A 40-Year Journey: Eco-Hydrological Dynamics of Haiderpur Wetlands (EHDW) with Multi-Landsat, Sentinel - 2 Satellite Data using Google Earth Engine (GEE) and Machine Learning

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Keywords: Google Earth Engine (GEE), Land Use and Land Cover (LULC), Landsat Imagery, Land Surface Temperature (LST), Urban Heat Island (UHI), Haiderpur, Sustainable Urban Planning, Modified Normalized Difference Water Index (MNDWI), Normalized Difference Vegetation Index (NDVI), Soil-Adjusted Vegetation Index (SAVI), Random Forest, Sustainable Development Goals (SDG) Goals.

Abstract

The Haiderpur region has undergone significant LULC changes over the decades, impacting ecological balance and urban development. However, the absence of a comprehensive, longitudinal LULC dataset has hindered detailed assessments of environmental transformations and UHI effects. This study aims to generate a thorough LULC classification dataset for Haiderpur, covering the period from 1990 to 2023. Utilizing the GEE platform along with Landsat 5, 7, and 8, Sentinel-2 multi-spectral imagery, we employed a Random Forest machine learning classifier to create a high-resolution (30 m) dataset capturing key land cover categories, including waterbodies, buildup, agriculture, bare soil, swamp vegetation, and forest. In addition to classification, the study incorporated spatial and temporal analyses using indices such as the MNDWI, NDVI, and SAVI. These indices facilitated a nuanced assessment of vegetation dynamics and water features from 1990 to 2023. The study also extends predictions of LULC into the future, projecting changes for the years 2025 and 2030. Moreover, LST variations were evaluated, highlighting significant thermal changes corresponding with LULC transformations. The dataset achieved an overall accuracy of 82%, underscoring its environmental monitoring reliability. Our findings indicate an increase in built-up areas, with corresponding impacts on thermal dynamics, while total wetland and forest areas exhibited more stability. This research confirms anthropogenic influence as a primary driver of change in the region. The Haiderpur LULC dataset aligns with other LULC resources, offering a robust tool for researchers and policymakers to support sustainable urban planning, conservation efforts, and climate change adaptation in Haiderpur and similar regions. This study contributes to SDGs, particularly Goal 6 (Clean Water and Sanitation), Goal 13 (Climate Action), and Goal 15 (Life on Land), by enhancing understanding and management of wetland ecosystems.

1. Introduction

1.1 Background Introduction

Wetlands, renowned for their ecological and economic benefits, serve as critical ecosystems that transition between aquatic and terrestrial environments. However, these vital areas have faced significant degradation due to climate change and human activities worldwide. In India, wetlands play a crucial role in biodiversity and ecosystem services, yet they are increasingly threatened by rapid urbanization, agricultural expansion, and industrial activities.

Monitoring changes in the extent and distribution of wetlands is essential for understanding their impact on biodiversity and ecosystem dynamics. Despite the importance of wetlands, there is a notable gap in comprehensive datasets that detail their long-term spatial and temporal variations. This deficiency poses challenges for evaluating changes in wetland health, carbon sequestration, greenhouse gas emissions, and other ecosystem services, hindering effective policy formulation and conservation efforts.

Globally, datasets such as the Global Surface Water Explorer and Sentinel-2 imagery have been utilized for wetland monitoring. However, many of these datasets focus on specific types of wetlands or timeframes, lacking the detailed classifications necessary for comprehensive analysis. This limitation underscores the need for more holistic datasets that capture all wetland categories over extended periods.

In India, the necessity for such comprehensive data is critical to supporting informed policymaking and sustainable management practices. This study proposes to address this gap by creating a long-term wetland classification dataset for the Haiderpur region, covering the period from 1990 to 2023. Utilizing advanced remote sensing technologies and machine learning classifiers, this dataset will enable detailed analysis of spatial and temporal changes in wetland categories, aiding conservation efforts and contributing to Sustainable Development Goals related to clean water, climate action, and biodiversity conservation. By providing a robust and comprehensive LULC dataset, the research aims to empower stakeholders and policymakers to better understand and manage India's vital wetland ecosystems.

1.2 Challenges, Research Gaps and Objectives

1.2.1 Challenges: Wetlands, as productive ecosystems that serve as a transition between land and water, provide significant ecological and economic benefits. Despite their importance, these ecosystems face increasing threats from climate change and human activities, such as urban development and agricultural expansion. This has resulted in substantial loss and degradation on a global scale. The Haiderpur region is no exception; it has experienced considerable transformations in land use and cover over the past few decades, which have adversely affected its ecological balance.

1.2.2 Research Gaps: The effectiveness of wetland management and conservation in Haiderpur is limited by the lack of comprehensive longitudinal datasets that capture the dynamic transformations of land cover across the region. Due to their limited scope and resolution, existing studies have not fully addressed the spatial and temporal changes in land use and cover. Moreover, assessments of vegetation dynamics, water features, and thermal variations crucial for a holistic understanding of the environment remain inadequately explored.

1.2.3 Objectives: This study aims to achieve the following objectives:

1. Develop a comprehensive, high-resolution (30 m) land use and land cover (LULC) dataset for the Haiderpur region from 1990 to 2023 using multi-spectral imagery from Landsat 5, 7, and 8, and a Random Forest machine learning classifier.

2. Accurately classify key LULC categories, including waterbodies, built-up areas, agriculture, bare soil, swamp vegetation, and forest.

3. Incorporate spatial and temporal analyses using indices such as the Modified Normalized Difference Water Index (MNDWI), Normalized Difference Vegetation Index (NDVI), and Soil-Adjusted Vegetation Index (SAVI) to evaluate vegetation dynamics and water features.

4. Conduct Land Surface Temperature (LST) assessments to analyze thermal variations and Urban Heat Island (UHI) effects in relation to land cover transformations.

5. Land-use land cover future prediction scenarios for the years 2025 and 2030 to provide valuable insights for future urban planning and environmental management.

6. Contribute to Sustainable Development Goals (SDGs), particularly Goal 6 (Clean Water and Sanitation), Goal 13 (Climate Action), and Goal 15 (Life on Land), by enhancing the understanding and management of regional land resources.

2. Material and Methods

2.1 Study Area: Haiderpur Wetland

The Haiderpur Wetland is a UNESCO-designated Ramsar site situated in the state of Uttar Pradesh, India, specifically within the Muzaffarnagar and Bijnor districts. Established in 1984 following the construction of the Madhya Ganga Barrage, the wetland occupies an expansive area of approximately 69 square kilometres (27 square miles). It forms part of the Hastinapur Wildlife Sanctuary and is strategically located within the Central Asian Flyway, serving as a crucial stopover site for winter migratory birds.

2.1.1 Geographical Features: The Haiderpur Wetland (coordinates:$29.376478^\circ N, 78.034001^\circ E$) is a significant human-made feature formed by the waters of the Ganges River and its tributary, the Solani River. Covering an area of 6,908 hectares, this wetland is nestled within the broad geographical expanse of North India.

2.1.2 Biodiversity and Conservation: The wetland is a biodiversity hotspot, hosting over 320 bird species, including endangered and migratory birds, alongside mammals such as leopards, wildcats, and gharials. Conservation initiatives led by local communities, the World Wide Fund for Nature, and government programs aim to protect and manage this critical habitat, ensuring its ecological integrity and role in global migratory networks.

2.2 Data

This study focuses on generating a comprehensive spatial indices-based, spatio-temporal Land Use Land Cover (LULC) future landcover prediction classification dataset for the Haiderpur region over a period from 1990 to 2023. The dataset is created using multi-spectral remote sensing images derived from Landsat 5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+), and Landsat 8 Operational Land Imager (OLI), Sentinel-2 European Space Agency (ESA), maintaining a high-resolution 30-meter spatial detail. This timeframe was chosen considering the significant ecological and urban development changes observed in the Haiderpur region. The data serves to capture key land cover categories, including waterbodies, built-up areas, agriculture, bare soil, swamp vegetation, and forest.

The dataset preparation involved several key processing steps on the Google Earth Engine (GEE) platform. Atmospheric and radiometric corrections ensured surface reflectance products accurately represented ground conditions, following methodologies similar to those employed in prior studies (Gorelick et al., 2017). Cloud filtering and median compositing techniques were applied to derive representative annual images, extracting an average from a comprehensive dataset covering each year’s 365 days, where we were able to get 106 Landsat composite images and 197 Sentinel composite images, respectively. These images were further cropped to focus on the Haiderpur region, ensuring precise and relevant data input.

2.3 Wetland classification system

Classification system for wetlands ”... areas of marsh, fen, peatland, and water, whether natural or artificial, permanent or temporary, and whether water is flowing, fresh, brackish, or salty, including areas of marine water the depth of which at low tide does not exceed 6 m” is how the Ramsar Convention on Wetlands defines the traditional global wetland classification system (Ramsar Convention Bureau 2001). Wetlands, India’s most recent and thorough wetland classification system, is based on the Ramsar definition and China’s wetland mapping history (Mao et al., 2020).

3. Machine Learning Classifier Selection

In this study, we utilized Google Earth Engine (GEE), a cloud-based geo-computation platform renowned for its machine-learning capabilities and vast repository of Earth Observation data (Gorelick et al., 2017). GEE was selected for its efficiency

Table 1. Wetland classification system

Category	Description
Natural wetland	**Inland marsh:** Wetland (Herbaceous Veg) **Lake:** Natural Waterbody (flowing water) **River:** Linear Waterbody (flowing water) **Coastal marsh:** Marsh-Wetland **Estuary water:** Swamp Waterbody **Tidal flat:** Inter-tidal: Low vegetation
Human made wetland	**Reservoir:** Artificial Waterbody with dam **Aquaculture pond:** Waterbody-aquaculture **Canal:** Artificial linear Waterbody

in sample collection and model training, proving advantageous in numerous remote sensing contexts (Mayer et al., 2021; Tassi et al., 2020), making it ideal for our Land Use Land Cover (LULC) analysis of the Haiderpur region.

Machine learning classifiers are generally divided into parametric and non-parametric categories. Parametric classifiers like the Maximum Likelihood Classifier (MLC) and Naïve Bayes often rely on assumptions about data distribution, which can be limiting when handling complex datasets (Liu et al., 2011). Conversely, non-parametric classifiers such as Random Forest (RF), Support Vector Machines (SVM), and Classification and Regression Trees (CART) are preferable for remote sensing due to their flexibility and non-restrictive data requirements (Belgiu and Drăguţ, 2016).

Random Forest (RF) has proven particularly effective for remote sensing data classification because of its robustness and accuracy. It manages high-dimensional and multi-collinear data efficiently, which reduces overfitting and improves result stability (Belgiu and Drăguţ, 2016; Hemmerling et al., 2021). RF also excels in computational efficiency, a significant benefit when handling the extensive dataset required for analyzing the Haiderpur region over a time span from 1990 to 2023.

Prior comparative analyses have consistently demonstrated RF's superiority in classification accuracy over other classifiers such as Binary Hierarchical Classifier (BHC), Linear Discriminant Analysis (LDA), and ANN (Chan and Paelinckx, 2008; Ham et al., 2005; Shang and Chisholm, 2014). Although SVM may occasionally perform slightly better in Object-Based Image Analysis (OBIA), RF remains favoured for its ease of use and reduced sensitivity to feature selection (Li et al., 2022; Van Dong et al., 2024).

Given RF's ability to deliver high accuracy with hyperspectral or multi-source data, along with its processing speed and stability, it stands out as the optimal choice for our LULC study of Haiderpur (Belgiu and Drăgut, 2016). The precedence set by Corcoran et al. (2013) in successful wetland classification using RF supports its applicability here. While deep learning algorithms, known for their thoroughness, were considered, their computational demands deemed them less suitable given the extensive temporal and spatial scope of our study (Jamali et al., 2021). Therefore, Random Forest is selected for its highest classification accuracy and operational efficiencies tailored to the complex and diverse features of the Haiderpur landscape.

4. Methodology

The methodology for the Haiderpur LULC study is built upon a structured and comprehensive approach, utilizing advanced remote sensing technologies and machine learning techniques to analyze land use and cover changes from 1990 to 2023. The study begins with data acquisition, utilizing Google Earth Engine (GEE) to source satellite imagery from Landsat 5, 7, and 8, as well as Sentinel-2. These datasets are meticulously preprocessed to ensure accuracy, involving atmospheric correction and the application of cloud masking and compositing techniques. Such steps are essential for eliminating noise and extracting clear annual composite images, thereby facilitating a consistent temporal analysis of the region.

Key satellite imagery indices, including the Modified Normalized Difference Water Index (MNDWI), Normalized Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI), and Land Surface Temperature (LST), are calculated to provide insights into various ecological dimensions.

The core of the study's analytical framework is the Land Use Land Cover (LULC) classification performed using the Random Forest (RF) algorithm. This method is favoured for its robustness and efficiency in handling complex datasets with nonlinear relationships. A rigorous data preparation process splits the dataset into 70% for training and 30% for testing to ensure comprehensive model validation. Hyperparameters within the RF model are meticulously fine-tuned through cross-validation to optimize performance and prevent overfitting.

Temporal and spatial analyses are central to understanding the evolution of LULC categories over the study period. These analyses track transitions in built-up areas, water bodies, and vegetation cover, aided by spatial overlays in GIS tools to visualize and quantify changes. The temporal analysis identifies trends and patterns, providing a basis for predicting future LULC scenarios for 2025 and 2030. By incorporating historical trends and socio-economic variables, such as population growth and urban planning data, the study enhances its predictive capabilities, offering insights into potential future changes.

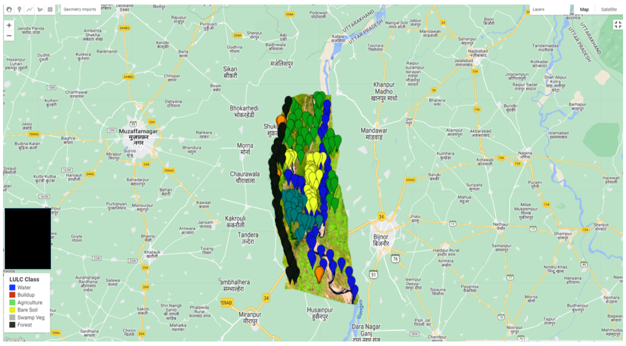

Figure 1. Trained Classes and Category features.

Table 2. Classification accuracy of four ML classifiers with five representative classes along the Haiderpur with varying Hyperparameters (HyP).

ML Classifier	HyP-1	HyP-2	HyP-3	HyP-4
RF	82.80%	78.50%	76.30%	74.90%
SVM	71.30%	69.80%	65.40%	62.70%
CART	72.75%	67.30%	68.00%	63.10%
GB	78.43%	73.25%	76.56%	69.05%

4.1 Footnotes

The methodology consists of three key stages: data preparation, input sample processing, and model training and accuracy assessment.

This contribution has been peer-reviewed. The double-blind peer-review was conducted on the basis of the full paper.
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4.1.1 Data Preparation: The process begins with acquiring Landsat 5, 7, and 8 satellite imagery at a 30-meter resolution. Cloud cover filtering and median compositing are applied to create clear and consistent images for analysis. To ensure the accuracy and reliability of the land use and land cover (LULC) classification in this study, specific radiometric and atmospheric corrections were applied to the raw Landsat-5, 7, 8, 9, and Sentinel-2 imagery. Radiometric corrections were performed to minimize sensor-related errors and retrieve surface reflectance values, thus allowing for consistent comparison across different sensor platforms and periods. Atmospheric corrections were applied using the Atmospheric Correction for Satellite Observations (ACORN) algorithm, which accounts for atmospheric scattering and absorption, ensuring that the data represent true surface conditions. Finally, the spectral bands, including RGB, NDVI, NDWI, LST, and SAVI, are added to enhance the granularity of the data. The dataset is segmented into 18 smaller patches to facilitate precise sub-image input for localized analysis.

4.1.2 Input Sample Processing: Labelled data comprising 5 land classes are extracted from the processed Landsat images, undergoing segmentation into manageable sub-masks. These form the foundation for generating input samples necessary for model training. The input samples incorporate both sub-images and sub-masks, providing a holistic representation of the area under study.

4.1.3 Model Training and Accuracy Assessment: The training dataset is divided into a 70/30 split, where 70% is used for model training and 30% for model validation, ensuring the model's robustness and generalization. The model integrates classification patches to produce comprehensive wetland classification maps from 1990 to 2023. For future predictions, machine learning models are utilized to forecast LULC changes for 2025 and 2030. Accuracy assessment is conducted by comparing outcomes against validation datasets, facilitating refinement and ensuring reliability. By systematically organizing data processing and rigorous model validation, the study provides robust and detailed classification outputs for the Haiderpur region.

4.1.4 Equations: In our study of the Haiderpur region, sample labelling for training and testing is conducted on Landsat images through visual interpretation, supplemented by a reference dataset. This ensures precise differentiation of land cover types. Using the Google Earth Engine (GEE) platform, we compute several indices to enhance classification features:

NDVI (Normalized Difference Vegetation Index): Utilizes near-infrared (NIR) and red (RED) bands to assess vegetation health and canopy density. NDWI (Normalized Difference Water Index): Highlights water bodies with the green (GREEN) and NIR bands. SAVI (Soil Adjusted Vegetation Index): A modification of NDVI that incorporates a soil brightness correction factor, using NIR and RED bands, ideal for areas with low vegetation density. LST (Land Surface Temperature): Derived from thermal infrared bands, LST provides insights into surface heat dynamics, which is crucial for analyzing temperature variations and identifying hot spots. UHI (Urban Heat Island): This represents the temperature difference between urban and surrounding rural areas, calculated from LST data, highlighting the impact of urbanization on local climate.

For labelling, five land categories are identified. Categories with clear boundaries, such as lakes and rivers, are labelled along their edges, while areas like marshlands without distinct perimeters are sampled with representative square patches. This comprehensive approach ensures accurate input for machine learning models and reliable classification results for the Haiderpur region's land use and land cover analysis.

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)} \tag{1}$$

$$MNDWI = \frac{(Green - SWIR)}{(Green + SWIR)} \tag{2}$$

$$SAVI = \frac{(NIR - Red)}{(NIR + Red + L)} \times (1 + L) \tag{3}$$

(where L is a soil adjustment factor, commonly 0.5)

$$LST = \frac{BT}{1 + \left(\frac{\lambda \cdot BT}{\rho}\right) \cdot \ln(\epsilon)} \tag{4}$$

where $\lambda wavelength of emitted radiance,$
$(Planck's constant, speed of light, Boltzmann constant)$
$BT is the brightness temperature, and \epsilon is emissivity.$

$$UHI = LST_{urban} - LST_{rural} \tag{5}$$

4.1.5 ML Classifiers: Random Forest is an ensemble learning method that constructs multiple decision trees during training and outputs the mode of the classes for classification. An ensemble method that builds multiple decision trees and merges them to get more accurate and stable predictions. Reduces overfitting by averaging the results of many deep trees trained on different parts of the same dataset.

$$\hat{y} = mode\{T_1(x), T_2(x), \ldots, T_n(x)\} \tag{6}$$

Classification and Regression Tree (CART): CART is a decision tree that is built using the Gini impurity for classification or variance for regression. A decision tree algorithm that is used for both classification and regression tasks. Splits data into subsets using measures like Gini impurity for classification or variance reduction for regression.

$$Gini(D) = 1 - \sum_{i=1}^{C} p_i^2 \tag{7}$$

Support Vector Machine (SVM): SVM finds the hyperplane that best separates the classes in the feature space. A binary classification algorithm that finds the optimal hyperplane which maximizes the margin between two classes. Effective in high-dimensional spaces and uses the kernel trick to handle non-linear separation. Hyperplane Equation:

$$f(x) = \mathbf{w} \cdot \mathbf{x} + b = 0 \tag{8}$$

Objective Function:

$$\min \frac{1}{2}\|\mathbf{w}\|^2 \quad subject to y_i(\mathbf{w} \cdot \mathbf{x}_i + b) \geq 1 \tag{9}$$

Gradient Boosting: An ensemble technique that combines weak learners, typically decision trees, to create a strong learner by iteratively minimizing a loss function. Sequentially adds trees that correct the errors of the existing ensemble, improving model accuracy. Update Rule:

$$F_m(x) = F_{m-1}(x) + h_m(x) \tag{10}$$

Gradient Descent Step:

$$h_m = \arg\min_h \sum_{i=1}^{n} L(y_i, F_{m-1}(x_i) + h(x_i)) \tag{11}$$

5. Results and Discussion

The series of maps depicting the Modified Normalized Difference Water Index (MNDWI) for Haiderpur from 1990 to 2024 illustrates significant temporal and spatial shifts in land cover. Over this period, notable changes in water bodies, swamps, marshy land, and vegetation are evident. The observed expansion and contraction of blue areas, representing water bodies, highlight the dynamic nature of water resources, potentially influenced by seasonal variations, climatic changes, and anthropogenic activities, such as irrigation and urban development. The reduction of green marshy land over the years indicates possible ecological transformations or land use changes impacting wetland areas.

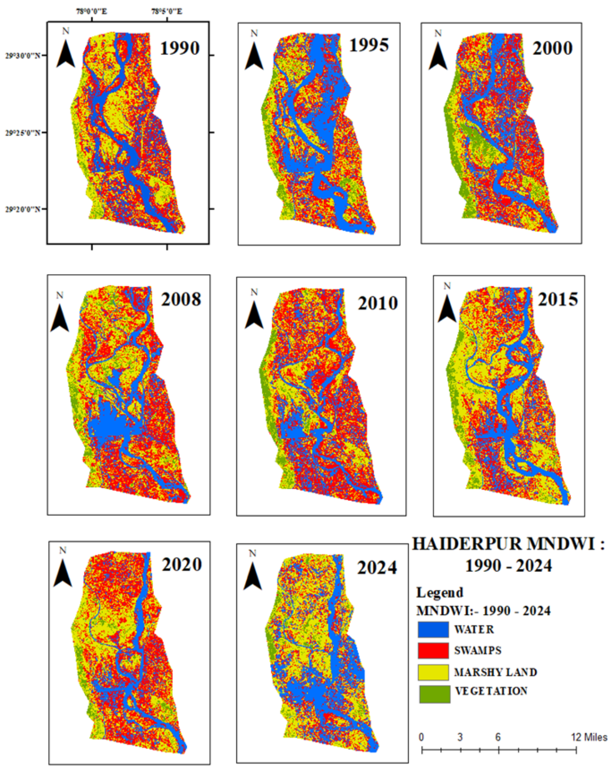

Figure 2. Modified Normalized Difference Water Index (MNDWI) for Haiderpur.

The Soil Adjusted Vegetation Index (SAVI) maps from 1990 to 2024 for the Haiderpur region reveal significant vegetation dynamics over the years. The variation in SAVI values, transitioning from green areas of high vegetation density to red areas with sparse cover, underscores the region’s ecological shifts. This analysis suggests that vegetation changes may be influenced by climatic variations, agricultural expansion, and land management practices. The progressive increase in green areas over certain periods indicates successful regrowth or conservation efforts, while the persistence of red zones highlights areas that could require focused ecological intervention. The selected L value effectively mitigates the influence of soil background reflectance, enhancing the accuracy of vegetation signal detection across heterogeneous soil types. Additionally, employing SAVI facilitates methodological continuity with prior research, supporting temporal comparisons with historical data from 1990 to 2023. This choice is further substantiated by SAVI’s established application in remote sensing, allowing for straightforward implementation without the intricate calibration demands posed by MSAVI2.

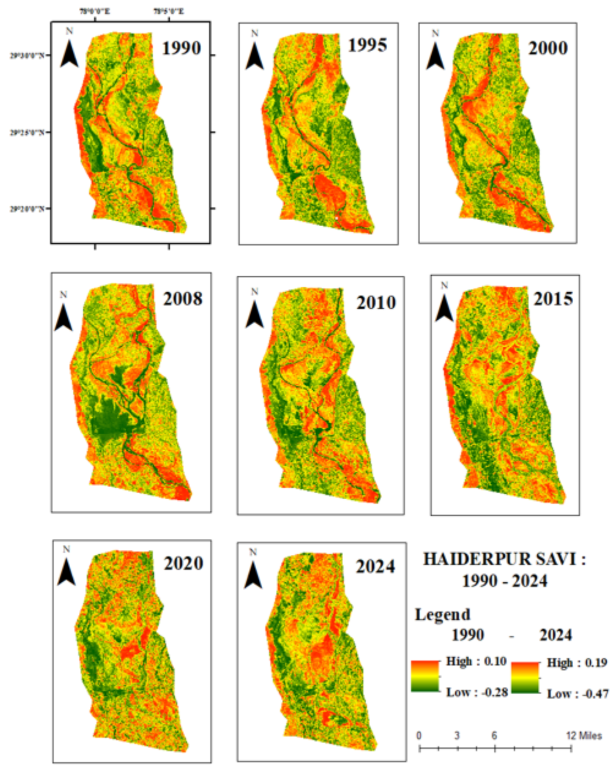

Figure 3. Soil Adjusted Vegetation Index (SAVI) for Haiderpur.

The Normalized Difference Vegetation Index (NDVI) maps for Haiderpur from 1990 to 2024 illustrate notable shifts in vegetation health and distribution over time. The green areas, denoting dense vegetation, show varying degrees of expansion and contraction, reflecting natural and anthropogenic influences on the landscape. The persistence of blue areas indicates stable water bodies, while the red swamps and yellow marshy lands point to significant transitions in wetland ecosystems. The increasing presence of vegetation areas over certain years suggests effective conservation efforts, yet the fluctuation in marshland and swamp areas signals a need for targeted management strategies.

The Normalized Difference Water Index (NDWI) maps for Haiderpur, spanning from 1990 to 2024, offer critical insights into the region’s hydrological dynamics and land cover changes. These maps reveal temporal fluctuations in moisture content,

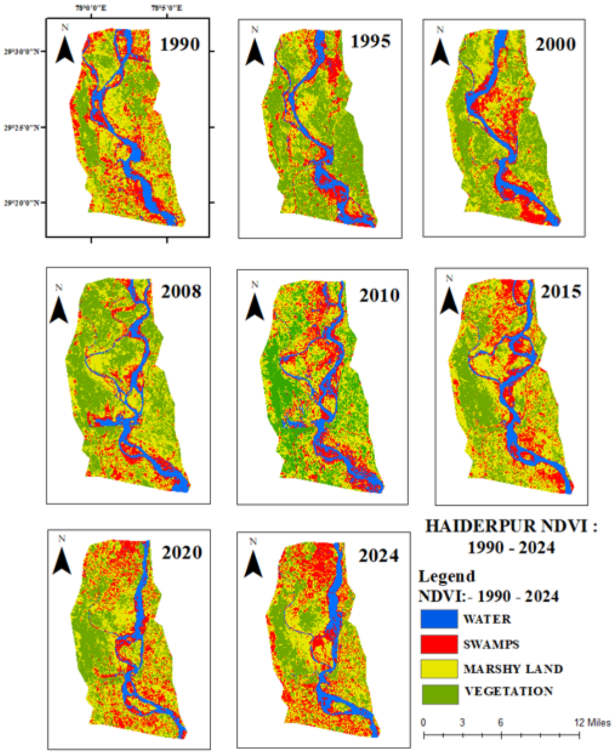

Figure 4. Normalized Difference Vegetation Index (NDVI) for Haiderpur.

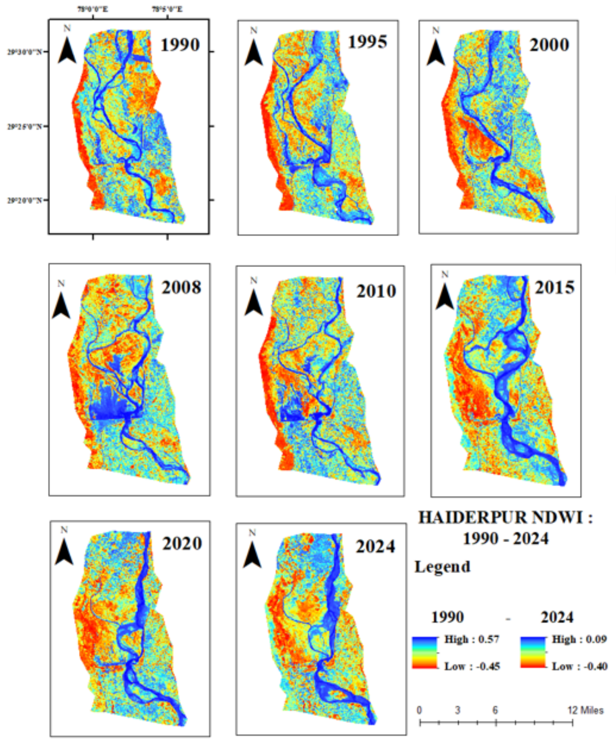

Figure 5. Normalized Difference Water Index (MNDWI) for Haiderpur.

with blue areas indicating high water levels and red areas showing low moisture content. Over the years, the shifting distribution of water bodies reflects both climatic influences and human activities impacting the landscape. Notable changes in water presence suggest variability in rainfall patterns and possible shifts due to water management practices. The persistence of red and orange zones signals challenges in soil and vegetation health, highlighting areas potentially affected by drought or intensified land use.

The Land Surface Temperature (LST) maps for Haiderpur from 1990 to 2024 provide a precise visualization of thermal changes across the region. Each panel highlights annual variations in surface temperature, using red to indicate higher temperatures often linked to urban expansion and green to denote cooler, vegetated areas. Over the years, the increasing prevalence of red zones suggests the intensification of the urban heat island effect, exacerbated by land cover changes like deforestation. The presence of green areas underscores the cooling influence of vegetation and water bodies.

5.0.1 Landuse Landcover and Future predictions: The study provides a comprehensive analysis of Land Use Land Cover (LULC) changes from 1990 to 2023, with predictions for 2025 and 2030. The temporal data indicates significant transformations across various land cover classes, including water bodies, built-up areas, agriculture, bare soil, swamp vegetation, and forested regions. Notably, there is a discernible increase in built-up areas over the observed period, suggesting ongoing urbanization. By contrast, agricultural areas, while expansive, exhibit fluctuations primarily influenced by environmental and anthropogenic factors. Predicted models for 2025 and 2030 suggest a continuation of these trends, with further expansion of built-up zones likely at the expense of natural areas such as forests and swamp vegetation. These predictive insights emphasize the urgent need for sustainable land management and urban planning strategies to mitigate adverse environmental impacts and maintain ecological balance. The study underscores the importance of leveraging historical LULC data to forecast future land cover dynamics and inform policy-making processes. This visual representation depicts the change detection in Haiderpur from 1990 to 2023, focusing on four key parameters: thermal radiance, fractional vegetation, urban heat island, and emissivity. The thermal radiance map indicates a gradient from severely high to least radiance, illustrating areas of potential heat accumulation. Notably, red and dark blue regions signify high thermal stress, which may correlate with increased urbanization.

The fractional vegetation map highlights changes in vegetative cover, with red areas indicating vegetation gain and green areas indicating loss. It suggests a mixed trend in plant cover, potentially influenced by urban expansion and agricultural activities. Monitoring these changes is crucial for assessing ecosystem health and biodiversity.

The urban heat island effect is mapped with a focus on heat index variations. Red areas point to regions with increased heat index, which may affect local climate and public health. This urban heat pattern emphasizes the importance of urban planning and green space allocation to mitigate adverse temperatures.

Finally, the emissivity map, in grayscale, serves to analyze surface properties affecting heat retention and dissipation. High emissivity areas, shown in lighter shades, may indicate surfaces with a higher capacity to release heat, which is essential for understanding urban materials’ role in temperature regulation. From 1990 to 2023, Haiderpur experienced a noticeable increase in the Urban Heat Island (UHI) effect, driven

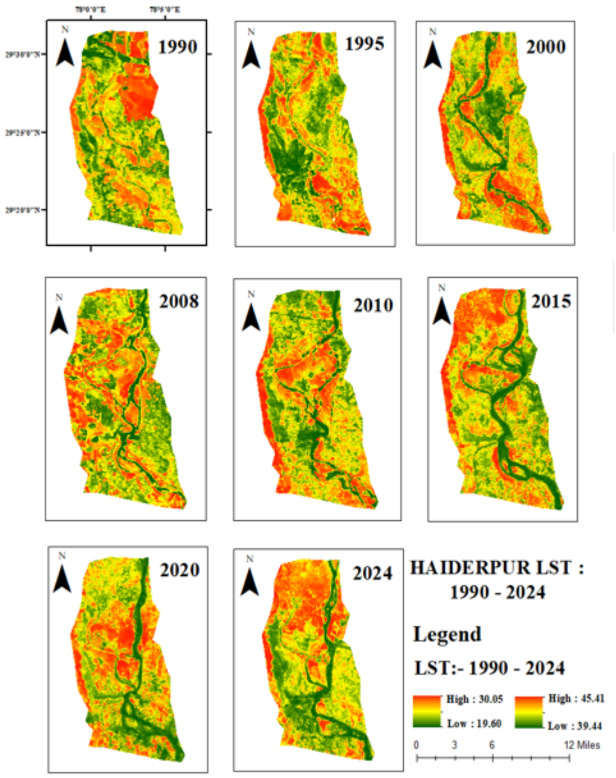

Figure 6. Land Surface Temperature (LST) for Haiderpur.

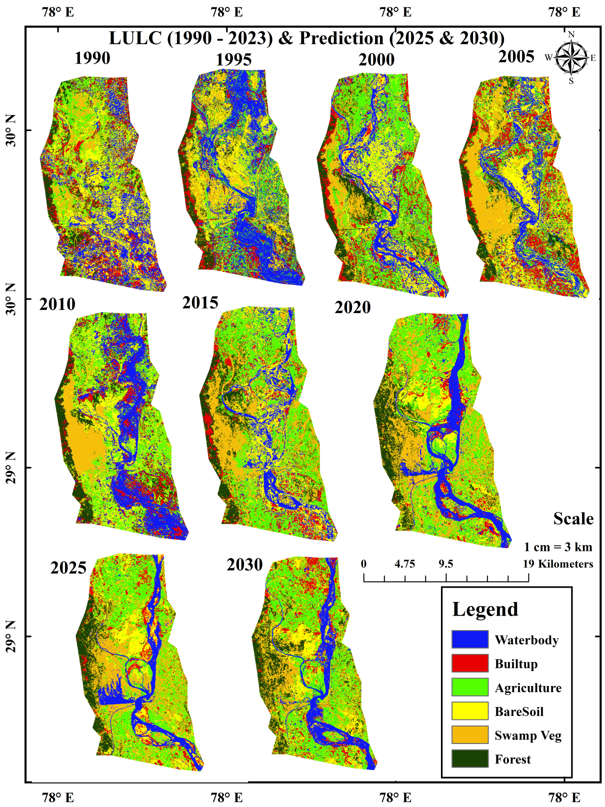

Figure 7. Land Use Land Cover (LULC) changes & Future prediction.

by expanding urbanization and reduced vegetation cover. The thermal radiance map highlights areas with high heat stress, corresponding to dense urban development. This intensification of UHI can lead to adverse environmental impacts, such as stress on local ecosystems and increased energy consumption for cooling. Meanwhile, the fractional vegetation map indicates a mixed pattern of vegetation gain and loss, underscoring the role of green spaces in mitigating UHI effects.

The graph depicts changes in land use and land cover (LULC) from 1990 to 2030 across six categories: Waterbody, Builtup, Agriculture, Barren Soil, Swamp Vegetation, and Forest. Over the years, significant shifts have been observed, particularly in the areas of agriculture and forests. Agriculture shows considerable growth, peaking in 2023, suggesting expansion due to increased farming activities. Forest areas also demonstrate fluctuations, indicating changes in reforestation or deforestation rates. Waterbody and built-up areas maintain relatively stable levels, indicating less dynamic changes, likely due to stable urban development and water conservation practices. The increase in Swamp Vegetation and fluctuations in Barren Soil highlight ecological and environmental interventions impacting these regions.

Key years such as 1995, 2005, and 2020 mark significant transitions, correlating with policy changes or environmental events. Projections for 2030 suggest potential stabilization or slight declines in some categories, reflecting adjustments in land management strategies. The comprehensive analysis of land use and land cover (LULC) changes in Haiderpur from 1990 to 2023 highlights significant transformations across various categories, notably in built-up areas and agricultural land. An upward trend in urbanization is evident, with built-up areas expanding at the expense of natural ecosystems, particularly forests and swamp vegetation. Predictions for 2025 and 2030 indicate a continuation of these trends for sustainable land management strategies to mitigate environmental impacts. Thermal radiance maps reveal heightened heat accumulation associated with urban areas, highlighting the intensity of the urban heat island (UHI) effect and stressing local ecosystems. The fractional vegetation index reflects mixed changes in vegetative cover, signaling the influence of urban expansion on ecosystem health.

6. Conclusion

In this study, we analyzed various factors influencing the thermal dynamics of the Haiderpur Wetland, focusing on Urban Heat Island (UHI) and Land Surface Temperature (LST) estimations using satellite datasets. The utilization of MODIS Terra and Aqua datasets proved essential due to their comprehensive coverage, providing global daily data at a 1 km resolution and capturing both daytime and nighttime temperature variations. These datasets enabled accurate monitoring of temperature fluctuations in the wetland area. The high-resolution Landsat-8 OLI/TIRS imagery significantly contributed to detailing the spatial patterns of thermal variation, thanks to its fine 30 m resolution. This resolution proved critical in optimizing assessments with other variables such as NDVI and emissivity.

The wetland, characterized by its unique ecological significance, displayed distinct NDVI values consistent with vegetative health, which remained positive throughout the year. Thermal data highlighted the impact of seasonal temperature variations affecting the wetland’s microclimate. Furthermore, integrating precipitation data from CHIRPS revealed patterns of declining annual precipitation, potentially exacerbating thermal stress and

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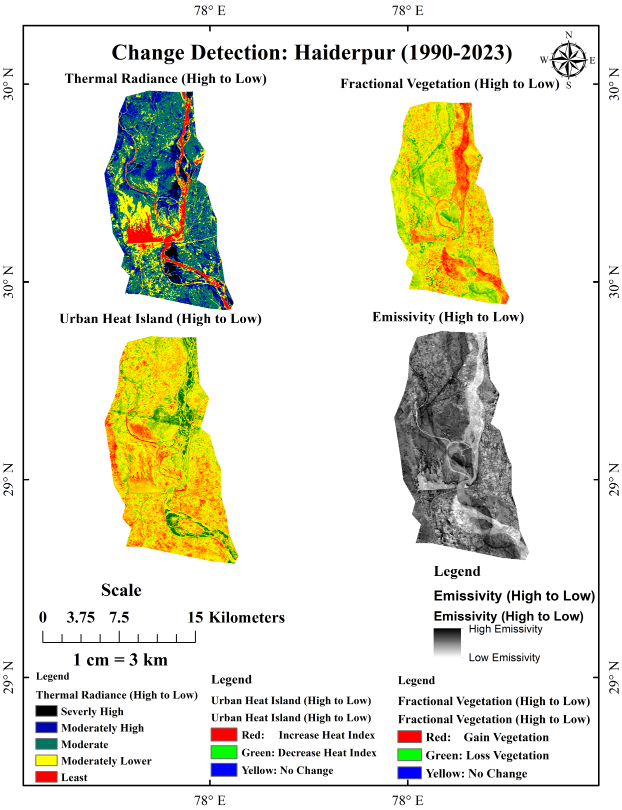

Figure 8. Haiderpur (fV, Thermal Radiance, Emissivity, UHI).

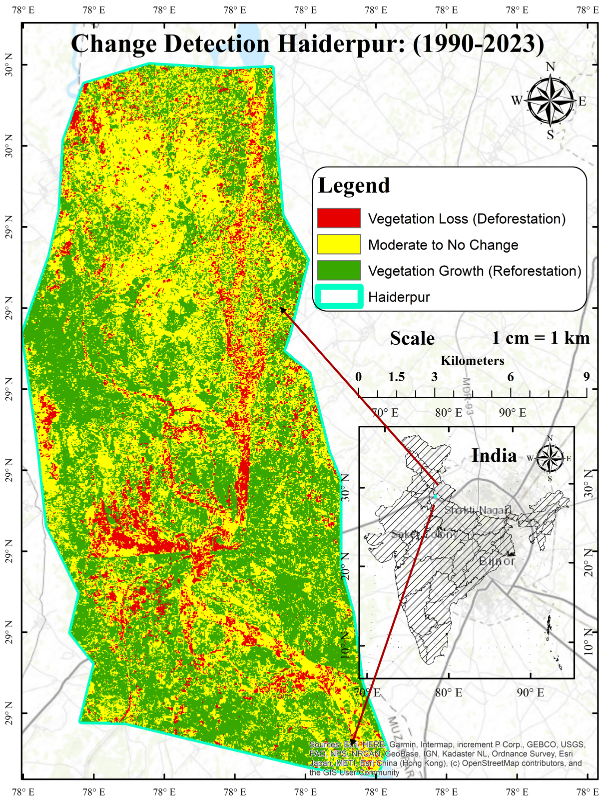

Figure 9. Haiderpur: Change Detection (1990-2023).

contributing to increased UHI and Surface Heat Island (SHI) effects. This is particularly pronounced during periods of extreme heat, where the absence of sufficient water and vegetation cover intensifies thermal conditions. Sentinel-1 (SAR) microwave imagery would be used to address thermal factors and cloud-cover factors in optical imagery.

In conclusion, understanding these dynamics emphasizes the need for targeted conservation strategies to mitigate rising temperatures and preserve the ecological integrity of the Haiderpur Wetland. Incorporating drought parameters in future analyses can further elucidate the environmental stressors impacting this critical habitat.

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