Atmospheric and Climate Sciences, 2025, 15(4), 742-760
https://www.scirp.org/journal/acs
ISSN Online: 2160-0422
ISSN Print: 2160-0414

Long-Term Assessment of Deforestation and Its Impacts on Aerosol Optical Properties and Climate Variables over Mau Forest Complex Using Multisensory Data

Caroline M. Jepchirchir, Geoffrey W. Khamala, John W. Makokha

Department of Science Technology and Engineering, Kibabii University, Bungoma, Kenya
Email: makokhajw@gmail.com

How to cite this paper: Jepchirchir, C.M., Khamala, G.W. and Makokha, J.W. (2025) Long-Term Assessment of Deforestation and Its Impacts on Aerosol Optical Properties and Climate Variables over Mau Forest Complex Using Multisensory Data. *Atmospheric and Climate Sciences*, **15**, 742-760.
https://doi.org/10.4236/acs.2025.154038

Received: July 7, 2025
Accepted: September 14, 2025
Published: September 17, 2025

Abstract

The deforestation has profound implications on aerosol properties and climatic variables. Deforestation disrupts local climate by altering temperature, aerosol optical properties and impacting air quality and modifies precipitation patterns; and degrades vegetation health. However, the long-term impacts of deforestation on aerosol optical properties and climate variables over Mau remain not very well investigated, especially considering the context of altered anthropogenic and natural emission sources. This study bridges this gap through a comprehensive assessment of deforestation impacts on aerosol optical properties and climate variables over Mau Forest complex bounded by (0.2S, 35.2E) and (0.8S, 35.8E) using multisensory data from 2001-2024. The findings by the present study reveal predominantly negative trends of NDVI, recorded by season JF, JJAS and OND of value −6.63032E−4 ± 0.00137, −1.356E−4 ± 0.00101 and −1.31586E−4 ± 7.59717E−4, respectively, indicating a decrease in vegetation health and density over the year often linked to rainfall patterns. Decline in NDVI is influenced by deforestation, which further exacerbates the impacts of natural reduction in vegetation cover. Conversely, during the season of MAM, the trend of NDVI is generally weak positive trend of value 4.70595E−4 ± 0.00193 year^{-1} indicating an increase in vegetation health and density. Furthermore, the spatial trends over domain region is characterized by Aerosol optical depth (<0.2) and high value of Angstrom exponent (>1) and moderate value >0.7, is attributed by 1) deforestation for example anthropogenic activities and human activities hence released significant amounts of aerosols particles into the atmosphere 2) climate change occasioned by meteorological parameters such as temperature inversions accompanied by reduced precipitation which are favorable conditions for increased aerosol emissions leading to the enhanced AOD. Correlation between NDVI and AOD is negative, attributed to increase in deforestation rate that results in reduced NDVI values. The statistically significant impacts of deforestation on aerosols optical properties and NDVI prove the modulating role of aerosol optical properties in regional climate processes. Policymakers must 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 Mau Forest complex in Kenya.

Keywords

Deforestation, NDVI, AOD, AE, Spatial-Temporal

1. Introduction

MAU forest complex is the largest mountainous forest in East Africa and is nestled in the heart of Kenya, which stands as one of the most vital ecological treasures in East Africa. The expansive forest system, which is often referred to as the water tower of the region, plays an indispensable role in supporting the livelihoods of millions [1]. The rivers 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, this essential resource faces an unprecedented threat: deforestation. According to Devouin *et al.* [2], the study defines deforestation as the permanent removal of trees to make room for activities other than forest growth, such as agriculture, infrastructure, or industrial development [3] [4]. This has therefore greatly affected the Mau Forest complex.

Forests play a critical role in filtering the air we breathe and protecting the Earth's surface from harmful ultraviolet rays but as a reality deforestation disrupts these natural processes. Deforestation has led to increased wind speed [5], which lifts heat and moisture away from the surface, contributing to a reduction in forest cover. This loss of cover reflects more sunlight, enhancing heating effect in less forested areas [6] [7]. However, as deforestation reduces the number of trees, temperatures rise because there is less transpiration, a process where plants release moisture into the atmosphere [8] [9]. This disruption weakens the natural rain cycle, causing irregular precipitation patterns, which in turn leads to more severe droughts and accelerates global warming. Further on consequence, deforestation increases in greenhouse gas (GHG) emissions, particularly carbon dioxide (CO_2). The rising concentration of CO_2 in the atmosphere significantly contributed to climate changed by absorbing energy, which leads to a warming effect [10]. Additionally, high and significant positive trends in AAOD were dominated over east Africa, this was attributed to an increased amount of biomass burning, variations in soil moisture, and changes in the rainfall pattern [11]. Further, CO_2 which is the most abundant greenhouse gas, has continued to increase in concentration due to human activities like fossil fuel combustion [12] [13]. Increase in CO_2 amplifies the greenhouse effect, wherein heat is trapped in the Earth's atmosphere, causing a rise in global temperatures [6] [14]. This temperature rise has far-reaching impacts on agriculture, ecosystems, and various organisms. Additionally, the loss of forests disrupted the climate, altering water flows, precipitation patterns, and potentially increasing droughts. On the other hand, forestation plays a vital role in regulating water by intercepting rainfall, reducing runoff, and attracting precipitation through high evapotranspiration rates [15] [16]. Also increase in deforestation resulted to a decline in NDVI values [17]-[19].

Further on effects of deforestation, burning of vegetation emitted aerosols; solid and liquid particles that are suspended in the atmosphere and constitute a vital component of Earth-atmosphere structure [20]. Aerosols impacted the Earth's climate directly by scattering and absorbing the incoming radiation from the Sun. Also, they affect the climate indirectly by changing the microphysical properties of clouds. They change the size and density of cloud droplets thereby modifying the cloud albedo, cloud formation, and the probability of having precipitation [21]-[23].

The research study assessed the influence of deforestation on selected aerosol optical properties and climate variables over the Mau Forest complex through (AE and AOD) and examines the trends in NDVI to access deforestation's effects on vegetation health and quantifying the impact of deforestation on aerosol properties and examines the trends in NDVI to access deforestation's effects on vegetation health. In addition, it analyzed the trends in aerosol characteristics by using temporal and spatio analysis. Moreover, this research will assist in solving glaring concerns from the ministry or department my research falls in Kenya.

2. Materials and Methods

2.1. Study Area

The study area is bounded by more than four counties: Narok, Nakuru, Bomet, and Kericho on (0.2S, 35.2E) and (0.8S, 35.8E) in Kenya and has an approximate area of 400,000 hectares (about 1544 square miles) and is the largest closed-canopy montane ecosystem in East Africa. The research was carried out in Mau Forest complex; Kenya as shown in **Figure 1** and was selected because of their significant role as water catchment areas and only mountainous forest in E.A. Climate of Mau Forest complex is generally tropical, though the elevation of the sites consists two topographic zones: lowlands and mountainous upland, with the altitude of the zones varying between 1800 to 3000 m ASL. Precipitation over the study domain shows bimodal rainfall patterns, with its annual rainfall being between 0.01 - 0.09 $kg\cdot m^{-2}\cdot s^{-1}$ and temperature ranging between (288 k - 298 k).

2.2. Instruments

MERRA-2 (Modern-Era Retrospective analysis for Research and Applications, version 2) and MODIS (Moderate Resolution Imaging spectroradiometer) Terra are valuable data sets for environmental data collection and analysis, particularly in atmospheric and land surface studies. MODIS terra offers high-resolution imagery and data on land and atmospheric [24] [25], while MERRA-2 provides a comprehensive, reanalyzed record of the earth's climate system.

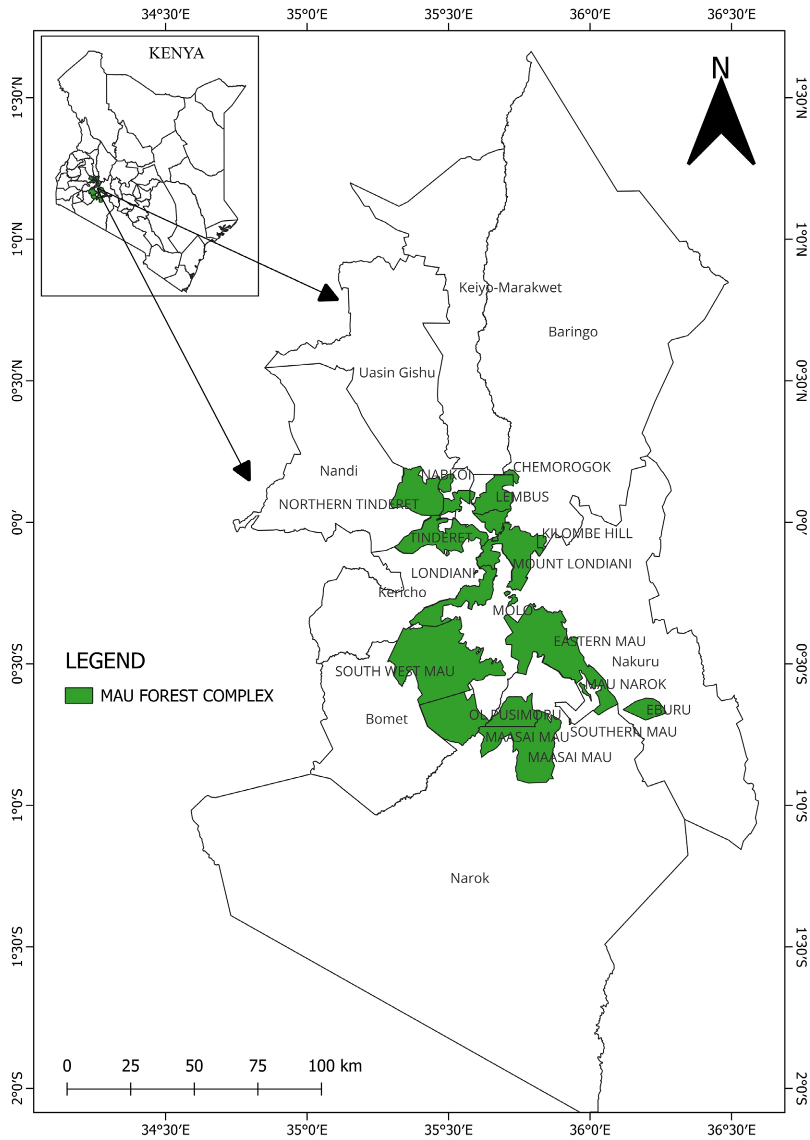


Figure 1. The domain map of Mau Forest complex.

MODIS Terra is used to measure aerosol properties by monitoring the ambient aerosol optical thickness over continents. It derives aerosol type over land. Aerosol Optical Depth (AOD) at 550 nm as primary products. The study used collection Level 3 daily and monthly mean aerosol optical depth @550 nm and Ångström exponent with spectral dependence between 412 and 470 nm over the land only [26] [27]. This spectral dependence for Ångström exponent was chosen since it is close to the top of the solar spectrum and therefore makes it more prone to the effects of solar radiation. The MODIS-Terra data products were retrieved from (http://giovanni.gsfc.nasa.gov/datasets) for a period of 24 years from January 2001-December 2024.

MERRA-2 MODEL. The Modern-Era Retrospective analysis for Research and Applications, version 2 (MERRA-2) is the first long-term global reanalysis to assimilate space-based observations of aerosols and represent their interactions with other physical processes [28] in the climate system including aerosols and provides comprehensive and consistent record of the Earth's climate system, using a combination of satellite observations, ground-based measurements, and numerical models [29]-[31]. As a matter of facts model is based on the version of the Goddard Earth Observing System, Version 5 (GEOS-5) atmospheric data from 2001 to 2024 at a spatial resolution of 0.5˚ × 0.625˚ with 72 layers and spanning the satellite era from 1980 to date [10] [28].

The present study, NMM2IMNXGAS_5.12.4. AODANA for monthly time-averaged data for Aerosol Optical Depth (AOD) and MERRA-2 M2TMNX-AER_5_12_TOTANGSTR monthly time-averaged data for Angstrom Exponent (AE) at spatial 0.5˚ × 0.625˚ from 2001 January to 2024 December were obtained for monthly and trends analysis. These data products were sourced from http://Giovanni.gsfc.nasa.gov/Giovanni/ for better performance over Mau Forest complex [24].

Combining MODIS and MERRA-2 data, particularly in the context of the Mau Forest complex, is beneficial for several reasons, including leveraging the strengths of both datasets to improve spatial and temporal coverage, and enhance the accuracy of analyses related to land cover, atmospheric conditions, and environmental changes [32]. Furthermore, it allows researchers to analyze how atmospheric conditions affect land cover changes or, conversely, how deforestation impacts local climate. For example, one could investigate how dust aerosols (from MERRA-2) influence vegetation health (using MODIS indices like NDVI) or how changes in forest cover (from MODIS) correlate with changes climate variables (from MERRA-2).

Resampling MODIS and MERRA-2 data, obtained for the Mau Forest Complex, is crucial for analyzing deforestation's impacts on aerosol optical properties and NDVI.MODIS data (NDVI, Ångström exponent, AE and aerosol optical depth, AOD) and MERRA-2 data (which includes aerosol reanalysis and climate variables) are collected at different resolutions. Resampling techniques used are like interpolation. This was used to match resolutions, allowing for meaningful comparisons of how deforestation affects these variables (AE, AOD and NDVI). For example, MODIS AOD data was used to resample and match the spatial resolution of MERRA-2 AOD data for a direct comparison. Similarly, MODIS NDVI data, which captures vegetation health and resampled to match the spatial scale of the deforestation analysis, enabling assessment of how forest cover changes correlate with vegetation health and aerosol loading.

2.3. Data Analysis

Trend Analysis

The raw data files were downloaded from NASA's online archives, encompassing monthly records from January 2001 to December 2024. These individual files were merged into a unified dataset using Climate Data Operators (CDO) software. This consolidation ensured temporal continuity necessary for robust trend analysis using linear regression model.

Linear regression model is a statistical method that examines the relationship between a dependent variable and one or more independent variables by fitting a linear equation to observed data [33]. It aims to hyperplane in higher dimensions (best-fit line) that represents the relationship between the variables. The present study used Equation (2.1) to find the trend in aerosol optical depth and angstrom exponent and investigate the trend of NDVI. This method has an advantage of evaluating the direction and magnitude of variations in long-term data [34] [35] and was therefore considered suitable for executing pixel-wise analysis.

In this regard, the linear regression model used is given in Equation (2.1)

$$Y_t = aX_t + b + N_t, t = 1, \cdots, T \tag{2.1}$$

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.

3. Results and Discussion

3.1. Seasonal Analysis of Normalized Vegetation Difference Index (NDVI)

Monthly Seasonal analysis of Normalized Vegetation Difference Index (NDVI)

The seasonal trends of NDVI over Mau Forest complex; Kenya from the year 2001 to 2024 as analyzed using the MODIS measurements, reveal interesting monthly variations in NDVI. Each trend represents the rate of change of NDVI per month either negative or positive. In general, Mau Forest complex is dominated by negative trends except MAM is a positive trend in NDVI (**Table 1**).

Table 1. Seasonal trend of NDVI over Mau Forest complex; Kenya.

Season	Mean NDVI	Trend ($year^{-1}$)	correlation
JF	0.698789	−6.63032E−4 ± 0.00137	−0.10772
MAM	0.705004	4.70595E−4 ± 0.00193	0.05435
JJAS	0.738763	−1.356E−4 ± 0.00101	−0.03008
OND	0.737331	−1.31586E−4 ± 7.59717E−4	−0.0387
Annual mean		−3.85944E−5 ± 7.20318E−4	−0.01263

During the season JF, JJAS and OND over domain region is predominantly by negative trends of p = −6.63032E−4 ± 0.00137 on JF, p = −1.356E−4 ± 0.00101 on

JJAS and $p = -1.31586E-4 \pm 7.59717E-4$ on OND, indicating a decrease in vegetation health and density over the year often linked to rainfall patterns. Decline in NDVI is influenced by deforestation [36] and seasonal dry periods, which further exacerbate the impacts of natural reduction in vegetation cover. Further deforestation, primarily driven by human activities like agriculture, charcoal burning, encroachment for settlement and logging are major contributor to these negative trends. Additionally, these activities directly reduce cover, leading to lower NDVI values and a degradation of the forest ecosystem. Uncertainties associated with these negative NDVI trends include limitations in NDVI accuracy, the influence of land cover changes, and the impact of climate variability. Specifically, NDVI can be affected by atmospheric conditions and saturation at high leaf area index, making it challenging to accurately assess vegetation health. Land use changes, such as deforestation for agriculture, also contribute to NDVI declines, but the specific drivers of these changes and their long-term impacts are not always clear. Furthermore, climate variables (temperature and precipitation) fluctuations, which are influenced by climate change, can significantly affect vegetation growth and NDVI values, introducing further uncertainty.

Conversely, during the wet season of MAM the trend of NDVI is generally positive, with weak positive trend of value $p = 4.70595E-4 \pm 0.00193\ \text{year}^{-1}$ indicating an increase in vegetation health and density. This suggests a positive response of the vegetation to rainfall patterns and other factors like soil condition, human activities and temperature.

Annual seasonal trend analysis of NDVI over Mau Forest complex Kenya

Annual seasonal trends of NDVI from the year 2001-2024 for the data obtained from MODIS Terra are either negative or positive. Negative significantly indicates increase in deforestation activities while positive indicates reduction in deforestation activities [36].

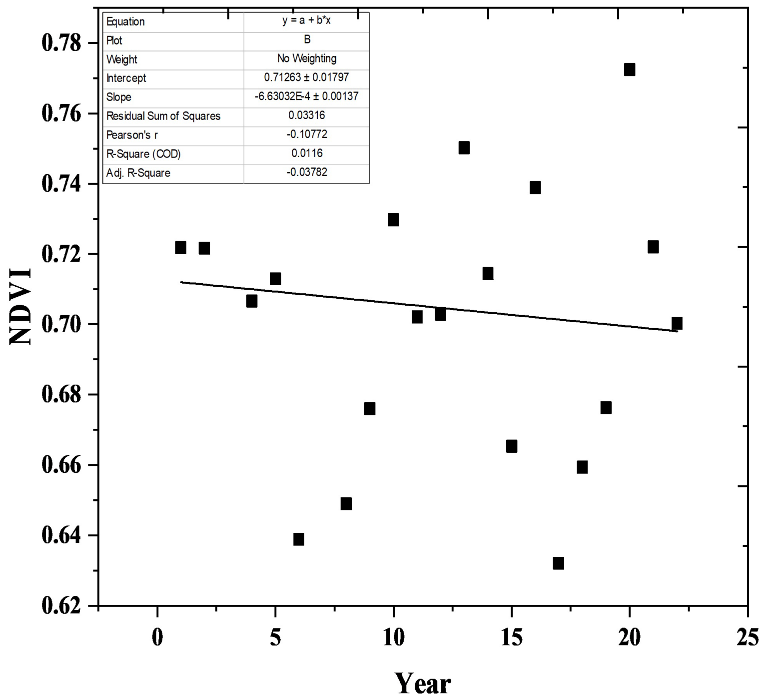
Figure 2(a) represents the seasonal trends of NDVI for a period of 24 years for monthly datasets of January and February (JF). JF seasonal trends recorded negative trend, typically indicating a decrease in vegetation greenness or density over time with Pearson's $r = -0.10772$ is attributed by seasonal change in climate, land cover, drought and human activities.

Figure 2(b) represents the seasonal trends of NDVI for MAM, for the year 2001-2024 showing the weak positive trend over time with Pearson's $r = 0.05435$, indicating slight increase in vegetation density or greenness, influenced by precipitation patterns and forest degradation.

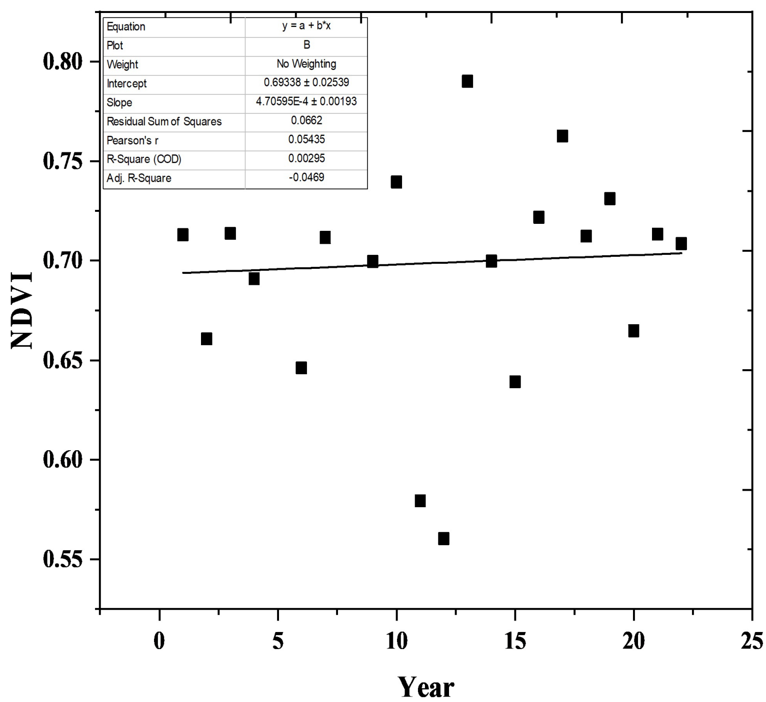
Figure 2(c) presents seasonal trends of JJAS, for the period of 2001-2024 reveals that negative trend of Pearson's $r = -0.3008$ significantly indicates a decrease in vegetation health and density over time. This means that as time passes, the NDVI values are getting lower, suggesting that the forest is experiencing degradation, possibly due to land-use changes, deforestation, or other environmental factors.

Figure 2(d) represents the seasonal trends of NDVI over OND, for the year 2001-2024, revealing the weak negative trend over time with Pearson's $r -0.0387$.

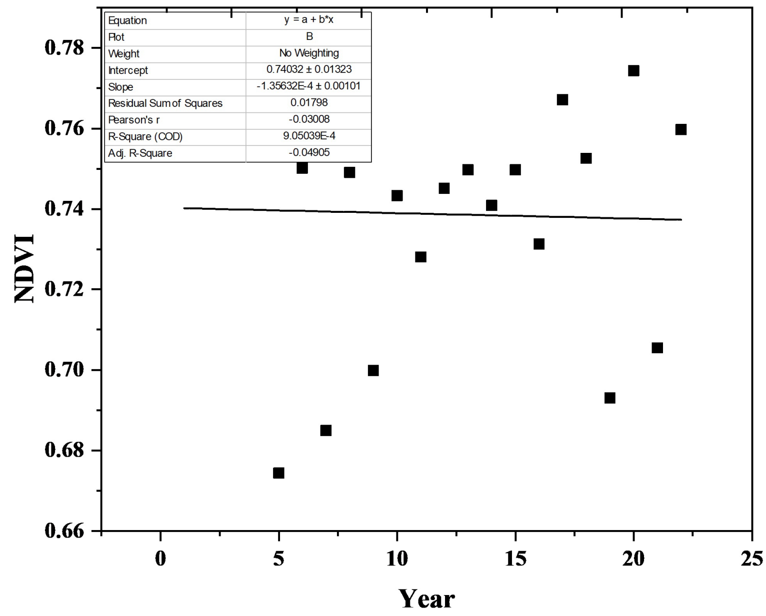
The weak negative correlation between NDVI and time suggests that there is a slight decrease in vegetation health or density over the period. However, this relationship is not strong, meaning that other factors likely play a more significant role in influencing NDVI values within the forest.



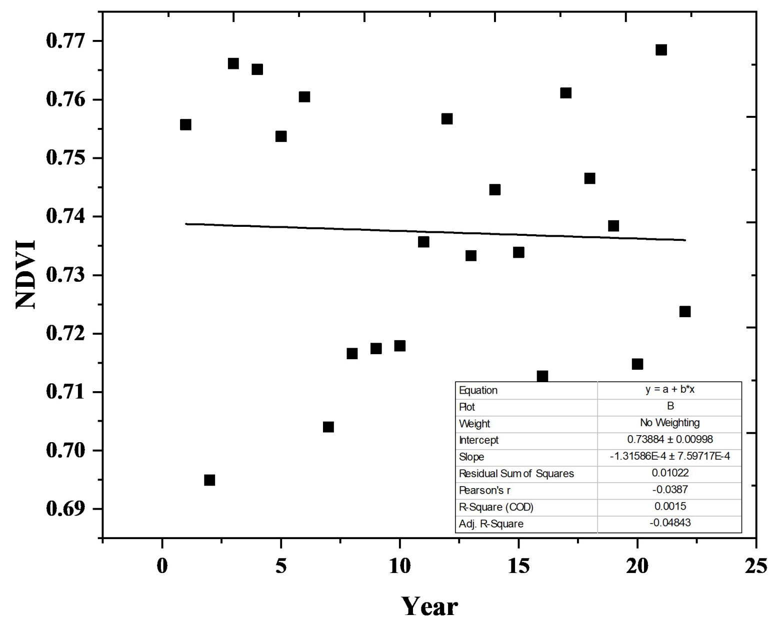
(a)



(b)



(c)



(d)

Figure 2. Seasonal trend of NDVI over Mau Forest complex.

3.2. Spatial and Temporal Variation of Aerosol Optical Depth and Angstrom Exponent

Spatial Variation of Aerosol Optical Depth (AOD)

The average spatial distribution of AOD over Mau Forest complex over Kenya during 2001-2024 is illustrated in **Figure 3** for data obtained from MERRA 2 reanalysis and geophysical trends of annual mean AOD_{550nm} sourced from MODIS Terra (dark and deep blue) over Mau Forest complex in **Figure 4**. The change in

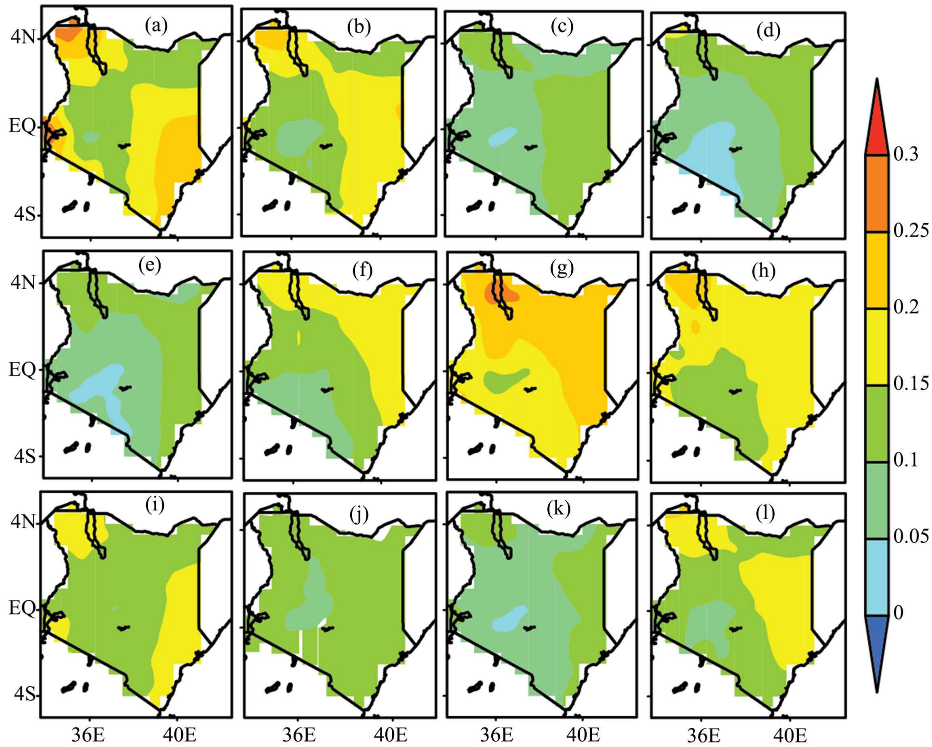


Figure 3. Annual spatial variation of Aerosol Optical Depth (AOD) using MERRA-2 Model data during 20001-2024 period.

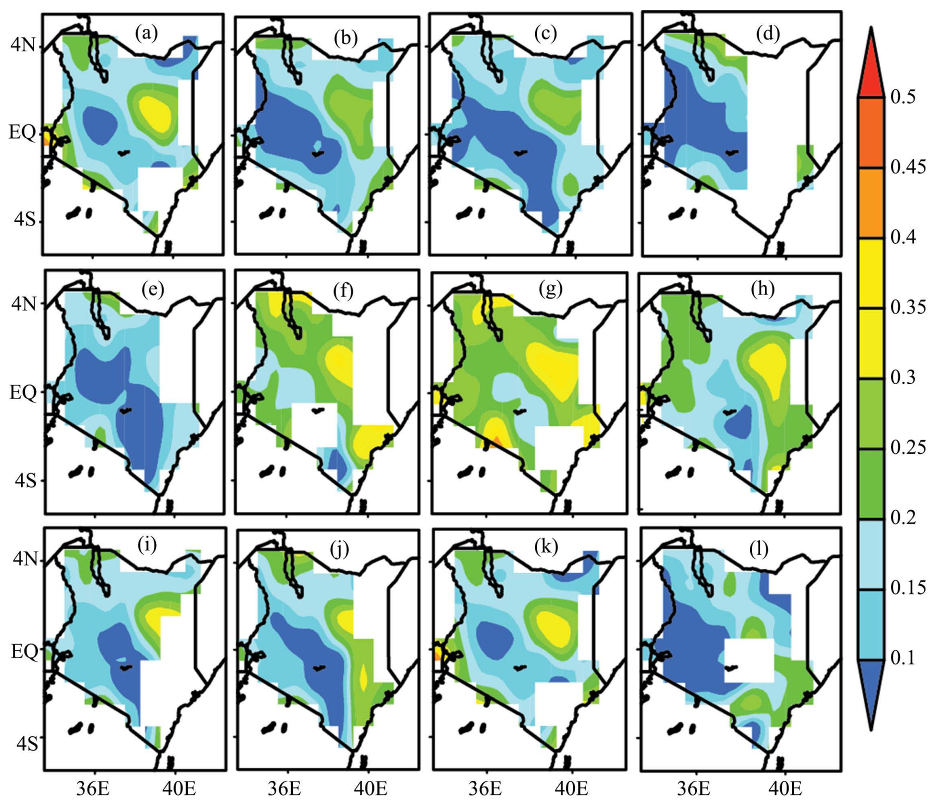


Figure 4. Annual spatial variation Aerosol Optical Depth (AOD) over Mau Forest complex using MODIS terra data during 2001-2024 period.

spatial annual mean AOD_{550nm} represents a general pattern of high, moderate, and low AOD, indicating distinct features of aerosol loading over different sites mainly Mau Forest complex. Moderate values ranging from 0.1 - 0.2 was recorded in Mau forest and low value of <0.1 was observed again This is attributed by deforestation, for example anthropogenic activities and human activities emitting significant amounts of aerosols particles into the atmosphere and climate change occasioned by meteorological parameters such as temperature inversions accompanied by reduced precipitation [37] which are favorable conditions for increased aerosol emissions leading to the enhanced AOD. In detail, deforestation often involves burning of forests, either intentionally or accidentally, which releases large amounts of smoke and particulate matter into the atmosphere. These particles scatter and absorb sunlight, increasing AOD. Additionally, exposed soil after deforestation can be a source of dust and other aerosols, further contributing to higher AOD.

Spatial Variation of Angstrom exponent (AE)

The annual spatial distribution of AE over Mau Forest complex, from 2001 Junaury-2024 December is illustrated in **Figure 5** for data obtained from MERRA 2 reanalysis. The research findings recorded the values of AE470-870 to vary between 0.5 and 1.3 with high values (AE470-870 > 1) dominating in the study region. Generally, it is linked to the dominance of fine-mode aerosol particles, influenced by increased anthropogenic activities, biomass and gas-to-particle conversation (certain atmospheric chemical reactions can convert gaseous pollutants into fine aerosols particles).

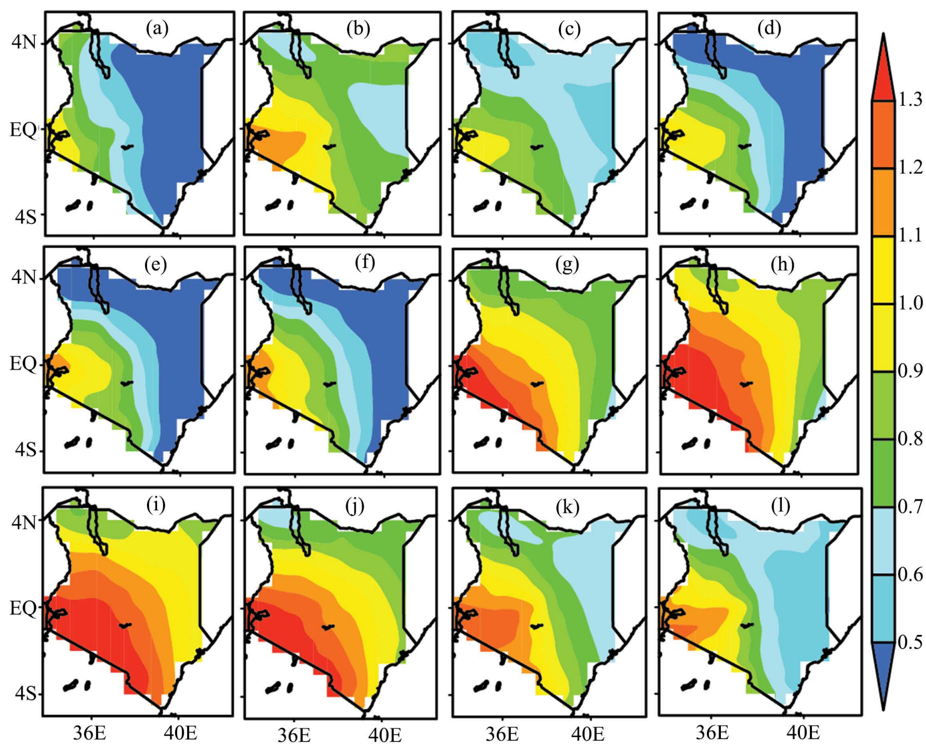


Figure 5. Annual spatial variation of Angstrom Exponent (A.E) over Mau Forest complex using MERRA-2 Model data during 2001-2024.

Moderate values were observed in Mau Forest complex of value 0.7 - 0.9 significantly associated with a mix of fine and coarse particles, or a strong of stronger presence of coarse particles. This is influenced by following factors, 1) by impact of wind patterns, wind transport dust from other areas for example monsoon winds carry dust from Arabian Peninsula to Kenya [38] [39], 2) dust and soil erosion, example is agricultural land, and activities like tillage and deforestation lead to soil erosion and dust emissions, contributing to coarse aerosols. 3) coagulation and aerosol aging and lastly seasonal variations.

3.3. Temporal Analysis of AOD and AE

3.3.1. Temporal Analysis of AE over Mau Forest Complex

The monthly temporary analysis of Angstrom exponent over Mau Forest complex from 2001-2024, based on MERRA-2 reanalysis data reveals a predominantly increasing trend across most months of the year, suggesting a long-term rise aerosol loading in the region of Mau Forest complex as shown on **Table 2**. Deforestation in the Mau Forest complex has a complex relationship with the AE, an indicator of aerosol particle size. Moreover, research done shows that deforestation leads to increased aerosol loading and decrease in AE due to dominance of larger particles from biomass burning and land clearing, the specific temporal trends are influenced by other factors like rainfall and seasonal variations [40]-[42].

Table 2. Temporal analysis of AE using MODIS Terra over Mau over Kenya.

Months	Mean value	Trend	Pearson (r^2)
January	0.6612 ± 0.0832	0.0014 ± 0.0025	0.1125
February	0.6449 ± 0.1971	0.0031 ± 0.0027	0.2247
March	0.6898 ± 0.2283	0.0083 ± 0.0021	0.6311
April	0.7310 ± 0.0843	0.0076 ± 0.0015	0.7286
May	0.6615 ± 0.0474	0.0013 ± 0.0020	0.1347
June	0.6321 ± 0.0243	−0.0001 ± 0.0021	−0.0137
July	0.8272 ± 0.2637	0.0047 ± 0.0038	0.2525
August	1.0218 ± 0.3237	0.0082 ± 0.0028	0.5156
September	1.0736 ± 0.2535	0.0105 ± 0.0024	0.6668
October	1.0770 ± 0.1733	0.0103 ± 0.0026	0.6365
November	0.9418 ± 0.0964	0.0061 ± 0.0018	0.5867
December	0.7583 ± 0.0256	−0.0000 ± 0.0026	−0.0009

The temporal analysis of AE with highest positive trends are perceived during the months of September p = (0.0105 ± 0.0024) and October p = (0.0103 ± 0.0026) indicating a shift towards smaller aerosol particles, potentially due to increased human activities like industrial emissions, agriculture and transportation, tends to produce finer aerosol particles, leading to a higher AE and changes atmospheric conditions. In addition, Moderate positive trends are observed during March p = (0.0083 ± 0.0021), April p = (0.0076 ± 0.0015), August p = (0.0082 ± 0.0028 and

November p = (0.0061 ± 0.0018) for data sourced from MODIS Terra, influenced by deforestation activities like increased biomass burning, land clearing for agriculture and reduced biogenic aerosols.

The months of January p = (0.0014 ± 0.0025), February p = (0.0031 ± 0.0027) May p = (0.0013 ± 0.0020) and July p = (0.0047 ± 0.0038) show a positive trend but comparatively lower. This is mainly attributed by changes in aerosol size distribution and composition, often linked to deforestation and biomass burning activities.

Contrary, June p = (−0.0001 ± 0.0021) and December p = (−0.0000 ± 0.0026) are the months with negative temporal trends, suggesting a slight long-term decline in Angstrom exponent. These negative trends contrast analysis, which observed high Angstrom exponent over the domain region. This discrepancy may reflect the episodic nature of emissions during these months—characterized by short-term biomass burning events—that do not translate into strong long-term trends. Uncertainties associated with temporal trends, include complex interactions within the forest ecosystem, including the impact of land cover changes, deforestation, and anthropogenic activities like agriculture and grazing. In addition, influence of natural variability in the climate system, limitations of climate models, and measurement errors from imprecise observational instruments errors.

3.3.2. Temporal Analysis of AOD Using MERRA 2 over Mau over Kenya

The temporal trends of AOD over Mau Forest from 2001 January-December 2024, as analyzed using the MEERA-2 models measurements, show interesting variation in Aerosol concentration (AOD) (**Figure 6**).

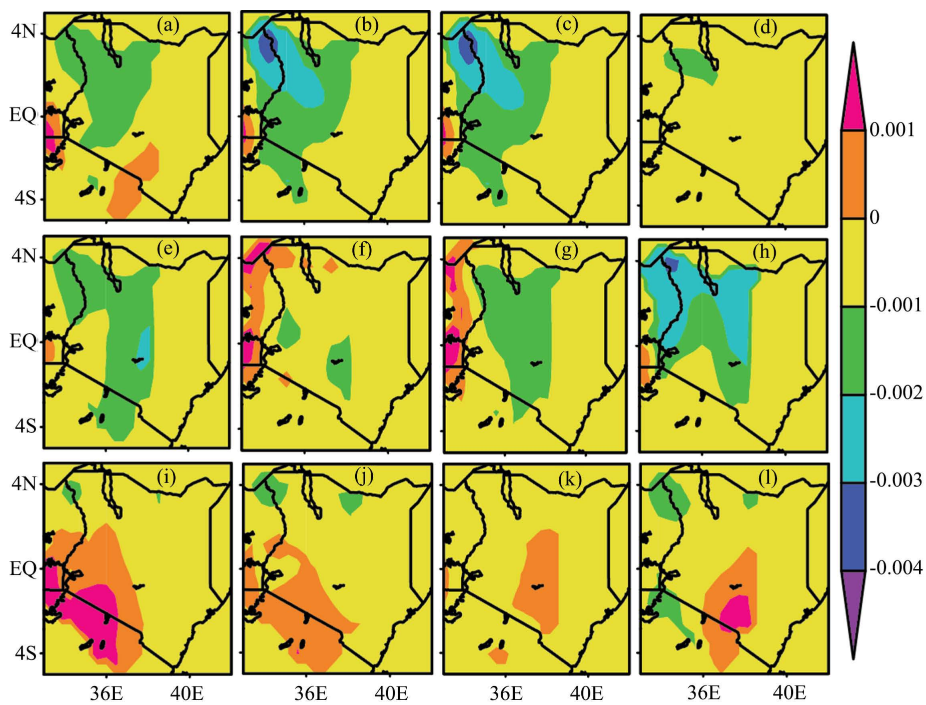


Figure 6. Temporal analysis of AOD using MERRA-2 Reanalysis over Mau over Kenya.

The positive trends are observed in Mau Forest complex of AOD is <0.001 this suggesting a reduction in aerosol loading due to targeted restoration efforts. These efforts, including reforestation and reduced deforestation, are contributing to a decrease in factors that increase AOD, such as dust and biomass burning this aligning to spatial results of AOD over domain region.

Contrary, negative trend of <-0.001 year^{-1} is observed over Mau Forest complex, influenced by the increased rainfall and decreased aerosol loading, likely due to reduced human activity and biomass burning. Most research done over Mau suggested that deforestation and land-use changes in the Mau Forest may also contribute to increased dust and other coarse aerosols, potentially impacting AOD trends [40]-[42]. Uncertainties arising are influenced by factors like seasonal changes, land cover alterations, limitations in satellite-based AOD retrieval and human activities, potentially leading to misinterpretations of degradation patterns and climate change impacts.

3.4. Correlation between AE and AOD with Normalized Difference Vegetation Index (NDVI)

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

The relationship between aerosol optical depth (AOD) and Normalized Difference Vegetation Index (NDVI) over Mau Forest complex, significantly influenced by the deforestation as the main factor and climate variables. Deforestation, particularly in areas with low rainfall, can lead to a decrease in NDVI, indicating degraded vegetation, while increase in AOD is due to, dust storms, biomass burning (e.g. land clearing) negatively impacted on vegetation health and reduced NDVI. Furthermore, on the study weak negative correlation was observed of value $r = -0.0906$ as shown on **Table 3**. Deforestation, NDVI and AOD reveal an inverse relationship. As deforestation decreases NDVI due to decreased vegetation health and density, it simultaneously increases AOD due to more emissions of aerosols to atmosphere. The correlation between NDVI and AOD highlights the impact of deforestation on both vegetation health in Mau Forest complex and atmospheric conditions. In detail, increase in AOD emissions to atmosphere, scatter and absorb incoming solar radiation affects the amount of sunlight reaching the earth's surface, potentially impacting plant growth and overall vegetation health.

Table 3. Correlation between AE and AOD with Normalized Difference Vegetation Index (NDVI) over Mau over Kenya.

Parameter	Slope		t-value	Correlation (r)
	Value	Std Deviation	$t = \frac{\text{Slope Value}}{\text{Std Deviation}}$	
NDVI vs AE	0.2205	0.5418	0.4070	0.0846
NDVI vs AOD	−0.4910	0.3832	1.2657	−0.0906

3.4.2. Correlation between Angstrom Exponent and Normalized Difference Vegetation Index (NDVI)

Deforestation and climate variables significantly affect NDVI and Angstrom exponent (AE) in the Mau Forest complex. On the study weak positive correlation was recorded of value r = 0.0846 shown in **Table 3**. This indicates that vegetation density and health (increase in NDVI), the size distribution of aerosols tends to shift towards smaller particles indicated by high angstrom exponent. The positive correlation is attributed by following factors, changes in atmospheric circulation patterns associated with denser vegetation could also influence the size distribution of aerosols, favouring the presence of smaller particles and increased biogenic aerosols emission due to deforestation. Deforestation reduces vegetation cover and alters climate variables, which in turn affect the size distribution of aerosols in the atmosphere, as shown by angstrom exponent. Further, more research needed to investigate the specific types of aerosols and their sources for better understanding and relationship between NDVI, deforestation, climate variables and aerosols.

4. Summary and Conclusions

This paper has provided a compressive analysis of long-term assessment of deforestation and its impacts on Aerosol optical depth and angstrom exponent and climate variables over Mau Forest complex over Kenya, and forms a basis for achieving a better and in-depth understanding of Spatial-Temporal variations in atmospheric aerosols and seasonal variation of Normalized Difference Vegetable Index (NDVI) over Mau Forest complex. The main conclusions drawn from the results are summarized as follows.

1) The season of JF, JJAS and OND is predominantly by negative trends of −6.63032E−4 ± 0.00137, −1.356E−4 ± 0.00101 and −1.31586E−4 ± 7.59717E−4, respectively, indicating decrease in vegetation health and density over the year often linked to rainfall patterns. Decline in NDVI is influenced by deforestation and seasonal dry periods. Conversely, MAM, the trend of NDVI is a weakly positive trend of value 4.70595E−4 ± 0.00193 year^{-1} indicating an increase in vegetation health and density.

2) The spatial trends over domain region are characterized by Aerosol optical depth (<0.2) and high of high value of (AE470-870 > 1), and Moderate value of 0.7 - 0.9 significantly associated with a mix of fine and coarse particles, or a strong of stronger presence of coarse particles. This is influenced by impact of wind patterns and anthropogenic activities.

3) The temporal analysis of AE with highest positive trends is perceived during the months of September (0.0105 ± 0.0024) and October (0.0103 ± 0.0026) indicating a shift towards smaller aerosol particles, potentially due to increased human activities and Moderate positive trends are observed during March (0.0083 ± 0.0021), April (0.0076 ± 0.0015), August (0.0082 ± 0. 0028) and November (0.0061 ± 0.0018), which is influenced by deforestation activities like increased biomass burning, land clearing for agriculture and reduced biogenic aerosols. While

months of January (0.0014 ± 0.0025), February (0.0031 ± 0.0027), May (0.0013 ± 0.0020) and July (0.0047 ± 0.0038) show a positive trend but comparatively lower. This is mainly attributed to changes in aerosol size distribution and composition, often linked to deforestation and biomass burning activities.

4) The positive trends of AOD < 0.001. This suggests a reduction in aerosol loading due to targeted restoration efforts.

Contrary, negative trend of <-0.001 year^{-1} was recorded and was influenced by the increased rainfall and decreased aerosol loading, likely due to reduced human activity and biomass burning.

5) Correlation between NDVI and AOD is weakly negative of value $r = -0.0906$, attributed to deforestation. Deforestation, NDVI and AOD reveal an inverse relationship. As deforestation decreases NDVI due to decreased vegetation health and density, it simultaneously increases AOD due to more emissions of aerosols to atmosphere. While correlation between NDVI and AE is weakly positive of value $r = 0.0846$, influenced by changes in atmospheric circulation patterns associated with denser vegetation which could also influence the size distribution of aerosols, favouring the presence of small particles and increasing biogenic aerosols emission due to deforestation.

Acknowledgements

I wish to thank the NASA LAADS and Giovanni online analysis and visualization system for providing and processing MERRA-2 and MODIS Terra satellite data used in this study.

Secondly to extend sincere gratitude to my supervisors Prof. John W. Makokha and Dr. Geoffrey Khamala for Kibabii University for their countless hours of reflecting, reading and encouraging throughout the process, and the Ministry of Higher Education, Science and Technology of Kenya and Kibabii University, for providing an opportunity to undertake my master's degree.

Lastly, I am always thankful to the almighty God for the gift of life and strength He gave me during my studies when things seemed not to work, He gave me hope in His words that He makes a way where it seems to be no way.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

[1] Cesareo, K., Walker, L., Varela, J. and Smith, A. (2021) Deforestation and Forest Degradation Threats WWF. World Wildlife Fund.

[2] Derouin, S. (2019) Deforestation: Facts, Causes & Effects. Live Science.com.

[3] Duguma, L.A., Atela, J., Minang, P.A., Ayana, A.N., Gizachew, B., Nzyoka, J.M., *et al.* (2019) Deforestation and Forest Degradation as an Environmental Behavior: Unpacking Realities Shaping Community Actions. *Land*, **8**, Article No. 26. https://doi.org/10.3390/land8020026

[4] Bodo, T. and Gimah, B.G. (2019) Curbing Human Activities That Degrade the Envi-

ronment: The Relevance of Environmental Adult Education. *Earth & Environmental Science Research and Review*, **2**, 1-7.

[5] Khamala, G.W., Makokha, J.W. and Boiyo, R. (2024) The Spatiotemporal and Dependency Analysis of Selected Meteorological Parameters and Normalized Difference Vegetation Index with Aerosol Optical Depth over East Africa. *Heliyon*, **10**, e39961. https://doi.org/10.1016/j.heliyon.2024.e39961

[6] Khamala, G.W., Makokha, J.W., Boiyo, R. and Kumar, K.R. (2023) Spatiotemporal Analysis of Absorbing Aerosols and Radiative Forcing over Environmentally Distinct Stations in East Africa during 2001-2018. *Science of the Total Environment*, **864**, Article ID: 161041. https://doi.org/10.1016/j.scitotenv.2022.161041

[7] Santos Orozco, D.L., Ruiz Corral, J.A., Villavicencio García, R.F. and Rodríguez Moreno, V.M. (2023) Deforestation and Its Effect on Surface Albedo and Weather Patterns. *Sustainability*, **15**, Article No. 11531. https://doi.org/10.3390/su151511531

[8] IPCC (2021) Summary for Policymakers. In: Masson-Delmotte, V., Zhai, P., Pirani, A., Connors, S.L., Péan, C., Berger, S., *et al*., Eds., *Climate Change* 2021: *The Physical Science Basis*. *Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge University Press, 3-32. https://doi:10.1017/9781009157896.001

[9] Hesslerova, P. and Pokorny, J. (2010) Forest Clearing, Water Loss, and Land Surface Heating as Development Costs. *International Journal of Water*, **5**, 401-418. https://doi.org/10.1504/ijw.2010.038732

[10] Makokha, J.W. and Angeyo, H.K. (2013) Investigation of Radiative Characteristics of the Kenyan Atmosphere Due to Aerosols Using Sun Spectrophotometry Measurements and the COART Model. *Aerosol and Air Quality Research*, **13**, 201-208. https://doi.org/10.4209/aaqr.2012.06.0146

[11] Khamala, G.W., Makokha, J.W., Boiyo, R. and Kumar, K.R. (2022) Long-Term Climatology and Spatial Trends of Absorption, Scattering, and Total Aerosol Optical Depths over East Africa during 2001-2019. *Environmental Science and Pollution Research*, **29**, 61283-61297. https://doi.org/10.1007/s11356-022-20022-6

[12] Makokha, J., Masayi, N., Barasa, P., Ikoha, P., Konje, M., Mutonyi, J., *et al.* (2024) Assessing the Long-Term Changes in Selected Meteorological Parameters over the North-Rift, Kenya: A Regional Climatology Perspective. *Hydrology*, **12**, 59-76. https://doi.org/10.11648/j.hyd.20241203.12

[13] Friedlingstein, P., O'Sullivan, M., Jones, M.W., Andrew, R.M., Gregor, L., Hauck, J., *et al.* (2022) Global Carbon Budget 2022. *Earth System Science Data*, **14**, 4811-4900. https://doi.org/10.5194/essd-14-4811-2022

[14] Lüthi, D., Le Floch, M., Bereiter, B., Blunier, T., Barnola, J., Siegenthaler, U., *et al.* (2008) High-Resolution Carbon Dioxide Concentration Record 650,000 - 800,000 Years before Present. *Nature*, **453**, 379-382. https://doi.org/10.1038/nature06949

[15] Sheil, D. (2018) Forests, Atmospheric Water and an Uncertain Future: The New Biology of the Global Water Cycle. *Forest Ecosystems*, **5**, Article No. 19. https://doi.org/10.1186/s40663-018-0138-y

[16] Ekhuemelo, D.O., Amonum, J.I. and Usman, I.A. (2016) Importance of Forest and Trees in Sustaining Water Supply and Rainfall. *Nigeria Journal of Education*, *Health and Technology Research*, **8**, 273-280.

[17] Malimbwi, R.E., Solberg, S., Luoga, E.J. and Zahabu, E. (2010) Assessing Forest Degradation in the Eastern Arc Mountains of Tanzania Using Multitemporal Landsat Data. *Journal of Applied Remote Sensing*, **4**, Article ID: 043536.

[18] Kinyanjui, M.J. (2010) NDVI-Based Vegetation Monitoring in Mau Forest Complex, Kenya. *African Journal of Ecology*, **49**, 165-174. https://doi.org/10.1111/j.1365-2028.2010.01251.x

[19] Pettorelli, N., Ryan, S., Mueller, T., Bunnefeld, N., Jędrzejewska, B., Lima, M. and Durant, S.M. (2011) The Normalized Difference Vegetation Index (NDVI): Unforeseen Successes in Animal Ecology. *Climatic Change*, **83**, 271-279.

[20] Khamala, G.W., Odhiambo, J.O. and Makokha, J.W. (2018) Seasonal Variability in Aerosol Microphysical Properties over Selected Rural, Urban and Maritime Sites in Kenya. *Open Access Library Journal*, **5**, 1-20. https://doi.org/10.4236/oalib.1104821

[21] Rotstayn, L.D. and Lohmann, U. (2002) Tropical Rainfall Trends and the Indirect Aerosol Effect. *Journal of Climate*, **15**, 2103-2116. https://doi.org/10.1175/1520-0442(2002)015<2103:trtati>2.0.co;2

[22] IPCC (2012) Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. In: Field, C.B., Barros, V., Stocker, T.F., Qin, D., Dokken, D.J., Ebi, K.L., *et al.*, Eds., *A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change*, Cambridge University Press, 582.

[23] Che, H., Gui, K., Xia, X., Wang, Y., Holben, B.N., Goloub, P., *et al.* (2019) Large Contribution of Meteorological Factors to Inter-Decadal Changes in Regional Aerosol Optical Depth. *Atmospheric Chemistry and Physics*, **19**, 10497-10523. https://doi.org/10.5194/acp-19-10497-2019

[24] NASA Earth Data Giovanni Webpage. https://giovanni.gsfc.nasa.gov/giovanni/

[25] Running, S.W., Justice, C.O., Salomonson, V., Hall, D., Barker, J., Kaufmann, Y.J., *et al.* (1994) Terrestrial Remote Sensing Science and Algorithms Planned for the MODIS-EOS. *International Journal of Remote Sensing*, **15**, 3587-3620. https://doi.org/10.1080/01431169408954346

[26] Kaufman, Y.J., Wald, A.E., Remer, L.A., *et al.* (1997) The MODIS 2.1-μm Channel-Correlation with Visible Reflectance for Use in Remote Sensing of Aerosol. *IEEE Transactions on Geoscience and Remote Sensing*, **35**, 1286-1298. https://doi.org/10.1109/36.628795

[27] Kaufman, Y.J., Tanré, D. and Boucher, O. (2002) A Satellite View of Aerosols in the Climate System. *Nature*, **419**, 215-223. https://doi.org/10.1038/nature01091

[28] Kahn, R.A., Gaitley, B.J., Martonchik, J.V., Diner, D.J., Crean, K.A. and Holben, B. (2005) Multiangle Imaging Spectroradiometer (MISR) Global Aerosol Optical Depth Validation Based on 2 Years of Coincident Aerosol Robotic Network (AERONET) Observations. *Journal of Geophysical Research*: *Atmospheres*, **110**, D10S04. https://doi.org/10.1029/2004jd004706

[29] Randles, C.A., da Silva, A.M., Buchard, V., Colarco, P.R., Darmenov, A., Govindaraju, R., *et al.* (2017) The MERRA-2 Aerosol Reanalysis, 1980 Onward. Part I: System Description and Data Assimilation Evaluation. *Journal of Climate*, **30**, 6823-6850. https://doi.org/10.1175/jcli-d-16-0609.1

[30] Gelaro, R., McCarty, W., Suárez, M.J., Todling, R., Molod, A., Takacs, L. and Zhao, B. (2017) The Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2). *Journal of Climate*, **30**, 5419-5454.

[31] Khan, R., Kumar, K.R., Zhao, T., Ullah, W. and de Leeuw, G. (2021) Interdecadal Changes in Aerosol Optical Depth over Pakistan Based on the MERRA-2 Reanalysis Data during 1980-2018. *Remote Sensing*, **13**, Article No. 822. https://doi.org/10.3390/rs13040822

[32] Aldabash, M., Bektas Balcik, F. and Glantz, P. (2020) Validation of MODIS C6.1 and

MERRA-2 AOD Using AERONET Observations: A Comparative Study over Turkey. *Atmosphere*, **11**, Article No. 905. https://doi.org/10.3390/atmos11090905

[33] Weatherhead, E.C., Reinsel, G.C., Tiao, G.C., Meng, X., Choi, D., Cheang, W., *et al.* (1998) Factors Affecting the Detection of Trends: Statistical Considerations and Applications to Environmental Data. *Journal of Geophysical Research*: *Atmospheres*, **103**, 17149-17161. https://doi.org/10.1029/98jd00995

[34] Kumar, K.R., Sivakumar, V., Yin, Y., Reddy, R.R., Kang, N., Diao, Y., *et al.* (2014) Long-Term (2003-2013) Climatological Trends and Variations in Aerosol Optical Parameters Retrieved from MODIS over Three Stations in South Africa. *Atmospheric Environment*, **95**, 400-408. https://doi.org/10.1016/j.atmosenv.2014.07.001

[35] Boiyo, R., Kumar, K.R. and Zhao, T. (2018) Optical, Microphysical and Radiative Properties of Aerosols over a Tropical Rural Site in Kenya, East Africa: Source Identification, Modification and Aerosol Type Discrimination. *Atmospheric Environment*, **177**, 234-252. https://doi.org/10.1016/j.atmosenv.2018.01.018

[36] Kumar, C. (2024) Monitoring Deforestation Using Satellite Imagery and Machine Learning.

[37] Yang, S., Xu, B., Cao, J., Zender, C.S. and Wang, M. (2015) Climate Effect of Black Carbon Aerosol in a Tibetan Plateau Glacier. *Atmospheric Environment*, **111**, 71-78. https://doi.org/10.1016/j.atmosenv.2015.03.016

[38] Gatebe, C.K., Tyson, P.D., Annegarn, H.J., Helas, G., Kinyua, A.M. and Piketh, S.J. (2001) Characterization and Transport of Aerosols over Equatorial Eastern Africa. *Global Biogeochemical Cycles*, **15**, 663-672. https://doi.org/10.1029/2000gb001340

[39] de Graaf, M., Tilstra, L.G., Aben, I. and Stammes, P. (2010) Satellite Observations of the Seasonal Cycles of Absorbing Aerosols in Africa Related to the Monsoon Rainfall, 1995-2008. *Atmospheric Environment*, **44**, 1274-1283. https://doi.org/10.1016/j.atmosenv.2009.12.038

[40] Makokha, J.W., Odhiambo, J.O. and Godfrey, J.S. (2017) Trend Analysis of Aerosol Optical Depth and Angstrom Exponent Anomaly over East Africa. *Atmospheric and Climate Sciences*, **7**, 588-603. https://doi.org/10.4236/acs.2017.74043

[41] Andreae, M.O. and Merlet, P. (2001) Emission of Trace Gases and Aerosols from Biomass Burning. *Global Biogeochemical Cycles*, **15**, 955-966. https://doi.org/10.1029/2000gb001382

[42] Bonan, G.B. (2008) Ecological Climatology. 2nd Edition, Cambridge University Press. https://doi.org/10.1017/cbo9780511805530