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*Full Length Article*

# Long-term Monitoring of Vegetation Dynamics in a Semi-arid Region Using Landsat Imagery under Climate-change and Population Pressure

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## Abstract

Climate change and population pressure have an immense effect on vegetation of semi-arid regions. Long-term changes in vegetation caused by the combined effect of these two drivers are still insufficiently quantified. Moreover, the simultaneous influence of anthropogenic versus climatic drivers of vegetation change in urbanizing semi-arid landscapes is still under-explored. To fill this gap, the present study was performed in a semi-arid region, assessing long-term changes in vegetation as well as population. This study describes a 34-year (1990-2024) temporal patterns of land use/land cover (LULC) and vegetation changes in the semi-arid desert of Bahawalpur, Pakistan. Significant ($P < 0.05$) seasonal variations in NDVI, relative humidity, temperature, precipitation and wind speed were observed. Expansion of built-up area from 8.46 to 71.81 km² with associated vegetation loss (79.74 to 38.23 km²) was revealed by LULC from 1990 to 2024. In this duration, the range of NDVI fluctuated from -0.06 to 0.73. Precipitation showed significant negative correlations with wind (r = -0.536, $P < 0.01$) while a strong positive correlation with relative humidity (r = 0.82, $P < 0.001$). This confirms the thermodynamic association of atmospheric moisture and rainfall. Additionally, population was strongly positively correlated with relative humidity (r = 0.712, $P < 0.001$) and negatively correlated with wind (r = -0.526, $P < 0.01$), suggesting reasonable urbanization-induced microclimatic modifications. These findings suggest that vegetation in semi-arid urban landscapes may now depend more on human activities such as population shifts and irrigation than directly on natural climate patterns, prompting concerns about how these ecosystems will cope with future climate-driven water shortages. These findings also provide a foundation for global sustainable ecosystem management planning.

**Keywords:** NDVI; Semi-arid ecosystem; Climate variability; Landsat imagery; Structural equation modelling

## Introduction

Vegetation is a key element of the ecosystem of the earth. It facilitates fresh oxygen, food and habitat (Piao *et al.* 2020; Walker *et al.* 2023), controls soil erosion (Tian *et al.* 2023), promotes climatic stability (Miralles *et al.* 2025; Fu *et al.* 2026) and regulates carbon, water, and energy balance (Chen *et al.* 2020; Chen *et al.* 2021). Changes in vegetation have a direct impact on ecosystem stability and human well-being (Liu *et al.* 2023). The growing population pressure in the past decades has worsened the land-use pressures, resource drainage, and environmental stress. This can further amplify the effects of climatic variability on terrestrial ecosystems (Molotoks *et al.* 2021; Xu *et al.* 2026), leading to a global reduction in vegetation cover.

Vegetation dynamics need to be monitored in a timely and correct manner to conserve the environment and human health. One of the important approaches to this monitoring is the spatiotemporal analysis of the environmental changes based on spectral indices (Koedsin *et al.* 2026). The effect of environmental changes on vegetation in urban areas of semi-arid regions is not well investigated, particularly in cases where population pressure may increase the effects of environmental alterations.

Long-term environmental monitoring has been aimed at vegetation indicators to assess the ecosystems in response to climate change and human activities (Li *et al.* 2015; Gao *et al.* 2022; Chen *et al.* 2024). This knowledge on seasonal trends, interannual variability and long-term trends is essential in the planning of the vulnerable areas (Rhif *et al.* 2022). Normalized Difference Vegetation Index (NDVI) is one of the most utilized measures of vegetation condition and productivity of the satellite-based indicators (Rouse *et al.* 1974). The estimation of vegetation greenness and

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photosynthetic activity is done in the form of NDVI that makes use of the difference between the red-light absorption and the near-infrared reflectance (Zeng *et al.* 2022). Multi-temporal satellite imagery-based time-series NDVI data have been effective in vegetation monitoring due to climate change (Gao *et al.* 2022; Fadl *et al.* 2024). Because of its easy interpretability, along with good correlation with biomass and plant cover, NDVI has found wide application in agricultural, forestry, ecological and environmental surveillance research (Zeng *et al.* 2022). Long-term NDVI time-series data can be trend analyzed to identify patterns, dormancy, changes in productivity and processes of degradation which are commonly studied as independent of climatic drivers. Besides, strong seasonal variability, irregular precipitation, and lack of data caused by cloud cover and atmospheric conditions are some of the challenges of vegetation monitoring in semi-arid regions. Combining NDVI information over representative seasonal scales has thus become common to enhance the strength of vegetation trend analysis.

Pakistan is one of those nations that are highly susceptible to climatic changes caused by temperature rise, abnormal heatwaves, and changed patterns of precipitation experienced over the past decades (Khan *et al*. 2019). Rapid urban growth has been witnessed in the Punjab province which is home to a significant percentage of the population of this country. The increase in population is exerting more pressure on the land resources and vegetation systems. The changes in vegetation have been reported in vast areas of Punjab, including Vehari, Lahore, Jhelum, Lodhran and Multan *etc*. (Hu *et al.* 2021; Majeed *et al.* 2021; Hussain *et al.* 2022; Hu *et al.* 2023; Tariq and Mumtaz 2023; Hussain *et al.* 2025). Although the Bahawalpur district with the semi-arid to desert conditions had great ecological and climatic importance, it was not given much consideration in long-term vegetation monitoring research.

There is an apparent research gap thus in measuring the long-term vegetation dynamics in Bahawalpur at combined climatic variability and population growth. Such a gap needs to be addressed to develop baseline information to support environmental monitoring and land-use planning and sustainable ecosystem management in such a vulnerable area. The hypothesis of this study was that the vegetation greenness in Bahawalpur District is significantly affected by both climate variability and population pressure, with human activity driving measurable fluctuations over time. Based on this, the present study provides insight into the spatial and temporal vegetation dynamics in Bahawalpur between 1990 and 2024 by applying the NDVI of Landsat. The climatic factors such as precipitation, temperature, relative humidity, and wind speed are studied with the rate of population growth to determine the relationship between them and vegetation variability. In particular, the study: (1) examined the changes in NDVI over time and season using statistical methods; (2) assessed the long-term changes in NDVI (3) determined the relative role of climatic factors and population increase due to the variability of NDVI using correlation analysis and structural equation modelling.

## Materials and Methods

### Study area

The study was conducted in Bahawalpur District (28°57′–29°31′ N latitude and 71°50′–72°36′ E longitude) in southern Punjab, Pakistan (Fig. 1). The district spans approximately 21,765 km², making it the largest district in Punjab by area, with elevations ranging from 114 to 126 m above sea level. Bahawalpur lies at the arid Bahawalpur Plain and the Cholistan Desert. It faces a hot, semi-arid to arid climate characterized by low and irregular precipitation, high summer temperatures, and strong seasonal variability.

Bahawalpur city is situated along the eastern bank of the Sutlej River and had a metropolitan population exceeding one million in 2021. The high rate of population increase the continuous development of cities and their closeness to desert ecosystems predisposes this region to environmental stress. These features make Bahawalpur a suitable case study to monitor the vegetation dynamics over a long period in the presence of both climatic variability and anthropogenic stressors.

### Data collection

The data of 34 years (1990 to 2024) of climatic variables such as air temperature, relative humidity, wind speed, and precipitation were retrieved from the NASA Prediction of Worldwide Energy Resources (POWER) database (https://power.larc.nasa.gov; Accessed: 21 December 2024). The retrieved data were at a spatial resolution of 0.5° x 0.5° and monthly time resolution. In the cases where it was possible, NASA POWER data were compared with the data of the Pakistan Meteorological Department (PMD), to verify consistency and reliability.

The macro trends database (https://www.macrotrends.net/cities/22035/bahawalpur/population) was used to obtain population data of urban Bahawalpur district (Fig. 1).

### Land use/land cover (LULC) classification

Land use/land cover (LULC) classification for urban Bahawalpur was performed from 1990 to 2024 using Landsat 5 TM and Landsat 8 OLI imagery within the Google Earth Engine (GEE) cloud-computing environment, and spatial maps were generated for the midpoints 1990, 2000, 2010 and 2024.Atmospherically corrected Top of Atmosphere (TOA) images were filtered for annual median (Jan-Dec) to ensure consistency and minimize phenological variability. Representative training samples (80-120) for water, barren land, vegetation, built-up area, and fallow land were generated using field knowledge and high-resolution

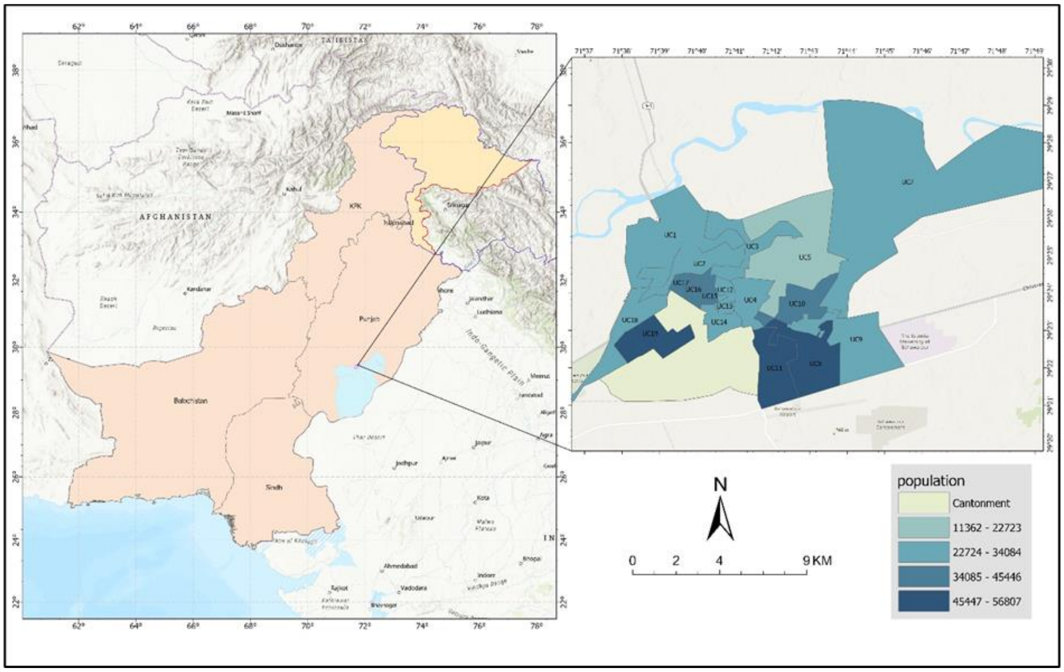


**Fig. 1:** Study area map (left) and the population dynamics (right) of urban Bahawalpur

Google Earth imagery. A Random Forest (RF) classifier (ee.Classifier.smileRandomForest) was implemented with 300 trees and five variables per split. The labelled dataset was divided using a 70:30 train–test split, where 70% of samples were used for model training and 30% for validation. The trained model was applied to generate pixel-based LULC maps for each study year. Classification performance was evaluated through Overall Accuracy, Producer's Accuracy, User's Accuracy, and the Kappa coefficient, providing a comprehensive assessment of classification reliability.

**NDVI estimation**

Vegetation condition was measured with the help of the Normalized Difference Vegetation Index (NDVI) which is a well-known spectral index to measure vegetation greenness and photosynthetic activity. NDVI was computed from 1990 to 2024 (34-years). For visualization purposes, cloud-free Landsat composites within Google Earth Engine were used for the same midpoint years: Landsat 5 TM for 1990, 2000, and 2010 and Landsat 8 OLI for 2024**.** NDVI was calculated, where Band 4 represents Near-Infrared (NIR) and Band 3 represents red reflectance. For Landsat 8 OLI (2024), NDVI was derived using Band 5 as NIR and Band 4 as Red. The standard formulation of NDVI was used to derive NDVI at the pixel level:

$$NDVI = (NIR-RED)/(NIR+RED) \qquad (1)$$

Where, NIR and RED are the near-infrared and red reflectance, respectively.

In the case of Landsat TM, ETM+ and OLI sensors, the spectral bands were selected based on sensor specifications. The NDVI has a range between -1.0 and +1.0 where higher positive values denote the existence of denser and healthier vegetation, near-zero values denote the existence of bare soil and negative values are normally attributed to water bodies or clouds (Rouse *et al*. 1974). Although NDVI is a continuous index and does not require thematic classification, quality assurance procedures were applied to ensure reliability. Visual inspection of NDVI maps was conducted to confirm consistency with known land cover patterns. NDVI distributions were evaluated across years to detect anomalies potentially caused by residual atmospheric effects or sensor inconsistencies.

**Statistical analysis**

All statistical analyses were conducted using R software (R Core Team 2025) on a 34-year dataset spanning from 1990 to 2024. One-way analysis of variance (ANOVA) was used to assess seasonal differences in NDVI, and climatic variables and Tukey honest significant difference (HSD) test was used to make post-hoc comparisons at a 95% confidence level. The quantification of linear relationships between NDVI, climatic variables and population growth rate was performed by Pearson correlation analysis with a heatmap to visualize the results. Growth rate is the rate of population growth per annum obtained using demographic data and was a demographic indicator used in the structural equation modelling (SEM) to test the multivariate relationships in a hypothetical model, where NDVI was taken as the response variable and climatic and demographic variables as predictors. The estimation of SEM was done through maximum likelihood, and the model fit was done through chi-square test, comparative fit index (CFI), and root mean square error of approximation (RMSEA). The correlation and SEM were only viewed as statistical relationships and not as causal. The drawbacks associated with the exclusion of soil moisture are admitted, and the aspects can also have additional effects on the vegetation dynamics and is considered in the subsequent studies.

## Results

Statistical analysis of the vegetation dynamics derived using Landsat showed that LULC, NDVI, climatic variables and population had statistically significant relationships. Analytical results of ANOVA, correlation analysis, and structural equation modelling (SEM) combined are used to describe the seasonal variability, long-term trends, and multivariate relationships.

### Seasonal change of NDVI and climatic variables

The estimates of the effect size ($\eta^2$) were significantly ($P < 0.001$) large, suggesting that there were strong seasonal effects on temperature ($\eta^2 = 0.89$), wind speed ($\eta^2 = 0.61$) and relative humidity ($\eta^2 = 0.59$) but NDVI had a lower, but significant ($P < 0.05$) seasonal effect ($\eta^2 = 0.08$). Tukey HSD test was used to compare two means of same variable in pair-wise analysis and the results showed significant ($P < 0.01$) increase in NDVI between January and May (Table 1). Relative humidity decreases ($P < 0.001$) strongly between May and September and temperature rises considerably between January and May. There is moderate non-significant precipitation decrease between January and September. A considerable difference in the wind speed of all seasonal comparisons (Table 1) was observed. In general, these findings suggest that there are strong seasonal variations in climatic variable conditions but NDVI exhibits weak seasonal variations.

### Land use/land cover (LULC) classification

A comparison of the multi-temporal land use/land cover (LULC) change in urban Bahawalpur between 1990 and 2024 (Fig. 2) shows a strong trend of landscape change. The largest change is the rapid increase in built-up area that increased from 8.46 km$^2$ to 71.81 km$^2$ (Table 2a), which also represents high levels of urbanization and horizontal extension. This has been done at the direct cost of vegetation and fallow land which had to be cut by 52 and 80% respectively which implies the reprocessing of agricultural and peri-urban vacant lots. Recent statistics of 2024 also note a worrisome increase in the barren land to 38.69 km$^2$, which might be a sign of land degradation or widespread soil bareness after construction (Table 2a). At the same time, water resources have been severely depleted since 1990, which highlights the pressure on the aquatic resources in this dry regime. The Training Overall Accuracy (T(OA)) and Training Kappa (T(Kappa)) coefficients (Table 2b), which were always above 0.97, shows that the spectral signatures with which the classification algorithm was trained were practically error-free, an excellent fit of the model to the reference pixels. Importantly, the Validation Overall Accuracy (V (OA) which varies between 0.83 and 0.88) and the Validation Kappa (V (Kappa) which varies between 0.80 and 0.86)) confirm the transferability and reliability of the classification.

### Temporal analysis of vegetation dynamics (NDVI) in Bahawalpur (1990-2024)

Normalized Difference Vegetation Index (NDVI) in Bahawalpur city shows subtle changes in vegetation during the 34 years of analysis duration. The average NDVI values show outstanding consistency (Fig. 3) that ranges slightly between 0.34 and 0.35 throughout the four time points (Table 2c). The mean vegetation greenness density in the remaining vegetated areas has been stable despite drastic change in the cover of vegetation area. The highest values of NDVI are never below 0.71-0.73, which means that in some areas, there are still healthy and dense vegetation, probably irrigated fields of agriculture or conservation zones. Noticeably, minimum values of NDVI increased to -0.06 in 2024 compared to the -0.16 of the year 1990 (Table 2c) demonstrating the decline of non-vegetated or water dominated pixels. The standard deviation decreased to 0.14 in 2024, reflecting a decreasing spatial heterogeneity of the vegetation condition. This low variability and constant values of means indicate that the vegetation is becoming homogenized with the remnant vegetation being found in fewer distinct classes, and the net change in vegetated area is reflected in the LULC data and not the NDVI intensity values.

### Correlation and regression-based predictors of NDVI

The bivariate relationships of NDVI with climatic and anthropogenic drivers are explained in the correlation matrix (Fig. 4). The water availability was found to be the basic determinant of vegetation in this semi-arid environment since NDVI was highly positively associated with precipitation (r = 0.82, $P < 0.001$). Increasing heat stress is a major contributor to photosynthetic deterioration in the semi-arid area under study since strong negative relationships between NDVI and temperature (r = -0.64, $P < 0.001$) were observed. Notable inverse relationship between temperature and precipitation (r = -0.73, $P < 0.001$) is typical when hot seasons are drier, which is another salient feature of this and most other drylands climates. True to this trend, relative humidity (RH) is a dependent moisture variable with a high positive relationship with precipitation (r = 0.82, $P < 0.001$) and a negative relationship with temperature (r = -0.64, $P < 0.001$). The wind speed has a moderate negative

**Table 1:** Seasonal variation in normalized difference vegetation index (NDVI) and climatic variables in Bahawalpur District determined using one-way analysis of variance (ANOVA) followed by Tukey's honest significant difference (HSD) test

| Parameter | $\eta^2$ | | Jan-May | Jan-Sep | May-Sep |
|---|---|---|---|---|---|
| NDVI | 0.08* | Difference | 0.045 ± 0.02 | 0.009 ± 0.02 | -0.037 ± 0.02 |
| | | t-value | 2.64* | 0.5 | -2.14 |
| Relative Humidity (%) | 0.59*** | Difference | 11.17 ± 2 | -5.6 ± 2 | -16.77 ± 2 |
| | | t-value | 7.44*** | -3.73*** | -11.18*** |
| Temperature (°C) | 0.89*** | Difference | -20.69 ± 0.28 | -18.1 ± 0.28 | 2.6 ± 0.28 |
| | | t-value | -74.78*** | -65.4*** | 9.4*** |
| Precipitation (mm) | 0.13** | Difference | -5.76 ± 4 | -16 ± 4 | -10.25 ± 4 |
| | | t-value | -1.29 | -3.58** | -2.29 |
| Wind (m/s) | 0.61*** | Difference | -1.57 ± 0.14 | -1.11 ± 0.14 | 0.46 ± 0.14 |
| | | t-value | -11.64*** | -8.26*** | 3.38** |

$\eta^2$ represents the effect size of month. Values are mean differences ± standard error between monthly pairs. *, **, and *** indicate statistical significance at $P < 0.05$, $P < 0.01$ and $P < 0.001$, respectively

**Table 2:** Land cover/land use (LULC) classification (a), and validation (b) with the temporal changes (c) in normalized difference vegetation index (NDVI)

| a) Land use (km$^2$) | 1990 | 2000 | 2010 | 2024 |
|---|---|---|---|---|
| Water | 20.76 | 9.11 | 12.57 | 10.38 |
| Barren | 17.99 | 21.58 | 14.7 | 38.69 |
| Vegetation | 79.74 | 52.8 | 68.31 | 38.23 |
| Built-up | 8.46 | 39.08 | 54.6 | 71.81 |
| Fallow Land | 40.12 | 44.49 | 16.88 | 7.95 |
| b) Years | T(OA) | T (kappa) | V(OA) | V(Kappa) |
| 1990 | 0.98 | 0.97 | 0.84 | 0.81 |
| 2000 | 0.99 | 0.99 | 0.83 | 0.8 |
| 2010 | 0.98 | 0.97 | 0.87 | 0.86 |
| 2024 | 0.99 | 0.99 | 0.88 | 0.85 |
| c) NDVI | Min. | Max. | Mean | Std. Dev |
| 1990 | -0.16 | 0.71 | 0.35 | 0.19 |
| 2000 | -0.11 | 0.73 | 0.34 | 0.18 |
| 2010 | -0.19 | 0.72 | 0.35 | 0.19 |
| 2024 | -0.06 | 0.71 | 0.35 | 0.14 |

T(OA): Overall training, V(OA): Overall validation, Kappa: Cohen's kappa is a statistical metric used in machine learning to score the performance of a classification model. Min, Max and Std, Dev. are the minimum, maximum, and standard deviation values of NDVI

relationship with precipitation and humidity showing its contribution in drying the atmosphere. There was a strong negative correlation with population (r = -0.76, $P < 0.001$). The high inter-correlations require the application of the causal models like Structural Equation Modelling (SEM) which can address collinearity and direct versus indirect routes.

**Structure equation modelling (SEM): drivers of vegetation dynamics in Bahawalpur**

The structural equation model (SEM) explained both direct and indirect processes that controlled the dynamics of vegetation greenness (NDVI) in Bahawalpur District between 1990-2024. There was a positive and significant correlation between the rate of population growth and NDVI (Fig. 5). This strong association implies that those regions with demographic growth are also characterized by an increase in vegetation greenness, which may be due to the so-called urban green infrastructure effect; with peri-urban agricultural intensification, irrigated horticulture, and controlled green areas accompanying urban settlement expansion in semi-arid settings. It is noteworthy that the direct climatic effects on NDVI were statistically not significant, which means that the vegetation greenness of this anthropogenically-modified landscape is not linked to immediate meteorological variability. Relative Humidity (RH) showed insignificant impact (β = 0.0048) indicating that atmospheric moisture in the air does not directly limit the vegetation vigor in the present circumstances. The trend in wind speed was non-significant but with a positive direction (β = 0.131) that could be due to aeolian processes of transport or microclimatic influences which should be considered in the future. Precipitation (ppt) showed a weak, non-significant negative relationship (β = -0.092) contrary to the expectation, which supports the explanation that vegetation in this area is supported mainly by irrigation and groundwater extraction, as opposed to its direct rainfall reliance.

The model (Fig. 5) also reflected high interdependence between the climatic variables in an indirect manner, and this indicated the atmospheric processes that controlled the availability of moisture in the region. Relative Humidity had a strong positive influence on precipitation (β = 0.834) which proved that the content of atmospheric moisture is the main determinant of precipitation occurrence- a well-known thermodynamic relationship in arid environments. Precipitation had a significant negative correlation with wind

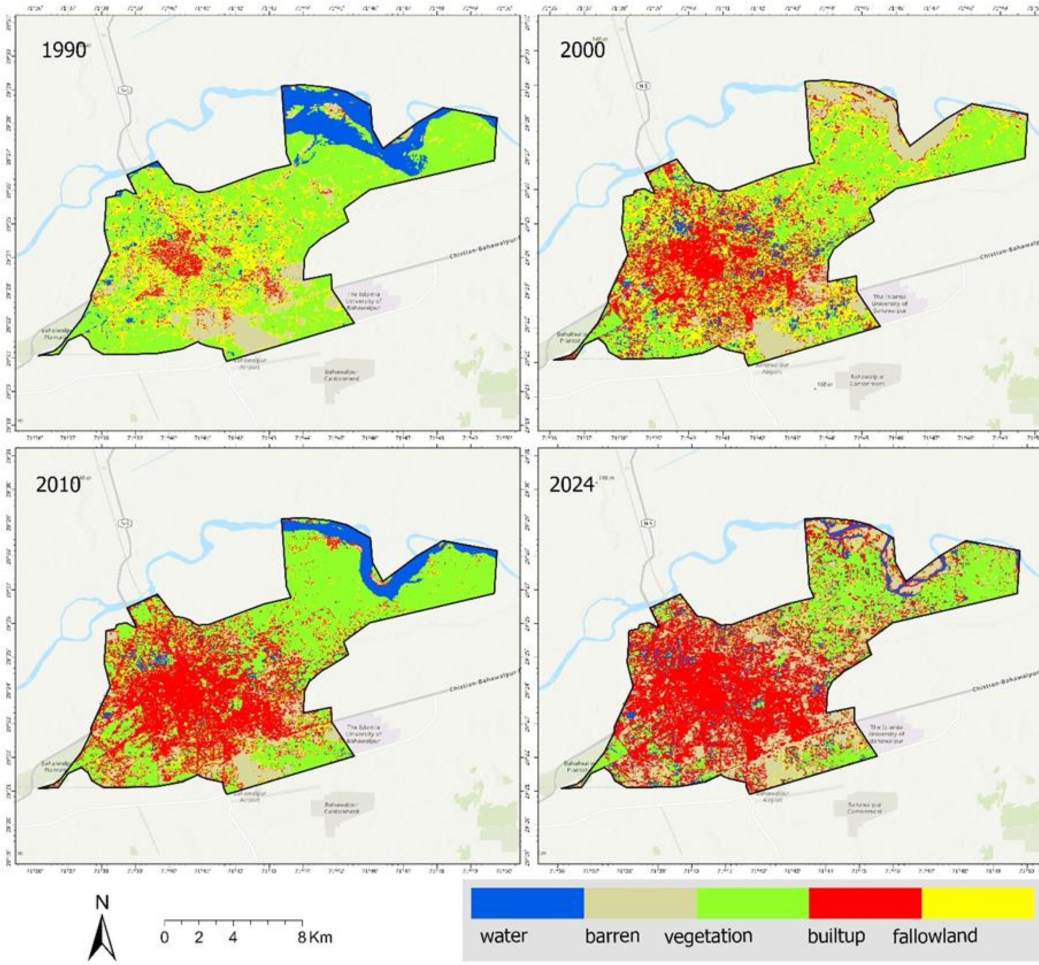


**Fig. 2:** Land use/land cover (LULC) classification of urban Bahawalpur (1990-2024). Median LULC values from four temporal subsets (1990, 2000, 2010 and 2024) were used to represent the central tendency of change. The longer interval from 2010 to 2024 was aimed to capture the latest maximum land cover dynamics

speed ($\beta$ = -0.249) indicating that an increase in wind speed may cause moisture to move out of the area or prevent the formation of convective precipitation. Population exhibited a non-significant negative relationship with precipitation ($\beta$ = -0.179) that did not provide any statistical evidence of the influence of urban rainfall or microclimatic alteration at this level landscape.

## Discussion

This study is a long-term evaluation of vegetation dynamics in the semi-arid Bahawalpur District based on LULC and NDVI derived through Landsat and combined with climatic variables and population parameters. The results are an effective quantitative model of vegetation response to interacting climatic and anthropogenic pressures at multiple temporal scales through the combination of seasonal investigation, correlation assessment, and structural equation modelling (SEM).

**Climatic control on the seasonal vegetation dynamics**

The strong seasonal fluctuations in the climatic variables especially the temperature, precipitation, relative humidity and wind speed show how climate is dominant in controlling the vegetation dynamics in this semi-arid environment (Fayech and Tarhouni 2021). The large magnitude of the estimates of effect on temperature, wind speed and relative humidity as opposed to the smaller but significant seasonal effect on NDVI, is indicative of a buffering or integrated vegetation response to climate and is not directly associated with the fluctuations in the atmosphere. The vegetation responses to water have been described in this moderated form in water-limited ecosystems, where the physiological constraints and the memory of soil moisture reduce the short-term changes in climatic conditions (Yuan *et al.* 2022; Liu *et al.* 2023).

The aspects of the increase in NDVI in winter to spring indicate good conditions of vegetation growth, such as a

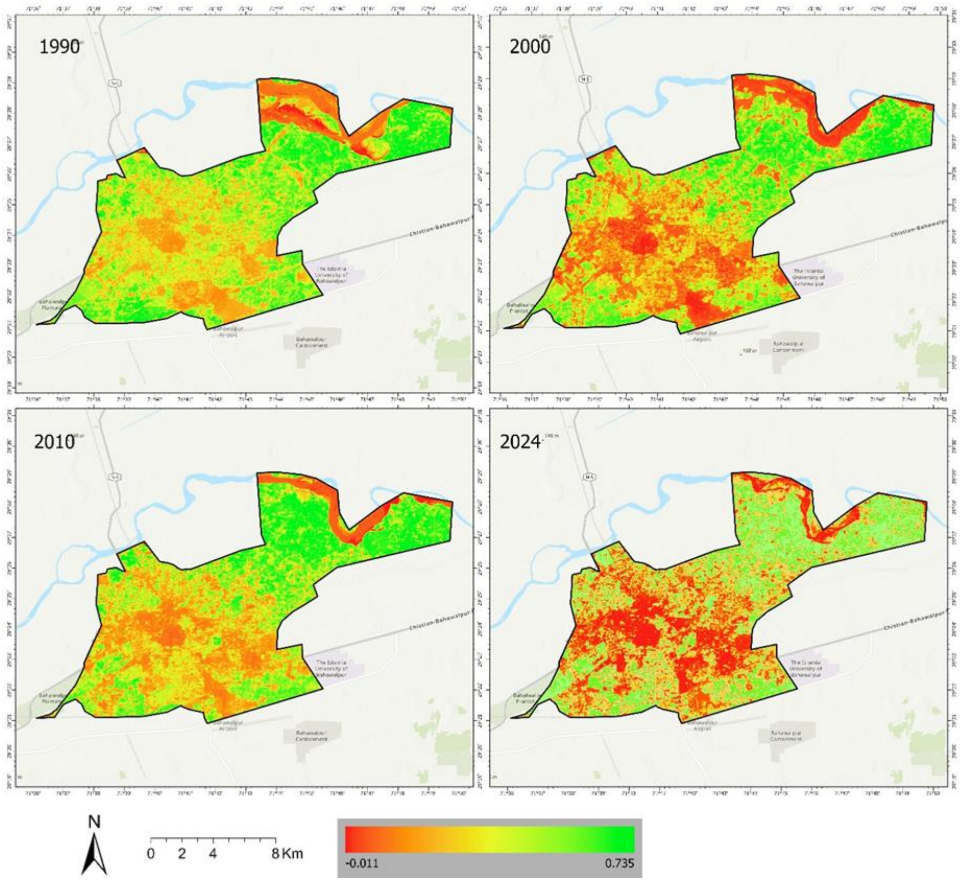


**Fig. 3:** Normalized Difference Vegetation Index (NDVI) dynamics in urban Bahawalpur over four defined intervals. The red-yellow-green colored gradient corresponds to low, medium and high greenness values, respectively

moderate temperature and better moisture content, and the opposite of the above in summer with abundant heat, low precipitation, and decreased relative humidity. These seasonal patterns are consistent with other studies of arid/semi-arid regions that have shown vegetation greenness during periods of transitional seasons and a fall in vegetation greenness during periods of thermal and hydrological stress (Fadl *et al.* 2024; Ren *et al.* 2026). The heavy seasonal dependence of the wind speed further highlights the importance of the wind in increasing the atmospheric drying and evapotranspiration demand which indirectly limits vegetation activity.

**Landscape transformation in arid urban systems**

The multi-decadal land use/land cover trends reported on Bahawalpur indicate that the landscape is in a state of fundamental restructuring, whereby the urban expansion is extremely high at the cost of farming and barren land. Massive growth in built-up area between 1990 and 2024 is among much higher urbanization rates ever recorded in such medium sized cities in the Indus Basin in Pakistan. This transformation aligns with broader global patterns observed by Zhong and Li (2024), who reported heterogeneous vegetation responses across 889 global cities under different urban development intensities. This study also explores same pattern as shown by Zhang *et al.* (2022) about urbanization which exerts both direct and indirect impacts on vegetation growth in 672 worldwide cities. The fact that the vegetation cover decreased at the same time by 52% namely 79.74 km2 to 38.23 km2, in the first place, seems to support the traditional discourse on urbanization as a destructive force per se against green infrastructure. Nonetheless, this interpretation needs a lot of nuances when it is combined with the outcomes of NDVI and SEM. The vegetation contraction took place in the areal sense with the stable mean values of NDVI (0.34-0.35) and, the positive relationship between the rate of population increase and the greenness of vegetation at the pixel scale. This apparent contradiction is consistent with Li *et al*. (2024), who reported indirect non-linear effects of landscape patterns on vegetation growth in rapidly urbanizing Kunming City.

Dramatic growth of the barren land to 38.69 km2 in 2024 was observed. That is the highest level during the entire timeframe of the research. This growth is probably a combination of: (i) construction sites and soil exposure in active development stages, (ii) peri-urban agricultural lands in the process of land use conversion, and (iii) possible

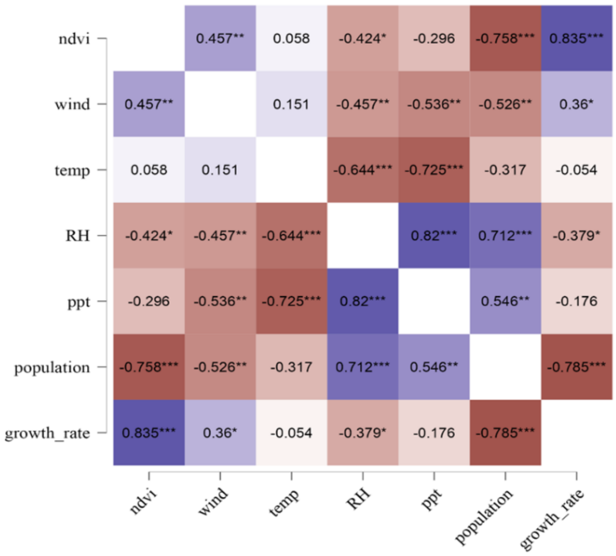


**Fig. 4:** Pearson correlation heatmap of NDVI, relative humidity (RH), wind, temperature, precipitation (ppt), population, and growth rate. Significance codes: * $P < 0.05$, ** $P < 0.01$, *** $P < 0.001$. The brown-white-blue gradient indicates negative (brown), neutral (white) and positive (blue) correlations

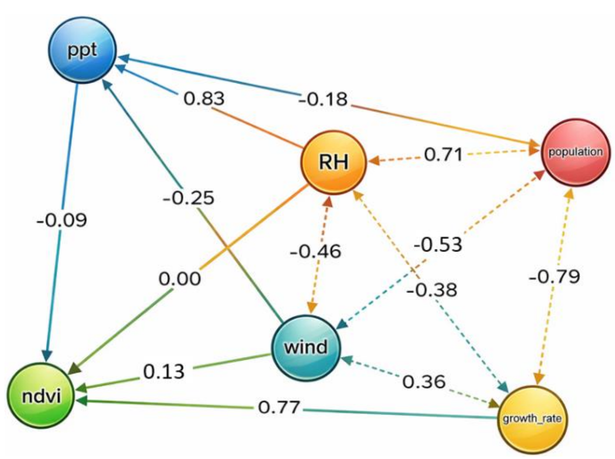


**Fig. 5:** Path diagram from structural equation modelling (SEM) with normalized difference vegetation index (NDVI) as the dependent variable. Direct effects of precipitation (ppt), relative humidity (RH), and wind on NDVI are shown with solid arrows, while dashed arrows represent mutual (covariance) effects among predictors. Numerical values in between arrow-lines denote path coefficients (estimates). In this SEM model, all path coefficients with an absolute value greater than 0.1 were statistically significant at $P < 0.01$

intensification of the aeolian processes as vegetation cover gets eroded by wind. Gao *et al.* (2022) similarly highlighted NDVI patterns indicating ecosystem stress in relation to combined climatic and anthropogenic pressures. The 2024 value however could be an indication of a threshold that has been reached and that the natural regeneration capacity has been overridden by the consistent anthropogenic pressure.

**Temporal stability of NDVI**

Fluctuation of NDVI over 34-years with overall stability shows that there is ongoing vegetation change during the study period, which is in line with overall findings of vegetation greenness decrease of dryland systems in the face of combined climatic and anthropogenic stresses (Zeng *et al.* 2022; Xu *et al.* 2026). Episodic climatic events, land-use changes, and management-related interventions are likely to modulate long-term vegetation dynamics in semi-arid ecosystems and change future patterns (Zhang *et al.* 2022; Wen *et al.* 2023; Zhong and Li 2024). However, the continuation of the weakening signal of NDVI highlights the risk of vegetation systems in Bahawalpur to be exposed to persistent environmental pressures.

**Indirect effects climatic factors as drivers of NDVI**

The results of correlation and SEM show that water availability is the main controlling factor of the vegetation dynamics in the study area. The high positive value of the NDVI and precipitation, and low positive value of NDVI and temperature indicate the essential significance of hydroclimatic balance in regulating photosynthetic rates and biomass increase in semi-arid ecosystems. The results are in line with the international evidence that has shown that variability in precipitation is the primary cause of vegetation greenness in water-deficient areas and is often more significant than the direct effect of temperature (Piao *et al.* 2020; Xu *et al.* 2026).

SEM findings further explain that climatic effects on NDVI are found to work *via* indirect means especially through precipitation. The dynamics of precipitation are greatly under the control of relative humidity and wind velocity, in which the humidity boosts and the wind suppress the availability of moisture. This cascade model underlines that vegetation response is controlled by combined atmospheric processes and not individual climatic factors. The same type of indirect climatic paths has been observed in dryland literature where vegetation productivity is jointly controlled by the demand of evapotranspiration, moisture in the atmosphere and rainfall efficiency (Chen *et al.* 2021).

The difference between robust seasonal influences of wind speed and relative humidity found in ANOVA and weak direct effects in SEM shows the scale-based dependence of vegetation-climate interactions. Short-term atmospheric variability is contained in seasonal analyses and long-term integrated relationships are embodied in SEM. This supports the importance of applying more than one approach of analysis to unravel complicated environmental processes on vegetation dynamics.

**Anthropogenic and population pressure**

It was observed that NDVI and population are strongly negatively correlated in their bivariate relationship which means that the population growth is accompanied with the deterioration of the vegetation condition. This trend is in line with international and regional literature that records the decline of vegetation greenness in fast urbanizing and land-converting regions because of infrastructural developments, land fragmentation, and resource exploitation (Zhang *et al*. 2022; Li *et al*. 2025).

The results of regression and SEM, however, show a rather complex relationship. The direct effect of population growth rate on NDVI in the SEM framework is a high positive, which creates the possibility that the initial or intermediate phase of land-use development can contribute to the increase in greenness by either agricultural land growth, irrigation, or controlled vegetation. These results are consistent with those that have found non-linear or threshold vegetation responses to urbanization, in which early stages of development can cause a temporary rise in NDVI before degradation prevails in higher levels (Li *et al.* 2024; Zhong and Li 2024).

Simultaneously, population and NDVI have a high negative correlation, which highlights the fact that the cumulative pressure of the demographic growth can be observed over a longer period. This seems to be a paradox as human impact on vegetation has a two-sided character, on the one hand, enhanced by short-term beneficial land utilization, and, on the other hand, harmed by long-term damages of resources overexploitation and fragmentation of the landscape. Mixed effects of this kind have been reported in semi-arid and urban-adjacent landscapes whereby heterogeneous land-use patterns are modulating demographic effects on vegetation (Smith *et al.* 2003; Molotoks *et al.* 2021; Cui *et al*. 2025). The overall outcome of the SEM results is that vegetation dynamics in Bahawalpur are mainly anthropogenic, mediated by demographic processes and other related land management practices, and that climatic variables can act only through their covarying relations, not necessarily by directly limiting NDVI.

Notably, the findings warn against the simplistic explanation of vegetation change as due to single drivers only. Rather, they emphasize the importance of multi-layered environmental monitoring systems which consider interacting climatic and anthropogenic factors especially in semi-arid areas with limited data. These integrative methods are becoming important in the study of ecosystem responses in the context of rapidly increasing global change (Li *et al.* 2015; Gao *et al.* 2022).

### Limitations of the study

There are several methodological weaknesses we prefer to be mentioned here. First, the 30-meter resolution of the Landsat-obtained LULC and NDVI might mask finer scale dynamics in vegetation of the urban matrix, such as small gardens, street trees and the vegetation in courtyards that all form urban green infrastructure. Second, the SEM only cannot authenticate actual causality; we suggest actual experimentation to validate the SEM results. Third, the 3-decade change is captured by the study but might not reflect the extended trajectories, specifically the ground water dynamics in multi-decadal scales. Lastly, there is lack of direct irrigation and soil data, which makes it impossible to quantify water and soil inputs to support vegetation.

## Conclusion

This study is a long-term evaluation of vegetation change in Bahawalpur District, Pakistan, based on Landsat-derived NDVI between 1990 and 2024. The findings reveal that seasonal and interannual climatic variability affect vegetation condition in this semi-arid region, while the precipitation and temperature have become the main factors. Wind speed and relative humidity also affect vegetation indirectly by controlling the dynamics of moisture and precipitation in the atmosphere. Though population increase exhibits a very negative correlation with NDVI at the bivariate level, the multivariate analysis indicates that there is a more complex relationship between demographic pressure and climatic conditions as well as land-use processes. The direct impact of population growth rate on NDVI in SEM is positive, indicating the possibility of a temporary increase in the greenness of the vegetation under the influence of the managed land use, even though the total population pressure will lead to its subsequent reduction.

This research creates a strong environmental surveillance framework by combining the multi-decadal remote sensing information with the advanced statistical modelling in an area that is vulnerable and semi-arid. The results highlight the need to consider both climatic and anthropogenic agents in the evaluation of vegetation change and present a quantitative framework that can be used to evaluate other dryland systems under similar environmental stresses.

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## Author Contributions

SR: Applied remote sensing, collected & processed data, and wrote the original manuscript. MJ: Conceptualized and supervised the study, performed the statistical analysis and generated illustrations, reviewed and edited the manuscript. SA and SS: Applied remote sensing software. MFM: Reviewed and edited the final draft. All authors have read and agreed to the published version of the manuscript.

## Conflict of interest

The authors declare no conflict of interest.

## Data Availability

Data presented in this study will be available on a fair request to the corresponding author.

## Ethics Approval

Not applicable to this study.

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## References

Chen J, W Fan, D Li, X Liu, M Song (2020). Driving factors of global carbon footprint pressure: Based on vegetation carbon sequestration. *Appl Ener* 267:114914 https://doi.org/10.1016/j.apenergy.2020.114914

Chen M, Y Xue, Y Xue, J Peng, J Guo, H Liang (2024). Assessing the effects of climate and human activity on vegetation change in Northern China. *Environ Res* 247:118233 https://doi.org/10.1016/j.envres.2024.118233

Chen Y, X Feng, H Tian, X Wu, Z Gao, Y Feng, S Piao, N Lv, N Pan, B Fu (2021). Accelerated increase in vegetation carbon sequestration in China after 2010: A turning point resulting from climate and human interaction. *Glob Change Biol* 27:5848–5864 https://doi.org/10.1111/gcb.15854

Cui L, S Zheng, Y Jin, Z Shen, X Dong, M Xu (2025). Understanding the nonlinear trade-off relationship to optimize urban-rural ecosystem services: A case study in arid and semi-arid region, China. *Habitat Intl* 166:103567 https://doi.org/10.1016/j.habitatint.2025.103567

Fadl ME, MA AbdelRahman, AI El-Desoky, YA Sayed (2024). Assessing soil productivity potential in arid region using remote sensing vegetation indices. *J Arid Environ* 222:105166 https://doi.org/10.1016/j.jaridenv.2024.105166

Fayech D, J Tarhouni (2021). Climate variability and its effect on normalized difference vegetation index (NDVI) using remote sensing in semi-arid area. *Model Earth Syst Environ* 7:1667–1682 https://doi.org/10.1007/s40808-020-00896-6

Fu Y, C Wu, S Gao, J Peñuelas, JJ Camarero, J Zhang, S Piao (2026). Vegetation greening drives long-term dust mitigation in Eastern Asia. *Nat Commun* 17:1729 https://doi.org/10.1038/s41467-026-68427-y

Gao W, C Zheng, X Liu, Y Lu, Y Chen, Y Wei, Y Ma (2022). NDVI-based vegetation dynamics and their responses to climate change and human activities from 1982 to 2020: A case study in the Mu Us Sandy Land, China. *Ecol Indic* 137:108745 https://doi.org/10.1016/j.ecolind.2022.108745

Hu P, A Sharifi, MN Tahir, A Tariq, L Zhang, F Mumtaz, SHIA Shah (2021). Evaluation of vegetation indices and phenological metrics using time-series modis data for monitoring vegetation change in Punjab, Pakistan. *Water* 13:2550 https://doi.org/10.3390/w13182550

Hu Y, A Raza, NR Syed, S Acharki, RL Ray, S Hussain, A Elbeltagi (2023). Land use/land cover change detection and NDVI estimation in Pakistan's Southern Punjab Province. *Sustainability* 15:3572 https://doi.org/10.3390/su15043572

Hussain S, M Mubeen, W Nasim, S Karuppannan, A Ahmad, M Amjad, W Akram (2025). Assessing the impact of land use land cover changes on soil moisture and vegetation cover in Southern Punjab, Pakistan using multi-temporal satellite data. *Geol Ecol Landsc* 9:817–832 https://doi.org/10.1080/24749508.2024.2338970

Hussain S, S Qin, W Nasim, MA Bukhari, M Mubeen, S Fahad, M Aslam (2022). Monitoring the dynamic changes in vegetation cover using spatio-temporal remote sensing data from 1984 to 2020. *Atmosphere* 13:1609 https://doi.org/10.3390/atmos13101609

Khan N, S Shahid, T Ismail, K Ahmed, N Nawaz (2019). Trends in heat wave related indices in Pakistan. *Stochastic Environ Res Risk Assessment* 33:287–302 https://doi.org/10.1007/s00477-018-1605-2

Koedsin W, S Pinkaew, JCW Chan, RJ Ritchie, A Huete (2026). Satellite-based species-level monitoring of mangrove phenology and climate responses using EVI and lagged environmental correlations (2013–2024). *Intl J Rem Sens* 47:3382–3404 https://doi.org/10.1080/01431161.2026.2631697

Li N, F Zhao, S Chen, C Li, Y Wang, Y Ma, L Chen (2024). Indirect non-linear effects of landscape patterns on vegetation growth in Kunming City. *NPJ Urb Sustain* 4:30 https://doi.org/10.1038/s42949-024-00165-w

Li X, H He, D Wang, Y Sun, Y Qin, K Wang, W Qiao (2025). Spatiotemporal dynamics of the normalized difference vegetation index and its multidimensional drivers in a rapidly urbanizing coastal city: A case study of Lianyungang, China (2000–2023). *Ecol Inform* 91:103397 https://doi.org/10.1016/j.ecoinf.2025.103397

Li Z, Y Chen, W Li, H Deng, G Fang (2015). Potential impacts of climate change on vegetation dynamics in Central Asia. *J Geophys Res Atmos* 120:12345–12356 https://doi.org/10.1002/2015JD023618

Liu P, Y Chi, J Chen, L Zhou (2023). Global climate regulates dimensions of terrestrial ecosystem stability. *Ecosphere* 14:1-12 https://doi.org/10.1002/ecs2.4577

Majeed M, A Tariq, MM Anwar, AM Khan, F Arshad, F Mumtaz, S Shaukat (2021). Monitoring of land use–land cover change and potential causal factors of climate change in Jhelum district, Punjab, Pakistan, through GIS and multi-temporal satellite data. *Land* 10:1026 https://doi.org/10.3390/land10101026

Miralles DG, JVGD Arellano, TR McVicar, MD Mahecha (2025). Vegetation–climate feedbacks across scales. *Ann New York Acad Sci* 1544:27–41 https://doi.org/10.1111/nyas.15286

Molotoks A, P Smith, TP Dawson (2021). Impacts of land use, population, and climate change on global food security. *Food Ener Sec* 10:1-20 https://doi.org/10.1002/fes3.261

Piao S, X Wang, T Park, C Chen, X Lian, Y He, JW Bjerke, A Chen, P Ciais, H Tommervik, RR Nemani, RB Myneni (2020). Characteristics, drivers and feedbacks of global greening. *Nat Rev Earth Environ* 1:14–27 https://doi.org/10.1038/s43017-019-0001-x

R Core Team (2025) *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing https://www.r-project.org/

Ren J, S Tong, G Bao, D Altantuya, X Li, H Ying, Y Bao (2026). Joint effects of hydrothermal conditions and phenological events on autumn vegetation senescence across the Mongolian Plateau. *Glob Ecol Conserv* 66:4048 https://doi.org/10.1016/j.gecco.2025.e04048

Rhif M, AB Abbes, B Martinez, RD Jong, Y Sang, IR Farah (2022). Detection of trend and seasonal changes in non-stationary remote sensing data: Case study of Tunisia vegetation dynamics. *Ecol Inform* 69:101596 https://doi.org/10.1016/j.ecoinf.2022.101596

Rouse JW, RH Haas, JA Schell, DW Deering (1974). Monitoring vegetation systems in the Great Plains with ERTS. *NASA Spec Publ* 20:309–317 https://ntrs.nasa.gov/api/citations/19740022614/downloads/19740022614.pdf

Smith JH, SV Stehman, JD Wickham, L Yang (2003). Effects of landscape characteristics on land-cover class accuracy. *Remote Sens Environ* 84:342–349 https://doi.org/10.1016/S0034-4257(02)00126-8

Tariq A, F Mumtaz (2023). Modeling spatio-temporal assessment of land use land cover of Lahore and its impact on land surface temperature using multi-spectral remote sensing data. *Environ Sci Pollut Res* 30:23908–23924 https://doi.org/10.1007/s11356-022-23928-3

Tian P, X Tian, R Geng, G Zhao, L Yang, X Mu, Y Liu (2023). Response of soil erosion to vegetation restoration and terracing on the Loess Plateau. *Catena* 227:107103 https://doi.org/10.1016/j.catena.2023.107103

Walker JE, C Angelini, AH Altieri, CW Martin, TZ Osborne (2023). Influence of climate-mediated shifts in wetland vegetation on prey fish habitat use and schooling dynamics. *Mar Ecol Progr Ser* 716:31–45 https://doi.org/10.3354/meps14364

Wen L, TJ Mason, S Ryan, JE Ling, N Saintilan, J Rodriguez (2023). Monitoring long-term vegetation condition dynamics in persistent semi-arid wetland communities using time series of Landsat data. *Sci*

*Total Environ* 905:167212 https://doi.org/10.1016/j.scitotenv.2023.167212

Xu Y, YG Lu, QY Dai, WT Huang, SC Zhou, RL Ma, YX Feng (2026). Tracking the dynamic changes in vegetation belts in China: Spatiotemporal insights into climate and human influences. *Reg Environ Change* 26:40 https://doi.org/10.1007/s10113-026-02533-x

Yuan Y, A Bao, G Jiapaer, L Jiang, PD Maeyer (2022). Phenology-based seasonal terrestrial vegetation growth response to climate variability with consideration of cumulative effect and biological carryover. *Sci Total Environ* 817:152805 https://doi.org/10.1016/j.scitotenv.2021.152805

Zeng Y, D Hao, A Huete, B Dechant, J Berry, JM Chen, M Chen (2022). Optical vegetation indices for monitoring terrestrial ecosystems globally. *Nat Rev Earth Environ* 3:477–493 https://doi.org/10.1038/s43017-022-00298-5

Zhang L, L Yang, CM Zohner, TW Crowther, M Li, F Shen, M Guo, J Qin, L Yao, C Zhou (2022). Direct and indirect impacts of urbanization on vegetation growth across the world's cities. *Sci Adv* 8:1-11 https://doi.org/10.1126/sciadv.abo0095

Zhong Q, Z Li (2024). Long-term trends of vegetation greenness under different urban development intensities in 889 global cities. *Sustain Cities Soc* 106:105406 https://doi.org/10.1016/j.scs.2024.105406