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ARTICLE

Exploration of Vulnerability of Temperature Changes in Southeastern Coastal Islands of Bangladesh through the 2 Decades of Spatiotemporal Data

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ABSTRACT

Bangladesh is one of the most vulnerable countries to climate change-related disasters and economic loss and damage. This study examines 20 years of satellite-derived land surface temperature (LST) data to investigate seasonal trends, changes in land use and land cover (LULC), and the relationship between temperature changes and the most common mangrove species in the Coastal islands of Bangladesh. The most noticeable temperature changes happened in the pre-monsoon and monsoon seasons. In December, on the other hand, there was a statistically significant cooling trend of −0.041 °C per year. At the same time, forest cover has been shrinking by an average of 26.36 km² per year, while coastal water bodies have been growing by 23.44 km² per year. Cluster analysis shows that temperatures change a lot from month to month outside of the pre-monsoon season. This suggests that the climate is unstable and could push the system beyond ecological thresholds. SARIMA modelling demonstrated 98.12% accuracy in predicting temperatures, highlighting the importance of temporal analysis in forecasting future stress thresholds. Species-specific temperature clustering shows how different mangrove species can handle heat: *Ceriops decandra* is more common in locations with higher temperatures, while *Heritiera fomes* is more common in areas with lower temperatures. These patterns show that ecosystem resilience is becoming less stable; therefore, we need to move from passive Conservation to proactive, species-informed, and thermally adaptive management practices.

Keywords: Coastal Islands; Economic Loss and Damages; Cluster Analysis; Satellite Data; Trend Analysis; Tree Species Distribution

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1. Introduction

Climate change is no longer a far-off threat to the environment; it is already a growing force that is changing ecosystems and pushing natural systems to their limits. Increasing heat waves, changing rainfall patterns, and more unpredictable weather events are not just signs of a warming world, but they are also tests of how well the environment can adapt. Forests, especially those in tropical and coastal regions, are among the most sensitive and responsive systems to environmental changes [1]. The IPCC determined that rising global temperatures and changing precipitation patterns are depleting forest biomass and biodiversity, which compromises their ecological functions [2]. In humid tropical areas, extended periods of drought and very high temperatures are making it harder for forests to grow back and stay strong [3]. Climate change and the health of forests, particularly in coastal and tropical areas, are significant concerns, as these ecosystems are fragile and crucial for maintaining a stable climate both locally and globally. Forest ecosystems play a crucial role in storing carbon, protecting biodiversity, and regulating the climate. However, they are currently facing unprecedented challenges due to climate change [4]. Forests help stabilize the environment by trapping carbon, but the climate they help stabilize is also making it harder for them to survive.

One of the main effects of climate change is that the sea surface temperature (SST) is rising. The rise in SSTs is altering ocean systems and the way heat is distributed in nearby land areas. Many studies show that SSTs have risen significantly around the world in the last century, especially in tropical and coastal regions [5,6]. These changes are not limited to marine systems, which is essential. The warming of the oceans also has effects on land, raising land surface temperatures (LSTs) and disrupting the delicate balance between soil moisture, evapotranspiration, and atmospheric feedbacks. This can alter wildfires, landslides, and precipitation thresholds [7]. Higher sea-surface temperatures have been linked to stronger tropical storms, changes in rainfall patterns, and variations in regional climates. All of these factors affect forests and other land-based ecosystems. A shocking 71.6% of the world's coastlines are seeing SSTs rise. The oceans are getting warmer, and so is the land around them [1].

Higher ocean temperatures are bad for nearby land ecosystems, especially mangrove forests, which are already under stress from rising sea levels and coastal erosion [8,9]. Additionally, studies indicate a strong correlation between SST and LST in coastal areas. This means that warmer oceans directly affect the LST of coastal areas. Additionally, rising SST makes coastal forests less able to handle environmental stress [10]. The Bay of Bengal, which includes the Coastal islands, is where this dynamic is most clear and dangerous. The Coastal islands are one of the largest and most important mangrove forests in the world. They are essential for storing carbon, protecting the coast, and regulating Temperature [11].

Bangladesh is highly vulnerable to CC due to its unique geographical location, poor infrastructure, low-lying topography, and high population density. Understanding potential climate change is essential for creating adaptation strategies and increasing resilience to CC. However, a few studies used CMIP5 models to assess future changes in Temperature in Bangladesh for various CC scenarios [12,13]. This was projected Tmax and Tmin over Bangladesh using the MME of eight CMIP5 GCMs. They projected an increase in Tmax by 1.3 °C–4.3 °C and Tmin by 1.8 °C–5.1 °C for different RCPs. They also projected the highest rise in Tmax and Tmin in the northern region and the lowest in the southeastern coastal area of Bangladesh [14]. This was found that higher increase in Tmax and Tmin in the southwest region than in other parts of Bangladesh [15]. Earlier research was mainly concentrated on a limited number of GCMs or RCMs for monthly or annual Tmax and Tmin projections at the regional or national scale [16,17]. Unfortunately, understanding the spatiotemporal trends and variations of future temperature changes at monthly, seasonal, and annual timescales is limited. Moreover, no extensive study has been conducted to project temperatures employing all existing CMIP5 GCMs at various time scales over Bangladesh [18,19]. Several studies show that the Bay of Bengal's sea surface temperatures (SSTs) rise all year round, except during the dry season [20,21]. Even during the monsoon season, it seems that freshwater inflows raise sea surface temperature (SST) levels, making the region's thermal stress worse [22,23]. The Temperature of the land adjacent also rises because of this. According to Shuva et al. [20], SSTs are increasing by 0.10–0.16 °C per decade during the day and by 0.18–0.27 °C per decade at night along the Bay of Bengal. This is a worrying trend. The rising sea surface temperatures (SSTs) are strongly linked to the increasing land surface temperatures (LSTs) in the

Coastal islands, which makes the climate less stable [12,22,24]. The IPCC reports indicate that greenhouse gas emissions are not only making coastal areas warmer, but they are also altering the seasons, which affects the timing, duration, and intensity of the seasons [9,25]. Long-term temperature data from the Coastal islands support these global predictions, like the IPCC's: temperatures are rising significantly before and after the monsoon season, but they get colder during the dry season [26]. Remote sensing data backs up these trends, showing that summer temperatures are at their highest and monsoon and dry season temperatures are at their lowest [27]. Forests, such as those found on the Coastal islands, are essential for maintaining regional microclimates by recycling moisture and allowing it to evaporate. Mangroves act as natural heat buffers by providing shade, keeping soil moist, and controlling wind patterns. In principle, higher SST should lead to higher temperatures. However, the coastal area near the Coastal islands has cooler temperatures during the dry season instead [10,22]. This is bad news since forests like those on the Coastal islands help keep the Temperature stable by releasing water vapor, which cools the area around them. Evapotranspiration rates in trees may be too high during the dry season, as there is insufficient moisture and lower temperatures. This can cause stress and perhaps harm biodiversity [9,25,27,28]. Some people say that these frigid, dry seasons could even cause the forest cover to go down. The land surface gets more direct sunlight when there is less vegetation, which could make temperatures even higher in other seasons [28]. Lower winter temperatures may enable mangrove habitats to expand northward, potentially replacing salt marshes in specific locations. The distinction between adaptability and ecological displacement is a crucial issue for future conservation policy [29].

Recent studies show that the Coastal islands have lost about 129 square kilometers of forest in the last few decades [22,30]. This exacerbates the effects of climate stressors. The changes in air and water temperatures that happen as a result can have a significant impact on where species live, how fast they breathe, and how mangroves and salt marsh plants reproduce [31]. Higher water temperatures may change the thermal conditions of mangrove ecosystems, which could affect the growth of mangrove plants and animals in the area [32]. As temperatures rise, many creatures exhibit sigmoid physiology, which means they undergo a rapid adaptation period, then reach an equilibrium, and subsequently start to deteriorate [33]. However, we do not know precisely what the temperature limits for collapse are, which makes forecasts more challenging. Also, a temperature rise could make the lack of water vapour worse, making it harder for mangrove plants to survive and develop in dry areas [33]. These thermal stressors do not operate independently. They face contemporary challenges such as pollution, habitat loss, and changes in salinity, which further exacerbate the risk to biodiversity and ecosystem services. These changes can have a profound impact on biodiversity, ecosystem services, and the livelihoods of local people. This means that people need to devise effective ways to adapt [34]. Temperature changes can make habitats less suitable, change where species live, and make concerns like habitat loss and pollution worse. To develop effective conservation plans and optimize resource utilization, it is essential to understand how Temperature influences biodiversity dynamics [35,36].

There is much writing about climate change and environmental change in the Coastal islands, but there are still significant gaps in the studies. Fu et al. [1], Mandal et al. [23], and Osland et al. [28] have examined global changes in sea surface temperature (SST) and salinity, as well as the impact of climate on mangrove ecosystems. However, their assessments often do not focus on specific regions. Chowdhury et al. [18], Sarker [10], and Shuva et al. [20] looked at Bangladesh's coastal region's climate, including SST, precipitation, and air temperature. However, they did not look at the ecological limits of the Coastal islands. There have not been many direct efforts to learn more about the area. Ghosh et al. [31] looked at how Temperature and precipitation affect mangrove species, but they did not look at how these factors change with the seasons or how LST affects species distribution. Barik et al. [32] also looked at how salinity affects the spread of mangroves, ignoring other climate parameters. Samanta et al. [22], on the other hand, only studied the Indian Coastal islands and did not look at how land surface temperature affects species.

One problem with these studies is that they lack extensive, species-specific LST analysis or ongoing ground-based meteorological monitoring in the Coastal islands. This has made it challenging to understand how changes in microclimates, particularly temperature fluctuations, impact the distribution of mangrove species and the stability of ecosystems over time. This work utilizes remote sensing and spatio-temporal methods to examine land surface temperature patterns in coastal islands from 2000 to 2023, aiming to fill existing gaps. This study also examines the impact of changes in land use and land cover (LULC) on temperature fluctuations. It does this by looking at the thermal preferences and distributions of four common mangrove species: *Heritiera fomes, Excoecaria agallocha, Sonneratia apetala*, and *Ceriops decandra*. This study also uses the SARIMA model to estimate future temperature changes. This is a crucial piece of information for proactive Conservation and ecosystem management as climate pressures intensify. The main goals of this project are to map out temperature changes over the last 20 years in the Coastal islands.

- Looking at how land cover changes and how forests are getting worse.
- Connecting changes in LST with the distribution of the most common mangrove species.
- Predicting temperature trends to figure out what the stress levels will be in the future.

This study examines the Coastal Islands region through four main goals, linking them to demonstrate how climate change's changing temperatures put stress on mangrove species.

2. Materials and Methods

The authors chose the southeastern coastal zone of Bangladesh for their study. They focused on three islands: Maheskhali, Kutubdia, and Sandwip. Climate vulnerability, rates of displacement, land erosion, and repeated disasters have been thought about when choosing people for the study. The Sandwip Island is part of the Chittagong district, which has an area of 762.42 km^2. Cox's Bazar district includes Kutubdia Island, which is 215.8 km^2 and is surrounded by the Bay of Bengal. Cox's Bazar district also includes Maheskhali Island, which is another coastal island. It has an area of 362.18 km² and is also surrounded by the Bay of Bengal. The Ganges River's tidal, supra-tidal, and fluvial processes form three islands. The terrain of these islands is mostly mudflats, sandy areas, and mild slopes (**Figure 1**).

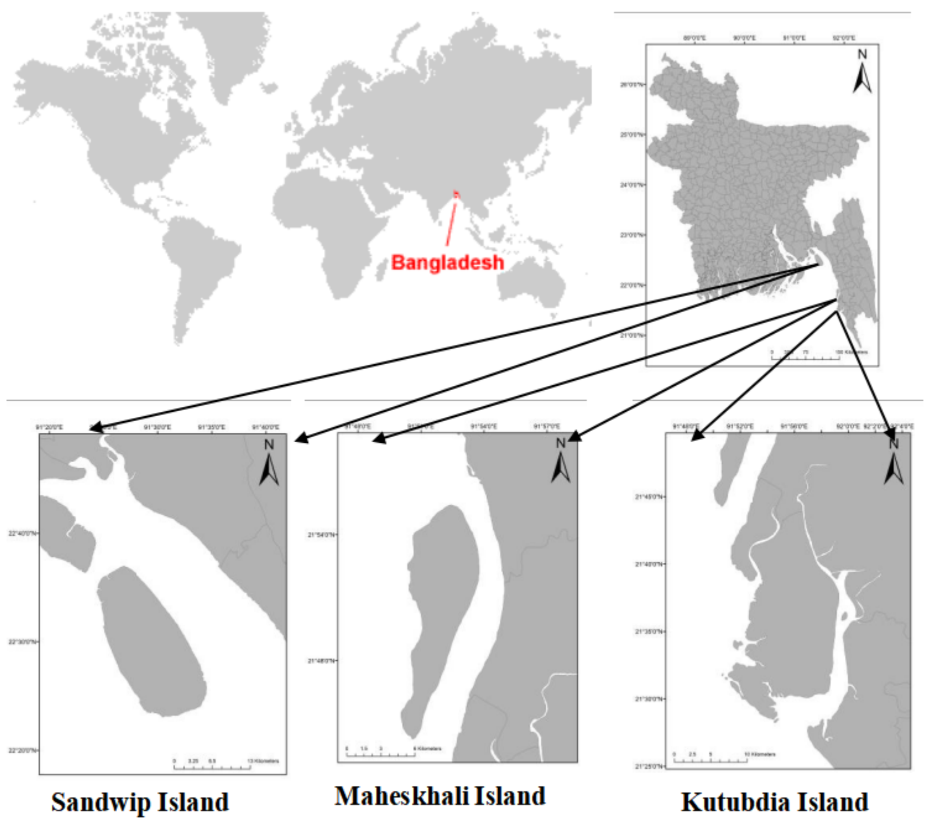


Figure 1. Geographical Location of the study areas.

2.1. Data Collection

This study used Landsat (5–8) and MODIS satellite data to look at land surface temperature (LST) and other features of the land. The Google Earth Engine (GEE) JavaScript interface was used to get and process the data. We configured the study's geographical scope by uploading a shapefile of the research area into GEE. This made it easier to filter relevant datasets by location. We used the given parameters to combine pixel-level measurements from the satellite bands to find the average daily temperatures across the study area. The bonus section provides information on the entire data extraction procedure and the coding scripts that accompany it.

The analysis spans the years 2000 to 2023, covering temperature and raster layers. Because there are not many ground-based weather stations in the Coastal islands region, we picked MODIS LST data because it is very accurate over vast areas with very little error. In clear skies, MODIS thermal readings are more precise than 1K at a spatial resolution of 1 km[37]. Different studies on long-term climate fluctuations in different parts of the earth indicate that it is likely that the impact of climate change will challenge and even reverse the advancements made in many African countries' socio-economic well-being[38]. A study in China found that there is only a minimal daytime bias of 1.32K, which is even less at night and when there are no clouds[39]. According to additional validation trials done in the US, the root mean square error (RMSE) values were less than 1.3K[40]. MODIS LST errors in the Bangladesh region are limited to ±1K, and data from satellites closely match data from the ground ($R^2 = 0.95$)[41,42]. Cloud interference, dust, or sensor problems can all affect satellite-derived land surface temperature data; however, these problems were not significant for this study[43]. It did not matter that a few pixels were missing because the monthly means were based on the average temperature data for the whole area. Because of this, this analysis did not need data imputation. This study employed the Mann–Kendall trend analysis approach[44,45], a standard nonparametric method for detecting a monotonic trend (either increasing or decreasing) in a time series dataset. This method does not assume a specific distribution, unlike parametric models, hence it is suitable for environmental and climate data. The null hypothesis says that there is no clear trend over time, while the alternative hypothesis says that the observed values have changed in a statistically significant way[46]. The approach checks to see if the data indicate a consistent change in direction, without requiring a linear trend. A p-value of 0.05 or lower is considered statistically significant and strongly suggests that there is a monotonic trend in the data[46]. The next part explains the statistical methods used in the analysis:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sgn\left(x_j - x_i\right) \tag{1}$$

In this context, x_j and x_i represent the values of sequences j and i, respectively; n denotes the length of the time series, and

$$Sgn(x_j - x_i) = \begin{cases} +1 & if\ (x_j - x_i) > 0 \\ 0 & if\ (x_j - x_i) = 0 \\ -1 & if\ (x_j - x_i) < 0 \end{cases} \tag{2}$$

If the test statistic value S is more than 0, it means that the dataset is going up. If the value S is less than 0, it means that the dataset is going down. In this case, xi and xj are single observations at times i and j, and n is the total number of observations in the time series. If the data are independent and identically distributed, the distribution of S can be close to a normal distribution. In this case, the variance of S is found using the following formula:

$$\mathrm{VAR(S) = n(n{-}1)(2n + 5)} \tag{3}$$

$$\mathrm{n(n{-}1)(2n + 5)} = \sigma^2 \tag{4}$$

Where σ represents the standard deviation, the relevance of the testing method is indicated by the statistical value Z, where |Z| ≥ 1.96 (corresponding to $p \leq 0.05$) is deemed significant.

$$Z => \begin{cases} \frac{S-1}{\sqrt{VAR\ (S)}},\ S > 0 \\ 0 \quad\quad ,\ S = 0 \\ \frac{S+1}{\sqrt{VAR\ (S)}}, S < 0 \end{cases} \tag{5}$$

$$\beta = Median\left\{\frac{y_j - y_i}{J - i},\ 1 \leq i \leq j \leq n\right\} \tag{6}$$

The MK is a non-parametric estimator based on Sen's slope estimator. It is defined by the time series showing an increasing trend with magnitude β when β > 0 and a decreasing trend with magnitude |β| in the other case[7,47].

2.2. Data Analysis

The Autoregressive Integrated Moving Average (ARIMA) model is widely used for predicting time series. It consists of three main parts: autoregressive (AR), integration (I), and moving average (MA). The Seasonal ARIMA (SARIMA) model is a variation of ARIMA that works exceptionally well with data that has seasonal patterns that repeat[48]. This study employed SARIMA to examine temperature patterns, taking into account natural seasonal fluctuations. Because daily temperature measurements fluctuate significantly and do not follow a consistent pattern, they were combined into monthly averages to improve the model's accuracy and consistency.

The raw daily data contained a lot of noise and rapid changes, making it difficult for prediction algorithms to function effectively. However, averaging the data into monthly averages made the forecasts far more stable and reliable. There were 276 monthly observations used for this study. This is a lot more than the 40 to 50 observations that are usually recommended as a minimum for reliable ARIMA modelling[49]. The three parameters that define an ARIMA model are p, d, and q. p is the number of autoregressive terms, d is the number of differencing steps needed for stationarity, and q is the number of lagged forecast errors in the moving average component[50]. Equation (7) shows how the ARIMA (p, d, q) model is usually written down mathematically:

$$\Phi_l(1-l)^d y_t = \theta(l)\varepsilon \tag{7}$$

In this equation, φl and θ (l) are the polynomial coefficients for the autoregressive (AR) and moving average (MA) parts of orders p and q, respectively.

The Seasonal ARIMA (SARIMA) model builds on the ARIMA framework to handle time series data with seasonal trends. It is written as SARIMA(p, d, q)(P, D, Q)s. The first set of parameters, p, d, and q, is for the model's non-seasonal parts. The second set of parameters, P, D, and Q, is for the model's seasonal autoregressive, differencing, and moving average parts. The subscript s shows how long the seasonal cycle lasts (for example, 12 for monthly data that shows annual seasonality). Seasonal polynomials are used to describe the seasonal framework of the SARIMA model. They capture repeating patterns at set intervals and are added to the overall model to make predictions more accurate when dealing with cyclical behavior.

$$\Phi_p(l^s)\rho_p(l)(1-l)^d(1-l^s)^d y_t = \theta_q\theta_q(l^s)\varepsilon_t \tag{8}$$

The SARIMA modelling strategy follows a structured process with three main steps: identifying the model, estimating the parameters, and testing the diagnostics, which ultimately leads to forecasting[48,51]. This study employed a modeling technique that utilized two different seasonal cycles, one with 12 periods and one with 24 periods, to examine short- and medium-term patterns in the temperature data. In the first step, you need to check if the time series is stationary. Differencing is used to stabilize the mean when the data show trends or seasonality. After that, the plots of the autocorrelation function (ACF) and the partial autocorrelation function (PACF) are looked at to find the best values for the model parameters. The Bayesian Information Criterion (BIC) makes it easier to choose a model by giving it a penalised likelihood score to find the simplest and best model. Once a candidate model is selected, its parameters are estimated using well-known methods developed[52]. These methods include autoregressive and moving average components. At this point, all the extra seasonal and non-seasonal coefficients are also figured out.

After the estimation, a diagnostic examination is done to see if the model accurately reflects how the observed data changes over time. This validation supports the model's assumptions, thereby enhancing its ability to predict more reliably. We use the Ljung-Box test to check for autocorrelation in the residuals and model fit indices, as shown in Equations (9) and (10), to check the overall goodness-of-fit:

$$Mean\ Absolute\ Error\ (MAPE) = \frac{1}{N}\sum_{i=1}^{M}\left|(X_m)_i - (X_s)_i\right| \tag{9}$$

$$Root\ mean\ square\ error\ (RMSE) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left[\,(X_m)_i - (X_s)_i\right]^2} \tag{10}$$

In this case, N stands for the total number of predicted observations, Xm stands for the actual (measured) values, and Xs stands for the projected values that the model came up with. The Ljung-Box test is a way to check if a time series model is good enough by looking for autocorrelations in the residuals. The null hypothesis (H0) says that the model fits the data well enough that there is no significant autocorrelation in the residuals. On the other hand, the alternative hypothesis (Ha) says that the model does not accurately reflect the structure of the data. The level of statistical significance, which is usually set at 0.05, tells you whether to accept or reject $H0$. This shows whether the model is statistically valid or not[48]. This study used satellite images from two different sources, Landsat 5 and Landsat 8, both of which have a spatial resolution of 30 m. We chose January images to examine since there are usually few clouds during this time, which makes the photos more transparent and easier to use. Before classifying the data, ENVI 5.1 was used to make sure that the data was accurate by making radiometric and surface reflectance modifications. We used ArcGIS 10.3 Desktop to process and classify images, focusing on two key types of land cover: vegetation and water bodies. Because the Coastal islands did not have many people living there or much land that was not being used, there was no need to establish more land use categories. In ArcGIS, a supervised classification method was employed to identify training sites by carefully examining the spectral and spatial characteristics of all images. We digitalized polygons for each type of land cover to show locations with similar land use and land cover (LULC) features. The classification approach employed the Maximum Likelihood algorithm, which analyzes the mean and standard deviation values of each pixel from the training data to determine the likelihood that the pixel belongs to a specific category [53]. After that, pixels were put into the class that best matched them, and similar classes were combined into one representative group. After the classification, the area covered by each land feature was measured in square kilometres.

To verify the accuracy of the classification, an accuracy check was performed using both historical reference images (such as those from Google Earth Pro) and publicly accessible ground-truth data. Using the "Create Accuracy Assessment Points" function in ArcMap, we made a set of 200 random validation points. To check how accurate the results were, an error matrix was created that juxtaposed categorized map outputs (rows) next to reference ground truth data (columns). We used the Kappa coefficient, which is a statistical measure that goes from −1 to +1, to measure how well the classifications agreed with each other. Values over 0.80 show perfect classification accuracy, values between 0.40 and 0.80 show moderate accuracy, and values below 0.40 show inadequate agreement [54]. We used the "Compute Confusion Matrix" tool in ArcMap to find the Kappa coefficients.

$$Kappa\ coefficient = \frac{(TS*TCS)-\sum(Col.total*row\ total)}{TS^2-\sum(Col.total*row\ total)} \tag{11}$$

TS is the total number of samples utilised to check for correctness, and TCS is the number of samples that were correctly classified. The total for each class is the sum of all the reference samples in that class, and the total for each row is the number of samples that were put into that category.

2.3. Statistical Analysis

We used tree distribution maps and temperature maps from all four seasons to look at the links between temperature and tree distribution patterns. First, we gathered temperature raster information from all four seasons during the course of the 24-year study. Then, all of the rasters were averaged to create one raster that shows the average temperature distribution across the Coastal islands for each season. After that, three distribution maps from several studies were put together, and four main species were found. A new raster was generated [36,55,56]. Then, the fishnet tool was used to produce data with 300,000 equally spaced points using ArcMap tools and a point shape file. After that, all of the necessary rasters were stacked on top of each other, and the points were utilized as geographical markers to get the pixel value from all of the raster's in one table.

The 300,000 sample points made many sample points inside each MODIS 1 km² pixel. Tree species in the Coastal islands grow in massive groups of identical trees over large areas. Having many sample points inside a single MODIS pixel helped us find tiny temperature changes. The Landsat data with better resolution, which mainly shows tree types, helped figure out which species were most common in each pixel. Several sample points inside a single MODIS pixel enhanced accuracy and ensured that the temperature data accurately represented the dominant tree species. This was because similar tree species tended to cluster together. We found a strong link between land surface temperature (LST) and tree species distribution by combining species data from Landsat with MODIS pixels and looking at how temperatures changed at different sample points. This method reduced differences in resolution and ensured that the LST data from MODIS accurately reflected the patterns of dominant tree species observed in Landsat. After filtering out specific blanks and inaccurate data points, the acquired data were used for statistical analysis to find a link between trees and the distribution of Temperature in space. **Figure 2** shows how the detailed workflow works.

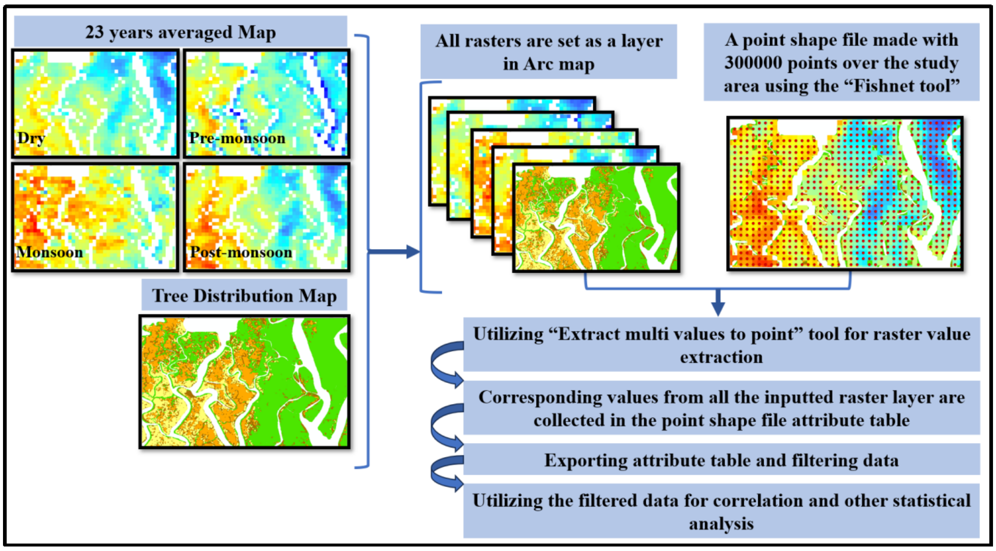


Figure 2. Process of extracting data from multiple raster's for statistical analysis.

3. Results

Bangladesh has four distinct seasons: pre-monsoon (March to May), monsoon (June to August), post-monsoon (September to November), and dry (December to February). These seasons show how the country's ecology works. The data and results of this study indicate that the rhythm is being broken. Data from the last 23 years show that April, which is the pre-monsoon season, has the highest average Temperature at 28.31 °C. On the other hand, January, which is the dry season, has the lowest average Temperature at 20.9 °C. The monthly average temperature changes that were recorded over the 23 years are shown in **Figure 3b**. June, the commencement of the monsoon, has the most variable monthly Temperature (1.56), which means that temperatures might change in ways that are hard to predict. This could affect the phenological and physiological processes of forest species.

On the other hand, October, which follows the monsoon, has the least variability (0.41), indicating that the Temperature remains stable for a short time. **Figure 3c** shows that this instability is even stronger: both the monsoon and pre-monsoon seasons have a temperature variability index of 1.075, which shows that the climate is becoming less stable during months that are important for biological life. The post-monsoon season, on the other hand, has the least volatility, with a score of 0.46.

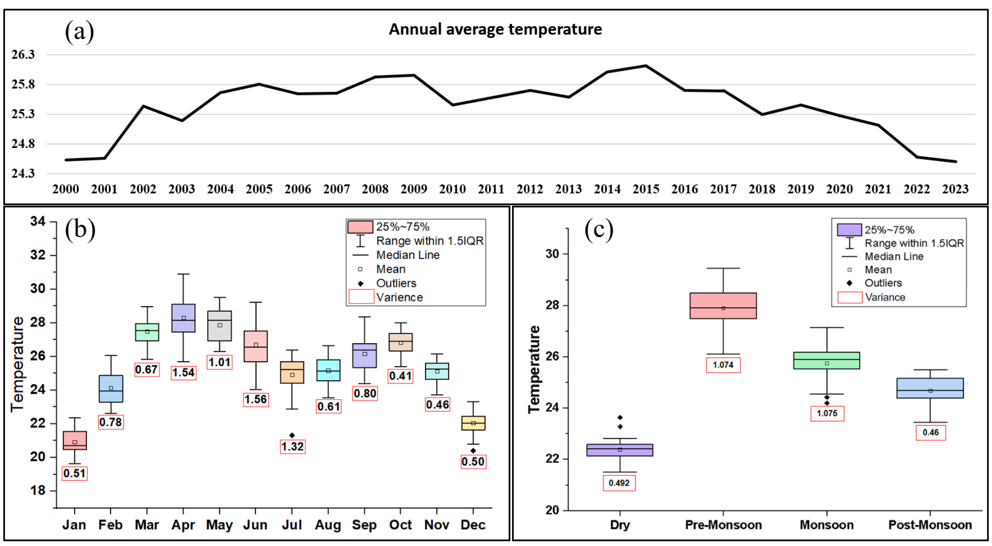


Figure 3. Temperature pattern of the study areas for the past 24 years, (**a**) yearly average LST, (**b**) monthly average temperature data, and (**c**) average seasonal Temperature.

The dendrogram in **Figure 4** shows a cluster analysis of the months based on 24 years of average temperature data. It illustrates the complexity of temperature patterns in the study areas during different seasons. The research reveals four main clusters, each representing a distinct seasonal and transitional period in the area. January and December, which are both dry-season months, form their own group since their temperatures are similar. February is different from the other months in this group since it does not fit with the dry season months. This shows that there are small changes. March, April, and May were all in the same group of months before the monsoon season. This indicates that the monthly temperature ranges stayed relatively constant during the pre-monsoon season. September, October, and June made up another group with similar temperature ranges. This is likely due to changing weather patterns, as these months typically mark the start or end of the rainy season. This is why they are all in the same group. The cluster that includes July and August, which are usually thought of as monsoon months, is the most interesting part of the dendrogram. These months share a temperature cluster with February and November, which are typically considered dry or post-monsoon months. The low temperatures during the monsoon are very different from what is usually expected, and they may be connected to how rain and humidity change the Temperature. This outlier cluster suggests that seasonal patterns are becoming less distinct, likely due to the effects of climate change, which can lead to unusual phenomena such as increased rainfall and temperature fluctuations. This change in Temperature between seasons shows that the climate is changing more broadly. Even while seasonal categories are common, monthly temperature trends in the Coastal islands are more variable, with one big exception: the pre-monsoon months, which are relatively stable.

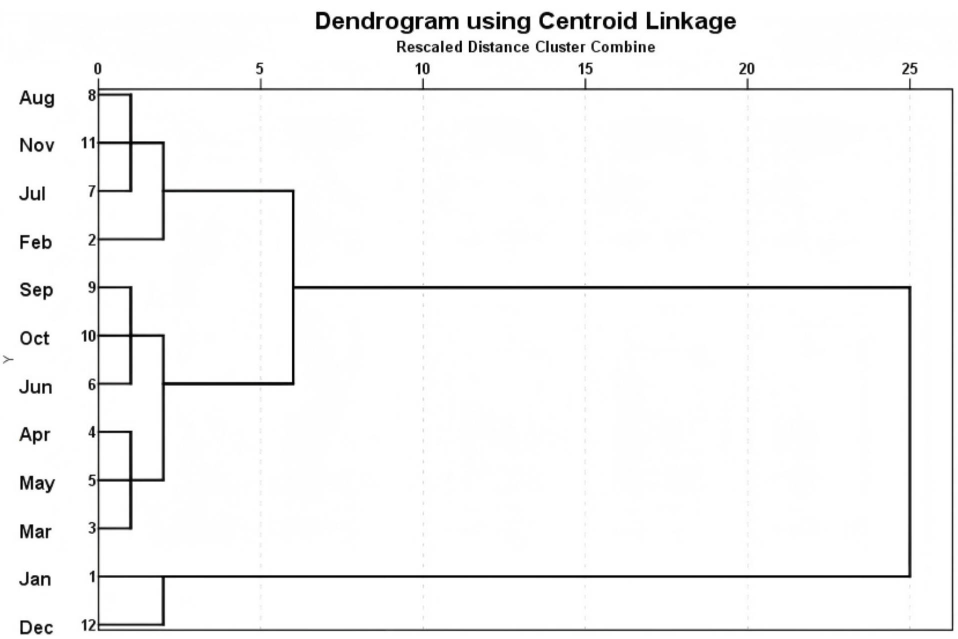


Figure 4. Cluster analysis of the monthly average Temperature of the study areas.

The study area encompasses three sub-districts and two districts in Bangladesh: Sandwip, Maheshkhali, and Kutubdia. In general, Sandwip always has the highest temperatures, whereas Kutubdia always has the lowest. The pre-monsoon season is the hottest time of year in all areas, with an average temperature of 27.35 ℃. The dry season, on the other hand, has the mildest weather, with an average temperature of 22.09 ℃. Sandwip has the greatest average Temperature during the dry season, at 22.59 ℃, while Kutubdia has the lowest average Temperature, at 21.79 ℃. The temperature differences stay the same all year long. For example, in the pre-monsoon season, the temperatures are similar (Sandwip: 27.84 ℃, Maheskhali: 27.11 ℃, Kutubdia: 27.11 ℃). In the monsoon season, the temperatures are also identical (Sandwip: 26.20 ℃, Maheskhali: 25.61 ℃, Kutubdia: 24.87 ℃). In the post-monsoon season, the temperatures are also similar (Sandwip: 24.94 ℃, Maheskhali: 24.33 ℃, Kutubdia: 24.05 ℃).

The average Temperature in all three regions is 25.15 °C. Sandwip has the highest average at 25.66 °C, and Kutubdia has the lowest at 24.73 °C.

The eastward temperature gradient shows that the Land Surface Temperature (LST) is getting lower as you go from west to east throughout the Coastal islands. Changes in land cover also affect how much the temperature changes. The amount and variety of tree species in these areas have a significant effect on temperature changes, as shown by the data in **Figure 5**. These changes show how climate change could alter local ecosystems. For example, temperature changes can change the kind of organisms that live in the Coastal islands, how quickly they grow back, and the balance of the ecosystem.

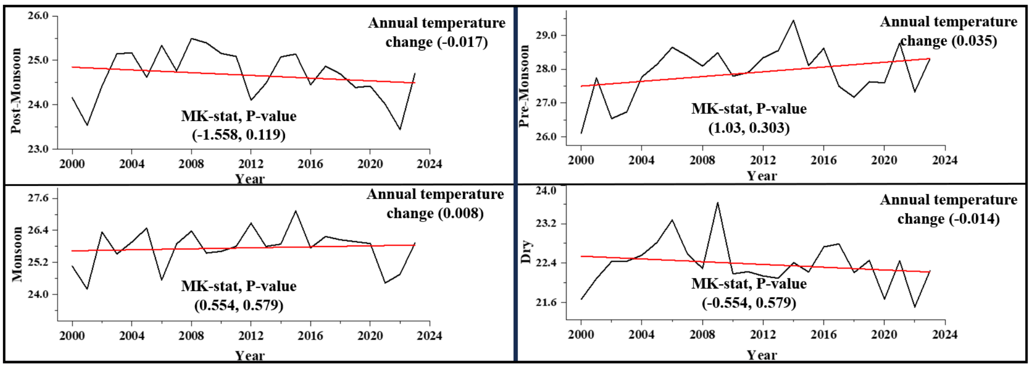


Figure 5. Trend analysis of the Temperature of the study areas: the average seasonal temperature trend.

The authors used the Mann-Kendall test to find steady temperature changes in the study areas over four different seasons: dry, pre-monsoon, monsoon, and post-monsoon. This statistical method is essential for understanding temperature changes, which could be a sign of bigger problems with the climate. The results of this study are shown in **Figure 5**, which shows how temperature patterns change over time.

Before the monsoon season, the Mann-Kendall (MK) statistic is 1.03, and the *p*-value is 0.303. This means that the Temperature has been going up steadily over this time period. There is an apparent temperature rise (0.035 °C each year according to Sen's slope), but this shift does not meet the criterion for being statistically significant. Still, this rise could be an early symptom of climate change, which can affect the health of forests and the behaviour of animals in the area.

During the monsoon season, the MK value is 0.555, and the *p*-value is 0.579. This means that the temperature trend is not statistically significant, but it is still increasing. The Sen's slope shows that the Temperature rises by 0.008 °C per year, which is the least of the four seasons. This slow rise could be linked to changes in rainfall patterns, which could disrupt the established monsoon dynamics that have traditionally controlled water supply and ecological cycles in the Coastal islands.

After the monsoon season, the MK value is −1.558, and the *p*-value is 0.119. This means that the temperature trend is significantly lowering, although not as much as it was during the dry season. The measured temperature drop of −0.017 °C per year lacks statistical significance, yet it aligns with climate models that predict cooling effects during transitional stages. This cooling could affect how animals move, how plants grow, and how carbon is stored in the Coastal islands' ecosystems, making the area more vulnerable to long-term climatic stress.

During the dry season, the MK statistic of −0.554 and a *p*-value of 0.579 show that the Temperature drops slightly during the dry season, with Sen's slope showing a yearly decreasing rate of 0.014 °C. These little drops, while not statistically significant, could have an impact on water stress, animal behaviour, and the health of forests during the dry months.

The average Temperature over the course of the year did not go up by a significant amount. The Mann-Kendall (MK) value of 0.132 and the *p*-value of 0.895 show that the average Temperature rose by 0.0054 °C each year, although this change was not statistically significant. These results show that even while there are clear patterns in how temperatures change, they do not match the requirements for statistical significance in the dataset that was studied. The results of the Mann-Kendall test indicate that the temperature variations are not significant enough to be definitively linked to long-term climate changes, despite being detectable (**Figure 5**).

The monthly trend analysis (**Figure 6**) shows that several months, such as November, August, July, June, May, April, and March, have big Temperature rises. These tendencies suggest climate change, but they lack sufficient statistical significance. May has the highest average temperature rise, 0.051 °C per year, which could mean that the weather is more stressful during this month. August, on the other hand, has the smallest rise, just 0.008 °C. This could be because more rain makes temperature extremes less extreme. The months of October, September, February, and January, on the other hand, tended to get cooler, but this trend was not statistically significant. December stands out because it has a statistically significant annual temperature drop of −0.0409 °C (MK value of −2.614, p-value of 0.008). This could be due to changes in seasonal cycles or the effects of changing weather patterns in the area. These numbers illustrate the complex and far-reaching consequences of climate change on the region's monthly temperature patterns.

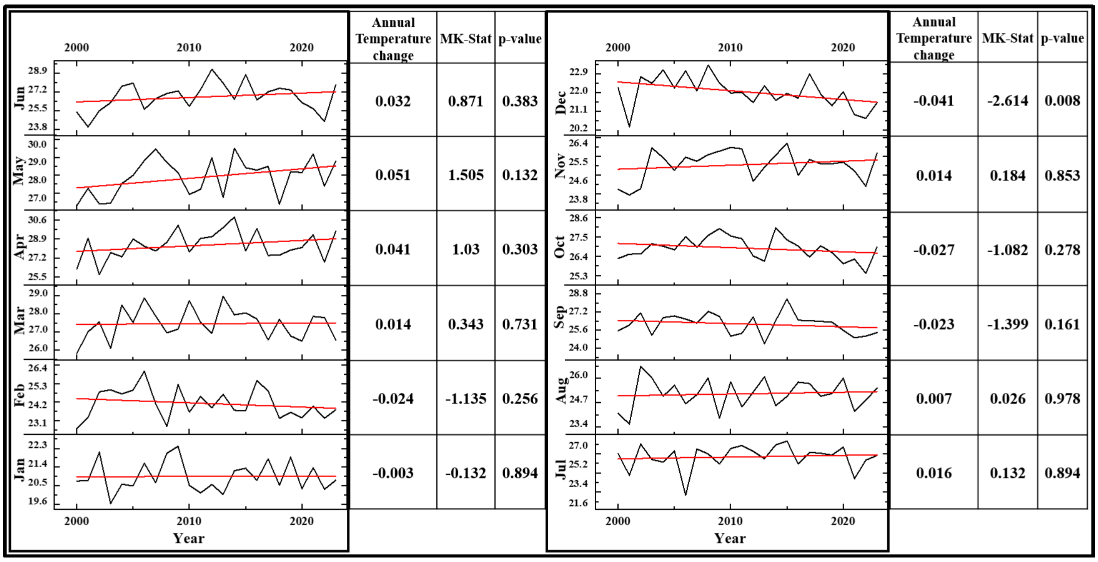


Figure 6. Trend analysis of the Temperature of the study areas - the average monthly temperature trend.

Different predictive models were used to guess how temperatures might change in the Coastal islands in the future, with a focus on accuracy and model fit. We used the Ljung-Box test, PD-MAPE (Predicted Data Mean Absolute Percentage Error), and PD-RMSE (Predicted Data Root Mean Square Error) to see how well the models worked. All of them were very good at predicting monthly average temperatures, with an accuracy rate of 98% (**Table 1**).

All of the predicted models had very low PD-MAPE (Predicted Data Mean Absolute Percentage Error) and PD-RMSE (Predicted Data Root Mean Square Error). On average, all of the models were able to predict the monthly average Temperature with 98% accuracy. Therefore, the best model for predicting Temperature will depend on how well it fits the data, the Ljung-Box test, and the residuals. All of the model significance levels are more than 0.05, which means that they all support the hypothesis perfectly for making predictions.

The model with the lowest BIC score is considered the best; however, you cannot simply look at BIC to determine that a model is the best. So, after looking at the residuals of all the models, the (1,0,0) (0,1,1) model at the 24th periodicity level is the only one that does not have any significant residuals in either autocorrelation or partial correlation. This means that this model is more accurate than all the other models that were evaluated. In addition, this model has the lowest PD-MAPE (1.86) and PD-RMSE (0.56) values while still having an acceptable level of R-squared, MD-RMSE (Model data Root Mean Square Error), and MD-MAPE (Model data Mean Absolute Percentage Error). So, at the 24th periodicity level, (1,0,1) (0,1,1) is the best model for predicting the Temperature in the Coastal islands. **Figure 7** shows all of the anticipated and observed data for all of the models. The temperature trend continues the pattern established in previous years.

Table 1. All tested models' fitness of prediction and model data.

Predicted Data				Model Data			Ljung-Box Test		
Model	**Periodicity Level**	**PD-MAPE**	**PD-RMSE**	**R-Squared**	**MD-RMSE**	**MD-MAPE**	**Normalized BIC**	**Statistics**	**Sig.**
(1,0,1) (0,1,1)	12	2.04	0.66	0.83	0.98	3.05	0.04	24.73	0.05
(1,0,0) (0,1,1)	12	2.04	0.67	0.83	0.98	3.05	0.01	26.08	0.05
(1,0,1) (1,1,1)	24	2	0.59	0.81	1.03	3.19	0.17	21.33	0.09
(1,0,1) (0,1,1)	24	1.86	0.56	0.81	1.03	3.17	0.15	23.89	0.07

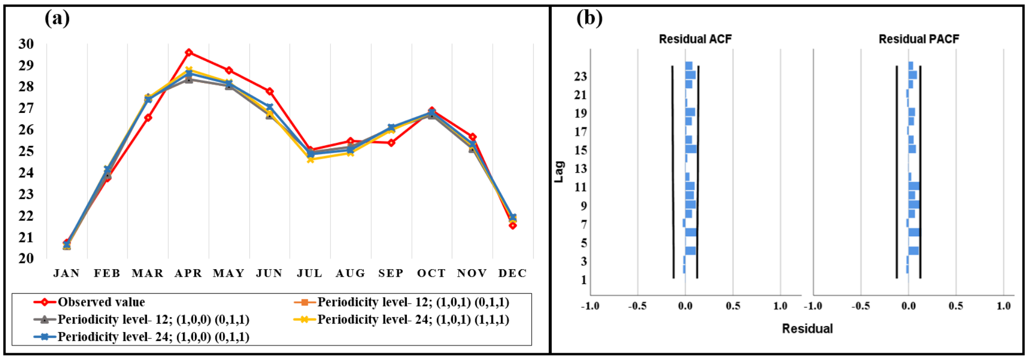


Figure 7. Prediction model for forecasting the Coastal islands' Temperature, (**a**) predicted and observed data, and (**b**) residual of (1,0,0) (0,1,1) at the 24th periodicity level model.

The authors used Landsat images with a resolution of 30 meters to do a detailed assessment of land use and land cover (LULC) in the Coastal islands. The study primarily focused on the forest and wetland areas of the region, as there were no residential or agricultural regions. The kappa coefficient for classifying images was quite reliable, with values between 0.90 and 0.95 when compared to historical data from Google Earth Pro. The study examined only two main types of land (forests and aquatic bodies), yet it still identified clear patterns in how land cover changed. **Figure 8** shows how much the forest area has shrunk. On average, it has been shrinking by 26.36 square kilometres every year. There is a statistically significant trend, with a Mann-Kendall value of −2.067 and a p-value of 0.0388. This supports the idea that climate change and human activities are putting stress on this unique ecosystem.

On the other hand, the size of bodies of water has been steadily growing at a rate of about 23.44 square kilometres per year. The Mann-Kendall value of 2.0665 and the p-value of 0.0388 show that this increase in waterbody coverage is statistically significant. From 2002 to 2022, the amount of aquatic bodies grew by 41.61%, while the amount of forest cover shrank by 2.86% (110.71 square kilometers). The findings show that the Coastal islands are changing, with rising sea levels and erosion making the region's ecosystem more vulnerable. This is likely due to climate change. The LULC map (**Figure 8**) shows how land cover has changed a lot in the last 20 years. This study highlights the importance of initiating conservation projects and adaptation techniques to mitigate the adverse effects of both natural and human-induced stresses on coastal islands.

The study focused on four main tree species in the Coastal islands: *Heritiera fomes, Excoecaria agallocha, Sonneratia apetala,* and *Ceriops decandra*. The goal was to find out how the distribution of these species relates to the land surface temperature (LST) in the area, which is an integral part of understanding how the climate changes in the area. **Figure 9** shows the distribution of various tree species, giving a complete picture of how they are spread out across the Coastal islands. The correlation study revealed a substantial relationship between the number of trees and Temperature in different seasons (**Table 2**). All of the correlation values were statistically significant at the 0.01 level, which means that they were essential. The study shows that the correlation coefficients for the dry, pre-monsoon, monsoon, and post-monsoon seasons are 0.613, 0.460, 0.440, and 0.650, respectively. Even while some seasons have smaller correlation values, the high statistical significance shows that there is a strong link between tree distribution and temperature changes, notably before and during the monsoon. There were strong and vital links between the dry and post-monsoon seasons and the land surface temperature in the Coastal islands. This shows that tree distribution patterns had a significant effect. There was a strong relationship between the dry and pre-monsoon seasons (0.777), which got stronger during the post-monsoon season (0.911). This illustrates how tree distribution directly impacts temperature patterns during these critical periods.

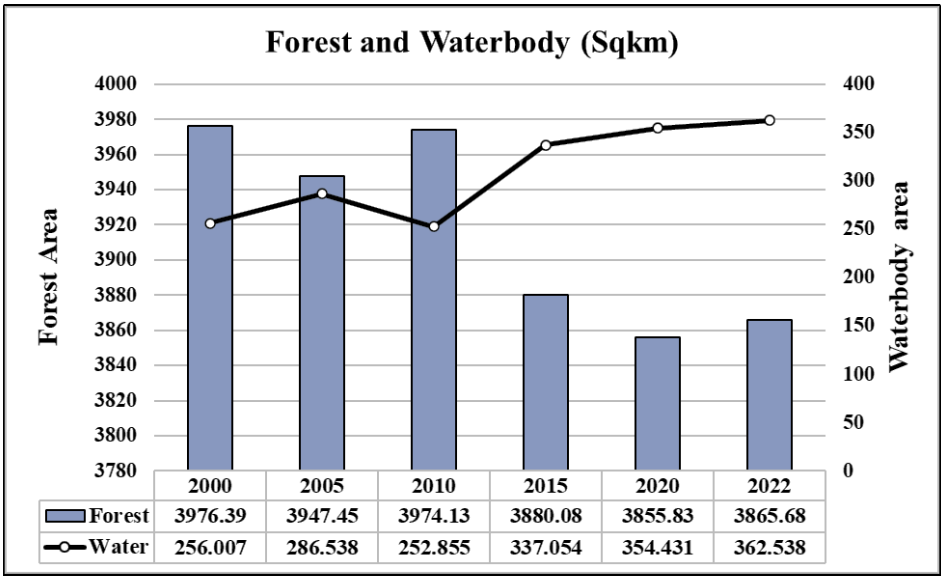


Figure 8. Land use and land cover (LULC) change over 24 years in the Coastal islands.

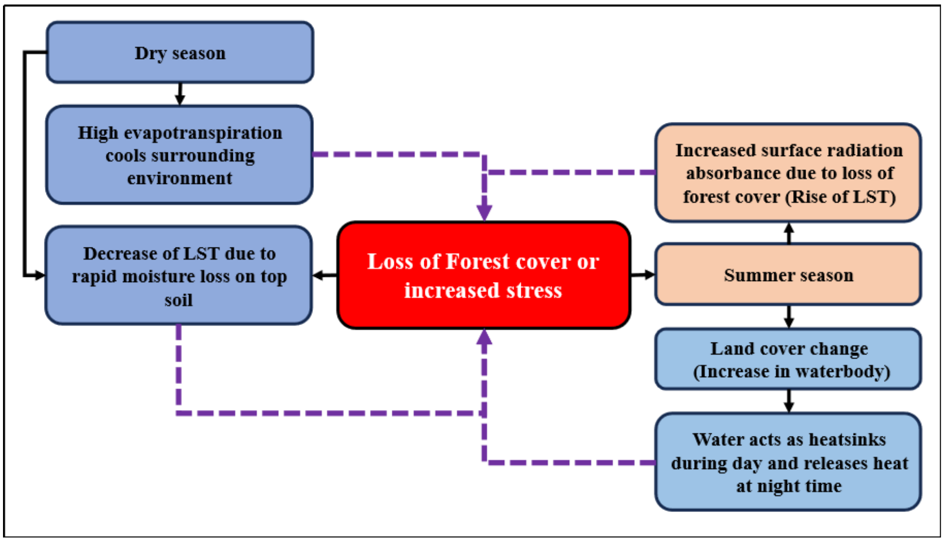


Figure 9. Negative feedback loop caused by extreme temperature fluctuation.

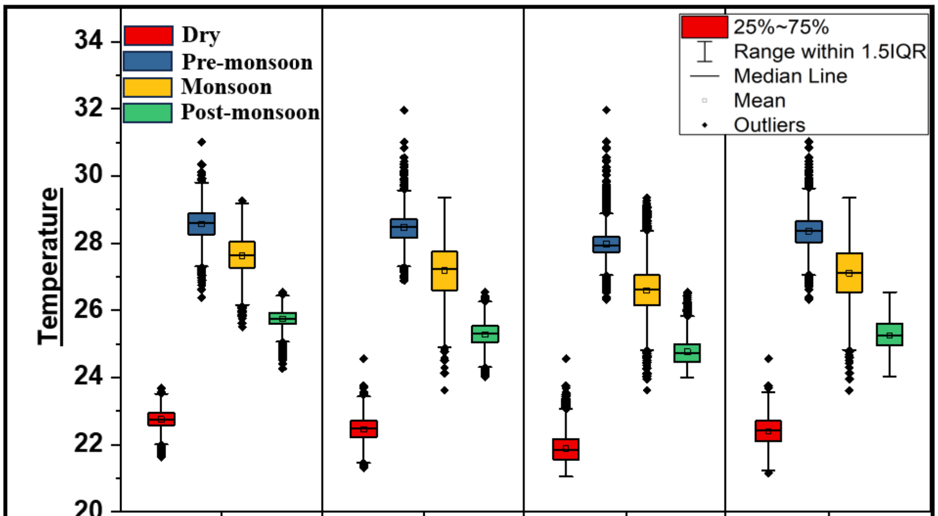
Table 2. Correlation between seasonal Temperature and tree distribution.

Correlations					
	Tree	**Dry**	**Pre-Monsoon**	**Monsoon**	**Post-Monsoon**
Tree	1				
Dry	0.613**	1			
Pre-monsoon	0.460**	0.777**	1		
Monsoon	0.440**	0.567**	0.528**	1	
Post-monsoon	0.650**	0.911**	0.628**	0.660**	1

** Correlation is significant at the 0.01 level (2-tailed).

The results show how important plants are in keeping the Temperature in the Coastal islands from changing too much from season to season. The existence and distribution of some tree species have a significant impact on the local climate, especially when it comes to keeping temperatures from getting too hot or too cold. Because of this, it is essential to protect these species to maintain the area's balance and help regulate the Temperature.

Further study showed that there were significant differences in how the Temperature was spread out between areas with different types of trees. The highest LST is in Sandwip (annual average 25.66 °C), followed by Maheskhali (annual average 25.05 °C), and the lowest is in Kutubdia (annual average 24.73 °C). This is true for all seasons. *Ceriops decandra* (Goran), primarily found in Sandwip, has the highest land surface temperature (LST) with a yearly average of 26.15 °C. This made it the warmest place all year. The *Exocoecaria agallocha* (Gewa) areas had the second-highest Temperature, with an average of 25.85 °C each year (**Figure 10**). The average annual Temperature of the land surface in areas with *Sonneratia apetala* (Keora) was somewhat lower, at 25.79 °C. The areas with the most *Heritiera fomes* (Sundari) trees, which make up most of the Sundarban, had the lowest average annual Temperature of 25.30 °C (**Figure 10**). The trend stays the same across many seasons. The Sundari tree zones always have the lowest average Temperature during the dry season, which is 21.88 °C. This means that *Heritiera fomes* has a significant impact on temperature control during the warmer months, as it is so prevalent in the area. The results confirm the idea that tree species, especially *Ceriops decandra* and *Exocoecaria agallocha*, which are common in the warmer parts of Sandwip, make the land surface temperature higher. On the other hand, *Heritiera fomes*, which is common in the cooler parts of Kutubdia, helps keep the Temperature down by acting as a natural temperature regulator. This demonstrates the importance of maintaining a diverse range of tree species in coastal islands to help stabilize the Temperature and the environment as a whole.



Season	*Ceriops decandra* (Goran)	*Exoceccaria agallocha* (Gewa)	*Heritiera fomes* (Sundari)	*Sonneratia apelatala* (Keora)
Dry	22.74°C	22.86°C	21.88°C	22.41°C
Pre-monsoon	28.55°C	28.49°C	27.96°C	28.37°C
Monsoon	27.59°C	27.18°C	26.58°C	27.13°C
Post-Monsoon	25.72°C	25.28°C	24.76°C	25.26°C
Annual Average	26.15°C	25.85°C	25.30°C	25.79°C

Figure 10. Land surface temperature (LST) of the Coastal islands based on tree species.

4. Discussion

This study discusses the intricate climate-vegetation feedback mechanisms influencing the Coastal islands ecosystem, wherein increasing and variable temperatures interact with alterations in land cover, hydrological stress, and species redistribution. Over the past 24 years, the Coastal islands have undergone not only a warming trend but also a thermal reconfiguration; seasonal extremes have intensified, and established ecological balances are being disrupted.

Long-term Land Surface Temperature (LST) data from the present study demonstrate considerable annual variability, with the minimum values observed in 2000 and 2022. From 2000 to 2009, a consistent increase in Temperature is noted, succeeded by irregular fluctuations from 2010 to 2015 and a period of relative cooling until 2022. These trends correspond with the established effects of the El Niño–Southern Oscillation (ENSO), which affects the Temperature of both LST and SST [57]. Furthermore, the Indian Ocean Dipole (IOD) modifies these thermal dynamics and influences the Bay of Bengal cyclone activity [58]. Temporal temperature analysis of the present study reveals significant fluctuations within the Coastal islands region, particularly on a monthly and seasonal basis during the pre-monsoon and monsoon periods. The ecological significance of these fluctuations is pronounced, particularly during the pre-monsoon and monsoon phases. These rapid intra-seasonal shifts alter the thermal niche of specific zonal clusters, making mangroves more vulnerable to environmental extremes. Moreover, shifts in monsoon circulation patterns exacerbate thermal instability, leading to erratic rainfall and evaporation cycles [25]. These findings are consistent with previous zonal and seasonal analyses, which confirm that the Coastal islands are experiencing accelerated climatic disequilibrium [21,26].

The trend analysis reveals an asymmetric seasonal pattern in LST changes. Pre-monsoon and monsoon temperatures are increasing, while post-monsoon and dry season temperatures are decreasing (**Figure 5**). The post-monsoon and dry seasons exhibited similar rates of temperature decline; however, the rising trend in the pre-monsoon season is twice the rate of decline, signifying an increasing seasonal temperature differential in a monthly scenario, a significant declining tendency was discovered for December (−0.041 °C/year) and minor declines in October, September, January, and February. In contrast, all other months exhibit warming trends. These patterns reflect global SST warming along 71.6% of the world's coastlines [1], a trend also observed along the Bangladeshi coast [10,26]. An increasing trend of SST was also observed on the Bangladesh coast, where SSTs have increased by 0.10–0.16 °C per decade (daytime) and 0.18–0.27 °C per decade (nighttime) [24]. Kelvin wave activity from the Ganges-Brahmaputra inflow during the southwest monsoon raises SSTs by 0.5–1 °C along the northeastern Indian coast [23]. Local LST studies confirm this asymmetric warming, where one study found that January LST dropped by ~1.85 °C over several decades, and another reported a 0.005 °C annual winter cooling trend [10,12]. These concerning trends are also found in this study analysis. The conflicting seasonal trends exacerbate thermal amplitude, heightening ecological stress and disrupting mangrove metabolic rhythms [33], a finding further validated by our study.

Land cover changes aggravate the climatic effects. Sea-level rise, sediment dynamics, and fluvial processes have all contributed to coastal erosion, which has dramatically altered the region's geomorphology. Between 1991 and 2021, 800.72 sq. km of land was lost [59], while 129 sq. km of forest cover vanished between 2000 and 2023 due to coastal retreat [12], which rate aligns with our research findings within the coastal area. This deforestation disrupts the local energy balance. Whereas dense forest once provided evapotranspirative cooling, newly exposed water bodies now absorb and re-radiate solar energy, affecting surface thermal dynamics. Water bodies have higher thermal inertia than terrestrial surfaces. In the dry season, they function as heat sinks, absorbing excess heat throughout the day and releasing it at night to mitigate temperature extremes [22]. During the dry season, when water is scarce, forests with intact vegetation can maintain higher moisture levels through their root systems, retaining water in the soil. However, due to the low moisture content during the dry season, trees tend to have a higher evapotranspiration rate, which further cools the surrounding environment [28].

Furthermore, the loss of canopy cover during the dry season removes the shade offered by trees, exposing the land surface directly to solar radiation. This enhances solar energy absorption, which causes higher surface temperatures in the summer [28]. So, land erosion has an impact on the LST of coastal islands, and a decrease in forest area contributes to significant temperature variations, causing them to be in a negative feedback loop (**Figure 9**).

The Coastal islands have not only become warmer over the past 24 years, but they have also changed how they heat up. Seasonal extremes have gotten worse, and established ecological balances are being thrown off. Long-term Land Surface Temperature (LST) data (**Figure 3a**) show that temperatures change significantly from year to year, with the lowest recorded in 2000 and 2022. There was a steady rise in Temperature from 2000 to 2009, followed by unpredictable changes from 2010 to 2015 and a period of relative cooling until 2022. These patterns are in line with what we know about the El Niño–Southern Oscillation (ENSO), which changes the Temperature of both LST and SST [57]. The Indian Ocean Dipole (IOD) also changes these thermal dynamics and affects the activity of cyclones in the Bay of Bengal [58]. Additionally, changes in monsoon circulation patterns exacerbate thermal instability, resulting in unpredictable cycles of rain and evaporation [25]. These results are in line with other zonal and seasonal studies that show the Coastal islands are experiencing faster climate change [21,26].

These temperature changes have significant effects on the environment. Studies show that even a 2 °C rise in dry mangrove areas lowers production, biomass, and survival, and also changes the types of species and their phenological rhythms [33]. When temperatures rise too high and there is not enough freshwater flowing in, mangrove systems become even more stressed, leading to biodiversity loss and changes in dominance [29].

In the Coastal islands, higher vapor pressure deficits hurt photosynthesis and water productivity, which lowers the health and ability to grow back of mangroves [33].

The trend analysis reveals that LST variations occur unevenly throughout the seasons. Temperatures are rising before and during the monsoon, but falling after the monsoon and throughout the dry season. The Temperature dropped at the same pace during the post-monsoon and dry seasons. However, the Temperature rose at twice the rate during the pre-monsoon season, which means that the temperature difference between the seasons is getting bigger. In a monthly scenario, there was a significant drop in Temperature for December (−0.041 °C/year) and small drops for October, September, January, and February. All other months, on the other hand, show warmer trends. These trends show that the sea surface temperature (SST) is rising along 71.6% of the world's coastlines [1]. This is also happening along the coast of Bangladesh [10,26]. On the coast of Bangladesh, SSTs have likewise been rising, by 0.10–0.16 °C per decade during the day and 0.18–0.27 °C per decade at night [24]. During the southwest monsoon, the Ganges-Brahmaputra influx causes Kelvin waves to move, which boosts SSTs over the northeastern Indian coast by 0.5–1 °C [23]. This study also shows these worrying patterns. The different seasonal trends make the thermal amplitude worse, which puts more stress on the ecosystem and throws off the metabolic rhythms of mangroves, as their study also found [59].

Predictive modeling adds a new layer to this complicated scenario. LASSO, MSTL, ALLSSA, and wavelet analysis are all advanced methods that work well with climate datasets that have a lot of dimensions and variables. SARIMA is the best model for forecasting univariate LST time series [60,61]. It properly reflects how trends and seasons change, and it can predict with about 98% accuracy. SARIMA's forecasts indicate that seasonal LST divergence will continue and intensify in the future, leading to increased thermal stress. At this rate, the difference in Temperature between seasons will keep getting bigger.

Changes in land cover make the effects of climate change worse. The region's geomorphology has undergone significant changes due to coastal erosion, which is caused by rising sea levels, altered sediment, and river processes. Between 1991 and 2021, 800.72 square km of land were lost, including 129 square km of forest cover between 2000 and 2023 due to shore retreat [22]. This rate of land loss aligns with our findings in the coastal area [62]. The cutting down of trees disrupts the local energy balance. In the past, dense forests cooled things down by evaporating and transpiring. Now, freshly exposed water bodies absorb and re-radiate solar radiation, which changes how heat moves around on the surface. Water bodies have more thermal inertia than land surfaces. During the dry season, they act as heat sinks, taking in more heat during the day and releasing it at night to keep temperatures from being too hot or too cold [22]. Forests with healthy vegetation can retain more moisture in the soil during the dry season, when water is hard to come by. This is because the trees' roots hold onto water, but because the air is so dry, trees tend to lose more water through evapotranspiration, which cools the area even more [28]. Also, when the canopy cover goes away during the dry season, the trees' shade goes away, leaving the ground directly exposed to the sun. This makes it easier for solar energy to be absorbed, which makes the surface temperatures greater in the summer [28]. Land erosion affects the Coastal islands' LST, and a loss of forest area causes significant Temperature, putting them in a negative feedback loop.

These changes in the weather and the shape of the land are changing where mangrove species live. According to our analysis, the continuous moderate to strong El Niño presence from 2002 to 2016, which influenced the global temperature rise, was followed by a weak El Niño that lasted until 2022. This period correlates with the LST of Coastal islands [60,62]. While the spread of *C. decandra* is associated with the higher LST, better suited to thermal stress, has proliferated in the warmer areas of Maheskhali and Sandwip, with Kutubdia being the only exception [35]. On the other hand, S. During this time, apetala grew in all areas. E. In Maheskhali and Kutubdia, *C. agallocha* was on the rise, but not in the hotter regions of Sandwip [35]. At the current rate, temperature rises will change species distribution and composition, with varying effects on productivity and reproductive phenology [31], which is consistent with the findings of this study. As LST rise persists, thermally sensitive species such as H. fomes may experience local extinction (Suitable habitat will decline by 45% by 2100). In contrast, heat-tolerant species like *C. decandra* are likely to expand their ecological niche [61]. Comparable poleward transitions have been noted in the Gulf of Mexico, where mangroves are supplanting temperate salt marshes [32]. Nevertheless, the Coastal islands lack the spatial continuity necessary for such migration. The expansion of mangroves to the north is physically limited by agricultural land and fragmented aquatic areas, indicating a forthcoming reduction in total forest area.

Islam et al. [63] stated that temperature rise is a concern for future agriculture in different regions of the globe. The statistical downscaling climate model (SimCLIM) was used for downscaling and to ensemble temperature projections (Tmax and Tmin) for the near (2021–2060) and far (2071–2100) periods compared to the base period (1986–2005). They found that the northern and northwestern parts of the country would experience the highest rise in maximum temperature (T_{max}) and minimum temperature (T_{min}), which have traditionally been exposed to temperature extremes. In contrast, the southeastern coastal region of Bangladesh would experience the least rise in Temperature. A higher increase in T_{min} than T_{max} was detected for all timescales, signifying a future decrease in the diurnal temperature range (DTR). This study suggests that the Coastal islands are ensnared in a detrimental climatic negative feedback loop. Increasing pre-monsoon and monsoon temperatures, in contrast to cooling during the post-monsoon and dry seasons, are disrupting the region's ecological patterns. These modifications diminish photosynthetic efficiency, disrupt species interactions, and weaken forest resilience. Land degradation and species displacement exacerbate environmental susceptibility. In the absence of targeted mitigation, these trends may lead to irreversible harm to the world's largest mangrove ecosystem.

Despite these ongoing efforts, there is still room for improvement, particularly in aligning climate policy with the biophysical realities of a rapidly warming Coastal islands. Adaptive zoning, modeled after dynamic frameworks such as Australia's Great Barrier Reef Marine Park, could use thermal mapping to inform seasonal restrictions on tourism and extraction, thereby protecting biodiversity hotspots [64,65]. Infrastructure policy should shift toward ecosystem-based engineering, replacing polders and embankments with mangrove bioshields and sediment-based restoration to mitigate the hydrological disruption caused by rigid development [66]. Furthermore, predictive tools validated in this study, such as SARIMA, should be integrated into national early warning systems, as demonstrated by examples from Vietnam's Mekong Delta, where machine learning forecasts support real-time agricultural planning [67]. Finally, policies should emphasize local knowledge and participation. Nepal's buffer zone forestry model exemplifies how decentralized governance can integrate community priorities with conservation objectives [67]. Without such bottom-up participation, climate resilience efforts risk becoming technocratic and unsustainable. A future-proof coastal islands policy must combine ecological science, engineering innovation, and grassroots stewardship before thermal feedback depletes the system's regenerative potential.

5. Conclusions

The Coastal island's mangrove forest is recognized as a biodiversity hotspot and serves as a vital provider of ecosystem services. However, according to an analysis of data spanning 24 years, it is evident that the ecological equilibrium of the coastal islands is under jeopardy, notably in terms of LST dynamics. This study provides a thorough assessment of the complex trend analysis of temperature fluctuations and their correlation with tree species on coastal islands. Notably, during the pre-monsoon and monsoon seasons, the Coastal islands region faces significant temperature variability, along with a rising temperature trend. In contrast, during the Dry and post-monsoon seasons, the Temperature decreases, indicating increased ecological stress and potential disturbances to species acclimated to specific temperature niches. Cluster analysis, which delves deeper into temporal patterns, demonstrates the non-linear nature of LST variations between months. Between 2002 and 2022, water body area increased by 41.61% while forest cover decreased by 2.86%, highlighting the extent of land cover change and its implications for temperature dynamics. Predictive modeling projections underscore the persistence of current temperature trends, indicating a future with wider temperature differentials between seasons. This forecast insight underscores the importance of taking early actions to reduce temperature extremes and protect the Coastal islands' ecological integrity. The relationship between tree canopy and LST distribution demonstrates the critical function that vegetation plays in modifying microclimates throughout the region. This growth pattern, along with the rising LST from 2000 to 2015, has been correlated with El Niño and La Niña. From 2000 to 2015, El Niño influenced global weather patterns and contributed to rising temperatures. Its impact on the LST of Coastal islands is also visible. As climate change is predicted to result in temperatures in the future, this may lead to a further increase in the population of C. decandra on coastal islands, while H. Fomes may decrease as they prefer lower LST. ULC analysis corroborates ecological degradation, indicating accelerated deforestation and the encroachment of aquatic systems, thereby reinforcing adverse thermal feedback loops.

Conservation initiatives must consequently extend beyond conventional forest preservation. Adaptive strategies, including the promotion of thermally resilient mangrove species, the integration of land-use and land-cover monitoring into early warning systems, and the revision of climate action policies to align with microclimatic conditions, are crucial. Without prompt intervention, the Coastal islands may shift from a protective barrier against climate extremes to a casualty of their declining resilience. Future management must synchronize scientific research, community engagement, and policy to ensure the ecological integrity of this globally significant mangrove forest. In essence, this study underscores the urgent need for proactive measures to mitigate temperature extremes and preserve the ecological integrity of the coastal islands. With each passing year, the stakes rise, necessitating swift action to protect this priceless natural heritage.

Author Contributions

P.B. was responsible for conceptualization the research, literature review, methodology framework and data analysis. N.N. was responsible for manuscript writing, editing the manuscript. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

Data will be made available upon request.

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Conflicts of Interest

The authors declare no conflict of interest.

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