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Revealing urban vegetation dynamics: Comprehensive NDVI time series analysis and forecasting using ARIMA/SARIMA models in Karachi

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Abstract. Climate change is increasing the vulnerability of cities, and it is therefore important to evaluate vegetation comprehensively for sustainability and resilience. This research utilizes advanced machine learning and remote sensing methods to examine urban vegetation dynamics in Karachi. Utilizing Google Earth Engine (GEE) for large-scale geospatial analysis, mean monthly NDVI values were obtained from Landsat 8 data from the years 2013 to 2022. Seasonal ARIMA (SARIMA) models were utilized to detect trends and seasonal variations in the NDVI time series. The results were utilized to forecast future NDVI trends, which were subsequently incorporated into conservation and urban planning initiatives following the model's verification of accuracy. The SARIMA (0,1,2)x(0,1,2,12) model was the most appropriate for the description of trend and seasonal behavior. The model provided the best overall fit among the tested configurations. Model diagnostics indicated a strong performance, with good values across standard statistical criteria such as log likelihood, AIC, BIC, and HQIC. Residual analysis further confirmed that the model adequately captured the underlying patterns. Predictions indicated a mean NDVI value of 0.196, with a 95% confidence interval of 0.146 to 0.246. Strong fluctuations in NDVI values over time included the highest values in September 2023 (0.232) and October 2024 (0.253), with lower values in the summer months, indicating clear seasonal fluctuations. This interdisciplinary effort offers a holistic assessment of urban vegetation dynamics with global applicability. By focusing on the importance of green spaces in the mitigation of urban heat island and climate adaptation, the research calls for their incorporation in urban planning. The findings provide practical recommendations toward sustainable development, urban planning, and environmental protection, demonstrating the capacity of sophisticated modeling methods to inform resilient urban ecosystems.

Keywords: Urban vegetation prediction, Time series, ARIMA/SARIMA prediction, urban vegetation dynamics, ML in ecology, Sustainable urban planning.

1. Introduction

The rapid urbanization of cities, especially in developing countries, brings about challenges in the realms of urban planning and environmental management (Alotaibi et al., 2025; Almulhim & Cobbinah, 2026). Karachi, the most populous metropolitan region of Pakistan, is confronting pressing challenges amidst its burgeoning population and haphazard urban sprawl, including land degradation, diminished vegetation, and the aggravation of urban heat islands (Li et al., 2020; Yu et al., 2024). Vegetation increasingly contributes to enhancing the resilience of cities and mitigating environmental stresses as cities grow. However, in spite of its significance, there is a lack of comprehensive information and useful methods for assessing the long-term dynamics of vegetation in cities. Although, previous research has focused on general trends within plant health, current literature predominantly reflects a lack of studies that track urban vegetation in such cities as Karachi using high-resolution remote sensing images and advanced machine learning tools. There has been insufficient integration of temporal data and climate factors to provide actionable insights for urban planning and conservation strategies. Moreover, machine learning models like ARIMA for time series forecasting of vegetation health have not been adequately explored in the context of rapidly urbanizing cities, especially in South Asia (Batool et al., 2019; Perry et al., 2024). This gap limits the ability of urban planners and policymakers to make informed decisions for sustainable city development and climate resilience.

Satellite image as a technology for remote sensing is a scanning method specifically well-suited for the tracking of vegetation dynamics with wide and redundant coverage data of value to various disciplines, most notably ecology (Smith et al., 2019; Winkler et al., 2024), especially urban (Sohail et al., 2020). The NDVI from Landsat 8 satellite imagery is widely utilized for the observation of vegetation cover and is a validated surrogate measure of vegetation density (Perry et al., 2024). The Normalized Difference Vegetation Index (NDVI), which is obtained from Landsat 8 imagery, is commonly used to evaluate vegetation health and is a good indicator of vegetation density (Perry et al., 2024). NDVI ranges from -1 to +1 and is the difference between red and near-infrared reflectance, with increasing values showing denser vegetation. With the development of cloud-based platforms such as Google Earth Engine (GEE), extensive geospatial analysis has become easier, allowing users to process large satellite datasets and perform sophisticated analyses (Soltani et al., 2021; Suman et al., 2025). Nevertheless, long-term NDVI trend forecasting has rarely been examined in fast-growing cities like Karachi, even though there is extensive research on NDVI and vegetation dynamics. This study fills this gap using remote sensing data, particularly time series of NDVI from Landsat 8 imagery to investigate long-term vegetation dynamics in Karachi. This study is supported by employing machine learning models like ARIMA and SARIMA models to forecast exact future vegetation trends for managing urban vegetation.

The primary objectives of this study are to: (1) quantify the temporal and seasonal variations in urban vegetation across Karachi using monthly NDVI derived from Landsat 8 imagery (2013–2022) within the Google Earth Engine (GEE) platform; (2) evaluate long-term vegetation trends to determine whether urban vegetation exhibits an overall greening or degradation pattern under the combined influence of urbanization and climate variability; (3) develop and validate a Seasonal Autoregressive Integrated Moving Average (SARIMA) model to characterize and forecast the temporal dynamics of urban vegetation; and (4) provide reliable predictions of future vegetation conditions to support sustainable urban planning, green infrastructure management, and climate change adaptation strategies.

The study tests the hypothesis that urban vegetation in Karachi exhibits significant long-term temporal trends and pronounced seasonal variability resulting from the combined effects of urbanization and climate variability. Furthermore, it is hypothesized that these dynamics can be accurately modeled and predicted using a SARIMA time-series approach, enabling reliable forecasting of future vegetation conditions for urban environmental planning. By integrating Google Earth Engine with SARIMA modeling, this study provides a robust framework for monitoring and forecasting urban vegetation dynamics, offering scientific evidence to support conservation planning, sustainable urban development, and climate resilience in rapidly urbanizing cities.

The integration of machine learning with remote sensing technologies offers significant potential for more accurate, scalable, and efficient monitoring of urban vegetation. This research will not only enhance our understanding of urban vegetation dynamics but also provide practical tools for promoting sustainable urban ecosystems. The findings will contribute to mitigating environmental challenges, such as the urban heat island effect, and support climate adaptation strategies in Karachi, with implications for similar cities globally (Omar & Kawamukai, 2021; Goodwin et al., 2022). By bridging the gap between remote sensing data and predictive modeling, this study will provide valuable insights for future urban planning and conservation efforts in rapidly urbanizing cities like Karachi. Recent studies from Pakistan and South Asia have increasingly employed remote sensing and NDVI-based analyses to monitor urban vegetation dynamics, assess the impacts of climate variability and rapid urbanization, and support sustainable urban planning. Building on these regional advances, the present study integrates Google Earth Engine and SARIMA time-series modeling to provide a robust framework for monitoring and forecasting urban vegetation dynamics in Karachi.

2. Materials and methods

2.1. NDVI Analysis and Forecasting Methodology

This study is divided into two key segments: 1) analyzing NDVI data using Google Earth Engine (GEE) with JavaScript, focusing on NDVI calculation and time series analysis, and 2) forecasting NDVI trends using SARIMA modeling in Python, which involves data collection, preprocessing, trend and seasonality detection, and model validation. Advanced ecological modeling is central to these analyses. The study first derives phenological data from NDVI and examines monthly time series data using GEE. Forecasting is carried out using ARIMA and Seasonal ARIMA (SARIMA) models, implemented in Python via Google Colab or Jupyter Notebook. This Seasonal Autoregressive Integrated Moving Average (SARIMA) model was employed to characterize the temporal and seasonal dynamics of the NDVI time series and to forecast future vegetation conditions. Because no exogenous variables were incorporated, the analysis represents a purely univariate time-series modeling approach.

This comprehensive methodology, as summarized in Table 1, enables accurate forecasting and supports urban planning and conservation strategies.

Table 1. Framework, methodology, and study application

Study	SARIMA modeling	Technological integration
NDVI Time Series Data	Data collection and preprocessing	Google Earth Engine (GEE) and SARIMA modeling
	Detect trends and seasonality	Integration of machine learning and remote sensing
	Specify and validate SARIMA model	Comprehensive analysis and forecasting
	Improves predictive accuracy	Advances urban ecology insights
	Applicable to agriculture, urban planning, and environmental conservation	Forecast NDVI trends
	Informs sustainable urban development	Provides insights into vegetation health and dynamics

2.2. Study area

Karachi has a distinctive terrain and climate. Karachi, Pakistan's biggest and most populated city, is located along the Arabian Sea coast in southern Pakistan and is known for its busy metropolitan landscape (Fig. 1). Its unique climate is influenced by its location at the confluence of the Arabian Sea and the Indus River Delta. Karachi has a hot desert environment with scorching summers and moderate winters, with the sea acting as a moderator of temperature extremes. This climatic diversity, combined with the city's rapid urbanization and diverse human activities, creates a dynamic environment that significantly impacts its green spaces and vegetation. Karachi's evolution as a bustling metropolis provides a compelling backdrop for investigating the interplay between urbanization, climate, and the city's natural ecosystems (Batool et al., 2019).

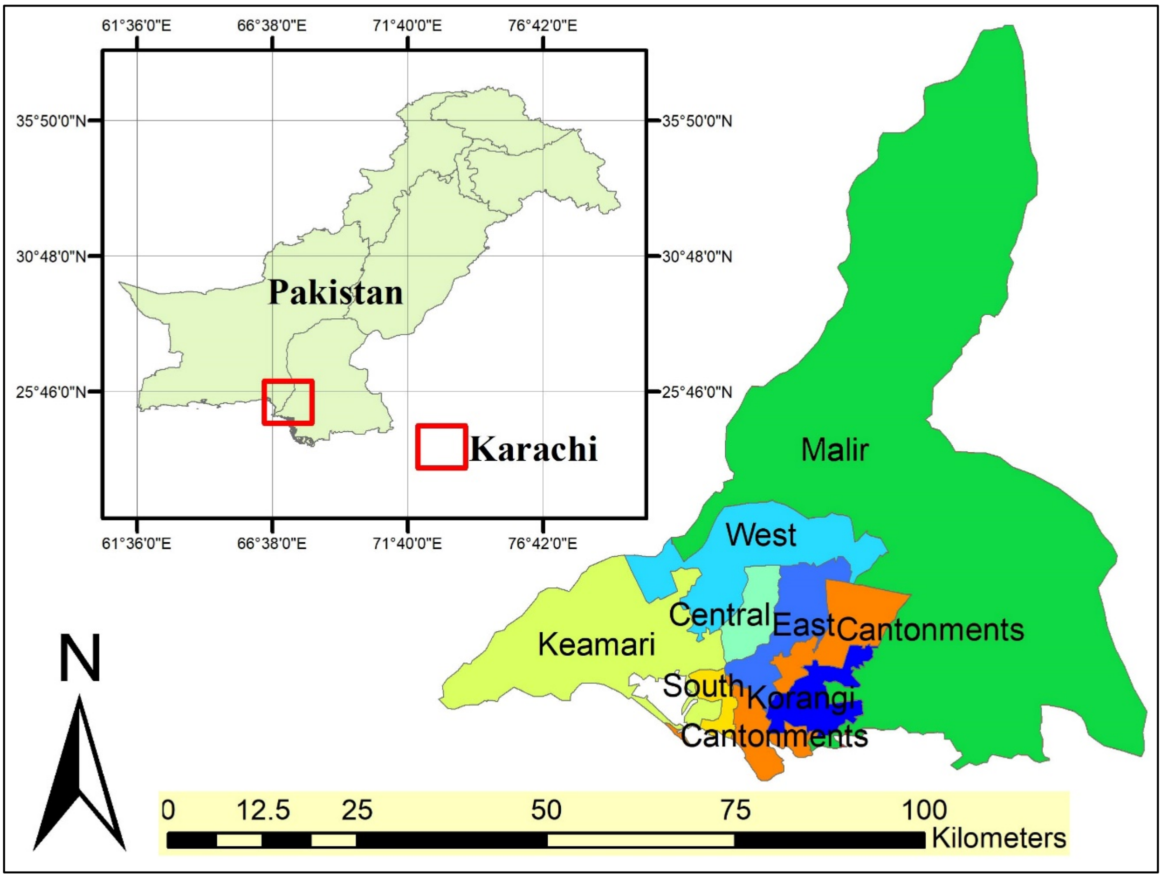

Figure 1. Study Area Karachi city

2.3. Data collection

2.3.1. Landsat 8 data

The Landsat mission, initiated in the 1970s, revolutionized Earth remote sensing with moderate-resolution imagery. Across eight missions spanning five decades, Landsat has evolved technologically, progressing from a visual interpretation project to an advanced operational mission. This evolution encompasses improvements in spectral, spatial, radiometric, and geometric capabilities (Table 2), as well as data collection methods, products, and accessibility (Sohail et al., 2020; Mohammed et al., 2022). Landsat data, spanning from Landsat 4 to Landsat 8 series, is readily accessible on the GEE platform (Table

3). Landsat 8 satellite imagery spanning the years 2013 to 2022 is acquired for the Karachi region. This imagery provides multispectral data, including bands necessary for NDVI calculation.

Table 2. Landsat spectral characteristics

Band	Wavelength Range (μm)	Description	Application
1	0.43 - 0.45	Coastal/Aerosol	Coastal water and aerosol detection
2	0.45 - 0.51	Blue	Water bodies, vegetation analysis
3	0.53 - 0.59	Green	Vegetation health and chlorophyll content
5	0.85 - 0.88	Near-Infrared (NIR)	Vegetation health, soil moisture
6	1.57 - 1.65	Shortwave Infrared 1 (SWIR 1)	Soil moisture, vegetation moisture
7	2.11 - 2.29	Shortwave Infrared 2 (SWIR 2)	Mineral analysis, soil properties
8	0.50 - 0.68	Panchromatic	High-resolution detail
9	0.43 - 0.45	Cirrus	Cloud detection
10	10.60 - 11.19	Thermal Infrared 1 (TIR 1)	Surface temperature
11	11.50 - 12.51	Thermal Infrared 2 (TIR 2)	Surface temperature

Table 3. Descriptive Statistics of NDVI (2013–2022

	NDVI
Count	117.000000
Mean	0.149187
Std	0.039016
Min	0.076750
25%	0.128000
50%	0.141875
75%	0.165125
Max	0.296833

2.4. Cloud computing with Custom JavaScript Function for NDVI, time series

A custom JavaScript function for NDVI is implemented to calculate the Normalized Difference Vegetation Index (NDVI) from Landsat 8 imagery. NDVI is computed using the NIR (Near-Infrared) and Red bands as NDVI = (NIR - Red) / (NIR + Red). Landsat 8 imagery is filtered to include only data within the specified temporal range (2013-01-01 to 2022-12-31). This step ensures that the analysis is focused on the desired time period. The add NDVI function is applied to each image in the filtered Landsat 8 collection, resulting in a collection of images with an additional NDVI band. This collection forms the basis for time series analysis. Custom visualization parameters are used to create and display RGB imagery. This includes providing the mean Landsat 8 image along with the layer of NDVI and a time-series graph of the NDVI in Figures 3 and 4.

2.5. Forecast NDVI values using ARIMA/SARIMA models

The dataset, consisting of monthly NDVI values for Karachi over several years, offers a comprehensive view of vegetation changes. Time series forecasting, based on past data, is a versatile method for predictions, with the ARIMA model (Box & Jenkins, 1976; Box et al., 2015) being a notable example. The NDVI time series data was collected to predict Karachi's NDVI values for 2023–2025 using ARIMA and SARIMA models. Data was carefully analyzed and imported using Python libraries, either from CSV files or APIs. To ensure temporal continuity, missing values were addressed using a forward fill technique. To simplify time series analysis, the 'Date' column was converted to *datetime* format and set as the *DataFrame* index. A time series plot was created to visualize trends and seasonal patterns, while descriptive statistics provided insights into the central trends and distribution of the NDVI values.

The ARIMA and SARIMA models were employed to capture non-seasonal components of the NDVI time series. The ARIMA model is defined as:

where B is the backshift operator, ϕi are the autoregressive coefficients, θi are the moving average coefficients, d is the differencing order, and ϵt is white noise.

The ARIMA (AutoRegressive Integrated Moving Average) model is expressed as:

$$(1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p)(1 - B)^d X_t = (1 + \theta_1 B + \theta_2 B^2 + \cdots + \theta_q B^q)\epsilon_t$$

where:

- X_t is the time series data at time t.
- B is the backshift operator, defined as $B^k X_t = X_{t-k}$.
- $\phi_1, \phi_2, \ldots, \phi_p$ are the autoregressive (AR) coefficients.
- $\theta_1, \theta_2, \ldots, \theta_q$ are the moving average (MA) coefficients.
- d is the order of differencing.
- ϵ_t is white noise (error term) at time t.

The SARIMA model extends ARIMA by incorporating seasonal effects. The SARIMA model is defined as:

$$\mathrm{SARIMA}(p, d, q)(P, D, Q)_s : \quad (1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p)(1 - B)^d (1 - B^s)^D$$

where s is the length of the seasonal cycle, and Θi are the seasonal moving average coefficients.

3. Results

3.1. Data acquisition preprocessing and initial results

The data was downloaded in NDVI geo.tiff and CSV format or accessed via GEE API (Fig. 2), and imported using Python libraries. Missing values in the NDVI time series were imputed using forward fill to maintain temporal continuity. The 'Date' column was converted to date time format and set as the Data Frame index for time series analysis. The NDVI time series was visualized to identify trends and seasonal patterns (Fig. 3). This is same data as Figure 6, but obtained using a different platform and codes. Summary statistics of the NDVI data were computed to examine central tendencies and dispersion (Table 3).

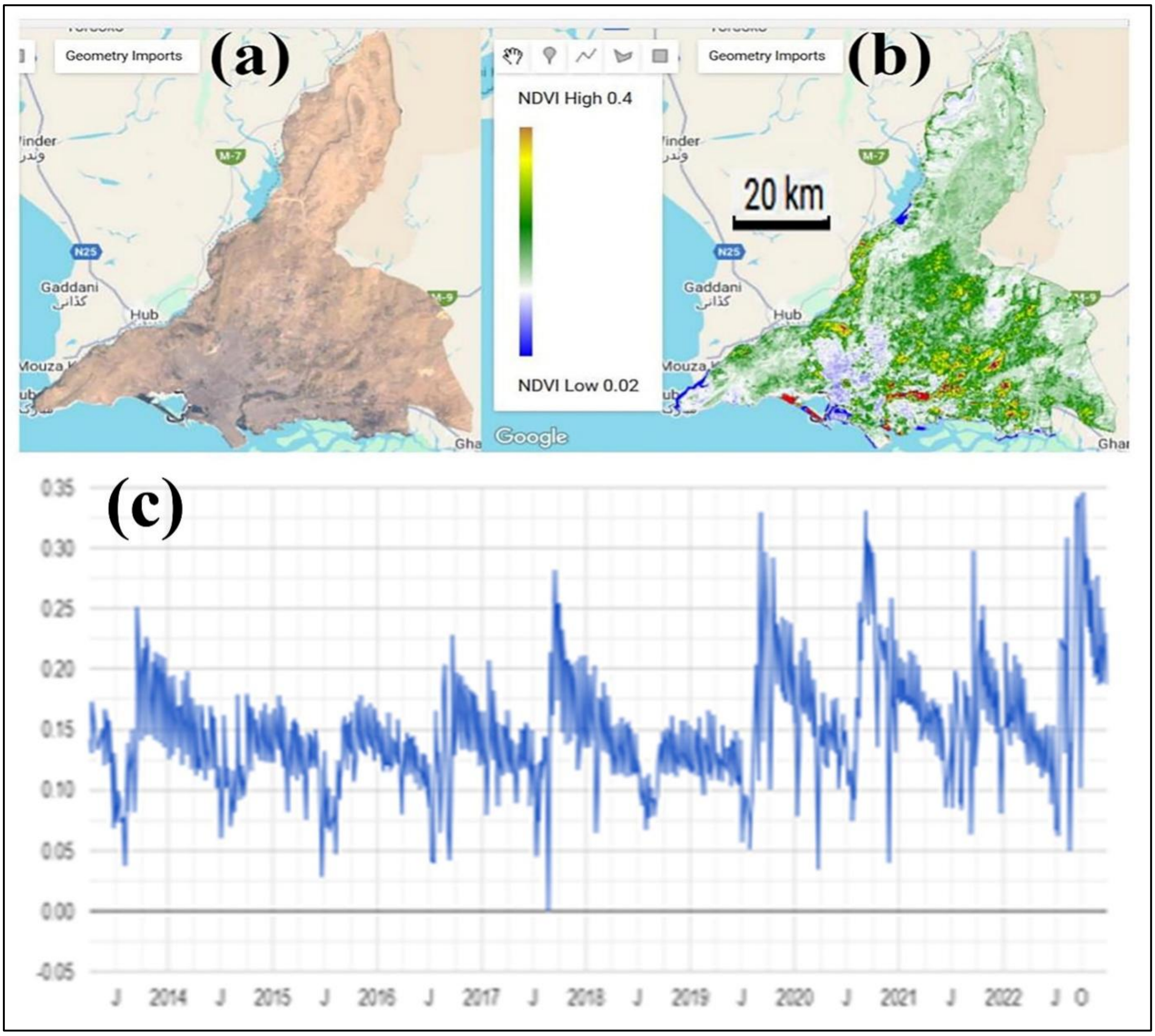

Figure 2. (a) Landsat 8 Image, (b) NDVI raster and (c) NDVI times (csv)

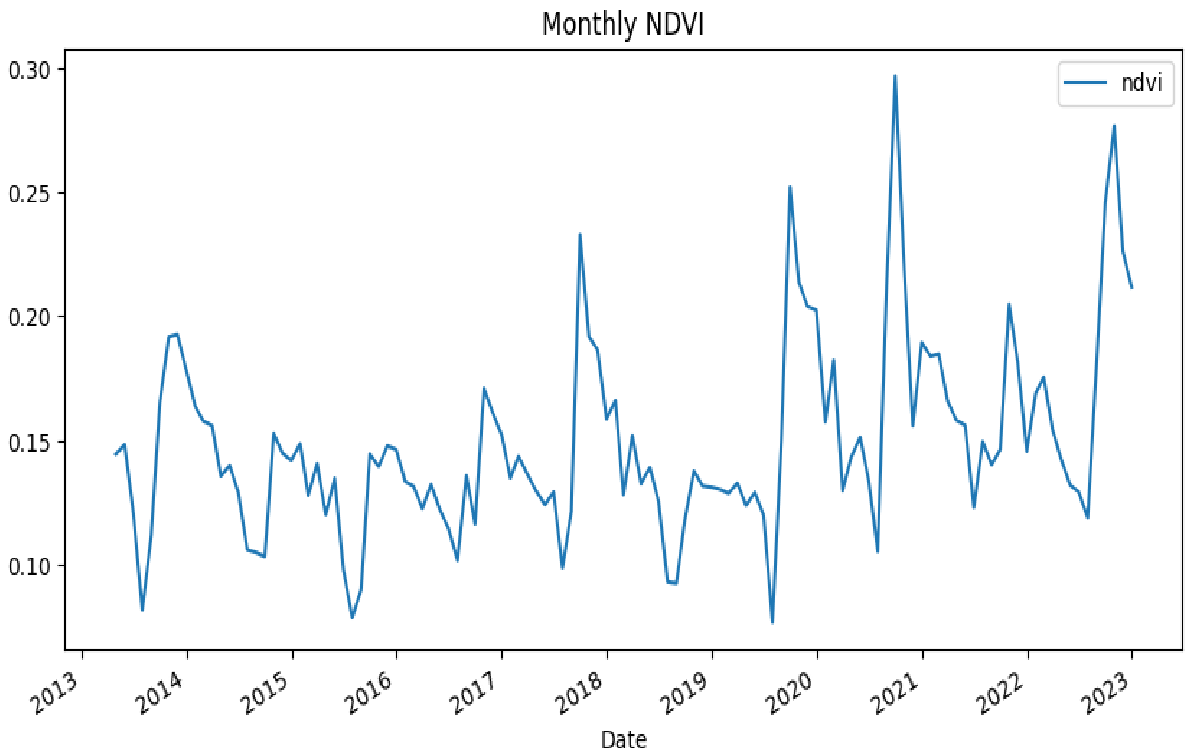

Figure 3. NDVI times

3.2. Decomposition plot

A decomposition plot breaks down a time series into its core components, providing a detailed analysis. The observed line displays the raw time series data, revealing the overall pattern. The trend line shows a clear upward trend, indicating a consistent increase over time. The seasonal component exhibits an identical seasonal distribution, highlighting repeating patterns. The Residual line captures only a few outliers, representing the remaining variability after accounting for trend and seasonality. This decomposition is vital for understanding the data's underlying structure, aiding in more accurate forecasting and comprehensive analysis. For the observed NDVI data, this is shown in Figure 4.

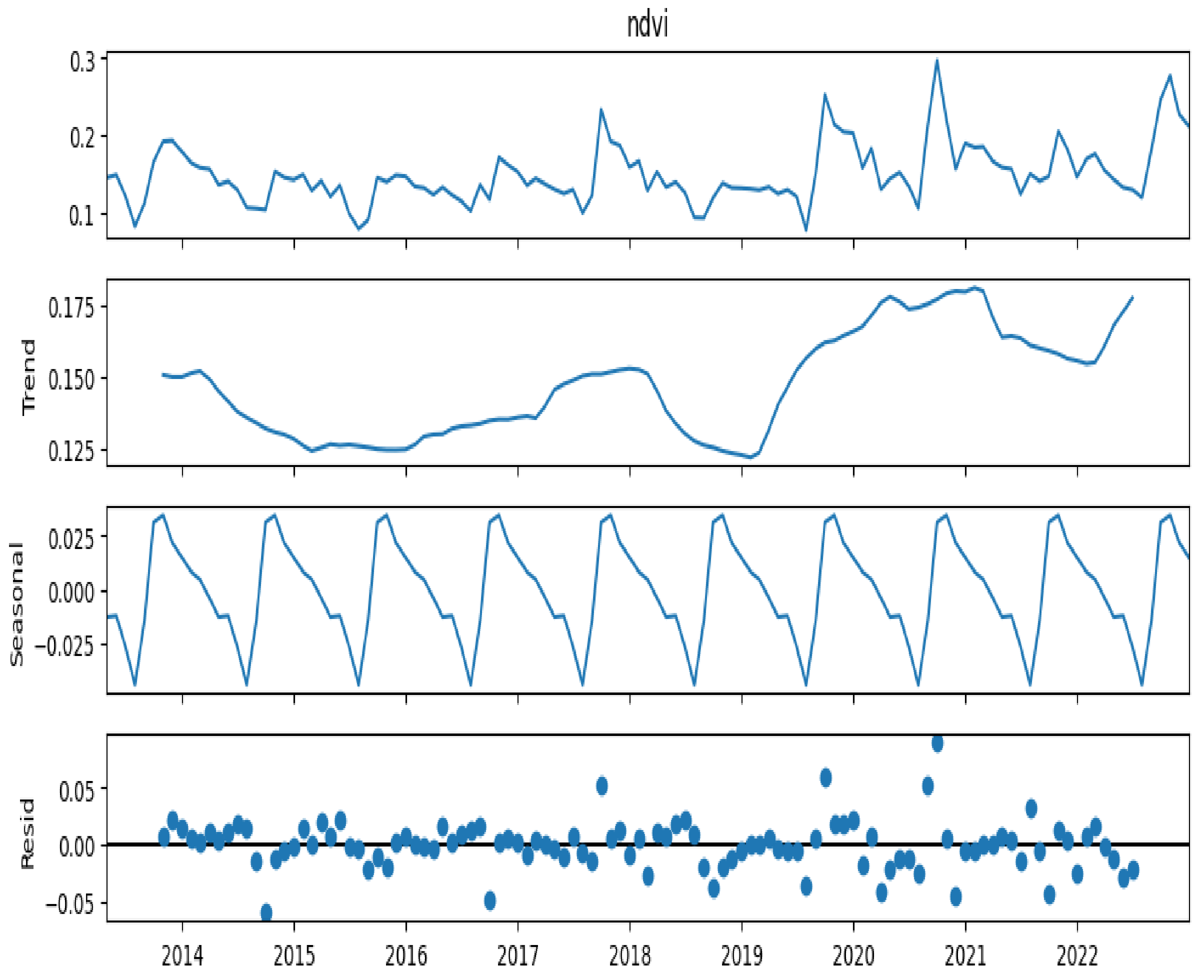

Figure 4. NDVI time series, its trend, seasonal distribution and residual

3.3. Augmented dickey-fuller (ADF)

The Augmented Dickey-fuller (ADF) test is a popular method for testing the stationary of a time series by assessing the null hypothesis that the time series has a unit root, indication non-stationarity. The test determines if the coefficient of the lagged level term is substantially different from zero after evaluating a regression model using the lagged terms of the series (Dwivedi et al., 2017; Rashid et al., 2024). A low p-value signifies the series is stationary and that the null hypothesis should be rejected. The chosen lag time may have an impact on the ADF test's efficacy and occasionally provide results that are not entirely conclusive (Ayitey et al., 2021).

Establish a state of stationarity a commonly used method is differencing, which eliminates patterns and seasonality by deducting the prior information from the present one. Seasonal differencing accounts for sporadic swings, where first-differencing handles linear trends. After differencing, the time series is re-tested for stationarity, and additional differencing may be applied if necessary, while differencing is effective in making a time series stationary excessive differencing can lead to loss of information and complicate the modeling process such as, ADF Statistic: -3.217574792440532; Critical Values:1%: -3.4954932834550623, 5%: -2.8900369024285117, and 10%: -2.5819706975209726.

Since the ADF statistic is less negative than the 1% critical value but more negative than the 5% critical value, and the p-value is less than 0.05, you can reject the null hypothesis (H_0) at the 5% significance level. This means you have sufficient evidence to reject the null hypothesis and conclude that the time series is likely stationary at the 5% level of significance.

3.4. ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) plots

The ACF and PACF plots are crucial tools in time series analysis, providing insights into the structure and behavior of the data (Fernández-Manso et al., 2011). For monthly sales data, a significant autocorrelation at lag 12 suggests an annual seasonality pattern, indicating that the data exhibits repeating behavior every 12 months. The ACF plot reveals the correlation between the time series and its lags, highlighting significant autocorrelation at specific intervals, which can point to seasonal effects or other patterns. Meanwhile, the PACF plot shows the direct correlation between the series and its lags after accounting for shorter lags, helping to identify the order of the autoregressive component in models. For NDVI data, significant seasonal patterns with peaks at regular intervals and significant spikes at lags corresponding to the seasonal period demonstrate clear seasonality, with both ACF and PACF indicating seasonal components (Fig. 5). These plots are instrumental for model selection, particularly for ARIMA and SARIMA models, by guiding the identification of autoregressive and moving average components and ensuring accurate forecasting by accounting for underlying seasonality and patterns.

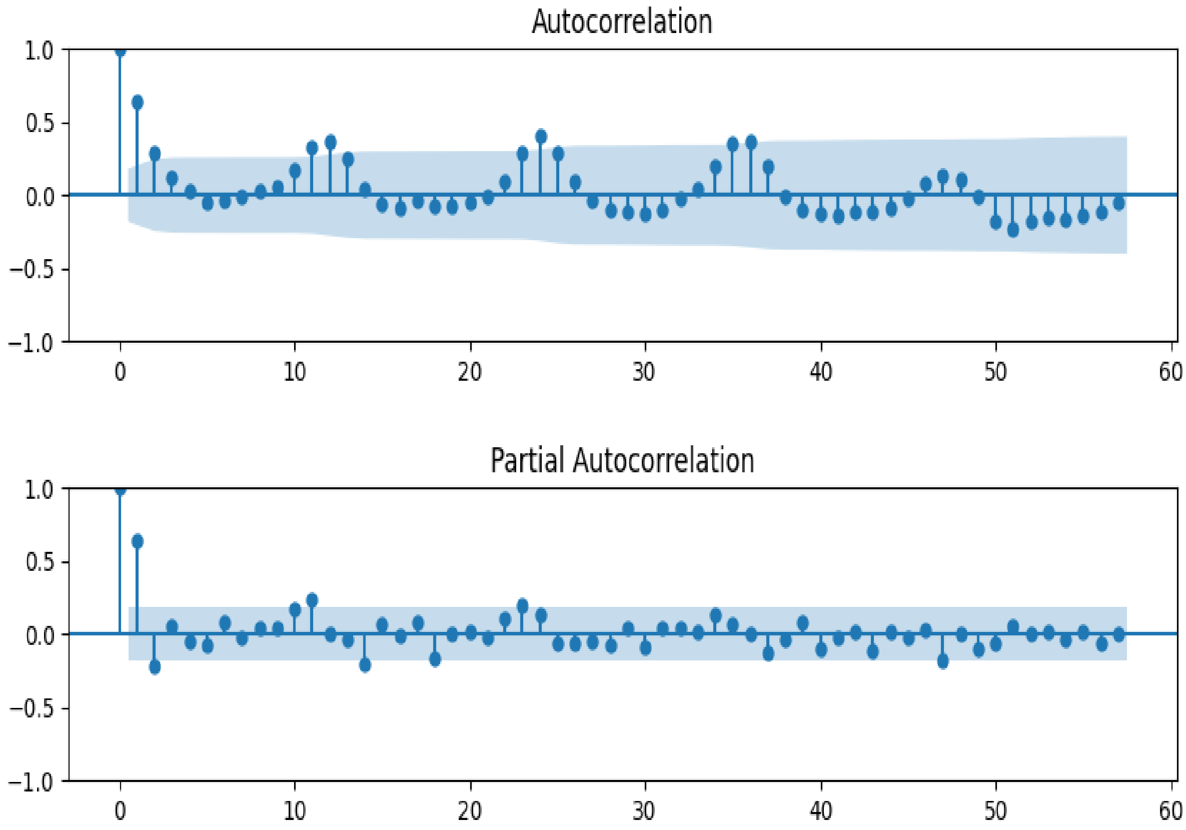

Figure 5. ACF and PACF plots of NDVI

3.5. Original and differenced time series plot

Figure 6 illustrates the raw NDVI data over time, providing insights into underlying trends, seasonal patterns, and irregularities. To make the time series stationary, differencing is applied, and the resulting plot is presented for comparison. This transformation aims to stabilize the mean and variance by removing trends and seasonality. A side-by-side comparison of the original and differenced plots reveals whether differencing has successfully achieved a more consistent mean and variance. This is a critical step before applying time series models like ARIMA or SARIMA, which require the data to be stationary.

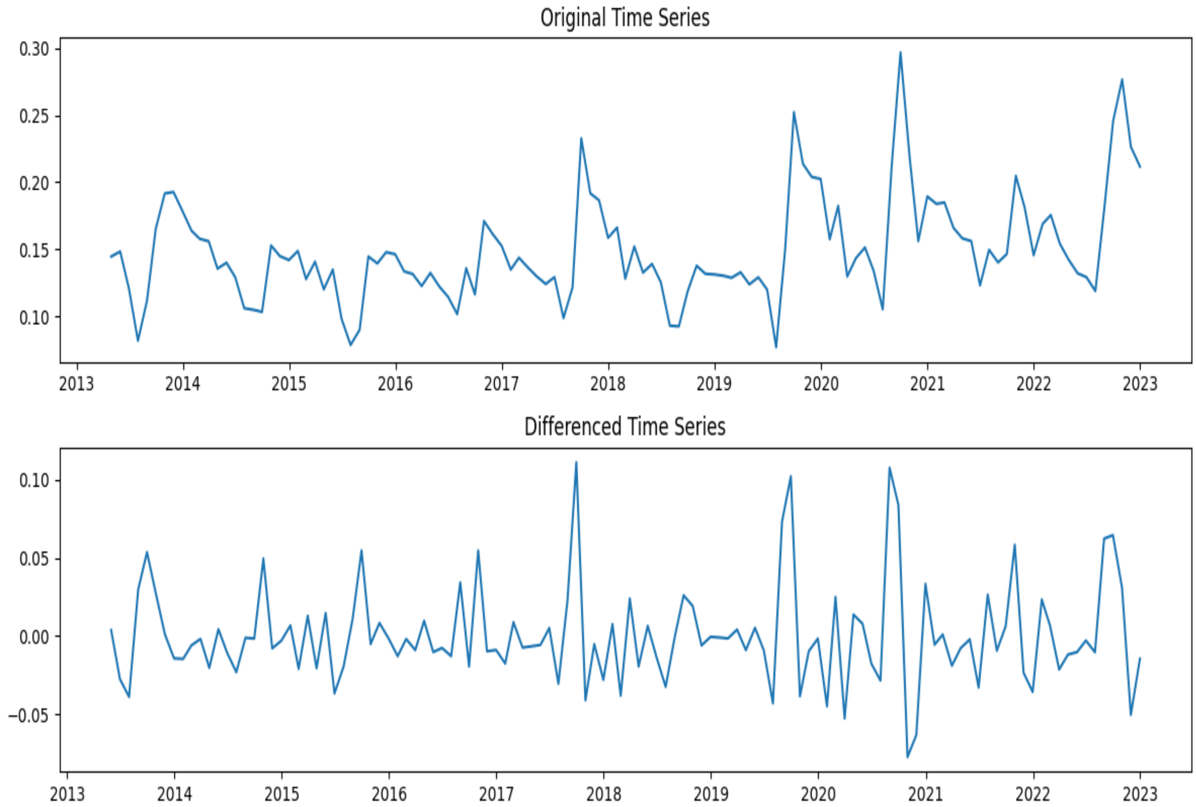

Figure 6. Original and differenced time series

3.6. Residual analysis and diagnostics

For diagnosing and validating the performance of time series models as in this study the standardizing residuals along with analyzing their histogram, normal Q-Q plot, and Correlogram is an essential part (Fig. 7). This standardizing residuals includes transforming them to have a mean of zero and a standard deviation of one which helpful in comparing residuals across different models or datasets.

The histogram of residuals provides a visual assessment of their distribution is allowing for the identification of deviations from normality. A normal Q-Q plot is used to assess as if residuals follow a normal distribution which is an assumption for many time series models. If the points in the Q-Q plot fall approximately along a straight line, it indicates that the residuals are normally distributed. The correlogram of residuals often represented by an ACF plot helps in detecting any remaining autocorrelation that might not have been captured by the model. When significant autocorrelation is present. It suggested that the model may need further refinement, also these diagnostic tools help ensure that the residuals of a time series model are well-behaved which is crucial for reliable forecasting and model accuracy.

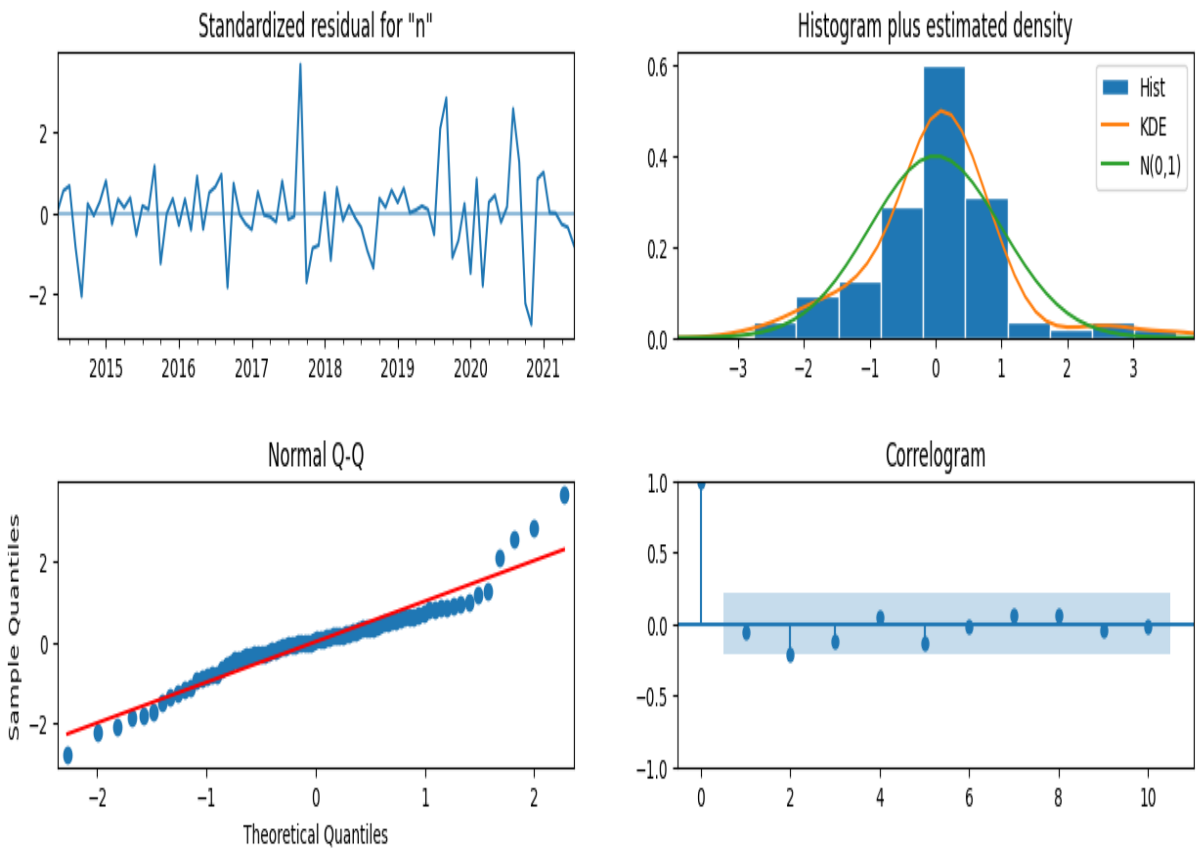

Figure 7. Residual Analysis, histogram, normal Q-Q plot, and correlogram

3.7. Model estimation in ARIMA

Model estimation in ARIMA involves fitting the ARIMA model to the time series data using the identified parameters. This step is crucial as it translates the theoretical ARIMA model into a statistical model that can be used to make forecasts. Here's a detailed discussion of this process:

Before fitting the ARIMA model, we need to specify the model based on the identified parameters:

- ARIMA(p, d, q):
  - **p**: The number of lag observations included in the model (Auto-Regressive part).
  - **d**: The number of times the raw observations are differenced (Integration part).
  - **q**: The size of the moving average window (Moving Average part).

For best and optimal ARIMA model for the NDVI time series data, the auto_arima function from the pmdarima library was utilized, the model fitting process was configured with non-seasonal and seasonal differencing orders set to 1 (d = 1, D = 1). This addressing both non-seasonal and seasonal stationarity requirements. The seasonal component was specified with a period of 12 (m = 12), reflecting the annual cycle of the data. The initial values for the non-seasonal AutoRegressive (AR) and Moving Average (MA) components were set to zero (start_p = 0, start_q = 0), and the maximum permissible combined order for AR and MA components was constrained to 6 (max_order = 6). The stationarity was assessed using the Augmented Dickey-Fuller test (test = 'adf'), The parameter (trace = True) was enabled to provide a detailed log of the model selection process aiding in the evaluation and selection of the most suitable ARIMA model for the time series (Table 4).

Table 4. Results of model estimation

ARIMA(p,d,q)	**Seasonal (P,D,Q)[S]**	**AIC**
ARIMA(0,1,0)	(1,1,1)[12]	AIC=-425.809
ARIMA(0,1,0)	(0,1,0)[12]	AIC=-371.699
ARIMA(1,1,0)	(1,1,0)[12]	AIC=-416.437
ARIMA(0,1,1)	(0,1,1)[12]	AIC=inf
ARIMA(0,1,0)	(0,1,1)[12]	AIC=inf
ARIMA(0,1,0)	(1,1,0)[12]	AIC=-409.863
ARIMA(0,1,0)	(2,1,1)[12]	AIC=-423.818
ARIMA(0,1,0)	(1,1,2)[12]	AIC=-423.227
ARIMA(0,1,0)	(0,1,2)[12]	AIC=-425.745
ARIMA(0,1,0)	(2,1,0)[12]	AIC=-420.928
ARIMA(0,1,0)	(2,1,2)[12]	AIC=-421.641
ARIMA(1,1,0)	(1,1,1)[12]	AIC=-430.737
ARIMA(1,1,0)	(0,1,1)[12]	AIC=inf
ARIMA(1,1,0)	(2,1,1)[12]	AIC=-429.104
ARIMA(1,1,0)	(1,1,2)[12]	AIC=-428.229
ARIMA(1,1,0)	(0,1,0)[12]	AIC=-379.068
ARIMA(1,1,0)	(0,1,2)[12]	AIC=-430.796
ARIMA(2,1,0)	(0,1,2)[12]	AIC=-440.651
ARIMA(2,1,0)	(0,1,1)[12]	AIC=inf
ARIMA(2,1,0)	(1,1,2)[12]	AIC=-438.681
ARIMA(2,1,0)	(1,1,1)[12]	AIC=-439.958
ARIMA(3,1,0)	(0,1,2)[12]	AIC=-440.193

ARIMA(2,1,1)	(0,1,2)[12]	AIC=-442.864
ARIMA(2,1,1)	(0,1,1)[12]	AIC=inf
ARIMA(2,1,1)	(1,1,2)[12]	AIC=-440.899
ARIMA(2,1,1)	(1,1,1)[12]	AIC=-441.876
ARIMA(1,1,1)	(0,1,2)[12]	AIC=-444.824
ARIMA(1,1,1)	(0,1,1)[12]	AIC=inf
ARIMA(1,1,1)	(1,1,2)[12]	AIC=-442.724
ARIMA(1,1,1)	(1,1,1)[12]	AIC=-444.327
ARIMA(0,1,1)	(0,1,2)[12]	AIC=-441.241
ARIMA(1,1,2)	(0,1,2)[12]	AIC=-443.362
ARIMA(0,1,2)	(0,1,2)[12]	AIC=-445.382
ARIMA(0,1,2)	(0,1,1)[12]	AIC=inf
ARIMA(0,1,2)	(1,1,2)[12]	AIC=-441.176
ARIMA(0,1,2)	(1,1,1)[12]	AIC=-444.673
ARIMA(0,1,3)	(0,1,2)[12]	AIC=-443.388
ARIMA(1,1,3)	(0,1,2)[12]	AIC=-441.376
ARIMA(0,1,2)	(0,1,2)[12]	AIC=-444.098
Best model: ARIMA(0,1,2)	**(0,1,2)[12]**	

3.8. SARIMA model results

SARIMA model summary in (Table 5) has been obtained. The resulted SARIMAX (0,1,2) x (0,1,2,12) model has been identified as the best fit for the dataset, offering a comprehensive representation of the time series with seasonal adjustments. The model includes no non-seasonal autoregressive terms (p=0), one non-seasonal differencing (d=1), and two non-seasonal moving average terms (q=2), along with no seasonal autoregressive terms (P=0), one seasonal differencing (D=1), and two seasonal moving average terms (Q=2) with a seasonal period of 12. The model's fit is reflected in its Log Likelihood of 227.691, AIC of -445.382, BIC of -432.160, and HQIC of -440.025, suggesting a good balance between fit and model complexity. The coefficients for the moving average terms are significant, with ma.L1 at -0.4447, ma.L2 at -0.2768, and seasonal terms ma.S.L12 at -0.9116 and ma.S.L24 at 0.2366. These results indicate a strong impact of the moving average terms and significant seasonal effects with lags of 12 and 24 periods. The very small sigma2 value of 0.0007 shows that the residuals are relatively small, indicating a well-fitting model in terms of residual variance.

Diagnostic tests reveal that while the model fits well according to AIC and BIC, there are some concerns. The Ljung-Box test shows no significant autocorrelation in the residuals (p = 0.87), but the Jarque-Bera test indicates that residuals are not normally distributed (p = 0.00), and the heteroskedasticity test (p = 0.00) suggests significant variance changes. Additionally, the skew (0.82) and kurtosis (5.34) of the residuals indicate some asymmetry and heavy tails, respectively, pointing to potential areas for further model refinement.

Table 5. SARIMA results

Dep. Variable:	y	**No. Observations:**	117
Model:	SARIMA (0, 1, 2)x(0, 1, 2, 12)	**Log Likelihood**	227.691
Date:	Sat, 10 Aug 2024	**AIC**	-445.382
Time:	15:38:10	**BIC**	-432.160
Sample:	04-30-2013	**HQIC**	-440.025
	- 12-31-2022		
Covariance Type:	opg		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
ma.L1	-0.4447	0.078	-5.730	0.000	-0.597	-0.293
ma.L2	-0.2768	0.097	-2.847	0.004	-0.467	-0.086
ma.S.L12	-0.9116	0.083	-11.049	0.000	-1.073	-0.750
ma.S.L24	0.2366	0.119	1.990	0.047	0.004	0.470
sigma2	0.0007	6.93e-05	9.482	0.000	0.001	0.001

Ljung-Box (L1) (Q):	0.03	**Jarque-Bera (JB):**	35.49
Prob(Q):	0.87	**Prob(JB):**	0.00
Heteroskedasticity (H):	3.97	**Skew:**	0.82
Prob(H) (two-sided):	0.00	**Kurtosis:**	5.34

The residual diagnostic tests indicate that the fitted SARIMA model successfully captured the temporal dependence in the NDVI time series, as evidenced by the non-significant Ljung–Box statistic ($p = 0.87$), suggesting no remaining autocorrelation in the residuals. However, the significant Jarque–Bera and Heteroskedasticity test results ($p < 0.001$) indicate that the residuals are not normally distributed and exhibit non-constant variance. These departures from the ideal assumptions are likely attributable to intermittent extreme environmental events, such as unusually intense monsoon rainfall, heatwaves, drought episodes, and other climatic anomalies that cause abrupt changes in vegetation conditions. Consequently, while the SARIMA model provides a robust representation of the underlying temporal and seasonal patterns, some short-term variability associated with extreme climatic events remains difficult to capture using a univariate time-series model.

3.9. NDVI and SARIMA model alignment and prediction

The SARIMAX(0,1,2)x(0,1,2,12) model has been applied to NDVI data, providing a comprehensive view of the actual and predicted NDVI values over time. The observed NDVI values are depicted by one line. This is capturing the true variations and seasonal patterns inherent in the data. In contrast, the second line represents the NDVI values predicted by the SARIMA model. With close alignment between these lines indicates the model's proficiency in effectively capturing trends and seasonal fluctuations. Equally, noteworthy deviations may suggest limitations in the model's predictive capacity. These are highlighting areas for potential improvement. The plot's tight x-axis scaling ensures. The data range is visible and facilitating a clear comparison between observed and predicted values (Fig. 8). This visual analysis is critical for evaluating the model's accuracy and understanding its performance in forecasting vegetation index trends.

The data in (Fig. 9) shows the observed and forecast NDVI values, displaying a rising trend and consistent seasonality, underscoring the model's effectiveness in capturing these patterns. As shown in (Fig. 10) illustrates the forecasting with lower and upper confidence intervals, providing a range within which the future values are expected to fall. Figure 11 combines the NDVI data with the forecast values, including the confidence intervals, offering a comprehensive overview of past trends and future predictions. Table 6 presents the predicted mean NDVI values with confidence intervals for the period from 2023 to 2025. For instance, in January 2023, the predicted mean NDVI value is 0.196 with a 95% confidence interval ranging from 0.146 to 0.246. Predictions indicate fluctuations in NDVI values over time, with notable peaks in September 2023 (0.232) and October 2024 (0.253), and lower values during the summer months, reflecting seasonal variations. The confidence intervals provide a measure of prediction reliability, showing the range within which future NDVI values are expected to fall, supporting robust forecasting for urban planning and conservation strategies.

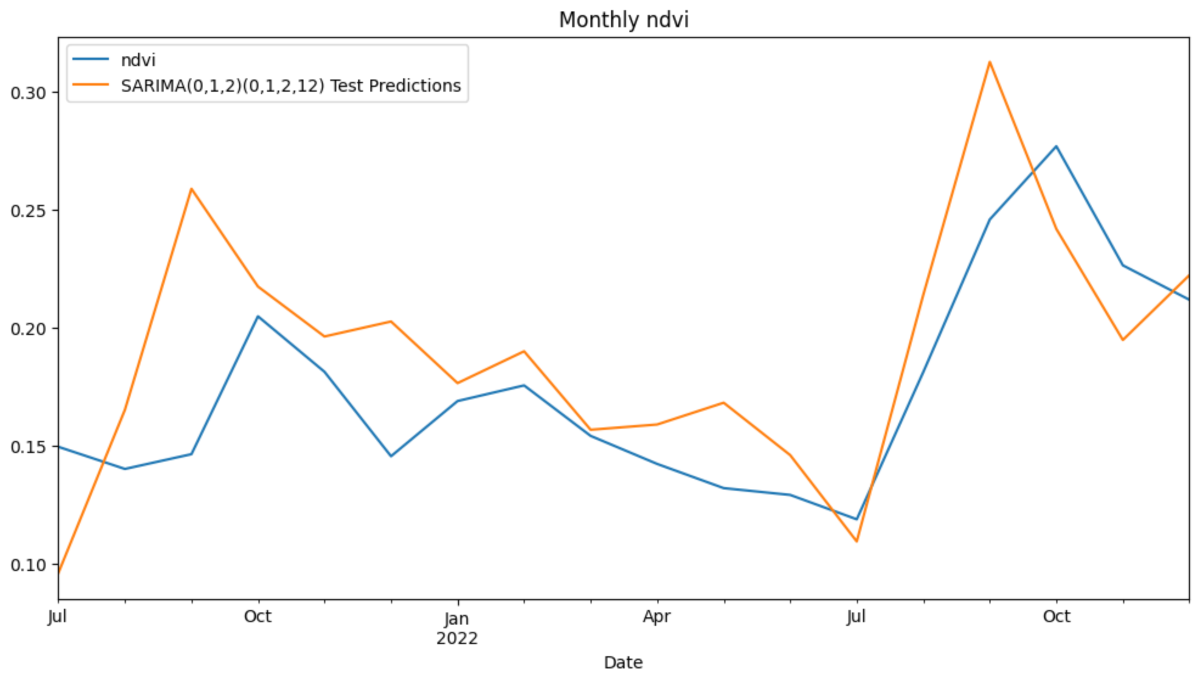

Figure 8. NDVI and SARIMA model alignment and prediction

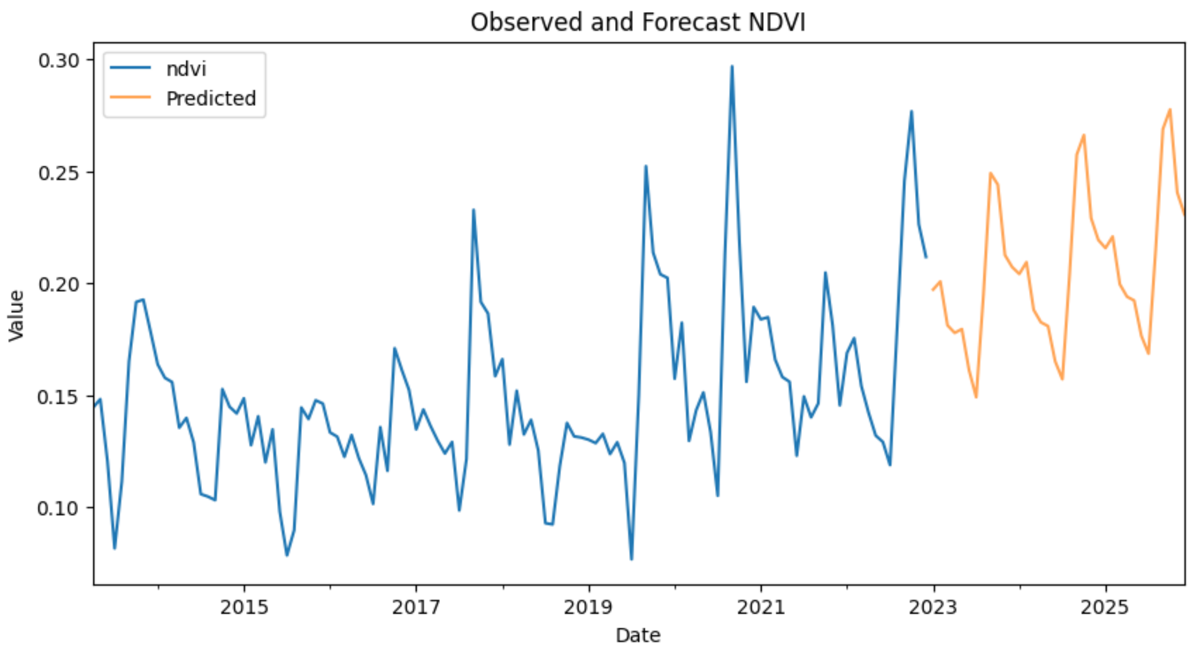

Figure 9. Observed and forecast

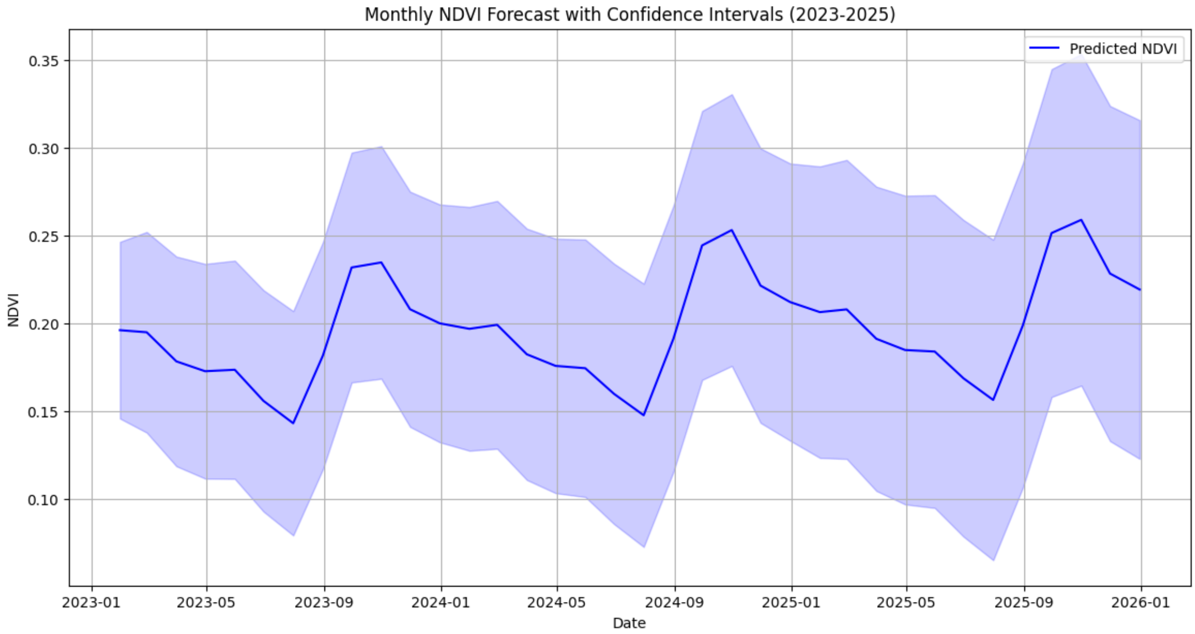

Figure 10. NDVI forecasting with lower and upper confidence intervals

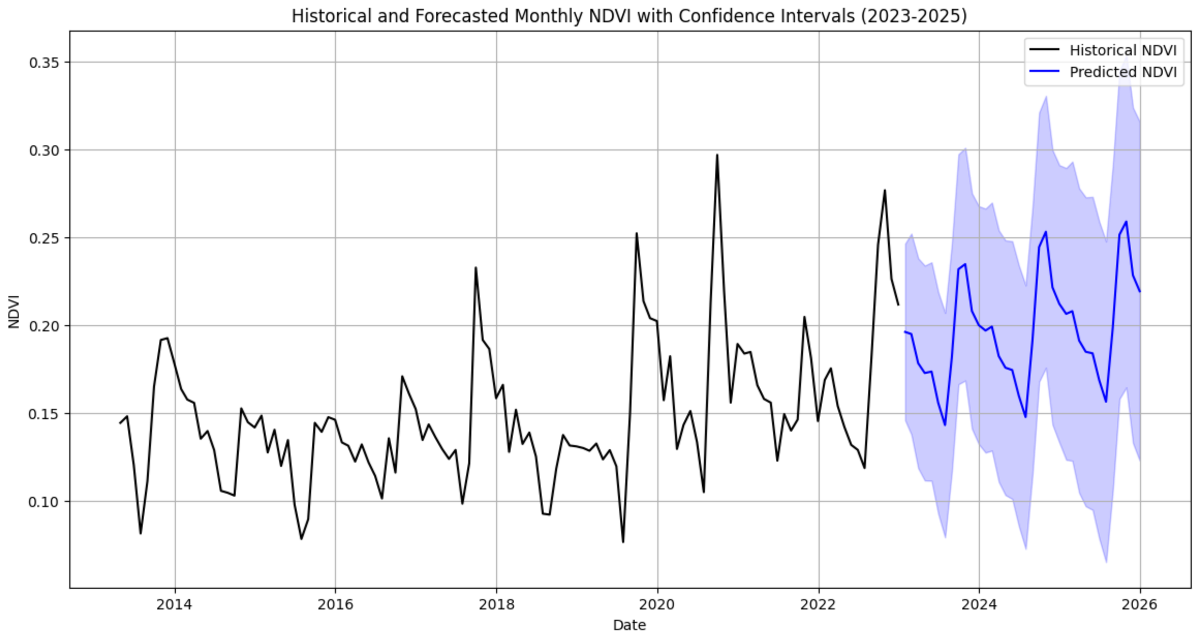

Figure 11. Historical NDVI with forecasting values with confidence intervals

Table 6. Predicted Mean Values with Confidence Intervals Over Time (2023-2025)

Date		Predicted Mean	Lower CI	Upper CI
1/31/2023	1/31/2023	0.196187	0.145955	0.246419
2/28/2023	2/28/2023	0.194998	0.137924	0.252071
3/31/2023	3/31/2023	0.17844	0.118812	0.238068
4/30/2023	4/30/2023	0.172837	0.111793	0.233882
5/31/2023	5/31/2023	0.173675	0.111593	0.235758
6/30/2023	6/30/2023	0.155952	0.09298	0.218925
7/31/2023	7/31/2023	0.143241	0.079443	0.207039
8/31/2023	8/31/2023	0.181729	0.117137	0.24632
9/30/2023	9/30/2023	0.231841	0.166475	0.297207
10/31/2023	10/31/2023	0.234727	0.168598	0.300855
11/30/2023	11/30/2023	0.208097	0.141216	0.274977
12/31/2023	12/31/2023	0.200075	0.132452	0.267698
1/31/2024	1/31/2024	0.196955	0.127641	0.266269
2/29/2024	2/29/2024	0.199234	0.128746	0.269723
3/31/2024	3/31/2024	0.182455	0.110987	0.253924
4/30/2024	4/30/2024	0.175878	0.103511	0.248244
5/31/2024	5/31/2024	0.174547	0.101325	0.247769
6/30/2024	6/30/2024	0.159977	0.085921	0.234034
7/31/2024	7/31/2024	0.147789	0.072913	0.222665
8/31/2024	8/31/2024	0.191258	0.115572	0.266943
9/30/2024	9/30/2024	0.244395	0.16791	0.320879
10/31/2024	10/31/2024	0.25314	0.175864	0.330416
11/30/2024	11/30/2024	0.221555	0.143496	0.299613
12/31/2024	12/31/2024	0.212166	0.133333	0.291
1/31/2025	1/31/2025	0.206454	0.123557	0.289351
2/28/2025	2/28/2025	0.208011	0.122984	0.293037
3/31/2025	3/31/2025	0.191278	0.104748	0.277807
4/30/2025	4/30/2025	0.184903	0.097108	0.272698
5/31/2025	5/31/2025	0.184024	0.095071	0.272977

6/30/2025	6/30/2025	0.168798	0.078736	0.258859
7/31/2025	7/31/2025	0.156501	0.065358	0.247643
8/31/2025	8/31/2025	0.198931	0.106727	0.291136
9/30/2025	9/30/2025	0.251438	0.158186	0.34469
10/31/2025	10/31/2025	0.258963	0.164675	0.35325
11/30/2025	11/30/2025	0.22841	0.133099	0.32372
12/31/2025	12/31/2025	0.219306	0.122983	0.315629

The observe variations in NDVI have important ecological implications for urban ecosystems health and resilience. Higher NDVI values represent denser and more vigorous vegetation with greater photosynthetic activity, reflecting healthier green spaces that enhance carbon sequestration, moderate the urban heat island effect, improve air quality, and support urban biodiversity. In contrast lower NDVI values indicate sparse or stressed vegetation, which may result from rapid urban expansion, reduced soil moisture, prolonged dry conditions, or heat stress. Such reductions in vegetation cover can diminish ecosystem resilience by weakening the capacity of urban landscapes to regulate temperature, retain moisture, and provide essential ecosystem services. Therefore, the temporal fluctuations observed in NDVI not only describe changes in vegetation cover but also reflect variations in the ecological condition and resilience of Karachi's urban environment under changing climatic and anthropogenic pressures.

4. Discussion

The integration of machine learning and remote sensing technologies on the Google Earth Engine platform has allowed for a comprehensive exploration of urban vegetation dynamics in Karachi. The analysis of NDVI time series, vegetation health, and geographic distribution has yielded valuable insights into the city's ecological landscape. The significance of this research extends beyond the technical methodologies employed. By contributing to the understanding of urban sustainability in Karachi, the study sets the stage for meaningful advancements. The interdisciplinary approach is coupled with alignment with global goals and positions the findings to offer not only theoretical understanding but also pragmatic recommendations for shaping the city's future. The positive influence on Karachi's urban development and environmental resilience becomes evident. The actionable insights derived from this research can inform policies and practices that contribute to the city's ecological well-being.

The success of this endeavor emphasize the important and transformative role that advanced technologies and collaborative efforts can play in addressing complex urban challenges. The importance of evaluating vegetation holds huge weightiness in the quest of sustainable urban development. The well-being and vigor of green spaces within urban areas are good and pivotal factors in fostering cities that are resilient and environmentally aware (De la Barrera et al., 2016). This study expresses importance of vegetation assessment. Also climate change adaptation and the pursuit of greening goals for sustainable urban development. These are all supported by the long-term monitoring capabilities offered by remote sensing data.

The pronounced seasonal fluctuations observed in the NDVI time series have important implications for urban planning and climate adaptation. Periods of reduced NDVI indicate times when urban vegetation is more susceptible to environmental stress, highlighting the need for targeted management interventions such as supplemental irrigation, maintenance of urban green spaces, and restoration of degraded vegetation. Conversely, periods of peak vegetation growth provide opportunities for evaluating the effectiveness of greening initiatives and planning future planting programs. Incorporating seasonal vegetation forecasts into urban planning can support the strategic allocation of resources, improve the design and management of green infrastructure, and enhance the capacity of cities to mitigate urban heat island effects, improve air quality, and strengthen resilience to climate variability and extreme weather events. Consequently, integrating remote sensing with SARIMA-based forecasting provides a practical framework for evidence-based urban ecosystem management and climate adaptation in rapidly growing metropolitan areas.

4.1. Advantage of the study

Importance of Vegetation Assessment: The greenery of large cities helps in the enriching urban wildlife the cleansing of the air and the enhancement of the city dwellers' health (Ramachandra et al., 2012). Since also NDVI and remote sensing techniques provide evidence of the status, location and transformation of the greenery, analyzing urban vegetation provides additional perspectives on the landscape that a complex system is (Perry & Enright, 2006; Khoperskov et al., 2024). Such knowledge, in turn, sets the foundation for practical attempts in order to promote urban designs which enhance the protection and development of urban green areas.

Climate Change Adaptation: With increasing impacts of climate change in cities, evaluation of vegetation cover becomes an instrument of adaptive strategy (Ahmed, 2018; Naik et al., 2024). It is important to mention that a well-maintained vegetation layer serves as an ecological shield reducing thermal loads, depressing UHI effect, and advancing climate change impacts (Li et al., 2020). These changes in vegetation patterns provide an opportunity for the cities to devise a coping strategy to environmental deterioration, thereby promoting a balance between urbanization and the environment (Salvo et al., 2024).

Urban Growth and Greening Goals for Sustainable Development: The urban expansion perspective is emerging as we realize the significant role of green areas in the design of cities (Sharma et al., 2024), Most of the Greener cities relate to healthier more livable conditions. Targeting with Sustainable development goals till 2030 today UN and other agencies include and incorporating green areas into urban landscapes in order to strike a balance between expansion and conservation of the environment (Tasnim et al., 2022). Evaluation in vegetation and greenery plays an important role in accomplishing these objectives providing insights into improving urban layouts for both natural health and human well-being (Lorenzo-Sáez et al., 2021).

Long-Term Monitoring with Remote Sensing Data: Remote sensing data, with its comprehensive and bird's-eye view perspective, facilitates the continuous monitoring of vegetation dynamics (Frick & Tervooren, 2019). The most important to accurate decision-making is in the capacity to monitor urban green areas over time. This sort of equipment enables city planners to observe changes in plant cover to assess the efficacy of greening projects. This modify plans for sustained environmental health. (Iverson & Risser, 1987; Yue et al., 2023). For long-term insights derived from remote sensing data contribute to the creation of resilient, adaptive urban spaces that advance in coordination with their natural surroundings (Singgalen et al., 2024).

The vegetation assessment is good to recognize climate change adaptation and sustainable urban growth is intrinsic to forging cities that are not only environmentally conscious but also resilient in the face of a changing climate (Szetey et al., 2021). The integration of long-term observing via remote sensing data improves our ability to make informed decisions about fostering urban landscapes that harmonize with nature while catering to the changing needs of urban populations. Because of the complexities of urbanization, prioritizing and nurturing our green spaces becomes critical for an environmentally friendly, vibrant, and climate-resilient urban future (Badapalli et al., 2023).

4.2. Reliable and accurate assessment of Karachi's urban vegetation

To further enhance the methodologies developed and tested by Qureshi et al. (2010, 2013) and Jansson (2014), the developed methodology will be validated based on the results of additional studies (Ghazal et al., 2015; Tariq & Mumtaz, 2023) and satellite data from satellites like Google Earth Engine have been carefully curated and then ground truth validation will comprise on-site measurements of the vegetative health. This approach in this case falls in line with what research was conducted by (Verma et al., 2020; Sohail et al., 2020). Besides theoretical perspectives, the project expands its focus to include the practical implications on urban planning in Karachi. Conservation efforts, species distribution mapping, and gathering empirical evidence form the core foundation of strategic efforts aimed at enhancing environmental conservation and enhancing urban resilience. Such initiatives are essential for the sustainable development of the city in the context of climate variability, which has been brought into focus by recent events of heatwaves and urban inundation (Qureshi et al., 2013).

This research will also potentially include techniques for the advance management of invasive plant species. Continued observations and confirmations of NDVI time series in relation to outcomes from machine learning can shape interventions into urban planning and restoration initiatives and improve forestation within the city. This all-inclusive model aims at theoretical understanding not only but to also ensure that there are tangible advantages for the city and those who reside there (Arshad et al., 2020; Aslam et al., 2021). The study attempts to analyze the dynamics of urban vegetation in order to understand time-series variations, taking advantage of a time series extension that continuously refreshes these values over the last decade and therefore explains seasonality and identifies persistent trends.

Development of recommendations would require interdisciplinary collaboration among those trained in machine learning and climatology, ecology, as well as even urban planning (Kamal, 2022). In its essence, the idea integrates green spaces and its potential incorporation in the urban design. The aim should be not only ecological integrity of urban landscapes but healthier and sustainable landscapes (Niemelä et al., 2011). The research activity must be maintained for a long period to become a foundation of informed decision making across sectors, including conservation, natural resources management, climate research, and urban development (Zaidi & Zafar, 2018; Huang et al., 2020).

4.3. Machine learning and cloud computing in vegetation assessment

The partnership between machine learning and cloud computing is one of the basic elements in the domain of data-driven decision-making (Burchfield et al., 2016; Zurqani et al., 2024). This partnership will enhance computational efficiency so that the results are accurate and reliable for the analysis of large NDVI time series datasets (Zhu et al., 2019; Dey et al., 2024). This may lay the grounds for evidence-based policies and strategic initiatives in urban development. This is a preponderate theme that the program supports global Sustainable Development Goals (De Sousa et al., 2020). It has been presented as a study that acknowledges the inter-linkages of urban vegetation dynamics with overarching environmental and societal objectives, which in fact provides a framework to attain a sustainable and resilient model of urban development in Karachi, as proposed by Baqa et al. (2021), Persello et al. (2022), and Mushtaq et al. (2024).

4.4. ARIMA SARIMA NDVI prediction and its applications

The NDVI data prediction using the SARIMA model offers various benefits (Panuju et al., 2012). Moreover, a SARIMA model is beneficial in handling the combination of both non-seasonal and seasonal trends prevalent in a time series. NDVI values have clear-cut seasonality mainly because variation in vegetation at time-of-year periodicity, as well as architecture of SARIMA, catches and puts a number to these seasonals (Omar & Kawamukai, 2021). Which results in proper fitting by the prediction than models, such as ARIMA which do not take care to even consider the seasonals. SARIMA models improve the predictability quality because they operate with seasonal factors very efficiently. Thus, they are adapted to data NDVI that has more complicated seasonal trends (Gonçalves et al., 2012). The SARIMA model's flexibility allows it to adapt to various NDVI data types, incorporating seasonal features and trends (Muradyan et al., 2019). Its adaptability improves forecast reliability and provides insights into data behavior. Additionally, SARIMA's resistance to noise and outliers strengthens its predictability, making it useful for plant data management in agriculture, forestry, and environmental monitoring (Han et al., 2010; Mutti et al., 2020). Statistical tests like AIC verify model suitability, ensuring efficient vegetation resource management.

4.5. Model performance and visualization

The SARIMAX(0,1,2)x(0,1,2,12) model is applied to NDVI data, providing a detailed view of actual and predicted NDVI values over time. The observed NDVI values are depicted by one line, capturing true variations and seasonal patterns inherent in the data, while the second line shows the NDVI values predicted by the SARIMA model. Tight x-axis scaling in the plot ensures that the full data range is visible, allowing for a clear comparison between observed and predicted values. Discrepancies highlight potential areas for improvement. Graphical analyses, including confidence intervals and historical-forecast mixes, further validate the model's accuracy in predicting NDVI changes over time. The SARIMA model excels in capturing both non-seasonal and seasonal trends in NDVI data, offering better forecasting accuracy than ARIMA. Its adaptability to various seasonal patterns enhances the reliability of predictions (Kafaki et al., 2009).

Proposed climate-resilient strategies: Drawing from the findings of our study, we propose several climate-resilient strategies to strengthen ecological resilience in response to climate change. These strategies focus on enhancing sustainability, conserving biodiversity, and promoting adaptive land management practices. Specifically, we recommend:

Afforestation and Reforestation Initiatives: We advocate for prioritizing afforestation and reforestation in regions exhibiting long-term vegetation decline. These efforts will not only restore local biodiversity but also contribute to carbon sequestration and overall ecological stability, thereby mitigating climate impacts.

Utilizing Remote Sensing Data for Land-Use Planning: Incorporating NDVI trends derived from remote sensing data into land-use planning is essential for identifying and protecting ecologically sensitive areas. This strategy ensures that conservation measures are both targeted and effective, facilitating proactive management of vulnerable ecosystems.

Promoting Drought-Resistant Plant Species: In areas prone to recurrent NDVI suppression due to drought or other climate stressors, the promotion of drought-resistant plant species is crucial. Such species will enhance vegetation resilience, thereby maintaining ecosystem health and supporting agricultural and ecological sustainability even under adverse climatic conditions. These strategies bridge our remote sensing findings with practical recommendations, offering actionable pathways for policymakers and land managers to enhance climate resilience, safeguard ecosystems, and mitigate the impacts of climate change.

4.6. Limitations and future research direction

This study has several limitations and are considered in interpreting the results. First, the use of Landsat 8 imagery restricts spatial resolution which may not capture fine-scale vegetation dynamics within mixed urban areas. Second, the dependence only on a single vegetation index (NDVI) may oversimplify vegetation health as other indices such as EVI or NDWI and other variables like land surface temperature and rain could provide balancing insights. Third, the SARIMA forecasting model is based on historical trends. This also assumes stationarity in climate and land-use conditions this may not fully reflect future variability under changing urbanization and climate pressures. Lastly, the study focus on Karachi as a single case study. This make limiting the generalizability of the findings to other urban contexts without further validation. Future research after this study findings could explore several directions. First, incorporating higher-resolution satellite imagery (e.g., Sentinel-2 or commercial datasets). This would allow for finer-scale mapping of vegetation dynamics within heterogeneous urban environments. Second, the integration of additional vegetation indices (such as EVI, SAVI, or evapotranspiration) could provide a more nuanced assessment of plant health, canopy stress, and water availability. Third, joining and combinations of NDVI time series with climatic, socioeconomic, and land-use datasets may improve understanding of the drivers of vegetation change in rapidly urbanizing contexts. Fourth, advanced machine learning approaches such as Random Forests, Gradient Boosting, or deep learning models could be employed to improve predictive accuracy beyond SARIMA. Finally, comparative studies across multiple cities would strengthen the generalizability of findings and support regional-scale strategies for urban sustainability and climate adaptation.

5. Conclusion

This study demonstrates how the integration of remote sensing, machine learning, and Google Earth Engine (GEE) can improve understanding of urban vegetation dynamics in Karachi. The analysis of NDVI time series provided useful insights into vegetation seasonality and trends, which can inform conservation and planning initiatives. The SARIMA approach enhanced the ability to model and forecast vegetation behavior, supporting potential applications in agriculture, biodiversity assessment, and climate-resilient urban strategies. The study highlights the value of geospatial and statistical approaches in monitoring urban ecosystems. Future work could build on this by incorporating higher-resolution datasets, diverse vegetation indices, and additional climate variables to develop a more comprehensive perspective. The findings provide useful guidance for urban greening, planning, and climate adaptation in Karachi.

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Code Availability

Source code: The source code is available for download at:

https://github.com/imranak32GEOG/ARIMA-SARIMA-models /blob/main/KHI_Veg_arimaSARIMA

or Colab: https://colab.research.google.com/drive/1cUH_1pBqQnfbs7-BVlF-6HEjIYq2o4Ao?usp=sharing

Conflicts of Interest

The authors declare no conflicts of interest in this research.

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