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Anomaly Detection in Selected Aerosol Optical Properties and Associated Climate Variables Using a Multivariate Hidden Markov Model: A Case Study over Kenya

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Abstract

Understanding aerosol climate interactions is crucial for monitoring atmospheric changes and supporting climate resilience efforts, particularly in vulnerable regions such as Kenya. This study applies a Multivariate Hidden Markov Model (HMM) to detect anomalies in key Aerosol Optical Properties (AOP) i.e., Aerosol Optical Depth (AOD), Single Scattering Albedo (SSA), and Ångström Exponent (AE) alongside associated climate variables; Surface Air Temperature (SAT) and Rainfall Rate (RR), over the period 2000-2022. Satellite-based datasets from MODIS, MERRA-2, and TRMM were used to derive monthly means, and descriptive statistics and linear regression were initially employed to characterize long-term variability. The objectives of this study were to examine the temporal and spatial variability of key aerosol and climate parameters over Kenya, detect and classify anomalies in the multivariate dataset using HMM and to interpret the climatic and environmental implications of detected anomalies and their possible causes. The HMM approach successfully identified temporal patterns and hidden states, enabling the detection of significant anomalous periods, particularly between 2010 and 2016, which aligned with regional biomass burning events and transboundary pollution episodes. Results indicate that AOD and SSA anomalies correspond with periods of elevated temperature and reduced rainfall, highlighting potential climate-aerosol feedbacks. The findings demonstrate the utility of multivariate HMMs in capturing the complex dynamics of aerosol-climate interactions and provide a foundation for improved air quality monitoring and climate impact assessments in Kenya which is critical for improving environmental monitoring and enhancing regional climate adaptation strategies.

Subject Areas

Environmental Sciences

Keywords

MODIS Moderate Resolution Imaging Spectroradiometer, MERRA-2 Modern Era Retrospective Analysis for Research and Application Version 2, TRMM Tropical Rainfall Measure Mission, MHMM Multivariant Hidden Markov Model

1. Introduction

Aerosols, comprising fine solid particles or liquid droplets suspended in the atmosphere, play a critical role in modulating the Earth's climate system through direct and indirect radiative forcing [1]-[3]. Key aerosol optical properties (AOPs) such as Aerosol Optical Depth (AOD), Single Scattering Albedo (SSA), and Ångström Exponent (AE) provide essential insights into aerosol concentration, composition, and particle size distribution [4] [5]. These properties influence cloud formation, surface energy balance, and precipitation dynamics, thereby affecting regional and global climate variability [6] [7].

In Kenya, the variability of aerosols is driven by a combination of natural processes such as dust transport from arid regions and volcanic activity, as well as anthropogenic emissions from urbanization, agriculture, and biomass burning [8] [9]. Seasonal weather patterns, including the Intertropical Convergence Zone (ITCZ) shifts, further modulate aerosol transport and deposition in the region [10]. Despite the significance of aerosol climate interactions in Kenya, comprehensive studies focusing on the joint variability and detection of anomalies in AOPs and associated climate variables such as surface air temperature (SAT) and rainfall rate (RR) remain limited.

Anomalies in these parameters signal significant shifts in atmospheric conditions, environmental stress or extreme events. Detecting such anomalies is critical for climate monitoring, environmental health assessments, and policy-making [11]. Traditional statistical methods often fail to capture latent dynamics or regime shifts in complex, multivariate time series data. In contrast, the Multivariate Hidden Markov Model (HMM) provides a probabilistic approach that identifies hidden states governing observable patterns, making it highly effective for anomaly detection in environmental datasets [12] [13].

Aerosols influence the Earth's radiative balance through scattering and absorption of solar radiation (direct effect), and by modifying cloud microphysical properties (indirect effect) [1]. The Aerosol Optical Depth (AOD) quantifies the columnar concentration of aerosols, while the Single Scattering Albedo (SSA) indicates the extent of scattering versus absorption. The Ångström Exponent (AE), derived from the spectral dependence of AOD, provides insights into aerosol size distribution [5] [4]. These properties influence cloud formation, surface energy balance, and precipitation dynamics, thereby affecting regional and global climate variability [6] [7].

In regions such as East Africa, seasonal biomass burning, urban emissions, and dust intrusions from the Sahara and Arabian Peninsula contribute significantly to aerosol variability [8]. Studies have found that elevated AOD levels over East Africa coincide with dry seasons and increased fire activity, suggesting a strong link between aerosols and regional climate dynamics [9].

Kenya, with its diverse geography and climatic zones, experiences significant aerosol variability. Satellite observations from MODIS and ground-based AERONET stations have shown moderate to high AOD levels in urban areas like Nairobi and along the coastal regions, often associated with biomass burning and vehicular emissions [14]. AE values in Kenya typically range between 1.0 and 1.4, indicating dominance of fine-mode aerosols, though coarse-mode particles dominate during dust transport events [15].

Climatic variables such as surface air temperature (SAT) and rainfall rate (RR) are also influenced by aerosol loading. Aerosols can suppress or enhance rainfall depending on their composition and vertical distribution, and they can alter surface temperature by modifying solar radiation [6] [16].

Detecting anomalies in climate and atmospheric datasets is essential for understanding extreme events and deviations from long-term trends. Traditional techniques such as z-score thresholding, time-series decomposition, and wavelet analysis have been widely used [11]. However, these methods often fall short when dealing with multivariate datasets or capturing hidden temporal dynamics. Studies have highlighted the limitations of univariate anomaly detection when dealing with atmospheric systems where variables are interdependent [17].

Hidden Markov Models (HMMs) are stochastic models that assume the presence of unobservable (hidden) states governing the behavior of observed variables over time. They have been successfully applied in meteorology, hydrology, and air quality research for pattern recognition, classification, and anomaly detection [13] [12].

The Multivariate Hidden Markov Model (MHMM) extends this framework by modelling multiple interdependent variables simultaneously, making it especially suited for detecting structural changes and latent states in environmental systems [18]. In recent years, MHMMs have been used to detect drought regimes, classify aerosol states, and identify shifts in climate patterns [19].

Despite its strengths, the application of MHMM to aerosol-climate interaction studies in sub-Saharan Africa, and particularly Kenya, remains limited. This research addresses that gap by integrating AOP and climate data using MHMM to uncover hidden anomalies across space and time.

This study applies a Multivariate Hidden Markov Model to analyze satellite-derived AOPs (AOD, SSA, AE) and associated climate variables (SAT, RR) over Kenya between 2000 and 2022. By leveraging data from MODIS, MERRA-2, and

TRMM, the research aims to uncover underlying state transitions and detect temporal anomalies in aerosol climate interactions. The specific objective of this study is to examine the temporal and spatial variability of key aerosol and climate parameters over Kenya, detect and classify anomalies in the multivariate dataset using HMM and interpret the climatic and environmental implications of detected anomalies and their possible causes. The findings will provide valuable insights into the behavior of aerosols in Kenya context and support informed decision-making in climate adaptation and air quality management.

2. Material and Methods

2.1. Study Area

The study was conducted over Kenya, bounded by Latitudes 5˚S - 5˚N and Longitudes, 34˚E - 42˚E (See **Figure 1**). The country covers an area of approximately 582,646 square kilometers and shares borders with Ethiopia to the north, Somalia to the east, Tanzania to the south, Uganda to the west, and South Sudan to the northwest [20]. Its south-eastern boundary lies along the Indian Ocean, a key influence on the country's climate and atmospheric dynamics.

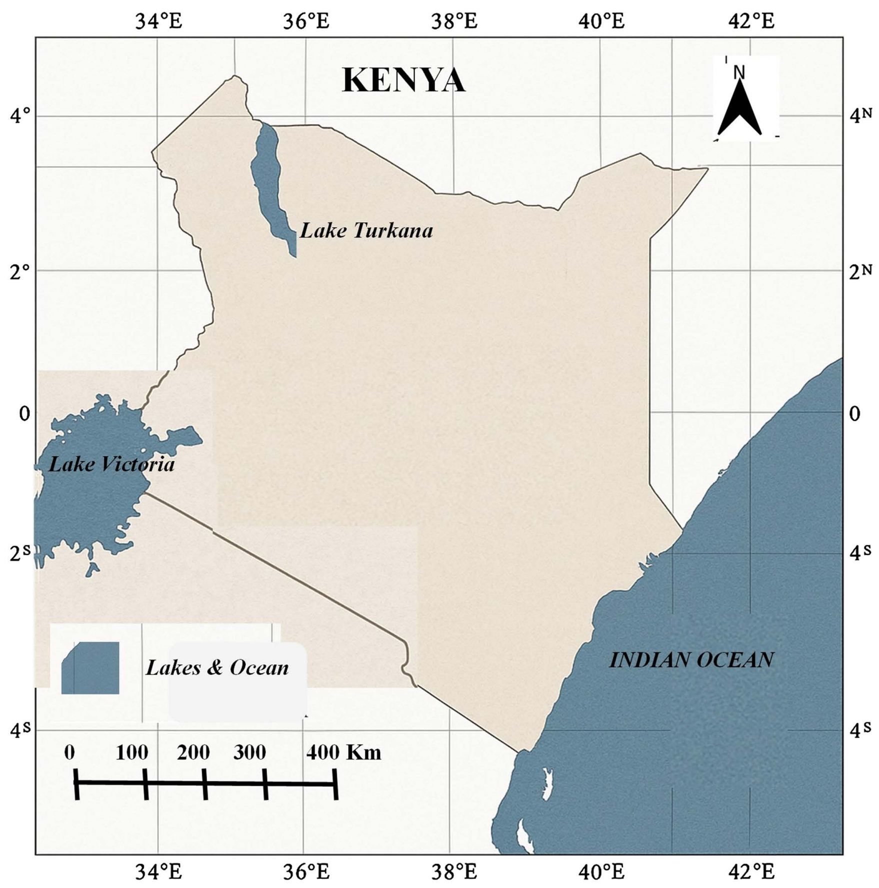

Figure 1. Showing study area.

Kenya exhibits a diverse climate pattern influenced by its equatorial location, varied topography, mountain, rift valley, plains, highlands and low lands, large water bodies like Lake Victoria, Lake Nakuru, Lake Baringo, Lake Naivasha, lake Turkana and Indian Ocean. Four climatic zones i.e., equatorial, tropical, semi-arid and arid. Equatorial basically in Western and parts of Nyanza, characterized by high rainfall and moderate temperatures [21]. Tropical dominating Central highlands i.e., Nyeri and Nairobi lang rains March-May and short rain October to December. Semi-arid and arid zone cover eastern, North-eastern regions areas like Garissa, Marsabit, Turkana, Lodwar, Moyale etc. very low rainfall with high temperature [21]. The country has experienced a warming trend over recent decades. Average annual temperature increased by about 0.34˚C per decade [1].

2.2. Data Sources

The study uses satellite-derived monthly data from 2000 to 2022 obtained from the following sources: from Giovanni. This study utilized monthly satellite datasets spanning 2000-2022, including MODIS (AOD, SSA), MERRA-2 (SAT and reanalysis precipitation and TRMM (Precipitation estimation). To ensure consistency all datasets were regridded to a common spatial resolution of 1˚ × 1˚. The native resolutions were MODIS (1˚ × 1˚) MERRA-2 (0.5˚ × 0.625˚) and TRMM (0.25˚ × 0.25˚). For MODIS retrievals only values with quality assurance flags greater than 2 were retained to minimize retrieval uncertainty. Missing values were gap-filled using linear interpolation to preserve temporal continuity without artificially amplifying variance. A sensitivity test comparing linear interpolation and cubic spline interpolation on selected time series showed negligible differences in anomaly detection outcome, justifying the adopted approach. To address spatial heterogeneity two approaches were considered, national means, which provided a robust signal of larger scale anomalies and regional clustering based on Kenya's major climate zones. While national means highlighted broad-scale events, regional analysis revealed localized anomalies, particularly enhanced AOD episodes in Northern and eastern Kenya.

2.2.1. Moderate Resolution Imaging Spectroradiometer (MODIS)

MODIS is a satellite sensor brought into the earth's atmosphere by the National Aeronautics and Space Administration (NASA) in partnership with Goddard Space Flight Centre (GSFC). It is divided into MODIS Aqua which orbits at 13:30 p.m. local time and MODIS Terra orbiting at 10:30 a.m. local time. Using a temporal resolution of 1 - 2 days and a swath of 2330 km, MODIS obtains its data in 36 bands. Out of the 36 bands, 5 bands are at 500 m, 2 bands at 250 m and 29 bands at 1 km [22]-[24] with two algorithms: Deep Blue (DB) and Dark Target (DT).

2.2.2. Modern Era Retrospective Analysis for Research and Application Version 2 (MERRA-2)

(MERRA-2) is the latest atmospheric reanalysis of the modern satellite era produced by NASAs Global Modelling and Assimilation Office [25] MERRA-2 production began in June 2014 in four processing streams, and converged to a single near-real time stream in mid-2015. Its products can easily be accessed online through the NASA Goddard Earth Sciences Data Information Services Centre (GESDISC). MERRA-2 assimilates observation types not available to its predecessor, MERRA, which includes updates to the Goddard Earth Observing System (GEOS) model and analysis scheme so as to provide a viable ongoing climate analysis beyond MERRAs terminus [26].

2.2.3. Tropical Rainfall Measure Mission (TRMM)

TRMM is a joint project established and launched 1997 between NASA and the Japanese space agency, JAXA. TRIMM provides the research and operational communities' unique precipitation information from space. Use of both active and passive microwave instruments and processing, low inclination orbit (35˚) make TRMM the world's foremost satellite for the study of precipitation and associated storms and climate processes in the tropics. TRMM is designed to measure rain rates from space using a combination of high-resolution radar, passive microwave radiometer and visible-infrared radiometer measurements from a spacecraft in a rapid precession. These measurements, averaged over a 500 km grid for a month, are expected to provide monthly mean rainfall to an accuracy of 10 - 15 percent [27].

2.3. Data Pre-Processing

All datasets were resampled to a common spatial resolution and averaged monthly. Missing values were filled using linear interpolation. Anomalies were standardized using z-scores to identify temporal outliers. Data was further normalized before modelling to ensure comparability among variables.

2.4. Exploratory Data Analysis

Descriptive statistical analysis was performed to evaluate the central tendency, dispersion, and distribution of each variable. Temporal trends were visualized through line graphs and seasonal plots. Linear regression was employed to detect long-term trends in AOPs and climate variables.

2.5. Multivariate Hidden Markov Model (HMM)

This study leverages Kenya's geographical and climatological diversity to assess anomalies in AOD, SSA, AE, SAT, and RR from 2000 to 2022 using a Multivariate Hidden Markov Model.

The HMM was implemented to detect hidden states representing normal and anomalous atmospheric conditions. Each state characterizes a distinct combination of AOP and climate values. The model assumes observations are generated from a mixture of multivariate Gaussian distributions conditional on an unobserved Markov chain.

The HMM was implemented using R programming software with the dependent Mixture Models Hidden Markov Models (depmixS4) package, allowing specification of multivariate emission distributions. Model parameters were estimated via maximum likelihood using the Expectation-Maximization (EM) algorithm. Model selection was based on the Bayesian Information Criterion (BIC), and the number of hidden states was optimized accordingly.

Limitations of the study include the spatial resolution of satellite data and the assumption of temporal homogeneity in HMM. Additionally, ground validation was limited due to sparse observational networks in some regions of Kenya.

2.6. Model Selection and Validation

The Multivariant Hidden Markov model was fitted to the coupled aerosol climate dataset (AOD, SSA, AE, SAT and RR). Model selection was based on the Bayesian information criterion (BIC), which indicated that a three-state model provided the optimal balance between complexity and explanatory power. The three hidden states were characterized by distinct state dependent means and variances, capturing transitions between baseline conditions, moderate anomalies and severe anomalies associated with high aerosol loading and suppressed rainfall. Transition probability matrices indicated persistent states memory, with severe anomalies showing strong recurrence during 2010-2016. A detailed summary of state -dependent parameters and BIC scores are presented in **Table 1** below.

Table 1. HMM model selection and state characteristics (5-state model).

Model HMM	No of hidden states	BIC score	State	Mean AOD	Mean SSA	Mean SAT	Mean RR (mm/month)	SPEI	variance	Dominant characteristics
	5	1380	S1	0.09	0.92	24.1	98.3	0.25	Low	Baseline
			S2	0.16	0.89	25.0	85.6	0.02	Low/moderate	Mild aerosol increase
			S3	0.24	0.87	25.8	70.4	−0.45	Moderate	Moderate anomalies
			S4	0.33	0.84	26.9	58.0	−1.02	High	Strong aerosol loading
			S5	0.40	0.81	27.6	44.7	−1.85	Very high	Severe anomaly

To assess detection skill, anomaly months flagged by the HMM were compared against independent datasets, including MODIS fire counts and the Standardized Precipitation Evapotranspiration Index (SPEI). Results revealed that high-probability anomaly months corresponded closely to peaks in biomass burning and drought episodes, lending confidence to the model's ability to detect physically consistent anomalies.

2.7. Anomaly Detection and Interpretation

The Viterbi algorithm was used to decode the most likely sequence of hidden states. States associated with extreme values (e.g., high AOD or low SSA) were classified as anomalous. Temporal distribution of anomalies was examined to assess frequency, persistence, and potential linkage with environmental events such as biomass burning or droughts.

3. Results, Discussion and Conclusion

3.1. Detected Anomalies in Aerosol Optical Depth (AOD)

Blue dots show Normal AOD mean values over time. Red dots show Anomalies detected in AOD means values over time that deviates significantly from expected range based on the HMM analysis. The period cover years between 2000 to 2022. x-axis shows years and the y-axis shows the corresponding AOD mean Values (See Figure 2).

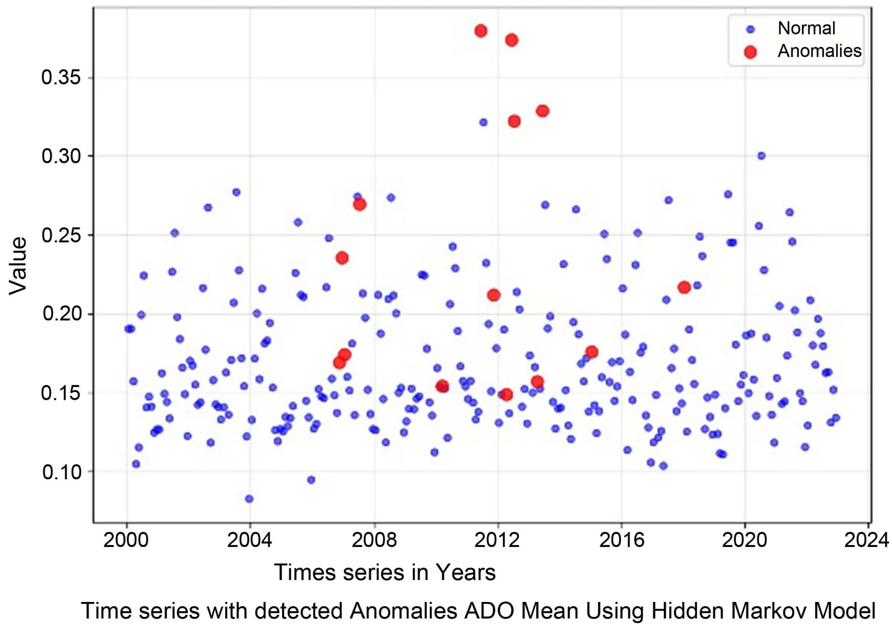

Figure 2. Time series with detected Anomalies AOD mean Using Hidden Markov Model (HMM) year 2000-2022.

Most of the AOD mean values fall between 0.10 and 0.25 suggesting a general moderate aerosol concentration over Kenya observed during the period.

The anomalies are relatively fewer, less than 20 values exactly 14 values out of 256 plotted points. They mainly occurred between 2007-2009. This could be attributed to enhanced biomass burning in East Africa and Central Africa, biomass burning increased due to changes in land-use, unsustainable agricultural practice and spread of dry conditions. Burning of biomass produced large quantities of aerosols hance increased AOD mean value [28] [29].

The La Nina event of 2007-2008 could led to drier conditions than normal over eastern Africa, this increased dust mobilization and reduced wet depositions of aerosols over the region. With less rainfall leads to less Aerosol scavenging hence increased AOD mean values [30]. More cluster between 2012-2014.

Scattered anomalies appeared in 2016 and 2019. This can be attributed to localized climate variability, ununiform biomass burning, dust outbreaks and anthropogenic activities. Land clearing in Kenya and Tanzania and Uganda contributed to aerosol loading at different times of the year due to variation in seasons [31].

Post El-Nino effect, moderate El-Nino 2015-2016 which ended 2016, the residual impacts, altered rainfall pattern, dry spell continued to 2017. The changes lead to drier vegetation increasing the chances of fire and reduced aerosol removal via rainfall hence increased AOD mean value [10] [32]. Highest anomaly appears to be around 2013, where AOD exceeds 0.35 a clear outlier. This could be attributed to increased Urban development in Kenya, Nakuru, Eldoret, Nairobi, Mombasa, Kisumu cities, there is high transport emission and industrial emission especially during low temperature, thus increase in aerosols loading in the Kenyan Atmosphere [21].

Higher AOD exceeds 0.35 mean can be attributed to severe drought condition in 2013, rainfall received in Kenya was below average, this led to dry surface conditions, hence more dust generation and reduced wet deposition of aerosols. More vegetation dried up hence increasing risk of fire breakout [30]. There were intense biomass burning in central and Eastern Africa based on the MODIS record, in Democratic Republic of Congo and Northern Zambia, transported by wind to Kenya, leading to an increase in AOD [33]. In 2013, there was a strong wind event that transported mineral dust from the Horn of Africa, Somalia and Arabian Peninsula into Northern Kenya which combined with local sources hance pushing AOD values beyond normal [34].

3.2. Time Series with Anomalies in Single Scattering Albedo (SSA) 2004-2022

From **Figure 3** green dots show Normal SSA mean values over time. Red dots show Anomalies detected in SSA means values over time that deviates significantly from expected range based on the HMM analysis. The period cover years between 2004 to 2022. x-axis shows years 2000-2024, values start 2004 to 2022 and the y-axis shows the corresponding SSA mean Values.

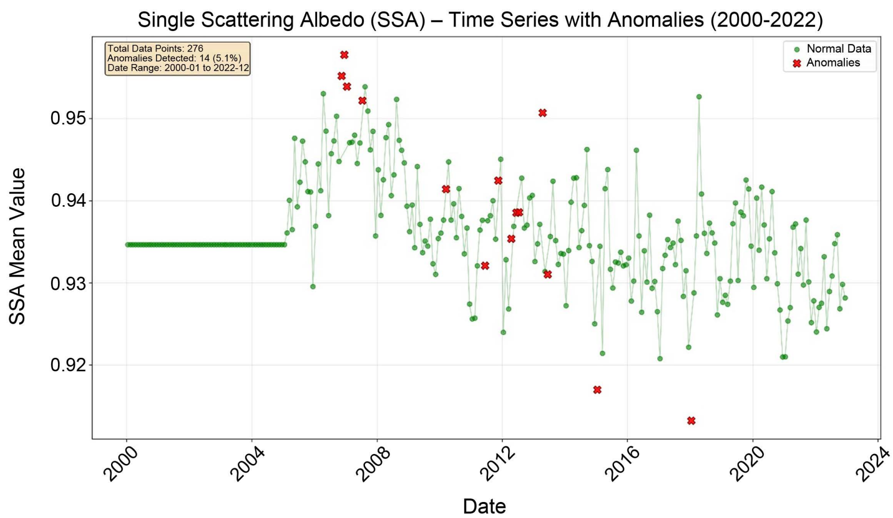

Figure 3. Time series with detected anomalies SSA mean using hidden markov model (HMM) year 2004-2022.

In 2006-2008 there was 4 indicators of values greater than 0.95, outliers' anomalies that significantly deviate from the normal expected patterns. This could be attributed to unusual dominance of scattering aerosols which is associated with cleaner, less-absorbing particles. The period may have experienced lower black carbon emissions and higher sulphate and nitrate level from agricultural fertilizers, reduced biomass burning [35] [36]. In 2006-2007 was wet in many parts of the country due to presence of El-Nino leading to decrease in fire and less absorbing aerosol production from smoke and BC hence low SSA [10]. Some of these outliers might be attributed to Satellite bias especially during low AOD conditions where SSA estimates can appear unusually high due to low absorbing aerosol content with high scattering aerosol contents [37].

In 2015-2019 there were 2 anomalies values less than 0.92 outliers' anomalies far much less than the expected. This can be attributed to enhanced biomass burning releasing a large amount of black carbon, which is absorbing aerosol hence reduction in SSA. Dry condition and agricultural practices during the season could have resulted into frequently fire breakout [14]. The strong El-Nino event of 2015-2016 disrupted normal rainfall pattern resulting into a dry spell in part of East Africa, Kenya being part of the affected countries within the region. There was increase fire activities, higher dust emissions which included more absorbing mineral components than scattering components [10]. Rapid urbanization and increased industrial emissions especially around Nakuru, Naivasha, Eldoret, Thika, Nairobi, Mombasa enhanced local BC emission which lower SSA values in urban regions [38].

In 2010-2014 there were 8 anomalies values falling between 0.93 and 0.95. This suggests a consistent presence of moderately absorbing aerosols than scattering aerosols over Kenya during that period. There was a mixture of absorbing and scattering aerosols during the period; BC and organic Carbon (scattering) emitted together in biomass burning. Kenya and its neighboring countries experienced seasonal fire which recurred [39]. Satellite-based fire activity based on MODIS show moderate sustained fire emission 2010-2014, which weren't intense enough to cause more absorbing aerosols [40].

Most of the SSA mean values fall between 0.93 and 0.95 suggesting a general moderate aerosol concentration over Kenya observed during the period. There was a mixture of scattering and absorbing particles over Kenya. The values transition from absorbing to scattering with rise from biomass burning i.e., dry-season burning in Kenya and neighboring countries produces a mixture of BC and organic Carbon. BC is absorbing aerosol while Organic Carbon is scattering aerosol, urban and transport emission and dust transport. There is influence of both natural and anthropogenic sources. The mixture of absorbing and scattering aerosols lower SSA [39].

Urban regions like Nairobi, Nakuru, Kisumu, Eldoret, Mombasa and Thika releases moderate levels of BC and Organic aerosols from transport, industries and domestic energy uses. They contribute to absorption yield to moderate SSA mean value [21]. Dust from Sahel are transported to Kenya bringing a mixture of absorbing and scattering aerosols, results into moderate SSA values [41]. Shift in wind direction influences aerosols locally or transported hence affecting their scattering and absorbing nature [10] [42].

3.3. Time Series with Anomalies in Angstrom Exponent (AE) 2000-2022

From **Figure 4** yellow dots show Normal AE mean values over time. Red crosses show Anomalies detected in AE means values over time that deviates significantly from expected range based on the HMM analysis. The period cover years between 2000 to 2022. x-axis shows years 2000-2024, values start 2000 to 2022 and the y-axis shows the corresponding AE mean Values 0.0 to 1.4 AE mean values.

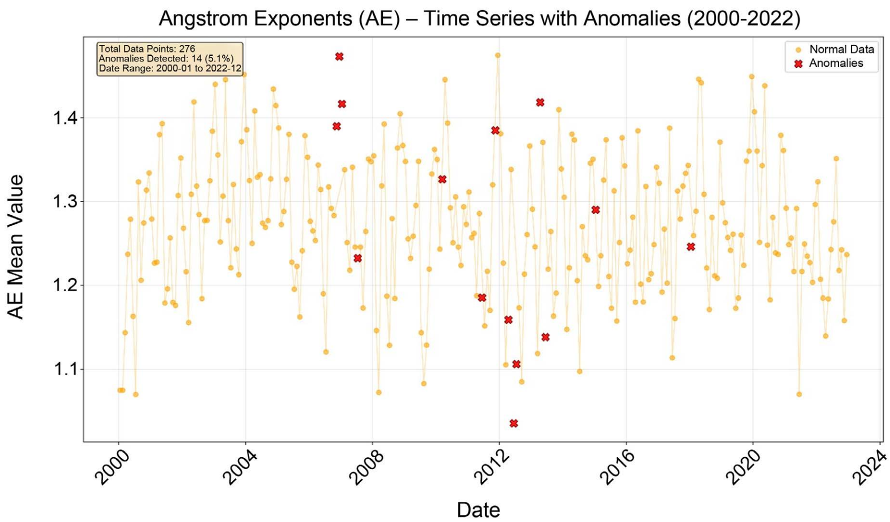

Figure 4. Time series with detected anomalies AE mean using hidden markov model (HMM) year 2000-2022.

Majority of Angstrom Exponent (AE) values over the study period range between 1.2 to 1.4, indicating normal mean levels associated with fine-mode aerosols. This attributed to a prevalence of anthropogenic activities which may include biomass burning aerosols contributing to fine-mode aerosols associated with higher AE values. AE values classified as AE > 1 fine-mode aerosols, AE < 1 course-mode aerosols. This was observed in similar studies [5].

The period between 2006-2009 recorded multiple anomalies in AE value, there was four anomalies, one between 1.2 - 1.3 AE mean values another one between 1.3 - 1.4 AE mean values and other two values far much greater than 1.4 AE mean values showing a great outlier AE mean value this indicated abnormal aerosol conditions over Kenya. These abnormal aerosol conditions could be attributed to regional biomass burning. During dry season Central Africa and East Africa contribute to elevated fine-mode aerosols due to increase in biomass burning. These fine mode-aerosols are transported by prevailing easterly and north-easterly winds bringing in Kenya aerosols from neighboring regions like Uganda, Congo

Basin and Ethiopia hence reflected into increased AE mean value [5] [43] [44].

In 2010-2016, nine anomalies between 1.1 AE mean values and 1.4 AE mean values with only one appearing less than 1.1 AE mean values and another one above 1.4 AE mean values. Variability which includes both high and exceptionally low AE value observed. Very low values in 2012 indicate dominance of coarse particles, possibly dust transported from arid and semi-arid regions [45]. The coarse-mode particles from dust intrusions from arid regions i.e., Northern Kenya and long distance transported dust from Eastern Ethiopia and Sahara Desert cause low AE values in the region. Reduced biomass burning leads to a cleaner atmospheric condition with fewer fine-mode aerosols particles resulting to decrease in AE mean value [5]. Elevated values 2011 and 2014 can be attributed to increase in fine-mode aerosols. Evidence of increased urban and industrial emission due to development of major urban centers such as Nairobi, Kisumu, Nakuru, Mombasa, Eldoret and Many industrial establishments in Thika, Saalgaa in Nakuru (Simba Cement), Bamburi Cement in Mombasa emission of a lot of smoke which consist of fine-mode aerosols. There is also evidence of biomass burning during dry season and also changes in wind and precipitation patterns hence affect aerosol transport and dispersion [44] [46].

Throughout the study period, the AE mean value remain within the range of 1.2 - 1.4 normal with notable anomaly observed in 2018 indicating a shift in aerosol particle shift within the year. This could be linked to localized meteorological or emission changes. The deviation may suggest an increased presence of course-mode aerosol or a mixture of fine-mode and course mode associated with both BC and organic burning [5].

No anomalies in AE mean values were detected during the post-2020 period suggesting a return to normal variability and stabilization in aerosol particle size distribution. This pattern implies a possible decline in episodic course-mode aerosol events as a result of consistent dominance with fine-mode aerosols during the recent years [5] [43].

3.4. Time Series with Anomalies in Rainfall Rates (RR)-2000-2015

From **Figure 5** purple dots show Normal RR mean values over time. Red crosses show Anomalies detected in RR means values over time that deviate significantly from expected range based on the HMM analysis. The period covered years between 2000 and 2015. x-axis shows years 2000-2024, values start 2000 to 2015 and the y-axis shows the corresponding RR mean Values 0.000 mm/day to 0.175 mm/day RR means values.

The majority of mean rainfall rate values between 2000 and 2015 ranged between 0.025 mm/day and 0.075mm/day, indicating relatively low to moderate precipitation levels during this period. The region is predominantly in Northern and Eastern Kenya, these regions experience lower rainfall compared to highland and lake regions like Lake Victoria and Mount Kenya region [10]. The low rainfall rate may also be influenced by climatic drivers such as the ENSO and the Indian Ocean

Dipole (IOD), they affect precipitations in East Africa, Kenya being part of the affected region [42].

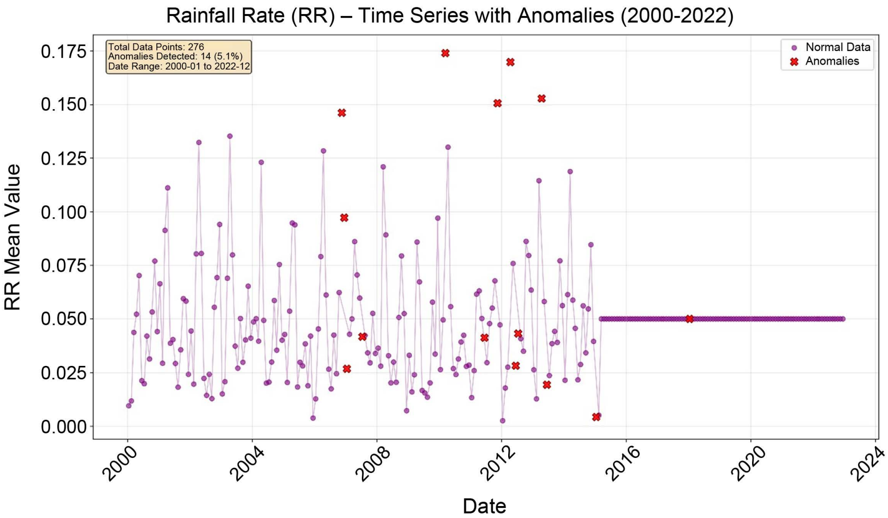

Figure 5. Time series with detected anomalies RR mean using hidden markov model (HMM) year 2000-2015.

Between 2000 and 2022, majority of years over Kenya recorded normal rainfall rate mean values, though were below 0.100mm/day. This indicated a very low average daily precipitation across much of the country. The arid and semi-arid climate zones i.e., Garissa, Wajir, Turkana, experienced limited unevenly rainfall distribution [10]. Although interannual fluctuations were present, largely driven by global climate system i.e., ENSO and IOD the trend remained within the low precipitation range [42]. The findings highlight a pattern of normal but marginal rainfall which critically affects agricultural practices, water availability and activate drought resilience in climate sensitive regions.

During the period 2006-2015, a total of 13 rainfall rate anomalies were detected over Kenya. 5 between 0.025 mm/day and 0.050 mm/day, 2 below 0.025 mm/day and 1 between 0.125 mm/day and 0.150 mm/day, 4 between 0.150 mm/day and 0.175 mm/day with one value almost 0.175 mm/day. This indicated a notable deviation from the long-term mean. Values above 0.025mm/day suggested short-term increases in precipitation associated with episodic events such as enhanced convective activity and ENSO related wet phases. Values below 0.025 mm. day indicated drier than normal conditions that may have been driven by droughts in arid and semi-arid regions in Kenya [10]. These anomalies can be attributed to large scale atmospheric oceanic interactions which may include IOD event and tropical circulation anomalies [43].

The analysis of rainfall rate trends over Kenya from 2000-2015 reveals a predominance of normal mean values with majority falling below 0.1mm/day, the country is characterized with low and variable precipitation patterns. 5.07% anomalies detected in the data were linked to the influence of ENSO and IOD. Findings underscore the sensitivity of Kenya's rainfall regime to regional and global climate systems and emphasize the need for robust climate monitoring and adaptation strategies specially to gap increase vulnerability to droughts and erratic rainfall patterns.

3.5. Time Series with Anomalies in Surface Air Temperature (SAT) 2000-2022

From **Figure 6**, red dots show Normal surface Air temperature mean values over time. Red crosses show Anomalies detected in SAT means values over time that significantly deviate from expected range based on the HMM analysis. The period covers the years between 2000 to 2022. x-axis shows years 2000-2024, values start 2000 to 2022 and the y-axis shows the corresponding Surface air temperature mean Values 295 K to SAT mean value 301 K.

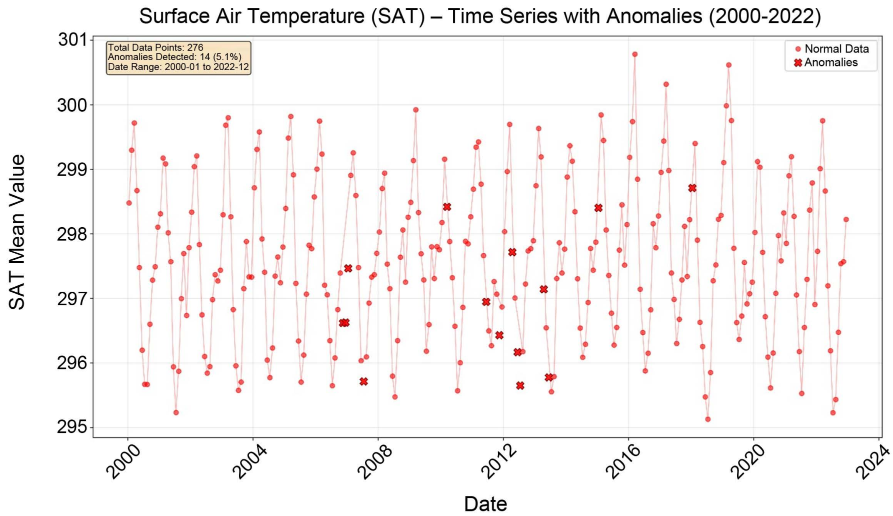

Figure 6. Time series with detected anomalies SAT mean using hidden markov model (HMM) year 2000-2022.

Between the year 200 and 2022, the majority of SAT mean values fell within the range of 296 K to 299 K (22.85˚C to 25.85˚C) which is reflection of normal climatological conditions in the country. Central highland and western Kenya experienced moderate temperature due to elevation and seasonal rainfall patterns [47]. The season was marked by instances of temperature anomalies associated with global warming and regional drought events.

Between 2006 and 2008, a total of four SAT anomalies were detected over Kenya, with some years exhibiting values above 297 K and other years with values less than 296 K. The anomalies depict a departure from the long-term average considering majority of SAT mean during 2000-2022 remained within the range of 296 K to 299 K. The deviation may be linked to prolonged drought conditions and cooler-than-average wet seasons influenced by ENSO and La Nina phases [10] [47].

Between 2010 and 2016, a total of eight SAT anomaly data points were detected over Kenya representing significantly deviations from the normal temperature pattern observed 2000-2022 period. The anomalies reflect unusual temperature fluctuations, with the lowest recorded falling below 296 K lie outside the topical range 296 - 299 K considered normal for majority of the regions in the country. The occurrences of multiple 8 anomalies within the seven-year range show a period of heightened climate instability, linked to regional droughts, cooler wet seasons and the influence of climate drivers such as La Nina and IOD [10] [21] [47].

During the period 2017 to 2022, the surface air temperature data over Kenya showed a remarkable stability, with only one anomaly point significantly deviating from the established normal pattern. However, this anomaly still fell within the range of normal 296 K to 299 K suggesting less severe deviation compared to earlier years. The stability in temperature can be attributed to climatological recovery and reduced influence of extreme global climate oscillations. Attributed to regional climate adaptation strategies, improved land surface management and natural variability [47] [48].

From 2000 to 2022, Surface air temperature over Kenya generally remained within the normal range of 296 - 299 K. Most anomalies concentrated between 2006-2016 reflecting periods of climatic stability. 2010-2016 recorded eight anomalies, while 2017-2022 showed only one mild deviation indicating a return to more stable temperature conditions in recent years. The trends highlight the temporal variability of regional and global climate drivers on Kenya's thermal variability.

Table 2. Transition probability matrix 5-state HMM.

From/to	State 1	State 2	State 3	State 4	State 5
State 1	0.84	0.08	0.05	0.02	0.01
State 2	0.10	0.72	0.12	0.05	0.01
State 3	0.06	0.14	0.62	0.12	0.06
State 4	0.03	0.06	0.14	0.60	0.17
State 5	0.02	0.03	0.06	0.19	0.70

The Multivariate Hidden Markov Model fitted to AOD, SSA, AE, RR, SAT and SPEI was evaluated using the Bayesian BIC a 5-state model produced the lowest BIC (1380) and was selected as optimal. State dependent parameter estimates (**Table 1**) indicate s a clear gradient from baseline conditions (state 1) through mild and moderate perturbation (state 2-3) to strong and severe anomaly regime (state 4-5).

Transition probability matrix **Table 2** highlights persistence within anomalous states, consistency within anomalous states, consistent with multi-month episodes of aerosol climate interactions. Each parameter exhibited anomalies in 5.08% of monthly observations over the study period. The consistency across variables suggests that the detected anomalies represent robust multivariate events rather than artifacts of individual datasets. Most extreme states (S_4-S_5) coincide with periods of elevated AOD, reduced SSA, higher surface air temperature suppressed rainfall, and negative SPEI values, aligning with biomass burning and drought episodes over Kenya.

4. Conclusion and Recommendations

4.1. Conclusions

The HMM successfully identified episodes of heightened aerosol loading that coincided with regional biomass burning and suppressed rainfall, particularly during the years 2010-2016. Comparison with five-count and drought indices confirmed the robustness of these detections. While national means captured the broad timing of anomalies, regional clustering revealed stronger spatial contrasts with northern and eastern Kenya showing more frequent and intense events.

There was AOD moderate variability with most values indicating low to moderate aerosol loading. Anomalies are influenced by regional biomass burning and transboundary pollution.

SSA over Kenya generally indicated the presence of moderately absorbing aerosols, with most mean values ranging between 0.93 and 0.95. Anomalies in SSA point to episodes of increased aerosol absorption due to biomass burning and urban emissions.

Angstrom exponent over Kenya predominantly remained within the normal range of 1.2 - 1.4. This indicated the dominance of fine-mode aerosols.

Rainfall rate predominance of normal mean values with the majority falling below 0.1 mm/day. Kenya is characterized by low and variable precipitation patterns. The findings underscore the sensitivity of Kenya's rainfall regime to regional and global climate systems and emphasize the need for robust climate monitoring and adaptation strategies, especially to address the increasing vulnerability to droughts and erratic rainfall patterns.

There is a climate shift leading to a slight rise in surface Air temperature in Kenya. The trends highlight the temporal variability of regional and global climate drivers on Kenya's thermal variability.

4.2. Recommendations

Establish aerosol monitoring stations across Urban, rural and arid regions to complement satellite data also analyze AOD, SSA and AE trends regularly to detect pollution events and dust transport. This effort will strengthen air quality monitoring and management.

Promote sustainable land use and vegetation cover by encouraging sustainable agricultural practices that limit land degradation a key driver of course aerosol anomalies. Regulations of land Use to prevent excessive deforestation and burning. Key sources of fine mode aerosols also implement afforestation and reforestation programs in semi-arid regions Turkana and Garissa, which reduces wind erosion and dust emission aerosols.

Mitigating emissions from anthropogenic sources by enforcement of emission control policies in major Urban Centers, Nakuru, Nairobi, Mombasa and Eldoret reduces fine mode aerosols; promoting clean cooking technology to reduce indoor and outdoor emission of biomass burning and having vehicle emission standards to reduce urban aerosol load.

Integrate Aerosol climate interaction into policy and planning. This can be achieved by developing data driven drought and flood risk maps using anomaly trends in RR and SAT and strengthening climate modelling and forecasting tools to include aerosol radiative forcing Impacts.

Raising public awareness through education about aerosol impacts on health, visibility and rainfall also encourages community-based observation networks to report unusual climate events.

Finally support research and capacity building through funding long term studies on aerosol climate interactions and Hidden Markov Model anomaly detection, promote remote sensing, aerosol modelling and environmental data science capacity building for young researchers in Kenya. Integrate the HMM based anomalies detection into national meteorological and climate surveillance programs.

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Conflicts of Interest

The authors declare that there is no conflict of interest in the publication of this work.

References

[1] IPCC (2021) Climate Change 2021: The Physical Science Basis. Cambridge University Press.

[2] 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. *OALib*, **5**, 1-20. https://doi.org/10.4236/oalib.1104821

[3] 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

[4] 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

[5] Eck, T.F., Holben, B.N., Reid, J.S., Dubovik, O., Smirnov, A., O'neill, N.T., *et al.* (1999) Wavelength Dependence of the Optical Depth of Biomass Burning, Urban, and Desert Dust Aerosols. *Journal of Geophysical Research*: *Atmospheres*, **104**, 31333-31349.

[6] Ramanathan, V., Crutzen, P.J., Kiehl, J.T. and Rosenfeld, D. (2001) Aerosols, Climate, and the Hydrological Cycle. *Science*, **294**, 2119-2124. https://doi.org/10.1126/science.1064034

[7] Kahn, R.A. and Gaitley, B.J. (2015) An Analysis of Global Aerosol Type as Retrieved by Misr. *Journal of Geophysical Research*: *Atmospheres*, **120**, 4248-4281.

https://doi.org/10.1002/2015jd023322

[8] Liousse, C., Assamoi, E., Criqui, P., Granier, C. and Rosset, R. (2014) Explosive Growth in African Combustion Emissions from 2005 to 2030. *Environmental Research Letters*, **9**, Article 035003. https://doi.org/10.1088/1748-9326/9/3/035003

[9] Otieno, V.O. and Anyah, R.O. (2013) CMIP5 Simulated Climate Conditions of the Greater Horn of Africa (GHA) Part II: Projected Climate. *Climate Dynamics*, **41**, 2099-2113. https://doi.org/10.1007/s00382-013-1694-z

[10] Nicholson, S.E. (2017) Climate and Climatic Variability of Rainfall over Eastern Africa. *Reviews of Geophysics*, **55**, 590-635. https://doi.org/10.1002/2016rg000544

[11] Zhang, Q., Ma, P. and Ma, J. (2016) Detection of Climate Anomalies Based on HMM. *Advances in Meteorology*, **2016**, Article ID 1830516.

[12] Visser, I., Speekenbrink, M. and Wagenmakers, E. J. (2010) A Tutorial on Hidden Markov Models in R. *Journal of Mathematical Psychology*, **55**, 85-103.

[13] Zucchini, W., MacDonald, I.L. and Langrock, R. (2017) Hidden Markov Models for Time Series: An Introduction Using R. 2nd Edition, CRC Press.

[14] Ichoku, C., Ellison, L.T., *et al.* (2012) Global Aerosol Characterization over Land Using AERONET Measurements. *Atmospheric Research*, **116**, 131-145.

[15] Kipkorir, E.C., Koech, R.K. and Adede, O.O. (2020) Seasonal Variability of Aerosol Optical Properties over Kenya. *Advances in Meteorology*, **2020**, Article ID: 3841207.

[16] Lelieveld, J., Evans, J.S., Fnais, M., Giannadaki, D. and Pozzer, A. (2002) The Role of Air Pollution in Climate Change and Health in Africa. *Environmental Research Letters*, **7**, Article 034018.

[17] Bessec, M. and Fouquau, J. (2008) The Non-Linear Link between Electricity Consumption and Temperature in Europe: A Threshold Panel Approach. *Energy Economics*, **30**, 2705-2721. https://doi.org/10.1016/j.eneco.2008.02.003

[18] Shumway, R.H. and Stoffer, D.S. (2017) Time Series Analysis and Its Applications: With R Examples. 4th Edition, Springer.

[19] Chakraborty, S., Joshi, P.K. and Roy, P.S. (2020) Monitoring Spatial Patterns of Drought Using Hidden Markov Models and Remote Sensing. *Ecological Indicators*, **115**, Article 106383.

[20] Central Intelligence Agency (2025) The World Factbook: Kenya. U.S. Government.

[21] Simiyu, A.H., Muthama, J., Ngaina, J. and Onwonga, R. (2018) Anthropogenic Contribution to Air Pollution with Background Emissions; Case of Nairobi, Mombasa and Kisumu. *International Journal of Scientific and Research Publications* (*IJSRP*), **8**, 381-402. https://doi.org/10.29322/ijsrp.8.8.2018.p8047

[22] Levy, R.C., Remer, L.A., Mattoo, S., Vermote, E.F. and Kaufman, Y.J. (2007) Second-generation Operational Algorithm: Retrieval of Aerosol Properties over Land from Inversion of Moderate Resolution Imaging Spectroradiometer Spectral Reflectance. *Journal of Geophysical Research*: *Atmospheres*, **112**, D13211. https://doi.org/10.1029/2006jd007811

[23] Hsu, C. W. and Kuo, T.H. (2003) 6-Bit 500 Mhz Flash A/D Converter with New Design Techniques. *IEE Proceedings-Circuits*, *Devices and Systems*, **150**, 460-464. https://doi.org/10.1049/ip-cds:20030604

[24] Hsu, T., Ke, H. and Yang, W. (2006) Knowledge-Based Mobile Learning Framework for Museums. *The Electronic Library*, **24**, 635-648. https://doi.org/10.1108/02640470610707240

[25] Mathur, B. (2022) Predicting Atmospheric Variables in the MERRA-2 Database Us-

ing Neural Networks. 2022 *International Conference on Emerging Techniques in Computational Intelligence* (*ICETCI*), Hyderabad, 25-27 August 2022, 125-131. https://doi.org/10.1109/icetci55171.2022.9921371

[26] Todling, R. and El Akkraoui, A. (2018) The GMAO Hybrid Ensemble-Variational Atmospheric Data Assimilation System: Version 2.0 (No. GSFC-E-DAA-TN54363). https://gmao.gsfc.nasa.gov/pubs/docs/Todling1019.pdf

[27] Theon, J.S. (1994) The Tropical Rainfall Measuring Mission (TRMM) *Advances in Space Research*, **14**, 159-165. https://doi.org/10.1016/0273-1177(94)90210-0

[28] Roberts, G., Wooster, M.J. and Lagoudakis, E. (2009) Annual and Diurnal African Biomass Burning Temporal Dynamics. *Biogeosciences*, **6**, 849-866. https://doi.org/10.5194/bg-6-849-2009

[29] Yue, Y. (2016) Spatial Continuous Biomass Burning Emission Inventory: Application to WRF-Chem Model over the Northern Sub-Saharan African Region. https://digitalcommons.unl.edu/geoscidiss/95/

[30] Nicholson, S.E. (2014) A Detailed Look at the Recent Drought Situation in the Greater Horn of Africa. *Journal of Arid Environments*, **103**, 71-79. https://doi.org/10.1016/j.jaridenv.2013.12.003

[31] Olorunfemi, I.E., Olufayo, A.A., Fasinmirin, J.T. and Komolafe, A.A. (2021) Dynamics of Land Use Land Cover and Its Impact on Carbon Stocks in Sub-Saharan Africa: An Overview. *Environment*, *Development and Sustainability*, **24**, 40-76. https://doi.org/10.1007/s10668-021-01484-z

[32] Palmer, P.I., Wainwright, C.M., Dong, B., Maidment, R.I., Wheeler, K.G., Gedney, N., *et al.* (2023) Drivers and Impacts of Eastern African Rainfall Variability. *Nature Reviews Earth & Environment*, **4**, 254-270. https://doi.org/10.1038/s43017-023-00397-x

[33] Ichoku, C., Giglio, L., Wooster, M.J. and Remer, L.A. (2008) Global Characterization of Biomass-Burning Patterns Using Satellite Measurements of Fire Radiative Energy. *Remote Sensing of Environment*, **112**, 2950-2962. https://doi.org/10.1016/j.rse.2008.02.009

[34] Schepanski, K. (2018) Transport of Mineral Dust and Its Impact on Climate. *Geosciences*, **8**, Article 151. https://doi.org/10.3390/geosciences8050151

[35] Bond, T.C., Doherty, S.J., Fahey, D.W., Forster, P.M., Berntsen, T., DeAngelo, B.J., *et al.* (2013) Bounding the Role of Black Carbon in the Climate System: A Scientific Assessment. *Journal of Geophysical Research*: *Atmospheres*, **118**, 5380-5552. https://doi.org/10.1002/jgrd.50171

[36] Liu, Y., Li, X., Ge, Q., Fang, X., Wang, T., You, W., *et al.* (2025) Carbonate Radical Ion as a Key Driver of Rapid Atmospheric Sulfate Formation. *npj Climate and Atmospheric Science*, **8**, Article No. 45. https://doi.org/10.1038/s41612-025-00905-4

[37] Remer, L.A., Mattoo, S., Levy, R.C. and Munchak, L.A. (2013) MODIS 3 Km Aerosol Product: Algorithm and Global Perspective. *Atmospheric Measurement Techniques*, **6**, 1829-1844. https://doi.org/10.5194/amt-6-1829-2013

[38] Nyaga, E.W. (2021) Aerosol Remote Sensing and Modelling: Estimation of Vehicular Emission Impact on Air Pollution in Nairobi, Kenya. Doctoral Dissertation, University of Nairobi.

[39] Ichoku, C. and Ellison, L. (2014) Global Top-Down Smoke-Aerosol Emissions Estimation Using Satellite Fire Radiative Power Measurements. *Atmospheric Chemistry and Physics*, **14**, 6643-6667. https://doi.org/10.5194/acp-14-6643-2014

[40] Justice, C.O., Giglio, L., Roy, D., Boschetti, L., Csiszar, I., Davies, D., *et al.* (2010)

Modis-Derived Global Fire Products. In: Ramachandran, B., Justice, C. and Abrams, M., Eds., *Remote Sensing and Digital Image Processing*, Springer, 661-679. https://doi.org/10.1007/978-1-4419-6749-7_29

[41] Mahowald, N.M., Scanza, R., Brahney, J., Goodale, C.L., Hess, P.G., Moore, J.K., *et al.* (2017) Aerosol Deposition Impacts on Land and Ocean Carbon Cycles. *Current Climate Change Reports*, **3**, 16-31. https://doi.org/10.1007/s40641-017-0056-z

[42] Anyah, R.O. and Qiu, W. (2011) Characteristic 20th and 21st Century Precipitation and Temperature Patterns and Changes over the Greater Horn of Africa. *International Journal of Climatology*, **32**, 347-363. https://doi.org/10.1002/joc.2270

[43] Kimani, W.M., Ouma, G. and Achieng (2021) Long-Term Analysis of Aerosol Optical Properties over East Africa Using Satellite Observations. *Atmospheric Research*, **257**, Article 105620.

[44] Stephens, G.L., Shiro, K.A., Hakuba, M.Z., Takahashi, H., Pilewskie, J.A., Andrews, T., *et al.* (2024) Tropical Deep Convection, Cloud Feedbacks and Climate Sensitivity. *Surveys in Geophysics*, **45**, 1903-1931. https://doi.org/10.1007/s10712-024-09831-1

[45] Boiyo, R., Kumar, K.R., Zhao, T. and Bao, Y. (2017) Climatological Analysis of Aerosol Optical Properties over East Africa Observed from Space-Borne Sensors during 2001-2015. *Atmospheric Environment*, **152**, 298-313. https://doi.org/10.1016/j.atmosenv.2016.12.050

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

[47] Ongoma, V., Chen, H. and Omony, G.W. (2016) Variability of Extreme Weather Events over the Equatorial East Africa, a Case Study of Rainfall in Kenya and Uganda. *Theoretical and Applied Climatology*, **131**, 295-308. https://doi.org/10.1007/s00704-016-1973-9

[48] Kogo, B.K., Kumar, L. and Koech, R. (2020) Climate Change and Variability in Kenya: A Review of Impacts on Agriculture and Food Security. *Environment, Development and Sustainability*, **23**, 23-43. https://doi.org/10.1007/s10668-020-00589-1