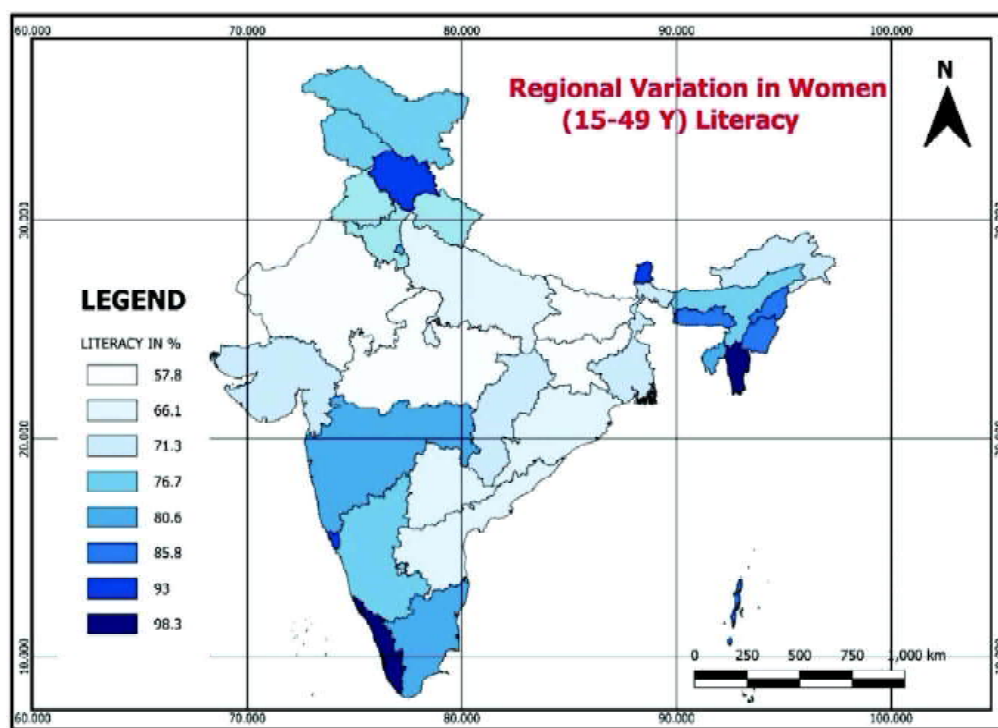
Source: Computed by the authors.

Categorization of Indian States/UTs based on female literacy rate among 15-49 age group and TFR (NFHS-5) has been done as reflected in Table 3 and Fig. 2a and Fig. 2b. Each state is categorized by the combined

value of the female literacy rate threshold (80%) and the TFR threshold (1.8). These values are employed to group the states and UTs into designated categories.

Table 3: Categories of States and UTs based on female literacy and TFR

Category	TFR and literacy	Features	States
1	High literacy with low TFR (literacy effectively lowers fertility here)	States achieving high social development typically have educated populations and small family sizes.	Delhi, Goa, Himachal Pradesh, Kerala, Punjab, Maharashtra, Nagaland, Tamil Nadu, West Bengal, Puducherry, Sikkim, Tripura, Lakshadweep, Andaman and Nicobar (14 States)
2	High literacy rates coexist with high TFR	Suggesting that other socio-cultural influences dominate.	Meghalaya, Mizoram, Manipur, (3 States)
3	Low literacy with high TFR	Development priority zones. Critical focus areas for education, family planning, and awareness.	Bihar, Uttar Pradesh, Assam, Chhattisgarh, Jharkhand, Telangana, Odisha, Dadra and Nagar Haveli (8 States)
4	Moderate literacy with low TFR	Despite lower literacy, these regions show lower-than-expected fertility, indicating other successful interventions.	Andhra Pradesh, Jammu and Kashmir, Arunachal Pradesh, Karnataka, Uttarakhand, Ladakh, Chandigarh (7 States)
5	Near Replacement Level (2.1) TFR	Achieving the TFR target of National Population Policy 2000	Rajasthan, Madhya Pradesh, Gujarat, Haryana (4 states)

**Fig. 2a:** Regional Variation in Women's Literacy in Age Group 15-49 based on data from NFHS 5 (2019-21)

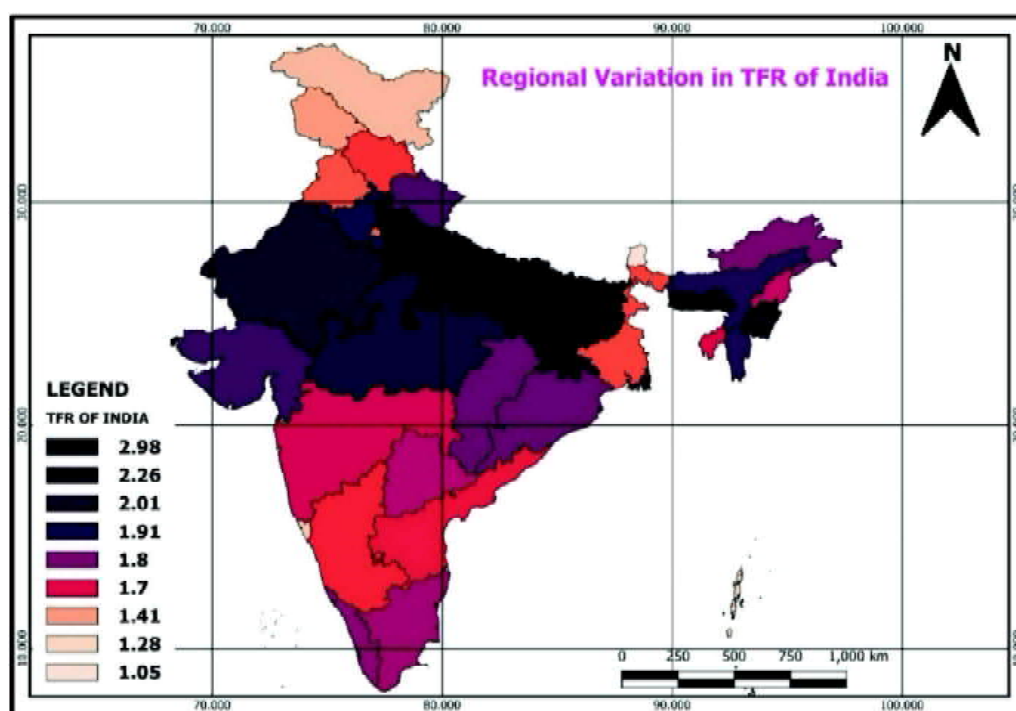


Fig. 2b : Regional Variation in TFR based on data from NFHS 5 (2019-21)

Religious Determinants of TFR

Religion is a powerful but context-dependent determinant of TFR. Apart from education, religion significantly impacts fertility rates, as prohibition or limited acceptance of contraception among certain religious groups shapes fertility patterns (Sharma et al., 2020). In diverse societies like India, the interplay between religion and caste, region, literacy, and access to services, making it essential to adopt an intersectional perspective in TFR analysis. Religion plays a significant role in shaping individual and communal attitudes towards marriage, contraception, childbearing, gender roles, and family planning. Certain religions encourage large families and view procreation as a religious duty, while others may promote family planning or impose fewer spiritual obligations on reproduction. Contrary to popular belief, studies indicate that contraceptive use has risen overall, with the largest increase among Muslims, narrowing the gap between religious communities. The prevalence rate increased from 41% to 56% (Alagarajan & Kulkarni, 2008). Religion differs in their perspective on contraception. In Islam, it varies by interpretation, and many Islamic

scholars endorsing contraception use. Religious beliefs, male decision-making, and community norms often override contraceptive awareness among Muslim women (Mandal et al., 2007). Conversely, Catholicism traditionally opposes artificial means of birth control while Hinduism generally does not oppose contraception. National policy in India actively promotes family planning. Buddhism's stance on birth control can differ by country and sect, ranging from neutrality to support. Religions often shape the age of marriage, polygamy norms, and gender roles. Early marriage often leads to higher fertility. In India, where religion is deeply tied to identity, fertility trends differ significantly across religious groups.

All religious groups have experienced a consistent decline in TFR over nearly three-decade span. Hindus experienced a decline in TFR of 3.3 in (1992–93) to 1.94 in (2019–21) (Fig. 3), indicating the successful interventions from the government to the majority of population. For Muslims, the TFR also decreased from 4.41 in (1992–93) to 2.36 in (2019–21), which narrow the gap with Hindus from 1.11 to 0.42 over the period, but remaining above the replacement level. For Christians,

the TFR decline from 2.87 to 1.88, was likely influenced by result of higher educational attainment in areas such as Northeast and Kerala. For Sikhs, the TFR decline was from 2.43 to 1.61 with the fluctuations being minor and possibly due to small sample sizes. The TFR of Buddhists declined from 2.13 (NFHS-2) to 1.39 (NFHS-5) which is

the lowest among the groups and is noted in more advanced or remote areas such as the Himalayas and Maharashtra. Jains started with a TFR of 1.9, then dropped to 1.2, and then slightly increased to 1.6. The consistently low rates are a result of focus on education and career. However, the data may be impacted by sample size.

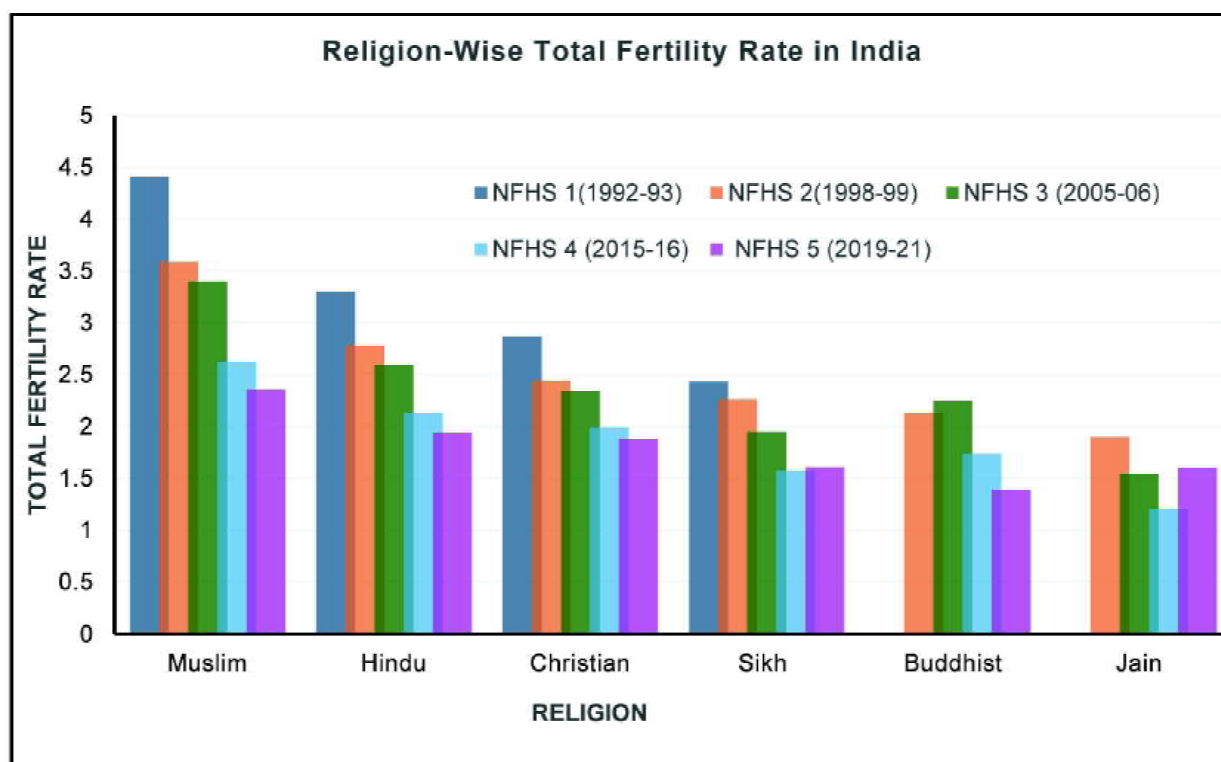


Fig. 3

The data shows that the Muslims record the highest average TFR at 2.17, followed by Christians (1.8), Sikhs (1.68), and Hindus (1.68). It is further observed that the Hindus and Sikhs exhibit similar rates, both of which are below the replacement level of 2.1 in majority of the states in the country (Fig. 4). This reflects the potential of stable or decreasing population in the absence of migration. TFR of Muslim tends to be higher than other religious groups in almost all states, frequently exceeding the replacement rate of 2.1. Even in regions where overall fertility is low (Kerala 1.79, Assam 1.87, West Bengal 1.64), Muslims register rates higher (Kerala 2.25, Assam 2.38, West Bengal 2.03), while Hindus and Christians remain significantly lower. The states with highest TFR for

specific groups are Bihar for Hindus (2.88), Haryana for Muslims (3.87), and Meghalaya for Christians (3.17). In the north-eastern region, fertility rates for Christians are significantly higher, whereas those among Hindus are notably low. The pronounced disparity in fertility rates, characterized by extremely low Hindu fertility and persistently high Muslim fertility, is particularly evident in (Haryana, Assam, Bihar, Uttarakhand, West Bengal). This demographic variation has contributed to ongoing discussions about population change, migration, and identity in the region. An integrated approach is required — managing explosive fertility rates in northern regions while promoting population stabilization in the southern and north-eastern areas.

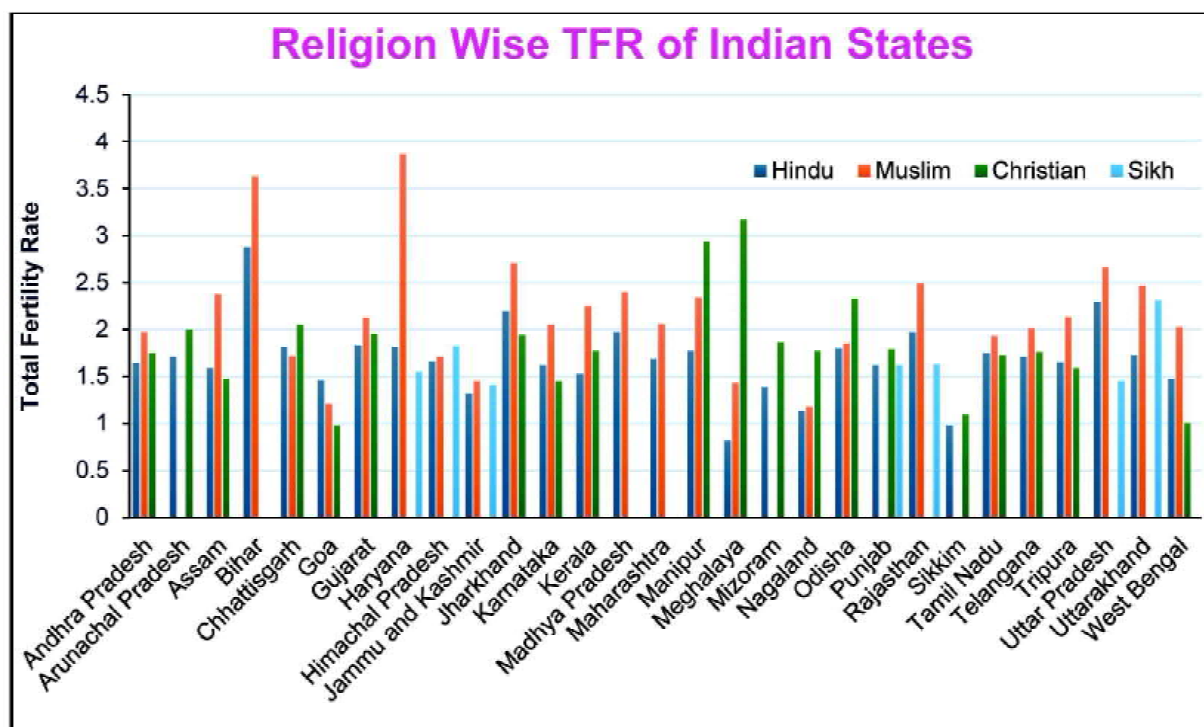


Fig. 4

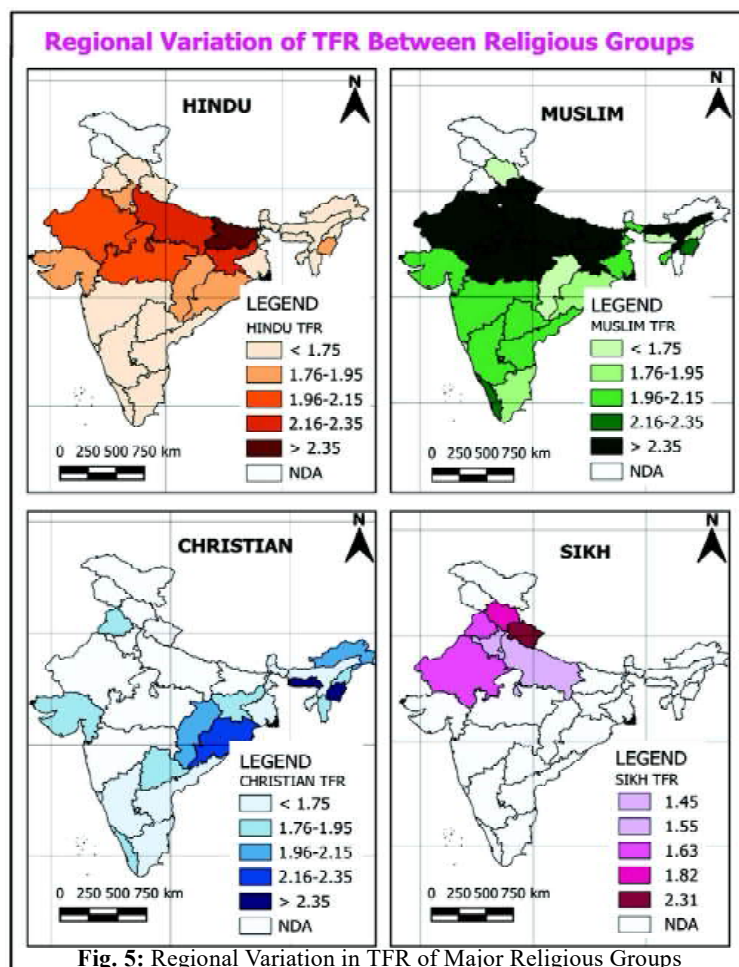
Table 4 presents a classification of Indian states according to the TFR among three major religious groups, distributed across five fertility categories. Current demographic data for Hindus in India indicate that 25 states now have fertility rates below the replacement level, with 18 states falling into the “Demographically Threatening” category, defined by a TFR of less than 1.75. Only a few states — specifically Uttar Pradesh, Bihar, and Jharkhand — maintain an above-replacement fertility rate. Hindu population stabilization in most states eases

demographic pressure and aids resource management. However, very low TFR among Hindus in 18 states may lead to population stagnation, labour shortages, higher dependency ratios, demographic imbalance, and slower economic growth. Although India’s total fertility rate (TFR) is declining nationwide, certain areas — particularly among Muslim populations in 17 states — continue to record TFR above the national average, with eight states reporting rates exceeding 2.35 (Table 4 and Fig. 5).

Table 4: Religion-wise category of states

Category	Hindu	Muslim	Christian
Demographically Threatening zone (Less than 1.75 TFR)	Arunachal Pradesh, Telangana, Sikkim, Himachal Pradesh, Kerala, Maharashtra, Assam, Tamil Nadu, Meghalaya, Tripura, Mizoram, Punjab, Nagaland, Andhra Pradesh, Karnataka, Goa, Uttarakhand, West Bengal (18 States)	Chhattisgarh, Goa, Himachal Pradesh, Meghalaya, Nagaland (5 States)	Assam, Tamil Nadu, Sikkim, Goa, Karnataka, Andhra Pradesh, West Bengal, Tripura
Below Replacement Level TFR (1.76-1.95)	Chhattisgarh, Gujarat, Haryana, Manipur, Odisha. (5 States)	Tamil Nadu, Odisha (2 States)	Gujarat, Jharkhand, Kerala, Punjab, Telangana, Nagaland, Mizoram,
Near Replacement Level TFR (1.96-2.15)	Madhya Pradesh, Rajasthan (2 States)	Andhra Pradesh, Gujarat, Karnataka, Maharashtra, West Bengal, Telangana, Tripura (7 States)	Chhattisgarh,
Above Replacement level TFR (2.16-2.35)	Uttar Pradesh, Jharkhand. (2 States)	Kerala, Manipur, (2 States)	Odisha,
Explosive (More than 2.35 TFR)	Bihar (1 State)	Assam, Madhya Pradesh, Haryana, Jharkhand, Uttar Pradesh, Bihar, Uttarakhand, Rajasthan, (8 states)	Manipur, Meghalaya.

Source: Computed by the authors.



The states where the TFR among Muslims is below 1.75, typically have a population share of less than 10 percent. The low fertility rates among the Christians in most states contribute to controlled population growth, which is associated with improved education and healthcare indicators. However, the combination of a small population base and migration trends may result in demographic shrinkage. A continuous decline in population could potentially diminish political representation and cultural influence.

Socio-Economic Factors Affecting TFR

TFR is influenced by a range of socio-economic factors, which include employment and income levels, urbanization, healthcare and contraceptive access, cultural and religious beliefs, marriage patterns and age at first birth, infant and child mortality rates, and government policies and incentives. Women's participation in the formal workforce often correlates with a delay in childbirth and fewer children. Household income is a significant factor influencing fertility decisions. The greater the financial resources, fewer the children a family may opt for, often due to the significant costs involved in child-rearing. In contrast, families with limited income might have more children, viewing them as potential contributors to household economic support. Urban areas typically provide enhanced access to higher education, healthcare services, and contraception. Additionally, the

increased living cost in urban environments often leads couples to choose smaller family sizes. Availability of healthcare, especially child health services, maternal health with family planning methods significantly impacts TFR.

Table 5 displays Total Fertility Rate (TFR) and Per Capita Income (At constant price, base year 2011-12) for each Indian state. The correlation coefficient (-0.697) indicates a moderately strong negative relationship. In other words, states with higher income level tend to have lower fertility rates. For instance, Goa (1.3), Sikkim (1.05), Tamil Nadu (1.7) and Telangana (1.75) demonstrate relatively high per capita incomes alongside low fertility rates, signaling stabilized or declining population growth. Conversely, the states of Bihar, Uttar Pradesh, Jharkhand and Meghalaya are characterized by lower income and higher fertility rates, often associated with challenges related to education, healthcare access and women's empowerment. The states such as Karnataka (1.67), Gujarat (1.86) and Haryana (1.91) report moderate fertility rates and increasing per capita incomes, reflecting ongoing demographic transition toward greater stability. The simple linear regression model as applied reveals a statistically significant inverse relationship between TFR and per capita income. The slope ($\beta = -0.000003841$) indicates that for every Rs. 1,000 increase in per capita income, TFR decreases by approximately 0.0038 children per woman.

Table 5: Per Capita Income and TFR

States	TFR (NHFS-5 2019-21)	Per Capita Income (2021-22)
Andhra Pradesh	1.68	117464
Arunachal Pradesh	1.8	115311
Assam	1.87	65726
Bihar	2.98	30779
Goa	1.3	310201
Gujarat	1.86	174539
Haryana	1.91	172657
Himachal Pradesh	1.66	141830
Karnataka	1.67	164471
Kerala	1.79	148790
Madhya Pradesh	1.99	61534

Maharashtra	1.71	138490
Manipur	2.17	46341
Meghalaya	2.91	60606
Mizoram	1.87	111180
Nagaland	1.72	79188
Odisha	1.82	79899
Punjab	1.63	116850
Rajasthan	2.01	80545
Sikkim	1.05	256507
Tamil Nadu	1.76	154427
Tripura	1.7	86539
Uttar Pradesh	2.35	42525
West Bengal	1.64	69890
Chhattisgarh	1.82	78377
Jharkhand	2.26	55126
Uttarakhand	1.85	149015
Telangana	1.75	154122

Source: CRS bulletin and NFHS-5.

Fig. 6 presents Total Fertility Rate (TFR) across five wealth quintiles during India's NFHS-3 (2005–06), NFHS-4 (2015–16), and NFHS-5 (2019–21) survey rounds. Every group has seen a consistent decline in

fertility from NFHS-3 to NFHS-5, indicating broad socio-economic transitions, greater access to contraception and fertility awareness.

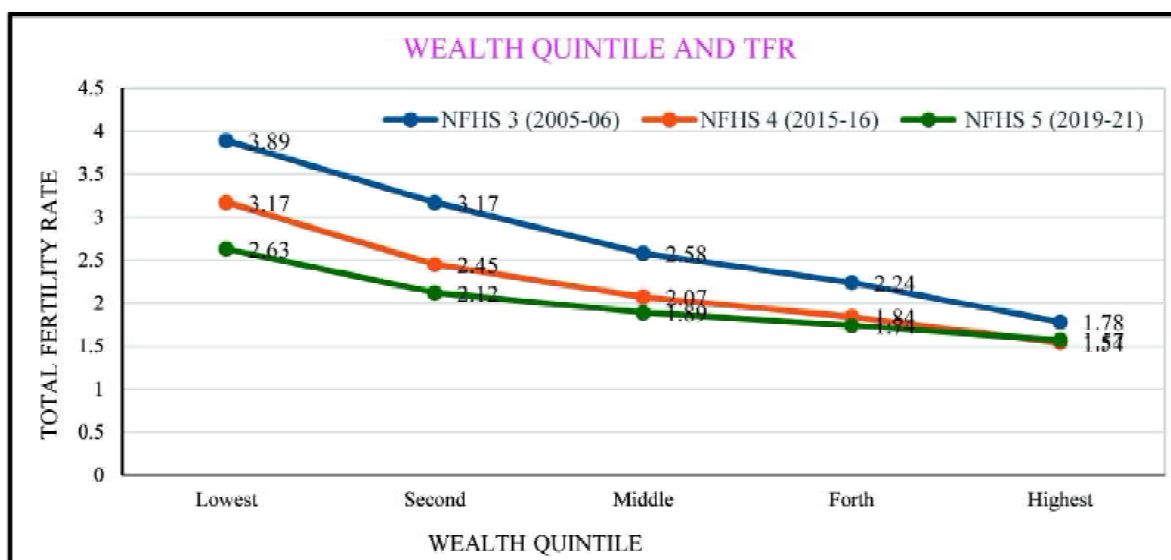


Fig. 6

The gap between the poorest and richest groups remains significant. In NFHS-3, the difference was $3.89 - 1.78 = 2.11$. In NFHS-5, the difference became $2.63 - 1.57 = 1.06$. Although the gap has decreased, fertility rates

continue to be high among lower-income groups. TFR for the highest quintile decreased from 1.78 to 1.54 in NFHS-4 but increased slightly to 1.57 in NFHS-5. This may indicate stabilization or reversal in fertility decline

due to lifestyle preferences. The lowest quintile witnesses a 1.26-point drop in TFR (from 3.89 to 2.63), showing the largest fertility decline over the 16-year span.

Conclusion

This study has analysed how religion, female literacy and socio-economic status influence India's Total Fertility Rate (TFR) using an intersectional approach. Using robust national data from NFHS rounds, the study reveals that TFR has declined nationally below the replacement level of 2.1, but inter-group and interstate disparities persist, especially among religious communities and socio-economic strata. In areas with positive residuals, interventions should promote literacy, economic opportunities and family planning to tackle cultural barriers. For negative residuals, policies may incentivize balanced family sizes and examine successful models like Sikkim's for wider adoption. Recent data show that in India, Hindu fertility rates have fallen below replacement in 25 states. Muslim populations in 17 states have higher-

than-average total fertility rates (TFRs), with eight of those states reporting TFRs above 2.35. This may contribute to regional population imbalances, resource strain, increased poverty in high-fertility minority areas, and possible socio-political tensions due to demographic differences. The TFRs for the Jain (1.6) and Buddhist (1.39) communities are among the lowest reported within Indian religious groups. Both rates fall below the replacement level of 2.1. Such demographic shifts could potentially reduce their representation and influence within democratic systems. As younger cohorts diminish, there is a risk that cultural, linguistic and religious traditions may lose vibrancy or, in the long term, face the possibility of extinction if current trends persist. Without an increase in birth rates or other mitigating measures, these populations are likely to continue a trajectory of steady decline. The poorest groups still show significantly higher fertility, though the gap with wealthier groups is closing, suggesting effective dissemination of family planning services.

References

- Alagarajan, M., & Kulkarni, P. M. (2008). Religious differentials in fertility in India: Is there a convergence? *Economic and Political Weekly*, 43, 44–53.
- Arokiasamy, P. (2009). Fertility Decline in India: Contributions by Uneducated Women Using Contraception. *Economic and Political Weekly*, 44, 55–64.
- Das, M., & Mohanty, S. K. (2012). Spatial pattern of fertility transition in Uttar Pradesh and Bihar: A district level analysis. *Genus*, 68, 81–106.
- Ghosh, S. (2018). Hindu–Muslim Fertility Differentials in India: Indirect Estimation at the District Level from Census 2011. *Indian Journal of Human Development*, 12, 37–51.
- Mandal, N., Mallik, S., Roy, R., Mandal, S., Dasgupta, S., & Mandal, A. (2007). Impact of religious faith & female literacy on fertility in a rural community of west Bengal. *Indian Journal of Community Medicine*, 32(1), 12. <https://doi.org/10.4103/0970-0218.53382>.
- NFHS-5_NRRreport_val1__NFHS-5_INDIA_REPORT (2). (n.d.).
- Shariff, A. (1995). Socio-Economic and Demographic Differentials between Hindus and Muslims in India. *Economic and Political Weekly*, 30, 2947–2953.
- Sharma, A.K., Nath, N. J., & Shukla, T. (2020). Effect of Religion and Education on Fertility in the EAG States of India: Evidence from NFHS-4. *SOCRATES*, 8(1si), 34. <https://doi.org/10.5958/2347-6869.2020.00005.9>.



Design and Development of Desktop Application for Environmental Indices Analysis using Python

P.R. Isiri¹, Y.B. Bhimambika¹, Munesh Ramji Kusuma²,
Mahesh Pathakoti^{2*} and P. Satyanarayana²

¹Visvesvaraya Technological University, Belagavi, Karnataka (India)

²National Remote Sensing Centre, ISRO, Balanagar, Hyderabad, Telangana (India)

**Corresponding Author's Email: mahesh_p@nrsc.gov.in*

Abstract

Geospatial technologies have become a crucial part of climate/atmospheric research, providing multiple tools for studying, analysing and modelling climate change impacts on a global scale, enabling informed decision-making and mitigation strategies. The present work attempts to design and demonstrate a desktop-based application to calculate and visualise satellite remote sensing-based environmental indices, such as NDVI, NDBI, NDWI, EVI, SAVI, etc. This study has made use of the open-source, offline-usable Streamlit program, which is based on Python and is helpful in places with spotty or restricted internet connectivity. This application is designed to use imagery from widely used Earth observation satellites, such as Landsat 5, 7, 8, 9, and Sentinel-2. In this framework, raster files as inputs (.tiff) are processed using a user-friendly graphical interface, which produce thematic results that can be downloaded. Validation against QGIS has demonstrated high consistency, with NDVI, NDWI on Sentinel-2 datasets. Taken together, the findings show that even in low-resource environments, this tool can provide reliable environmental monitoring. This indicates that the framework offers a solution which is easy to use, free and accessible to researchers, farmers and policy makers, who wish to enhance the accessibility of remote sensing.

Keywords: Geospatial technologies, climate, Streamlit, Python, Environmental Indices, open-source, offline application.

Introduction

The rapid global urbanization phenomenon has significantly heightened the importance of monitoring the changes in the environment (Singh et al., 2024). To monitor these changes governments and organizations increasingly rely on environmental indices (Huete, 1988) to assess ecosystem health and guide conservation efforts. Environmental indices serve as powerful tools for measuring ecological health, guiding policy decisions and tracking progress toward sustainability goals.

Combination of Remote sensing and GIS softwares has proved their importance in monitoring these indices with the help of satellite images over a large area without going to the field (Apostolopoulos & Nikolakopoulos, 2021). Vegetation and environmental indices such as the Normalized Difference Vegetation Index (NDVI) have become essential tools for monitoring ecosystem dynamics, supporting applications from agriculture to climate assessment (Rousel et al., 1974). By emphasizing certain land surface conditions, environmental indices like

the Soil Adjusted Vegetation Index (SAVI), Normalized Difference Water Index (NDWI), and others help in deriving insightful information from satellite data. Meanwhile, commercial softwares such as ArcGIS (Esri, 2024) require paid licenses, which can be cost-prohibitive. Various open-source platforms, such as QGIS (QGIS Development Team, 2024) and SNAP (Zuhlke et al., 2015), provide extensive remote sensing analysis capabilities, but their large installation sizes and steep learning curves restrict accessibility. Cloud-based tools like Google Earth Engine (Kumar & Mutanga, 2018) offer computational convenience but rely on stable internet connectivity. Commercial software like ArcGIS need licence, which requires more money. Recent works have explored browser-based and Streamlit-driven geospatial visualization (Hanansyah et al., 2022; Zulkoffli et al., 2024) yet most remain online-dependent. The present study bridges this gap by developing a completely offline, modular application for vegetation and environmental indices computation with verified accuracy against established software.

The application allows users to upload multispectral satellite images as inputs, which calculates several environmental indicators, categorizes the results, and provides both visualization as well as export functionality of outputs, which supports data-driven decision-making at the local level. This initiative attempts to provide researchers, farmers, educators, and policymakers with a useful tool for localized environmental analysis. By providing a free, easy-to-use solution without sacrificing functionality or scientific rigor, the aim is to democratize access to remote sensing capabilities.

Methodology

The processing mechanism for the classification of indices and steps involved in creating the desktop application are described in Fig. 1. Using open-source Python

modules and a modular design approach, the development allows future improvements and scalability.

A. Overview of the System Architecture

The following layers make up the application architecture:

- ◆ Input Layer: Multispectral satellite imagery (in GeoTIFF format) including bands like Red, Blue, Green, and other bands are inputs by users.
- ◆ Processing Layer: To calculate environmental indices, spectral bands are processed using Rasterio and Numpy.
- ◆ Analysis Layer: The Matplotlib library (Hunter, 2007) is used to categorize and display index values.
- ◆ Interface Layer: A graphical user interface (GUI) that is interactive is offered by Streamlit.

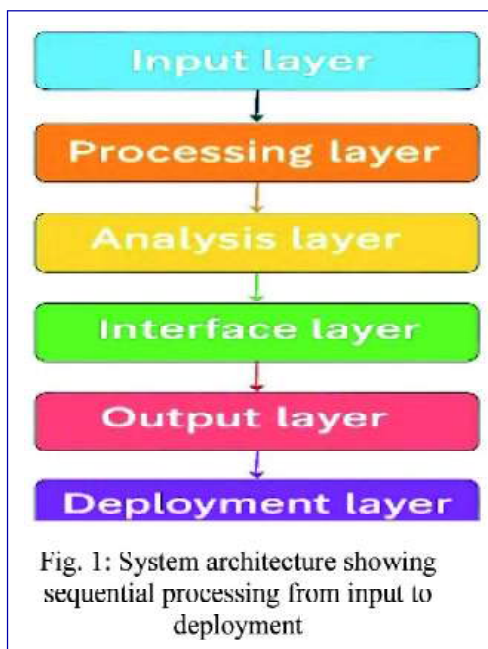
- ◆ Output Layer: GeoTIFF raster, and picture files are all exportable.
- ◆ Deployment Layer: PyInstaller is used to package the application into a standalone executable for offline desktop use.

B. Input Data Acquisition and Preprocessing

The process starts with users uploading “multispectral raster datasets” in “GeoTIFF format” using a “Streamlit-based GUI” based on the selected Environmental Index for calculation. The “rasterio library (Gillies, *et al.* 2013)”, which offers strong capabilities for reading, writing, and modifying georeferenced raster data, is then

used to process these datasets. The application recognizes and extracts particular “spectral bands” upon ingestion that are necessary for calculating different “environmental indices”, such as the “Red and Near-Infrared (NIR)” bands for “NDVI” or “Blue, Red, and NIR” for “Enhanced Vegetation Index (EVI)” and others.

The input images are transformed into NumPy arrays for efficient calculation. The system includes a number of alternative preprocessing processes to guarantee data quality and analytical consistency across various sources and acquisition times. These consist of :



- ◆ Radiometric normalization, which adjusts for variations in light or sensors.
- ◆ No Data value masking, which removes erroneous or absent pixels that could skew calculations.
- ◆ To rescale raw pixel values to a specified reflectance range (such as 0–1 or 0–10000) appropriate for comparison study, use dynamic range scaling.

These preprocessing methods improve the input data's comparability and integrity while also promoting computational stability in later phases including classification, visualization, and index calculation. In order to ensure geospatial accuracy and compatibility with external GIS platforms, metadata like coordinate reference systems (CRS) and spatial resolution are also maintained throughout the process.

C. Index Calculation

The automatic derivation of many environmental indices, each described by a standardized mathematical formula based on multispectral reflectance values derived from satellite data, forms the application's central computing engine. The quantitative evaluation of vegetation, water, soil, and built-up regions is made easier by these indexes. For effective pixel-by-pixel computations, spectral bands are extracted from the input raster data and processed using NumPy.

$NDVI = (NIR - Red) / (NIR + Red)$ (Rouse, 1974)

$EVI = 2.5 \times (NIR - Red) / (NIR + 6 \times Red - 7.5 \times Blue + 1)$ (Huete et al., 1997)

$NDWI = (Green - NIR) / (Green + NIR)$ (McFeeters, 1996)

$NDBI = (SWIR - NIR) / (SWIR + NIR)$ (Zha et al., 2003)

D. Interfaces Thematic mapping and classification

The application uses thematic mapping and classification to improve the analytical usefulness of derived environmental indices. Using predetermined threshold ranges, continuous index values are categorized into distinct, semantically relevant classes. The environmental significance of the index, such as vegetation health, urbanization intensity, and others is reflected in the qualitative descriptors (low, moderate, and high) that correlate to each range.

For instance, the following classification levels are used for the NDVI:

Example: NDVI Classification
 $NDVI < 0.2$! Bare soil or built-up
 $0.2 \leq NDVI < 0.5$! Moderate vegetation
 $NDVI \geq 0.5$! Healthy vegetation

By allowing users to differentiate between various land cover types, plant conditions, and environmental states, these categories improve the perception of landscape elements.

The matplotlib library is used to color-code the categorized outputs, giving each category a distinct color according to its thematic significance to improve readability and interpretability. Extra visual components like colorbars, legends, and class labels are added.

These visualizations are incorporated in the Streamlit environment using the st.pyplot function to provide seamless integration inside the application interface. This enables users to interactively view categorization findings, with outputs being displayed in real time. This thematic classification method makes spatial decision-making easier for applications like urban planning, land cover assessment, and environmental monitoring.

E. Development of User Interface

Fig. 2 shows the interactive UI creation using Streamlit in the frontend. Important elements of the interface include the following:

1. GeoTIFF bands can be uploaded using File Uploaders (st.file_uploader).
2. Rasterio is used to read uploaded files for additional processing.
3. Environmental indices can be dynamically selected using checkbox menus (st.selectbox, st.multiselect). Action Buttons (st.button) to initiate downloads, classification and index computations.
4. Visualization panels with st.pyplot() produced in Streamlit that show raw bands, calculated indices, and classed maps created with matplotlib.pyplot.
5. Download options for index maps (PNG/GeoTIFF) are available via st.download_button.
6. Users are guided through the procedure via status feedback that includes st.success, st.error, and st.spinner.

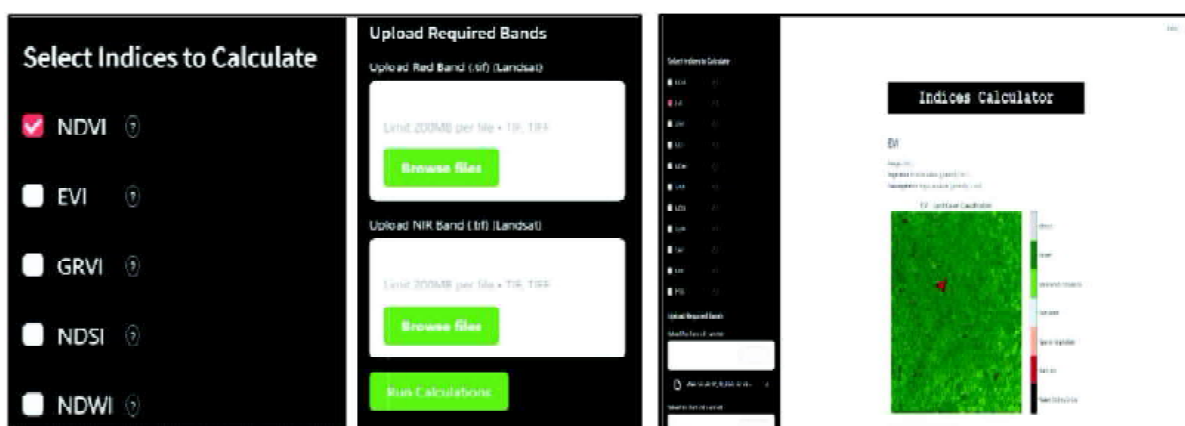


Fig. 2: UI for selecting Index and uploading required bands.

F. Generation of Output

The generated outputs can be downloaded in two ways as mentioned in the step-5 given above.

❑ **GeoTIFF Output:** The GeoTIFF format downloaded outputs help users who need spatial data compatibility with GIS systems like QGIS or ArcGIS. These files can be directly integrated with external geospatial analytic tools. The output image provides classified data values which gives deeper insights to experts, enhances their understanding, and supports making informed and appropriate decisions.

❑ **PNG/JPEG Output:** The application creates color-coded index and classification maps as PNG or JPEG pictures to facilitate simple sharing, reporting, and display. Matplotlib.pyplot, which manages color mapping,

labelling, legends, and formatting, is used to construct these pictures.

Demonstration Dataset

To demonstrate the working of the application, satellite data of sentinel-2 over Telangana region was used. Fig. 3 is the False Color Composite (FCC) image generated by merging (Layer stacked) Bands 8, 4, 3. Various indices calculated for the same region are discussed in the results section.

Results and Discussion

Vegetation Indices

In Fig. 4A, 4B, 4C (1,2,3) show the results generated by 3 Different Vegetation Indices (VIs) - NDVI, EVI, SAVI. Generally, these indices are used to highlight the vegetation in the Area of Interest (AOI), but these can also be used to estimate other classes. The arrangement of the VIs results helps the users to compare the them with great ease. For example, it is evidently visible that along the banks of Musi River, EVI and SAVI shows similar land classification [dense vegetation]. However, NDVI shows lesser dense vegetation class in the same region. Another significant difference is in the Hussain Sagar Lake region. Here, NDVI and SAVI shows that most part of region is bare soil, unlike EVI which mostly shows water. It can be due to shallow depths of water with higher pollutants and sedimentation, contributing to the low NDVI & SAVI values.

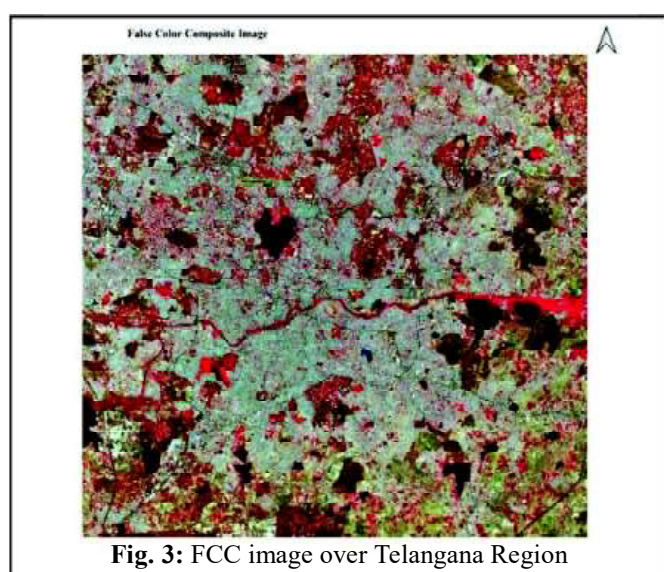


Fig. 3: FCC image over Telangana Region

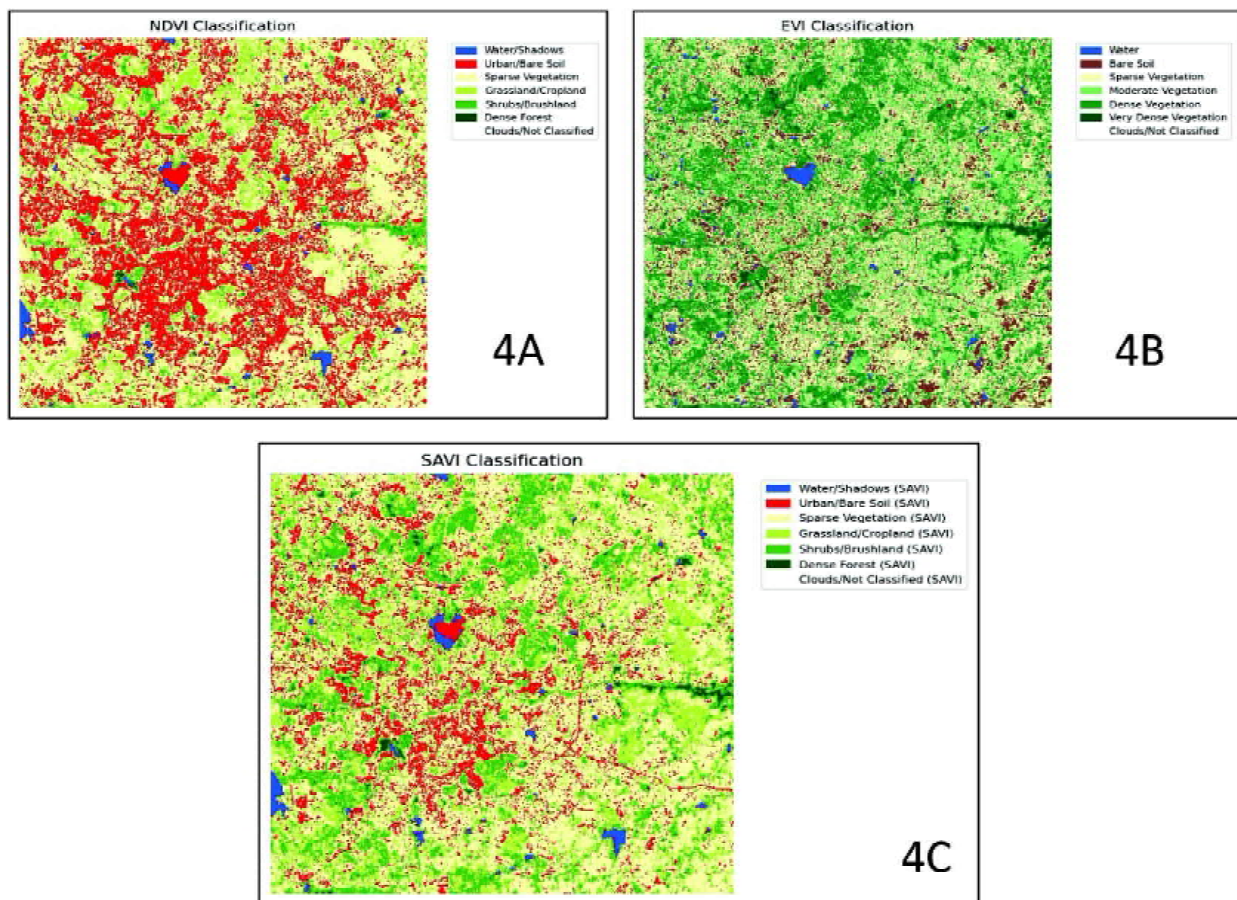


Fig. 4 : Vegetation Indices, 4A(NDVI), 4B(EVI) and 4C(SAVI)

NDWI- Normalized Difference Water Index

NDWI is frequently used to locate and define water bodies. Lakes, rivers, and other water features are easily distinguished in this classification, indicated by the blue patches that correlate to water bodies and have high NDWI values. Because of their lower moisture content, vegetated areas like forests, croplands, and grasslands which make up the majority of the Fig. 5 have NDWI values. Results of this analysis clearly underscores the water depth variability in the Hussain Sagar lake.

NDBI- Normalized Difference Built-up Index

The NDBI is primarily utilized to identify built-up and urban regions and is employed in this case for land cover

classification, as shown in the Fig. 6. Different land cover categories are visibly differentiated by color on the classification map. For example, built-up areas are prominently displayed in red, signifying regions with high NDBI values. Other terrain types, such as grasslands, sparse/densely vegetated areas, are represented by green hue tones, whereas blue parts represent water bodies or snow. Significant urban development inside the study region is suggested by the image's red dominance. The classed output helps to understand terrain heterogeneity and urban expansion. This application helps the users to study the results based on their interest in terms of vegetation, water, or other classes too.

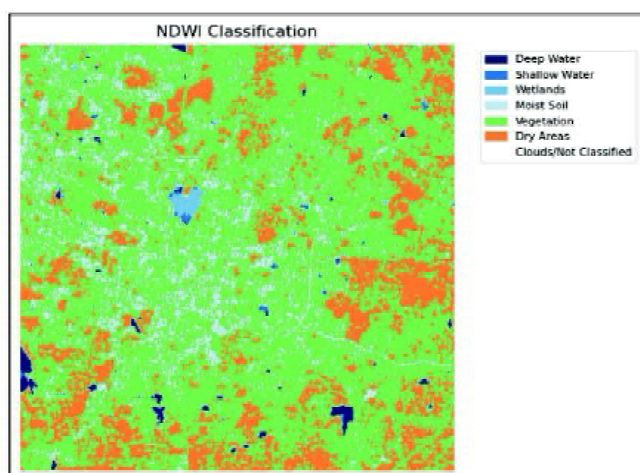


Fig. 5: NDWI classified Image

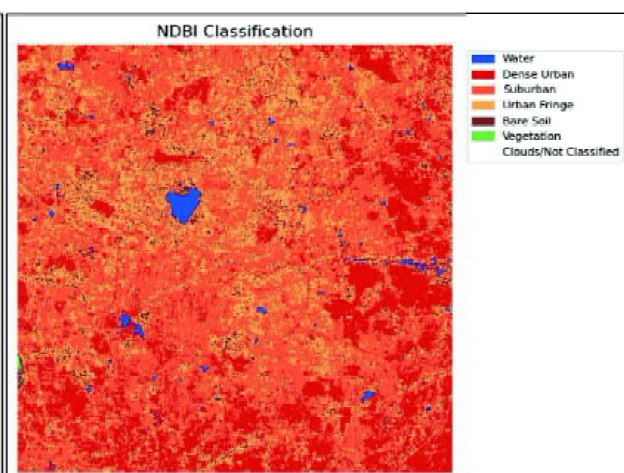


Fig. 6: NDBI Classified Image

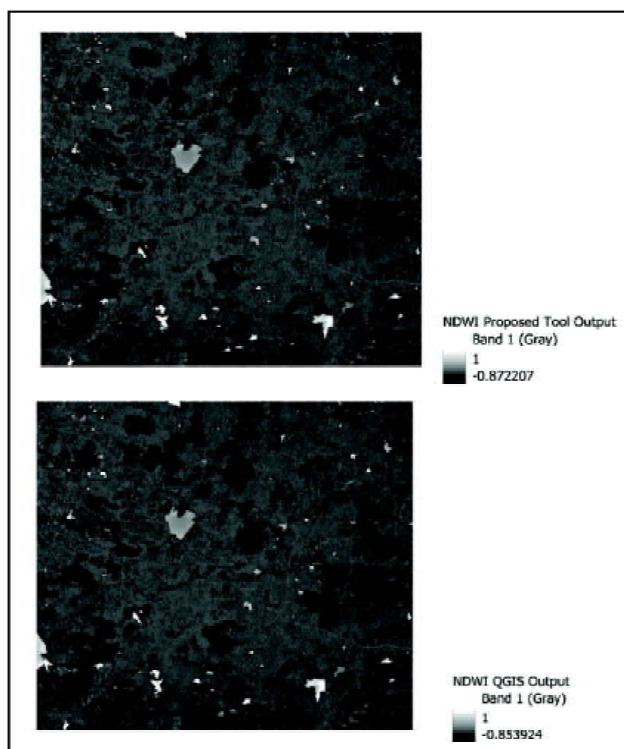
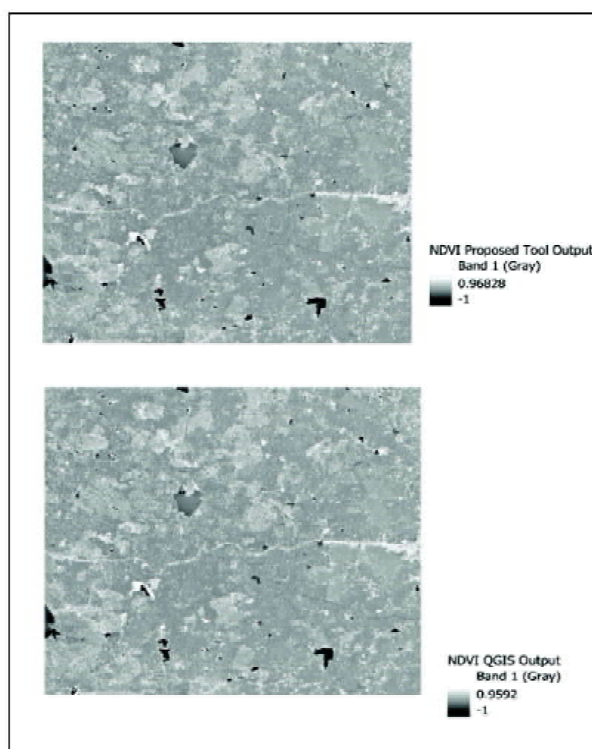


Fig. 7 : Comparision of Outputs from QGIS and Offline Proposed Tool

Fig. 7 shows NDVI, NDWI outputs generated by the application as compared with those from QGIS. After comparing the difference of the results using raster calculator no major difference were found indicating that our implementation reliably reproduces the NDVI, NDWI computations of existing remote sensing platforms.

Conclusion

Addressing the inadequacies of existing environmental monitoring systems such as QGIS or SNAP, which require

complex installations and expert knowledge, Google Earth Engine (GEE) which are sometimes unavailable due to their need for constant internet connectivity is the primary objective of this work. This study shows how open-source technology may be used to create a stable, offline-capable desktop program that allows precise, real-time environmental index analysis.

The application offers a straightforward and user-friendly interface for calculating and analysing vegetation, water, fire, and stress-related indices, in contrast to many

sophisticated remote-sensing applications. The application greatly enhances usefulness in practical field situations by simplifying critical processes including satellite data upload, spectral band extraction, index computation, and categorized visualization. Because portability and field-readiness are given top priority in the design, crucial environmental assessments can be completed without interference from technological issues or connectivity constraints.

Furthermore, the modular design guarantees future extensibility- new indices or functionalities can be introduced with no alteration to current codebase. Its usefulness for both technical and non-technical users is further increased by integrated visualization tools and download choices.

The main scientific question addressed in this work is whether a desktop application that is offline and is accessible to non-experts on standard hardware. Can it provide accurate, multi-index environmental analysis? It can be shown that the answer is yes. The program uses only local computing resources to reproduce key features of well-known GIS and cloud platforms through validation and practical usage. It shifts the process from expert-dependent, centralized platforms to an offline,

user-driven, decentralized solution. By doing this, it democratizes access to remote sensing technologies, making them available to local authorities, agricultural personnel, students, and field researchers who were previously shut out because of infrastructural or budget limitations. This study supports the creation of new standards for environmental monitoring, usability and accessibility. It shifts the process from expert-dependent, centralized platforms to an offline, user-driven, decentralized solution. By doing this, it democratizes access to remote sensing technologies, making them available to local authorities, agricultural personnel, students, and field researchers who were previously shut out because of infrastructural or budget limitations. This study supports the creation of new standards for environmental monitoring, usability and accessibility.

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References

- Apostolopoulos, D., & Nikolakopoulos, K. (2021). A review and meta-analysis of remote sensing data, GIS methods, materials and indices used for monitoring the coastline evolution over the last twenty years. *European Journal of Remote Sensing*, 54(1), 240–265. <https://doi.org/10.1080/22797254.2021.1904293>.
- Barik, R. K., Dubey, H., Samaddar, A. B., Gupta, R.D., & Ray, P.K. (2016). FogGIS: Fog Computing for geospatial big data analytics. *2016 IEEE Uttar Pradesh Section International Conference on Electrical, Computer and Electronics Engineering (UPCON)*, 613–618. <https://doi.org/10.1109/UPCON.2016.7894725>.
- Esri. (2024). *ArcGIS Pro* (Version 3.x) [Computer software]. Environmental Systems Research Institute. <https://www.esri.com/en-us/arcgis/products/arcgis-pro/overview>.
- Gillies, S., Ward, B., & Petersen, A.S. (2013). *Rasterio: Geospatial raster I/O for Python programmers*. <https://github.com/mapbox/Hanansyah>, M.P., Rivani, A.P., Sanjaya, H., & Jaelani, L.M. (2022). Development of Vegetation Changes Monitoring Application in Kalimantan Island (2000–2021) with MODIS Satellite Imagery using Streamlit Platform. In *2022 IEEE Asia-Pacific Conference on Geoscience, Electronics and Remote Sensing Technology (AGERS)* (pp. 48–53). IEEE.
- Huete, A.R. (1988). A soil-adjusted vegetation index (SAVI). *Remote Sensing of Environment*, 25(3), 295–309.
- Huete, A.R., Liu, H. Q., Batchily, K.V., & VanHuang, S., Tang, L., Hupy, J.P., Wang, Y., & Shao, G. (2021). A commentary review on the use of normalized difference vegetation index (NDVI) in the era of popular remote sensing. *Journal of Forestry Research*, 32(1), 1–6.

- Hunter, J.D. (2007). Matplotlib: A 2D graphics environment. *Computing in Science & Engineering*, 9(3), 90–95.
- Kumar, L., & Mutanga, O. (2018). Google Earth Engine applications since inception: Usage, trends, and potential. *Remote Sensing*, 10(10), 1509.
- McFeeters, S.K. (1996). The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features. *International Journal of Remote Sensing*, 17(7), 1425–1432.
- QGIS Development Team. (2019). *QGIS Geographic Information System*. Open Source Geospatial Foundation.
- Rousel, J.W., Haas, R.H., Schell, J.A., & Deering, D.W. (1974). Monitoring vegetation systems in the Great Plains with ERTS. In *Third Earth Resources Technology Satellite-1 Symposium* (Vol. 1, pp. 309–317). NASA.
- Singh, S., Shukla, A., & Jain, K. (2024). Assessing the urbanization-induced impact on environmental parameters of a city from a remote-sensing perspective. *Remote Sensing Applications: Society and Environment*, 34, 101169.
- Streamlit Inc. (2025). *Streamlit: The fastest way to build data apps in Python*. Available online: <https://streamlit.io> (Accessed: 17 Feb. 2025).
- Zha, Y., Gao, J., & Ni, S. (2003). Use of normalized difference built-up index in automatically mapping urban areas from TM imagery. *International Journal of Remote Sensing*, 24(3), 583–594.
- Uhlke, M., Fomferra, N., Brockmann, C., Peters, M., Veci, L., Malik, J., & Regner, P. (2015). SNAP (Sentinel Application Platform) and the ESA Sentinel 3 Toolbox.
- Zulkoffli, Z., Navaratnam, S., Jusoh, M.N.H., Ramli, R., & Shamsudin, S. F. (2024). Interactive Geospatial Visualization of Soil Types in Peninsular Malaysia Using In-Situ Data and Streamlit. *International Journal of Advance Computational Engineering and Networking (IJACEN)*, 12(12), 29–34.



Harnessing Geospatial Data and GeoAI for Conservation and Sustainable Development of Rann of Kachchh

Lakshmi Kanta Kumar^{1*}, Mahavir Prasad Meena², Kanakapudi Prabhoji³
and Dharmendra Kumar Singh¹

¹National Institute for Geo-informatics Science & Technology, Survey of India,
Hyderabad, Telangana (India)

²National Geospatial Data Registry and the Unified Geospatial Interface, Survey of India,
Dehradun, Uttarakhand (India)

³Gujarat Daman & Diu Geospatial Directorate, Survey of India, Gandhinagar, Gujarat (India)

**Corresponding Author's Email: lakshmikanth.soi@surveyofindia.gov.in*

Abstract

The Rann of Kachchh, with its vast saline marshes and seasonal salt flats, forms a unique ecosystem, where life thrives against extremes, supporting the endangered Indian wild ass and other Schedule-I species (Wildlife Protection Act, 1972), viz. Indian Wolf, Desert Fox and Chinkara along with a rich diversity of migratory birds amidst a stark and barren landscape. The Rann of Kachchh is witnessing industrialization and playing a major role in the region's economic development and transformation over recent decades. Due to unforeseen rapid industrialization and boom in tourism, the unique ecosystem of the Rann of Kachchh is facing several conservation challenges. Considering the uniqueness of the Rann of Kachchh, there is an urgent need for an environmental protection plan to balance the conservation and industrialization for sustainable development of Kachchh. Keeping this in view, the present study focuses on development of environmental protection plan for Rann of Kachchh to safeguard the rich biodiversity and natural water flow of the region using earth observation data collected by Sentinel-2 and Cartosat-3 sensors along with Survey of India's topographical data base. The Analytical Hierarchy Process (AHP) method has been adopted to prepare a conservation plan of the entire region. A GeoAI mechanism based on Random Forest and Convolutional Neural Network (CNN) has been developed for detection of spatio-temporal changes using medium and very high-resolution earth observation data for efficient environmental management.

Keywords: Environmental Plan, Conservation, Sustainability, Analytical Hierarchy Process, GeoAI, Kachchh.

Introduction

The Rann of Kachchh, located in the western part of India, is an ecologically significant region known for its vast saline marshes, seasonal salt flats, and rich biodiversity (Ishnava et al., 2011). The unique ecosystem of this arid landscape provides habitat for a variety of

species such as the Indian wild ass, Indian wolf, desert fox, and chinkara, all of which are protected under Schedule-I of the Wildlife Protection Act, 1972. Additionally, the region serves as a crucial stopover for migratory birds (Anil K. Rathwa, 2022), further emphasizing its ecological importance (Pardeshi et al.,

2010). Despite its environmental significance, the Rann of Kachchh is undergoing rapid industrialization, including the growth of salt production, renewable energy projects, and increasing tourism (Bansal and Parthasarathy, 2021; Reddy et al., 2016; Swarna et al., 2013). This transformation, while contributing to the economic development of the region, has raised concerns about the long-term sustainability of the ecosystem and its wildlife.

Human-induced pressures such as unregulated salt extraction, expansion of renewable energy infrastructure and unplanned tourism are fragmenting habitats, disturbing migratory routes, and altering hydrological dynamics in the Rann (Bansal and Parthasarathy, 2021; Goswami et al., 2025; Reddy et al., 2016). There is a growing need to address the delicate balance between economic growth and environmental protection to ensure the continued existence of the unique biodiversity and the natural water systems of the region. The increasing human interventions require an effective environmental protection plan that can mitigate the impacts of industrialization and preserve the ecological integrity of the area for future generations.

Remote sensing and GeoAI techniques have proven essential for monitoring and managing environmental changes, particularly in unique ecosystems like arid regions (Amin et al., 2024; Ge et al., 2020; Li and Hsu, 2022) such as the Rann of Kachchh. Earth observation data, acquired from remote sensing sensors such as Sentinel-2, and Cartosat-3, provide valuable insights into land cover changes and spatiotemporal dynamics (Kantakumar et al., 2016). The remote sensing datasets are vital for tracking the impacts of industrialization and tourism on the region's delicate ecosystem. GeoAI, integrating machine learning algorithms such as Random

Forest (Ge et al., 2020) and Convolutional Neural Networks (CNN) (Guo et al., 2018; Pierdicca and Paolanti, 2022), enhances the detection of spatiotemporal changes, including the expansion of salt pans, solar panels (Kausika et al., 2021), and wind turbines, enabling efficient monitoring and management. The use of remote sensing and GeoAI thus offers a critical means to monitor ecological health, detect environmental stressors and inform policy decisions for sustainable land use and resource management. By leveraging these technologies, the study aims to establish a robust environmental protection plan to safeguard the biodiversity and natural water flow of the region, balancing conservation efforts with industrial growth for sustainable development.

The objectives of this study are:

- (i) to develop an Environmental Protection Plan aimed at safeguarding eco-sensitive areas, preserving wildlife habitats, and maintaining the current natural water flow across the desert and creek regions while allowing industrialization and economic activities in the region; and
- (ii) to create an Action Plan for monitoring encroachments and violations through satellite-based observations and GeoAI.

Study Area

The Rann of Kachchh, located in Gujarat, India, spans approximately for 20,269 square kilometres and is divided into two distinct regions: the Great Rann and the Little Rann (Fig. 1). It is located between 23°05'N to 24°42'N latitudes and 68°10'E to 71°46' Elongitudes. The annual average precipitation in the region is 453 mm, making it a challenging environment for both wildlife and human activity.

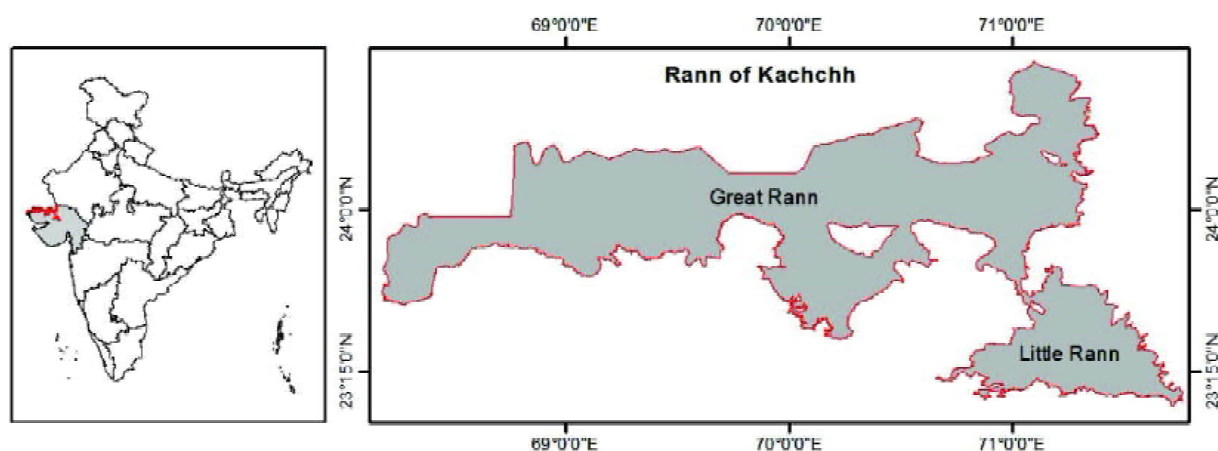


Fig. 1: Study area map showing Rann of Kachchh

Dataset

The study incorporates various datasets to evaluate the land use and environmental features of the Rann of Kachchh. Land use and land cover data for the year 2024 was derived from yearly median surface reflectance imagery, computed from 1,157 scenes of Sentinel-2 imagery, with a spatial resolution of 10 meters. Topographic data is sourced from the Survey of India Open Series Map, offering vector data from 2005.

Information on forests, sanctuaries, and eco-sensitive zones is obtained from vector datasets provided by the Gujarat State Forest and Land Records Department. Water bodies in the region are identified using the Global 3 arc-second Water Body Map (G3WBM), which has a spatial resolution of 90 meters (Yamazaki et al., 2015). Together, these diverse datasets form a robust foundation for analyzing the region's land use, biodiversity, and ecological zones. Fig. 2 shows the above-mentioned datasets used in this study.

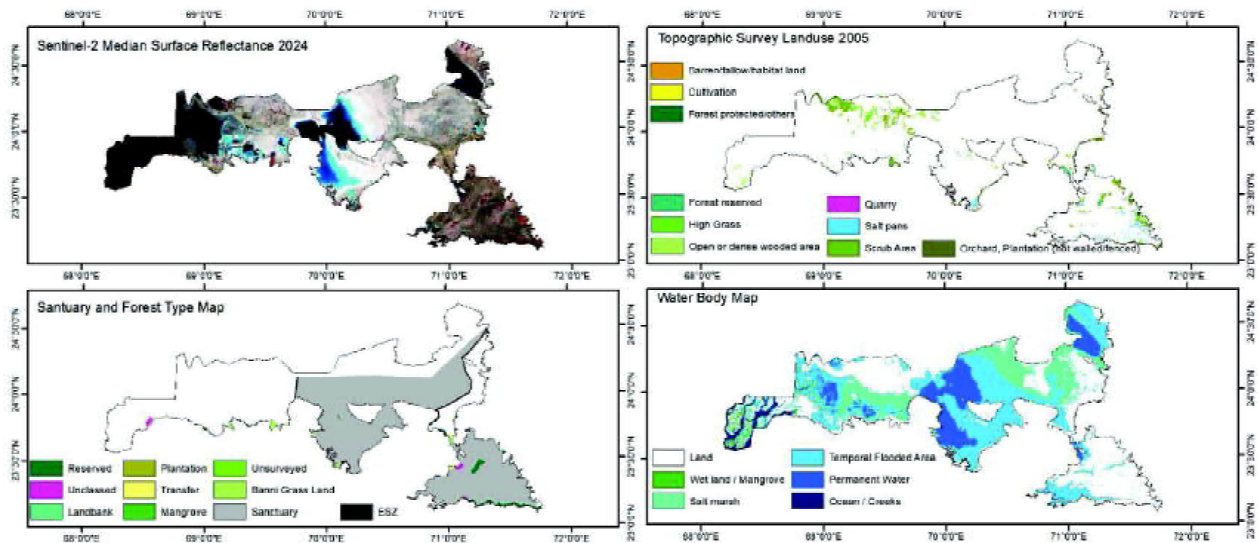


Fig. 2: Input datasets

Methods of Analysis

The methodology employed in this study involves several image analysis and deep learning techniques for analysing

the land use and environmental features of the Rann of Kachchh. A Random Forest algorithm was utilized to generate the land use and land cover map from Sentinel-

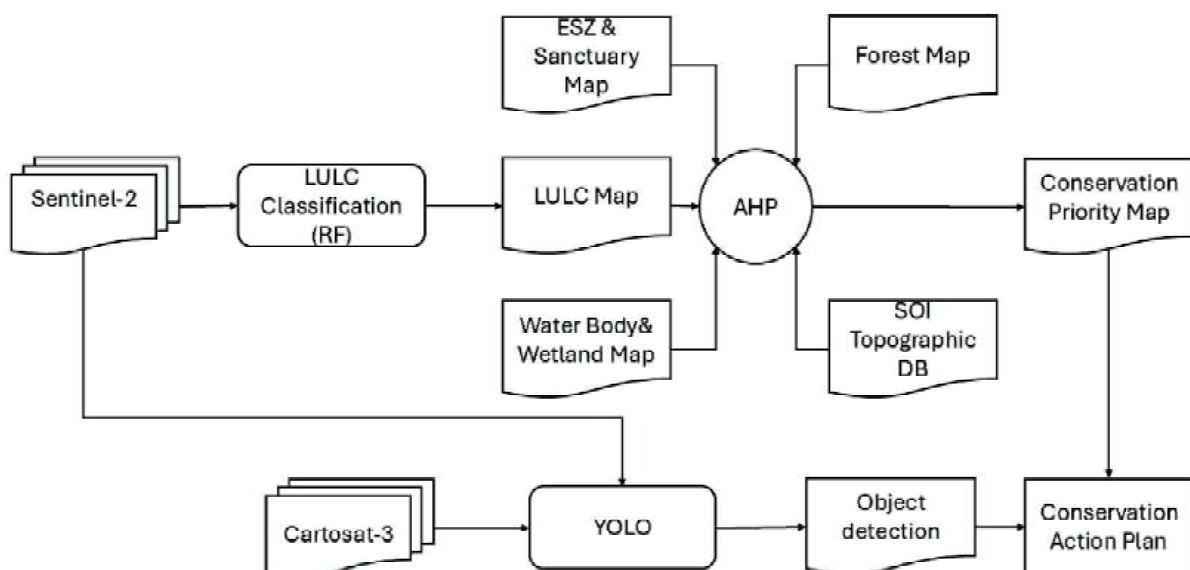


Fig. 3 : Methodology flowchart

2 imagery. The Analytical Hierarchical Process (AHP) was then applied to develop a criterion map for conservation planning. Additionally, for object detection, a Convolutional Neural Network (CNN) based on the YOLO (You Only Look Once) framework was used to detect salt pans, solar panels, and wind turbines across Sentinel-2 and Cartosat-3 datasets. These methods combined allow for a comprehensive and accurate analysis of the region's land cover and environmental changes. Fig.3 shows the methodology flowchart.

Random Forest (RF) in Land Use and Land Cover Classification

Random Forest (RF) has been widely used in land use and land cover classification due to its ability to handle large and complex datasets with high dimensionality (Belgiu and Drăguț, 2016). RF works by constructing many decision trees during training and outputs the mode of the classes for classification jobs. One of the key advantages of RF in land use and land cover classification is its robustness to overfitting, especially when dealing with noisy data or large-scale datasets. Its ability to handle a wide variety of input features, such as spectral bands and texture measures from satellite imagery, further enhances its effectiveness in distinguishing between different land cover types.

Analytical Hierarchical Process (AHP)

The Analytical Hierarchical Process (AHP) is a structured decision-making method that is particularly useful in complex, multi-criteria decision analysis (MCDA) problems (Sipahi and Timor, 2010). It helps in evaluating and prioritizing different factors by converting qualitative assessments into quantitative measures. AHP is advantageous in conservation planning, where multiple conflicting criteria, such as biodiversity, land use, and ecological sensitivity, need to be considered simultaneously (Sipahi and Timor, 2010). The process allows stakeholders to systematically break down complex problems into manageable hierarchies, enabling informed and transparent decision-making. By assigning weights to different criteria based on their relative importance, AHP helps to ensure that the most critical factors are prioritized when preparing conservation plans. Its flexibility and ease of use make it an ideal tool for

environmental management, where various spatial, ecological, and socio-economic factors must be integrated to create a balanced and effective conservation strategy (Fatemi et al., 2021).

Convolutional Neural Network (CNN) based YOLO

Convolutional Neural Networks (CNNs) have revolutionized image processing tasks, including object detection, by automatically learning spatial hierarchies of features from raw data. YOLO (You Only Look Once), a state-of-the-art CNN-based approach, has become particularly popular for real-time object detection in satellite imagery. The main advantage of YOLO is its ability to detect objects with high accuracy and efficiency in a single forward pass, making it faster compared to traditional object detection methods. This is particularly beneficial in large-scale remote sensing applications, where processing time is critical. YOLO excels in detecting multiple objects in images and is highly effective for monitoring dynamic features like salt pans, solar panels, and wind turbines on remote sensing images. YOLO's combination of speed and accuracy makes it an ideal tool for real-time environmental monitoring and change detection in the Rann of Kachchh.

Results and Discussion

The results of this study provide valuable insights into the land use, environmental changes, and conservation challenges of the Rann of Kachchh. This section presents an analysis of the findings from the various remote sensing techniques and methods applied, including land use and land cover classification, conservation planning, and object detection, followed by a discussion of their implications for sustainable environmental management in the region.

Land Use and Land Cover Classification

A total of 1,157 scenes from Sentinel-2 surface reflectance Level-2A products, spanning from January 1, 2024, to January 1, 2025, were accessed through Google Earth Engine (Gorelick et al., 2017). These scenes were used to generate a yearly median surface reflectance image for 2024, which was then applied for land use and land cover classification using RF classifier, i.e. Classifier. Smile Random Forest (Google Earth Engine, n.d.)

algorithm. Accuracy assessment was performed using independent random validation samples distributed across all LULC classes. A confusion matrix was generated to calculate producer's accuracy, user's accuracy and overall accuracy (Table 1). The overall accuracy of the

classification is 97.9% with a Kappa coefficient of 0.96. Cross-validation was conducted using a 70:30 split of training and validation datasets to minimize overfitting. The classification results are presented in the Fig. 4.

Table 1: User and Producer accuracies of Land use and Land cover classification

Class Name	Producer's Accuracy	User's Accuracy
Builtup	0.73	0.86
Water	0.96	1.00
Forest	0.25	0.93
Shrub	0.98	0.61
Agriculture	0.88	0.56
Fallow Land	0.66	0.74
Water on Salt Marsh/ Saltpan	0.85	0.45
Salt Pan	0.82	0.54
Solar Panels	0.99	0.97
White Rann	1.00	1.00
Rann	0.99	0.99
Wetland	0.94	0.96
Mangrove	1.00	0.93
Overall Accuracy		97.90%
Kappa Coefficient		0.96

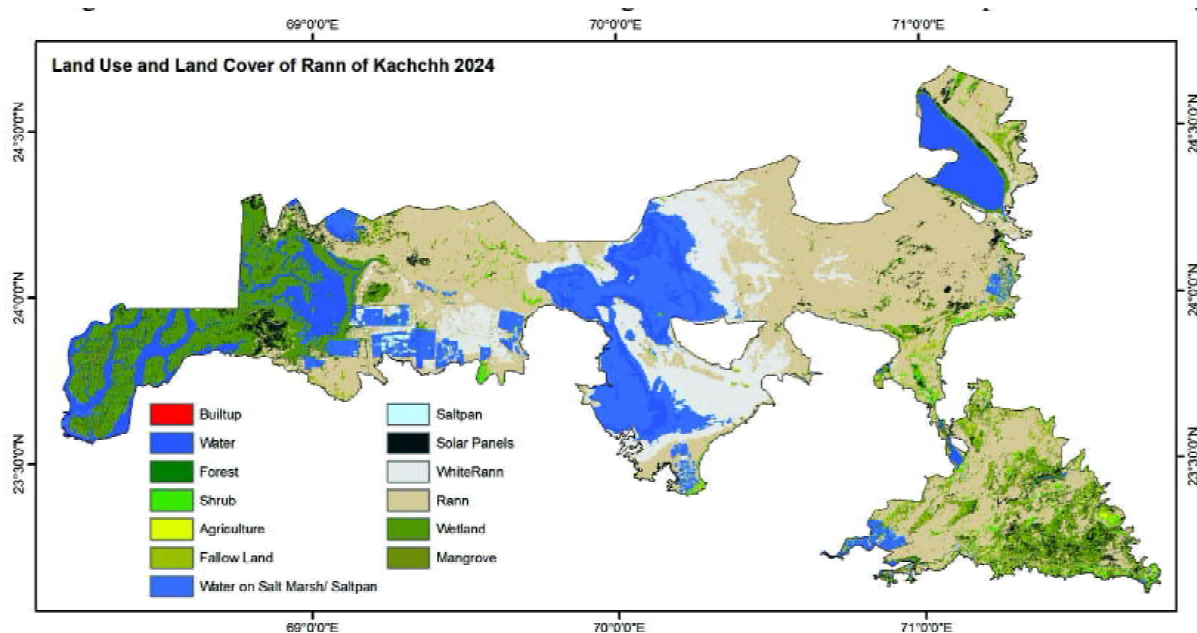


Fig. 4: Land use and land cover map of Rann of Kachchh for the year 2024 based on Random Forest classification using Sentinel-2.

Analytical Hierarchical Process (AHP)

In this study, various input datasets were evaluated using the Analytical Hierarchical Process (AHP), including wildlife sanctuaries and eco-sensitive zones, forest types, spatiotemporal water bodies, and Survey of India topographic and land use/cover maps. Each of these datasets was assigned a weight based on its relative importance, with values ranging from 1 to 5. A weight of 1 indicates areas with the least conservation priority, while a weight of 5 represents the highest conservation priority. Fig.5 illustrates the criterion weights assigned to wildlife sanctuaries and eco-sensitive zones, forest types,

spatiotemporal water bodies, as well as Survey of India topographic and land use/cover maps. The individual criterion maps were integrated into a single composite criterion map using the maximum operator. The resulting final criterion map with conservation priorities is shown in Fig.6. The AHP-derived conservation map highlights corridors linking the Little Rann Wildlife Sanctuary with the Great Rann as crucial for sustaining species movement. The accuracy of LULC classification directly influences downstream conservation prioritization in the AHP model. Misclassification of vegetation or water bodies and wetlands could bias weight assignment and lead to misrepresentation of critical priority zones.

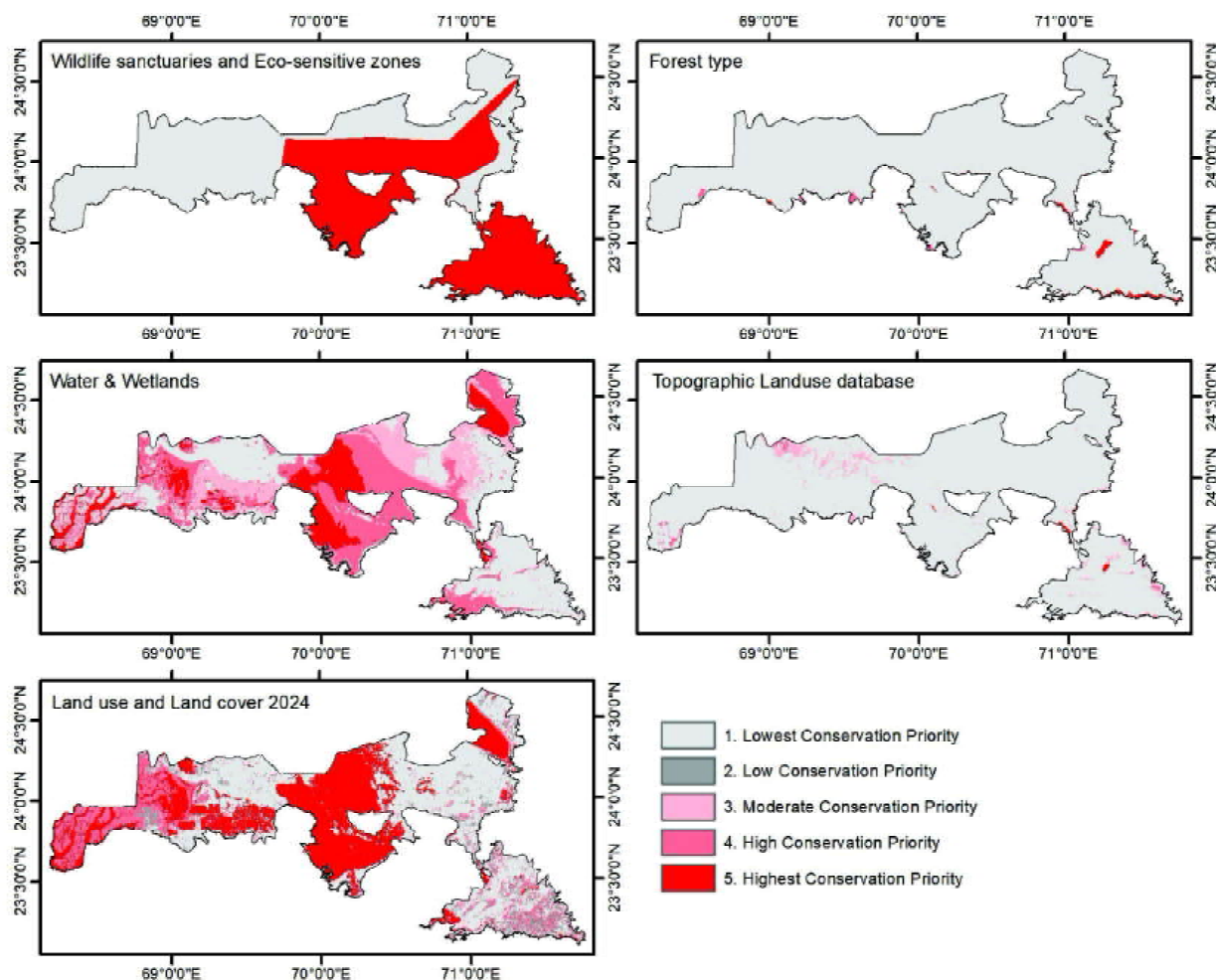


Fig. 5 : Criterion maps used in Analytical Hierarchical Process (AHP)

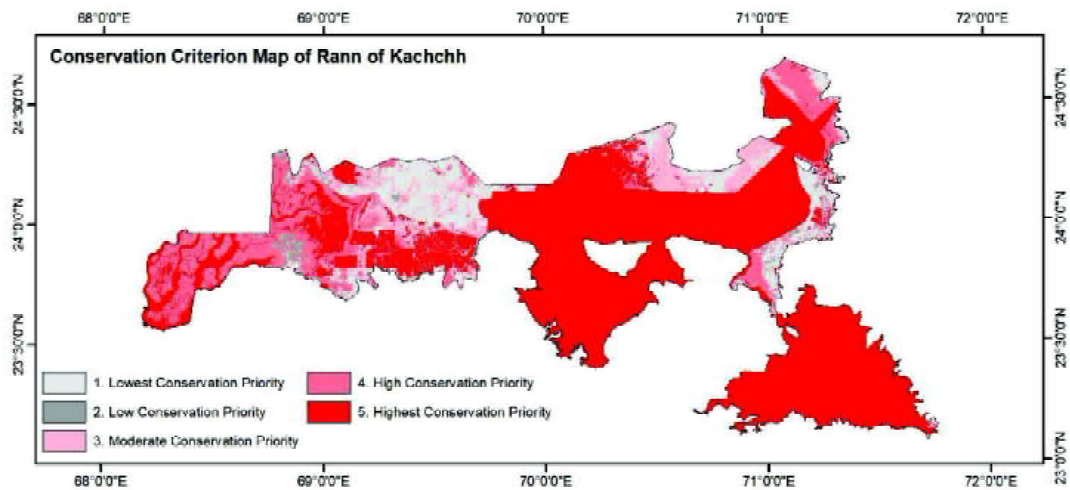


Fig. 6: Conservation Criterion Map of Rann of Kachchh

Object Detection using YOLO

The YOLO (You Only Look Once) models were trained on custom datasets created from remote sensing imagery, specifically Sentinel-2 and Cartosat-3, using the open-source image annotation tool LabelImg (“HumanSignal/labelImg”, 2025). These models were utilized to detect saltpans, solar panels, and wind turbines (on Cartosat-3 imagery only) for monitoring anthropogenic developments in the Rann of Kachchh. The detection accuracy for saltpans and wind turbines on Cartosat-3 imagery was 96.5% and 94.3% respectively (Fig.7), while

for Sentinel-2, the accuracy was 67.1% for saltpans and 81.8% for solar panels (Fig.8). These results highlight the significant impact of spatial resolution on object detection performance, with Sentinel-2-based detections consistently showed lower confidence compared to those derived from Cartosat-3 imagery. The object detection errors false positives or false negatives may affect the accuracy of anthropogenic impact mapping. YOLO-based detections indicate rapid proliferation of renewable energy installations and saltpans. These spatial patterns underscore the need for spatial zoning policies that balance development with ecosystem preservation.

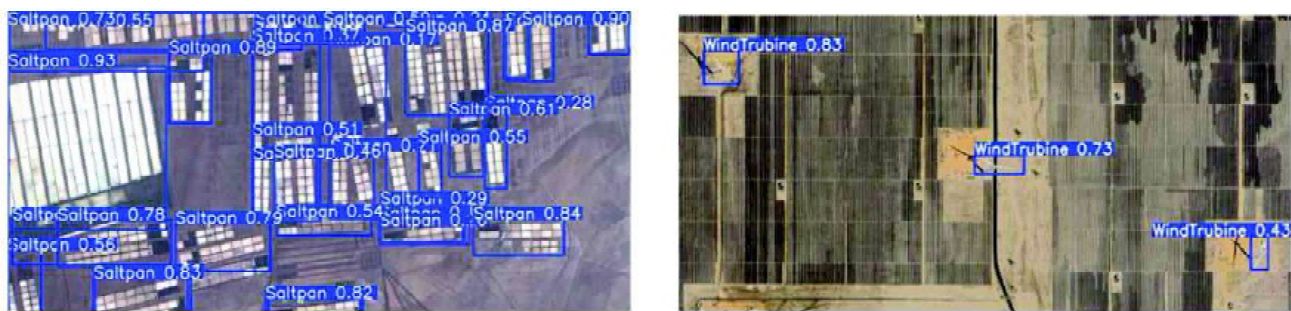


Fig. 7: Object detection of saltpans and wind turbines on cartosat-3 image using YOLO

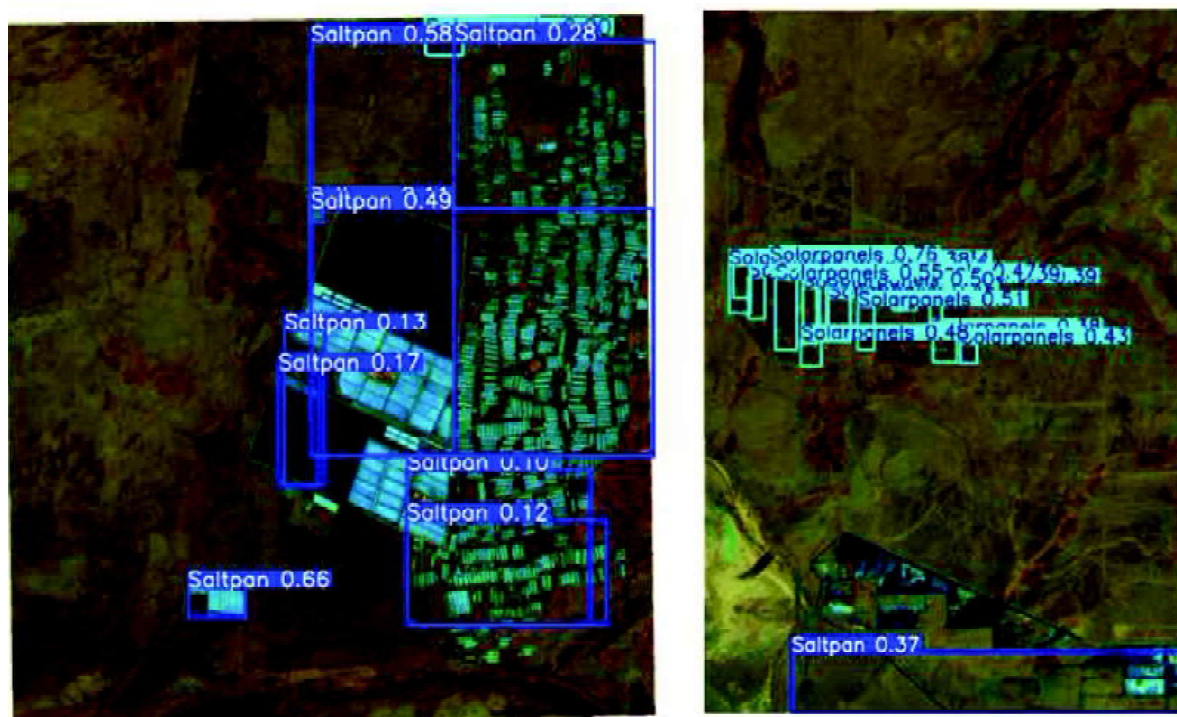


Fig. 8: Object detection of salt pans and solar panels on Sentinel-2 image using YOLO

Conclusion

This study proposes an environmental protection plan based on earth observation data from Sentinel-2, Cartosat-3, Topographical Database from Survey of India and Eco-sensitive Zones and Forest maps from Gujarat State land records and forest department, employing the AHP and GeoAI techniques, including Random Forest and CNN, for environmental monitoring. The study showcased YOLO's Object detection to detect salt pans and wind turbines on very high-resolution Cartosat-3 images. Findings suggest that the presence of salt pans in the Wild Ass Sanctuary of Little Rann requires attention due to potential ecological threats, while the Kachchh Desert Sanctuary showed minimal disturbance. Although the preliminary results provide useful insights, further refinement is crucial, particularly in delineating natural water flow using higher temporal and spatial resolution data spanning over a decade. Additionally, addressing

misclassification errors in land use maps is crucial for developing a more accurate and comprehensive conservation priority strategy. The proposed remote sensing data-based GeoAI framework can facilitate monitoring of anthropogenic changes by enabling automated change detection using Sentinel and Cartosat datasets.

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References

- Amin, G., Imtiaz, I., Haroon, E., Saqib, N. us, Shahzad, M.I., Nazeer, M., 2024. Assessment of Machine Learning Algorithms for Land Cover Classification in a Complex Mountainous Landscape. *J. Geovisualization Spat. Anal.* 8, 34. <https://doi.org/10.1007/s41651-024-00195-z>.
- Anil K. Rathwa, 2022. Breeding of Lesser Flamingo *Phoeniconaias minor* in the Little Rann of Kachchh, Gujarat. *Flamingo Gujarat* V 3.

- Bansal, N., Parthasarathy, R., 2021. Fiscal incentives and industrialisation: the case of Kachchh, Gujarat. *J. Soc. Econ. Dev.* 23, 71–92. <https://doi.org/10.1007/s40847-020-00131-z>.
- Belgiu, M., Drăguț, L., 2016. Random forest in remote sensing: A review of applications and future directions. *ISPRS J. Photogramm. Remote Sens.* 114, 24–31. <https://doi.org/10.1016/j.isprsjprs.2016.01.011>.
- ee.Classifier.smile Random Forest | Google Earth Engine [WWW Document], n.d. Google Dev. URL <https://developers.google.com/earth-engine/apidocs/ee-classifier-smilerandomforest> (accessed 2.20.25).
- Fatemi, M., Rezaei-Moghaddam, K., Karami, E., Hayati, D., Wackernagel, M., 2021. An integrated approach of Ecological Footprint (EF) and Analytical Hierarchy Process (AHP) in human ecology: A base for planning toward sustainability. *PLOS ONE* 16, e0250167. <https://doi.org/10.1371/journal.pone.0250167>.
- Ge, G., Shi, Z., Zhu, Y., Yang, X., Hao, Y., 2020. Land use/cover classification in an arid desert-oasis mosaic landscape of China using remote sensed imagery: Performance assessment of four machine learning algorithms. *Glob. Ecol. Conserv.* 22, e00971. <https://doi.org/10.1016/j.gecco.2020.e00971>.
- Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., Moore, R., 2017. Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sens. Environ., Big Remotely Sensed Data: tools, applications and experiences* 202, 18–27. <https://doi.org/10.1016/j.rse.2017.06.031>.
- Goswami, Shalini, Goswami, A.K., Goswami, Shinjini, 2025. Rann of Kachchh: A Unique Coastal Wetland Ecosystem, in: Chattopadhyay, S. (Ed.), *Marine and Coastal Resources of India: Selected Case Studies*. Springer Nature Switzerland, Cham, pp. 527–537. https://doi.org/10.1007/978-3-031-81276-7_29.
- Guo, W., Yang, W., Zhang, H., Hua, G., 2018. Geospatial Object Detection in High Resolution Satellite Images Based on Multi-Scale Convolutional Neural Network. *Remote Sens.* 10, 131. <https://doi.org/10.3390/rs10010131>.
- Human Signal/labelImg, 2025.
- Ishnava, K., Ramarao, V., Mohan, J.S.S., Kothari, I.L., 2011. Ecologically important and life supporting plants of little Rann of Kachchh, Gujarat. *J. Ecol. Nat. Environ.* 3, 33–38.
- Kantakumar, L.N., Kumar, S., Schneider, K., 2016. Spatiotemporal urban expansion in Pune metropolis, India using remote sensing. *Habitat Int.* 51, 11–22. <https://doi.org/10.1016/j.habitatint.2015.10.007>.
- Kausika, B.B., Nijmeijer, D., Reimerink, I., Brouwer, P., Liem, V., 2021. GeoAI for detection of solar photovoltaic installations in the Netherlands. *Energy AI* 6, 100111. <https://doi.org/10.1016/j.egyai.2021.100111>.
- Li, W., Hsu, C.-Y., 2022. GeoAI for Large-Scale Image Analysis and Machine Vision: Recent Progress of Artificial Intelligence in Geography. *ISPRS Int. J. Geo-Inf.* 11, 385. <https://doi.org/10.3390/ijgi11070385>.
- Pardeshi, M., Gajera, N., Joshi, P.N., 2010. Kachchh biosphere reserve: Rann and biodiversity. *Res. J. For.* 4, 72–76.
- Pierdicca, R., Paolanti, M., 2022. GeoAI: a review of artificial intelligence approaches for the interpretation of complex geomatics data. *Geosci. Instrum. Methods Data Syst.* 11, 195–218. <https://doi.org/10.5194/gi-11-195-2022>.
- Reddy, C.S., Pasha, S.V., Jha, C.S., 2016. Spatio-temporal changes associated with natural and anthropogenic factors in wetlands of Great Rann of Kachchh, India. *J. Coast. Conserv.* 20, 145–155. <https://doi.org/10.1007/s11852-016-0425-0>.
- Sipahi, S., Timor, M., 2010. The analytic hierarchy process and analytic network process: an overview of applications. *Manag. Decis.* 48, 775–808. <https://doi.org/10.1108/00251741011043920>.
- Swarna, K., Biswas, S.K., Harinarayana, T., 2013. Development of Geotourism in Kutch Region, Gujarat, India: An Innovative Approach. *J. Environ. Prot.* 2013. <https://doi.org/10.4236/jep.2013.412157>.
- Yamazaki, D., Trigg, M.A., Ikeshima, D., 2015. Development of a global ~ 90 m water body map using multi-temporal Landsat images. *Remote Sens. Environ.* 171, 337–351. <https://doi.org/10.1016/j.rse.2015.10.014>.
- Wildlife Protection Act, 1972, Act No. 53 of 1972. https://www.indiacode.nic.in/bitstream/123456789/12931/1/wildlife_%28protection%29_act%2C_1972_no._53_of_1972_date_09.09.1972.pdf.



Short Communication

Mapping the Topographic Development of Sagar Region in Madhya Pradesh: Some Perspectives

Navneet Franklin James

Pradan (Professional Assistance for Development Action)

Janakpur Road, Jaisinghnagar, Madhya Pradesh (India)

**Corresponding Author's Email : geo.navi17@gmail.com*

Abstract

This research paper examines the geomorphological aspects of topographic development in the Sagar region of Madhya Pradesh, focusing on landforms associated with the Vindhyan and Deccan Trap formations. The study analyzes the impact of erosion, weathering and geological history on landscape evolution. It also evaluates slope characteristics, terrain analysis and the broader implications of geomorphology on environmental stability and land-use planning. The methodology involves Digital Elevation Models (DEM), field surveys and satellite imagery to categorize slopes and identify landforms for mapping. The findings suggest that while Vindhyan formations exhibit mature erosional features, Deccan Trap formations display characteristic step-like topography with fertile black cotton soil. These results have significant implications for agricultural planning, infrastructure development and sustainable land management.

Keywords: Topographic development, Geomorphology, Vindhyan Landforms, Deccan Trap, slope analysis, black cotton soil, land use planning, Sagar region.

Introduction

Topography plays a fundamental role in shaping landscapes, influencing human settlement patterns, agricultural potential and natural resource distribution. Studies on geomorphology emphasize that landforms evolve due to weathering, erosion and tectonic processes over millions of years (Strahler, 1952). The Sagar region, located in central India, showcases distinct landforms influenced by two major geological formations: the Vindhyan system and the Deccan Trap.

Erosion and drainage systems are critical factors in landscape evolution (Horton, 1945). Research has shown that fluvial processes play a significant role in shaping the geomorphology of semi-arid regions

(Schumm, 1956). Additionally, climatic variations contribute to soil erosion and deposition, impacting landform development (Melton, 1957). The analysis of these geomorphic processes helps in understanding terrain stability and planning for sustainable land management (Montgomery, 2007).

The Study Area

The Sagar region, located in Madhya Pradesh (Fig. 1), exhibits a combination of Vindhyan sedimentary formations and Deccan Trap basaltic flows. The hydrological patterns, tectonic activity and climatic conditions of the region have significantly influenced landform development (James & Panday, 2018). These

formations result in diverse geomorphic features, including ridges, escarpments, wind gaps and plateaus.

The role of climate and tectonics in shaping river systems and landscapes in central India has been extensively studied (Raj & Jain, 2017). River dynamics and erosion patterns contribute to the formation of valleys,

residual hills, and drainage networks (Leopold, Wolman, & Miller, 1964). In particular, the Vindhyan terrain has been subjected to prolonged erosional activity, leading to its characteristic landscape features (Singh & Dubey, 2021).

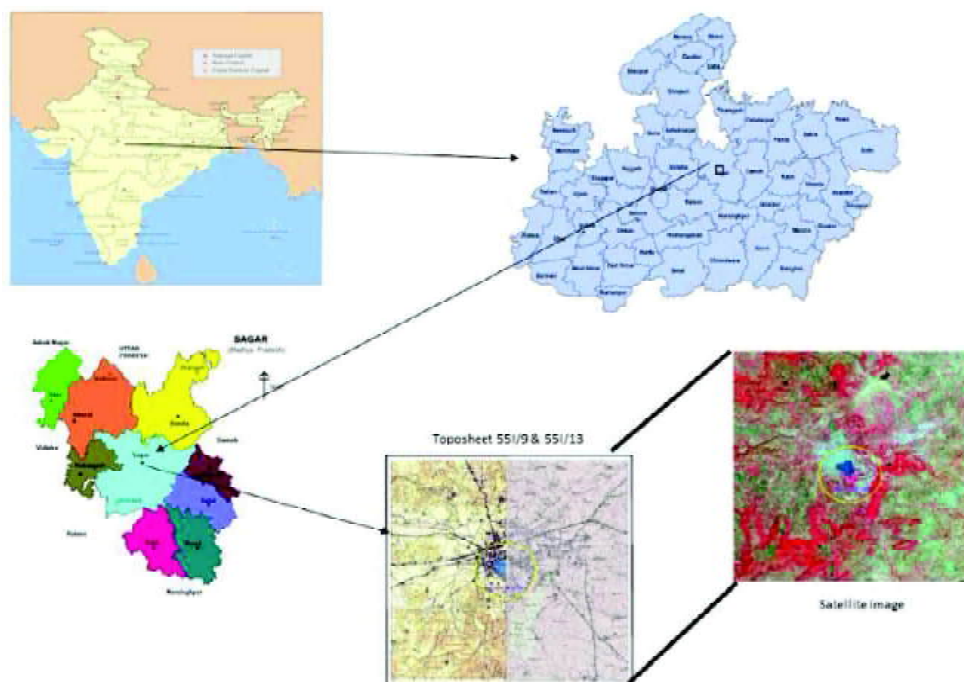


Fig. 1: Location Map of the Study Area (Sagar Region, Madhya Pradesh)

Materials and Methods

This study employs a combination of remote sensing, GIS mapping and field surveys to analyze topographic development. Digital Elevation Models (DEM) are widely used for terrain classification and slope analysis (Bishop et al., 2012). Additionally, geological maps and satellite imagery aid in identifying landform characteristics, while field investigations provide ground-truthing for remote sensing data (James, 2022).

GIS and remote sensing techniques have significantly improved the accuracy of geomorphological studies (Goudie, 2018). The morphometric analysis of drainage basins has become a key tool in understanding regional landform dynamics (Schumm, 1956). Furthermore, soil sampling and hydrological data analysis provide insights into soil composition and water retention patterns (Montgomery, 2007).

Limitations

The study is subject to certain limitations, including the availability of high-resolution DEM data, seasonal variations affecting field observations, and challenges in accessing remote areas for detailed surveys. Additionally, the influence of anthropogenic factors on geomorphology was not extensively examined. The complexity of geological formations and the long-term timescale of erosion and weathering processes also pose challenges in drawing direct correlations between specific environmental changes and topographic development. Despite these limitations, the study provides valuable insights into the geomorphological characteristics of the Sagar region (Fig. 2).

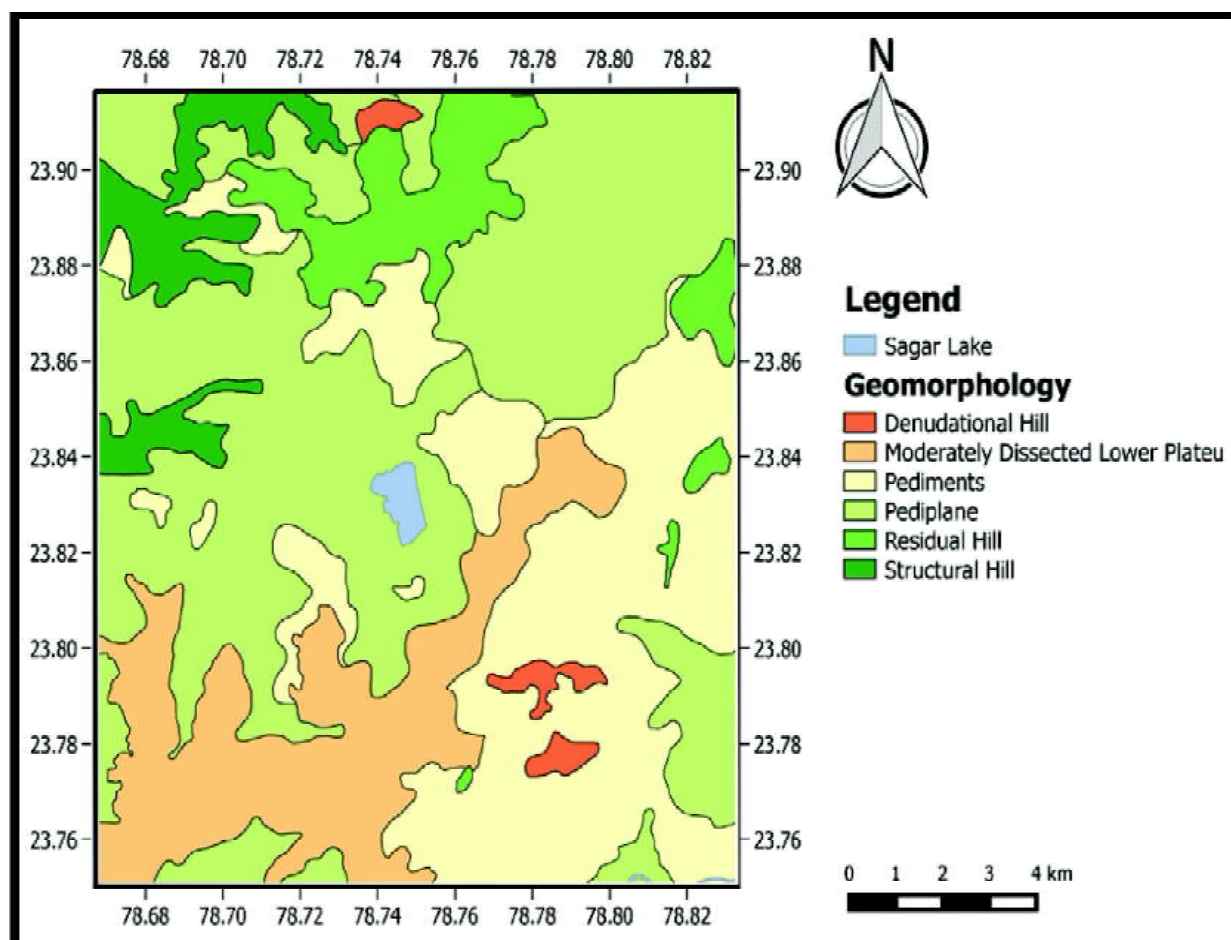


Fig. 2 : Geomorphological Characteristics of the Study Area

Results and Discussion

Vindhyan Landforms

The Vindhyan region exhibits ridges and residual hills formed due to ancient erosional processes. These features provide insights into past tectonic activities and sedimentary deposition patterns (Horton, 1945). Escarpments in this region are shaped by differential erosion along joints and faults, influencing soil retention, vegetation growth, and water flow (Strahler, 1952).

Wind gaps, which are abandoned river valleys, play a crucial role in understanding past hydrological conditions and stream evolution (Melton, 1957). Additionally, caves in the Vindhyan formations, formed through joint-controlled weathering, offer significant geological and archaeological insights (Leopold et al., 1964). The presence of cascades and step-like waterfalls

in secondary streams further highlights active fluvial processes in this landscape (Schumm, 1956).

Ridges and Residual Hills

These features are remnants of ancient erosional processes, with hard sandstone formations resisting weathering. The ridges provide insight into past tectonic activities and sedimentary deposition patterns, influencing regional hydrology and land use.

Escarpments

Formed due to differential erosion along joints and faults, escarpments create distinct landscape divisions. These steep slopes impact soil retention, vegetation growth, and the flow of surface water, contributing to varied microclimates within the region (Fig. 3).

Wind Gaps

Former river valleys abandoned due to stream capture or changes in water flow patterns. These gaps are significant for studying paleoclimatic conditions and the evolution of river systems. They also serve as corridors for wind movement, influencing local weather conditions (Fig. 4).

Caves

Developed through joint-controlled weathering, providing geological and archaeological insights. The caves in the

Vindhyan formations are crucial for studying past climatic conditions, ancient human habitation and mineral deposition (Fig. 5).

Cascades

Step-like waterfalls indicating active fluvial processes in secondary streams. These formations enhance biodiversity, supporting aquatic ecosystems and influencing sediment transport in river systems (Fig. 6).

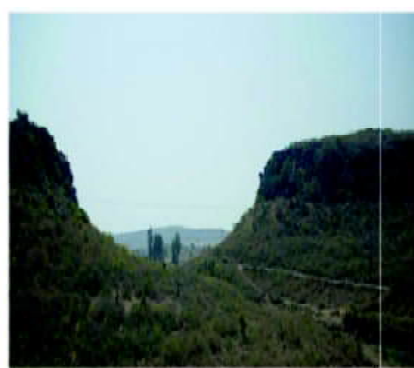
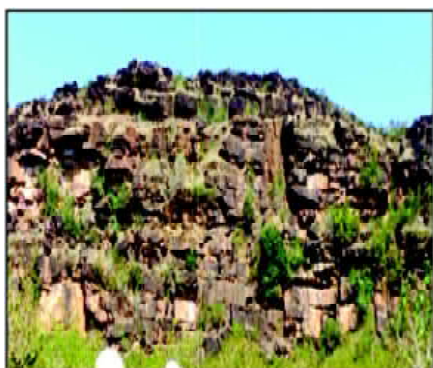


Fig. 3 : Escarpment Vindhyan Hill Area **Fig. 4 :** Wind Gap in the West of Sagar-Bhopal Road



Fig. 5 : Caves in Vindhyan Inlier

Fig. 6 : Cascade Vindhyan Hill

Deccan Trap Landforms

The Deccan Trap region, characterized by flat-topped plateaus and step-like basaltic formations, exhibits unique geomorphological features (Kale & Gupta, 2001). These landforms have developed due to successive lava flows, resulting in distinct horizontal stratification (James & Panday, 2018).

Spheroidal weathering is a common process in basaltic terrain, leading to the formation of rounded boulders and aiding in soil development (Goudie, 2018).

The black cotton soil found in this region is highly fertile but exhibits significant water retention properties, which impact agricultural productivity (Montgomery, 2007). Sustainable water management strategies are crucial for maintaining soil health in these areas (Singh & Dubey, 2021).

Flat-Topped Plateaus

Formed by successive basaltic lava flows, creating horizontal stratification, these plateaus impact regional

climate, water retention, and land-use patterns, making them key areas for agriculture and settlement (Fig. 7).

Stepped Topography

Layered basalt formations resembling staircases, characteristic of Deccan Traps. This topography influences drainage patterns and soil erosion, requiring careful land management practices.

Spheroidal Weathering

Onion-peel weathering resulting in rounded boulders, aiding soil formation. This process plays a crucial role in

soil fertility and groundwater recharge, affecting agricultural productivity (Fig. 8).

Black Cotton Soil

Highly fertile but water-retentive soil, crucial for agriculture but prone to expansion and contraction. This soil type supports major crops like cotton and soybean but requires efficient irrigation and drainage management to prevent waterlogging and soil degradation (Fig. 9).



Fig. 7 : Flat-Topped Topography of Deccan Trap



Fig. 4 : Spheroidal Weathering of Basalt

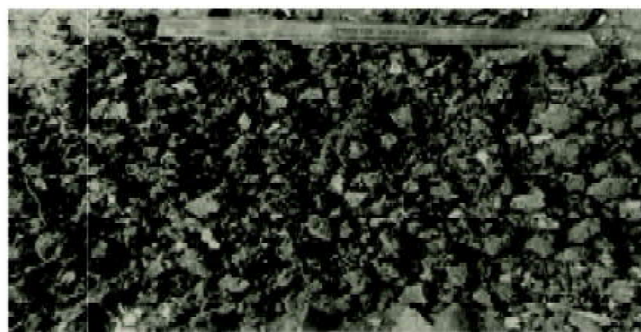


Fig. 4 : Black Cotton Soil from Kanera Dev

Slope Analysis

The study utilizes **slope degree and aspect maps** to assess terrain characteristics and erosion risk (Bishop et al., 2012). Slope analysis plays a critical role in infrastructure development, as areas with steep slopes are prone to landslides and erosion (James, 2022). The aspect of slopes influences microclimate, vegetation distribution and land-use decisions (Strahler, 1952). Mapping these

variations assists in designing sustainable land-use plans and agricultural practices (Leopold et al., 1964).

Slope Degree and Percent Maps

Used for terrain classification and erosion risk assessment. These maps help in planning infrastructure projects, identifying areas susceptible to landslides, and managing soil conservation efforts (Fig. 10).

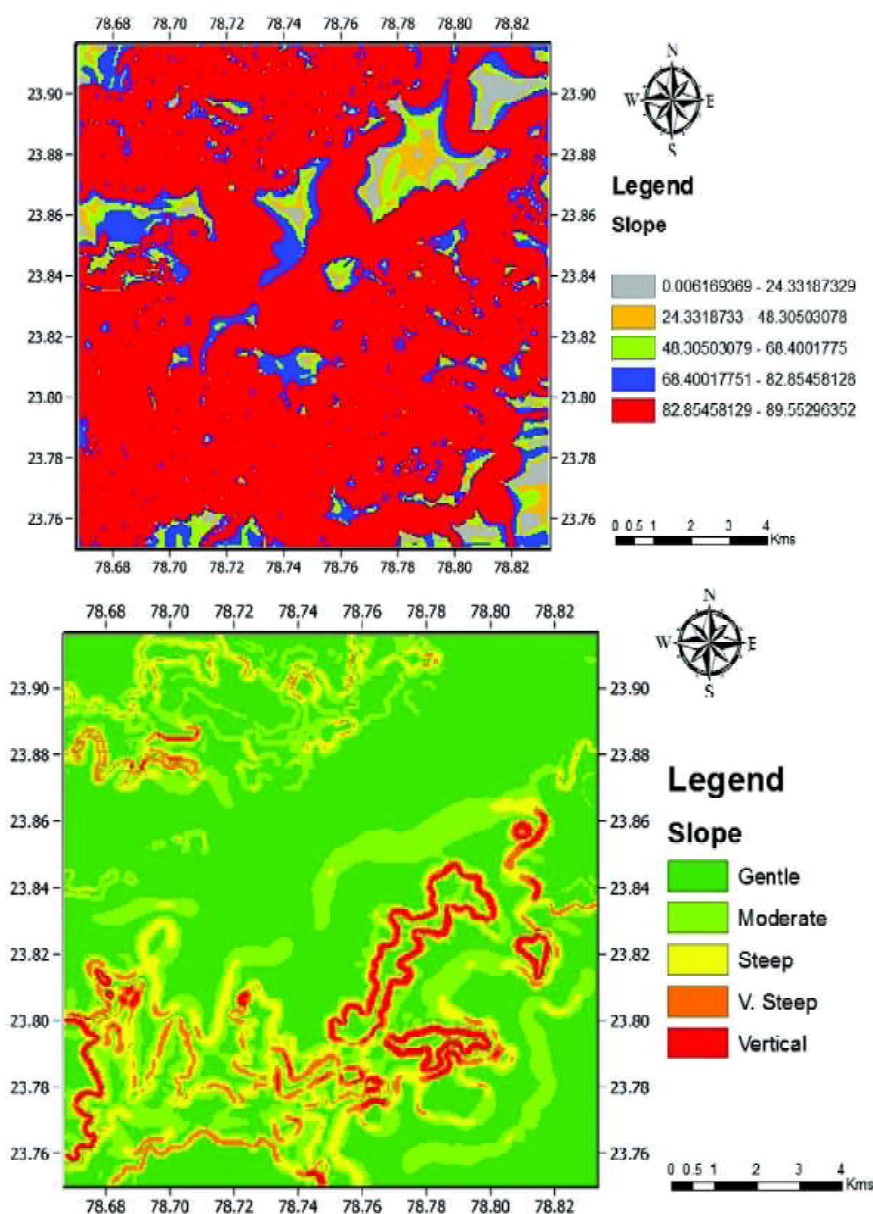


Fig. 10 : (a) 0 to 100 Percent Slope & (b) Degree Slope

Aspect Mapping

Determines slope direction, influencing microclimate, vegetation, and land-use decisions. Understanding aspect variations assists in agricultural planning, water resource management, and ecological conservation (Fig. 11).

Impact of Geomorphological Characteristics on Topography

On Vindhyan Terrain: Well-drained landscapes with limited soil fertility, significant for infrastructure

development and historical studies (James & Panday, 2018). The presence of escarpments and residual hills influences settlement patterns, transportation routes, and tourism potential (Singh & Dubey, 2021).

On Deccan Trap Terrain: The Deccan Trap terrain supports fertile soils, making it ideal for agriculture (Montgomery, 2007). However, terrain characteristics demand careful water management and soil conservation strategies (Goudie, 2018). Sustainable farming techniques can help optimize land use while mitigating soil degradation risks (Raj & Jain, 2017).

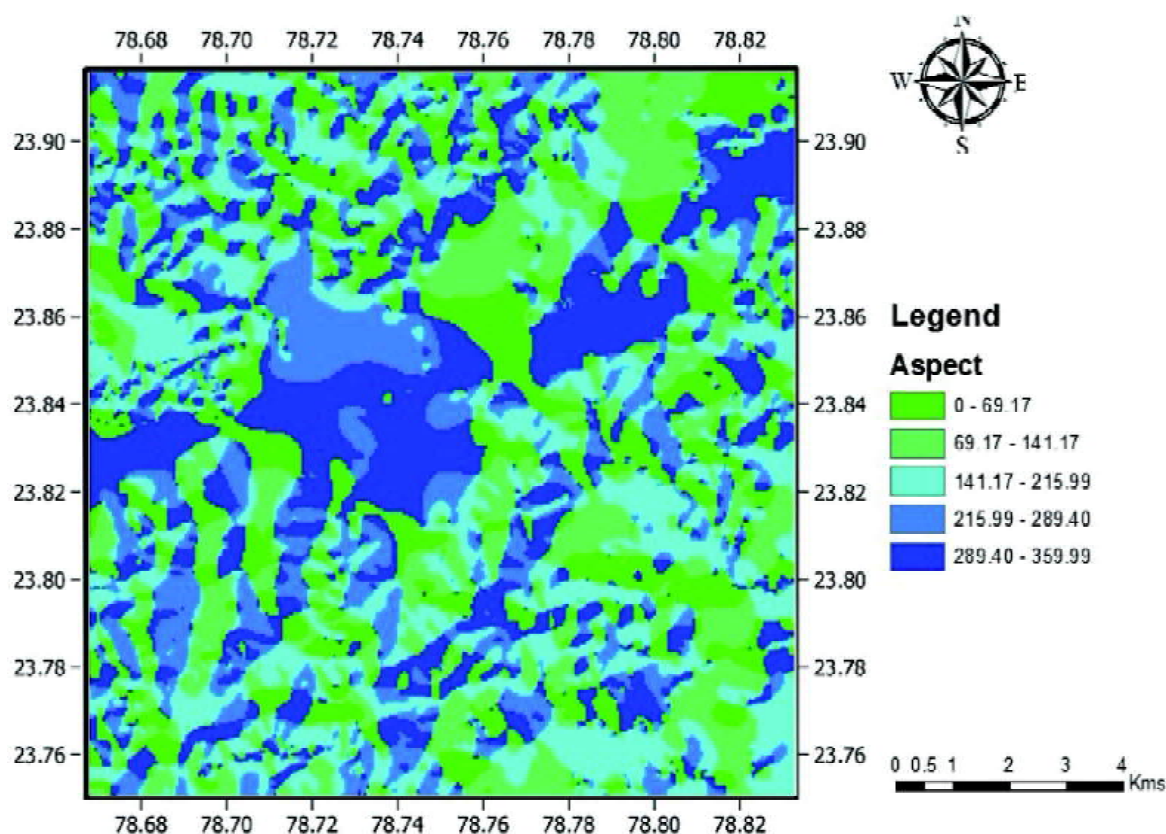


Fig. 11 : Aspect Map

Conclusion

The foregoing discussion reveals that topographic development of the Sagar region is shaped by geological history, erosional processes and climatic variations. The Vindhyan formations exhibit mature erosional features, whereas the Deccan Traps display step-like topography and fertile black cotton soil.

Understanding these geomorphic processes is essential for sustainable land-use planning and

environmental conservation (Kale & Gupta, 2001). Future research should integrate climate change modeling and anthropogenic impact assessments to better understand long-term landscape evolution (Raj & Jain, 2017). Additionally, advanced remote sensing and GIS methodologies can enhance the accuracy of geomorphological studies (Bishop et al., 2012).

References

- Bishop, M.P. et al. (2012): Geospatial Technologies and Digital Geomorphology. *Geomorphology*, 137, 5-26.
- Goudie, A.S. (2018): Human Impact on the Natural Environment: Past, Present, and Future. Wiley-Blackwell.
- Horton, R.E. (1945): Erosional development of streams and their drainage density: hydro-physical approach to quantitative geomorphology. *Geol. Soc. Amer. Bull.*, no.56, pp.275-370.
- James, N.F. & Panday, S. K. (2018): Lithological and Structural characterization of rocks around Sagar, District Sagar, Madhya Pradesh, India, *IJCRT*, Volume 6, Issue 1, Pages 1184 – 1196.
- James, NF (2022): Morphometric analysis of drainage basin of Sagar Lake, district Sagar M.P. & surrounding area using GIS and RS Techniques. *IJARIIIE*, Vol-8 Issue-5, Pages 1851 – 1855.
- Kale, V.S., & Gupta, A. (2001): Introduction to Geomorphology. Orient Black Swan.

- Leopold, L.B., Wolman, M.G., & Miller, J.P. (1964): *Fluvial Processes in Geomorphology*. W.H. Freeman & Co., San Francisco.
- Melton, M.A. (1957): *An analysis of the relations among elements of climate, surface properties and geomorphology*. Dept. Geol., Columbia University, Technical Report, 11, Proj.NR389-042.off. of Nav. Res., New York.
- Montgomery, D.R. (2007): Soil erosion and agricultural sustainability. *Proceedings of the National Academy of Sciences*, 104(33), 13268-13272.
- Raj, R., & Jain, V. (2017): Impacts of tectonics and climate on the evolution of river systems in central India. *Geomorphology*, 295, 15-30.
- Schumm, S.A. (1956): Evolution of drainage systems and slopes in badlands at Perth Amboy, New Jersey. *Geological Society of America Bulletin*, 67, 597-646.
- Singh, S. & Dubey, A. (2021): GIS and Remote Sensing-Based Morphometric Analysis of River Basins in Central India. *Journal of Earth System Science*, 130, 153.
- Strahler, A.N. (1952): Hypsometric (area-altitude) analysis of erosional topography. *Geological Society of America Bulletin*, 63, 1117-1142.

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