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Spatiotemporal Assessment of Deforestation Effects on Aerosol Optical Characteristics and Climate Variability over the Mau Forest Complex Based on MERRA-2 Reanalysis

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Abstract

The deforestation has far-reaching effects on aerosol characteristics and climatic variables. Deforestation disrupts the local climate by altering temperature, aerosol optical properties, and impacting air quality. Further, it also modifies precipitation patterns at varied scales. Nevertheless, the long-term impacts of deforestation on climate variables and aerosol properties over Mau remain not very well explored, especially considering the context of altered natural emissions and anthropogenic sources. This study bridges this gap through an in-depth analysis of deforestation impacts on aerosol characteristics and climate variables over the Mau Forest complex bounded by (0.2S, 35.2E) and (0.8S, 35.8E) using satellite and model-derived data from 2001 to 2024. The findings of the present study reveal that Aerosol optical depth (<0.2) and Ångström exponent (>1) are predominantly attributed to deforestation and climate change. The Correlation analysis found that surface temperature has a strong negative correlation with Aerosol Optical Depth (AOD), with a coefficient of <−0.3, and is influenced by deforestation activities such as land clearing, agricultural activities, and dust storms. In addition, precipitation identified a moderate positive correlation with AOD, with values ranging from 0.1 to 0.4, attributed to factors such as the complex interplay of aerosol types, size distribution, and dust and atmospheric dynamics like strong winds, which can transport aerosols over long distances, and the presence of moist air masses. Besides aerosol optical depth (AOD), Ångström Exponent (AE), precipitation, and temperature are interconnected, influencing each other through complex atmospheric processes. Increased precipitation led to reduced AOD due to wet scavenging of aerosols. On the other hand, temperature affects aerosol formation and distribution. Changes in AOD, in turn, can impact precipitation patterns and temperature through radiative forcing. In short, the investigation indicates that aerosols' optical properties over the Mau Forest complex exhibit distinct spatial and temporal patterns driven by both human and natural processes. The statistically significant correlations with meteorological parameters such as precipitation and temperature prove the modulating role of aerosol optical properties in regional climate processes. The policymakers must therefore prioritize emission control actions targeted at biomass burning, and scientists must keep investigating high-resolution aerosol optical properties-climate interactions using integrated ground and satellite observations to advance climate impact assessment over the Mau Forest complex in Kenya.

Subject Areas

Environmental Sciences

Keywords

AOD, AE, SAT, Precipitation and Correlation

1. Introduction

Mau forest complex is the largest drainage basin in Kenya. It is snuggled in the heart of Kenya and stands as one of the most vital ecological treasures in East Africa (EA). It is the largest water tower [1] and is the source of twelve rivers which drain into Lake Baringo, Lake Nakuru, Lake Turkana, Lake Natron, and Lake Victoria [2] [3]. These rivers that originate from Mau flow through some of Kenya's most important agricultural and wildlife regions, providing water for farming, power generation, and even the famous Maasai Mara ecosystem. However, anthropogenic activities have led to deforestation and the destruction of wetlands in the fertile upstream [4]. According to [5] [6], the study defines deforestation as the conversion of forest to other land use, independently of whether human-induced or not. This has therefore greatly affected the Mau Forest complex.

Forests are vital to life on earth, providing environmental roles like regulating climate by absorbing carbon dioxide, air and water purification, supporting the global water cycle, and soil protection, but as a reality, deforestation disrupts these natural processes. Deforestation has greatly impacted the climate at local, regional, and global scales, as highlighted by [7] releases stored carbon, reduces carbon absorption, disrupts water cycles and weather patterns, contributes to greenhouse gas emissions, and causes a double hit [8]. Aerosols, tiny solid particles or liquid droplets suspended in the atmosphere, are critical to understanding the earth's climate, air quality, and public health [9]. These particles originate from natural sources like biological material and desert dust storms[10]and human activities such as fossil combustion, agricultural practices, deforestation, and industrial emissions [11]. As a matter of fact, deforestation poses a global challenge to humanity, due to its vast contribution towards emissions of aerosols and greenhouse gases (GHGs) into the atmosphere and the effects on the hydrological cycle. The rising concentration of CO_2 in the atmosphere significantly contributes to climate change by absorbing and emitting energy, which leads to warming effects [12]-[18]. Also, increase atmospheric aerosols through activities such as burning, logging, and soil disturbance, and the specific contributions of these processes in the Mau Forest [18]. Further, an increase in deforestation increases the surface temperature, leading to increased evaporation and reduced evapotranspiration [19]-[21]. Aerosols have impacted the earth's climate directly by scattering and absorbing the incoming radiation from the Sun [12] [13]. Also, they affect the climate indirectly by changing the microphysical properties of clouds [22]. They change the size and density of cloud droplets, thereby modifying the cloud albedo, cloud formation, and the probability of having precipitation [23]-[25].

Keeping the aforementioned effects in mind, the research study assessed the influence of deforestation on aerosol properties and climate variables over the Mau Forest complex through quantifying the impact of deforestation on local climate parameters, including trends in temperature and precipitation, and analyzed the trends in aerosol properties (AE and AOD) and their interrelationship through spatiotemporal analysis.

2. Material and Methods

2.1. Study Area

The study area is bounded by four counties: Bomet, Narok, Nakuru, and Kericho on latitudes 0.25˚S - 0.67˚S and 1.55˚S and longitudes 35.67˚E - 36.17˚E, and the largest closed-canopy montane ecosystem in E. A [18]. Further, it has an approximate area of 400,000 hectares (about 1544 square miles). The research was carried out in the Mau Forest complex, Kenya, as shown in **Figure 1**, and was purposely selected because of its significant role as the largest mountainous forest in East Africa and also the largest water drainage in Kenya. The climate of the Mau Forest complex is generally tropical, though the elevation of the sites consists of two topographic zones: lowlands and mountainous upland, with the altitude of the zones varying between 1800 and 3000m above sea level (ASL), which influences the rainfall patterns [26]. The temperature ranges between (15 - 27) degrees Celsius, and annual precipitation is between 0.01 - 0.09 $kg \cdot m^{-2} \cdot s^{-1}$ [18].

2.2. Instruments

MERRA-2

The Modern-Era Retrospective analysis for Research and Applications, version 2 (MERRA-2) is a reanalysis dataset produced by NASA that provides a comprehensive record of Earth's atmospheric conditions from 1980 to the present. It combines a modern data assimilation system with satellite and conventional observations (upper air, aircraft, and surface) to create a consistent dataset of atmospheric variables [13] [18]. MERRA-2 is a global reanalysis dataset that includes the

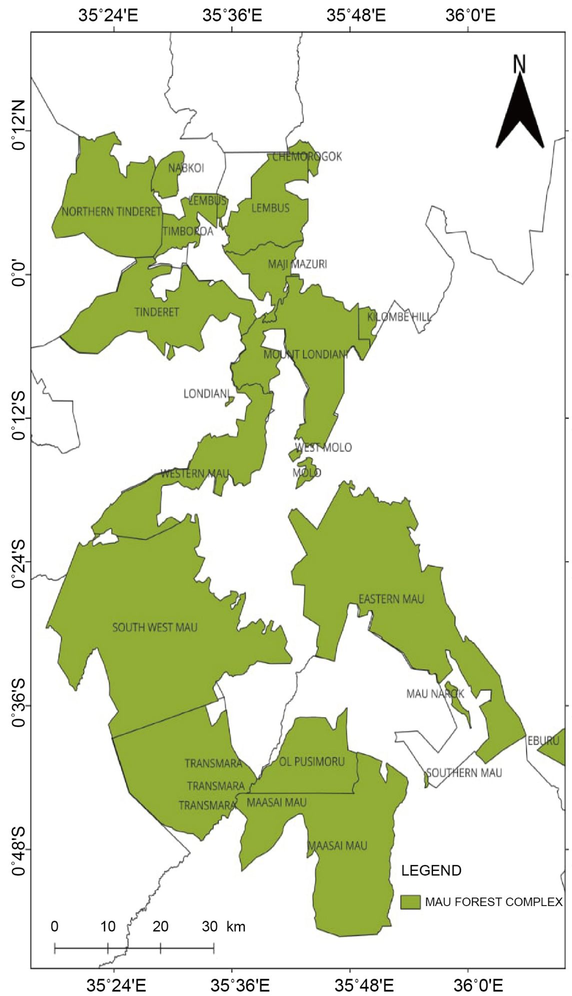

Figure 1. The domain map of Mau Forest complex, Kenya.

assimilation of space-based aerosol observations, making it the first long-term reanalysis to couple aerosols with other climate variables. It simulates dust, sea salt, sulfate, black carbon, and organic carbon aerosols using the GOCART model and provides data on their optical properties (like AOD at 550 nm) and interactions with the climate system, which is crucial for studying their effects on radiation and circulation. This data is used for research, including developing climate indicators and evaluating the impact of aerosols on regions around the world. MERRA-2 has been extensively evaluated against independent observations from sources like AERONET, ground stations, and aircraft, with studies using methods like RMSE, MAE, and correlation to assess data quality [27]. Moreover, MERRA2 has its limitations; it has a single pixel average data across diverse land covers. Because the Mau forest is heavily fragmented by agricultural land and settlements, the coarse resolution of these distinct categories leads to inaccurate surface flux estimates and, lastly, a lack of spectral detail.

MERRA-2 is based on the version of the Goddard Earth Observing System, Version 5 (GEOS-5) atmospheric data from 2000 to 2024 at a spatial resolution of

$0.5^\circ \times 0.625^\circ$ with 72 layers and spanning the satellite era from 1980 to date [28] [29]. The Platform incorporates data from a wide range of sources, including weather stations, satellites, and other observational platforms, to produce a high-resolution, global dataset of atmospheric and surface conditions. In the present study, NMM2IMNXGAS_5.12.4.AODANA for monthly time-averaged data of Aerosol Optical Depth (AOD) and MERRA-2 M2TMNXAER_5_12_TOTANG-STR monthly time-averaged data for Ångström Exponent (AE) at spatial $0.5^\circ \times 0.625^\circ$ from 2001 January to 2024 December were obtained for monthly and temporal trends analysis, MERRA-2 M2TMNXLND_5_12_4_TSURF for monthly time-averaged data for surface temperature and MERRA-2 M2TMNXFLX_5_12_4_PRECTOT monthly time averaged data for Total Surface Precipitation at spatial resolution of $0.5^\circ \times 0.625^\circ$ from 2001 to 2024 were retrieved for correlation analysis. These data products were sourced from http://Giovanni.gsfc.nasa.gov/Giovanni/ for better performance over the Mau Forest complex.

2.3. Data Analysis

2.3.1. Trends Analysis

Several statistical approaches exist to quantify trends in the time series of a geophysical variable. In the present work, linear regression analysis was used to estimate monthly trends in AOD and AE alongside climate variables. This method has the advantage of evaluating the direction and magnitude of variations in long-term data [30]-[34], and was therefore considered suitable for executing pixel-wise analysis.

In this regard, the linear regression model used is given in Equation (1):

$$Y_t = aX_t + b + N_t, \quad t = 1, \cdots, T \tag{1}$$

where Y_t is the geophysical variable for which the trend is being determined, b is the offset (y-intercept), which represents the value of Y_t at the beginning of the time series. X_t is the independent variable representing time series ($X_t = \frac{t}{12}$, where t is the individual month in the time series), a is the trend estimate of the geophysical variable under consideration, while N_t is the noise in the time series.

2.3.2. Correlation Analysis

The Pearson correlation coefficient is a statistical measure that quantifies the strength and direction of a linear relationship between two variables. Pearson correlation coefficient (R_{xy}) between 0 and 1 is positive correlation, between 0 and −1 is negative correlation, and 0 means no correlation [35]. The correlation analysis between AOD, AE, and climatic variables is therefore calculated using Equation (2):

$$R_{xy} = \frac{\sum_{i=1}^{n}\left(x_i - \bar{x}\right)\left(y_i - \bar{y}\right)}{\sqrt{\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2}\sqrt{\sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2}} \tag{2}$$

where R_{xy} is the Pearson correlation coefficient between variable x and variable y, with a value between −1 and 1, n is the sample size, x_i is the value of NDVI or

AOD in the i-th month, and y_i is the mean monthly climate variable in the ith month, while $\bar{x}$ and $\bar{y}$ are the means of the two variables.

3. Results and Discussion

3.1. Spatial Variation of Temperature and Precipitation

The average spatial temperature obtained from MERRA-2 reanalysis for the period of 2001-2024 over the Mau forests complex reveals a predominantly high temperature. The surface temperature was given in degrees Celsius over the entire study. The spatial mean of temperature ranges between 15 and 32 degrees Celsius, identifying high temperature, influenced by deforestation [36], for example, anthropogenic activities, which released significant amounts of aerosol particles into the atmosphere, hence affecting the climate indirectly, for example, meteorological parameters such as temperature inversions accompanied by reduced precipitation [23]. The increase in CO_2 amplifies the greenhouse effect, wherein heat is trapped in the Earth's atmosphere, causing a rise in global temperatures [37] [38].

3.2. Spatial Variation in Precipitation

Spatial variation in precipitation over the Mau Forest complex for the period of 24 years (2001-2024) is illustrated in **Figure 2**, data obtained from MERRA 2 reanalysis. The total precipitation was given by $kg \cdot m^{-2} \cdot s^{-1}$. The spatial patterns of monthly mean shows distinct varying precipitation patterns, characterized by low and moderate ranging from precipitation 0.01 - 0.09 $kg \cdot m^{-2} \cdot s^{-1}$ is attributed by i) deforestation [39] for example anthropogenic activities, this released significant amounts of aerosols particles into the atmosphere hence affect the climate indirectly for example meteorological parameters such as temperature inversions accompanied by reduced precipitation [23] [40], ii) human activities like overgrazing, which degrade vegetation cover, also affect precipitation patterns, iii)altitude and topography, higher attitude areas receive more rainfall due to orographic conversely, leeward sides of mountains or with low elevation experience low rainfall and soil moisture, amount of moisture in the soil plays role in precipitation.

3.3. Spatial Variation of Aerosol Optical Depth and Ångström Exponent

3.3.1. Spatial Variation of Aerosol Optical Depth (AOD)

The average spatial distribution of AOD over the Mau Forest complex in Kenya during the period (2001-2024) is illustrated in **Figure 2** for data obtained from MERRA 2 reanalysis, which represents a general pattern of high, moderate, and low AOD, indicating distinct features of aerosol loading over different sites, mainly the Mau Forest complex. Moderate values ranging from 0.1 to 0.2 was recorded in Mau Forest and low value of <0.1 was observed again This is attributed by the following activities: i) climate change occasioned by meteorological parameters such as temperature inversions accompanied by reduced precipitation [41] which are favorable conditions for increased aerosol emissions leading to the enhanced AOD; ii)deforestation for example anthropogenic activities and human activities hence released significant amounts of aerosols particles into the atmosphere [18] [42].

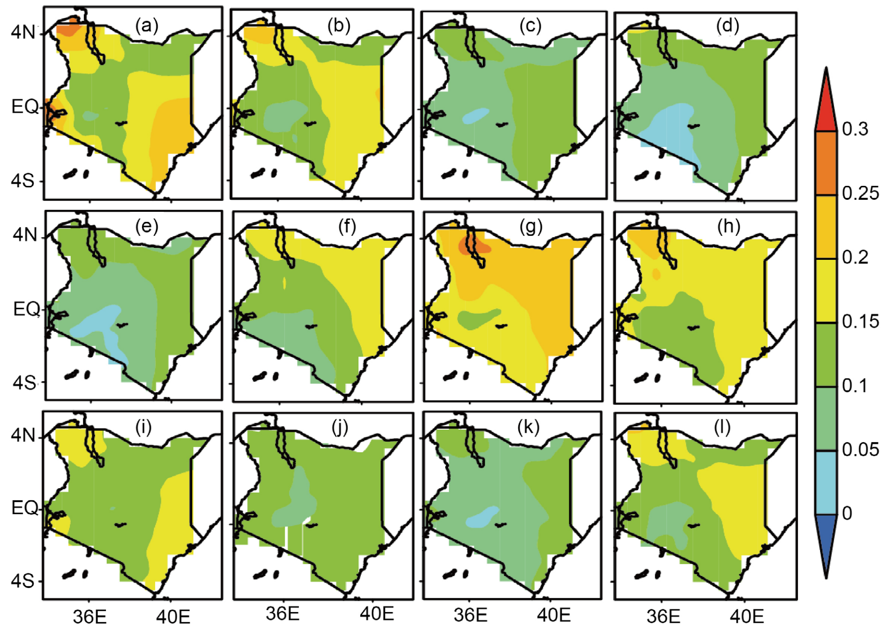

Figure 2. Annual spatial variation of Aerosol Optical Depth (AOD) during the 2001 -2024 period.

3.3.2. Spatial Variation of Ångström Exponent (AE)

The annual spatial distribution of Ångström exponent over Mau Forest complex between 2001Junaury -2024 December is illustrated in **Figure 3** for data obtained from MERRA 2 reanalysis, the values of AE470-870 were observed to vary between 0.5 and 1.3 with high values (AE470-870 > 1) dominating in the study region (Mau Forest complex) Kenya is generally linked to the dominance of fine-mode aerosol particles and is attributed by gas-to-particle conversation(certain atmospheric chemical reactions can convert gaseous pollutants in to fine aerosols particles, increased anthropogenic activities and biomass [43] [44].

Moderate values were observed in the Mau Forest complex, with values of 0.7 - 0.9 being significantly associated with a mix of fine and coarse particles, or a stronger presence of coarse particles. This is influenced by the following factors: i) the impact of wind patterns, wind transports dust from other areas, for example, monsoon winds carry dust from Arabian Peninsula to Kenya coast [32], ii) dust and soil erosion, example is agricultural land, and activities like tillage and deforestation lead to dust emission and soil erosion, contributing to coarse aerosols, iii) coagulation and aerosol aging, and lastly seasonal variations.

3.4. Temporal Variation of Surface Temperature and Precipitation

Trends show the rate of change in temperature over time either positively or

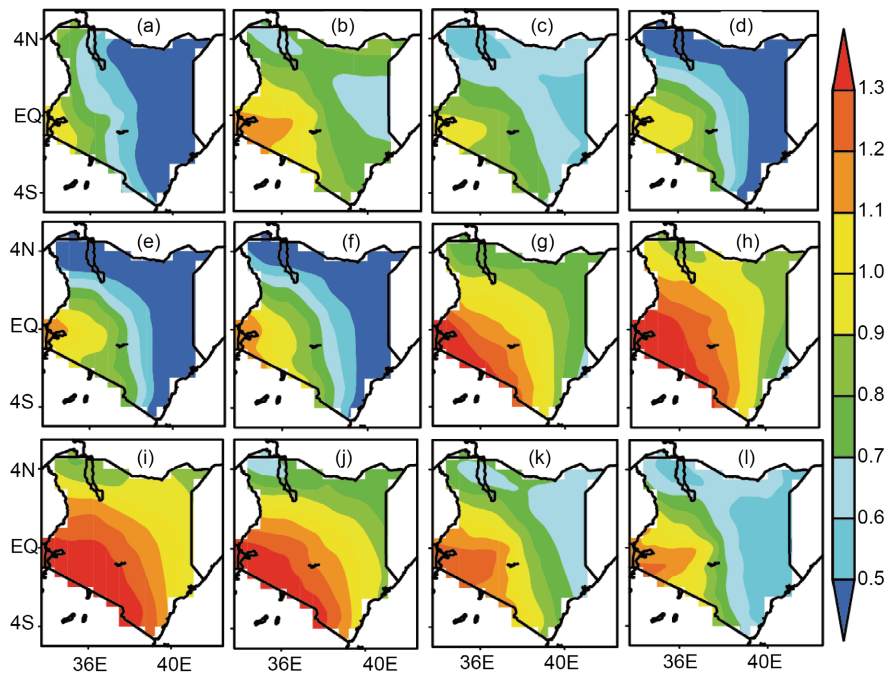

Figure 3. Annual spatial variation of Ångström Exponent (A.E) over Mau Forest complex during 2001-2024 period.

negatively. The temporal trends of surface temperature over Mau Forest complex from Jan 2001 to 2024 Dec using the MERRA 2model measurements reveal a predominantly increasing trend across most months of the year, suggesting a long-term rise in temperature. In general, Mau Forest exhibits positive trends in temperature throughout the year except in the months of April and May. The highest positive trends are observed during the months of August to November, with trends values (0. 0173 ± 0.0089), (0. 0154 ± 0.0103), (0. 0244 ± 0.0109), (0. 0219 ± 0.0131) year^{-1} consecutively indicating significantly warming trend, with a noticeable shift in annual average temperature over the past few decades, warming is linked to factors like deforestation driven by logging and agricultural expansion and climate change including increased temperature and altered precipitation.

Moderate positive trends are perceived during the months of February (0. 02194 ± 0.0131), march (0. 0058 ± 0.0160), June (0. 0086 ± 0.0117), July (0. 0092 ± 0.0109) and December (0. 00923 ± 0.0130) as shown on Table 1 While the month of January also show positive but comparatively very low trend, with trend value (0. 0003 ± 0.0113) is significantly influenced by land use changes and deforestation, highlights the complex interplay between climate change and human activities. Research done by [45] links forest cover loss to warmer and drier local temperatures.

Conversely, April and May are the only months with negative temporal trends, suggesting a slight long-term decline in surface temperature, influenced by the following factors: increased rate of precipitation and wet scavenging effects, enhanced cooling effects.

Table 1. Surface temperature over Kenya.

Months	Mean SAT (˚C)	Trend ($Year^{-1}$)	Pearson (r^2)
January	25.01 ± 0.0502	0.0003 ± 0.0113	0.0052
February	25.81 ± 0.1597	0.0059 ± 0.0093	0.0043
March	25.96 ± 0.2120	0.0058 ± 0.0160	0.0752
April	24.77 ± 0.5355	−0.0009 ± 0.0178	−0.0102
May	23.82 ± 0.0779	−0.0067 ± 0.0101	−0.1380
June	22.90 ± 0.3887	0.0086 ± 0.0117	0.1519
July	22.36 ± 0.5996	0.0092 ± 0.0109	0.1732
August	22.75 ± 0.6817	0.01728 ± 0.0089	0.3738
September	23.79 ± 0.8669	0.01541 ± 0.0103	0.2986
October	24.39 ± 1.0869	0.02444 ± 0.0109	0.4221
November	24.23 ± 0.5787	0.02194 ± 0.0131	0.3303
December	24.53 ± 0.3094	0.00923 ± 0.0130	0.1466

The temporal trends of precipitation over the Mau Forest complex recorded either positive or negative over the period of 24 years. A strong positive trend is observed of value 0.1 on **Figure 4**, significantly impacted by deforestation activities, increasing emissions of aerosol concentration in the atmosphere, affecting Microphysical properties of clouds by acting as cloud condensation nuclei (CCN) that aid in the formation of clouds. Furthermore, recent studies indicate a complex trend in precipitation, with some areas experiencing increases in precipitation during certain seasons while others show decreases.

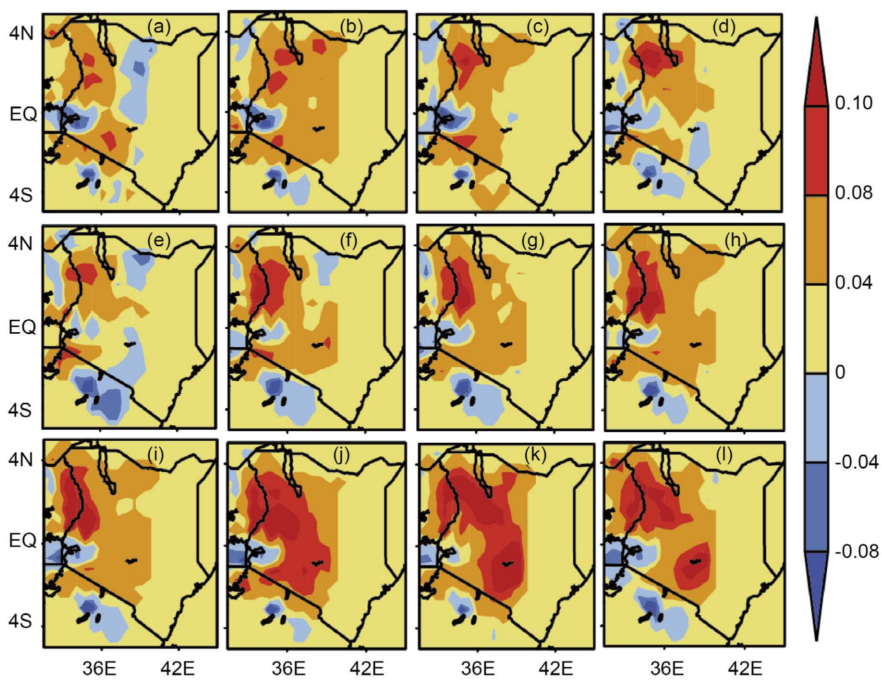

Figure 4. Temporal analysis of total precipitation over the Mau Forest complex in Kenya.

On the other hand, negative trends are recorded of value −0.04 over Mau forests complex in Kenya, suggesting a slight long-term decline in total precipitation. However, the negative trend indicates a decrease in precipitation over time. This decline is linked to deforestation, the removal of forest cover, which reduces the forest's ability to retain moisture and influence local rainfall patterns. Alongside the rainfall decline, there is a constant increase in temperature, further exacerbating the impact of reduced rainfall.

3.5. Correlation between Aerosol Optical Properties and Climate Variables

3.5.1. Correlation between AE and Precipitation

The relationship between the Ångström exponent and precipitation is complex and multifaceted. While a higher Ångström exponent suggests an increase in CCN and potentially more cloud droplets, the ultimate impact on precipitation efficiency and overall precipitation patterns depends on various factors, including aerosol type and climate change. Furthermore, correlation is influenced by factors like monsoon precipitation, which leads to wet scavenging of aerosols in the atmosphere, resulting in high AE. As a matter of fact, precipitation acts as a natural cleansing agent, washing aerosols from the atmosphere. Pearson's correlation coefficients for Ångström exponent against total surface precipitation range between 0 and 0.2. This means that there is a very weak or non-existent positive linear relationship.

The positive correlation coefficients indicate a very weak positive relationship between AE and precipitation, as shown in Figure 5, which is attributed to factors such as the complex interplay of aerosol types, size distribution, dust, and atmospheric dynamics like strong winds that can transport aerosols over long distances, and the presence of moist air masses [38]. Additionally, a positive correlation is observed, especially in the region, which underscores the importance of considering specific precipitation and atmospheric processes.

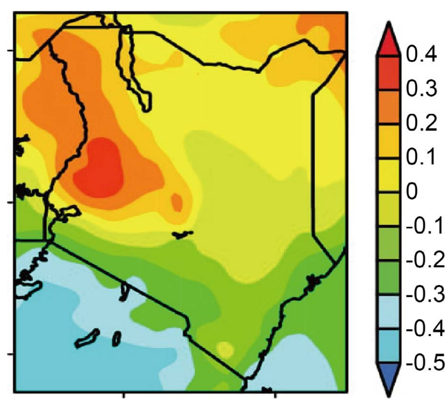

Figure 5. Correlation between AE and precipitation over the Mau Forest complex in Kenya.

3.5.2. Correlation between AOD and PR

The relationship between aerosol optical depth and total surface precipitation over the Mau Forest complex in Kenya can be complex and influenced by various factors. Studies in the Mau Forest complex region generally show a negative correction of value < 0.2. shown in **Figure 6**. This means that higher AOD values are associated with lower precipitation rates, and vice versa. This relationship is primarily due to the impact of aerosols on cloud formation, radiative forcing, and development. In addition, AOD is a measure of the amount of light that is scattered and absorbed by aerosols in the atmosphere. Higher AOD values indicate a greater concentration of aerosols in the atmosphere. The Mau Forest complex region experiences a unique combination of natural and anthropogenic factors that influence aerosol concentration and precipitation patterns [34]. Several studies done by researchers have also consistently shown a negative correlation between AOD and total surface precipitation. This suggests that increased aerosol concentrations are associated with reduced rainfall [42].

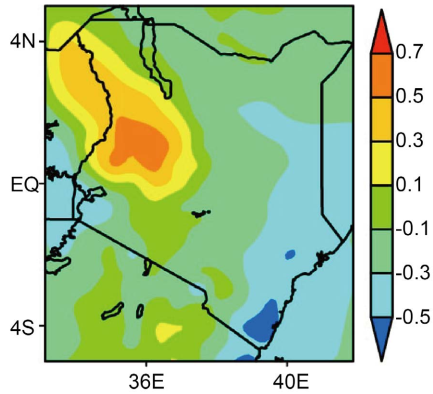

Figure 6. Correlation between AOD and PR over the study domain.

On the other hand, sources of aerosol emissions, such as deforestation activities, e.g., industrial activities, biomass burning, and residential combustion, can introduce aerosol into the atmosphere. The interactions between these emission sources and temperature can influence the spatial and temporal distribution of aerosol concentrations. Atmospheric stability, transport mechanisms, and local meteorological conditions also contribute to the negative correlation.

3.5.3. Correlation between AE and SAT

The relationship between surface temperature and the Ångström exponent over Mau Forest complex is complex and influenced by the following factors, mainly deforestation, i) Aerosols composition (e.g., dust, black carbon, sulfate) influences its absorption and scattering properties, ii) Aerosol size: larger aerosols tend to scatter more light, while smaller aerosols absorb more light and lastly atmospheric circulation: atmospheric circulation patterns can influence aerosols transport and deposition, affecting their distribution and impacts on temperature. Furthermore, the correlation between AE and surface temperature is a negative correlation of 0.2 and 0.1 over the Mau Forest complex, as shown in **Figure 7**.

Deforestation in the Mau Forest Complex is correlated with increased surface temperatures and changes in the Ångström exponent, which is an indicator of aerosol particle size. Deforestation leads to a reduction in evapotranspiration and tree cover, causing a localized warming effect. The removal of vegetation also alters aerosol characteristics, affecting the Ångström exponent, which reflects the relative abundance of larger versus smaller aerosol particles [45].

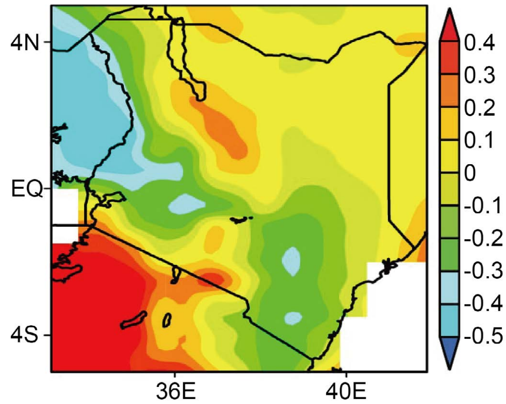

Figure 7. Correlation between Ångström exponent and land surface temperature.

3.5.4. Correlation between AOD and SAT

Deforestation in the Mau Forest Complex is correlated with increased surface temperatures and changes in aerosol optical depth (AOD). These changes can affect regional climate and weather patterns [43]. The relationship between aerosol optical depth and land surface temperature over Mau Forest complex on data obtained from MERRA 2 from 2001 to 2024 shows that it's a strong negative correlation with coefficient values of −0.4 and −0.3, influenced by the deforestation activities like land clearing, agricultural activities, and dust storms. AOD affects the earth's radiative balance, playing a role in climate regulation [46].

Changes in AOD can lead to shifts in temperature, impacting weather patterns and potentially affecting water availability in the region. In addition, changes in AOD can alter the amount of solar radiation reaching the surface, affecting the land surface temperature.

3.6. Correlation between Aerosol Optical Depth and Normalized Difference Vegetation Index (NDVI)

Table 2. Correlation between Normalized Difference Vegetation Index (NDVI) and climate variables (temperature and precipitation) over Mau, Kenya.

Parameter	Slope		t-Value	Correlation (r)
	Value	Std Deviation	$t = \frac{\text{Slope Value}}{\text{Std Deviation}}$	
NDVI vs PR	0.62114	1.1281	0.5507	0.1570
NDVI vs SAT	0.0074	2.6581	0.0028	0.1241

3.6.1. Correlation between NDVI and PR

In the Mau Forest complex, the correlation between precipitation and NDVI is weak positive with a value of 0.1570, as recorded in **Table 2** above. This indicates that as precipitation increases, the normalized difference vegetation index tends to increase, showing more vegetation [47] [48]. Moreover, deforestation can complicate this relationship. While deforestation initially leads to a decrease in NDVI due to forest loss, it can also indirectly lead to a positive correlation between precipitation and NDVI in some areas, particularly where land is converted to agriculture. This determines that agricultural activities often rely on precipitation, and the increased vegetation cover results in a stronger correlation with rainfall and vice versa. Furthermore, deforestation disrupts this natural relationship. Clearing forests for agriculture or other uses first reduces the forest cover and NDVI, but the newly established agricultural lands are mostly dependent on precipitation for their productivity [18] [48]. Therefore, in these converted areas, NDVI shows a positive correlation with precipitation, even though the overall forest cover has decreased.

3.6.2. Correlation between NDVI and SAT

The relationship between NDVI and temperature over the Mau Forest complex is weakly positive, with a value of 0.1241, as shown in **Table 2** above. This reveals high temperatures with increased vegetation health, which is likely not a direct result of deforestation. Deforestation would typically lead to a decline in NDVI and an increase in temperature due to the removal of the cooling effects of vegetation and the release of stored carbon. Instead, the perceived positive correction is likely due to other factors like seasonal variations, rainfall patterns, or specific forest types within the complex that respond differently to changes in temperature [47]. Some forest types are resilient to high temperatures and even show increased NDVI under warmer conditions. Further, temperature and NDVI naturally fluctuate with seasons, hence it is possible that the positive correlation is caused by seasonal patterns.

4. Conclusions and Recommendations

The AOD, AE, precipitation, and temperature are interconnected, influencing each other through complex atmospheric processes. Increased precipitation led to reduced AOD due to wet scavenging of aerosols; on the other hand, temperature affects aerosol formation and distribution. Changes in AOD, in turn, can impact precipitation patterns and temperature through radiative forcing.

The relationship between the normalized difference vegetation index (NDVI) and temperature is weakly positive, with a value of 0.1241. This indicates that higher temperatures are associated with increased vegetation health and is likely not a direct result of deforestation. While the correlation between precipitation and normalized difference vegetation index (NDVI) is weakly positive, with a value of 0.1570, it indicates that as precipitation increases, the normalized difference vegetation index tends to increase, showing more vegetation.

In the future, the use of high-resolution regional climate models (RCMs) and advanced statistical or machine learning approaches is recommended to improve prediction accuracy and identify nonlinear relationships between aerosol properties and climatic variables. These techniques can uncover hidden patterns and forecast future trends under different emission scenarios.

Given the information on MERRA 2 reanalysis, it lacks extensive validation; henceforth, future research should obtain data from the following: temperature and precipitation, from sources like ERA5 reanalysis data or other relevant datasets. These are essential for understanding the broader climate context and potential impacts of deforestation.

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Conflicts of Interest

The authors declare no conflicts of interest.

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