

Empirical Orthogonal Transformation and Trend Analysis of Aerosols in West Africa

Sharafa S. B.^{1*}, Aliyu R.², Ibrahim B. B.³, Akpootu D. O.⁴, Tijjani B. I.⁵,
Darma T. H.⁵, Saidu I. G.⁴, Alaiyemola S. R.⁴ and Ayedun F.⁶

¹Department of Physics, University of Ilorin, Ilorin, Nigeria.

²Department of Physics, Kano State University of Science and Technology, Wudil, Kano, Nigeria.

³Physics/Electronics Unit, Kwara State Polytechnic, Ilorin, Nigeria.

⁴Department of Physics, Usmanu Danfodiyo University Sokoto, Sokoto, Nigeria.

⁵Department of Physics, Bayero University Kano, Kano, Nigeria.

⁶Department of Pure and Applied Science, National Open University of Nigeria.

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Abstract

Properties of aerosols in Cinzana and Ilorin in Western Africa were studied using data on aerosol properties for a period of 16 years (2000–2015). Moderate Resolution Imaging Spectroradiometer (MODIS) is the data source. There has been an inadequate report on the aerosol loading patterns between these two West African Nations. The trend analysis and Empirical Orthogonal Transformation (EOT) evaluation were analyzed. Statistical Package for the Social Sciences (SPSS) software was used for the EOT analysis. Monthly averaged measurements of aerosol optical depth at 550 nm (AOD550), Angstrom exponent estimated for the wavelength pair of 470 and 660 nm (AE470-660), cloud fraction (Ncloud), fine mode fraction (FMF), and single scattering albedo (ω) over the two nations were analysed using EOT, while the trend of AE and AE were analyzed. The trend suggests higher aerosol loading at the Ilorin station and possibly more aerosol types at the Cinzana station. Aerosol loading in Cinzana is lower during the dry season than during the rainy season. The EOT analysis shows that the two stations were characterised by four (4) seasons. The rainy and dry seasons were both characterized by two phases each.

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1. Introduction

Aerosols in the atmosphere are created by both human activities and natural processes, and are moved directly (or formed in places) due to the physicochemical variations of the released gas-phase in the atmosphere. They are essential in modulating the Earth's radiation budget. Their negative impact on health, plants, and solar radiation applications has been widely researched (Havemann, 2006; Ramachandran & Rupakheti, 2020; Nisa et al., 2022). They have been found to perform key roles in climate change by affecting the radiative equilibrium of the Earth's surface (Wang et al., 2020). This process is known as aerosol radiative forcing (ARF). Aerosols also affect the macro- and microphysical characteristics of clouds by acting as cloud condensation nuclei (CCN) and ice nuclei (IN), thereby indirectly affecting the Earth's radiation budget (Wang et al., 2020). Because of these overwhelming aerosol effects, there are complex nonlinear mechanisms that lead to aerosols affecting Radiative Forcing (RF), specifically aerosol–cloud interaction, which remains one of the largest concerns in global climate projections. The RF idea has found usefulness in the guiding principle framework as a precursor to global warming potential, paralleling ozone layer depletion potentials (Ramaswamy et al., 2019) formulation, quantification, application, and utilization of

“radiative forcing” (RF).

Mineral dust pollution is a big issue in West Africa. Around 40% of the yearly aerosols released to the troposphere are mineral dust emitted from arid regions. The region is also disturbed by biomass-burning aerosol episodes, too (Aliyu et al., 2019). Most researchers working on properties of aerosol and their impacts focused on aerosols from biomass burning and dust (Tanré et al., 2003; Sharafa et al., 2019; Rezaei et al., 2019)Iran, is an interesting location for aerosol studies because it is affected by anthropogenic pollution and desert dust aerosols. The aim of this study was to discriminate the aerosol types using satellite data over the city. Method: The study was performed using Level-2 daily Aerosol Optical Depth (AOD). Empirical Orthogonal Transformation (EOT) has been used to evaluate the MODIS C006 Level 2 aerosol optical depth (AOD) and Angstrom exponent (AE) products and to compare the data with AERONET AOD and AE readings (Aliyu et al., 2019). It has also been used to find the link between aerosols and rainfall in Ilorin (Sharafa et al., 2018). Gianelli et al. (2007) reported significant information on both the physical processes in the atmosphere above the instrument and the instrument's performance; this information can be obtained by conducting an EOT

* Corresponding author e-mail: sb69010@gmail.com, sharafa.sb@unilorin.edu.ng

analysis of AOD data. Li et al. (2013) used an EOT method to investigate the spatial and temporal unpredictability in multisensor aerosol retrievals and to examine the uniformity and changes across data sets.

In spite of all the advancement made in comprehending atmospheric aerosols and their impacts on climate, aerosol studies are still characterized with lots of uncertainties (Fawole et al., 2019; Aliyu et al., 2019; Ramachandran & Rupakheti, 2020). This is, partly because of the deficiency in the available information on aerosols' spatio-temporal changes and their associated characteristics (Tanré et al., 2003; Sharafa et al., 2018). For these reasons, various measurement methods (Knapp, 2002; Alam et al., 2011; Cheng et al., 2012; Granados-Muñoz et al., 2016) have been developed to measure aerosols across diverse regions of the world. Ground-based remote sensing networks, such as Aerosol Robotic Network (AERONET; (Holben et al., 1998)) and other remote sensing networks, offer nonstop datasets at several wavelengths to describe aerosol optical, microphysical and radiative properties. Studies using this type of network have been emerged in different parts of the globe (Holben et al., 1998; Cheng et al., 2012; Boiyo et al., 2017; Sharafa et al., 2018; Aliyu et al., 2019). Earlier studies over Africa (Adesina et al., 2014; Tan et al., 2015"ISBN": "1537552015", "ISSN": "16807324", "abstract": "Obtaining continuous aerosol-optical-depth (AOD; Sharafa et al., 2023) show the presence of fine and coarse-mode aerosols from a variety of natural and man-made sources giving rise to changes in concentration at diverse spatio-temporal scales.

Given the significant importance of aerosols locally and regionally, this study aims to examine the EOT of aerosol optical and microphysical characteristics, as well as trends in Cinzana and Ilorin, two sites in West Africa. The analysis used Level 2.0 (high quality cloud-screened and quality assured) data of some aerosol characteristics extracted from MODIS satellite for 15 years (February 2000 to July, 2015) to study (i) the latent characteristics of the two sites and (ii) the trend.

1.1 Empirical Orthogonal Transformation (EOT)

Empirical orthogonal transformation (EOT) is adaptable and has been used to reduce dimensionality and extract features. This technique allows scientists to conduct exploratory probes of underlying variables, shrink data in large datasets, and also test individual models. The procedure is mathematical and it changes a quantity of (possibly) correlated variables into fewer uncorrelated variables known as principal components (Chan & Mozurkewich, 2007). The EOT technique aims to decompose the data matrix into a set of independent, orthogonal eigenvectors, with the initial eigenvector representing the most variance, the second eigenvector amplifying the most of the outstanding variance, etc. (Landau & Everitt, 2004; Leech, Barrett, & Morgan, 2005). EOT has been applied to climate variables such as SST to examine climate modes (Monahan et al., 2009). EOF modes are interpreted individually, independent of other modes. In fact, it can be shown that no such attribution can generally be made. This review demonstrates that in general individual EOF modes (i. Li et al. (2013) used an EOT approach to

analyze the spatial and temporal variability in multisensor aerosol retrievals and examine the consistency and differences between the data sets. The eigenvectors (factors) are rotated to attain simple structure (Brown, 2009b). This process can be done in a number of ways, depending on whether the factors are thought to be correlated (oblique) or uncorrelated (orthogonal). The orthogonal (rotated through 90°) rotations are Equamax, Quartimax, and Varimax while the oblique (no rotation) is Direct Oblimin and Promax. Quartimax minimizes the number of factors required to provide details for each variable. Varimax reduces the number of variables with elevated loadings on each factor and makes small loadings even smaller. Oblique rotation is more complex. Also, oblique rotation gives a pattern matrix that includes the factor and factor correlation matrix that comprises the correlations among the factors (Yong & Pearce, 2013). To decide between using orthogonal and oblique rotation, a request must be made for direct oblimin rotation with the chosen number of factors (Brown, 2009a) and look at the correlations among factors. Check the factor correlation matrix for correlations around 0.32 and beyond. If correlations is more than 0.32, then a possibility of overlap in variance among factors exist, enough variance to use oblique rotation.

If the value of the determinant of each dataset is less than 0.00001, EOT cannot be conducted. The Kaiser-Meyer-Olkin (KMO) measure is adequate if its value is greater than 0.50. The Bartlett test should yield a p-value less than 0.05; this result indicates that the variables are sufficiently correlated to provide a realistic basis for the use of EOT.

The table of the rotated component Matrix, t , is necessary for interpreting the analysis results. Typically, component correlations are less than are deemed low while that of or more are typically considered acceptable.

The tendency of empirical modes to inadequately capture typical communality across subdomains of large datasets can be addressed by categorizing the variance using a rotation technique.

Generally, a rotation is a linear change of the modes that attempts to discover a new location for the coordinate axes, such that forecasts of the variables onto those axes make the spatial or temporal structure of the modes easier to interpret.

The rotated component matrix and component transformation matrix are shown for orthogonal rotations. For oblique rotations, the pattern, structure, and component correlation matrices are revealed. Also, both have the component score coefficient matrix (Eigen vectors) displayed.

2. Materials and Methods

2.1. Collection of Data

West Africa has been reported to have a clear seasonal cycle. Dry season starts in November and s in February, while the rainy season begins in March and ends in October (Sultan & Janicot, 2003).

Multisensor Aerosol Products Sampling System (MAPSS) (<http://giovanni.gsfc.nasa.gov/mapss/>) provides collocated data of AERONET and MODIS that was used for this analysis (Petrenko et al., 2012).

Measurements of MODIS AOD, AE, cloud fraction (N_{cloud}), fine mode fraction (FMF), and single scattering albedo (ω_0) from 2000 to 2015 was used in this study. Trend analysis and EOT evaluation were carried out for two stations in West Africa. The AERONET stations covered are Cinzana and Ilorin. Some useful information about the stations is shown in Table 1 and Figure 1.

Table 1. Information about Cinzana and Ilorin

S/ No	Country	Aeronet station	Station Abbreviation	Longitude	Latitude
1.	Mali	Cinzana	CIN	5°W	13°N
2.	Nigeria	Ilorin	ILO	4°E	8°N



Figure 1. Map of Africa showing the location of Cinzana and Ilorin (West Africa)

Figure 1 shows the positions of Cinzana and Ilorin on a map of Africa.

2.2 Analysis

The data used for this study are daily. The data were converted to mean monthly and mean seasonal data for the study period. The datasets were separated into two parts: rainy and dry seasons.

Time-series graphs of the data were used to determine the overall and seasonal trends in the variation of the AE and AOD data series at the two stations. Values of the average, standard deviation, Coefficient of Variation (CV), and Seasonal Fraction (SF) of the AE and AOD data were calculated. The SF (Soni et al., 2015) of AOD signifies the mean seasonal contribution (percentage) to the sum of annual AOD and is defined as the ratio of the sum of AOD in each season to the total AOD in all seasons during a year, that is:

$$SF(\%)_{For\ AOD} = \frac{AOD_s}{AOD_y} \times 100\% \dots\dots\dots (1)$$

where AODs is the sum of AOD in a particular season, and AODy is the sum of AOD in all months of a year.

Similarly, the seasonal fraction of AE represents the mean seasonal contribution (percentage) to the total annual AE and is defined as the ratio of the sum of AE in each season to the total AE in all seasons during a year, that is:

$$SF(\%)_{For\ AE} = \frac{AE_s}{AE_y} \times 100\% \dots\dots\dots (2)$$

CV in (%) is used to analyze the temporal variability of AOD and AE. It is the ratio of standard deviation to the mean of the dataset (Soni et al., 2015) and is defined as:

$$CV(\%) = \frac{Standard\ deviation}{mean} \times 100\% \dots\dots\dots (3)$$

Empirical orthogonal transformation (EOT) is used to analyze latent modes (i.e., patterns) of variability and how they change with time. The technique is an explanatory means, which permits a time display and a space display of the space-time field that can be valuable to atmospheric scientists.

EOT is useful in analyzing aerosol data mainly because of two reasons: (1) the composition of aerosols is complex, and diverse aerosol types have diverse methods of generation, transformation, and deposition. The EOT technique may aid in separating different aerosol sources or processes like conveyance and elimination; (2) the aerosol data are relatively noisy, due to complexities of surface reflectance, cloud screening, instrument calibration, and assumptions during retrievals. Normally, a considerable amount of the noise should be arbitrarily shared, and EOT analysis will sieve the noise into different modes, while sieving signals in the leading modes.

Precisely, let us assume A is the data matrix of size $V \times W$, where V is the number of parameters and W is the number of observations at each station. Then the EOTs can be deduced by evaluating the eigenvectors of the covariance matrix C, which is

$$C = \frac{1}{W-1} AA^T \dots\dots\dots (4)$$

C is a $V \times V$ real, positive semidefinite matrix, and this can be rewritten as

$$C = E\Lambda E^T \dots\dots\dots (5)$$

Λ is a diagonal matrix whose elements are the V eigenvalues of C, and E is an orthogonal matrix whose columns are the V orthogonal eigenvectors, i.e., EOTs. Individual EOT has a matching time series, the Principal Components (PCs), and can be calculated from

$$P = A^T E \dots\dots\dots (6)$$

P is a $V \times W$ matrix whose columns are the V PCs. So P and E satisfy

$$A = EP^T \dots\dots\dots (7)$$

Combining Eqns. (1), (2), and (4), we have

$$\Lambda = \frac{1}{W-1} P^T P \dots\dots\dots (8)$$

Since Λ is diagonal, the principal components are mutually orthogonal, and their eigenvalues are the same as their variances.

EOT using direct Oblimin rotation was conducted on the monthly-averaged aerosol data from each station to determine if oblique or orthogonal rotation is the best for each station (Brown, 2009b). The Rotated Component Matrix table is key to understanding the analysis results. The content of the items with high weights for each factor was examined to see whether they fit together conceptually and can be named.

$$\tau_{ext}(\lambda) = \beta \lambda^{-\alpha_{ext}} \dots\dots\dots (9)$$

where τ_{ext} is the AOD at a chosen wavelength λ while β is the Angstrom turbidity coefficient, and α is the AE.

3. Results and Discussion

3.1 Analysis of the trends

The trend analysis of AOD and AE in the selected AERONET stations is presented here.

3.1.1 Trends of Aerosol Optical Depth (AOD)

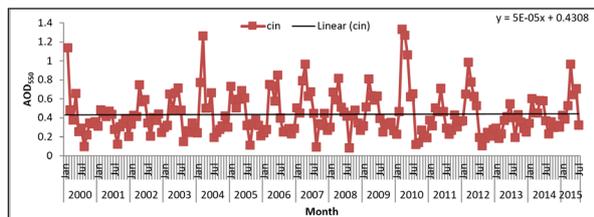


Figure 2. AOD trend in Cinzana (Mali) for periods between 2000 and 2015

Figure 2 shows the equation and trend of AOD550 in CIN. Though this station is close to the desert, only five of the average AOD have values exceed 1.0. The average AOD trend during the dry season is -0.001 month⁻¹, and it is 0.0006 month⁻¹ in the rainy season. The mean AOD in the dry season is 0.4333, while it is 0.4375 during the rainy season. Rainfall and wind speed affects aerosols negatively while temperature enhances them (Masoudi & Gerami, 2018). They are also affected by temporal and local scale perturbations (Banankhah, Nejadkoorki, & Sodaeezadeh, 2014).

The overall period has an average value of 0.4357 and a trend of 0.00005 month⁻¹. Zhang et al., (2024) also reported an increasing AOD trend in Africa. A decreasing trend is observed in the dry-season data over the years, indicating a reduction in aerosol loading during this period. During the rainy season, the washout of atmospheric aerosols could not cause a reduction in the loading. This means that biomass burning, exhaust from automobiles and farming activities, etc., could be the reason for the observed increment. It could also be due to the delayed onset of the rainy season. The highest variance (54.11%) at this station occurred in the dry season; the overall data (51.82%) had the second-highest, and the rainy season (50.42%) had the least. In a 40-year study period of global AOD spanning 1980 to 2018, analysis of seasonal and monthly changes in AOD showed that its maximum value was recorded in the south part of the Sahara Desert. The Sahara Desert also accounts for about 80 % of the dust emissions (Zhao et al., 2025).

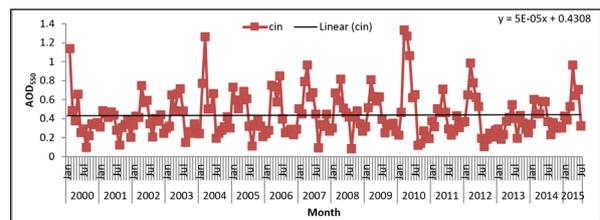


Figure 3. AOD trend in Ilorin (Nigeria) for periods between 2002 and 2015

Figure 3 shows the equation and trend of AOD550 in ILO. This station is farther from the desert than Cinzana station. The observed aerosol loading indicates that there are more dust episodes in Ilorin. This can only be linked to the Intertropical Convergence Zone (ITCZ). The average AOD trend during the dry season was 0.0008 month⁻¹, and the mean in the rainy season was 0.0004 month⁻¹. This plot displays a steady decrease in aerosol loading during the dry season and a gradual increase during the rainy season. These observations could be due to the early onset of rain and/or the increase in anthropogenic aerosols entering the environment. The mean AOD in the dry season was 0.8081 and 0.5659 in the rainy season. The overall period had an average value of 0.6870 and also an increasing trend of 0.0002 month⁻¹. The overall data had the highest variance (43.56%), followed by the dry season (39.68%) and then the rainy season (38.69%).

3.1.2 Angstrom Exponent (AE) Trends

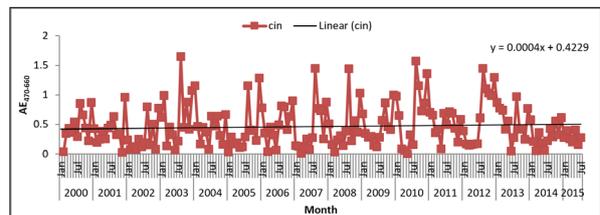


Figure 4. AE₄₇₀₋₆₆₀ trend in Cinzana (Mali) for periods between 2000 and 2015

Figure 4 shows the equation and trend of A 470-660 in CIN. The average α trend during the dry season was 0.00217 month⁻¹, and during the rainy season, it was 0.000248 month⁻¹. The mean AE was 0.479 in the dry season and 0.455 in the rainy season. The overall period has an average value of 0.465 and with a trend of 0.000447 month⁻¹. An increasing trend is observed at the station over the years, with a gradual increase in fine-mode aerosol loading. The rainy season at this station also had the highest variance (76.26%), trailed by the overall data (75.48%) and the rainy season (74.95%).

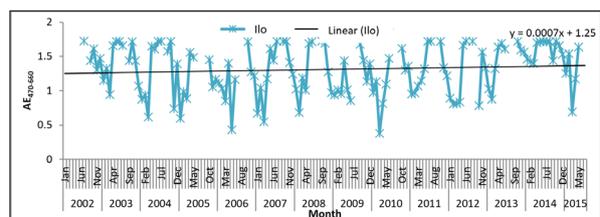


Figure 5. AE₄₇₀₋₆₆₀ trend in Ilorin (Nigeria) for periods between 2002 and 2015

Figure 5 shows the equation and trend of AE470-660 in ILO. The AE trend during the dry season was 0.00429 month⁻¹, and during the rainy season, it was -0.000582 month⁻¹. The mean AE was 0.747 in the dry season and 1.085

in the rainy season. The overall period has an average value of 0.921 and also an increasing trend of 0.000557 month⁻¹. The AE trend at this station shows a consistent increase in coarse-mode aerosols over the years during the rainy

seasons. The highest variance (51.25%) was observed in the rainy season, trailed by the overall data (46.58%), while the least is the dry season (39.22%).

Table 2. Mean, trends and coefficient of variation (CV) of AOD₅₅₀ and AE₄₇₀₋₆₆₀ in Cinzana and Ilorin

Description	Mean	trend (month ⁻¹)	CV (%)	Summary of findings
Cinzana				
AOD	0.4357	0.00005	51.82	High aerosol loading but with a slowly increasing variability
AE ₄₇₀₋₆₆₀	0.4652	0.00040	75.47	Coarse mode aerosols, slowly increasing fine mode but high variability
Ilorin				
AOD	0.6870	0.00020	43.56	High aerosol loading but with an slowly increasing variability
AE ₄₇₀₋₆₆₀	1.3115	0.00070	26.93	Dominated by fine mode aerosols, slowly increasing fine mode variability

Table 2 shows the mean, trend and CV of AOD₅₅₀ and AE₄₇₀₋₆₆₀ in Cinzana and Ilorin. The mean AOD show that there is greater aerosol loading in Ilorin than in Cinzana during the period under consideration. Also, the mean values of AE show that coarse-mode aerosols dominate in Cinzana, while fine-mode aerosols dominate in Ilorin. The CV values show the level of dispersion of the data around the mean. The AOD data in Cinzana are more dispersed (51.82 %) around the mean than those in Ilorin (43.56 %). Similarly, the AE data in

Cinzana (75.47 %) is more dispersed around the mean value than that of Ilorin (26.93 %). These observations suggest that there is high aerosol loading in both stations, but that of Ilorin is higher. The observations for the AE components are not similar, either. The mean AE for Ilorin shows that fine-mode aerosols dominate the atmosphere, whereas coarse-mode aerosols dominate in Cinzana. The CV values for AE indicate that more aerosol types may be present in Cinzana, while fewer (singular) types may be present in Ilorin.

Table 3. Seasonal mean values, trends, and coefficient of variation (CV) of AOD₅₅₀ and AE₄₇₀₋₆₆₀ in Cinzana and Ilorin

Description	Dry season			Rainy season		
	mean	trend (month ⁻¹)	CV(%)	mean	trend (month ⁻¹)	CV(%)
Cinzana						
AOD	0.4333	-0.0010	54.11	0.4375	0.0006	54.42
Summary	High loading but decreasing. High variability			High loading, and increasing. High variability		
AE ₄₇₀₋₆₆₀	0.4789	0.0022	74.92	0.4554	0.0002	76.16
Summary	Coarse mode aerosols, slowly increasing fine mode. High variability.			Coarse mode aerosols, slightly increasing fine mode. High variability		
Ilorin						
AOD	0.8081	0.0008	39.68	0.5659	0.0004	38.69
Summary	High loading and increasing. Low variability			High loading and increasing. Low variability		
AE ₄₇₀₋₆₆₀	1.1139	0.0043	25.86	1.5091	-0.0004	19.77
Summary	Fine mode aerosols, slowly increasing fine mode. Low variability.			Fine mode aerosols, decreasing fine mode. Low variability		

Table 3 displays the values of the seasonal averages, trend and the CV of AOD₅₅₀ and AE₄₇₀₋₆₆₀ observed at the two stations.

During the dry season, the mean AOD values show higher aerosol loading in Ilorin than in Cinzana during the period under consideration. Also, the mean values of AE show that coarse-mode aerosols dominate in Cinzana, while fine-mode aerosols dominate in Ilorin. The CV values show that the AOD data in Cinzana are more dispersed (54.11 %) around the mean than those in Ilorin (39.68 %). Similarly, the AE data in Cinzana (74.92 %) are more dispersed around the mean than those in Ilorin (25.86 %). These observations suggest that the AOD loading in Cinzana and Ilorin is similar, while the AE components are not. More aerosol types may

be present in Cinzana while fewer (singular) types may be present in Ilorin. The decreasing trend in AOD during the dry season in Cinzana is highly unusual, as the dry season is typically characterized by increasing AOD loading.

During the rainy season, the mean AOD values show higher aerosol loading in Ilorin (0.5659) than in Cinzana (0.4375). This is similar to what was obtained in the dry season. Also, the averaged values of AE show that coarse-mode aerosols (AE < 1.0) dominate in Cinzana, while fine-mode aerosols (AE > 1.0) dominate in Ilorin. The CV values show that the AOD data in Cinzana is greatly dispersed (54.42 %) around the mean value than that of Ilorin (38.69 %). Similarly, the AE data in Cinzana (76.16 %) is more dispersed around the mean value than that of Ilorin (19.77 %).

These observations suggest that the AOD loading in Cinzana and Ilorin is similar, while the AE component shows that the aerosol types are not similar. More aerosol types may be present in Cinzana, while fewer types may be present in Ilorin. The increasing trend of AOD during rainy season in Cinzana is also highly unusual because the rainy season is always characterized by decreasing AOD loading

Table 4. The value of Seasonal fractions (SF) of AOD and AE in Cinzana and Ilorin

AOD ₅₅₀		AE ₄₇₀₋₆₆₀	
Dry season SF (%)	Rainy season SF (%)	Dry season SF (%)	Rainy season SF (%)
CIN			
41.16	58.84	42.62	57.38
ILO			
58.81	41.19	42.47	57.53

Table 4 depicts the value of the SF of both AOD₅₅₀ and AE₄₇₀₋₆₆₀ in Cinzana and Ilorin.

In the dry season, the seasonal contribution of AOD in Cinzana and Ilorin was 41.16 % and 58.81% respectively. The values became 58.84 % and 41.19% during the rainy season. These results corroborate the observation in Table 3 where aerosol loading was low during dry season and high during rainy season in Cinzana. This may suggest that there is an overlap between rainy season and dry season in the station.

In the dry season, the seasonal contribution of AE in

Cinzana and Ilorin is 42.62 % and 42.47 %, respectively. The values become 57.38 % and 57.53 % in the rainy season. These results show that the trend of the contribution of aerosol types is similar in both stations.

3.2 EOT results and interpretation

3.2.1 Cinzana (Mali)

Table 5. Component Correlation Matrix for Cinzana station (Mali) using Direct Oblimin rotation

Component	1	2	3	4
1	1.000	0.140	0.167	0.283
2	0.140	1.000	0.040	0.166
3	0.167	0.040	1.000	0.059
4	0.283	0.166	0.059	1.000

From the results of the direct oblimin analysis of aerosol data from Cinzana in Table 5, it can be seen that all off-diagonal correlations are less than 0.32, indicating that the best rotation for this dataset is an orthogonal rotation.

The value of the determinant in this station is 0.428. Therefore, an EOT analysis can be performed on data from this station. The data are also adequate, as the KMO value is 0.558. Also, the data is highly correlated enough for this type of analysis, as indicated by the statistical significance. Quartimax rotation provides the best description of this station, as it minimizes the number of factors needed to describe each variable.

Table 6. The explained total variance and Rotated Component Matrix of data for Cinzana station using Quartimax rotation

Parameters	Component				
	1	2	3	4	
AE ₄₇₀₋₆₆₀	0.929				
AOD ₅₅₀	-0.898				
FMF		0.992			
ω_o			0.992	0.976	
N _{cloud}					
Eigenvalues	1.992	0.985	0.938	0.805	Before rotation
% of Variance	39.849	19.706	18.767	16.099	
Cumulative %	39.849	59.555	78.322	94.420	
Eigenvalues	1.651	1.039	1.018	1.012	After rotation
% of Variance	33.029	20.790	20.366	20.236	
Cumulative %	33.029	53.819	74.185	94.420	
Months (%)	5.15 months of rainy period	2.64 months of dry period	1.97 months of dry period	1.57 months of rainy period	

Table 6 shows the explained total variance and the rotated component matrix for Cinzana station (Mali) using Quartimax rotation.

The four principal components extracted for this station, after rotation, are shown in the columns of Table 6. Before rotation, Component 1 explained 39.849 % of the variance, Component 2 explained 19.706 % of the variance, Component 3 explained 18.767 %, and Component 4 explained 16.099 % of the variance. This means that 94.420 % of the variance can be explained by this method of analysis. The remaining 5.580

% is the noise signal. The values for the individual variances explained changed after the Quartimax rotation. Component 1 now explained 33.029 % of the variance, Component 2 now explained 20.790 % of the variance, Component 3 now explained 20.366 %, and Component 4 now explained 20.236 % of the variance. The total percentage of the variance explained, and the noise signal remain unchanged.

The Table also illustrates the aerosol parameters and the correlation coefficients of the rotated components in Cinzana, after suppressing all other coefficients below 0.4.

The first component in Table 6 is most strongly extracted from AOD and AE, with their regression coefficients shown in the first column. This indicates a rainy season because of the negative (inverse) correlation of τ_{550} (reduction in the atmosphere) with component 1.

The second component is extracted from FMF, with the correlation coefficient in column 2. This indicates a dry and warm season because FMF is synonymous with the absorption of electromagnetic radiation, thereby warming the Earth.

The third component had only ω_o with a correlation coefficient in the third column. This indicates a dry and cold dry season (it has values above 0.92 in this station (Sharafa et al., 2023)) because it is synonymous with scattering of electromagnetic radiation into space, thereby reducing the amount reaching the Earth.

The fourth component had only Ncloud with a correlation coefficient in the fourth column. This also indicates a rainy season because an increase in cloud cover always brings about more precipitation.

The latent characteristics of this station is that there are well pronounced rainy and dry seasons. As expected, the rainy season is characterized by a reduction in aerosol load (negative sign for AOD). Two phases characterize the dry season; (1) hot dry season and (2) cold dry season (harmattan). The total rotated eigenvalues for the rainy and dry seasons are 2.663 (53.265 % of variance) and 2.057

(41.156 % of variance), respectively. This variance translates to 6.72 months of rainy season and 4.61 months of dry season. The remaining 0.68 months could not be classified. The unclassified period in Cinzana may be a result of a brief pause during the rainy season or a little precipitation during the dry season.

3.2.2 Ilorin

Table 7. Component Correlation Matrix for Ilorin station (Nigeria) using Direct Oblimin rotation

Component	1	2	3	4
1	1.000	0.055	-0.187	-0.233
2	0.055	1.000	-0.220	-0.309
3	-0.187	-0.220	1.000	0.018
4	-0.233	-0.309	0.018	1.000

From the results of the direct oblimin analysis of aerosol data from Cinzana in Table 7, it can also be seen that all off-diagonal correlations are less than 0.32 (similar to the Cinzana analysis), indicating that the best rotation for this dataset is an orthogonal rotation.

The value of the determinant at Ilorin station is 0.569. Therefore, an EOT analysis can be performed on data from this station. The data is also adequate, as the value of the KMO measure is 0.545. Also, the data is highly correlated enough for this type of analysis because it is statistically significant. Quartimax rotation was adopted for this station as well.

Table 8. The explained total variance and Rotated Component Matrix for Ilorin station using Quartimax rotation

Parameters	Component				
	1	2	3	4	
N_{cloud}	0.918				
AOD_{550}	-0.653	-0.446			
$AE_{470-660}$		0.969			
ω_o			0.959		
FMF				0.980	
Eigenvalues	1.818	1.111	1.008	0.585	Before rotation
% of Variance	36.354	22.227	20.154	11.706	
Cumulative %	36.354	58.581	78.734	90.441	
Eigenvalues	1.257	1.167	1.088	1.011	After rotation
% of Variance	25.134	23.332	21.753	20.222	
Cumulative %	25.134	48.466	70.219	90.441	
Months (%)	3.02 months of rainy period	2.80 months of rainy period	2.61 months of dry period	2.43 months of dry period	

Table 8 shows the explained total variance and the rotated component matrix for Ilorin station (Nigeria) using Quartimax rotation.

From Table 8, four principal components were also extracted. Before the Quartimax rotation, component 1 explained 36.354 % of the total variance, component 2 explained 22.227 % of the total variance, component 3 explained 20.154 % of the total variance, while component 4 explained 11.706 % of the total variance. This means that

90.441 % of the variance can be explained by this method of analysis. The remaining 9.559 % constitutes the noise signal. After the Quartimax rotation, component 1 explained 25.134 % of the total variance, component 2 explained 23.332 % of the total variance, component 3 explained 21.753 % of the total variance, while component 4 explained 20.222 % of the total variance. The total percentage of variance that can be explained using this method of analysis and the noise signal remains unchanged.

The Table also depicts the parameters and the extracted components' correlation coefficients for the rotated components in Ilorin, after suppressing coefficients below 0.4.

The first component is extracted most strongly from Ncloud and AOD, with their correlation coefficients shown in the first column. These indicate a rainy season because of the inverse correlation between the component and AOD. This correlation also shows that there is a significant reduction in atmospheric aerosol content (as cloud condensation nuclei (CCN)) as Ncloud increases during this season.

The second component consisted of AOD and AE with their correlation coefficients in column 2. This correlation also indicates the rainy season. The negative correlation of AOD at this station also supports the inverse power-law relationship between the two parameters.

The third component had only ω (it has values above 0.98 in this station (Sharafa et al., 2023)) with a positive

correlation coefficient in the third column. This indicates a cold and dry (harmattan) season because of the increased scattering of electromagnetic radiation in the station.

The fourth component had FMF with a correlation coefficient in column 4. This indicates a hot and dry season because of the capacity of FMF to absorb electromagnetic radiation. AOD has a complex correlation coefficient i.e., it is correlated in both components 1 and 2.

This indicates that this station has two types of rainy seasons and dry seasons, just like Cinzana. The difference between the two stations is that the warmth in Cinzana is more pronounced than that of Ilorin. The total rotated eigenvalues for the rainy and dry seasons are 2.434 (48.446 % of variance) and 2.099 (41.975 % of variance), respectively. This translates to 5.82 months of rainy season and 5.04 months of dry season. The remaining 1.14 months could not be classified. This unclassified period in Ilorin may be due to a brief pause during the rainy season or a brief period of precipitation during the dry season.

3.3 Visual summary of key results

Analysis/Station	Cinzana	Implication	Ilorin	Implication
Trend of AOD	0.00005 month ⁻¹	Increasing trend for the period under review	0.00020 month ⁻¹	Increasing trend for the period under review
Seasonal trend of AOD	-0.0010 month ⁻¹ Dry season	Decreasing trend	0.0008 month ⁻¹ Dry season	Increasing trend
	0.0006 month ⁻¹ Rainy season	Increasing trend	0.0004 month ⁻¹ Rainy season	Increasing trend
Trend of AE	0.00040 month ⁻¹	Increasing trend	0.00020 month ⁻¹	Increasing trend
Seasonal trend of AE	0.0022 month ⁻¹ Dry season	Increasing trend	0.0043 month ⁻¹ Dry season	Increasing trend
	0.0002 month ⁻¹ Rainy season	Increasing trend	-0.0004 month ⁻¹ Rainy season	Decreasing trend
CV of AOD	54.11 % Dry season	medium data variability	39.68 % Dry season	Low variability of data
	54.42 % Rainy season	Medium data variability	38.69 % Rainy season	Low variability of data
CV of AE	74.92 % Dry season	Very high variability of data	25.86 % Dry season	Very low data variability
	76.16 % Rainy season	Very high data variability	19.77 % Rainy season	Very low data variability
Seasonal fraction of AOD	41.16 % Dry season	Less aerosol loading during the dry months.	58.81 % Dry season	More aerosol loading during the dry months.
	58.84 % Rainy season	More aerosol loading during the rainy months	41.19 % Rainy season	Less aerosol loading during the rainy months
Seasonal fraction of AE	42.62 % Dry season	Less aerosol types during the dry months.	42.47 % Dry season	Less aerosol types during the dry months.
	57.38 % Rainy season	More aerosol types during the rainy months	57.53 % Rainy season	More aerosol types during the rainy months
EOT	Two types of dry season accounting for 4.61 months. Two types of rainy season accounting for 6.72 months. 0.68 Months of unclassified season	Evidence of two types of dry and rainy seasons.	Two types of dry season accounting for 5.04 months. Two types of rainy season accounting for 5.82 months 1.14 Months of unclassified season	Evidence of two types of dry and rainy seasons.

4. Conclusions

Research on trend and EOT assessment of aerosol parameters in the Western part of Africa is scarce. We

leveraged the availability of AERONET stations in these countries to account for the trends and fundamental modes of these parameters in this part of the continent. This research

aims to establish a link between the trend and EOT of aerosol parameter values in these countries.

The distribution of aerosols in western Africa has been studied using their optical and physical parameters. It was discovered that the aerosol loading in Cinzana does not follow the traditional pattern of having more aerosols in the atmosphere during the expected dry season (October to March). It can also be observed that there is a higher amount of aerosols in the atmosphere of Ilorin than in Cinzana. This result can only be linked to the ITCZ. Also, there are indications that more aerosol types may be present in Cinzana, as higher aerosol loading was detected during the rainy season. Coarse-mode aerosol episodes are much more frequent in Cinzana than in Ilorin during the period under review.

In general, both AOD and AE show increasing trends at the two stations, but seasonal differences were observed. Only the AOD in Cinzana during the dry season and the AE in Ilorin during the rainy season showed a decreasing trend; the others showed an increasing trend.

The seasonal fraction shows that AE makes a similar contribution at both stations during the rainy season, but has a dissimilar impact during the dry season.

The EOT analysis, with a Quartimax rotation, indicates that the aerosol parameters obtained from the Cinzana and Ilorin stations are similar in character but not identical. Both have four underlying characteristics because of the four principal components extracted. The extracted components translated into four seasons, which are two types of rainy and dry seasons, i.e., (1) a cloudy rainy season, (2) a warm rainy season, (3) a warm and dry season, and (4) a cold (harmattan) dry season.

Field experiments can be carried out in the future to provide additional insight into activities that may have led to the outcomes of the analysis of aerosol parameter trends and the EOT evaluation.

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