# Spatiotemporal Transformations of Leaf Area Index and Dust: Implications for Long-Term Land Degradation Assessment

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**ABSTRACT:**

In the contemporary era, where environmental crises such as climate change, desertification, vegetation cover decline, and increasing dust storms have become major challenges for nations. Long-term analysis of ecological indicators is crucial, particularly in sensitive and semi-arid regions like the Zagros forests. This research investigates the temporal and spatial variations of Leaf Area Index (LAI) and Dust Particulate Matter (DPM) over a 25-year period (2000 to 2025) in the forests of Lordegan County, Chaharmahal va Bakhtiari Province. Landsat and MODIS satellite imagery, processed using the Google Earth Engine (GEE), were used to extract and normalize data. This study leverages the integration of Landsat and MODIS data via Google Earth Engine (GEE), enabling long-term analysis of LAI and DPM even with limited field measurements. The results demonstrate that LAI values are higher in the central and northwestern regions, ranging from 0.15 to 0.78, while DPM concentrations are greatest in the northern and western areas, varying from 0.12 to 0.65. Time series analysis and statistical modeling revealed a significant inverse relationship between LAI and DPM levels ($R^2$ = 0.8134); consequently, years with weaker vegetation cover show increased concentrations of suspended particulates in the atmosphere. These findings indicate that the reduction of vegetation cover adversely affects the intensification of dust phenomena and land degradation. The results of this study can be utilized in formulating management programs to reduce forest vulnerability, combat desertification, and improve the ecological conditions of semi-arid regions.

## 1. INTRODUCTION

Global forest ecosystems face significant threats, including habitat conversion, fragmentation, and changing environmental conditions (Lambin and Meyfroidt, 2011). The longevity of trees makes them particularly vulnerable to these pressures, as they struggle to adapt to rapidly evolving environments (Lindner et al., 2010). The Zagros forests, with their long history and exposure to environmental challenges, are experiencing heightened vulnerability due to increasingly incompatible environmental changes (Abbasi and Bakhtyari, 2012).

Due to their long history and harsh environmental conditions, the Zagros forests have faced numerous stresses and disturbances, making them increasingly vulnerable to environmental changes (Raeisi, 2025). Previous research on forest vulnerability has focused on identifying factors that influence natural hazards, exacerbate them, and ultimately lead to forest degradation (Mbithi and Wisner, 1973; Kamau et al., 1989; Reardon and Matlon, 1989; Cutter, 1996; FIVIMS, 2000; FEWSNET, 2000). Indeed, assessing ecosystem vulnerability is crucial in tools available for achieving the objective of ecosystem conservation and providing effective management strategies and planning to minimise the destructive impacts arising from existing stresses (Lures et al., 2003).

Leaf Area Index (LAI) is a key metric widely used to assess forest health (Pellegrini et al., 2009; Li et al., 2013; Ellison, 2015). An increase in this index, and similar parameters, indicates a more resilient forest ecosystem, better equipped to withstand hazards and damage. It is crucial for understanding light absorption, productivity, carbon cycling, and other ecological processes (Morales, 2012; Parker, 2020). LAI measurements are essential for evaluating forest biomass, structure, and recovery from disturbances like typhoons (Chang et al., 2020). Studies have shown that forests may take years to fully recover their LAI after major disturbances, highlighting the importance of long-term monitoring (Chang et al., 2020). Satellite-derived LAI data have been used to assess global terrestrial ecosystem resilience, revealing that arid and semiarid regions generally exhibit lower resilience compared to evergreen broadleaf forests (Wu and Liang, 2020). While LAI is a fundamental characteristic of vegetation, its absolute value may not always directly drive biomass or production, and the spatial organization of leaf area within canopies can be more important than total LAI (Parker, 2020).

Our study forests in the Zagros vegetation region are continuously exposed to degradation from various hazards, including uncontrolled livestock grazing, rising air temperatures, declining annual precipitation, dust storms, and other factors. All of these contribute to the increasing vulnerability of the region's forests. The intensification of these environmental hazards has led to increased degradation and a decline in the quality of these forests, transforming them into sensitive ecosystems that require protection. The increasing trend of climatic variables and their subsequent impact on the heightened sensitivity and vulnerability of forest habitats over the long term demonstrates that, without proper monitoring and management in the coming years, these forests will be increasingly affected by climate change, as well as natural and human-caused hazards. Consequently, this will result in further

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quality degradation and the destruction of these forests (Mafi-Gholami et al., 2025). Given that the adverse consequences of these factors consistently pose serious threats to forest ecosystems, particularly the Zagros forests (Ahmadi, 2019), it is essential to prioritize planning and managing these forest ecosystems. Achieving this goal depends on adequate awareness and information about the sensitivity of these ecosystems (Paul et al., 2020).

Accordingly, this study investigates the temporal and spatial dynamics of LAI and dust particles in the forests of Lordegan County, Chaharmahal va Bakhtiari Province, Iran, over an extended period. This time series research is intended to assess land degradation. The concurrent, long-term (25-year) monitoring of LAI and dust offers a powerful approach to inform ecological understanding, climate modeling, and resource management strategies within these vulnerable semi-arid ecosystems.

## 2. RELATED WORKS

Background research in the field of forest sensitivity relates to indices that are affected by hazards. The robustness of these indices leads to a reduction in their sensitivity and vulnerability. In this context, Upgupta et al. (2015) examined the vulnerability of Western Himalayan forests to climate change. Following the methodology presented by Sharma et al. (2015), indicators such as canopy cover, among others, were considered as criteria for the sensitivity of these forests to climate change.

The monitoring of dust particles using remote sensing and geographic information systems in Khuzestan Province was conducted (Tagha et al., 2013); this research utilized the NDDI index and a thermal threshold of 290 Kelvin in band 32 for reconstruction. Subsequently, by combining the brightness temperature difference of dust in bands 32-31-29 (wavelengths 12-11-8.5 micrometers) measured by MODIS with negative brightness temperature differences between bands 31 and 32, images were obtained that clearly showed dust concentration, yielding better results compared to visible wavelengths.

Research conducted by Bayat et al. (2016) examined the impact of dust particles on vegetation cover changes. This study demonstrated that dust particles have an inverse relationship with vegetation cover reduction. With the increase in dust storms after 2002, the annual total concentration of dust particles has a high coefficient of determination (0.85) with the NDVI index.

Luvall et al. (2011) utilized MODIS satellite imagery and an atmospheric dust transport model to evaluate the phenology and dispersion of Juniperus sp. pollen to make necessary predictions for preventing damage to tree health caused by pollen dispersion. Further to these studies, in 2014, Prachi and Pravin employed the NDVI and MNDVI indices derived from MODIS sensor multispectral images to detect and monitor two dust storms. They stated that selecting an appropriate algorithm to achieve this objective depends on ground conditions, density of dust columns, presence of clouds in satellite imagery, geographical location, and image acquisition time.

Research conducted by Mansourmoghaddam et al. (2022) performed monitoring and temporal-spatial prediction of suspended dust in the atmosphere using Google Earth Engine (GEE). The results indicated a negative correlation between rainfall, relative humidity, and vegetation cover and a positive correlation between wind speed, number of frost days, temperature, heat island variations, and sunshine hours with AOD values.

More recently, Haque et al. (2022) employed Google Earth Engine (GEE) and satellite imagery to analyze the spatio-temporal dynamics of air pollutants and AOD levels over Bangladesh. Their results confirmed the effectiveness of GEE for monitoring atmospheric aerosols and their relationship with climatic and anthropogenic factors, supporting the relevance of multi-temporal satellite-based analyses in environmental studies such as the present research.

Ghafarian et al. (2023) further explored satellite-based dust monitoring by integrating MODIS and Sentinel-5 imagery in Khuzestan Province using Google Earth Engine (GEE). The study identified high AOD areas in urban and industrial regions and showed a strong correlation between the two sensors, demonstrating that long-term dust monitoring is effective even when ground measurements are limited.

Sur et al. (2025) employed Google Earth Engine integrated with Sentinel-2A imagery to estimate LAI across different phenological stages of wheat in arid regions of India. Their findings confirmed the capability of GEE to accurately derive LAI values through multi-temporal satellite data, supporting its effectiveness for vegetation monitoring.

More recently, Abdelrahman et al. (2025) integrated Google Earth Engine (GEE) with remote sensing and GIS data to analyze the spatio-temporal variations of atmospheric pollutants. Their study, although based on Sentinel-5P data, supports the effectiveness of multi-sensor satellite observations for long-term environmental monitoring similar to the MODIS-based approach used in this research.

Unlike some studies that employed Sentinel-5P (Abdelrahman et al., 2025), this research uses MODIS data for long-term LAI and dust monitoring due to its continuous availability since 2000, suitable spatial resolution, and validated accuracy for aerosol optical depth retrieval. Integration of Landsat and MODIS data via GEE enabled seamless 25-year analysis, overcoming limitations of conventional single-sensor approaches and missing field data.

## 3. MATERIALS AND METHODS

### 3.1 Profile of the study area

The research area focuses on the forest habitats of Chaharmahal va Bakhtiari Province, specifically within Lordegan County. Lordegan County covers 2,359 square kilometers and is located between 31°9’ and 31°44’ North latitude and 50°16’ and 51°20’ East longitude (Statistical Yearbook, 2019). The forests of Lordegan encompass approximately 130,000 hectares (specifically 127,305 hectares), constituting 46% of the county’s total area (Figure 1). Persian oak (Quercus brantii) is the dominant tree species in these forests (Yaghmaei et al., 2009).

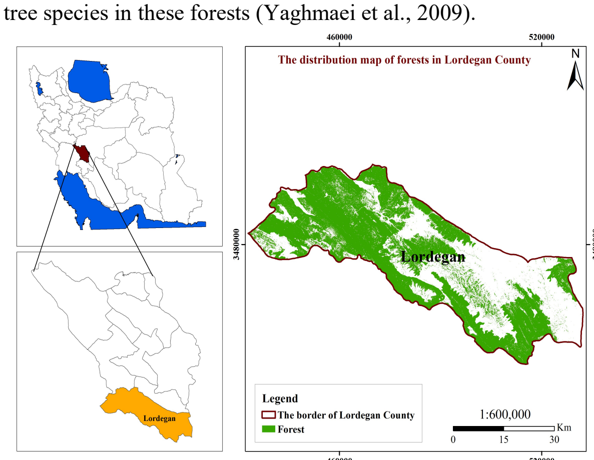


**Figure 1**. Study area.


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### 3.2 Examining Leaf Area Index (LAI) Changes

To conduct this assessment in the Zagros forests of Lordegan County, Chaharmahal va Bakhtiari Province, we used the corrected Collection 2 imagery series from Landsat 7, 8, and 9 satellites, employing the ETM+/OLI/OLI-2 sensors (Gorelick et al., 2017). This dataset covers a 25-year period, from 2000 to 2025 (Table 1). The imagery available within GEE platform requires no pre-processing or initial corrections (geometric, radiometric, etc.) as it is provided ready for analysis. Given the time-consuming nature of data processing in conventional systems, we utilized the GEE cloud computing platform. GEE offers access to the complete Landsat archive, along with numerous transparent datasets from NASA (Irons et al., 2012), the European Space Agency (ESA), and other sources. Its ability to access various types of Landsat imagery (1 to 9) at different processing levels makes GEE a novel and rapid approach to forest assessment that can be effectively implemented.

| Satellite Specifications | Date | Row /Pass |
|---|---|---|
| Landsat 7 ($ETM^+$) | 1999- Present | 164/38 |
| Landsat 8 (OLI) | 2013- Present | 164/38 |
| Landsat 9 (OLI-2) | 2021- Present | 164/38 |

**Table 1**. Specifications of the Utilised Landsat Satellites.

Within the GEE platform, we calculated Leaf Area Index (LAI) – a significant indicator of forest health (Jonkheere et al., 2004; Matsushita et al., 2007) – for all years with acceptable summer imagery.
After calculating LAI for the 25-year period, we normalized the values (ranging from 0 to 1) within GEE to enable direct comparison and analysis alongside fluctuations in dust and fine particulate matter (Equation 1).

$$Xnormal = \frac{X - X\min}{X\max - X\min} \quad (1)$$

where x = Original data value
$x_{min}$ = Minimum value in the dataset
$x_{max}$ = Maximum value in the dataset
$x_{normal}$ = Normalised value between 0 and 1

A notable innovation in this study is the integration of Landsat (7, 8, 9) and MODIS satellite imagery within the Google Earth Engine (GEE) platform to calculate LAI and DPM over a 25-year period. Unlike traditional approaches that rely on single-sensor datasets or require extensive pre-processing, our method allows for the seamless extraction, normalization, and temporal-spatial analysis of large-scale ecological data. This approach enhances temporal resolution, reduces processing time, and enables direct comparison of LAI and DPM trends across multiple years and sensors, providing more accurate and consistent long-term assessments of vegetation dynamics and dust particulate matter. It is particularly useful for periods with missing field data or when access to ground-based measurements is limited, ensuring continuity and reliability of long-term monitoring.

### 3.3 Examining Dust and Fine Particulate Matter Changes

Atmospheric dust is a significant environmental concern, primarily due to its impact on climate. By influencing the absorption and scattering of solar radiation, dust can alter both incoming shortwave radiation and outgoing longwave radiation, leading to either warming or cooling effects (Afifi, 2016). Beyond climate impacts, dust can also reduce moisture reserves (Rasooli et al., 2010), trigger outbreaks of pests and diseases (Yousfi et al., 2018), decrease chlorophyll content in vegetation (George and Ilias, 2007), cause leaf shedding and tissue death, diminish photosynthetic activity and overall production, and alter leaf pigmentation, among other detrimental effects (Salehi et al., 2018).

To assess dust and fine particulate matter conditions in the Zagros forests of Lordegan County, Chaharmahal va Bakhtiari Province, we utilized the MCD19A2 Version 6 product derived from the MODIS sensor aboard the Terra satellite (Lyapustin, 2022). Specifically, we used the normalized Aerosol Optical Depth (AOD) product (Ackerman et al., 2004) via the GEE web-based platform. Daily AOD images were retrieved through GEE, aggregated into monthly averages, and then further averaged annually for the 25-year period from 2000 to 2025. These annual AOD values were then normalized (0 to 1) to allow for direct comparison with the LAI data (Equation 1).

The accuracy and precision of MODIS AOD imagery for dust monitoring have been validated by previous research and air quality control stations in the study area (Mansourmoghaddam et al., 2022). AOD is a dimensionless index, and when normalized, ranges from 0 to 1; values between 0.1 and 0.5 indicate relatively clear air, while higher values suggest dusty conditions (Ackerman et al., 2004).

AOD reflects the distribution of dust aerosols in the atmosphere and the size of suspended particles within an atmospheric column (Ackerman et al., 2004; Chu et al., 2002; Van Donkelaaret al., 2006), which is primarily influenced by surface emission sources (Hu, 2009). Given that the AOD values indicate the presence of suspended particles in the atmosphere (regardless of their origin or trajectory), we use the term “atmospheric suspended particles” in this study. By monitoring dust spatially and temporally, we can predict trend changes and facilitate optimal decision-making before critical thresholds are reached (Mansourmoghaddam et al., 2022).

## 4. RESULTS

Figure 2 Normalised map of average changes in LAI over 25 years (2000-2025). According to Figure 2, the central and northwestern parts exhibit higher LAI compared to other areas.

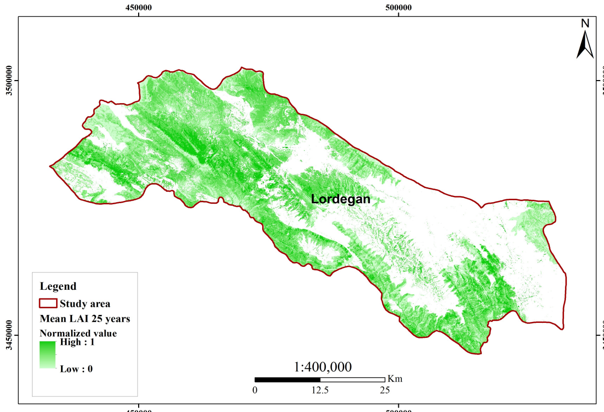


**Figure 2**. The map of average changes in LAI.

Figure 3 the normalized map of average dust and particulate matter levels over 25 years (2000-2025).

Based on Figure 3, the northern, western, and northwestern regions exhibit higher dust and particulate matter concentrations compared to other areas.

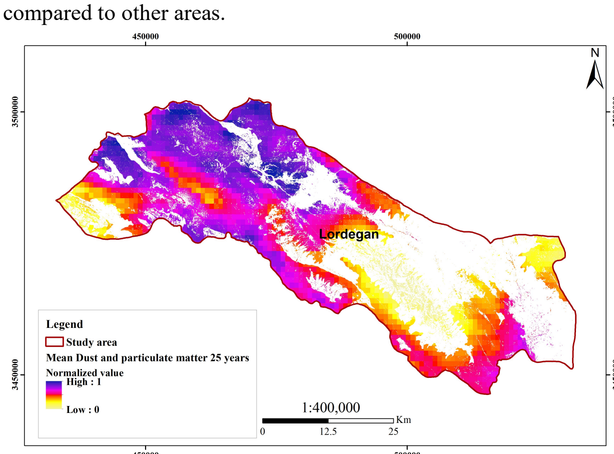


**Figure 3**. The map of average changes in dust and particulate matter.

The normalised chart of changes in LAI and dust and particulate matter (Figure 4) demonstrates a decrease in LAI and an increase in dust and particulate matter over 25 years.

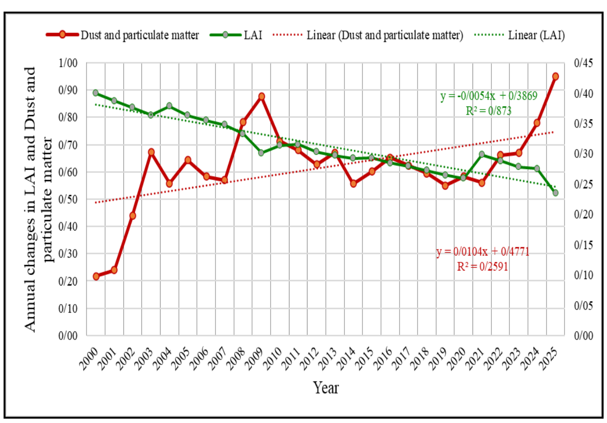


**Figure 4**. The normalised Annual changes of LAI, dust, and particulate matter

Regression modeling revealed that a cubic equation (third-degree polynomial) provided the best fit for the time series data of both LAI and dust/particulate matter, with $R^2$ values of 0.9229 and 0.8134, respectively. This indicates that the temporal trends of both vegetation cover and atmospheric dust are non-linear over the study period (Table 2).

| Dependent variable | LAI | Dust and particulate matter |
|---|---|---|
| Independent variable | Time | Time |
| Linear equation<br>$R^2$ | y = -0/0054x + 0/3869<br>$R^2$ = 0/873 | y = 0/0104x + 0/4771<br>$R^2$ = 0/2591 |
| Cubic equation<br><br>$R^2$ | y = -1E-06$x^3$ + 0/0003$x^2$ - 0/0113x + 0/413<br>$R^2$ = 0/9229 | y = 0/0003$x^3$ - 0/014$x^2$ + 0/1767x + 0/0211<br>$R^2$ = 0/8134 |
| Logarithmic equation<br>$R^2$ | y = -0/05ln(x) + 0/4303<br>$R^2$ = 0/8716 | y = 0/1236ln(x) + 0/3262<br>$R^2$ = 0/4397 |

**Table 2**. Coefficients of determination for LAI and dust and particulate matter.

Analysis of dust and particulate matter peaks and LAI valleys across the 25-year time series reveals an inverse relationship between LAI and atmospheric dust levels (Figure 5). Declines in vegetation cover, as indicated by LAI, are generally associated with increases in airborne dust and particulate matter concentrations, a pattern likely driven by a combination of environmental and human-induced factors. Notably, dust and particulate matter peaked in 2002, 2004, 2012, 2015, 2021, 2024, and 2025, coinciding with troughs in the LAI index.

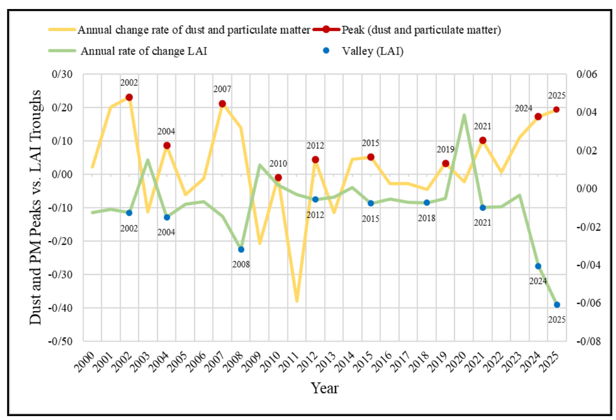


**Figure 5**. Peak dust, particulate matter, and valley points of the LAI index in a 25-year time series.

## 5. CONCLUSIONS AND DISCUSSION

Forests across the globe are subject to various threats (Ryan et al., 2008; Ojoyi et al., 2016), and forest sustainability is threatened by a complex set of interacting factors (Lambin and Meyfroidt, 2011). Investigating factors related to vulnerability in forest habitats is considered highly important (Pellegrini et al., 2009; Ellison, 2015; Wang et al., 2024). One of the key aspects of assessing forest vulnerability is identifying and mapping effective hazards (Buckle et al., 2001; Carina and Keskitalo, 2008), such as dust and particulate matter, that impact these ecosystems.

The results showed that forest habitats in central and northwestern regions have higher LAI values than other areas. Considering that LAI is one of the main indicators of forest health, higher LAI values in certain areas suggest a lower vulnerability in those regions.

The analysis of peak points of dust and particulate matter and valley points of LAI in a 25-year time series reveals an inverse relationship between the two variables, which is consistent with the findings of Luvall et al. (2011) and Bayat et al. (2016). LAI ranged from 0.15 to 0.78, with higher values in the central and northwestern regions, whereas DPM concentrations varied from 0.12 to 0.65, with the highest levels observed in the northern and western areas. Time series analysis indicated a significant inverse correlation between LAI and DPM ($R^2$ = 0.8134), suggesting that reductions in vegetation cover are associated with increased atmospheric particulate matter. Since the center of dust originates from the western part of the country, particularly along the border with Iraq, the northern, western, and northwestern regions closer to Khuzestan Province experience more dust and particulate matter than other parts. This can significantly affect the forests in this area, especially when combined with other environmental hazards such as drought.

Various studies have indicated that one cause of the decline in the Zagros forest ecosystems is the influence of a combination of abiotic factors, including particulate matter and dust (Attarod et al., 2016). The 25-year temporal analysis shows that in certain years, there is a significant synchrony between a sharp increase in dust and particulate matter (peaks) and a sharp decrease in LAI (valleys). This synchrony may indicate environmental pressure on vegetation and the onset of land degradation processes.

Specifically, dust peaks and LAI valleys were recorded simultaneously in 2002, 2004, 2012, 2015, 2021, 2024, and 2025. This coincidence may be due to various factors such as drought, land-use changes (Shahkooeei and Rahmani, 2019), or human-induced pressures (e.g., overgrazing), which lead to vegetation loss and increased airborne particulate matter.

Furthermore, isolated dust and particulate peaks were observed in 2007, 2010, and 2019, which may reflect periods of intensified erosion or dust storms, although LAI did not decrease simultaneously in these years. Also, in 2008 and 2018, LAI valleys occurred without concurrent dust and particulate peaks. This may indicate specific climatic conditions or biological stressors (such as pests or plant diseases) that led to vegetation decline without a marked increase in dust and particulates.

The relationship between LAI and dust/particulate matter is bidirectional and complex. A decrease in LAI due to deforestation, overgrazing, or drought can reduce the natural resistance of land to wind erosion, resulting in greater and more widespread dust and particulate emissions. On the other hand, an increase in dust and particulates can further reduce LAI. If this vicious cycle is not identified and managed promptly, it may lead to irreversible ecosystem degradation.

The simultaneous analysis of these two indicators over 25 years demonstrates where vegetation cover has declined, where dust sources have expanded, and which trends may intensify. Such knowledge enables forest and natural resource experts to identify critical dust hotspots, evaluate the effectiveness of vegetation restoration projects, provide evidence-based informa-tion for designing anti-desertification programs, and, ultimately, develop climate adaptation strategies through predictive modeling.

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