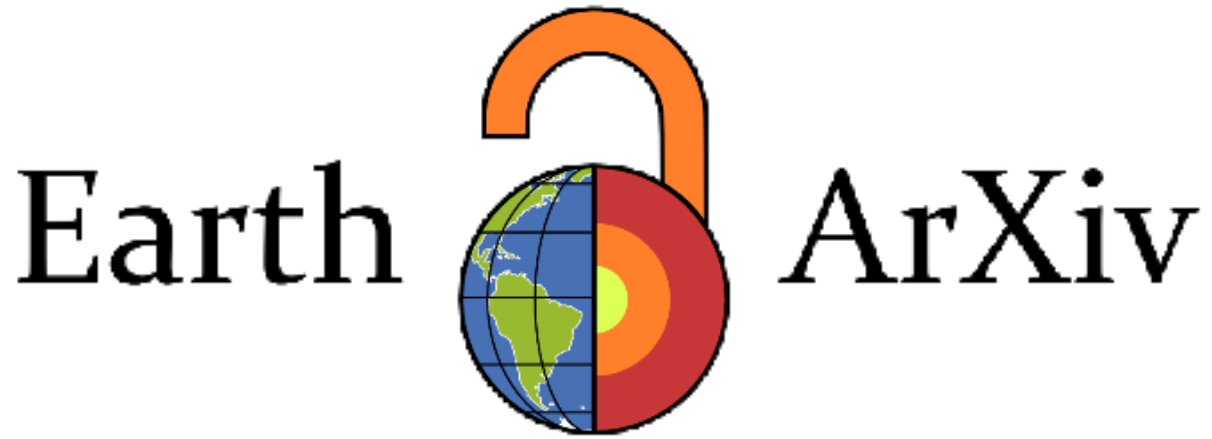




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Understanding Spatiotemporal Dynamics of Urban Water
Bodies via Multi-Classifer Machine Learning Approaches
in Semi-Arid Ahmedabad City

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ABSTRACT

The research examines the spatiotemporal change of water bodies in Ahmedabad city in western part of India which is a rapidly urbanizing area. It integrates high-resolution remote sensing data with modern machine learning approaches. Understanding the long-term pattern is crucial to understanding and managing the water resources in the changing climate, also city experiences the low precipitation with long summer months that makes managing water resources more challenging. The study utilizes the Landsat-8 imagery from 2013 to 2024 to indices that highlights the water signatures. Normalized Difference Water Index (NDWI) and Modified Normalized Difference Water Index (MNDWI) are computed using green, near infrared and mid-infrared Landsat bands. Machine learning classifier algorithms are used to identify the water area and non-water area pixel. The selected algorithms are classification and regression trees (CART), minimum distance (MD), naïve bias (NB) and random forest (RF) for that training data points are collected with visual inspection of available satellite images and manual in-situ inspection. Train and testing data is split in 80-20 to train and validate the classification of water area. A time series are generated for 12 years in both monthly and yearly scale. The primary objective is to assess the water area changes across the past decade, changing water area due to the anthropogenic impacts and climatic factors effect on it due to abrupt changing climate. Furthermore, the study attempted to provide a systematic approach to analysis the water area changes and patter identification that will be useful for policy making on water resource management for the city. The study demonstrates the essential requirement for data-driven governance of water resources, providing insights into sustainable urban development and environmental conservation strategies aligned with Sustainable Development Goals (SDGs) 6 and 11, which focus on clean water and urban sustainability. Based on the analysis of the water area time series a slight upward trend is evident with both yearly and monthly tread with Mann-Kendall test across all the classifiers. Temperature has significantly driver of water change and precipitation has low impact in the long-term water area change. CART and Naïve Bayes showed better performance, with CART being linearly sensitive to temperature and others exhibiting non-linear precipitation dependencies. The deployed machine learning models underscoring the effectiveness of combining remote sensing with machine learning. The research enhances hydrological monitoring and ongoing environmental evaluations by adeptly combining traditional remote sensing methods with modern computational methodologies.

1 Introduction

India's arid regions are experiencing significant challenges associated with water resources management, with climate change and anthropogenic activities progressively influencing water body dynamics¹⁻³. This study explores the spatiotemporal changes in water body areas in the west part of Indian arid region from 2013 to 2024, giving an essential understanding of sustainable water resource management in these sensitive ecosystems. The arid zones of India occupy a large amount of the country's geographical location, covering around 38.7 million hectares, with 31.7 million hectares under hot arid conditions Goyal et al.⁴ and predominantly distributed across northwestern India (28.57 million hectares), covering western Rajasthan (19.6 million hectares, 69%), northwestern Gujarat (6.22 million hectares, 21%), and southwestern regions of Haryana and Punjab (2.75 million hectares, 10%)⁴. The arid region in India characterized by low rainfall (varying from <100 mm to 500 mm yearly) along with high evapotranspiration rates, increased temperatures and experience substantial water stress⁵. The surface water resources in India's arid regions are under stress due to lake of replenishment and irregular monsoon pattern⁶⁻⁸. The major loss of the limited rainwater is primarily caused by high atmosphere temperatures and low humidity in the environment places^{9,10}. Based on the hydrological characteristics, the arid zones of can be categorized into three zones, Zone I: regions with major input of surface water from more humid areas, zone II: apparent lands with absent stream networks, and zone

III: apparent lands with primitive or absent stream networks¹¹. Climate change possesses greater threat primarily in arid and semi-arid regions with increased frequency of drought and dry spells^{12–14}. According to The Intergovernmental Panel on Climate Change (IPCC) arid and semi-arid regions which constitute 40% of the world's land surface, is particularly sensitive to climate change consequences¹⁵. The global climate change, along with land use modifications and land cover changes, is projected to accelerate the decrease in water availability and biological productivity in drylands¹⁵. Ramachandran et al. (2015)⁷ conducted a study east coast of South India using the De Martonne Aridity Index reveals an increase in aridity toward the end of the 21st century and this growth is related primarily to increased mean annual temperatures. The research found that the locations previously identified as having a semidry climate (with index values ranging from 13.7 to 16.4 mm/°C) can anticipate substantial drying trends under climate change scenarios⁷. Remote sensing techniques have been found invaluable in detecting and monitoring water bodies by utilizing satellite imagery to identify water bodies based on their spectral signatures^{16–19}. The remote sensing-based approach enabled researchers to map surface water bodies in regions like western India and notice changes over time⁴. In the last decade, Government of India (GOI) initiated substantial measures to address prolonged water shortages and water stressed conditions in the arid regions, such as *Jal Shakti Abhiyan: Catch the Rain (JSA:CTR)*, helped to establish network of water conservation structures²⁰. Additionally, GOI launched the program to map the aquifer and to promote sustainable management of groundwater resources under National Aquifer Mapping and Management Program (NAQUIM) and the total mappable is reached to 2.5 million km²²⁰.

Even with the several initiatives by Government of India and growing concern over water resources in arid regions, there remains a gap in a comprehensive study determining the changes in water body areas across Indian arid and semi-arid regions during the past decade^{21–23}. The study conducted in the previous study often focused on shorter time period that are insufficient to provide the long-term pattern and understand of water area change. As the change in long term aridity index with the past decade in the many regions indicates these regions required continuous monitoring²⁴. Due to climate fluctuations and inadequate soil and water management practices semiarid regions of India have been experiencing increased water scarcity^{25,26}. As India still primarily an agriculturally based economy and water is progressively becoming a critical limiting factor for ecosystem functioning especially in agriculture and industrial production^{27,28}.

The study address the research gap by assessing the water body area change throughout the city of Indian arid city of Ahmedabad from the time period from 2013 to 2024. Employed the multi classifier approach that works better in the heterogeneous land use of urban landscape. Long term spatio-temporal satellite imagery data is used to classify the study area in two classes of water and non-water area. The classification is performed on both yearly and monthly dataset obtained from Landsat-8 program. To understand the dynamics of water area change a rigorous statistical and time series analysis techniques are employed. Stationarity, seasonality and randomness are assessed to understand the modelability and prediction of future water area change. Further the study discussed the implications of climatic variable and climate extreme impacts of water area. Ensemble model-based approaches are explored to identify the best classifier and climate variation that can help to predict the water area change dynamics. The outcomes of this study will be beneficial to enhance our understanding of how water resources in arid regions are responding to climate change and human interventions and will influence methods for sustainable water management in these vulnerable environments. The study intends to understand that with the continuous urbanization and changing climate impacted the water body area in the Ahmedabad city, the approaches explored here provide the blueprint to examine the time series for arid area that will be useful for the further modelling and development of water conservation scheme by water resource managers. Key questions motivating this study include: What is the rate of water body loss or gain in Ahmedabad? How do urbanization and policy gaps contribute to these changes? Which ML algorithm operates better for water body classification in this context?

The study is structured as follows: Section 1 (Introduction) outlines the novelty, objectives, and practical significance of the research. Section 2 (Study Area and Data) describes the geographical scope of the investigation, the spatial extent of the study region, and the datasets employed, including their sources and key characteristics. Section 3 (Methodology) presents the analytical framework, detailing the statistical tests, computational tools, and procedures used for data processing. Section 4 (Data Analysis and Results) synthesizes the core findings derived from the analysis. Section 5 (Discussion) interprets the outcomes within the broader context of Water Area Dynamics, addressing implications, limitations, and linkages to existing research. Finally, Section 6 (Conclusion and Future Perspectives) concludes the study by highlighting key takeaways, broader implications, and future research directions to advance the field.

2 Study Area and Data

Ahmedabad city is chosen as an investigation location, the region belonging to a semi-arid climate, and the Koppen Geiger climate zone²⁹ is *BS/h*, commonly found in the tropics and subtropics. It becomes hot summers, warm to cool winters, and receives uncertain precipitation and the average elevation is 53m (Figure 1). The precipitation data is obtained from CHIRPS Daily (Climate Hazards Center InfraRed Precipitation with Station Data, Version 2.0 Final)³⁰, available on the Google Earth Engine Data Catalog. This dataset provides global coverage from 50°S to 50°N latitude, including regions with insufficient

ground data, at a 0.05° (5.5 km) resolution for thorough regional study. It produces daily composites, which can be aggregated into monthly or seasonal datasets for trend study. The technology integrates infrared satellite imagery (NASA/NOAA) with ground station data to minimize biases, especially in challenging terrain, and utilizes the CHP climatology to rectify systematic errors, boosting accuracy for drought prediction and hydrological modeling. The primary band measures precipitation (mm/day), with values ranging from 0 to 1,444.34 mm/day. The temperature data is collected from the ERA5-Land Monthly Aggregated dataset³¹, which provides high-quality, global climate reanalysis data at a monthly temporal resolution. Derived from the ECMWF's ERA5 reanalysis, this dataset contains major meteorological variables such as temperature, precipitation, evaporation, soil moisture, and surface runoff at a $0.1^\circ \times 0.1^\circ$ spatial resolution.

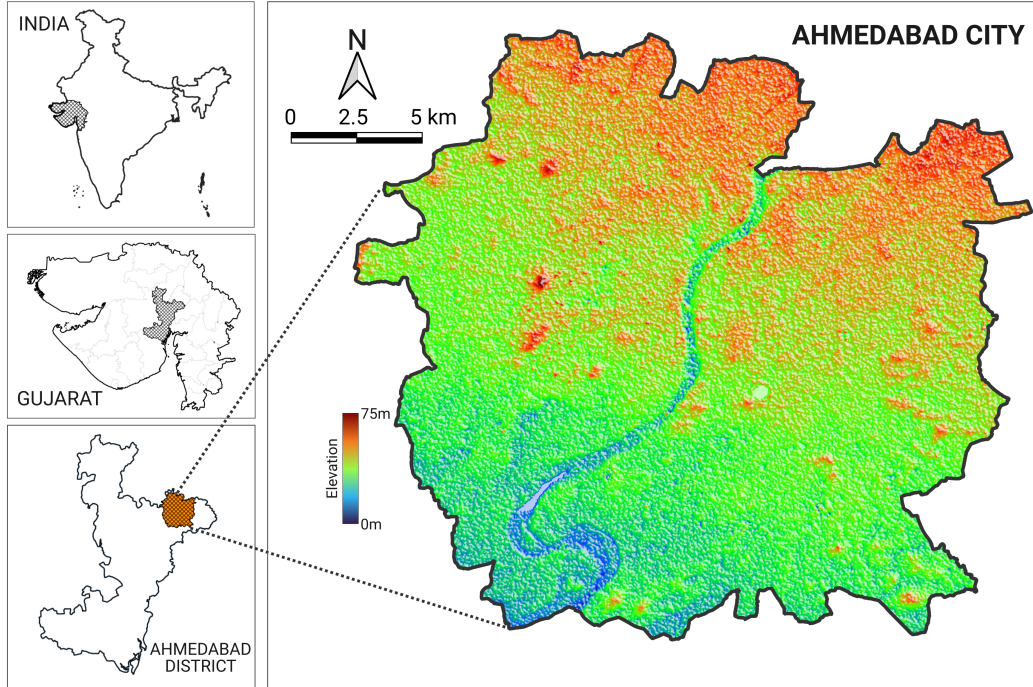


Figure 1. The Study area is Ahmedabad City with an area of approximately 450 km^2 , the climate is semi-arid, and has the Sabarmati River with key lakes Kankaria, and Vastrapur. The color shows the variation of the elevation.

The Water Area classification data is obtained from the USGS Landsat 8 Level 2, Collection 2, Tier 1 dataset [U.S. Geological Survey (USGS). (2021)], which provides atmospherically corrected surface reflectance (SR) and land surface temperature (ST) data from Landsat 8's Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS). Hosted on Google Earth Engine (GEE), this dataset covers the period from March 18, 2013, to March 30, 2025, with a 16-day return interval and global coverage. It features a 30-meter resolution for optical bands (ultra blue, blue, green, red, near-infrared, and two shortwave infrared bands) and a 100-meter resolution for thermal bands, making it appropriate for vegetation analysis, land cover classification, and environmental monitoring.

3 Methodology

Assessing the change and prediction in the water area necessitates initially recognizing how the water area changes over the long period and then determining an appropriate working methodology for identifying the trend that leads to an acceptable modeling approach.

3.1 Water Area Classification

To quantify water body dynamics, the investigation calculates annual water areas by adopting a pixel-based summation approach, where water pixels (classification = 1) are multiplied by their respective pixel areas using the *ee.Image.pixelArea()* function. Null values are managed by setting them to zero before aggregating the overall area within the AOI. The procedure ensures that the classification is robust and accurate that produces the binary classification of water pixel and non-water pixels that leads to the water area time series that will be further used for water area change dynamics. With this procedure 12 years (2013 - 2024) of time series data generated that allow to analyze the change patterns detection over the long time. To quantify the long-term

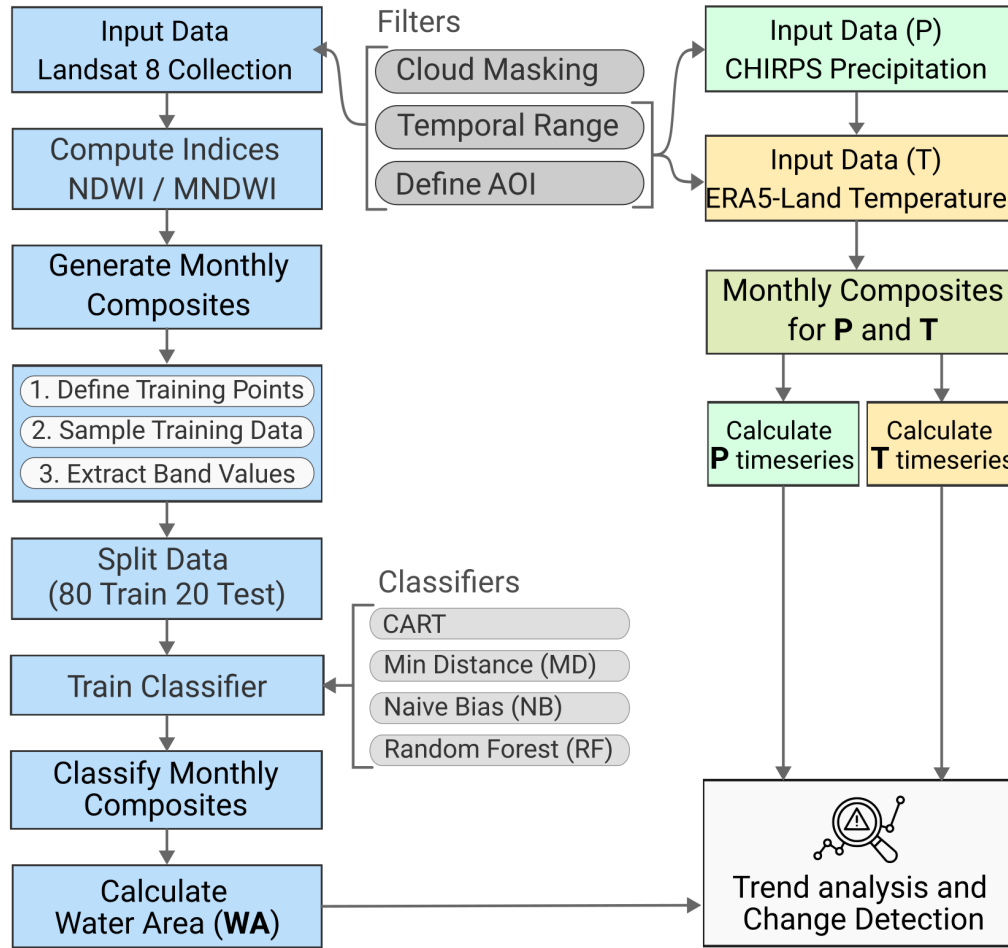


Figure 2. Methodology to extract the water area, precipitation, and temperature using remote sensing data.

change in the water resource, change the study combines remotes sensing techniques, multi-spectral data computation and supervised classification algorithms. The methodology incorporates finding suitable Landsat data products, whose spectral band data spanning from 2013 to 2024. Spatial filtering it performed by shapefile of Ahmedabad city boundary after that cloud masking using the QA_PIXEL band, and atmospheric correction to mitigate interference. As the study computed the water area in yearly and monthly scale, median for corresponding timescale are computed. After that spectral indices including the Normalized Difference Water Index (NDWI)³² and Modified NDWI (MNDWI)³³ are computed for water detection. The next step to create a labelled dataset of water area, for that we use satellite image and on field inspection and created a point that ensures the water pixels that will be used in the supervised classification to the water class and other the all the pixels will be classified non water classes. A total of four supervised machine learning classifiers, Classification and Regression Trees (CART), Minimum Distance (MD), Naïve Bayes, and Random Forest) are trained on labeled samples derived from median composites, utilizing spectral bands (B2 - B7) and water indices as input features to classify land cover. The classifiers provides the binary classification with water and non-water calculation that is later clipped with Ahmedabad city boundary shapefiles. Validation process employed by computing kappa coefficient and overall accuracy by splitting the labeled data in 80% training and 20% testing dataset, along with the manual inspection for the selected to ensure the reliability of the classification. Finally, the classified binary data is converted into time series data. The method represents application of remote sensing, spectral indices, and machine learning for landcover classification that will be useful for water management strategies and dynamic analysis of environmental change and water area change (Figure 2). The study utilizes four classifier algorithms; a brief description of each is provided below.

Classification and Regression Tree (CART) Classifier

CART is a decision tree algorithm that recursively divides the feature space into regions, assigning a class label (for classification) or a constant value (for regression) to each zone. The fundamental principle is Recursive Binary Splitting. The splitting criteria depend on Gini impurity, which quantifies the probability of misclassifying a randomly chosen element (cf. Eq. 1), where $p_{i,k}$ denotes the proportion of samples in region S that belong to class i for split k . The optimal tree split selection reduces the weighted Gini impurity of the child nodes, utilizing the criteria outlined in equation 2, where S_L and S_R represent the left and right partitions after the split. The study implemented the CART algorithm in GEE's inbuilt *ee.Classifier.smileCart()* function. The utility of the CART classifier is that it is an interpretable tree structure (visualizable splits) that allow user to understand the classification path and useful to understand the classification process.

$$G(k, S) = 1 - \sum_{i=1}^K (p_{i,k})^2 \quad (1)$$

$$k^* = \arg \min_k \left(\frac{|S_L|}{|S|} G(k, S_L) + \frac{|S_R|}{|S|} G(k, S_R) \right) \quad (2)$$

Minimum Distance (MD) Classifier:

The minimum distance classifier allocates pixels to the class corresponding to the nearest mean spectral signature by minimization of Euclidean Distance with all the available classes. MD is computationally efficient and presumes that classes follow normal distribution. Equation 3 shows the computed distance with $d(x, \mu_k)$ where x is a pixel vector and μ_k class mean, the optimum pixel class assignment performed by equation 4. MD is implemented with *ee.Classifier.minimumDistance()* classifier function. This classifier works well when training is challenging, and the dataset is large; it performs effectively with separable classes.

$$d(x, \mu_k) = \sqrt{(x - \mu_k)^T (x - \mu_k)} \quad (3)$$

$$k^* = \arg \min_k d(x, \mu_k) \quad (4)$$

Naive Bayes (NB) Classifier:

Naive Bayes applies Bayes' theorem for classification by assuming features are conditionally independent given the class, simplifying calculations; despite its "naive" assumption. It calculates the posterior probability of assigning class labels. Bayesian probabilities are determined in the following manner for this classifier, as demonstrated in equations 5- 7. Now, to compute the final water class by assigning x to the class k^* with the highest posterior with equation 8. The *ee.Classifier.naiveBayes()* classifier is utilized for the water area classification. Naïve Bias is efficient at processing high-dimensional data and robust to irrelevant features while requiring minimum training data.

$$\text{The prior probability of class } k : P(k) = \frac{\text{Number of samples in } k}{\text{Total samples}} \quad (5)$$

$$\text{Likelihood of } x \text{ given } k : P(x|k) = \prod_{i=1}^n \frac{1}{\sqrt{2\pi\sigma_{k,i}^2}} \exp \left(-\frac{(x_i - \mu_{k,i})^2}{2\sigma_{k,i}^2} \right) \quad (6)$$

$$\text{Posterior probability} : P(k|x) \propto P(x|k) \cdot P(k) \quad (7)$$

$$k^* = \arg \max_k P(k|x) \quad (8)$$

Random Forest (RF) Classifier:

Random Forest is an ensemble method that generates several decision trees (CART) and aggregates the predictions through majority voting (classification). The process of ensemble learning starts with Bootstrap Aggregating (Bagging) where the initial algorithm trains B trees on random subsets of data (with replacement). For classification, the final prediction is made by majority vote using Equation 9. RF is implemented with GEE's *ee.Classifier.smileRandomForest()* prevents overfitting using bagging and feature randomness. Alongside RF, CART is also employed because, unlike the CART model, RF's rules are not easily interpretable³⁴.

$$k^* = \text{mode}(\{T_1(x), T_2(x), \dots, T_B(x)\}) \quad (9)$$

3.2 Model Validation Metric and Trend Analysis

In order to confirm the water availability in the selected location over an extended period of time, training data points are obtained by manual visual sampling using accessible long-term satellite imagery and input from Ahmedabad city residents. Further, training data is classified into only two classes **0**: water class, and **1**: Non-water class, and the split into training (80%) and testing (20%) subsets using a randomized approach. This ensured accurate assessment by excluding data used for model training from validation. For the test Set Classification, the trained classifier is applied to the withheld test subset to predict class labels (water/non-water). A confusion matrix is developed by comparing predicted classifications against ground truth labels. Key measures produced are Overall Accuracy (OA), which is the fraction of correctly classified samples, and Kappa Coefficient (κ), which is the measure of agreement between predicted and actual classifications, corrected for chance. Kappa Coefficient's values closer to 1 imply significant agreement, while numbers approaching 0 reflect a random possibility. This metric is prioritized for its robustness in imbalanced datasets. GEE provides the Kappa Coefficient and Overall Accuracy function for spatial datasets.

The monthly and annual aggregate scales for temperature, precipitation, and water areas are calculated (see Appendix A) which assist researchers in comprehending the long-term patterns of change in the city's water signature. Now we execute the analysis to identify the trend in Yearly, Seasonal, and Monthly data. Also, to better understand the classifier's role, we check the classifier's interchangeability. In addition, stationarity is essential to examine and understand the Seasonality and forecasting capabilities of the time-series data. Next, we analyze the correlation between climatic variables and water area. Further, correlation and cross-correlation analyses are performed to understand the relationship between climate variables and water area. Finally, three hypotheses are evaluated to assess how the classifier responds to climate variables.

- H1: Classifiers disagree most during extreme climatic conditions.
- H2: Each classifier responds uniquely to the precipitation/temperature.
- H3: Ensemble metamodel superiority-ensemble prediction outperforms the ensemble classifiers.

4 Data Analysis and Results

The results are arranged into six subsections to address distinct analytical objectives. Section 4.1 compares classifier performance and interchangeability across machine learning classifiers and Section 4.2 examines long term trends (2013 - 2024) in water area change. Section 4.3 investigates temporal patterns, including seasonal and inter-annual variability. Section 4.4 quantifies relationships between water area fluctuations and climatic drivers. Section 4.5 evaluates water classification accuracy through visual interpretation of spectral indices and model outputs. Section 4.6 tests hypotheses on meta-model superiority and climatic sensitivity and impact of climate extreme on classifiers' outputs.

4.1 Classifier Performance and Interchangeability

The classification is performed by choosing water class and non-water class with 80% training and 20% validation points. Validation metrics: kappa, and overall accuracy (OA) are greater than 0.75 for all the 4 classifiers. Random Forest is performing best with 0.87 kappa coefficients. Given the heterogeneity in the city water bodies, water areas time series are slightly different from each classifier, another factor is the 30m resolution of pixel from Landsat-8 a higher resolution can significantly change the classification pattern in the urban setting^{10,35-37}.

Bland-Altman Plots (Figure 3) assess agreement between classifiers is a graphical approach used to compare two different measurement procedures or methods for quantifying the same variable. It is particularly useful in analyzing agreement between two approaches, rather than simply verifying correlation. The Bland-Altman plot emphasizes whether the two approaches provide equivalent findings throughout a range of values, making it a significant tool in method comparison studies. Bland-Altman plots are applied to examine the agreement between two classifiers in predicting water area, with each data point's x-axis

value representing the mean of both measurements ($Mean = \frac{Water\ Area_1 + Water\ Area_2}{2}$), serving as an approximated consensus. The y-axis denotes the difference between classifiers, where positive values reflect overestimation by the first classifier relative to the second, and negative values indicate underestimation. Horizontal lines indicate the mean bias (red) as well as complete agreement (dashed, $y=0$). These plots enable the examination of systematic biases, the number of variations, and the consistency of disagreements over varied water area magnitudes, thereby elucidating the reliability and comparability of the classifiers.

Bland–Altman Plots: Pairwise Comparison of Water Area Classifiers

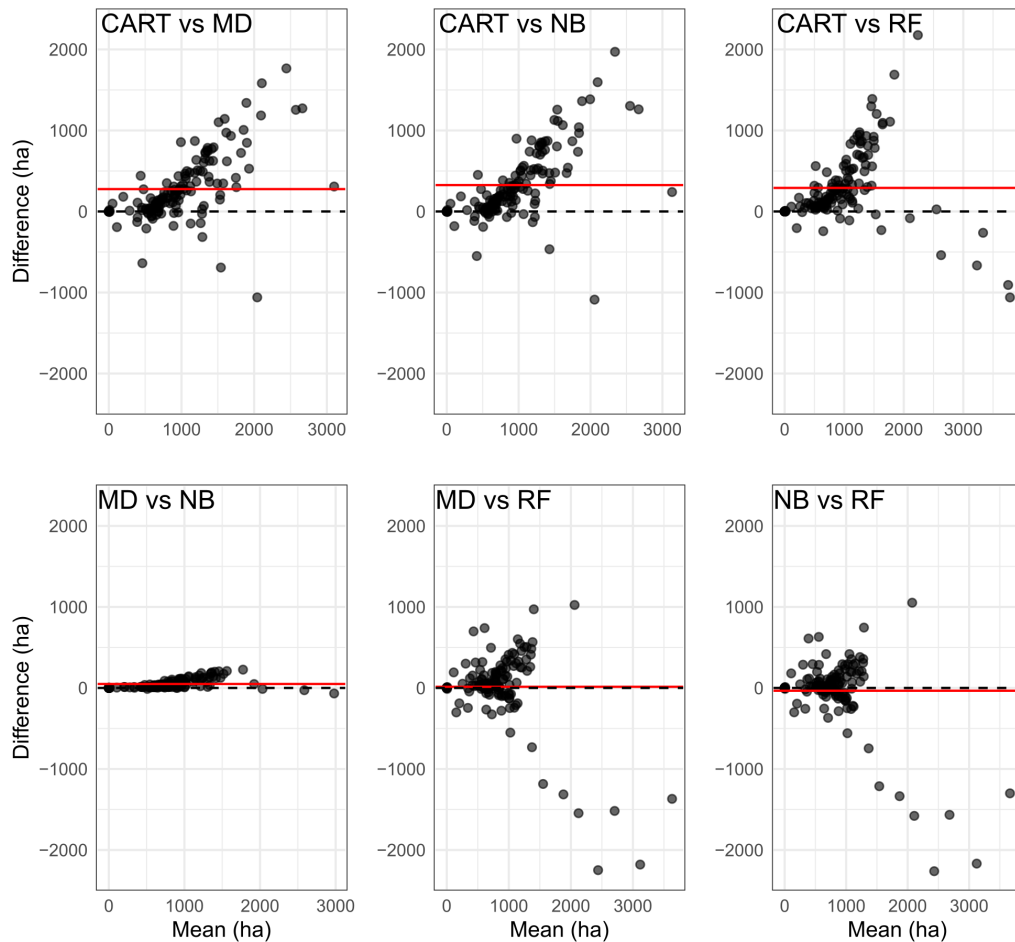


Figure 3. A Bland-Altman plot is a graphical method used to compare two different measurement techniques or methods for quantifying the same variable. The plot explains how similar or different two variables are.

4.2 Long-Term Water Area Trends (2013 - 2024)

Study classified Landsat reflectance band data of 2013-2024 to water and non-water class, utilize 4 distinct classifiers in these approaches that generate four water area time series. The analysis is performed on monthly and yearly scales; some initial months of 2013 data are not accessible as it is the start of the data stream of Landsat-8. The justification for choosing this study region is to make more consistent data that we acquired from a single satellite system and to generate data from the same set of sensors. The study did not consider the Landsat-9 data available from February 10, 2022, onwards, due to the same reasons. The annual water area trend is presented in Figure 5, yearly data from 2013-2024 shows a slight increase in water area across the years. All classifiers' findings do not completely overlap, but the pattern indicates similarities among them.

Also generated the monthly data of climatic variables and water area, and a summary is presented in Table 1. The summary indicates, the models exhibit the highest mean outputs and variability during the monsoon and winter, with lowest and most consistent predictions in summer. Precipitation peaks in summer and is negligible in winter, while temperature is highest in summer and lowest in winter. Overall, wetter seasons drive greater model magnitudes and uncertainty, whereas dry summer

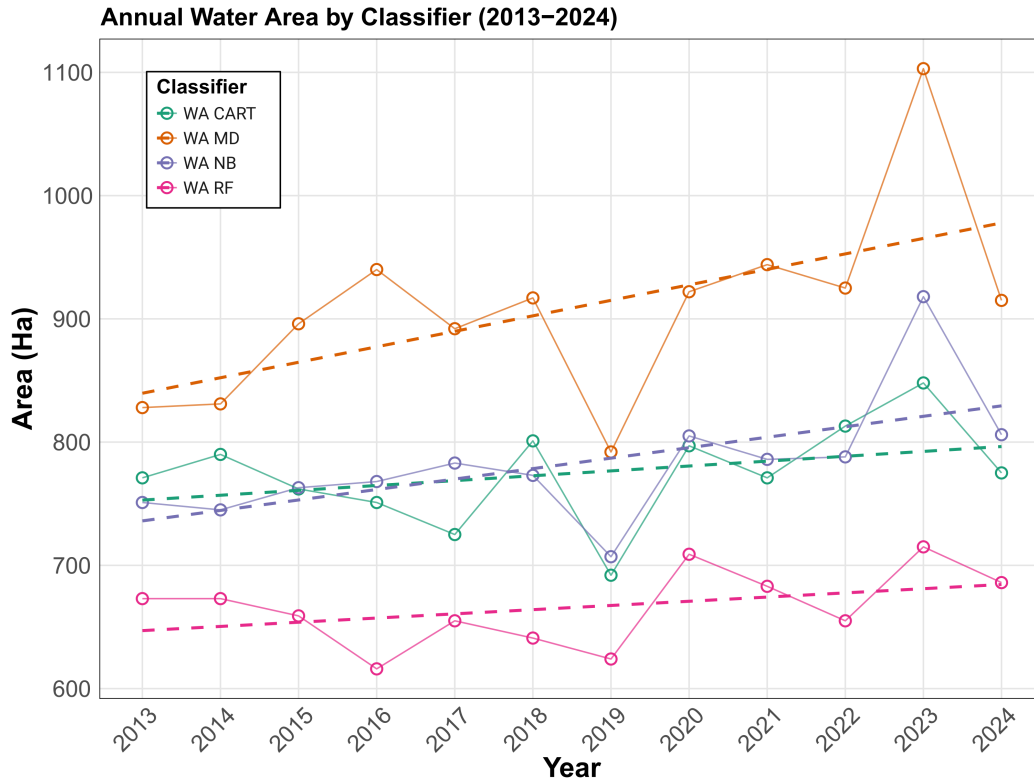


Figure 4. Variation of water area across 12 years starting from 2013 to 2024. The yearly time series shows a slight increase the water area.

conditions yield more stable forecasts.

Table 1. Summary of the data extracted with Classifier and Seasons.

Variables	Functions	Seasons		
		Winter	Summer	Monsoon
CART (ha)	mean	1471	668	1222
	median	1595	624	1174
	sd	644	476	741
MD (ha)	mean	1037	599	896
	median	1014	604	851
	sd	415	289	555
NB (ha)	mean	938	576	870
	median	923	583	815
	sd	360	277	559
RF (ha)	mean	819	561	1108
	median	836	515	868
	sd	270	497	943
Precipitation (mm month-1)	mean	0.6	123.6	111.9
	median	0.0	35.1	30.0
	sd	1.4	178.7	155.3
Temperature (°C)	mean	22.7	31.4	26.9
	median	21.9	31.5	27.3
	sd	2.8	2.0	1.5

Also, the variance between seasons and classifiers is displayed in Figure 5, Winter shows the greatest water extent across

the four classifiers, with CART resulting in the highest median and widest spread. Summer produces the lowest and most tightly clustered predictions across models, reflecting minimal water presence this may be caused by higher temperature leading to more evaporation. Monsoon estimates lie between these extremes, with moderate medians and variability, and RF displaying comparatively greater dispersion. The 12 year monthly averaged water area are shown in the Figure 6, August is having largest variation and as anticipated summer months captures the lowest amount of water area across all the classifiers. To identify the variation of water area changes across the temporal space, the Mann- Kendall test³⁸ was conducted. The Mann-Kendall trend analysis identified significant patterns in water area trends across classifiers and temporal scales. The reports show (Table 2) significant monthly and yearly trends.

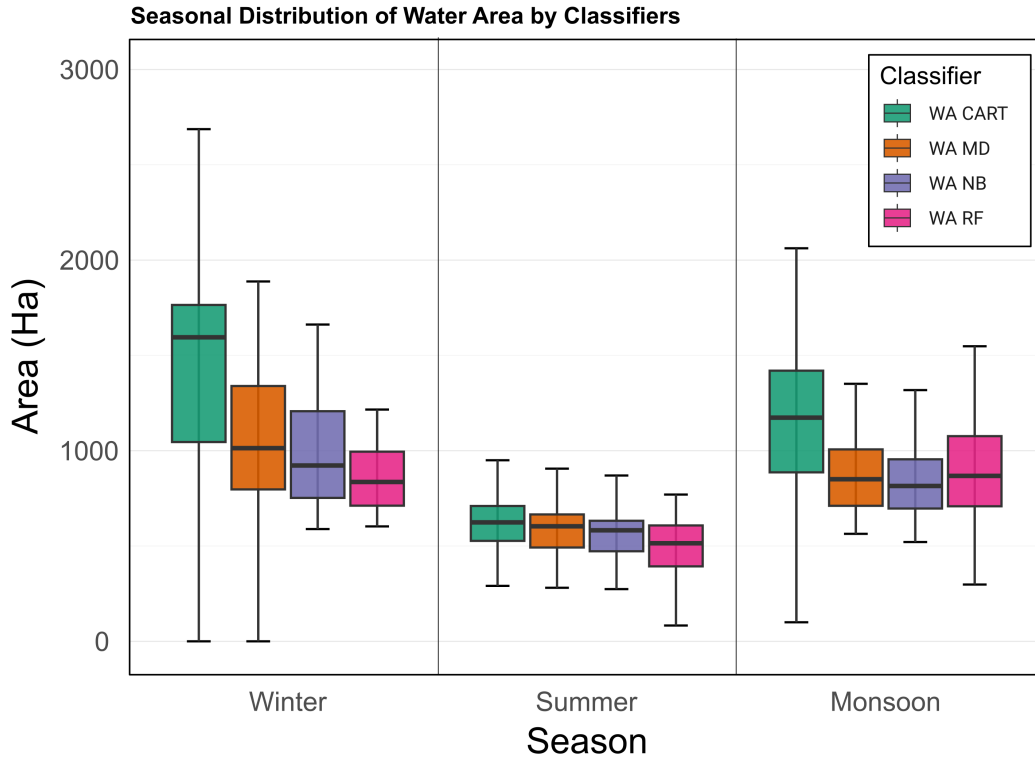


Figure 5. Variation of Water area identified by different classifiers and grouped by Seasons. CART shows the highest variation for winter and Monsoon season. All the classifiers are aggregated and show very little variation in the summer season. Also, CART is over-predicting the area as well.

Table 2. Mann-Kendall test output for all the classifiers.

Classifier	Time Scale	Z-Score	p-value	Tau (τ)	Significance
CART	Yearly	1.10	0.271	0.260	Not Significant
CART	Monthly	2.51	0.012	0.142	Significant
MD	Yearly	1.99	0.047	0.455	Significant
MD	Monthly	2.59	0.010	0.146	Significant
NB	Yearly	2.95	0.003	0.667	Significant
NB	Monthly	2.56	0.010	0.144	Significant
RF	Yearly	0.90	0.370	0.215	Not Significant
RF	Monthly	2.93	0.003	0.165	Significant

Annually, the NB and MD classifiers demonstrated statistically significant increasing patterns ($\tau = 0.667$, $p - value = 0.003$ and $\tau = 0.455$, $p - value = 0.047$, respectively), while CART and RF showed non-significant trends ($p - value > 0.05$). In contrast, monthly analyses found significant upward trends for all classifiers ($p - value < 0.05$), despite weaker Kendall's Tau values ($\tau = 0.142 - 0.165$), underlining the importance of sample size ($n = 144$ vs. $n = 12$) on statistical power. Notably, NB demonstrated the most significant annual trend magnitude, whereas RF exhibited the weakest annual trend but the strongest

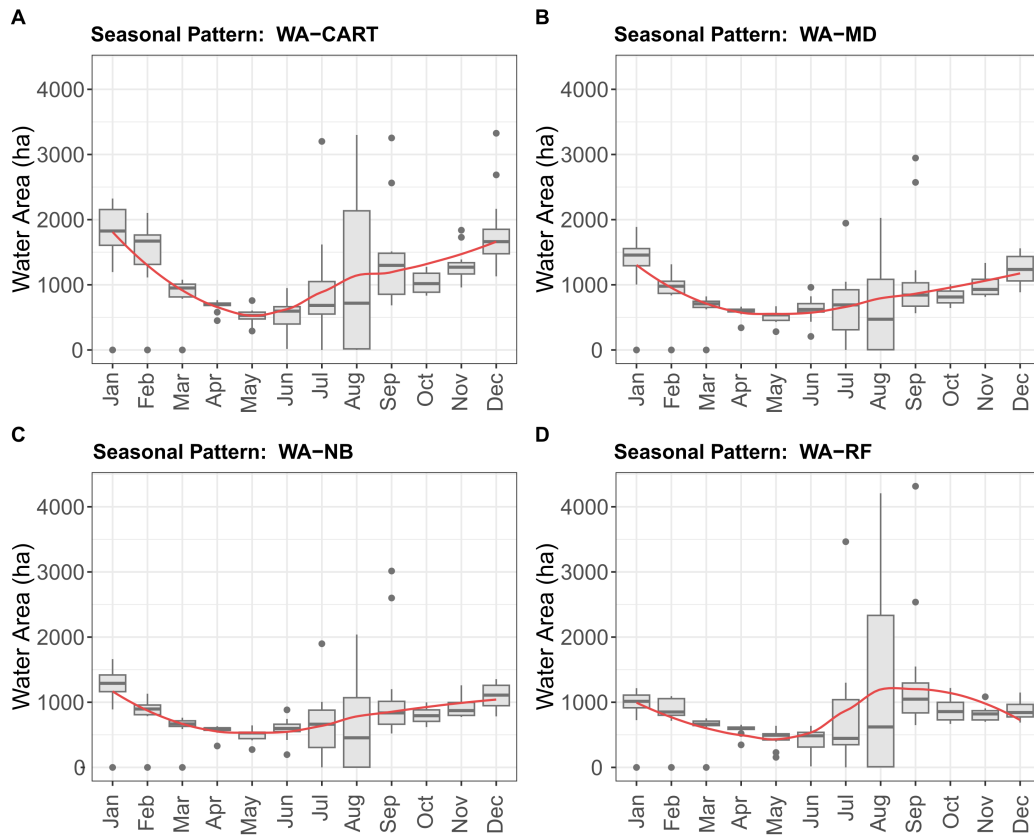


Figure 6. Seasonal variation of classified water-body area in Ahmedabad (2013-2024) as estimated by four machine-learning algorithms. Monthly boxplots display the distribution of water extent (ha) across years, and the red LOESS curves illustrate the mean seasonal trajectory for (A) CART, (B) Minimum Distance, (C) Naïve Bayes, and (D) Random Forest classifiers.

monthly trend, showing distinct sensitivity to temporal granularity. These results emphasize the importance of dataset resolution and classifier selection in hydrological trend detection, with monthly data aiding significance detection and annual data favoring classifiers capturing higher monotonic relationships. Water area fluctuations are apparent in yearly and monthly data and Table 2, demonstrates the increasing water area trend in Ahmedabad city, based on yearly and monthly time-series analysis.

4.3 Temporal Dynamics: Seasonality, Stationarity, and Predictability

To examine the pattern in timeseries autocorrelation is performed then STL explains the component of the time series at the end ADF/Ljung-Box test performed to identify the stationarity of the series. To forecast future values utilizing persistence or seasonality, autocorrelations are essential for understanding dynamics and gaining insight into the temporal behavior of each variable. Autocorrelation analysis is performed to quantify the periodicity in water-area time series this will help in guiding model identification, feature engineering and residual diagnostics. Figure 7 shows the sample autocorrelation functions (ACFs) all four water area time series and climatic variables. Water area from CART (Panel A), MD (Panel B), NB (Panel C) and RF (Panel D)—alongside their primary climatic drivers, monthly precipitation (Panel E) and temperature (Panel F), over lags of 0-36 months. Figure 8 shows the autocorrelation of water area and climatic variables varying from -1 to +1. All the water area CART, MD, NB, and RF display a similar trend reaching unity at lag 0 month and a sharp decrease in the correlation ranges from 0.4 to 0.8. There sharp negative correlation at lag of 4-8 months. All water area shows a clear spike in the seasonal interval of lag 12, 24, and 36 months, indicating strong yearly periodicity. Beyond these lag autocorrelations lead to near zero under the 95% significance level (red dashed line). The pattern in the water area shows that the predictive modelling requires season and autoregressive elements. Climatic time series has a further higher seasonality as compared to the water area. Precipitation and temperature both show the impact of monsoon and seasons in the autocorrelation values, and autocorrelation never plateaus with wider lag windows.

To assess the nuanced comparison of long-term consistency, seasonal trend reliability and detecting classification noise across classification, STL (Seasonal-Trend decomposition using) approach is used. It reveals the difference between trend

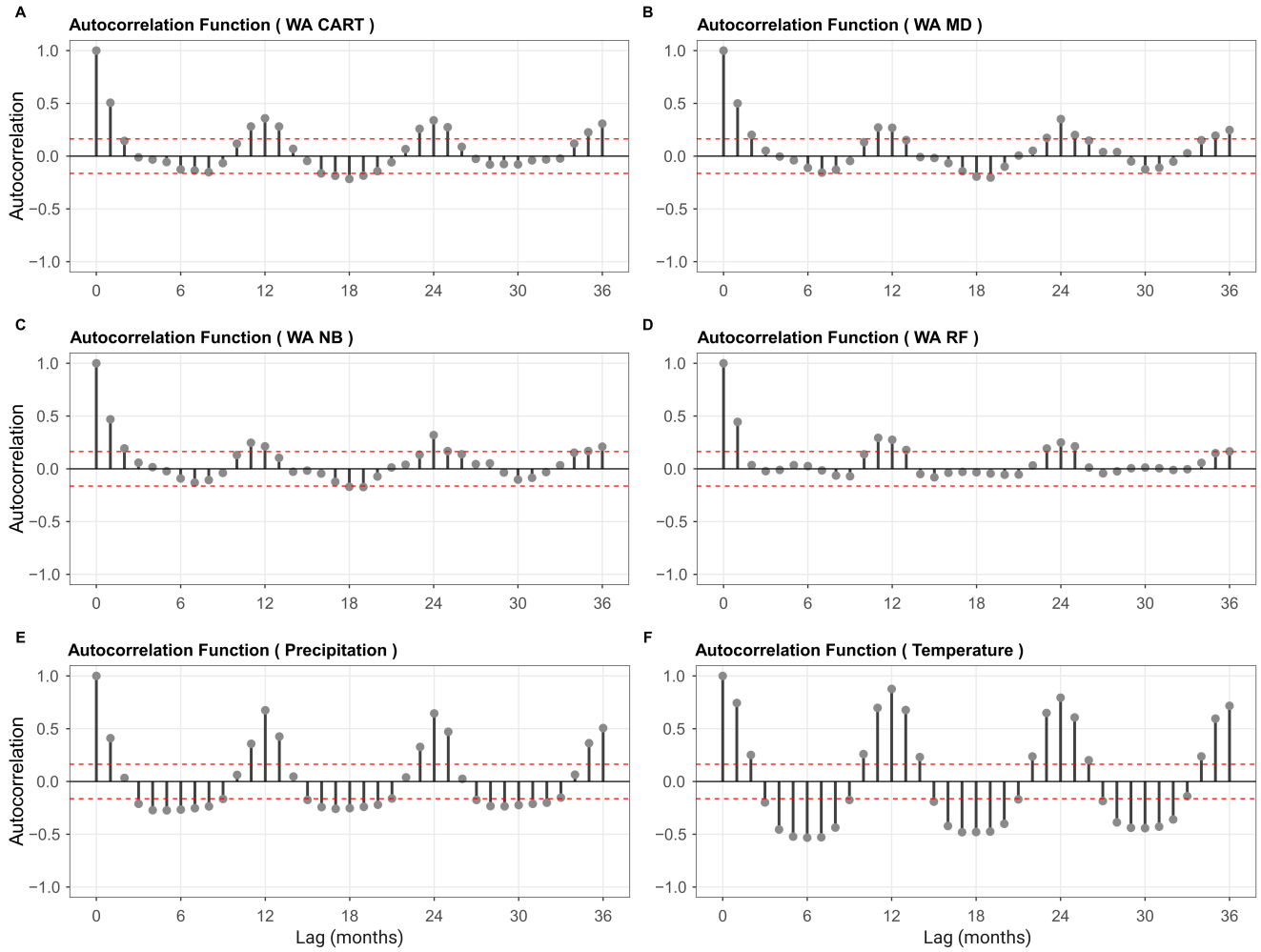


Figure 7. Autocorrelation between the monthly data time series for climatic and water areas. X-axis (Lag): Represents time lags in months, ranging from 0 to 36 months. The Y-axis (Autocorrelation) represents the autocorrelation coefficient, which ranges from -1.0 (perfect negative correlation) to +1.0 (perfect positive correlation), with zero indicating no correlation.

direction and anomaly patterns in the time series that helps to identify the most temporally reliable classifiers for water area detection and analysis. STL is a robust and flexible method for dissecting complex time series into three additive components: trend, seasonal, and remainder³⁹ (cf equation 10).

$$Y_t = Trend_t + Seasonal_t + Remainder_t \quad (10)$$

The STL decomposition techniques are well suited for the time series data having long-term variation and strong seasonality. STL can able to accommodate the non-linear trend and seasonality and abrupt changes, which is important for effective time series modeling, and allows us to analyze the water area change dynamics that are influenced by climatic changes, anthropogenic change, and remote sensing data uncertainties.

Figure 8 illustrates the STL decomposition for Surface water area (WA) time series generated with Landsat 8 dataset for the time interval of 2013 - 2024 using four classifiers, (A) Classification and Regression Tree (CART), (B) MD, (C) NB, and (D) RF. Each panel displays the four subplots with complete time series, trend, seasonality, and remainder component for the period for 2013 to 2024. From the observation, the clear seasonality is visible from the Seasonal (Year) subplot. The subplot shows an increase in water area since 2020, which is gradually decreasing by 2024.

The second row of each subplot shows the long-term temporal trend of water area change for each classifier. Random Forest and Naive Bias show the smooth upward trend for the duration of 2015 to 2018 signifies the constant water gain. There was a sharp decrease in 2018 and an abrupt jump in 2022 reported by all the classifiers. CART shows an oscillatory trend

with a less prominent growth trend. The reason for this could be the low sensitivity of spectral variation. It was also observed that CART is more susceptible to cloud cover and leads to unreliable prediction of water area. The remainder component of each subplot shows the unexplained noise of the time series. Higher peaks are visible after 2020 for all the classifiers, also RF and CART produce a higher magnitude of remainder as compared to MD and NB. Where NB displays more scattered but moderate residuals that symbolize the intermediate sensitivity towards noise. At last, STL decomposition analysis highlights the divergence between machine learning classifiers when capturing the long-term trend, even though they agree on the seasonal trend.

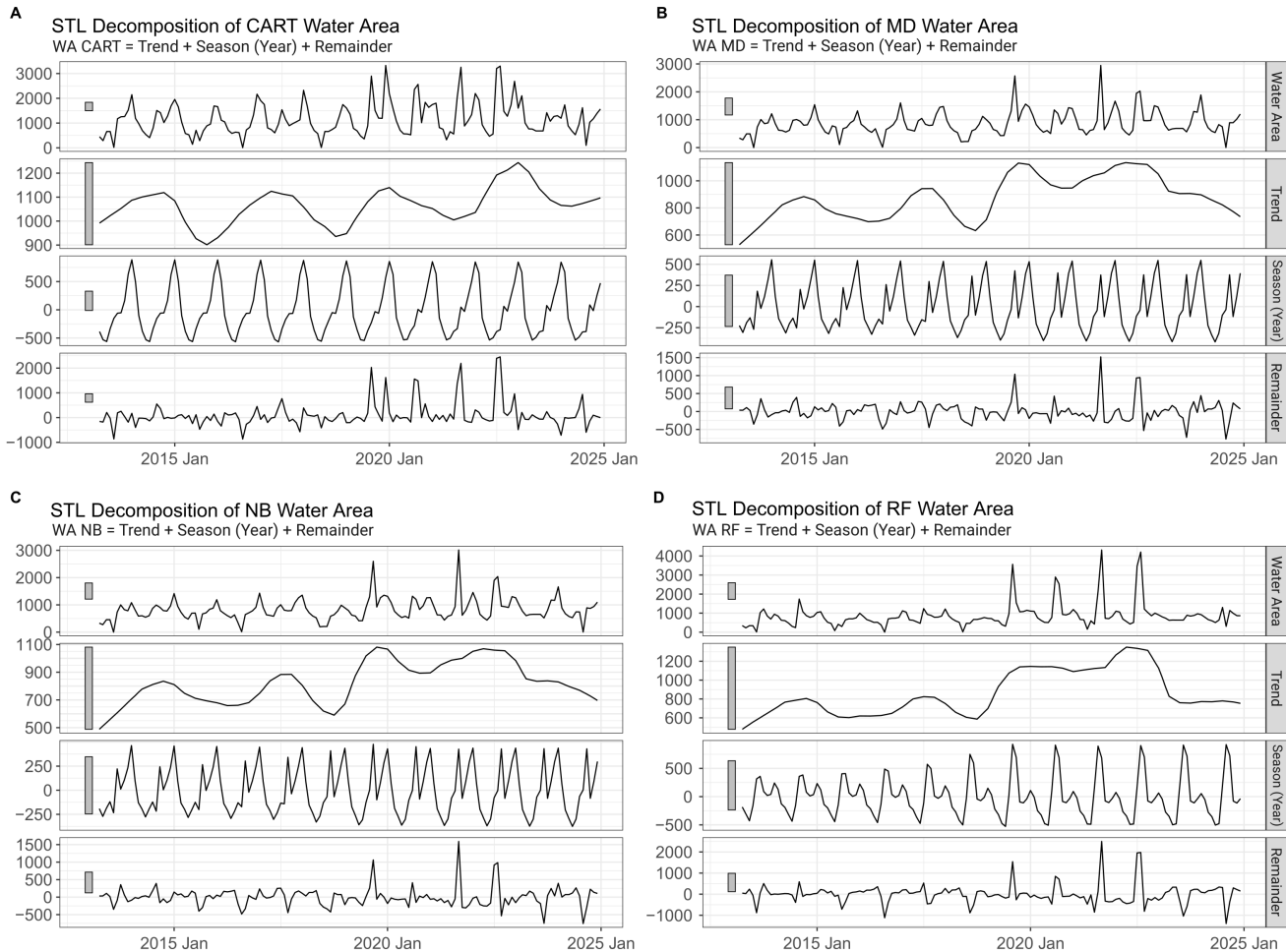


Figure 8. Seasonal and Trend decomposition is used to decompose the time series into components to understand the trend and noise.

Modeling time series requires a comprehensive review of two fundamental properties: *stationarity* and *unpredictability*. The current investigation employs the Augmented Dickey-Fuller (ADF) test to measure stationarity and the Ljung-Box test (LB) to evaluate randomness in the time series data. A stationary time series has constant mean, variance, and autocorrelation over time, which is a key assumption for many time series models (e.g., ARIMA). Further, ADF examines the null hypothesis that the time series has a unit root (non-stationary). If the p-value is less than a significance level (0.05 for this instance), reject the null hypothesis, demonstrating stationarity, which suggests the time series is stationary.

Further, the Ljung-Box test examines whether autocorrelations differ from zero up to a specified lag (24 in this analysis). The Ljung-Box test evaluates if there is significant autocorrelation in a time series at multiple delays. It evaluates the null hypothesis that the residuals (or the time series itself) are independently distributed. By applying the Ljung-Box test to each classifier's time series, we can measure how effectively each classifier captures temporal dependencies. Lower autocorrelation in residuals indicates improved performance.

In addition, the Null Hypothesis (H_0) indicates there is no autocorrelation up to the specified lag and the alternative

Hypothesis (H_1) says there is significant autocorrelation at one or more delays. If the p -value is greater than the significance level, you fail to reject the null hypothesis, showing no substantial autocorrelation. Results of the ADF test and LB test are shown in Table 3. Further, all classifiers reject the null hypothesis ($p = 0.01$), indicating stationarity, whereas the Box-Ljung test reveals all p -values are significant ($p < 0.05$), suggesting the presence of autocorrelation in the residuals. A thorough understanding of the time series data helps us to model with ARIMA and XGBoost ensemble learning (see result section, hypotheses testing: H3).

Table 3. ADF test and LB test results showing stationarity in the timeseries

Classifier	Augmented Dickey-Fuller Test			Ljung-Box Test		
	Statistic	Lag Order	p-value	X2	Time Lag	p-value
WA CART	-5.6683	5	0.01	160.15	24	<0.01
WA MD	-5.5397	5	0.01	127.82	24	<0.01
WA NB	-5.3629	5	0.01	100.87	24	<0.01
WA RF	-4.8641	5	0.01	85.685	24	<0.01

4.4 Relationship Between Water Area and Climatic Drivers

To understand how climatic variables such as temperature and precipitation change the water area, we performed correlation analysis in Figure 11 that links water area with climatic variables. Then cross-correlation with Lag (Figure 10) is investigated to identify the primary climatic driver of Water Area change for all four Classifiers. At last, the Phase Diagram (Figure 13) overlay water area density on precipitation-temperature space that helps to understand shifting in precipitation and temperature (e.g., due to climate change) affect water distribution.

The impact of climatic variables on water area time series is investigated using a correlation study (Figure 9). Notable trends include substantial positive correlations for WA NB (0.82) and WA MD (0.71), contrasting with weaker or adverse interrelationships in other circumstances. The values, revealing variations in predicting performance between approaches, are obtained from time-series residuals or model outputs. The amount of precipitation does not demonstrate a substantial connection between the water area, while the temperature has obvious relationships with the water area time series.

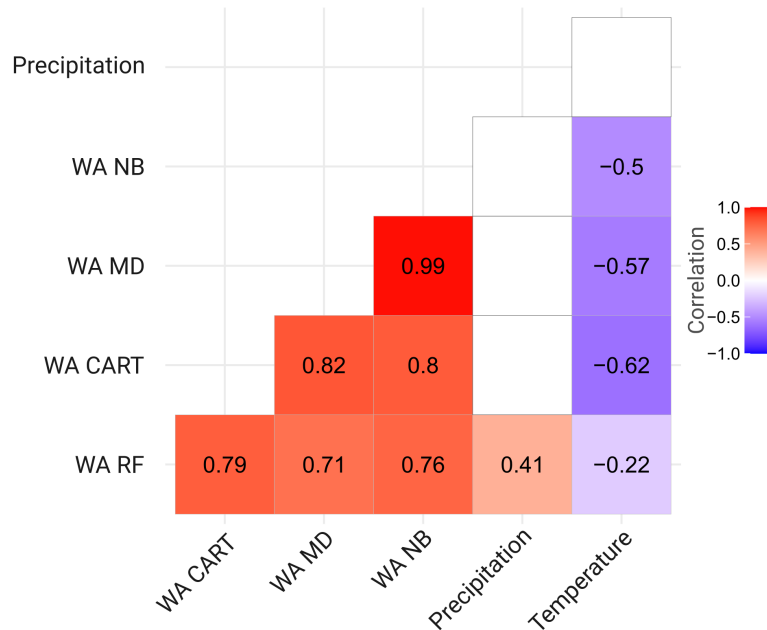


Figure 9. Correlation analysis between climatic data and four models (WA NB, WA MD, WA CART, WA RF), showing correlation coefficients ranging from -1.0 to +1.

In Figure 10, across all panels, the x-axis depicts the lag (from -12 to +12 months), and the y-axis indicates the cross-correlation coefficient, ranging from -1 to +1. The red dashed lines indicate the significance thresholds at the 5% level, allowing

straightforward identification of statistically substantial relationships. Whereas negative delays indicate that WA estimates might predict changes in climatic conditions, positive lags indicate that changes in temperature or precipitation occur before changes in WA estimates. The research conducted demonstrates that the degree and significance of these correlations vary depending on the model utilized and the climate driver evaluated. Notably, precipitation demonstrates stronger and more frequent significant associations with WA compared to temperature, underlining the dominant role of precipitation in influencing water availability.

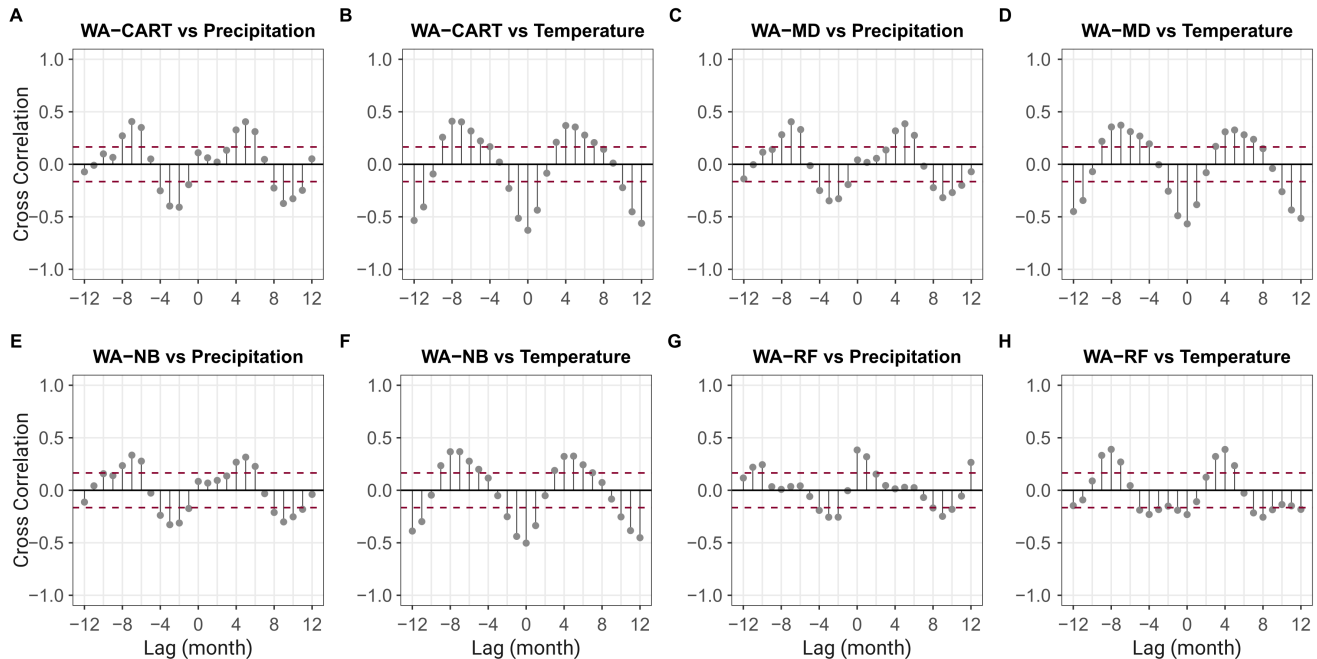


Figure 10. Cross-Correlation with lag for Classifier and climatic variables. Panels A to H illustrate the cross-correlation results between climatic variables and water area.

Study on water area spatial relation with climatic variables are shown in Figure 11 phase diagram with climatic variable. The climatic phase space is a dynamic fingerprint of how surface water responds to shifting precipitation and temperature regimes, an essential component of drought and hydrological variability research. Here's how you can interpret it:

1. **Climatic Conditions Driving Water Area Presence:** The high density of points (purple areas) in the low-precipitation and mid-temperature zones implies continuous water presence even under drier conditions. Scattered high-water area observes (yellow/white significant dots) under higher-precipitation regimes demonstrate the ephemeral or event-based expansion of water bodies, during flood pulses or monsoons.
2. **Classifier Sensitivity:** All classifiers exhibit a similar overall pattern, but with subtle differences:
 - CART and NB present a slightly broader variation in water area forecasts during mid-to-high precipitation, exhibiting an increased sensitivity to flexible conditions.
 - RF demonstrates more conservative grouping, because of its ensemble smoothing nature, which makes it less prone to noisy or extreme data points.
 - MD is underestimating in the upper-left humid region (low temperature, high precipitation), a known limitations in distance-based categorization where class distributions overlap.

4.5 Visual Inspection of Classification Accuracy

To Emphasize consistent detection of major water bodies (Sabarmati River, lakes) vs. discrepancies in ephemeral zones. The Figure 12 show the identified water bodies from CART classifier shows prominent water bodies (Sabarmati River, Vasna barrage, Kankaria Lake etc.).

Climate–Water Area Phase Space Dynamics

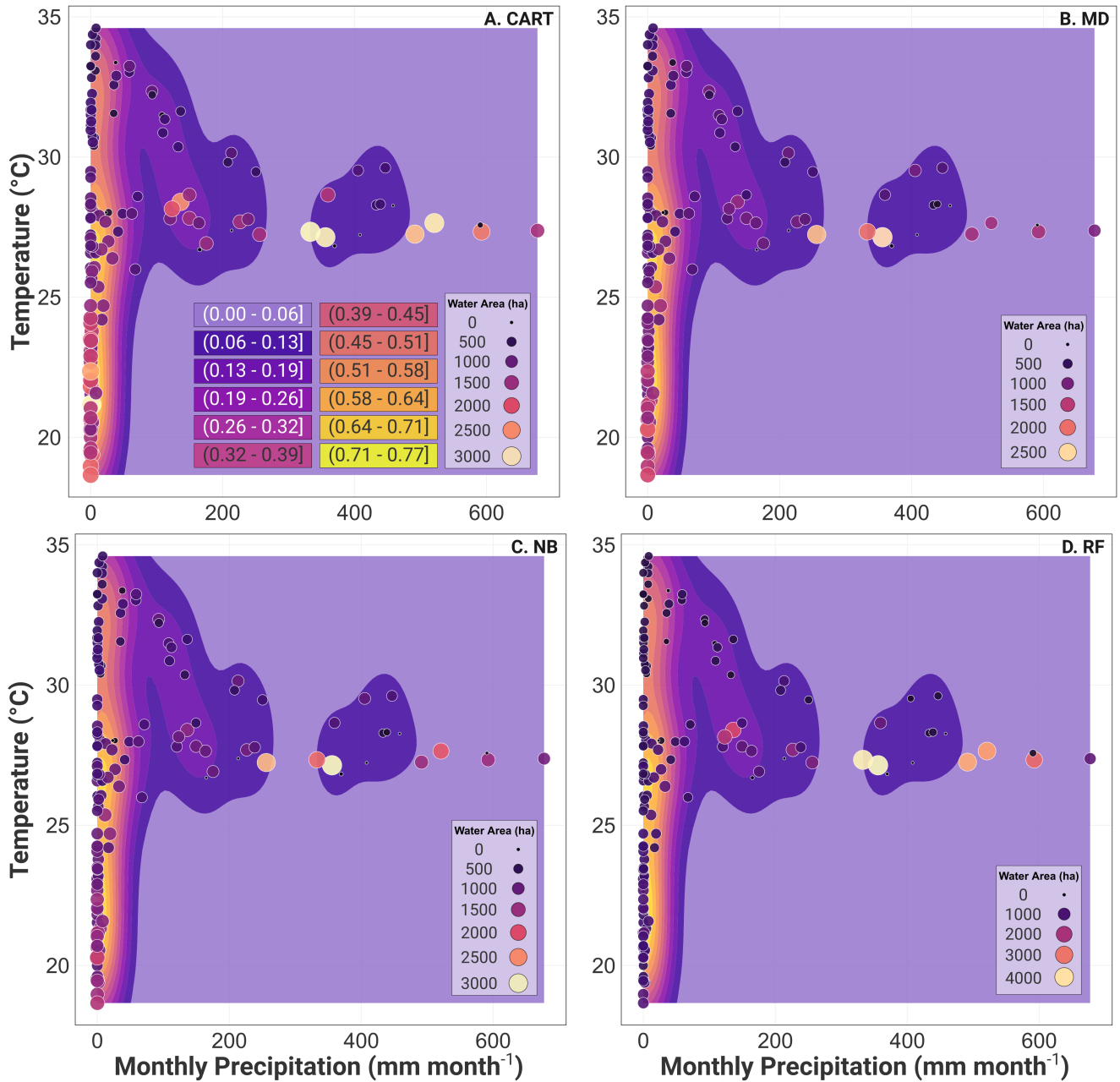


Figure 11. Plotted temperature (°C) vs. monthly precipitation (mm/month) across a 12-year span, overlaying the classified water area (in hectares) using four different classifiers CART, MD, NB, RF in each subplot. Contour plots represent the density of classified water area presence under different climatic conditions (purple to yellow gradient). Colored dots whose color indicates water area, and size represent the water area in hectares for each observation.

The Figure 13 illustrates the spatiotemporal persistence of water bodies in Ahmedabad City as identified by four distinct machine learning classifiers: (a) CART, (b) MD, (c) NB, and (d) RF. Each colored pixel signifies the number of years (1 to 12) a water body was identified across 12 years of period between 2013-2024, with darker shades (e.g., blue and purple) denoting short or ephemeral presence and brighter shades (e.g., yellow and green) suggesting continuous or constant water coverage. Consistent trends are observed among classifiers along significant hydrological features, including the Sabarmati River and notable lakes (e.g., Kankaria, Vastrapur), but differences occur in periphery areas and ephemeral zones. CART

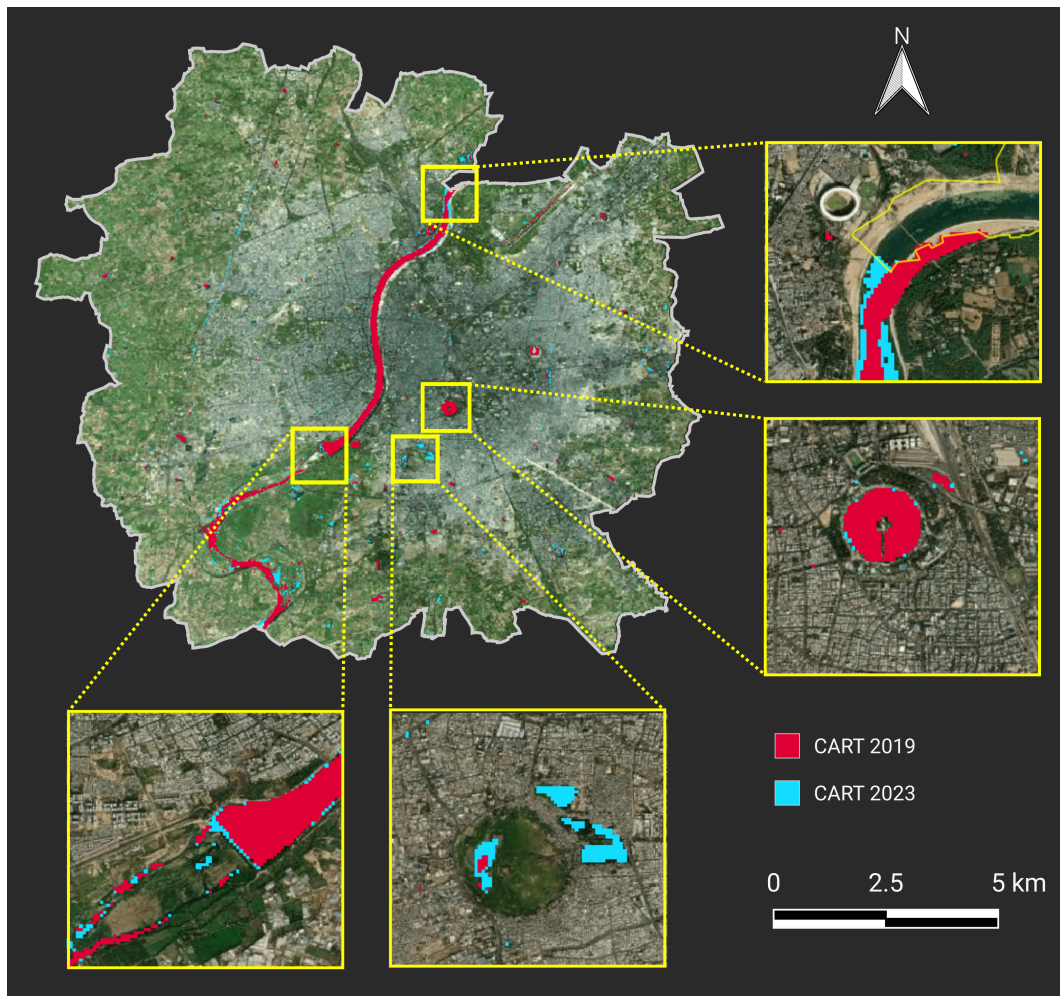


Figure 12. Examine the water area detected by a classifier (CART) in two different years. Red and Blue represent the water area for 2019 and 2023, respectively. The classifiers accurately identify the various hydraulic structures such as Vasna barrage (a), Chandola Lake unbounded lakes (b), Kankaria Lake (c), and the cutoff of Sabarmati River till Ahmedabad City boundary(d).

and NB demonstrate a wider detection of short-term water bodies, particularly in the southern and western regions, while MD takes on a more conservative strategy, excluding numerous smaller or short-term water bodies. RF, in comparison, highlights persistent features with negligible overestimation. The inter-model variances in Figure 13 demonstrate the various likelihoods of classifiers to spectral ambiguity, seasonal variations, and surface water diversity, emphasizing the significance of methodological triangulation in urban hydrological assessments.

4.6 Hypothesis Testing

The study evaluated three specific hypotheses to answer how extreme climatic change can affect classification accuracy, model disagreement and optimum model combination with ensemble learning.

4.6.1 Hypothesis - 1: Classifiers disagree most during extreme climatic conditions

To determine whether classifier disagreement intensifies during adverse circumstances, the methodology indicates divergence as the monthly standard deviation of predictions from four machine learning classifiers. Climate extremes are characterized using thresholds: precipitation extremes are identified as months more than the 90th percentile of historical precipitation, while temperature extremes are indicated when variations from the median exceed ± 5 units. A Generalized Additive Model (GAM) with a Gamma distribution and log-link function is applied to model divergence against continuous climate variables (precipitation and temperature, represented by smooth terms) and binary extreme indicators, including their interaction. This approach investigates non-linear climatic effects and evaluates whether simultaneous precipitation and temperature extremes

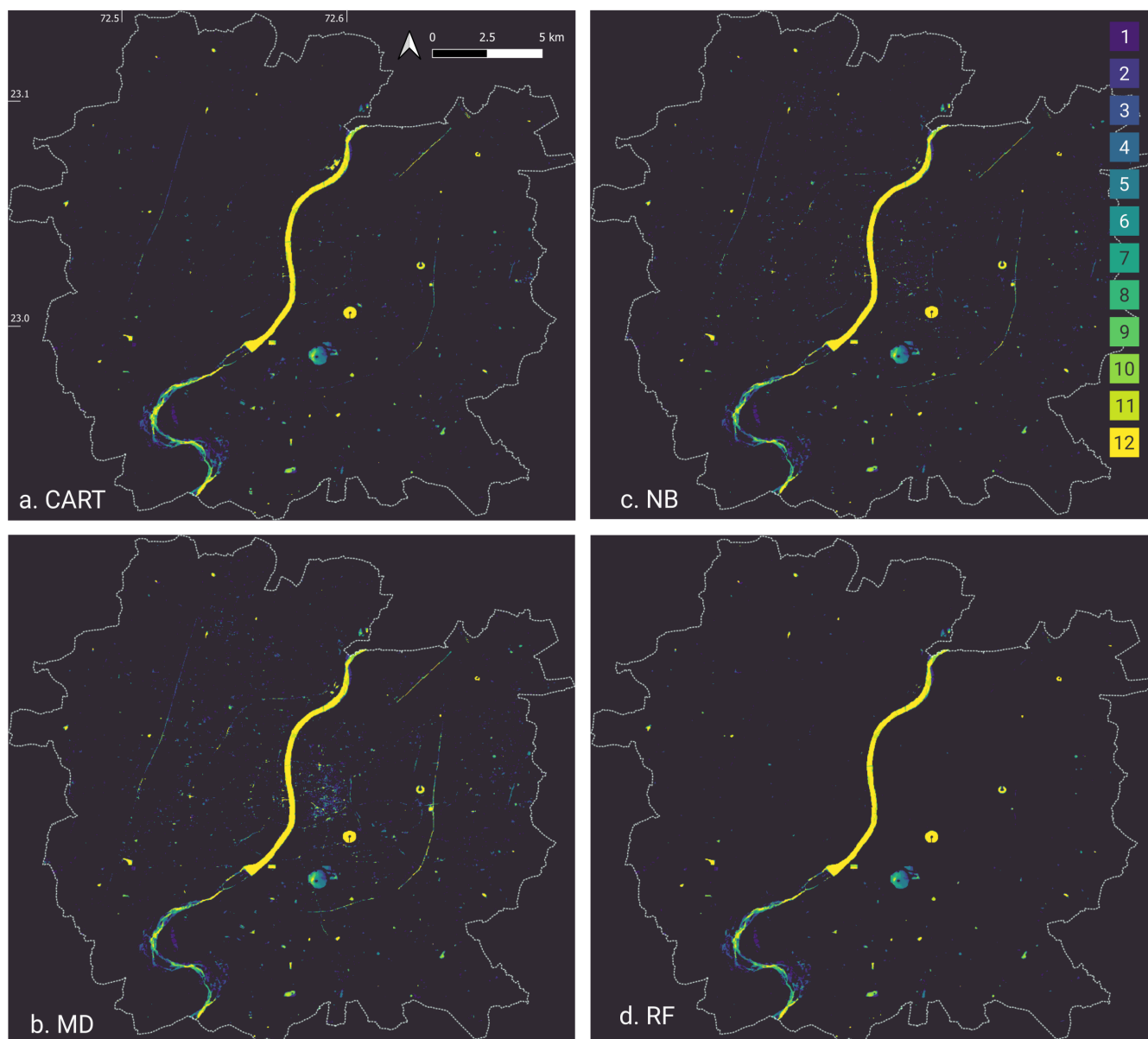


Figure 13. Yearly water presence maps for Ahmedabad City for 12 years, generated with classifiers: (a) CART, (b) Minimum Distance, (c) Naïve Bayes, and (d) Random Forest. Color scale indicates the number of years (1-12) each pixel was classified as water, highlighting the spatial and temporal persistence of water bodies across the region.

amplify disagreement.

Table 4. Classifiers disagreement over the extrema climatic condition hypothesis test results with GAM modeling

Term	Estimate	p-value	Interpretation
PARAMETRIC COEFFICIENTS (EXTREME EVENTS)			
Precipitation Extreme	-0.306	0.517	No significant effect of precipitation extremes alone.
Temperature Extreme	-0.043	0.778	No significant effect of temperature extremes alone.
Precipitation + Temperature Extreme	NaN	NaN	Incomputable-no extreme events overlapping in the data
SMOOTH TERMS (CONTINUOUS CLIMATE)			
Precipitation	1.06	0.002	Near-linear positive relationship with divergence.
Temperature	1.00	<0.001	A strong linear relationship with divergence.

The results of this hypothesis test in presented in the Table 4 and the conclusions from this test explains study rejects the null hypotheses which means classifiers do not disagree more during extreme climate conditions. It also explains classifier disagreement increases linearly with both precipitation and temperature, but extremes (as defined) add no explanatory power.

4.6.2 Hypothesis - 2: Classifier-specific climate sensitivity: Each classifier responds uniquely to the precipitation/temperature

To examine whether individual classifiers demonstrate distinct responses to climatic variables (temperature and precipitation), a Generalized Additive Model (GAM)-based technique is utilized. The methodology individually models the relationship between each classifier's monthly predictions and climatic drivers while controlling temporal trends. Classifier-Specific Models: Four classifiers (WA CART, WA MD, WA NB, WA RF) were analyzed. For each classifier, a GAM was fitted with the structure in the equation 11.

$$\text{Classifier Output} \sim s(\text{precipitation}) + s(\text{temperature}) + s(\text{date}) \quad (11)$$

Here, $s(\cdot)$ denotes a smooth spline function to capture nonlinear effects.

Table 5. Classifier-Specific Climate Sensitivity Results

Classifier	Precipitation			Temperature			Temporal Trend		
	EDF	F	p-val	EDF	F	p-val	EDF	F	p-val
CART	8.86	7.15	<0.001	1	91.62	<0.001	8.34	4.83	<0.001
MD	8.78	5.37	<0.001	1.74	30.55	<0.001	7.84	4.64	<0.001
NB	8.8	6.18	<0.001	1.28	32.55	<0.001	7.8	4.17	<0.001
RF	8.94	17.62	<0.001	1.31	9.24	<0.001	6.56	2.83	<0.01

Values show effective degrees of freedom (EDF) and F-statistics for each smooth term and p -val represents the statistical significance. EDF > 1 indicates nonlinear relationships; EDF $\approx$ 1 implies linearity, the result shown in the Table 5 and the conclusions are described in sensitivity of precipitation, temperature and temporal dynamics.

- **Precipitation Sensitivity:** Universally nonlinear, suggesting complex threshold-driven responses.
- **Temperature Sensitivity:** Linearity in CART vs. weak nonlinearity in others implies algorithmic differences in thermal thresholds.
- **Temporal Dynamics:** Unique long-term/seasonal trends highlight classifier-specific biases unrelated to climate.

Each classifier has unique climate fingerprints, such as CART is linearly associated with Temperature, MD is Rain complexity driven and RF is the most rain sensitive. This indicates that classifiers are not interchangeable, they encode different climate sensitivities.

4.6.3 Hypothesis - 3: Ensemble meta-models are superior, and ensemble prediction outperforms the ensemble classifiers

This hypothesis indicates that ensemble meta-models incorporating numerous classifiers exhibit more significant predictive accuracy compared to individual classifiers. To assess this, a stacked ensemble framework has been developed using R programming language. The methodology includes four stages:

1. **Data Preparation:** A consensus target variable (Observed) is generated as a weighted average of two base classifiers (WA MD and WA RF), initialized with equal weights (0.5:0.5). Temporal features (Season, Month, Year) are encoded, and synthetic spatial identifiers were introduced for aiding spatial-temporal analysis.

$$\text{Observed} = a \cdot \text{classifier}_1 + b \cdot \text{classifier}_2 \quad \text{with } a + b = 1 \quad (12)$$

2. **Model Development:** A spatial-temporal cross-validation approach grouped data by location-year interactions to reduce leakage. An XGBoost regression model (cf Eq 12) was trained using environmental predictors (e.g., precipitation, temperature) and classifier outputs, with hyperparameters improved through early stopping on a 30% validation subset Figure 14. Three weighting strategies for the consensus target (equal [0.5:0.5], MD-heavy [0.7:0.3], RF-heavy [0.3:0.7]) were investigated. Models are evaluated using root mean squared error (RMSE) on held-out test data, comparing environmental-only predictors to a stacked model incorporating classifier outputs.

3. **Model Evaluation:** The optimum weighting scheme (RF-heavy: 0.3:0.7) has remained for final model training. Bootstrap resampling (1,000 iterations) evaluated uncertainty in RMSE estimates, while XGBoost features significance analysis revealed key predictors in the stacked ensemble. The study tests an ensemble meta-model (stacked model incorporating environmental variables and individual classifiers) that outperforms Environmental-only models, Individual classifiers (CART, MD, NB, RF) Simple averaging baselines.
4. **The final model performance comparison:** Environmental Model RMSE is 514.50 ha, Stacked Model RMSE is 72.47 ha, and Simple Average RMSE is 187.98 ha. The test data set (30%) is plotted in the Figure 15.

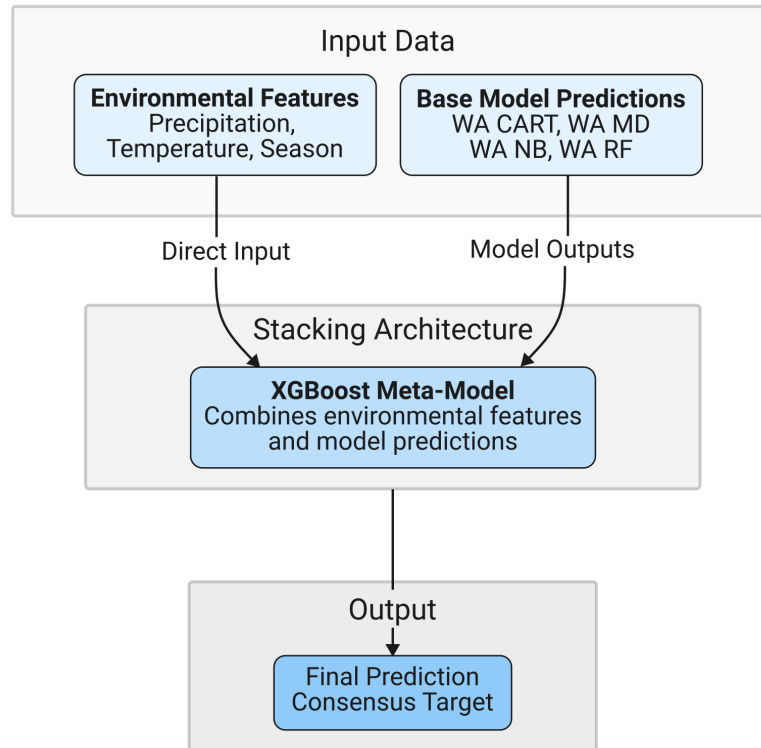


Figure 14. Model Stacking Architecture

5 Discussion

5.1 Water Area Generations Algorithms and Methodology

The study employs comprehensive remote-sensing and machine-learning architecture to map water-based bodies. Landsat 8 imagery (2013 - 2024) was pre-processed in GEE by spatially filtering to the Ahmedabad area and masking clouds via the QA_PIXEL band. The workflow computes water-sensitive indices - the NDWI and MNDWI - to increase water identification. Monthly median composites provide temporal consistency. Four supervised classifiers (CART, MD, NB, and RF) were trained on labeled water/non-water data utilizing spectral bands and these indices. The algorithms were implemented utilizing GEE's built-in classifiers for scalable processing. CART provides an interpretable decision-tree structure without distributional assumptions, NB handles high-dimensional features with minimal training data, MD is computationally efficient when classes are well-separated, and RF (an ensemble of CARTs) reduces overfitting through bagging and randomized feature selection. GEE enabled instantaneous analysis of the entire Landsat time series on a petabyte-scale dataset. Classification results were evaluated with curated dataset prepared with manual inspection and in-situ observation: a random 20% test split was withheld to compute confusion matrices, overall accuracy, and Kappa coefficient⁴⁰. This validation ensures reliable accuracy assessments and ensures against the model bias.

5.2 Trend and Statistical Analysis of Water Area

The multi-year water-area time series demonstrates significant seasonality and a minor long-term increase. Similar results are found in the study by Nyberg et al., (2024)⁴¹. Yearly totals from 2013 to 2024 show a modest rise in water coverage.

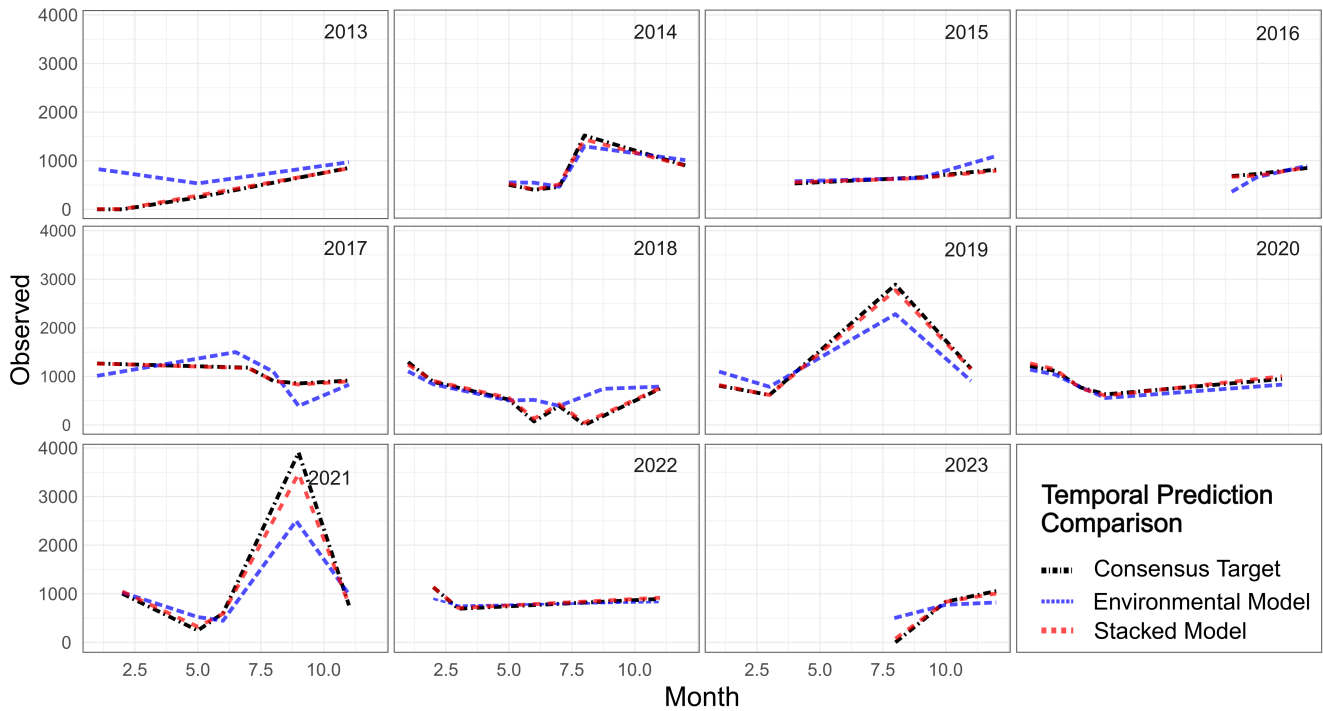


Figure 15. Temporal validation plot between time and observed values for Consensus target, environmental model output, and stacked model output.

Mann-Kendall trend tests confirm slight upward trends for some classifiers: for example, the Naïve Bayes and Minimum Distance models both show statistically significant positive trends ($\tau \approx 0.67$ and 0.46 , $p < 0.05$), whereas CART and RF do not. In contrast, analyses at monthly resolution provide significant upward trends for all classifiers ($\tau \approx 0.14 - 0.17$, $p < 0.05$), highlighting that a higher sample size improves trend detection. Seasonal decomposition (STL) indicates repeated annual cycles, with water area peaking during monsoon months. Pairwise agreement analysis by Bland-Altman plots, indicates modest systematic differences between classifiers, indicating that the four techniques broadly agree on the pattern of water-area changes. All classifier-derived time series were determined to be stationary (Augmented Dickey-Fuller $p < 0.05$), while the Ljung-Box test suggests substantial autocorrelation in the residuals. This indicates that water-area alterations, while stable in mean and variance, are temporally sensitive and predictable by time-series models. Notably, the discovered increased pattern - even though a minor - runs opposite to forecasts of reduction under urbanization, reflecting the impacts of local water-conservation programs or interannual rainfall variability. These statistical findings underline the necessity for consistent hydrological monitoring and indicate that urban water bodies in Ahmedabad may be more resilient than anticipated.

5.3 Climatic Variable Effect on Water Area and Ensemble Model Utility

Climatic drivers exert significant impacts on water-area dynamics. Correlation investigations between monthly climatic anomalies and classifier-derived water area reveal extremely high positive correlations for some models (e.g. correlation 0.82 for NB, 0.71 for MD) and weaker or negative associations for others. Cross-correlation study further suggests that precipitation establishes stronger and more frequent significant delays with water area than temperature. A phase-space scatterplot (precipitation vs. temperature) colored by classified water area demonstrates that water bodies persist under dry conditions (points dense at low-precipitation) and that significant water-area occurrences occur primarily during high-precipitation regimes. Classifiers differ in sensitivity: CART and NB predict broader water-area variability at moderate-to-high rainfall (more sensitivity), while Random Forest produces conservative, smoothed estimates, and MD frequently underestimates water under very wet conditions. Hypothesis tests demonstrate that classifier disagreement does not spike only in extreme months (H1 rejected): disagreement increases constantly with precipitation and temperature rather than only during designated extremes. Each algorithm reveals a unique climate-response fingerprint (H2 confirmed): for example, all models have nonlinear precipitation responses, while CART's dependence on temperature seems linear whereas other models have more complex thermal impacts. Finally, the ensemble meta-model (XGBoost stacking of classifiers with climate features) demonstrates exceptional accuracy: its RMSE (72.5) is lower than that of a simple average classifier (187.98) or a climate-only model

(514.50). This emphasizes the ensemble's capacity for utilizing several data sources and minimizing individual model biases. Such a stacking technique decreases prediction error and offers immense potential for robust hydrological forecasting under fluctuating climate circumstances.

6 Conclusion and Future Perspectives

This study explored the spatiotemporal dynamics of water area change over the 12 years (2013 - 2024), and the study was conducted on Ahmedabad, a city in the western region of India. This paper utilized the remote sensing data from Landsat-8 and trained the four machine learning classifiers, namely CART, MD, NB, and RF. Monthly and yearly time series datasets are prepared for all classes and climatological variables (temperature and precipitation) time series for the same span are also generated. Then we explored the relationship between the classifiers and climatic variables, trend in water area change, and optimum classifier and climatic variable combination. First assessed the water area classification was assessed using the kappa coefficient, and overall accuracy was later the manual impaction. To understand the dynamics of water area, change and impact of climatic variables, statistical tests the performed, such as the Mann-Kendall test for trend confirmation, and the Bland-Altman Test for classifiers agreement. The methodology explored the trend and statistical analysis of water area, and the climatic variable effect on water area, and finally explored the ensemble model utility.

The results show a modest but significant increase in the water area of Ahmedabad city over 12 years, which contradicts the assumption of shrinking the water bodies' area due to rapid urbanization and climate stress. The potential reasons for this increase are the water conservation initiative (National Jal Shakti Abhiyan) by the Government of India that promotes the rainwater harvesting system for all new structures, restoration of traditional water bodies, and control over the water body encroachment in the past decade in the city of Ahmedabad. This increase in the water area is also the implication of the successful implementation of the policies that are designed to work against climate change in the arid region of India. Furthermore, government initiatives aimed at rejuvenating the Sabarmati River at several places inside the city and preserving significant lakes, such as Kankaria and Vastrapur, enhanced this increase in the water area trend. The study explores only twelve years of data; there, we want to focus on only Landsat 8 data, which allows us to test the sensitivity of classifier algorithms. Found the yearly fluctuations are a weak pattern, unlike the monthly pattern that shows a more prominent pattern. Precipitation has lower control on the water area dynamics compared to the temperature, and the temperature is a prominent driver of change in the water area of the city. Water area change is susceptible to inconsistent change and reduces future vulnerability. It requires adaptive management strategies to effectively manage the water resources of the city.

The classifiers examined by this study are CART, MD, NB, and RF demonstrated difference in the water area classification but detect overall similar pattern of the change and seasonality. RF shows the highest Kappa coefficient > 0.85 in our different input train dataset. CART's interpretability through decision trees and its ability to deal with non-linear relationships make it particularly helpful in differentiating water bodies among complex land-use patterns, while NB's efficiency with high-dimensional data prevented overfitting risk factors. However, significant divergences in classifier outputs were identified under specific environmental circumstances; for instance, CART demonstrated linear sensitivity to temperature fluctuations, while NB and RF exhibited non-linear responses to variations in precipitation. Though MD proved to be computationally efficient, it became apparent to underestimate water area in humid situations due to overlapping spectral signatures. These variations highlight the critical nature of classifier selection, which should be based on regional climatic and land-cover locations and raise caution against dependency on single-algorithm techniques in dynamic circumstances.

Further, the significant contribution of this study is the development of a stacked ensemble meta-model that integrates environmental factors, including precipitation and temperature, with classifier outputs. This novel approach generated a substantial reduction in prediction errors, demonstrating an 85% improvement compared to models utilizing only environmental data (RMSE: 72.47 vs. 514.50) and exceeding simple classifier averaging (RMSE: 187.98). The improved performance of the ensemble model can largely be because of its ability to deal with a variety of data sources, minimize the biases inherent in individual classifiers, and capture non-linear relationships between climatic factors and hydrological responses. Employing XGBoost for feature optimization, together with spatial-temporal cross-validation, this approach exhibited high scalability for large-area monitoring and forecasting. Such models are crucial for policymakers seeking to anticipate potential risks associated with water scarcity, optimize conservation investments, and align strategies with Sustainable Development Goals (SDGs) 6 (clean water) and 11 (sustainable cities).

Despite the advancements in hydrological monitoring approaches provided in the present work, numerous limitations require attention for future research endeavors. These include the requirement for better temporal and spatial resolution, the introduction of strong ground truth validation procedures, the incorporation of General Circulation Model (GCM)-based climate predictions, and an assessment of socio-economic factors. In the context of these considerations, this research highlights the transformative potential inherent in integrating remote sensing, machine learning, and ensemble modeling for sustainable water governance. By addressing the highlighted shortcomings and adopting interdisciplinary approaches, future investigations might further bridge the gap between hydrological understanding and effective policy, thus assuring equitable water security in arid

and rapidly urbanizing areas.

Author contributions statement

A.D. conceptualized the study and performed the data analysis. A.D. and S.V. analyzed the results and drafted the manuscript, M.B. and I.Z. analyzed the results and reviewed the draft. All authors reviewed the manuscript.

Additional information

Competing interests

On behalf of all authors, the corresponding author states that there is no conflict of interest.

Availability of materials and data

All data and code supporting the findings of this study are available in the GitHub repository: [202505_J_WA_AHM](https://github.com/202505_J_WA_AHM).

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