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Explainable artificial intelligence for climate change impact assessment using multi-temporal geospatial data

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Abstract

Climate change increasingly affects urban environmental systems through changes in Temperature, vegetation, water availability, and land-surface conditions. Previous studies have assessed individual or multiple climate hazards using remote sensing and machine learning; however, limited integration of compound climate impacts, fine-scale spatial assessment, temporal variability, and model interpretability remains a research gap. This study aimed to develop an integrated and explainable framework for assessing climate-change impacts in Lucknow. Landsat 8-9 Operational Land Imager (OLI)/ Thermal Infrared Sensor (TIRS) and ERA5-Land datasets were preprocessed and spatially harmonized, followed by climate-impact indicator extraction, multi-temporal feature engineering, Categorical Boosting (CatBoost)-based modelling, Climate Change Impact Index (CCII) development, SHapley Additive exPlanations (SHAP)-based interpretation, and spatio-temporal assessment. The framework assessed four dimensions: heat impact, vegetation stress, water stress, and land-surface change. The CatBoost model achieved Coefficient of Determination (R^2) values ranging from 0.89 to 0.94 and Root Mean Square Error (RMSE) values ranging from 0.044 to 0.056 across these dimensions. Overall, the proposed framework effectively integrated prediction, explainability, and spatial assessment, providing a comprehensive basis for climate-impact monitoring and supporting future applications with higher-resolution datasets and advanced spatio-temporal modelling approaches.

Keywords: CatBoost, Climate Change, Climate Change Impact Index, Remote Sensing, SHapley Additive exPlanations

Introduction

The effects of climate change are bringing changes in environmental circumstances with increased exposure of natural and human-made systems to various effects of climate change such as heat, drought, flood, water stress, deterioration of vegetation, and others ^[1]. These changes are heterogeneous in nature and differ greatly in terms of time; hence, their assessment relies heavily on data that can describe the changes geographically and temporally. Multi-temporal geospatial technologies have proven to be an excellent way of observing these changes by virtue of the use of satellite imagery, climatic data, land cover, and other types of spatial data ^[2, 3]. Data collected over different times makes it possible to analyze environmental changes related to climate change. However, there are difficulties associated with analyzing multitemporal geospatial data due to its voluminous nature and characteristics ^[4-6].

Artificial Intelligence (AI), machine learning, and Geospatial Artificial Intelligence (GeoAI) have been increasingly utilized for evaluating complex interactions of climatic and environmental phenomena, hazards, the impact of drought, flood vulnerability, land use, and climate adaptation ^[7, 8]. Various works have utilized Light Gradient Boosting Machine (LightGBM), Extreme Gradient Boosting (XGBoost), Random Forest (RF), and Analytical Hierarchy Process (AHP) for spatial risk assessment; Explainable Artificial Intelligence (XAI) methods like SHAP have been used for assessing contributions of individual features to model results ^[9]. However, the existing approaches do not address compound and synergetic effects of climate-based hazards. Fine-scale assessments as well as socioeconomic vulnerability have not been sufficiently addressed ^[10]. In addition to that, the use of certain

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time windows as well as geographically confined case studies limited the evaluation of temporal dynamics and the general applicability of models developed [11]. It is thus evident that there is a need of framework allowing temporal geospatial data to be combined with prediction and interpretability.

To overcome these limitations, this research suggests an explainable AI framework for assessing the impact of climate change at multiple temporal scales in Lucknow based on the integration of geospatial and climate data. Landsat 8-9 OLI/TIRS and ERA5-Land data were combined to construct four dimensions of climate-impact effects, namely heat effect, vegetation stress, water stress, and land surface changes. Temporal feature engineering was done to extract anomaly, trend, variability, and historical-to-recent change information from the dataset, and CatBoost was used to model the association of features with the outcome of climate-impact effects. SHAP further enables the interpretation of feature importance and identification of factors influencing the prediction results.

The novelty of the study is the combination of multi-temporal geospatial data analysis, climate impact indicator extraction, temporal feature engineering, CatBoost machine learning algorithm application, CCII construction, and SHAP explainability technique within one climate change impact assessment model. The purpose of this study is the assessment of climate impacts during different time periods, estimation of their spatial and temporal dynamics, identification of influential climatic and environmental factors, and providing explainable climate impact predictions. The key contributions of this study are:

- Proposed an explainable AI-based approach for assessing impacts of climate change through multiple time periods in Lucknow using geospatial and climatic data.
- Utilized Landsat 8-9 OLI/TIRS and ERA5-Land datasets to create indicators of heat impact, vegetation stress, water stress, and land-surface changes.
- Calculated indicators for anomalies, trends, variabilities, and change from historic to recent periods.
- Proposed CatBoost-based approach with CCII and SHAP-based explainability for identifying factors affecting climate impact predictions.

The remainder of this research is structured as follows. Section 2 reviews related studies. Section 3 exhibits the methodology and proposed framework. Section 4 discusses the results, and Section 5 concludes the paper and outlines future research.

Literature Review

This section reviews and summarizes previous studies related to climate-change impact assessment, multi-temporal geospatial analysis, machine learning-based modelling, and XAI for environmental assessment.

Singh *et al.* (2026) [12] introduced LightGBM with SHAP to assess Delhi's multi-hazard risk using 22 predictors. The model achieved R^2 of 0.98 and Mean Absolute Error (MAE) of 0.01 across spatial validation folds, demonstrating predictive performance for regional multi-hazard assessment and risk characterization.

Yao *et al.* (2026) [13] developed XGBoost with SHAP to assess multi-hazard risk and land-use effects in Ningbo. Results showed that green/forest land dominated risk

patterns, while built-up and green/forest land thresholds were identified at 20.0% and 2.0%, respectively, region-wide.

Bovkir (2026) [14] employed GeoAI with SHAP to assess climate adaptation needs across 1, 187 European regions. The Climate Change Adaptation Index (CCAI) used 44 indicators and identified heat stress, precipitation, and renewable energy as important contributors to regional adaptation needs.

Chauhan and Ngangom (2026) [15] applied an AHP-based geospatial approach to assess four climate-induced hazards in Ladakh. The resulting maps achieved accuracies of 75%, 80%, 88%, and 90% for floods, landslides, snow avalanches, and droughts, respectively, overall.

Hrast Essenfelder *et al.* (2025) [16] introduced an expert-driven XAI model using XGBoost to detect agricultural climate hazards. The model provided hazard detection, uncertainty estimation, and drivers, supporting risk management and adaptation through understanding of climate extremes.

Sanderson *et al.* (2023) [17] developed XFIMNet, an explainable encoder-decoder model using multispectral and Synthetic Aperture Radar (SAR) imagery for flood mapping. The model achieved Intersection over Union (IoU) values of 0.5862 and 0.7031 using Sentinel-1 and Sentinel-2 imagery, respectively, demonstrating flood detection.

Zhang *et al.* (2023) [18] utilized an explainable XGBoost-SHAP pipeline to predict drought impacts and interpret climatic drivers. The model achieved F2 scores of 0.883 nationally and 0.942 at the state level, providing interpretable insights into climatic factors influencing drought impacts.

Zhang *et al.* (2023) [19] employed ML models, including RF, to assess multi-hazard risk and social vulnerability in Idaho. RF performed best across hazard and vulnerability datasets, while 15.88% of cities were classified as high-risk multi-hazard and vulnerable.

Research Gaps

Although current literature has shown some advances in the field of multi-hazard assessment, there are still many drawbacks that should be addressed. Current research has shown many cases of single or multiple hazard assessment without taking into account their compounding and synergies effects, thus not enabling proper risk characterization [12, 16, 19]. In most of the cases, regional-scale assessment was carried out, and fine-resolution spatial analysis as well as socioeconomic vulnerability were not taken into account properly [13, 15, 17]. There are also problems with uncertainty calibration and temporal generalization since many studies are conducted under specific conditions [15, 16].

Research Methodology

This section provides an overview of the study area, data sources, techniques, and proposed research framework used in the study.

Study Area

The experiment was performed in Lucknow, Uttar Pradesh, India, which is situated at around 26°51' N latitude and 80°57' E longitude, with an elevation of around 123 m above mean sea level and an area covering approximately

350 km². The climate of the city is humid subtropical with precipitation of about 1,000 mm per year. The mentioned features make Lucknow appropriate for studying the variability of heat effect, vegetation stress, water stress, and

land surface changes with multi-temporal geospatial data. The geographical location of Lucknow, Uttar Pradesh, India is depicted in Figure 1.

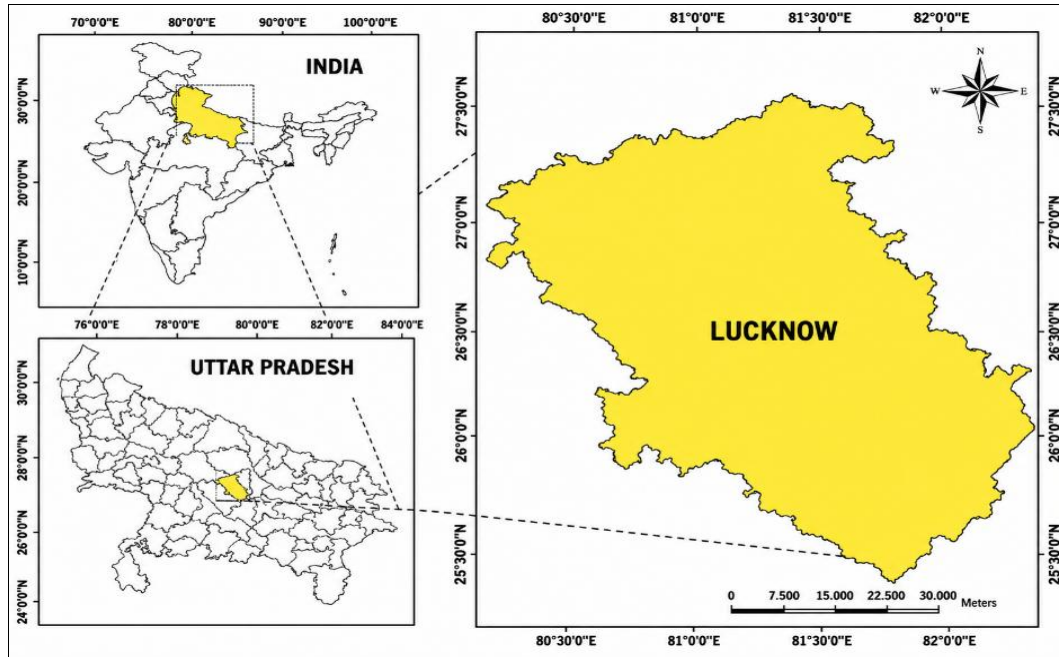


Fig 1: Study area and spatial analysis grid of Lucknow [20]

Data Collection

Primary and secondary sources were used in the study to assess the impact of climate change on Lucknow through multiple periods. Primary sources consisted of the spatial boundary of Lucknow, whereas secondary sources were Landsat 8-9 OLI/TIRS Collection 2 Level 2 images and ERA5-Land climate data.

Primary Data

The primary data consisted of the Lucknow spatial boundary data obtained from the Lucknow Remote Sensing Application Centre (LRSAC). The boundary was used to delineate the study area and provide a common spatial framework for integrating the multi-temporal datasets.

Secondary Data

Landsat 8-9 OLI/TIRS

The satellite images were obtained from EarthExplorer, which is a US Geological Survey (USGS) portal. The Landsat 8 and Landsat 9 images provide surface reflectance and land surface temperature data at 30-meter spatial resolution. The data have been utilized to obtain indicators of heat impact, vegetation stress, water stress, and land-surface change. The Landsat 8 images are available since 2013, whereas Landsat 9 images are available since 2022 [21].

ERA5-Land

The ERA5-Land data [22] were sourced from the Copernicus Climate Data Store. This dataset has climate and land surface variables such as Temperature, precipitation, and soil water data dating back from 1950 onwards. The dataset has a spatial resolution of about 9 kilometers. The variables were used as climate predictors for further analysis.

Techniques Used

This section presents the CatBoost, CCIL, and SHAP techniques used for climate impact modelling and interpretation.

CatBoost

CatBoost is a gradient-boosting machine learning technique that establishes the relation between multi-temporal climatic, remote-sensing, geospatial, and temporal variables and climatic impact outcomes [23]. CatBoost constructs an ensemble of decision trees such that each tree constructed minimizes the prediction error of the ensemble constructed previously. The general form of the prediction function is given by:

$$\hat{y}_i = \sum_{k=1}^K f_k(x_i), \quad f_k \in \mathcal{F} \quad (1)$$

Where $\hat{y}_i$ represents the predicted climate-impact value for observation i , x_i represents the input features, K denotes the number of boosting iterations, and f_k represents the k^{th} decision tree.

The objective function is expressed as:

$$\mathcal{L} = \sum_{i=1}^n l(y_i, \hat{y}_i) + \sum_{k=1}^K \Omega(f_k) \quad (2)$$

Where $l(y_i, \hat{y}_i)$ represents the prediction loss, and $\Omega(f_k)$ controls the complexity of the individual trees.

In this study, CatBoost models the relationships between multi-temporal input features and the four climate-impact dimensions: heat impact, vegetation stress, water stress, and land-surface change.

Climate Change Impact Index

The CCII is developed by integrating the four standardized climate-impact dimensions: heat impact, vegetation stress, water stress, and land-surface change. The index provides an overall measure of climate-impact intensity for different spatial and temporal units. It is calculated as:

$$CCII_i = \frac{H_i + V_i + W_i + S_i}{4} \quad (3)$$

Where $CCII_i$ represents the Climate Change Impact Index for observation i , while H_i , V_i , W_i , and S_i represent the standardized heat impact, vegetation stress, water stress, and land-surface change values, respectively.

SHAP

SHAP is an XAI technique that interprets CatBoost predictions by quantifying the contribution of individual input features to each prediction. The SHAP explanation is expressed as:

$$f(x) = \phi_0 + \sum_{j=1}^M \phi_j \quad (4)$$

Where $f(x)$ denotes the model prediction, ϕ_0 denotes the expected model output, M stands for the number of input features, and ϕ_j characterizes the contribution of feature j .

The SHAP value for feature j is formulated as:

$$\phi_j = \sum_{S \subseteq N \setminus \{j\}} \frac{|S|!(M-|S|-1)!}{M!} [f(S \cup \{j\}) - f(S)] \quad (5)$$

Where S symbolizes a subset of features, N denotes the complete set of features, and $f(S)$ signifies the model prediction using the features in subset S .

In this study, SHAP identifies the relative importance and positive or negative contribution of climate, remote-sensing, geospatial, and temporal features to the climate-impact predictions.

Proposed Methodology

The proposed methodology begins with study area selection and the acquisition of multi-temporal geospatial datasets for Lucknow. The complete process flowchart of the methodological framework is depicted in Figure 2 through the methodology architecture. The acquired datasets are preprocessed and harmonized spatially, which involves processing for handling missing values, noise elimination, and spatiotemporal normalization. Climate impact indicators are calculated for heat impact, vegetation stress, water stress, and land surface changes. At the same time, multi-temporal feature engineering is done to extract the anomaly, trend, variation, and change features. These features are utilized in climate impact modeling using the CatBoost algorithm, and then all four dimensions of the impact are combined to formulate the CCII. Feature contribution interpretation is performed through SHAP, followed by spatiotemporal climate impact assessment to discover climate impact patterns and changing factors.

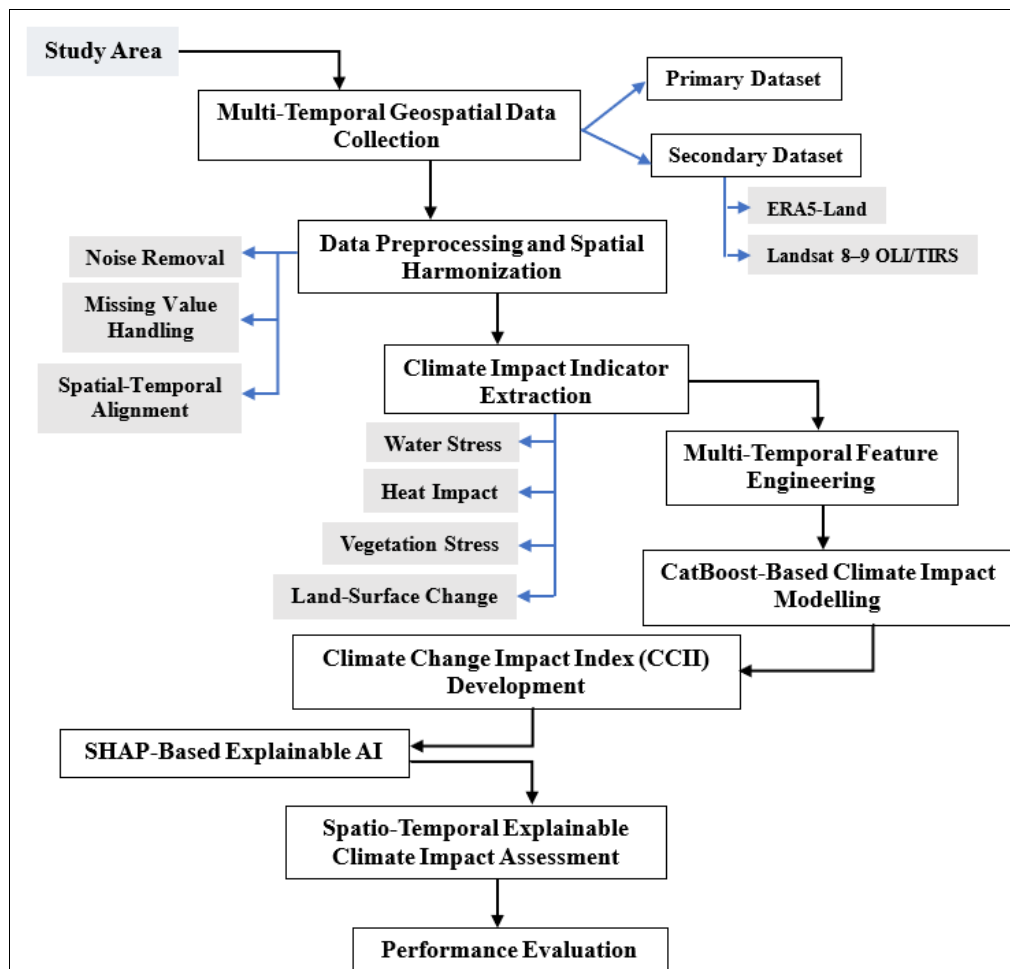


Fig 2: Proposed methodology

Pseudo code

Input:

B ← Lucknow spatial boundary

L ← Multi-temporal Landsat 8-9 data

E ← Multi-temporal ERA5-Land data

Output:

CCII maps

SHAP-based impact drivers

 R^2 , MAE, RMSE, Mean Absolute Percentage Error (MAPE)

1. Load B, L, and E

2. Clip L and E using B

3. For each time period t do

4. Handle missing observations in L and E

5. Remove noise from the datasets

6. Harmonize spatial and temporal dimensions

8. Extract:

H_t ← Heat-impact indicatorsV_t ← Vegetation-stress indicatorsW_t ← Water-stress indicatorsS_t ← Land-surface-change indicators

10. Calculate temporal features:

A_t ← AnomalyT_t ← TrendVary_t ← VariabilityC_t ← Historical-to-recent change

11. End For

12. Construct feature matrix X from:

Climate features

Remote-sensing features

Geospatial features

Temporal features

13. Construct target matrix Y from:

H, V, W, S

14. Divide X and Y chronologically into:

Training set

Validation set

Test set

15. Train CatBoost model M on the training set

16. Tune M using the validation set

17. Predict:

 $\hat{Y} \leftarrow M(X_{\text{test}})$

18. For each spatial-temporal unit i do

19. Standardize H_i, V_i, W_i, S_i

20. Calculate:

CCII_i = Aggregate(H_i, V_i, W_i, S_i)

21. End For

22. Calculate SHAP values:

 $\Phi \leftarrow \text{SHAP}(M, X_{\text{test}})$

23. For each time period t do

24. Generate CCII spatial map

25. Generate SHAP contribution map

26. Identify dominant impact dimension

27. Identify dominant climate-impact drivers

28. End For

29. Calculate model performance:

 $R^2 \leftarrow R^2(Y_{\text{test}}, \hat{Y})$ MAE ← MAE(Y_{test} , $\hat{Y}$)RMSE ← RMSE(Y_{test} , $\hat{Y}$)MAPE ← MAPE(Y_{test} , $\hat{Y}$)

30. Return CCII maps, SHAP results, dominant drivers, and performance metrics

End

Results and Analysis

In this section, the findings of the climate-change impact assessment framework proposed for Lucknow are presented. The CatBoost model was configured with the following hyperparameters: 500 iterations, a learning rate of 0.05, a tree depth of 6, and a random seed of 42. The proposed model was evaluated using the following metrics:

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (6)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (7)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (8)$$

$$MAPE = \frac{100}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \quad (9)$$

Where y_i represents the actual climate-impact value for the i -th observation, $\hat{y}_i$ represents the corresponding predicted value obtained from the CatBoost model, $\bar{y}$ denotes the mean of the actual values, n represents the total number of observations, and i denotes the index of each observation, ranging from 1 to n .

The framework uses the Lucknow spatial boundary dataset as primary data and Landsat 8-9 OLI/TIRS satellite imagery and ERA5-Land climate datasets as secondary datasets. The acquired data were preprocessed through missing-value treatment, noise reduction, cloud-contaminated observation processing, and spatio-temporal harmonization.

Once the preprocessing and spatial-temporal alignment of the collected datasets were completed, the four climate impact indices were calculated as measures of the main aspects of environmental changes associated with the climate of Lucknow. These four climate impact indices are the annual values of the Heat Impact Index, Vegetation Stress Index, Water Stress Index, and Land-Surface Change Index. The annual variations of these four indices over the study period are presented in Table 1. They exhibit an increasing trend over time throughout the entire study period.

Table 1: Multi-temporal climate-impact indicators

Year	Heat Impact Index	Vegetation Stress Index	Water Stress Index	Land-Surface Change Index
2013	0.42	0.35	0.38	0.29
2014	0.45	0.37	0.41	0.31
2015	0.48	0.40	0.44	0.34
2016	0.51	0.43	0.47	0.36
2017	0.49	0.45	0.46	0.39
2018	0.55	0.48	0.50	0.42
2019	0.58	0.52	0.54	0.45
2020	0.56	0.55	0.52	0.47
2021	0.61	0.58	0.57	0.51
2022	0.65	0.61	0.60	0.54
2023	0.68	0.64	0.63	0.57
2024	0.72	0.67	0.66	0.60

Based on the indicators related to the impact of climate on the environment, multi-temporal features were derived in order to represent their behavior in time over the entire study period. Figure 3 illustrates the changes in anomaly, trend, variability, and historical to recent change from 2013

to 2024. The anomaly feature changed from 0.07 to 0.20, whereas the trend changed from 0.05 to 0.14 and variability changed from 0.01 to 0.05. The most significant change was observed in the historical to recent change feature, which changed from 0.08 in 2013 to 0.42 in 2024.

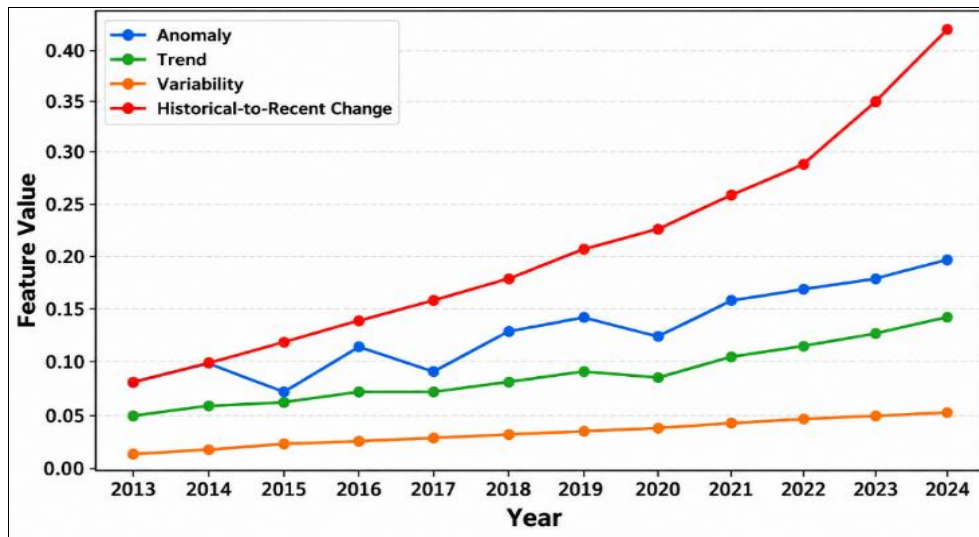


Fig 3: Multi-temporal feature variations

Based on the characteristics of multiple time frames, the performance of the CatBoost model is presented based on the comparison of the actual values with the predicted values of the four climate impact dimensions. Figure 4 demonstrates a high level of agreement between the actual values and the predicted values during the entire study

period, as the value of Heat Impact grows from 0.36 to 0.73 in the actual values and from 0.34 to 0.70 in the predicted values. The Vegetation Stress dimension increases from 0.31 to 0.62 and from 0.30 to 0.60 correspondingly, while the Water Stress dimension increases from 0.39 to 0.56 and from 0.38 to 0.55 correspondingly.

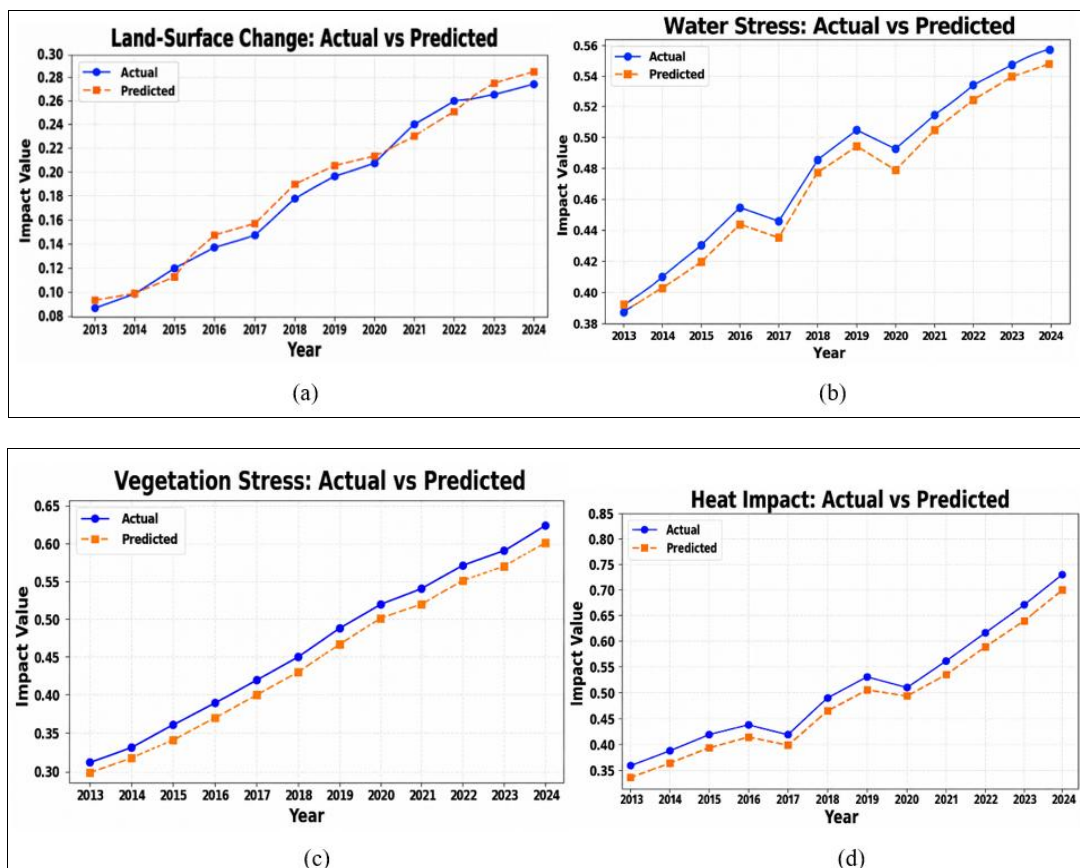


Fig 4: Actual and predicted climate-impact values: (a) Land-Surface Change, (b) Water Stress, (c) Vegetation Stress, and (d) Heat Impact.

The analysis of the CCII index from the point of view of the CatBoost modeling results demonstrated a positive trend for this parameter throughout the study period. As can be seen

in Figure 5, the CCII index rose from 0.35 in 2013 to 0.66 in 2024, with a stable value of 0.44 from 2016 to 2017 and 0.52 from 2019 to 2020 and then rose to 0.66 in 2024.

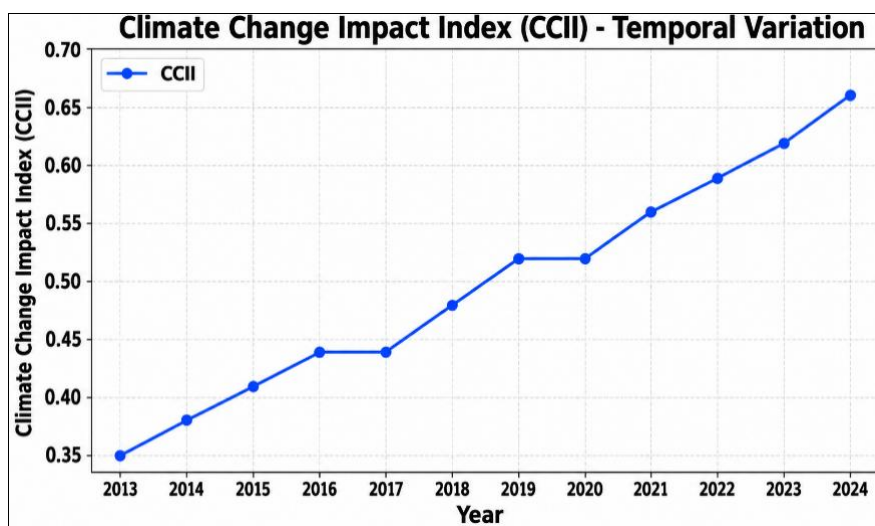


Fig 5: Temporal variation of the CCII

Based on the CCII findings, SHAP analysis was carried out for the interpretation of the contributions of the input features to the CatBoost model. According to Figure 6, the SHAP value of Temperature was found to be broadly distributed between -0.20 and 0.14 , whereas that of Precipitation and Vegetation Index were broadly distributed

between -0.18 and 0.22 , and -0.16 and 0.21 , respectively. On the other hand, the values for Soil Moisture were found to be broadly distributed between -0.15 and 0.12 , whereas those for Humidity and Land Surface Temperature had comparatively smaller ranges. Elevation and Historical Change had the lowest SHAP value ranges.

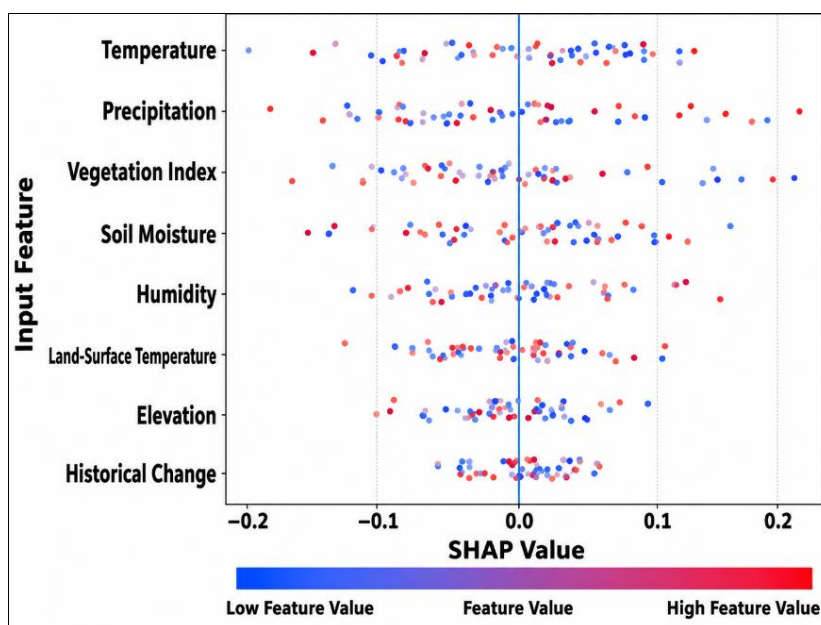


Fig 6: SHAP summary of feature contributions

Using the interpretative analysis of SHAP, the spatial pattern of CCII was analysed in the established spatial grid. As can be seen in Figure 7, the CCII ranged from 0.31 to 0.66, where the minimum CCII was 0.31 in Grid Row 4,

Column 0, whereas the maximum value was 0.66 in Grid Row 0, Column 3. The high CCII was clustered in the upper-right portion of the grid, whereas low CCII was found in the lower-left portion of the grid.

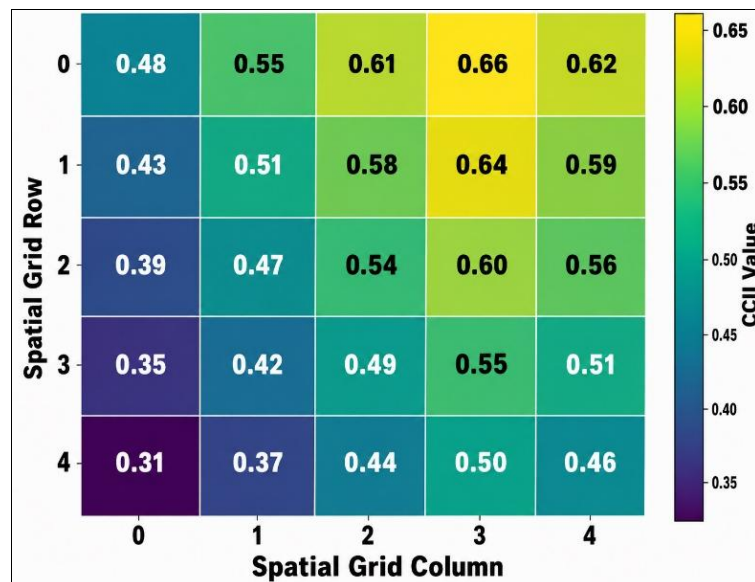


Fig 7: Spatial distribution of the CCII

Building on the spatio-temporal assessment, the final CatBoost model was evaluated using the performance measures presented in sTable 2. The table summarizes the R^2 , MAE, RMSE, and MAPE values for the four climate-impact dimensions and provides an overall assessment of model performance.

Table 2: Performance analysis

Climate Impact Dimension	R^2	MAE	RMSE	MAPE (%)
Heat Impact	0.94	0.031	0.044	5.82
Vegetation Stress	0.92	0.034	0.048	6.47
Water Stress	0.91	0.037	0.051	7.13
Land-Surface Change	0.89	0.041	0.056	7.86

Discussion

The results demonstrate that the proposed framework effectively captured the multi-dimensional and spatio-temporal characteristics of climate impacts in Lucknow. The four climate impact indicators displayed increasing trends throughout the analysis time period, while multi-temporal feature engineering allowed capturing temporal variations, trends, variability, and historical-to-current changes. The obtained results of the CatBoost algorithm model display a good correspondence between real and predicted data concerning Heat Impact, Vegetation Stress, Water Stress, and Land Surface Change. The constructed CCII has increased from 0.35 in 2013 to 0.66 in 2024, while its spatial values have varied from 0.31 to 0.66, meaning that there is heterogeneity of the climate impact intensity within the studied territory. The SHAP analysis showed Temperature, Precipitation, and Vegetation Index as the relatively significant features, both with positive and negative contributions in the model predictions. Additionally, the model revealed a high prediction capacity, with R^2 varying from 0.89 to 0.94, MAE of 0.031 to 0.041, RMSE of 0.044 to 0.056, and MAPE of 5.82% to 7.86%. Overall, these findings indicate that the suggested framework provides a consistent approach for modelling, integrating, interpreting, and assessing climate-change impacts across spatial and temporal dimensions.

Conclusion and Future Scope

Climate change is increasingly affecting urban and environmental systems through changes in Temperature, vegetation, water availability, and land-surface conditions. Previous studies have examined individual climate indicators using remote sensing and machine learning; however, limited integration of multi-temporal indicators, explainable modelling, and spatial assessment remains a key gap. This study aimed to develop an integrated and interpretable framework for assessing climate-change impacts in Lucknow. Multi-temporal Landsat 8-9 OLI/TIRS and ERA5-Land data were processed and harmonized, followed by climate-impact indicator extraction, multi-temporal feature engineering, CatBoost modelling, CCII development, and SHAP-based interpretation. The CatBoost model achieved R^2 values ranging from 0.89 to 0.94 and RMSE values ranging from 0.044 to 0.056, demonstrating strong predictive performance across the four climate-impact dimensions. Future research can extend the framework using higher-resolution datasets, additional climate indicators, and advanced spatio-temporal modelling approaches.

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