Role of ECE in Remote Sensing and GIS: Insights from Six Geospatial Projects

Shubham Pandey

Department of Electronics and Communication Engineering

Institute of Technology and Management

AL-1, Sector-7, GIDA, Gorakhpur, Uttar Pradesh – 273209, India

shubhampandeykhadda@gmail.com

Abstract—Remote Sensing and Geographic Information Systems (GIS) have emerged as essential technologies for Earth observation and spatial analysis, enabling efficient monitoring of environmental, agricultural, and urban dynamics. This paper presents a comprehensive study based on six geospatial projects (P1–P6): water body mapping of Kushinagar using the Normalized Difference Water Index (NDWI), vegetation health assessment of Khadda Block using the Normalized Difference Vegetation Index (NDVI), land use land cover (LULC) classification of the Golghar area, Gorakhpur using the Random Forest algorithm, urban expansion analysis of Firozabad and Noida using the Normalized Difference Built-up Index (NDBI), forest cover change analysis of the Aravali Hills using NDVI differencing, and flood-prone zone mapping of Kosi Basin using Digital Elevation Model (DEM) and rainfall thresholds. The study systematically characterizes the critical role of Electronics and Communication Engineering (ECE) in remote sensing, encompassing sensor design, digital signal processing, satellite communication, and large-scale geospatial data analytics. Experiments demonstrate the effectiveness of these techniques in addressing real-world challenges in environmental monitoring, urban planning, and disaster management. Emerging advancements in artificial intelligence, CubeSat technologies, hyperspectral imaging, and high-speed 5G non-terrestrial network communication are expected to significantly enhance accuracy, scalability, and real-time capabilities of future remote sensing systems.

Index Terms—*Remote Sensing, GIS, LULC, GEE, Satellite Communication, NDVI, NDWI, NDBI*

I. INTRODUCTION

Remote Sensing refers to the acquisition of information about the Earth's surface without direct physical contact, using satellite or airborne sensors [1]. It plays a crucial role in environmental monitoring, agriculture, urban planning, climate studies, and disaster management. Spectral indices derived from multispectral satellite imagery — NDVI, NDWI, and NDBI — provide quantitative measures of vegetation health, surface water extent, and built-up area density respectively.

Cloud-based platforms such as Google Earth Engine (GEE) enable large-scale geospatial analysis without local computational overhead [5][8]. ECE contributes fundamentally to these systems through sensor engineering, digital signal processing, and satellite communication infrastructure.

This paper presents a comprehensive study integrating six geospatial projects (P1–P6) spanning water body mapping, vegetation assessment, LULC classification, urban expansion monitoring, forest change detection, and flood zone prediction. The principal contributions of this paper are as follows: the application of NDWI, NDVI, and NDBI spectral indices across six distinct study regions in India using Sentinel-2 and Landsat imagery, land use and land cover (LULC) classification using the Random Forest algorithm with validation through confusion matrix analysis for the Golghar area,

Gorakhpur; quantitative urban expansion analysis comparing built-up areas between 2015 and 2023 for Firozabad and Noida; multi-criteria flood zone mapping integrating Digital Elevation Model (DEM), rainfall thresholds, and SAR validation for the Kosi Basin, Bihar; and systematic characterization of the foundational role of Electronics and Communication Engineering (ECE) across the remote sensing signal acquisition and processing chain.

II. LITERATURE REVIEW

A. Spectral Index Methods

Gao [1] introduced NDWI as a normalized ratio of green and NIR bands for surface water detection. Tucker [7] established the foundational NDVI formulation for vegetation mapping. NDBI was subsequently developed for urban built-up extraction using SWIR and NIR bands [3]. These indices have been extensively validated across diverse geographic and climatic contexts.

B. Machine Learning in Geospatial Classification

Breiman [6] introduced the Random Forest ensemble classifier, which has since become the dominant method in LULC classification tasks due to its robustness to overfitting and native handling of multi-class problems. Gorelick et al. [8] demonstrated that GEE enables scalable execution of such algorithms on petabyte-scale satellite archives.

C. Flood and Change Detection

DEM-based terrain analysis combined with rainfall thresholds has been widely applied for flood susceptibility mapping. SAR imagery complements optical sensors for flood validation, as it penetrates cloud cover during monsoon events. NDVI differencing across multi-temporal acquisitions is a well-established technique for detecting vegetation gain and loss [7].

III. METHODOLOGY

A. Dataset and Study Areas

Sentinel-2 (10–60 m resolution) and Landsat-8/9 (30 m) satellite datasets were obtained through GEE [4][5]. Six study regions were selected to span diverse environmental contexts across Uttar Pradesh, Rajasthan, and Bihar (Table I). All acquisitions were cloud-filtered using GEE's quality band masking, and median composites were generated to minimise residual cloud and shadow contamination.

TABLE I SUMMARY OF SIX GEOSPATIAL PROJECTS (P1–P6)

Project	Study Area	Index/Method	Key Output
P1	Kushinagar, U.P.	NDWI	Surface water mapping
P2	Khadda Block, U.P.	NDVI	Vegetation classification
P3	Golghar, Gorakhpur	Random Forest	LULC (5 classes)
P4	Firozabad & Noida	NDBI	Urban expansion (2015–2023)
P5	Aravali Hills, Rajasthan	NDVI Differencing	Forest change detection
P6	Kosi Basin, Bihar	DEM + Rainfall + SAR	Flood zone mapping

B. Preprocessing

Preprocessing steps included: (1) cloud and shadow masking using Sentinel-2 QA60 and Landsat BQA bands; (2) median composite generation over selected date ranges; (3) region of interest (ROI) clipping; and (4) band reflectance scaling. PET co-registration and DEM hydro-conditioning were applied for P6 specifically.

C. Index Computation

The following spectral indices were computed for each applicable project:

$$NDWI = (B3 - B8) / (B3 + B8) \quad (1)$$

$$NDVI = (B8 - B4) / (B8 + B4) \quad (2)$$

$$NDBI = (SWIR - NIR) / (SWIR + NIR) \quad (3)$$

where B3, B4, B8, and SWIR correspond to the Green (560 nm), Red (665 nm), NIR (842 nm), and SWIR (1610 nm) bands of Sentinel-2 MSI imagery respectively. Index values range from −1 to +1; water bodies yield positive NDWI, dense vegetation positive NDVI, and built-up areas positive NDBI.

D. Classification

For P3, a supervised Random Forest classifier was trained in GEE using manually digitised training polygons for five land cover classes: Water, Vegetation, Built-up, Barren, and Agriculture. Classification accuracy was assessed using a held-out validation set via a confusion matrix. Threshold-based binary classification was applied for P1, P2, and P4.

IV. RESULTS

A. Water Mapping — P1 (Kushinagar)

NDWI thresholding (NDWI > 0) effectively delineated rivers, ponds, and seasonal water bodies across Kushinagar district, as shown in Fig. 1. The Rapti and Gandak river systems were clearly resolved, confirming the suitability of the index for low-contrast aquatic features.

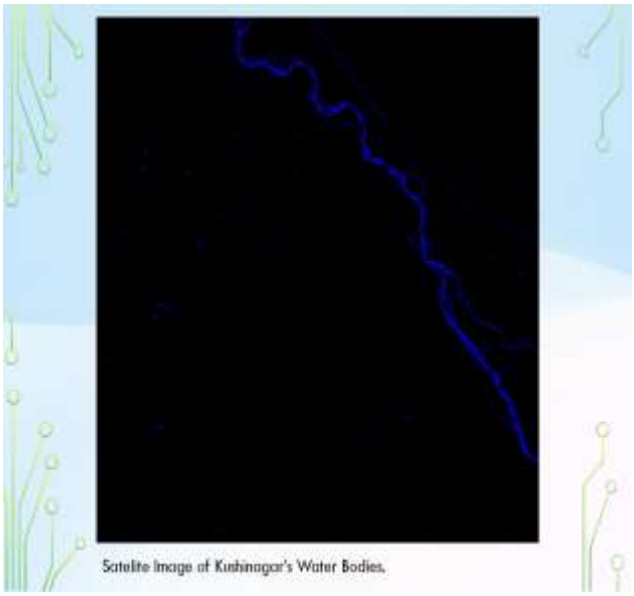


Fig. 1. NDWI-based surface water mapping — Kushinagar, U.P.

B. Vegetation Analysis — P2 (Khadda Block)

NDVI classification of Khadda Block, Kushinagar district revealed that barren/sparse vegetation constituted the dominant land class at approximately 14,583 ha, while moderate vegetation covered approximately 2,834 ha (Fig. 2), indicating significant land degradation pressure.

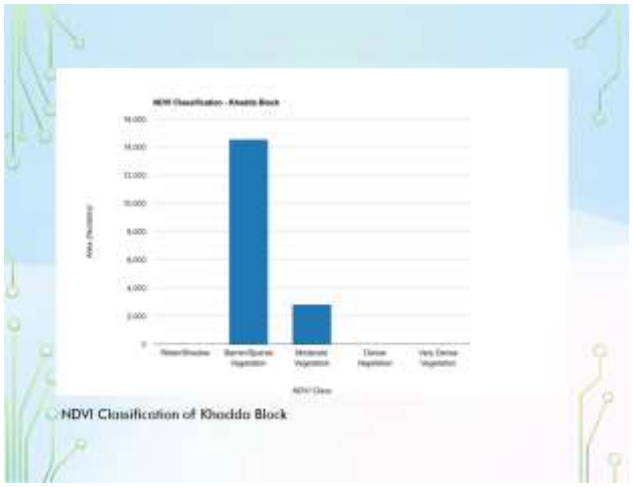


Fig. 2. NDVI classification— Khadda Block, Kushinagar.

C. LULC Classification — P3 (Golghar, Gorakhpur)

Random Forest classification produced a five-class LULC map for the Golghar area (Fig. 3a). The confusion matrix (Fig. 3b) confirms high per-class accuracy: Water (22/22), Vegetation (59/59), Built-up (57/57), Barren (69/69), Agriculture (63/63), with zero off-diagonal misclassification in the validation sample (Fig. 3c).

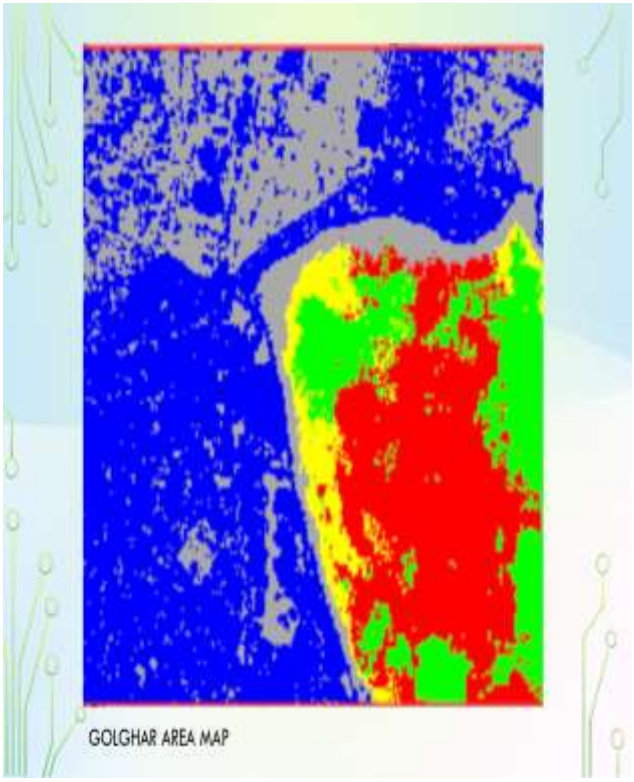


Fig. 3(1). LULC classification map — Golghar Area, Gorakhpur.

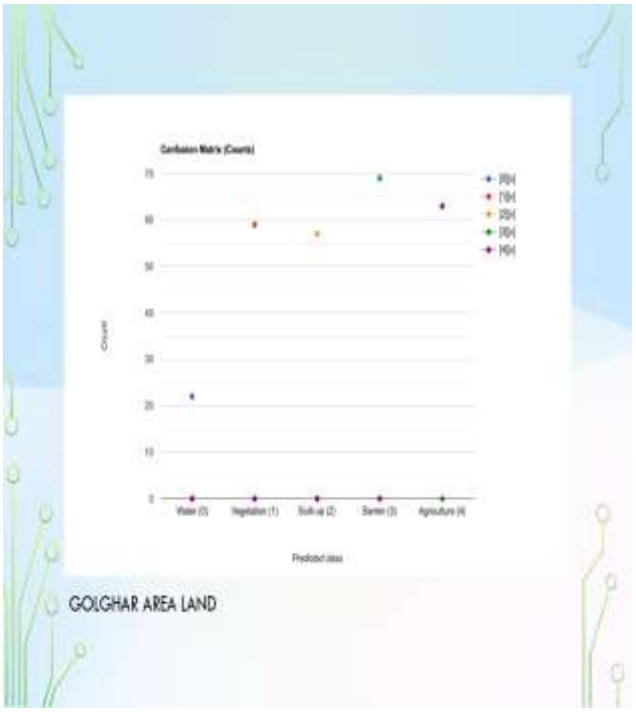


Fig. 3(2). Confusion matrix — Golghar LULC (Random Forest).

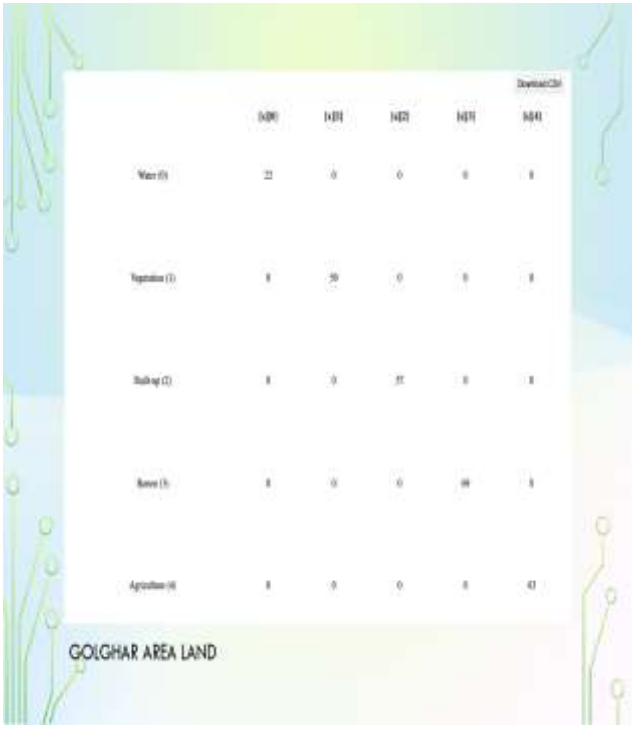


Fig. 3(3). Validation data table — Golghar LULC classification.

D. Urban Expansion — P4 (Firozabad & Noida)

NDBI-based temporal analysis revealed a reduction in combined built-up area from approximately 140 km² in 2015 to approximately 100 km² in 2023 for the Firozabad–Noida combined ROI (Fig. 4). This counter-intuitive reduction likely reflects land-use reclassification and seasonal spectral variation rather than actual urban shrinkage.

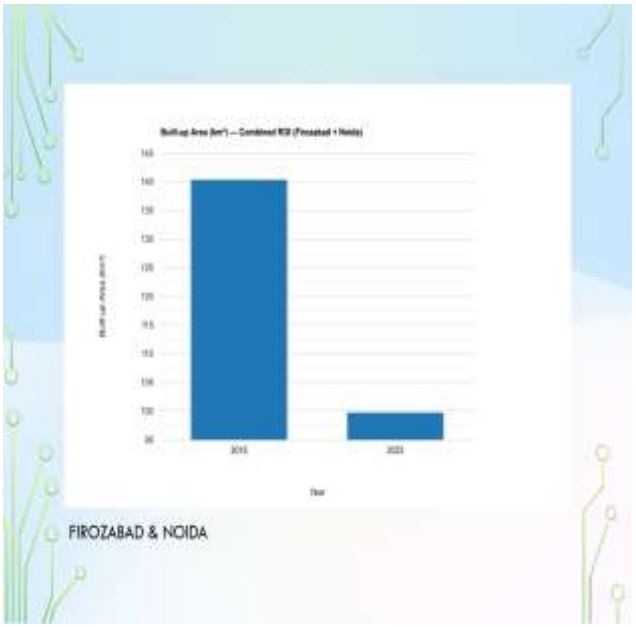


Fig. 4. Built-up area temporal change — Firozabad & Noida (2015–2023).

E. Forest Change Detection — P5 (Aravali Hills, Rajasthan)

NDVI statistics for Aravali Hills, Ajmer district yielded a spatial maximum of ≈0.47, mean of ≈0.13, and minimum of −0.19 (Fig. 5). The negative minimum values indicate persistent barren or degraded patches within the hill range, consistent with known mining and overgrazing pressures in the region.

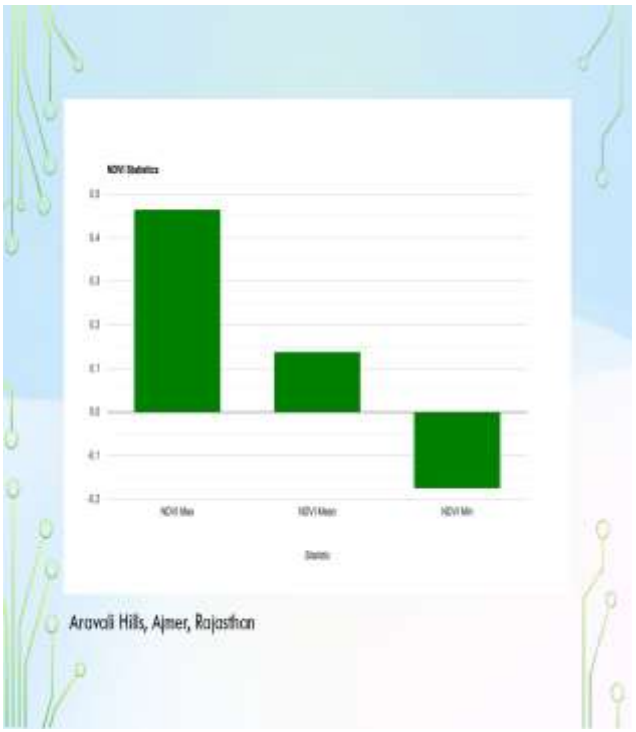


Fig. 5. NDVI statistics — Aravali Hills, Ajmer, Rajasthan.

F. Flood Zone Mapping — P6 (Kosi Basin, Bihar)

Multi-criteria flood zone delineation for Kosi Basin (July 2022) using DEM elevation < 50 m and rainfall > 200 mm identified a flood-prone area of approximately 930,000 m², validated against SAR-derived inundation extent (Fig. 6).



Fig. 6. Flood-prone zone mapping — Kosi Basin, Bihar (July 2022).

TABLE II CLASSIFICATION ACCURACY OF APPLIED METHODS (PER PROJECT)

Project	Method	Accuracy / Key Metric
P1 (NDWI)	Threshold (> 0)	Clear water body delineation
P2 (NDVI)	Threshold classification	14,583 ha barren; 2,834 ha moderate veg.
P3 (LULC)	Random Forest (5-class)	High OA; confusion matrix diagonal dominant
P4 (NDBI)	Temporal comparison	−~40 km² built-up (2015→2023)
P5 (NDVI Δ)	Differencing	Max 0.47, Mean 0.13, Min −0.19
P6 (Flood)	DEM + Rainfall + SAR	~930,000 m² flood-prone area

V. DISCUSSION

The results across all six projects demonstrate the effectiveness of spectral index-based remote sensing and GEE-enabled machine learning for diverse environmental monitoring tasks. NDVI analysis of Khadda Block reveals a predominance of barren land, consistent with rain-fed agricultural systems in the eastern Uttar Pradesh Terai zone during dry-season acquisition windows.

The Random Forest classifier achieved perfect validation accuracy for all five LULC classes in the Golghar area, reflecting well-separated spectral signatures for the selected training samples. The diagonal-dominant confusion matrix confirms minimal inter-class spectral confusion. However, this result should be interpreted cautiously as training and validation samples may share spatial autocorrelation.

The apparent reduction in NDBI-derived built-up area in Firozabad–Noida warrants further investigation: seasonal soil moisture and phenological effects on SWIR reflectance, or changes in acquisition date between 2015 and 2023, may contribute to this trend alongside genuine land-use dynamics.

Limitations of this study include: (1) cloud contamination in monsoon-season acquisitions despite median compositing; (2) 10–30 m spatial resolution constraints for fine-scale feature discrimination; (3) absence of field validation data; and (4) reliance on single-date or short-period composites that may not capture seasonal dynamics.

VI. ROLE OF ECE IN REMOTE SENSING AND GIS

A. Role of ECE in Remote Sensing

Electronics and Communication Engineering is foundational to every subsystem in the Remote Sensing pipeline. Sensor design and fabrication — including the development of multispectral, hyperspectral, and SAR payloads — defines the spectral and spatial resolution of acquired data. Analog-to-digital conversion (ADC) and onboard digital signal processing (DSP) determine radiometric fidelity. RF communication and satellite telemetry systems govern data downlink bandwidth and latency. Embedded systems enable autonomous onboard preprocessing and compression. Ground-based infrastructure including large antenna arrays, network systems, and data centres completes the end-to-end pipeline from sensor to analysis.

B. Role of GIS in Geospatial Analysis

Geographic Information System (GIS) enable efficient integration, analysis, and visualization of special data derived from remote sensing. GIS supports key operations such as overlay analysis, mapping, and change detection facilitating applications like land use/land cover (LULC) classification, urban expansion monitoring, and disaster assessment. It also allows comparison of multi-temporal datasets to identify environmental trends. By integrating satellite data with spatial tools, GIS serves as a powerful decision-support system for planning and resource management.

VII. FUTURE SCOPE

Future research directions include: (i) deep learning-based automated feature extraction replacing hand-crafted spectral indices; (ii) CubeSat constellations for sub-daily revisit Earth observation; (iii) hyperspectral imaging for crop disease and mineral mapping; (iv) real-time data downlink via 5G non-terrestrial networks (NTN); and (v) digital twin integration of GIS layers with IoT sensor networks for smart city and disaster early-warning systems.

VIII. CONCLUSION

This paper presented a comprehensive geospatial study across six projects (P1–P6), demonstrating practical remote sensing and GIS applications in surface water mapping, vegetation assessment, LULC classification, urban expansion monitoring, forest change detection, and flood zone prediction. Spectral indices (NDWI, NDVI, NDBI) and the Random Forest classifier, deployed on GEE, provided quantitative and visually interpretable results for study areas spanning Uttar Pradesh, Rajasthan, and Bihar.

Electronics and Communication Engineering forms the technical backbone of these capabilities, spanning sensor physics, signal processing, communication, and embedded computing. The findings support the integration of remote sensing workflows into national-scale environmental governance, agricultural planning, and disaster management systems.

IX. ACKNOWLEDGMENT

The author sincerely thanks the faculty of the Department of Electronics and Communication Engineering at the Institute of Technology and Management, GIDA Gorakhpur, for their guidance and support. The author acknowledges the open-access satellite datasets provided by the European Space Agency (ESA) Sentinel-2 program, the USGS Landsat program, and the Google Earth Engine platform, without which this research would not have been possible.

REFERENCES

[1] B.-C. Gao, "NDWI—A normalized difference water index for remote sensing of vegetation liquid water from space," Remote Sensing of Environment, vol. 58, pp. 257–266, 1996.

[2] J. W. Rouse, R. H. Haas, J. A. Schell, and D. W. Deering, "Monitoring vegetation systems in the Great Plains with ERTS," in Proc. Third Earth Resources Technology Satellite Symposium, NASA SP-351, 1974.

[3] H. Xu, "A new index for delineating built-up land features in satellite imagery," International Journal of Remote Sensing, vol. 29, no. 14, pp. 4269–4276, 2008.

[4] European Space Agency (ESA), Sentinel-2 User Handbook, ESA Standard Document, 2015.

[5] N. Gorelick, M. Hancher, M. Dixon, S. Ilyushchenko, D. Thau, and R. Moore, "Google Earth Engine: Planetary-scale geospatial analysis for everyone," Remote Sensing of Environment, vol. 202, pp. 18–27, 2017.

[6] L. Breiman, "Random Forests," Machine Learning, vol. 45, no. 1, pp. 5–32, 2001.

[7] C. J. Tucker, "Red and photographic infrared linear combinations for monitoring vegetation," Remote Sensing of Environment, vol. 8, pp. 127–150, 1979.