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Unveiling fractional vegetation cover dynamics: A spatiotemporal analysis using MODIS NDVI and machine learning

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ABSTRACT

Understanding the dynamics of Fractional Vegetation Cover (FVC) is crucial for effective environmental monitoring and management, especially in regions like Pakistan that are sensitive to climate change. This study employs an innovative approach using MODIS NDVI data and the Pixel Dichotomy Model (PDM) to analyze the spatiotemporal dynamics of FVC across Pakistan from 2003 to 2020. Our findings reveal an overall increasing trend in FVC, with the highest value recorded in 2017 (0.37) and the lowest in 2004 (0.26). The Hurst exponent analysis (R/S ratio = 0.718) indicates a degree of long-term memory in the FVC time series. Rainfall was found to positively correlate with FVC (r = 0.6), while Land Surface Temperature (LST) and the Compounded Night Light Index (CNLI) exhibited negative correlations (r = −0.59 and r = −0.43, respectively). The Random Forest regression model highlighted CNLI as the most influential predictor (importance = 62.4%), emphasizing the need to consider human-induced factors in environmental management. These results provide critical insights for sustainable land management and contribute to understanding vegetation-climate interactions in arid and semi-arid environments."

1. Introduction

FVC is a crucial parameter in climatic studies, quantifying the proportion of ground covered by vegetation. It influences surface energy balance, evapotranspiration rates, and carbon sequestration, making accurate FVC measurements essential for modeling and predicting climate change impacts (Anees et al., 2022b). Unlike other vegetation indices such as NDVI and EVI, which measure vegetation health through greenness but are influenced by soil background and atmospheric conditions, FVC offers a precise measure of vegetation density and spatial distribution. LAI focuses on vertical vegetation structure, while FVC directly quantifies horizontal coverage, making it valuable for ecological

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assessments, land cover change detection, and habitat suitability analysis (see Fig. 1).

FVC is also crucial for understanding interactions with hydrological processes, such as groundwater recharge and soil moisture retention. Areas with higher FVC typically have better soil structure and increased organic matter, enhancing water infiltration and reducing surface runoff. These hydrological insights are not captured by NDVI, EVI, or LAI, highlighting the unique value of FVC in environmental monitoring and management. As a comprehensive quantitative index, FVC is widely used in ecological environment assessments, groundwater enrichment assessments, groundwater level monitoring (Zhao et al., 2023), and soil degradation and desertification monitoring. It also represents vegetation growth trends (Muhammad et al., 2023a, 2023b; Mehmood et al., 2024a, 2024b, 2024c, 2024e; Pal and Ziaul, 2017). Additionally, FVC can significantly aid in groundwater enrichment. Areas with higher vegetation cover tend to have better soil structure and increased organic matter, which improve water retention and infiltration rates (Lal et al., 2021). This process reduces surface runoff and promotes water percolation into deeper soil layers, enhancing groundwater recharge. The role of FVC in the hydrological cycle underscores its importance in sustainable water resource management.

Recent research on FVC dynamics has highlighted various methodologies and their applications in understanding environmental and ecological changes. For instance, Wang et al. (2022) introduced an improved FVC estimation model by integrating the optimized dynamic range vegetation index (ODRVI) model, which enhances sensitivity to water content, roughness degree, and soil type. Additionally, using MODIS data, Hill and Guerschman (2020) explored the levels and trends in FVC across global grassland types and savanna woodlands. Their analysis demonstrated significant variations in FVC trends, driven by interactions between drought, livestock utilization, and agricultural expansion. Mehmood et al. (2024e) used NDVI to assess the impact of climatic variability on vegetation dynamics in Pakistan. The study identified a strong relationship between NDVI values and climatic variables, indicating that temperature and precipitation are crucial in vegetation changes. Furthermore, surface soil moisture (SM) is critical for biotic life and geophysical processes, but its spatiotemporal evolution under global warming remains uncertain. Over 40 years, 48% of the global vegetated area has been drying, while 9% has shown a wetting pattern. This study reveals that the drying areas often correspond to increased evapotranspiration or decreased precipitation, with significant implications for soil water resource conservation and management (Lal et al., 2023; Mehmood et al., 2024a; Mehmood et al., 2024c; Mehmood et al., 2024e).

Vegetation plays a crucial role in ecosystems, significantly influencing land surface energy, the biogeochemical cycle, and hydrology (Akram et al., 2022; Pan et al., 2023; Mehmood et al., 2024a). Researchers have utilized the FVC to effectively and statistically assess surface vegetation coverage and its temporal changes (Pal and Ziaul, 2017; Mehmood et al., 2024d). Annual variations in FVC are attributed to increased population and urbanization, which significantly alter vegetation quantity (Mirzaei et al., 2020). Climatic elements, particularly temperature and rainfall, also play a critical role in influencing FVC dynamics. These climatic variations can either enhance FVC, promoting crop growth (Aslam et al., 2022; Mehmood et al., 2024c) or lead to a decline in FVC, potentially resulting in land cover flooding (Pal and Ziaul, 2017). Understanding these dynamics is essential for comprehending the broader impacts of climatic and anthropogenic factors on vegetation patterns (Andreevich et al., 2020; Anees et al., 2024b). Traditional surface measuring methods for FVC include the photographic method, the sample strip method, the sample point method, and the spatial quantitative meter (Deng et al., 2021). These methods are limited by short measuring ranges, time-consuming processes, labor intensity, and potential constraints due to natural conditions. With advancements in remote sensing technology, remote sensing monitoring based on the link between vegetation spectral information and vegetation coverage has emerged as the primary method for obtaining FVC over broad regions (Wang et al., 2022; Mehmood et al., 2024a, 2024c, 2024e).

Landsat, MODIS (Moderate-resolution Imaging Spectroradiometer), GaoFen (GF), SPOT (Systeme Probatoire d'Observation de la Terre), and other satellite data sources are the most commonly used for remote sensing estimation of FVC (Mirzaei et al., 2020; Pal and Ziaul, 2017; Shao et al., 2020). These sources utilize various wavelength bands, such as the blue band (450–520 nm), the green band (520–590 nm), the red band (630–690 nm), and the near-infrared band (770–890 nm) (Kang et al., 2021; Mehmood et al., 2024a, 2024c, 2024e). Vegetation indices based on these bands, such as the normalized green-red difference index (NGRDI), the normalized green-blue difference index (NGBDI), the visible-band difference vegetation index (VDVI) (Song et al., 2023), and the normalized difference vegetation index (NDVI) (Mehmood et al., 2024a, 2024c, 2024e), have demonstrated excellent accuracy in remote sensing estimations of FVC (Mudereri et al., 2021). However, there have been few applications of FVC estimation in dry and semi-arid environments. In recent years, understanding the dynamics of FVC has become increasingly important for ecological monitoring, especially in regions vulnerable to climatic and anthropogenic pressures. This study not only focuses on the spatiotemporal dynamics of FVC but also rigorously analyzes the driving forces, climatic factors like rainfall and temperature, and human activities as indicated by the CNLI that influence these dynamics. Notably, FVC estimation in dry and semi-arid environments has been challenging due to sparse vegetation, high soil reflectance, and seasonal variability, which complicate remote sensing analyses. Our study addresses these challenges by leveraging advanced methodologies and robust datasets, thus providing a comprehensive understanding of FVC dynamics across Pakistan's diverse landscapes. The primary motivation for this study is to address the challenge of accurately quantifying and understanding the dynamics of FVC in Pakistan, a region characterized by diverse ecosystems and significant climatic variability. By employing an innovative approach that integrates MODIS NDVI data with the Pixel Dichotomy Model (PDM) and advanced machine learning techniques, this research seeks to uncover the spatiotemporal trends in FVC over 18 years. Specifically, we analyze the influence of climatic factors (temperature and rainfall) and anthropogenic drivers (urbanization) on vegetation cover. The study also introduces the use of the Hurst exponent to assess the long-term persistence of vegetation dynamics, providing new insights into the resilience and stability of ecosystems. The findings of this research have significant implications for ecological assessment, groundwater enrichment, soil degradation monitoring, and sustainable water management. By enhancing our understanding of vegetation dynamics, this study contributes to developing more effective ecosystem management and conservation strategies in Pakistan (Mehmood et al., 2024a, 2024c, 2024e).

2. Material and methods

2.1. Study area

Pakistan, located in South Asia between latitudes from approximately 24°–37° N and longitudes from 60° to 77° E spans an area of 87.98 million hectares (see Fig. 1). Of this, 4.57 million hectares, or 5.2 percent of the country's total area, are covered by forests (Yaqoob, 2018). Pakistan ranks as the sixth most densely populated country globally, with an average population density of 2.6 persons per square kilometer (Baig et al., 2021). Since gaining independence in 1947, Pakistan's population has grown at an average annual rate of 2.7 percent, increasing from 32.5 million to 208 million by 2017 (Statistics, 2017). Within its forestry sector, commercial forestry constitutes 32.8 percent of forested land, while the remaining two-thirds is preserved for watershed protection, soil conservation, and climate regulation services. Pakistan's climate varies widely across different regions. The north-western and northern high mountainous areas experience severely cold

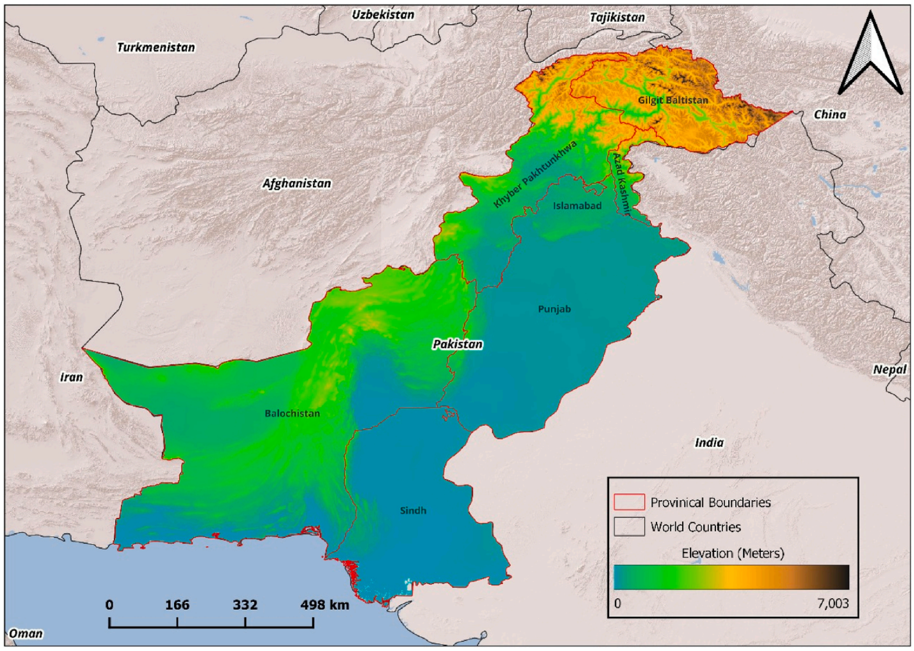

Fig. 1. Study area map.

winters, although April and September offer more pleasant weather. Summers across various regions are typically dry and hot, whereas winters are chilly and dry. The southern coastal regions, for instance, benefit from a milder climate than other areas. Annual rainfall across the country ranges significantly from 160 to 1200 mm, depending on the specific location. This variability in precipitation, combined with pronounced diurnal temperature fluctuations, results in relatively low humidity levels nationwide (Baig et al., 2021).

2.2. *Remote sensing data and preprocessing*

2.2.1. *MODIS data*

MODIS data from NASA's satellite system was used, which captures images in visible and thermal wavelengths to assess changes in vegetation cover. The VI has been proven to be the most reliable indicator of the health of forest vegetation (Gu et al., 2013). This study used NASA's MODIS NDVI data (MOD13Q1, Version 6.1) (https://earthexplorer.usgs.gov/), obtained from 2003 to 2020 at a spatial resolution of 250 m and a temporal resolution of 16 days. A total of 12 temporal images were selected each year, with one image per month. These images were preprocessed to ensure consistency in spatial extent and resolution and to mask out pixels impacted by cloud cover or low-quality conditions using the provided quality assurance layers (Mu et al., 2022). The selection of 12 images was guided by the need to balance temporal coverage with data quality and computational efficiency. Monthly images effectively capture the major vegetation growth stages while reducing redundancy and ensuring the robustness of the mean NDVI calculation for annual analysis. This approach allowed us to produce a consistent dataset that accurately represents the vegetation dynamics throughout the year (Mehmood et al., 2024a, 2024c, 2024e). The NDVI values were accumulated for each pixel across the 12 images for each year, calculated to derive the mean NDVI value, and generated an annual NDVI raster that captures the average vegetation status (Yan et al., 2022). NDVI is a crucial indicator for assessing vegetation health and coverage, providing standardized plant density and growth health measurements. NASA Earth Observations (NEO) datasets were used to select high-quality MODIS NDVI data while reducing atmospheric noise (Ustin and Middleton, 2021). The relevant data was selected based on the phenological time series to ensure accuracy and consistency in monitoring vegetation status across Pakistan.

2.2.2. *Nighttime light remote sensing data*

Data from nighttime lights are used in this research to compute CNLI and to analyze human activities, such as urbanization. The sensor is primarily used for nighttime light observations of the surface of the Earth, focusing on urban areas and other artificial light sources (Small et al., 2005; Anees et al., 2022a, 2022b). We used the nighttime lights datasets and the MODIS NDVI images to link FVC with CNLI, allowing us to forecast vegetation cover (Mirzaei et al., 2020; Pal and Ziaul, 2017; Shao et al., 2020; Wu, 2014; Anees et al., 2022a, 2022b). In this manner, significant yearly changes in FVC were identified, and spatial patterns of vegetation dynamics were observed (Shao et al., 2020; Anees et al., 2022a, 2022b).

Nighttime light is commonly utilized to investigate the regional aspects of urbanization because earlier studies showed that it provides an understanding of the artificial light intensity (Anees et al., 2022a, 2022b; Chen et al., 2022). Human activity, such as urbanization, was examined in this study by using a harmonized nighttime light dataset (https://doi.org/10.6084/m9.figshare.9828827) from 2003 to 2020. The spatial resolution of this nighttime light data is 30 arc-seconds. It indicated a temporally consistent trend and was tagged in GEOTIFF file format with digital numbers (DN) from 0 to 63. Moreover, because of higher uncertainties in low-DN regions, we only focus on areas with DN values greater than 10 in conformity with the usage notes of this nighttime light data (Li et al., 2020). Researchers have investigated various national, global, and regional study topics because of long-term data availability with a modest spatial resolution (He and Gao, 2015; Elvidge et al., 2009). From 2003 to 2020, data were retrieved, and mean values were determined.

2.2.3. *Meteorological data*

The European Center for Medium-Range Weather Forecasts (ECMWF) version 5 reanalysis (ERA5) dataset (https://cds.climate.copernicus.eu/) was used for the meteorological data (Hersbach et al., 2020). Compared to the previous ERA-Interim reanalysis product, ERA5 is the current generation of ECWMF reanalysis data, having better spatial and temporal resolution, a more accurate radiative transfer model, and more refined assimilation techniques. These datasets have a horizontal resolution of $0.1^\circ \times 0.1^\circ$, accessible from 1979 to the present. Here, we used data from ERA5 from 2003 to 2020. LST is the ERA5 meteorological factor employed in this research to examine its impact on FVC. The climate pattern in Pakistan is due to the South Asian monsoon, which substantially affects vegetation. Climatic factors are used in this research to show how vegetation cover and this parameter interact. PERSIANN-CDR was utilized to estimate rainfall from remotely sensed information. This dataset is comprised of daily rainfall data from the satellite. The NOAA CDR Initiative and National Climatic Data Center (NCDC) have recognized it as a valuable source of high-resolution rainfall data that can be used in climate research throughout the globe. It is possible to use PERSIANN-CDR to examine global rainfall trends (Santos et al., 2021). The layers' configuration demonstrates a predisposition towards certain spectral resolution units. To address inherent biases in the spatial representation of meteorological factors, an approach was adopted where every layer was reprojected to a projected coordinate system (Cox et al., 2020).

The methodology employed in this study ensured that the spatial integrity of the utilized datasets was carefully maintained. The datasets had varying original spatial resolutions—MODIS NDVI data at 250 m, meteorological data (rainfall) at 27.75 km, and CNLI data at 1 km and different temporal resolutions ranging from 16 days to monthly. To mitigate potential biases from these discrepancies and promote consistency across the datasets, each dataset underwent a rigorous resampling and reprojection process to a unified coordinate system. Specifically, the MODIS NDVI data, with its native 250-m resolution, was used as the reference spatial resolution. The meteorological data (rainfall), originally at 27.75 km resolution, was downscaled to match the 250-m resolution using bilinear interpolation, suitable for continuous data. Similarly, CNLI data at 1 km resolution was resampled to 250 m using nearest-neighbor interpolation, which is appropriate for categorical data like urbanization indicators. Temporal discrepancies were addressed by aligning all datasets to a monthly time scale, where the MODIS NDVI 16-day composites were averaged to create monthly values. This rigorous resampling procedure ensured that all datasets were harmonized to a common spatial resolution of 250 m and a monthly temporal resolution. Such preprocessing was critical for maintaining the spatial and temporal consistency required for accurate analysis, reducing the risk of spatial inconsistencies in the derived results. (see Table 1)

2.3. FVC estimation

The Pixel Dichotomy Model (PDM) requires a solid linear connection between the FVC and the remote sensing data. Individual or multiple band data can extract vegetation information; however, a vegetation index (VI) can better represent the vegetation information. Many vegetation indices have been found to reduce or eliminate the impacts of radiometric factors such as satellite observation angle, solar altitude, cloud, topography and shadows, and atmospheric conditions. NDVI is the most effective (Mehmood et al., 2024a, 2024c, 2024e), and PDM employed the NDVI as a standard source for vegetation coverage assessment (Anees et al., 2022a; Anees et al., 2022b; Zhang et al., 2013; Wang et al., 2022; Gao and Zhang, 2019).

Table 1
List of different datasets and sources.

Datasets	Data	Scale	Years	Source
MODIS	MODIS TERRA	16 days temporal resolution; spatial resolution (250 m)	2003–2020	https://earthexplorer.usgs.gov/
Meteorological	Rainfall	Monthly data (27.75 km)	2003–2020	https://chrsdata.eng.uci.edu/
	Temperature			https://cds.climate.copernicus.eu/
CNLI	The nighttime lights datasets	(1 km)	2003–2020	https://doi.org/10.6084/m9.figshare.9828827

In this study, the Pixel Dichotomy Model (PDM) was employed using NDVI as the primary vegetation index, which is particularly effective in regions with variable climatic conditions, like Pakistan (Mehmood et al., 2024a, 2024c, 2024e). To enhance the accuracy of FVC estimation under dry conditions, we recalculated NDVImin and NDVImax values for each year to reflect annual variability in vegetation dynamics. This annual recalibration ensured the model accurately captured the true extent of vegetation cover each year, even under drought stress. By normalizing NDVI values annually, we maintained consistency across the entire time series, ensuring comparable FVC estimates across different years. This approach made the PDM method robust against atmospheric variability, particularly in dry and semi-arid regions, ensuring accurate FVC estimation under challenging conditions. The formula for calculating NDVI is as follows:

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{1}$$

The vegetation fractions of each year are estimated based on NDVI data. As a result, a yearly percentage of vegetation cover was calculated by averaging twelve months' vegetation cover data.

In this study, the values of NDVImin and NDVImax were calculated for each year individually, based on the NDVI data from that specific year. This approach allowed us to capture the annual variability in vegetation conditions, which climate variations and land use changes can influence. However, we employed a normalization process to ensure consistency in the FVC product across the entire time series from 2003 to 2020. This process involved standardizing the NDVI values each year by calculating the NDVImin and NDVImax within the same dataset, thereby consistently maintaining the relative scale of NDVI variations. By doing so, we ensured that the FVC values derived for each year were comparable across the entire study period, allowing us to analyze temporal trends in vegetation cover accurately.

From 2003 to 2020, the FVC was determined using the following formula:

$$\mathrm{FVC} = \frac{\mathrm{NDVI} - \mathrm{NDVImin}}{\mathrm{NDVImax} - \mathrm{NDVImin}} \tag{2}$$

NDVImin and NDVImax are the lowest and highest values of NDVI, respectively (Cheng and Li, 2019).

2.4. FVC trends analysis

FVC data from 2003 to 2020 were used for trend analysis using Hurst exponent (Peng et al., 2012). The Hurst exponent is often determined via the R/S method developed by Hurst. Hurst popularized using the rescaled range (R/S) analytical method for calculating the Hurst exponent: The first step is to divide the long-time series into several shorter ones. Hurst (1951) proposed the following five general equations for R/S analysis, and they can be used in any time series.

$$\left(\frac{R}{S}\right)_s = ks^H \tag{3}$$

where k is a constant and s is the total length of the shorter time series, with 1 being less than s, s being less than N, and the total time series length is denoted by N. The time series range is (R), and the standard deviation is (S). The following formula is for determining each size distribution's range.

$$R = \max (Z_1, Z_2, \ldots, Z_s) - \min (Z_1, Z_2, \ldots, Z_s) \tag{4}$$

The cumulative series, denoted by Z_s, is calculated as:

$$Z_s = \sum_{i=1}^{s} y_i \tag{5}$$

Taking the sample mean and subtracting it from each shorter time series gives an adjusted time series, y_s, where s = 1, 2, …, N.

$$y_s = x_s - \overline{x} \tag{6}$$

and

$$\overline{x} = \frac{\sum_{i=1}^{N} x_i}{N} \tag{7}$$

The Hurst exponent is calculated as the slope of the line plotted among $(R/S)_s$ and s on the log–log scale.

The R/S analysis approach is straightforward as it doesn't need complicated mathematical modeling or assumptions about the underlying data's distribution. It requires just elementary knowledge of statistics, such as determining the range and standard deviation of a sample of data. Therefore, R/S analysis does not require a particular probability distribution for the data and is unaffected by outliers (Kotenko et al., 2022).

2.5. Driving forces analysis

The driving forces analyzed in this study include temperature, rainfall, and CNLI for Pakistan. The hypothesis tested in this study is as follows.

Null Hypothesis (H0). There is no significant relationship between FVC and its driving factors (temperature, rainfall, urbanization, and CNLI).

Alternative Hypothesis (H1). There is a significant relationship between FVC and its driving factors (temperature, rainfall, urbanization, and CNLI).

We used the Random Forest regression model to test these hypotheses and assess the statistical significance of the relationships (Anees et al., 2024a). The results support rejecting the null hypothesis, indicating that the driving factors significantly influence FVC dynamics. Finally, the satellite data were analyzed in a spatiotemporal framework by applying new approaches and consolidated methods such as GIS spatial analysis, Hurst exponent, Random Forest Regression to identify the main factors causing FVC changes and examine the correlation of FVC with other variables.

2.5.1. Weighted overlay analysis and spatial correlation

Extracting values to points analysis is an effective method for obtaining information from several study areas, such as geographic information. The working principle is to extract grid pixel values based on a set of point features and record these values to the attribute table of the output feature class. The weighted overlay is one technique of modeling suitability. The following procedure for this analysis was used in ArcGIS. Each raster layer is given a weight in the analysis of suitability. Raster values are reclassified to a common scale of suitability. Raster layers are overplayed, multiplying each raster cell's suitability value by its layer weight and totaling the values to find a value of suitability. These values are written to new cells in an output layer. The symbology in the output layer is based on these values (Zhang et al., 2021).

2.5.2. Random Forest Regression (machine learning algorithm)

Random Forest Regression is a popular algorithm for regression problems predicting continuous outcomes (Luo et al., 2024; Anees et al., 2024a). Breiman (2001) and Iannace et al. (2019) describe it as an ensemble learning strategy that mixes many decision trees to improve the model's performance. The RF can find the best predictor automatically, and its ability to give accurate performance and minimize overfitting arises from its use of many tree features (Anees et al., 2024a; Luo et al., 2024). A regression tree is created when numerous linear segments are combined, and the RF model is created using trees grown by random vectors. Tree predictors give numerical results as their output (Breiman, 2001; Luo et al., 2024; Anees et al., 2024a; Shahzad et al., 2024).

Assuming a regression problem with n data and M variables, the intention is to determine $\widehat{f}_{rf}^{B}(x)$ in x. Computing variance is reduced when using bootstrap aggregation or bagging averages. Every bootstrap pattern (b = 1, 2, 3, …, B) is represented by this model. Selecting the m variables of M at random is the first step in building the RF model; then, the most influential variable is chosen from the m variables, and the node is split into two successive daughter nodes (Safari, 2020; Anees et al., 2024a; Luo et al., 2024). Repeating the steps outlined above until the required node size is reached at each terminal node is what it takes to build an RF with T_b tree from bootstrapped data. The expression for the value predicted at point x is:

$$\widehat{f}_{rf}^{B}(x) = \frac{1}{B}\sum_{b=1}^{B} T_b(x) \tag{8}$$

(see Fig. 2)

3. Results and discussion

3.1. FVC distribution at different periods

The data from 2003 to 2020 reveals that the average yearly FVC was 31%. In 11 out of the 18 years, the FVC was below this average; in the remaining years, it was above 31%. This cyclic trend hints at periodic shifts in vegetation cover. In 2004 and 2007, severe dry spells (Chand et al., 2006) characterized by limited rainfall and extended daylight hours led to decreased FVC. This highlights vegetation's sensitivity to extreme weather conditions and their direct impact on coverage. Despite relatively stable annual rainfall levels (ranging from 499.872 mm to 669.798 mm) over the 18 years studied, FVC responses were inconsistent. This suggests that factors beyond rain, such as temperature variations and human activities (urbanization), play crucial roles in influencing vegetation health. Notably, 2020 experienced a substantial increase in vegetation coverage, resulting in notably higher FVC. Favorable environmental conditions, including increased rainfall, optimum temperatures, or reduced human activities (urbanization), likely facilitated this surge in vegetation growth (Li et al., 2020). This detailed analysis underscores the intricate web of factors influencing vegetation dynamics. It emphasizes the multifaceted nature of vegetation responses to environmental changes beyond mere rainfall, showcasing the complexities of understanding and interpreting FVC fluctuations (see Fig. 2).

During the initial phase from 2003 to 2010, Pakistan experienced a relatively stable period in FVC, fluctuating consistently between 0.26 and 0.3. This steady state indicated a consistent and balanced vegetation cover across the country, suggesting an environment conducive to sustained growth. From 2011 to 2016, there was a gradual but noticeable increase in FVC, rising from 0.3 to 0.36. Probable contributors to this growth include increased rainfall, lower temperatures, and a reduced CNLI. These favorable conditions likely supported enhanced vegetation health and expansion. Between 2014 and 2017, FVC values averaged between 0.35 and 0.37, indicating a sustained period of increased vegetation cover. This sustained growth might be attributed to conducive weather conditions, optimal rainfall, and potentially reduced urbanization, allowing for a healthier and more expansive vegetation cover. In 2018–2019, FVC exhibited minor fluctuations, averaging around 0.34, but slightly increased to 0.35 in 2020 (Fig. 3). These variations might be linked to natural shifts in climatic conditions or slight

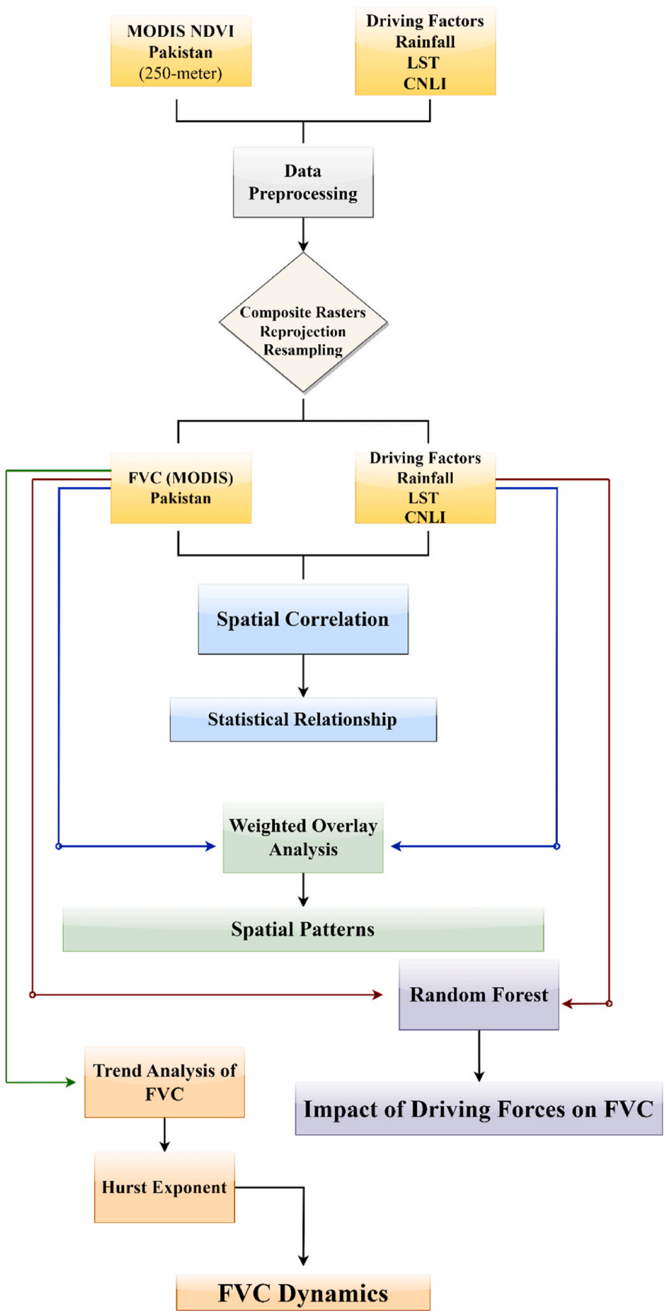

Fig. 2. Technological flowchart outlines the key steps in methodology.

human-induced changes, resulting in subtle alterations in vegetation cover.

A closer examination highlights the influence of environmental factors such as rainfall patterns, temperature changes, and the CNLI in driving shifts in FVC. Periods of increased or sustained FVC potentially align with more favorable environmental conditions and reduced human disturbances, emphasizing the combined impact of natural elements and human activities on vegetation dynamics. Understanding these nuanced fluctuations in FVC provides valuable insights into the complex interplay between environmental factors and human influences on vegetation health. This knowledge underscores the importance of adaptive conservation strategies and sustainable land management practices to preserve and enhance vegetation health across diverse ecosystems in Pakistan.

Our results presented variations in FVC per annum in different years, as shown in Fig. 4. Various factors influence FVC, causing fluctuations in vegetation cover. Regions with high vegetation typically experience less human disruption, favorable climatic conditions, and specific landforms. In contrast, areas with low vegetation face challenges due to urbanization, less favorable climatic conditions, and particular landforms. The spatial distribution of FVC over the 18 years shows that the northeast and southwest parts of the research area usually have lower vegetation coverage due to human interference and specific landforms. The areas characterized by mountains, particularly in the northwest and northeast regions, have limited human influence and exhibit moderate to high vegetation quality. This spatial pattern is closely connected to regional urbanization differences, where fewer disturbances and favorable climatic conditions in the northern hilly parts of Pakistan lead to greater FVC values. Conversely, human disturbance is critical in the southeastern zone, resulting in a low FVC.

3.2. FVC spatio-temporal dynamics by hurst exponent

The Hurst Exponent was used to analyze the dynamics of FVC across all time (Peng et al., 2012). Results showed the Hurst exponent value for Pakistan's annual FVC data from 2003 to 2020. The estimated value of the R/S Hurst ratio is 0.718. As it is more than 0.5, the FVC time series data exhibits some degree of long-term memory or autocorrelation. Accordingly, the FVC values in Pakistan show some persistence or trend over time, as the Hurst exponent is between 0.5 and 1. If the Hurst exponent is greater than 0.5, the series displays persistence or memory effects, which may suggest structural changes over time in the vegetation's dynamics. This suggests that past values of FVC influence future values, indicating sustained trends or patterns. Environmental factors like rainfall, temperature variations, and urbanization likely negatively impact vegetation health, contributing to this sustained behavior. The Hurst exponent's confirmation of persistent trends underscores the importance of long-term monitoring and understanding environmental influences on vegetation dynamics. It emphasizes the necessity for adaptive strategies and sustained efforts in managing and preserving vegetation health. Understanding the persistent nature of FVC changes, highlighted by the Hurst exponent, aids in comprehending the long-term impacts of environmental factors on vegetation. It highlights the significance of prolonged analysis for effectively managing and conserving vegetation cover. There have been notable trends in Pakistan's annual FVC values over the past 18 years. From 2003 to 2020, annual FVC values in Pakistan fluctuated slightly but stayed consistent overall, increasing little in some years. However, there were also times of decline; the FVC values could have been affected by several causes, such as changes in rainfall, temperature, and urbanization. FVC changes in Pakistan may be distinguished using the dataset over a longer time frame. For instance, a rising trend in FVC values over time may indicate a progressive increase in plant cover, while a falling trend may indicate a decline in plant life. Our findings confirm this conclusion; we found that urbanization had a negative impact on FVC. This finding significantly contributes to our knowledge of plant cover's long-term dynamics and predictability in urban areas. As more people move into cities, vegetation cover gradually decreases.

3.3. FVC driving forces

However, our analysis revealed that human activities, such as urbanization, and environmental conditions, such as temperature and rainfall, have impacted the dynamics of FVCs. The study area experienced changes due to human activities and climatic factors between 2003 and 2020. The spatial distribution of FVC exhibited a pattern of decreasing coverage from north to south and from colder mountainous regions to warmer plains. These trends corresponded to variations in CNLI and temperature, indicating their influence on vegetation health. Inequalities in urbanization levels were apparent in the distribution of FVC, illustrating the impact of urban development on vegetation cover. Notably, distinct CNLI and temperature variations affected FVC,

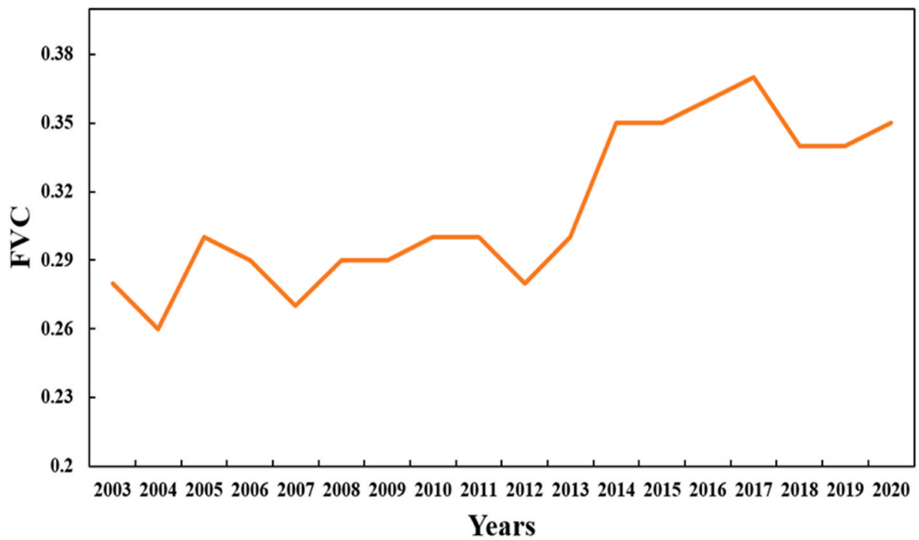

Fig. 3. MODIS data were used to determine the dynamics of FVC in Pakistan from 2003 to 2020.

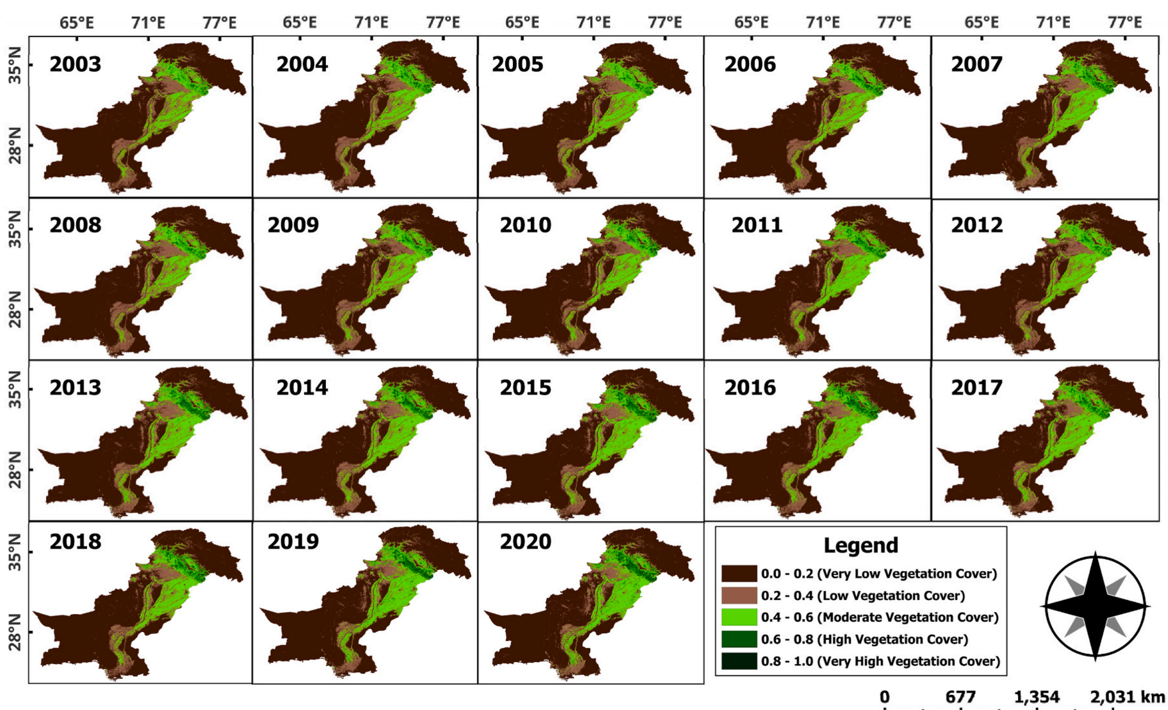

Fig. 4. FVC map of Pakistan from 2003 to 2020.

resulting in lower values during increased CNLI and temperature periods. Rainfall emerged as a positive factor influencing FVC, directly affecting vegetation health. Variations in rainfall and temperature significantly impacted plant growth by regulating photosynthesis and respiration rates, ultimately affecting vegetation vitality and health.

The study highlighted varying effects of climate change on plant growth across regions. Correlations examined between FVC, rainfall, temperature (Shobairi et al., 2022; Usoltsev et al., 2020, 2022), and CNLI depicted the complex interplay among these factors, emphasizing their collective influence on vegetation dynamics. Rainfall and temperature played critical roles in regulating photosynthesis and respiration rates in plants, impacting vegetation growth. This understanding explains their substantial impact on observed FVC variations across different regions. The research extensively explored correlations between FVC, rainfall, temperature, and CNLI, shedding light on the intricate relationships among these factors and their combined influence on Pakistan's vegetation dynamics. In essence, this analysis delineates the complex relationships between environmental factors, urbanization, and FVC in Pakistan. It underscores the profound impact of climate elements like rainfall and temperature on vegetation health, emphasizing the necessity of considering these factors for effective vegetation management and conservation across diverse geographic regions.

3.3.1. Relationship between FVC and rainfall

The maps of FVC for 2003–2020 (Fig. 5) have been analyzed against the mean annual rainfall. Visual inspection of the maps shows the variability in vegetation cover density at the research site, which is influenced by rainfall, playing a significant role in vegetation growth.

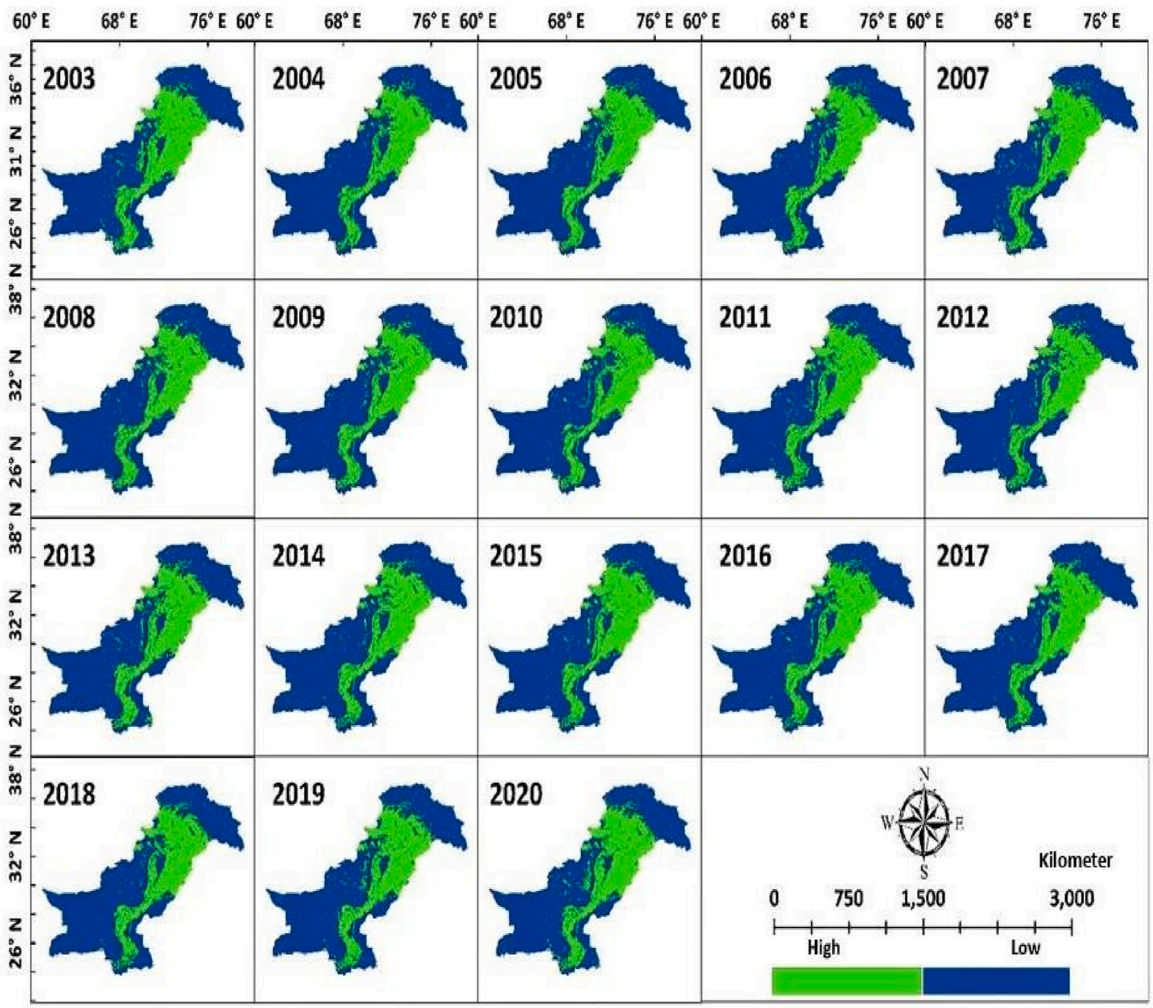

Fig. 5. Weighted overlay of FVC and Rainfall from 2003 to 2020 in Pakistan.

However, because many small tributaries, distributaries, and canals supply water to these regions, the shift in plant cover density as a function of rainfall seems less severe in the east and north. Indeed, these regions show a constant vegetation pattern (see Table 1).

Furthermore, rainfall patterns in the study area show substantial yearly variation in duration and distribution. Table 2 shows that over the study period (2003–2020), the lowest recorded annual rainfall was 400.72 mm in 2007, and the highest record was almost 692 mm in 2017. Results showed a decreasing trend in rainfall with latitude, with a smaller decline in the north and a more significant decline in the south. On the other hand, mountain ranges and the foot-hills receive more rain than the surrounding plains. The average distribution of decadal rainfall is between 400 and 692 mm, as summarized in Table 2. These results confirm the climatic trend between 1970 and 1996, as demonstrated by other researchers (Zakieldeen, 2009).

Moreover, the visual inspection of the regions where the annual mean of rainfall is between 500 and 700 mm illustrates an excellent spatial correlation with vegetation cover density from 2003 to 2020. Although this visual analysis shows a particular good trend regarding some specific geographic locations, the results demonstrate that the FVC and the rainfall values are not uniform and strongly homogeneous during the study period, as summarized in Table 2. Even if these two variables change yearly, they follow the same trend. These findings corroborate the results obtained by Mohammed et al. (2015).

To establish a causal relationship between the rainfall and FVC, a correlation analysis was carried out for each year during the study period (2003–2020). Fig. 6 displays the results of a statistical analysis showing an important correlation between the time series of FVC and the interannual variability of rainfall. The R^2 values vary between 0.49 and 0.57 from 2003 to 2020. However, the correlations between these variables in this research are significant enough to allow the use of rainfall as an indicator for FVC changes. These results corroborate the

Table 2
FVC and rainfall from 2003 to 2020 in Pakistan.

Year	FVC (Mean)	Rainfall (mm)
2003	0.28	572.28
2004	0.26	423.74
2005	0.30	557.95
2006	0.29	500.02
2007	0.27	400.72
2008	0.29	600.40
2009	0.29	500.88
2010	0.30	670.85
2011	0.30	670.20
2012	0.28	549.83
2013	0.30	609.75
2014	0.35	641.27
2015	0.35	659.66
2016	0.36	671.18
2017	0.37	692.09
2018	0.34	530.64
2019	0.34	513.14
2020	0.35	570.37

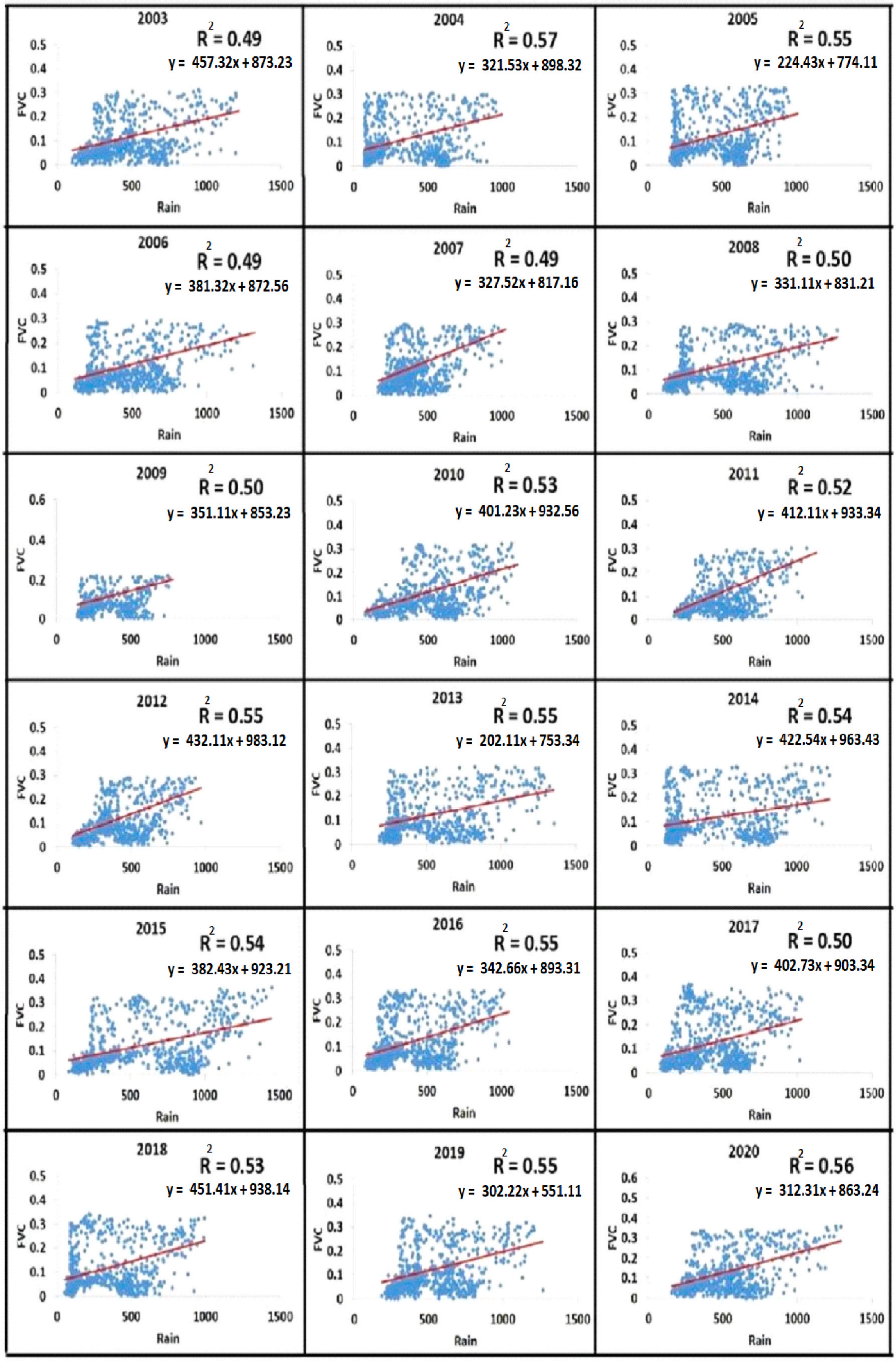

Fig. 6. Relationship of FVC and Rain in Pakistan. Number of samples are 270 and confidence level is 95%.

findings of Tucker and Nicholson (1999) and other studies that demonstrated a similar correlation between FVC trends and rainfall (Herrmann et al., 2005). The correlation between rainfall and FVC can be variable. However, the findings remain useful as input in the carbon cycle models and climate impact modeling.

3.3.2. Relationship between FVC and temperature

The LST is affected by different surface conditions, so areas with vegetation accumulation tend to have lower LST than vegetation-free areas. By absorbing sunlight and transpiration of water through its leaves (Yasmeen et al., 2023), vegetation creates a natural air-conditioning system. Changes from forest to rangeland and rainfed farming land use reduce the vegetation cover, remove the cooling system of natural surfaces, and increase LST (Hussain et al., 2024a). Fig. 7 shows the differences between the FVC and LST in the study area between 2003 and 2020. LST has decreased wherever the vegetation has increased and vice versa.

Minimum LSTs of 17.45 °C and 16.65 °C were recorded in 2016 and 2017, indicating cooler conditions. Conversely, maximum LSTs of 21.91 C (2009) and 21.97 C (2012) depict warmer temperatures (Table 3). The lower temperature in 2017 was linked to dense forest cover, aligning with cooler average temperatures. On the other hand, increased LSTs hint at potential climate change effects, suggesting potential future consequences due to rising temperatures. The notable temperature drop in 2017, attributed to increased rainfall, coincided with higher FVC. This correlation between rainfall, lower temperatures, and enhanced FVC underscores precipitation's impact on vegetation health and LSTs. LST fluctuations may signify climate variability, potentially influenced by broader climate change. The observed temperature changes, notably cooler temperatures due to increased forest cover and rainfall, may reflect temporary shifts influenced by local environmental conditions. Understanding these temperature fluctuations is crucial for anticipating and addressing the potential impacts of climate change on vegetation and the overall environment. Monitoring such changes aids in planning effective conservation and adaptation strategies for future environmental well-being.

Table 3
FVC and LST from 2003 to 2020 in Pakistan.

Year	FVC (Mean)	LST (°C)
2003	0.28	20.12
2004	0.26	21.04
2005	0.30	17.90
2006	0.29	18.59
2007	0.27	19.90
2008	0.29	18.64
2009	0.29	21.91
2010	0.30	21.47
2011	0.30	21.81
2012	0.28	21.97
2013	0.30	20.77
2014	0.35	18.46
2015	0.35	18.56
2016	0.36	17.45
2017	0.37	16.65
2018	0.34	20.67
2019	0.34	20.67
2020	0.35	18.43

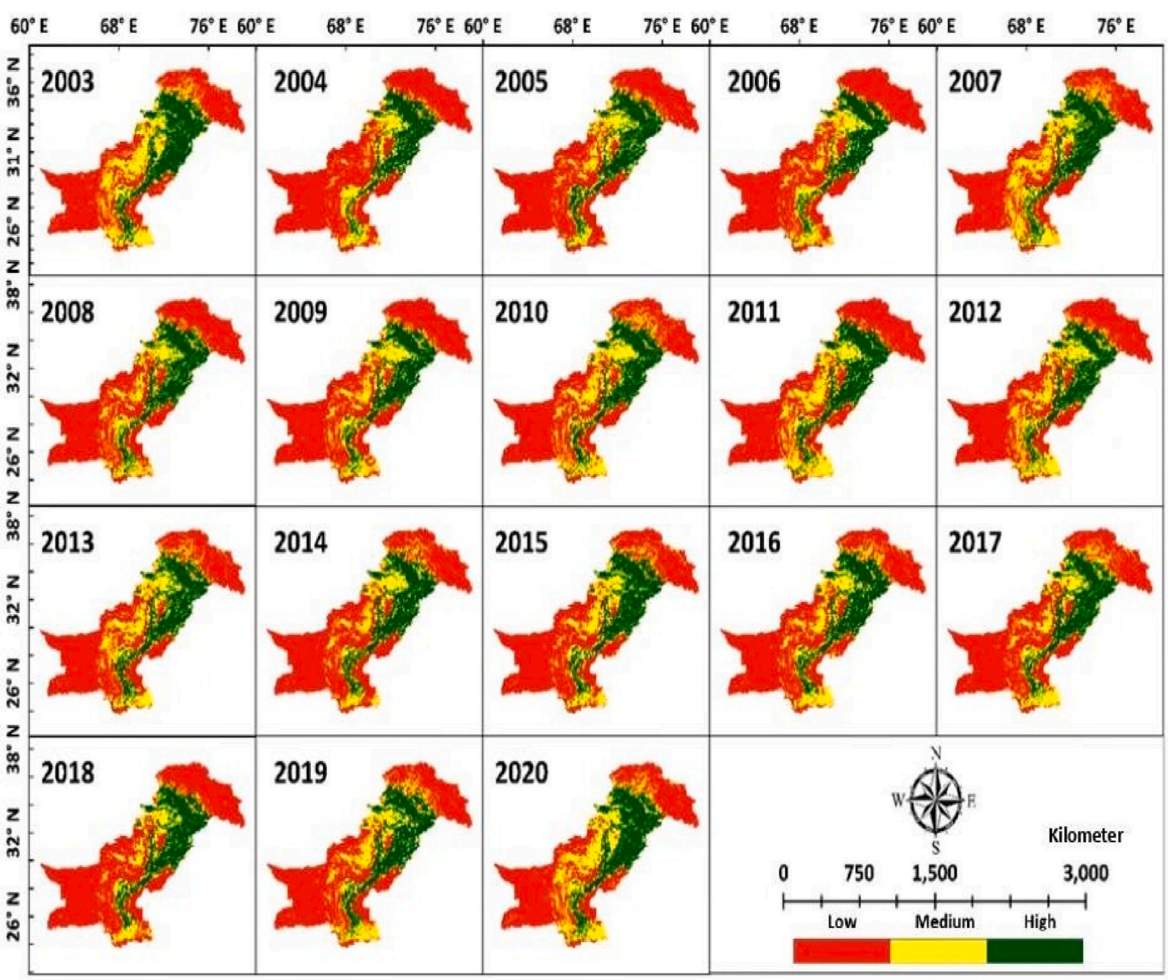

Fig. 7. Weighted overlay of FVC and Temperature from 2003 to 2020 in Pakistan.

During the study period, forest land had a lower average temperature than sparse forest and rangeland, mainly due to the high moisture content in forest land and the greater degree of evapotranspiration. Water bodies have the lowest average temperature due to their high-water heat capacity. Changes between 2003 and 2020 showed that land use types were subject to an increase in average temperature, which can be attributed to the increasing trend in temperature (Hussain et al., 2024b). The results exhibited a rise in average LST in areas where urbanization increased. This indicates increased heat-producing human-based activities, such as converting forest land to agriculture. The average temperature was higher in several regions, except for areas with vegetation cover.

For a better analysis of the relationship between LST and FVC, the correlation coefficients between LST and FVC were calculated (Fig. 8). The highest negative correlation coefficient was obtained in 2010 and 2020. The lowest negative correlation coefficient was observed in 2006. A comparison of LST and FVC values from 2003 to 2020 concluded that low vegetation density occurs in regions with higher average temperatures. As shown in Fig. 8, the FVC correlation is negative with temperatures in different years.

Due to the decrease in forest area and the increase in human-induced land uses, the areas with lower temperatures have reduced, and the higher-temperature regions have experienced notable growth during the 18 years. Natural vegetation coverage in the region is being replaced and converted to lower-value land uses, as evidenced by the decline in forested areas and the rise in agricultural and rangeland uses. The increase in population density is directly related to the rise in LST in the study area and, consequently, the increase in agricultural land.

3.3.3. Relationship between FVC and CNLI

We used nighttime light imageries to track urban changes. The CNLI was calculated from 2003 to 2020. Popular uses of nighttime light imagery include analyzing the environmental implications of urban expansion, mapping nighttime sky illumination, and assessing natural catastrophes and forest fires. Calculating CNLI data, as shown in Table 4, dynamically determined the urbanization process. Computing CNLI changes showed that urbanization was more dominant in the southern and eastern parts of the area (Fig. 9). CNLI closely relates to human economic activities such as mine, urbanization, and agriculture and enables the evaluation of population density. This spectacle led to a vegetation coverage reduction on the mentioned region's surface because vegetation coverage is influenced by urbanization at the Pakistan level. CNLI is regarded as an essential indicator for assessing urbanization trends.

A research work conducted by Chand et al. (2006) stated that urbanization monitoring over Indian regions by using nighttime lights satellite data concluded that over 98% accuracy was found between several satellite data sets and ground observations in determining urbanization trends. Nighttime light data directly relates to human activities (urbanization) and affects land cover dynamics. For example, when urbanization increases, the value of nighttime light data also increases, which can be a threading factor for the FVC. These findings are consistent with our result, so human activities such as urbanization are rising annually and will subsequently have different consequences.

The CNLI provides national-level details for industrial development, urbanization processes, and population density. The spatial correlation determines the link between the FVC and CNLI over 18 years. CNLI variations were observed yearly during this period, as shown in Fig. 9. These variations are also because of different government policies. Decreased or increased streetlights due to government policies after 06:00 p.m. is one of the reasons for yearly changes in CNLI. The mean values of CNLI are shown in Table 4. Human action, like urbanization, is linked to the CNLI (Chand et al., 2006).

Urbanization is fundamentally a land use type. Cultivated land and specific urban greening spaces are the primary sources of expansion in fast-growing areas. The FVC calculated from MODIS was used as the vegetation indicator in this study to assess the influence of urbanization on urban greenness. Urbanization and industrialization have spread from east to west, north to south. The spatial and temporal changes of FVC and CNLI were examined. The study area experienced changes due to human activities between 2003 and 2020 (Mirzaei et al., 2020; Pal and Ziaul, 2017; Shao et al., 2020; Wu, 2014). On the other hand, those regions with medium and high vegetation coverage percentages experienced the least urbanization changes during this period. However, our analysis revealed that human activities (urbanization) had impacted the dynamics of FVC (Mallick et al., 2008).

Human activities (urbanization) increased throughout 2004, 2006, 2007, 2009, 2012, and 2013, but we saw ecological protection and reforestation with reduced human activities from 2014 to 2020. In addition, we confirmed that the study area's east, north, and west regions had a medium and high percentage of vegetation coverage and less urbanization change from 2003 to 2020 (Fig. 10). We may use the above indicators to show that urbanization has reached a standstill, indicating that FVC is concentrated in the north and east between 2010 and 2020. However, human activities like urbanization affect FVC dynamics, as we discovered via our research.

Based on the time series of NDVI (Mehmood et al., 2024a, 2024c, 2024e) in connection to nighttime light data, our study produced extensive maps displaying geographical patterns and the assessment indicators of FVC change. Because of human activities, FVC dynamics, natural changes, and climatic conditions, all lands must be monitored regularly to assess no forest, degraded, or forest areas. Human disturbance, such as urbanization, is prominent in the southern region, resulting in poor FVC.

To evaluate FVC changes over time, it was monitored from 2003 to 2020. By spatial correlation analysis, the connection between CNLI and FVC was identified (Fig. 11). In the previous two decades, interannual variability of FVC in the periphery of the enlarged built-up area exhibited a substantial decrease, and urbanization has increased significantly. The CNLI and FVC correlation coefficients show how urbanization has affected vegetation distribution. It is possible to monitor green cover in urban areas through urbanization. For example, the reduction in urbanization intensity and the modest negative influence on FVC in the city core may be observed. The decrease in FVC coincided with an increase in CNLI. FVC decreased in the extended region mainly because of the occupation of built-up areas, but FVC increased in the area, significantly impacting the green development policy.

3.3.4. Relationship between FVC, CNLI, and climate factors

People and the climate play a role in FVC changes. The relationship between rainfall, temperature, CNLI, and FVC was studied using the Pearson correlation coefficient (Table 5). FVC is favorably correlated with rainfall and negatively correlated with temperature and CNLI (Fig. 12). FVC is linked to precipitation because the rate at which water evaporates in the rainy season is lower. However, there is no effect on the plant's ability to photosynthesize, which leads to an increased vegetation cover. Because of the rain, substantial vegetation areas can grow well, leading to much vegetation and a higher FVC. City development has affected the area's average FVC each year.

3.4. FVC prediction using Random Forest Regression

A higher number of trees can potentially improve the model's predictive performance but also increase computational time (Anees et al., 2024a; Luo et al., 2024). The parameter "1" indicates that at each node split, only one randomly selected predictor variable (out of LST, Rain, and CNLI) was considered. This setting prevents strong bias towards a specific variable during tree-building. Since 'importance = TRUE' was specified, the model calculated the variable importance measures for the predictor variables (LST, Rain, and CNLI). The model's results and interpretation benefited by analyzing the variable importance measures. These measures provide information about the relative importance of

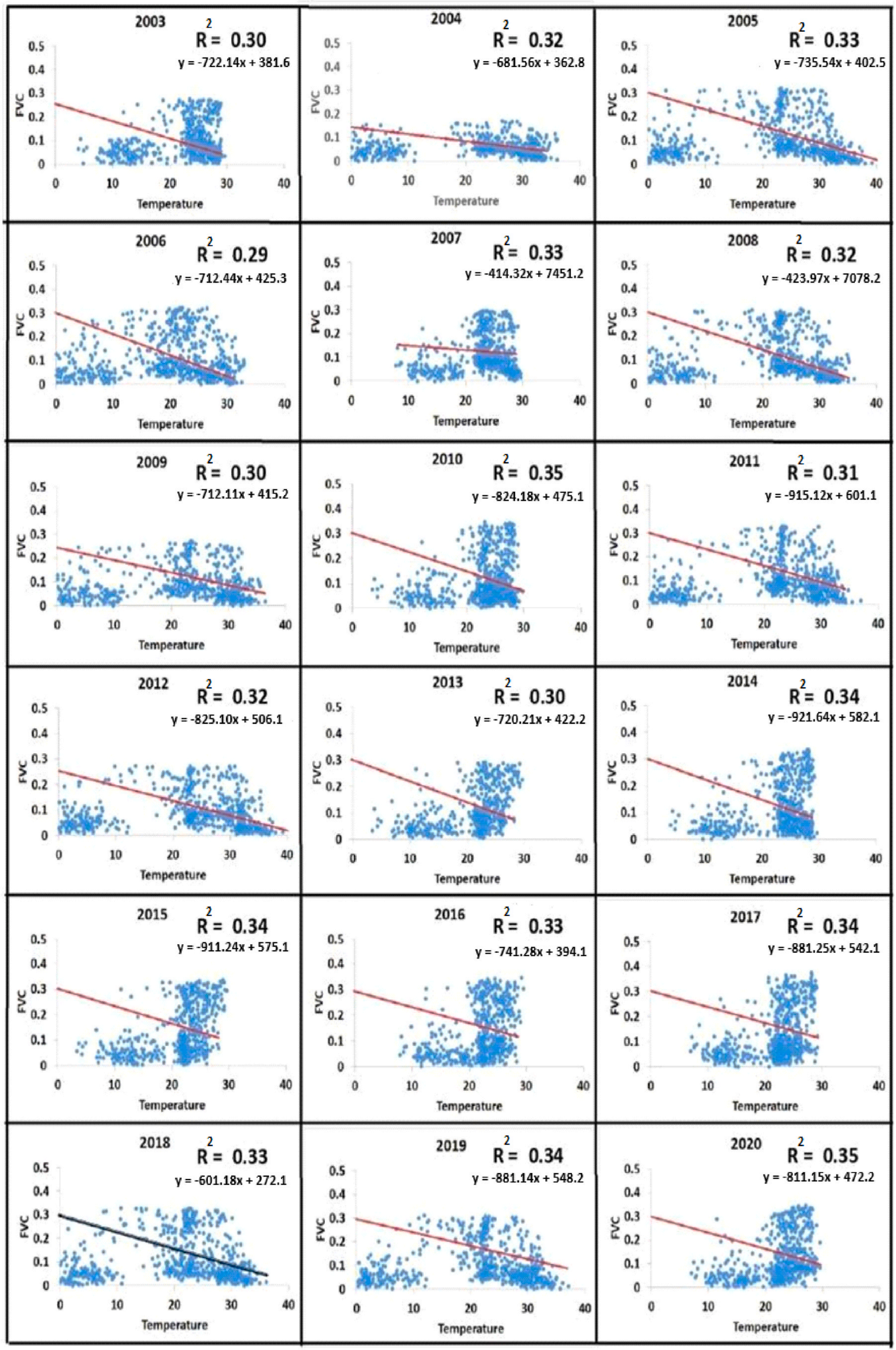

Fig. 8. Relationship of FVC and Temperature in Pakistan. Number of samples are 270 and confidence level is 95%.

Table 4
FVC and CNLI from 2003 to 2020 in Pakistan.

Year	FVC (Mean)	CNLI
2003	0.28	0.10
2004	0.26	0.23
2005	0.30	0.16
2006	0.29	0.23
2007	0.27	0.28
2008	0.29	0.19
2009	0.29	0.24
2010	0.30	0.11
2011	0.30	0.11
2012	0.28	0.28
2013	0.30	0.21
2014	0.35	0.17
2015	0.35	0.17
2016	0.36	0.16
2017	0.37	0.14
2018	0.34	0.18
2019	0.34	0.17
2020	0.35	0.16

the predictor variables in predicting the FVC. Examining the variable importance determined which variables contribute the most to the model's predictive accuracy (Anees et al., 2024a; Luo et al., 2024). A higher percentage indicates a more important variable.

3.4.1. Variable importance

The variable importance measures obtained from the Random Forest model are illustrated in Fig. 13. The outcomes show what percentage of weight each variable should be given in the Random Forest model (Anees et al., 2024a; Luo et al., 2024). The relative weight of each of these factors is described as follows. First, the CNLI is the most important factor, having relative importance of 62.40%. This suggests that it plays a significant role in the model's predictions (Anees et al., 2024a; Luo et al., 2024). Indicators of urbanization, such as a higher CNLI, may have an impact on the results of the model.

The relative influence of predictor LST is 28.30%. It is also very significant. Although not as crucial as CNLI, LST is still an important consideration. Possible link to changes in the FVC caused by rising temperatures and their effect on the model's projections. Research related to environmental dynamics and land management techniques in many regions, including Pakistan, is greatly aided by LST and FVC analyses. LST is a crucial variable in ecological studies since it directly

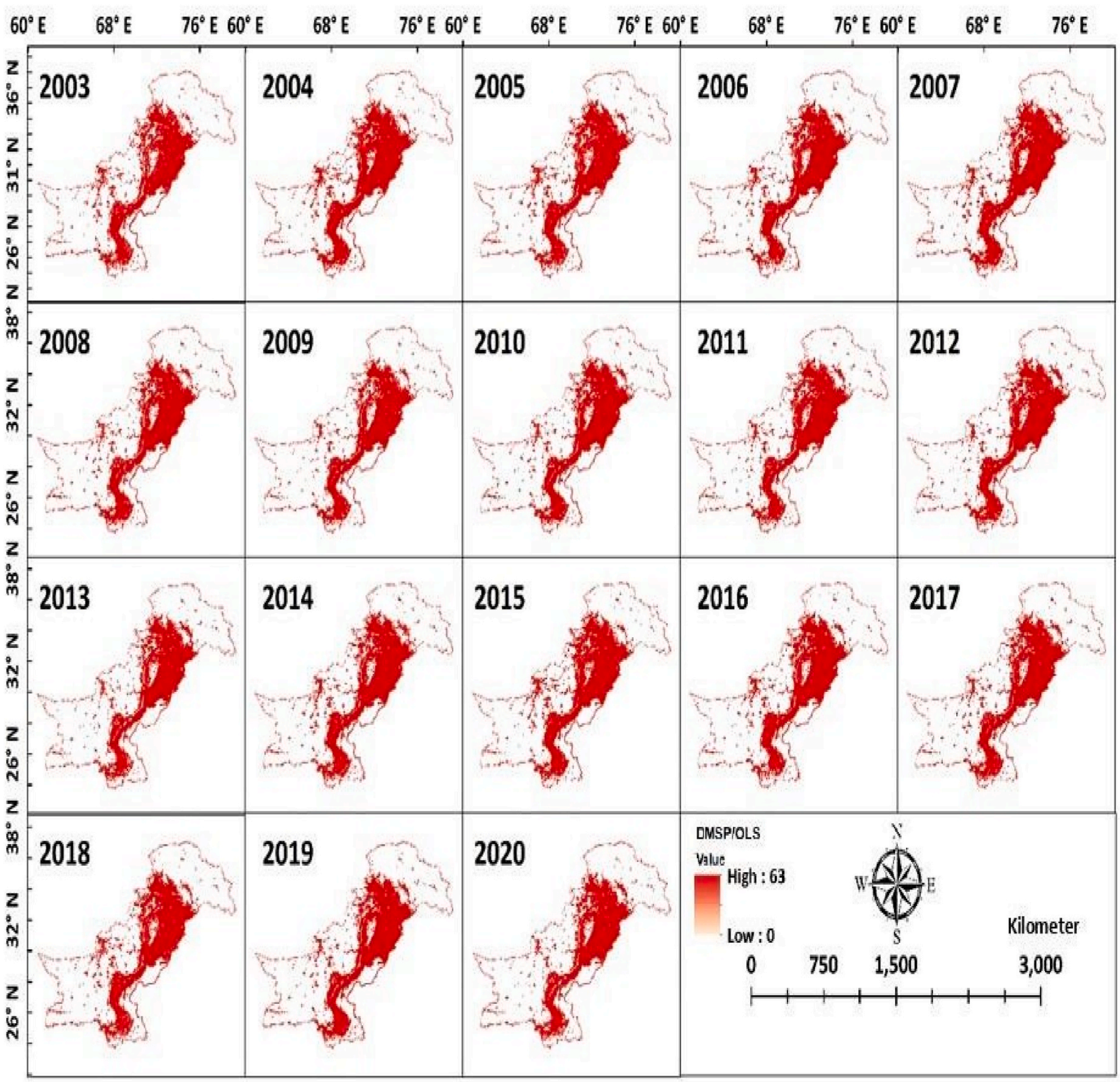

Fig. 9. From 2003 to 2020, evening illumination of the research region.

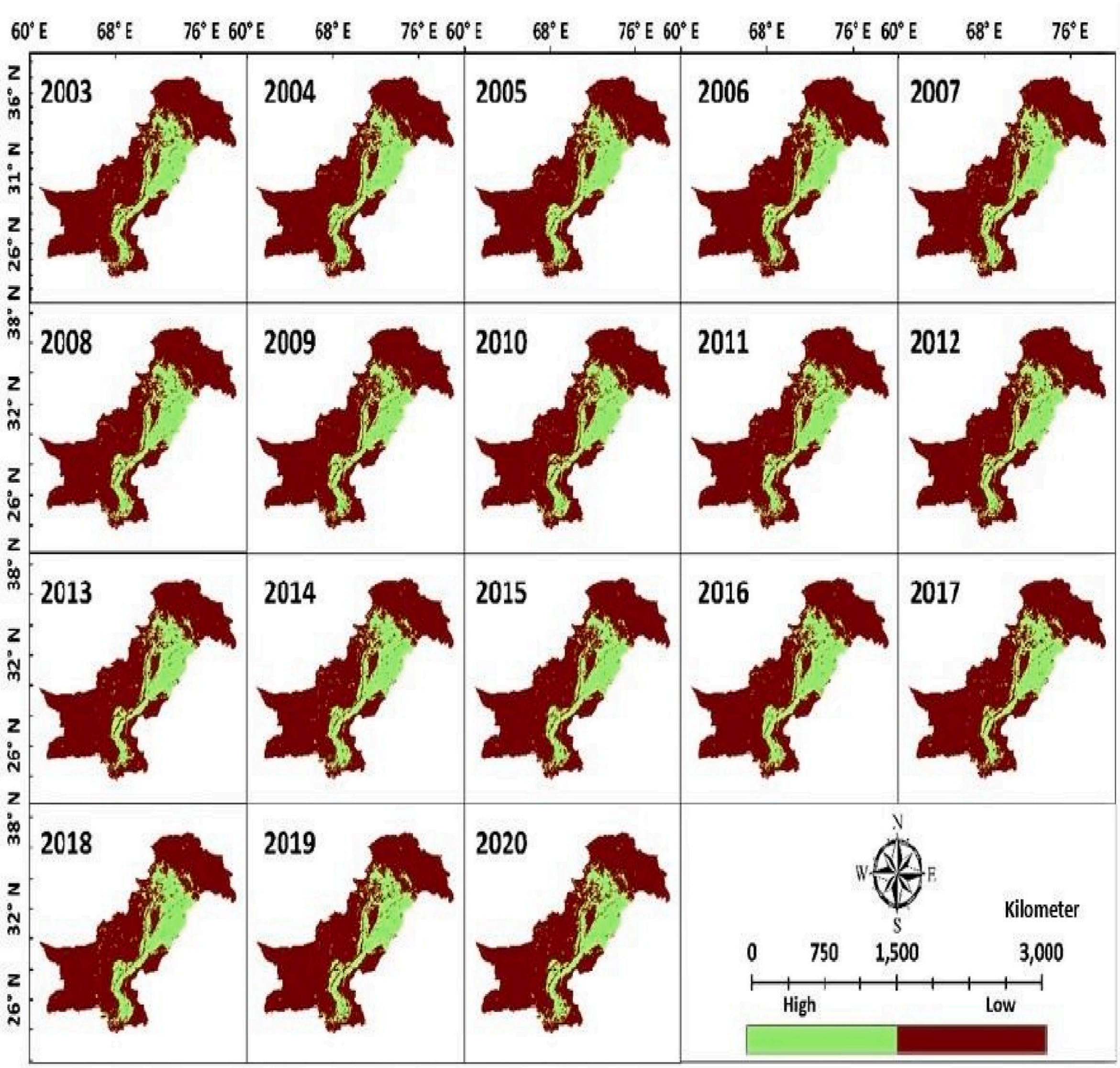

Fig. 10. Weighted overlay of FVC and CNLI from 2003 to 2020 in Pakistan.

measures the temperature at the earth's surface. It highlights the relationship between surface energy balance, global warming, and the effects of urban heat islands. LST is affected by various factors, such as land cover, land use, and vegetation. Better knowledge of LST trends in Pakistan aids in assessing heat stress, monitoring the effects of urbanization, and creating efficient land management strategies. FVC is key in ecosystem maintenance, temperature control, and conservation. Remote sensing data is frequently used in FVC studies to assess the spatial distribution and changes in vegetation cover over time. By conducting FVC analysis, researchers can better understand plant health, cover, water-vegetation linkages, and species suitability. Several investigations worldwide have shown such metrics' significance (Anees et al., 2022a, 2022b).

Our study's results are similar to Zhang et al. (2015). Higher levels of vegetation cover are associated with lower LSTs, demonstrating a strong correlation between these two variables. They are studied for seasonal correlations, and FVC negatively correlates with LST; our findings are consistent with Guha and Govil (2020). This correlation can highlight the interplay between temperature and plant growth (Haider et al., 2017; Jallat et al., 2021; Khan et al., 2020, 2024). Changes in urbanization and impervious surfaces are two examples of land use and land cover changes that can substantially affect LST. Assessing the urban heat island effect and improving sustainable urban planning practices can be aided by mapping and monitoring these changes (Badshah et al., 2024).

The relative influence of predictor Rain is 9.30%. This indicates that rain is a factor in the model but is less important than CNLI and LST. Although rainfall can impact ecological and environmental processes, it is given less importance in this framework. While lower than LST, this value suggests that Rain moderately influences the model's predictive accuracy. This indicates that splitting on the Rain variable contributes slightly but not as much as LST for improving relative importance. The studies on the role of rainfall and FVC in Pakistan are vital for understanding the country's environmental dynamics and land management practices. Rainfall is a critical climatic factor that influences various aspects of the environment, including vegetation growth, hydrological processes, and ecosystem functioning. Understanding rainfall patterns and their relationship with other environmental variables, such as FVC, is crucial for sustainable land and water resource management. Our research has confirmed a significant positive correlation between rainfall and FVC (Anees et al., 2022a, 2022b). Sufficient rainfall, which provides water for plant growth, leads to increased FVC in the research area. Increased rain and FVC have been found to promote ecosystem services. These findings highlight the importance of studying the relationship between rainfall, FVC, and ecosystem functioning in Pakistan.

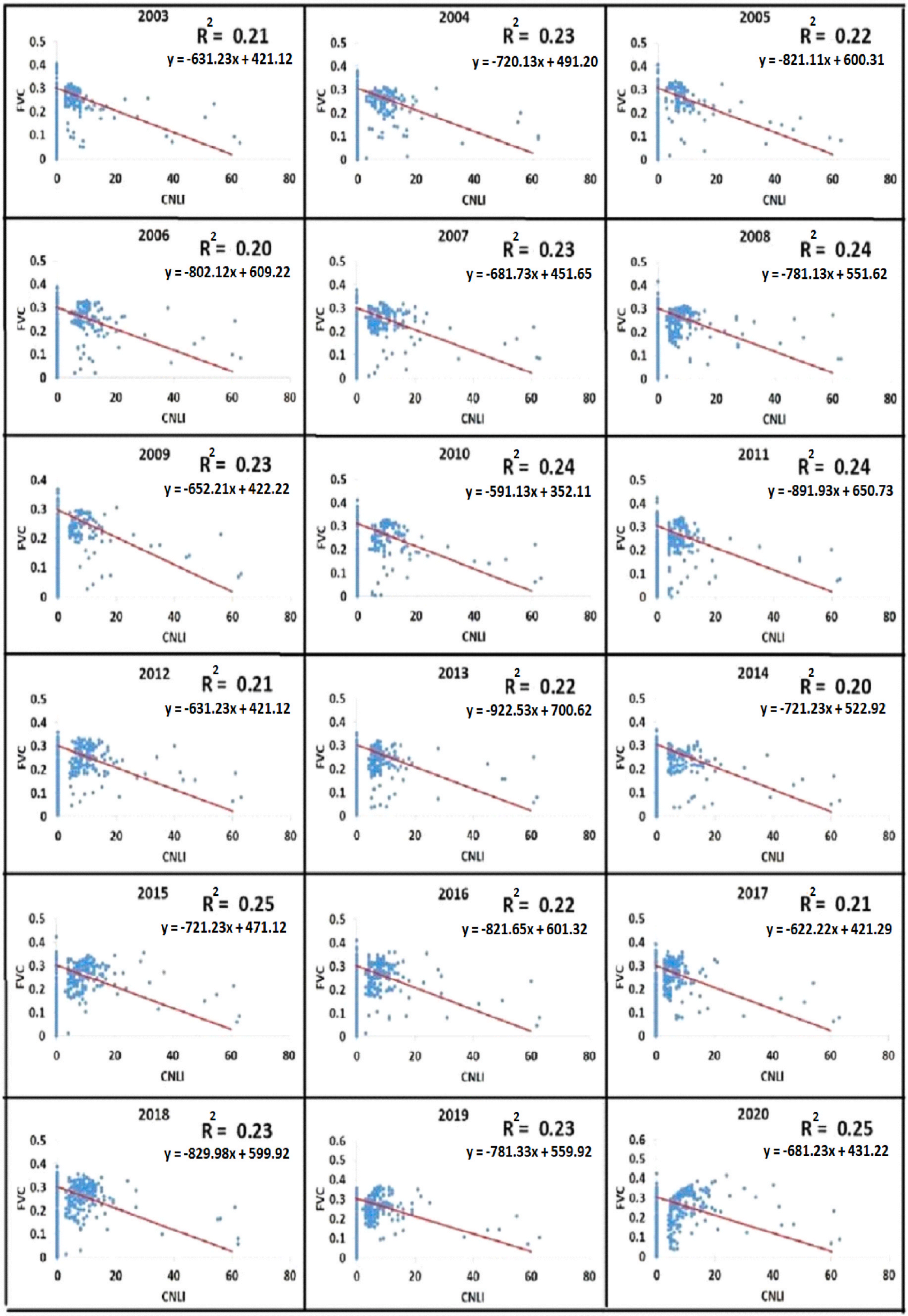

Fig. 11. Relationship of FVC and CNLI in Pakistan. Number of samples are 125 and confidence level is 95%.

Table 5
Correlation between CNLI, FVC, and climate factors.

Variables	FVC (mean)	LST (°C)	Rainfall (mm)	CNLI
FVC (mean)	**1**	**−0.59**	**0.6**	−0.43
LST (°C)	**−0.59**	**1**	−0.33	0.23
Rainfall (mm)	**0.6**	−0.33	**1**	**−0.7**
CNLI	−0.43	0.23	**−0.7**	**1**

Values in bold recorded significant correlation with a significance level of alpha = 0.05.

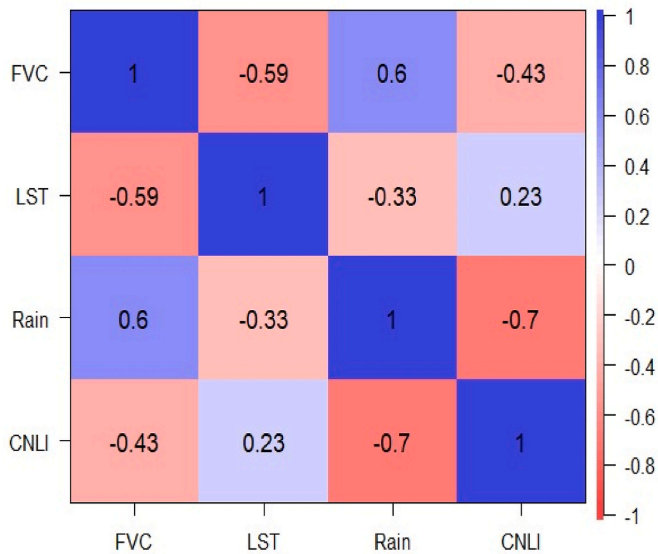

Fig. 12. This figure is generated by R programming, which illustrates the correlation of FVC with different factors.

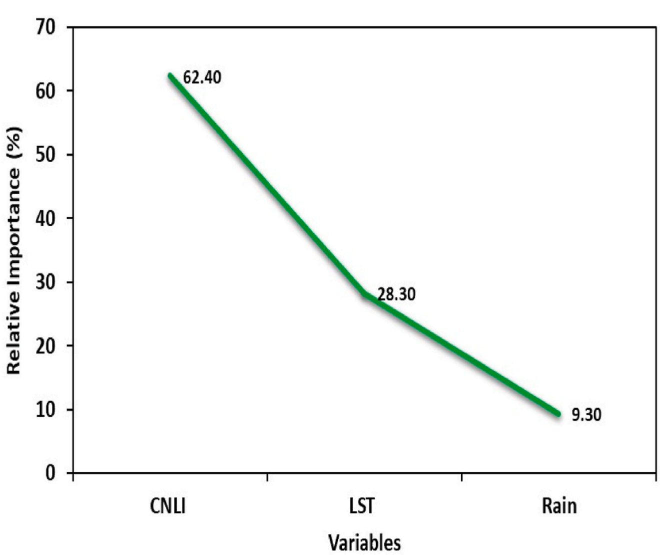

Fig. 13. Variable importance with RF model.

Each variable's relevance percentage reflects its weight in the prediction process as a whole (Anees et al., 2024a; Luo et al., 2024). Based on the results, we can conclude that CNLI has the highest importance, followed by LST and Rain. The role of the CNLI and FVC studies in Pakistan can provide a valuable understanding of urbanization patterns and environmental dynamics (Anees et al., 2022a, 2022b; Sohail et al., 2023). Understanding the interactions between CNLI and FVC is essential for comprehensive monitoring and management of the environment (Anees et al., 2022a, 2022b).

3.4.2. *Accuracy assessment of training set*

The accuracy assessment results for the Random Forest Regression model on the training set are shown in Fig. 14.

The Root Mean Squared Error (RMSE) value of 0.008 is the square root of the MSE and measures the average magnitude of the residuals. It represents the standard deviation of the errors by the model. A lower RMSE indicates better model performance. The R^2 value of 0.89 indicates that approximately 89% of the dependent variable (FVC) variability can be explained by the predictor variables (LST, Rain, and CNLI) in the model. It is a measure of how well the model fits the data. Higher R^2 values indicate a better fit. The R-value of 0.94 indicates a very strong positive correlation between the predicted and actual values (Anees et al., 2024a; Luo et al., 2024). It measures the linear relationship, intensity, and direction between the expected and actual values. When the R-value is larger, the correlation is more substantial. Overall, the RMSE, R^2, and R-value indicate that the model performed well on the training set.

3.4.3. *Accuracy assessment of validation set*

The accuracy assessment results for the Random Forest Regression model on the validation set are presented in Fig. 15.

The RMSE value of 0.011 is the square root of the MSE and provides a measure of the average magnitude of the residuals on the validation set. With R-value of 0.89, the Random Forest model accounts for 89% of the variation in the dependent variable. The R^2 of 0.80 indicates that the Random Forest model can explain the target variable's variability. Lower RMSE values suggest higher model performance since they signify fewer errors in the predictions by the model (Anees et al., 2024a; Luo et al., 2024). The Random Forest regression model performed adequately on the validation set, as shown by these results. The high R and R^2 values suggest that the values predicted and observed for the dependent variable are highly correlated. The small RMSE value indicates that the model's predictions are also reasonably close to the actual values (Anees et al., 2024a; Luo et al., 2024).

The study employed MODIS NDVI data to assess and analyze

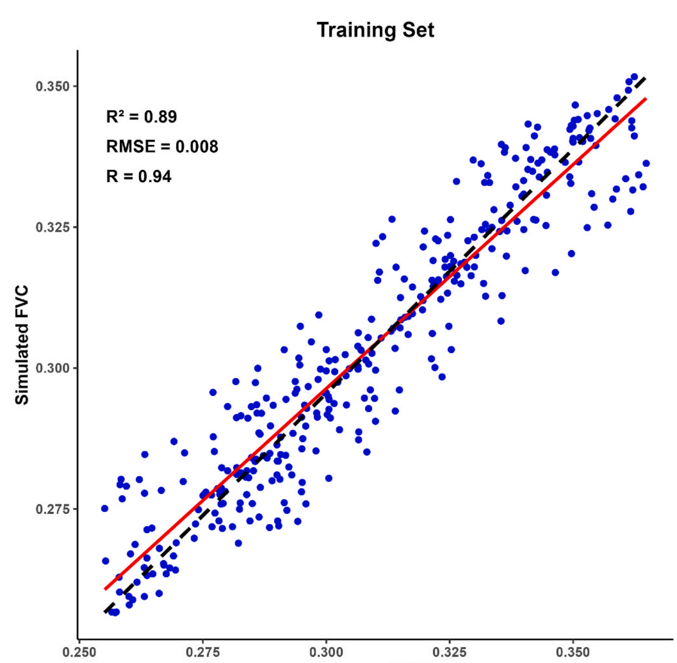

Fig. 14. RF training set.

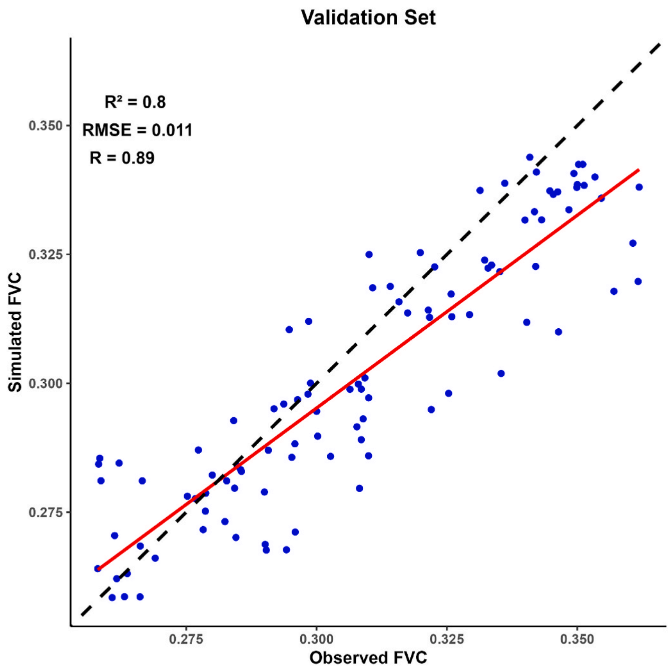

Fig. 15. RF Validation set.

Pakistan's nationwide FVC over 18 years. The findings revealed a consistent overall increasing trend in Pakistan's FVC, with an average value of 0.31. Notably, fluctuations were observed between 2003 and 2012, while a steady increase was noted from 2013 to 2020. Moreover, regions characterized by mountainous terrain exhibited notably higher FVC, reaching up to 70%, possibly due to lower urbanization levels. The analysis utilizing the Hurst exponent underscored the long-term memory or persistence in vegetation dynamics, showcasing a value (0.718) signifying substantial autocorrelation in the FVC time series data. Factors influencing FVC were identified, with rainfall showing a positive correlation (0.6), while LST and CNLI exhibited negative correlations (−0.59 and −0.43, respectively). The Random Forest regression model demonstrated strong performance, displaying low RMSE (0.008) and high R^2 (0.89) values. Notably, CNLI emerged as the model's most influential predictor (62.40%), underscoring its significance in understanding urbanization patterns and environmental dynamics. CNLI is a proxy for urbanization and human activities, significantly impacting vegetation cover. High CNLI values indicate areas with intense human activity, often leading to reduced vegetation cover due to land use changes, infrastructure development, and other anthropogenic factors. Therefore, CNLI emerges as a critical predictor in our model, as it encapsulates the extent of human influence on vegetation dynamics. This study highlights the crucial role of CNLI in comprehensively monitoring and managing environmental changes, emphasizing the importance of studying its interactions with FVC for a holistic ecological understanding in Pakistan.

4. Conclusions

MODIS NDVI, climatic, landforms, and nighttime light data were used to study FVC changes from 2003 to 2020. The study reveals that the average FVC value was 31%. Key factors affecting FVC include climate variables like rainfall and temperature and the CNLI, which serves as a proxy for human activities such as urbanization. Interestingly, landforms, particularly hilly areas, exhibit higher FVC than plains. Various analytical methods were employed in this study. The Hurst exponent assessed the persistence of FVC patterns over time. Additionally, weighted overlay analysis was used to understand the impact of rainfall, temperature, and CNLI on FVC distribution. Correlation analysis measured the relationships between FVC and its influencing factors. It was found that FVC correlates positively with rainfall but negatively with CNLI and temperature. A machine learning approach, specifically a Random Forest (RF) regression model, was employed to predict FVC using factors like LST, Rain, and CNLI. The model performed strongly, with an R^2 value of 0.89, indicating that the predictor variables can explain approximately 89% of FVC variability. The analysis highlights the significant impact of rainfall, urbanization, and temperature on FVC fluctuations. It underscores the importance of considering both environmental and human-induced factors when assessing changes in vegetation cover.

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data and material

The authors confirm that the data links supporting the findings of this study are available within the article.

CRediT authorship contribution statement

Shoaib Ahmad Anees: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Kaleem Mehmood:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Akhtar Rehman:** Writing – review & editing. **Nazir Ur Rehman:** Writing – review & editing. **Sultan Muhammad:** Writing – review & editing. **Fahad Shahzad:** Writing – review & editing. **Khadim Hussain:** Writing – review & editing. **Mi Luo:** Writing – review & editing, Formal analysis, Investigation. **Abdullah A. Alarfaj:** Writing – review & editing. **Sulaiman Ali Alharbi:** Writing – review & editing. **Waseem Razzaq Khan:** Writing – review & editing, Formal analysis, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors confirm that the data links supporting the findings of this study are available within the article.

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