

ORIGINAL RESEARCH

An EOT Approach to Analyze the Temporal Variability of Rainfall Data and Some Aerosol Properties over Ilorin using MODIS Data

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Abstract

Many remote sensing techniques and passive sensors have been developed to measure global aerosol properties. In this paper, aerosol properties in Ilorin, like optical depth (τ_{550}), Angstrom exponent ($\alpha_{470-660}$), single scattering albedo (ω_0), and fine mode fraction (FMF), together with cloud fraction (N_{cloud}) from the Moderate Resolution Imaging Spectroradiometer (MODIS), as well as Rainfall (RF) data were analyzed using Empirical Orthogonal Transformation (EOT) analysis. The EOT is used to check for underlying constructs that may have characterized the atmosphere in the study area. The data set covers the period from March 2000 to June 2015. Analysis results show that four (4) principal components with eigenvalues greater than one (1), were extracted. These components explained 89.118% of the total variance. The first component is extracted most strongly on RF and N_{cloud} . This indicates a cloudy-rainy season. The second component is extracted on τ_{550} and $\alpha_{470-660}$. These also indicate a rainy season. The third component is extracted on ω_0 . This indicates a dry and cold dry. The fourth component had only FMF, and it indicates a dry and warm. This shows that the structure of the atmosphere in the study area during this period is strongly characterized by cloudiness, clear sky, scattering and absorption of electromagnetic radiation. The climatology of the station also shows the predominance of coarse and reflecting aerosols.

Keywords: Basement Complex; Conductive Zones; Road Instability; Electrical Resistivity

1 Introduction

Atmospheric aerosols are suspensions, in air, of solid or liquid particles, which are often observed as dust, smoke and haze. Earth's climate forcing is affected by the direct and indirect effects of aerosols. The direct effect is caused by large aerosol particles which can scatter radiation back to space whereas the indirect effect tends to cool it (Charlson and Pilat, 1969; McCormick and Ludwig, 1967). Through the indirect

effect, aerosol particles can modify the microphysical and radiative properties of clouds. Clouds developing in a contaminated environment are inclined to have many smaller droplets. These characteristics could end in a suppression of rainfall and lengthier cloud lifespan. Absorption of arriving solar radiation by aerosols can reduce the cloud fraction (N_{cloud}). Aerosols can be due to both natural and anthropogenic processes. Natural aerosols are dusts, sea salts, and sulfuric acid particles. The acid particles are occasionally injected into the stratosphere by volcanic eruption and may persist for years, whereas the other types of aerosols are only present for a few weeks in the lower troposphere. Anthropogenic aerosols originate from urban and industrial emissions, agricultural burning, domestic fires, deforestation, construction sites and farming practices. The analysis of large, multidimensional data set can most times be greatly facilitated by splitting the set into its constituent Principal Components (PCs) us-

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ing Principal Component Analysis (PCA). The PCA is sometimes referred to as Empirical Orthogonal Transformations (EOTs) (Bracher *et al.*, 2015) or Eigenvector Analysis (EA) and has been in use since the late fifties in the atmospheric sciences (Gianelli *et al.*, 2007; O'Rourke and Hatcher, 2005). Each PC has a corresponding eigenvalue, which determines how much the PC in question contributes to the total variance of the set. Often, most of the variance in a data set can be accounted for by its first few eigenvectors. Empirical orthogonal transformation (EOT) is often used in climate studies to analyze possible patterns of variability and how they change with time. This analysis is not based on physical principles. Rather, a field is partitioned into mathematically orthogonal (independent) modes which sometimes may be interpreted as atmospheric modes. The method is in essence an explanatory tool, which allows a time display and a space display of the space-time field that may be useful to the atmospheric scientists. The existence of fast and efficient algorithms has facilitated its widespread use. Understanding optical properties of aerosols is important in investigations of climate change, since aerosols have a major impact on the radiative energy balance (Charlson *et al.*, 1992). Studies have reported the aerosol climatology in West Africa, but aerosol observations in this region are still scarce. Mineral dust aerosols has been on the increase over West Africa (Prospero *et al.*, 2002) and the cause of this increase is still unknown. Dust particles were investigated during the SHADE (Saharan Dust Experiment) campaign over West Africa, while their radiative effects were measured in the solar spectrum by ground-based measurements (Tanré *et al.*, 2003). The particles found during field measurements were only dust with relatively low absorption properties. Surface networks, such as the Aerosol Robotic Network (AERONET), provide a needed long term coverage, while measurements by satellite instruments provide extensive spatial coverage (Holben *et al.*, 2001). But insufficient information on the aerosol features at local and regional levels as well as the inadequacy with which the existing models represent the spatio-temporal heterogeneity is a concern (Kaufman *et al.*, 2002; Solmon *et al.*, 2006). A better understanding of aerosol optical, microphysical and radiative properties is a crucial challenge for climate change studies (Boiyo *et al.*, 2018). In spite of all these studies, there is a need to replicate some of these studies in the sub-Saharan African region using a larger sample size. In this study, EOT analysis is applied to some MODIS aerosol parameters and RF data over Ilorin AERONET station. The goal is to determine the latent variables in each of the stations. The temporal characteristics of monthly variability in

these meteorological and optical properties of aerosol over the study area and their connection to the latent structure were also analyzed. The datasets used in this study are described below.

2 Empirical Orthogonal Transformation (EOT)

Empirical orthogonal transformation (EOT) is multipurpose and has been used, for example, in dimensionality reduction and pattern extractions. This analysis permits researchers to conduct investigative analyses of latent variables, reduce data in large datasets, and test specific models. It is a mathematical procedure that transforms a number of (possibly) correlated variables into smaller uncorrelated variables called principal components (Chan and Mozurkewich, 2007). The first principal component accounts for as much of the variability in the data as possible, and each succeeding components accounts for as much of the remaining variability as possible (Landau and Everitt, 2004; Leech *et al.*, 2005). EOT has been traditionally applied to climate variables such as SST to examine climate modes (Monahan *et al.*, 2009). Gianelli *et al.* (2007) showed that much information of both physical processes in the atmosphere above the instrument and the performance of the instrument itself can be uncovered by conducting an EOT analysis of optical depth data. Li *et al.* (2013) used an EOT approach to analyze the spatial and temporal variability in multi-sensor aerosol retrievals and examine the consistency and differences between the data sets. The eigenvectors (factors) are rotated in an attempt to achieve simple structure (Brown, 2009b). This is done differently depending upon whether the factors are believed 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 involves the minimization of the number of factors needed to explain each variable. Varimax minimizes the number of variables that have high loadings on each factor and works to make small loadings even smaller. Oblique rotation is more complex than orthogonal rotation. Additionally, oblique rotation produces a pattern matrix that contains the factor or item weights and factor correlation matrix that includes the correlations between the factors (Yong and Pearce, 2013). To decide between orthogonal and oblique rotation, a request should be made for direct oblmin rotation with the desired number of factors (Brown, 2009a) and look at the correlations among factors. Check the factor correlation matrix for correlations around 0.32 and above. If correlations exceed 0.32,

then there is a possibility of overlap in variance among factors, enough variance to warrant oblique rotation. The eigenvectors (factors) are rotated in an attempt to achieve simple structure (Brown, 2009a). This is done differently depending upon whether the factors are believed 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. Oblique rotation is more complex than orthogonal rotation. Additionally, oblique rotation produces a pattern matrix that contains the factor or item weights and factor correlation matrix that includes the correlations between the factors (Yong and Pearce, 2013). To decide between orthogonal and oblique rotation, a request should be made for direct oblimin rotation with the desired number of factors (Brown, 2009a) and look at the correlations among factors. Check the factor correlation matrix for correlations around 0.32 and above. If correlations exceed 0.32, then there is a possibility of overlap in variance among factors, enough variance to warrant oblique rotation. If the value of the determinant of each dataset is less than 0.00001, PCA cannot be conducted. The Kaiser-Meyer-Oikin (KMO) measure is adequate if greater than 0.50. The Bartlett test should be significant (i.e., a significance value of less than 0.05); this means that the variables are correlated highly enough to provide a reasonable basis for component analysis. The Rotated component Matrix table is key for understanding the results of the analysis. Usually, component correlations lower than are considered low while that of or greater are typically considered high.

3 Theory of Empirical Orthogonal Transformation (EOT)

EOT refers to a method of data analysis for building linear multivariate models of complex data sets. The linear multivariate EOT models are developed using orthogonal basis vectors (eigenvectors) usually called the Principle Components (PC). EOT aims at reducing the dimensionality of complex problems and minimizing the effects of measurement error. It is possible to build an empirical mathematical model of data as described in the equation below where $T_{i,j}$ is a $n \times m$ matrix of Principle Component scores and $T_{i,j}^T = T_{j,i}$ is the $m \times n$ matrix of eigenvectors.

$$A = T_{i,j} T_{i,j}^T = T_{i,j} \cdot T_{j,i} = T_{i,i} \quad (1)$$

The eigenvectors in $T_{i,j}$ can be used to form a set of orthonormal raw basis vectors for A. The eigenvectors are also called loadings. The columns of $T_{j,i}$ are called

scores and are mutually orthogonal but not normalized. They can be used to form a set of column basis vector of A. For each independent source of variation in the data, a single PC (eigenvector) is expected in the model. The first PC explains as much as possible of the total variance of the data in matrix A. The second component explains as much as possible of the remaining variance and so on (Landau and Everitt, 2004; Leech *et al.*, 2005).

$$\begin{pmatrix} \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & A = T_{i,i} & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots \end{pmatrix} = \begin{pmatrix} \dots & \dots & \dots \\ \dots & \dots & \dots \\ \dots & T_{i,j} & \dots \\ \dots & \dots & \dots \\ \dots & \dots & \dots \end{pmatrix} \begin{pmatrix} \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & T_{j,i} & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots \end{pmatrix}$$

In the projection of a matrix onto itself, one of the dimensions gets removed and we are left with a measure of the dispersion of the structure with itself across of the removed dimension (or the sampling dimension). If the sampling dimension is time, then the resultant dispersion matrix is the matrix of the covariance of the spatial locations with each other, as determined by their variations in time. In the second case, the covariance at different times is obtained by projecting on the sample of different spatial points. Either of these dispersion matrices may be scientifically meaningful, depending on the issue at hand. These matrices generated can be either positive definite or positive semi-definite covariance/correlation matrices and are usually symmetrical. The propensity of the empirical modes to extract inadequately representative communality among subdomains of large datasets can be remedied by grouping the variance through a rotation procedure. A range of such procedures are available (Richman, 1986). In general, a rotation is a linear transformation of the modes that try to find a new location for the coordinate axis, such that projections of the variables onto those axes makes the spatial or temporal structure of the modes simpler. A full discussion of the advantages and disadvantages of rotated empirical modes is given by (Jolliffe, 1987; Richman, 1986, 1987). In nearly all applications, the rotation is used to simplify the spatial structure by isolating regions with similar temporal variability (e.g. (Barnston and Livezey, 1987; Horel, 1981; Kawamura, 1994; Mestas-Nunez and Enfield, 1999)). The resultant rotated space patterns are generally more robust than their unrotated counterparts (Cheng *et al.*, 1995). On the other hand, the rotation can also be utilized to simplify the temporal structures by separating time

Table 1 Aeronet Stations in the Sub-Saharan Africa and Their Coordinates

S/N	Country	Station	Long.	Lat.	Alt.	Rainy Season
1	Nigeria	Ilorin	4°E	8°N	350 m	Apr. – Oct.

periods with related space patterns (e.g. (Fernandez, 1995)). The rotated component matrix and component transformation matrix are displayed for orthogonal rotations. For oblique rotations, the pattern, structure and component correlation matrices are displayed. In addition, they all have component score coefficient matrix (Eigen vectors) displayed.

4 Materials and Methods

4.1 The meteorology of the study sites

Ilorin is associated with a marked seasonal cycle. From November to February, it is dominated by dry north-easterly winds from the Sahara. Large amounts of mineral dust from the Sahel and Sahara are transported across the station, which in combination with human-induced biomass burning and automobile exhaust wastes, lead to persistent haze because of the lack of wet removal. From March onwards the south-westerly winds begin to penetrate, bringing with them moister air, more clouds and precipitation (Sultan and Janicot, 2003).

4.2 Data Collection

The MODIS data used in this work were downloaded from the website of Multi-sensor Aerosol Products Sampling System (MAPSS) (<http://giovanni.gsfc.nasa.gov/mapss/>) because it provides a consistent sampling approach that enables easy and direct inter-comparison and validation of the different quality assured aerosol products from the two sensors in a uniform and consistent way (Petrenko et al., 2012). The long time-series (2000-2010) of precipitation (RF) data and MODIS measured aerosol optical depth at 470 nm (τ_{470}), aerosol optical depth at 550 nm (τ_{550}), aerosol optical depth at 660 nm (τ_{660}), cloud fraction (Ncloud), fine mode fraction (FMF) and single scattering albedo (ω_0) were used in this study for EOT evaluation over Ilorin. The coordinates, altitude and rainy season of the stations are shown in Table 1. Precipitation (rainfall, RF) data (collected from NIMET archive) is a measure of the amount of rainfall received in a particular location. It is measured in millimeters (mm). The aerosol optical depth (AOD, τ) is a measure of aerosol loading. Unpolluted atmospheric conditions should have τ values between 0.04 and 0.06 (Tan et al., 2015). The Angstrom exponent (AE, α) value

provides first-hand information on the aerosol size distribution trend. The α value varies from 1 to 3 for fresh and aged smoke, and urban aerosol particles, while it is nearly zero for coarse mode aerosols such as dust and sea salt (Eck et al., 1999). The Ncloud is a measure of the amount of cloud in the atmosphere. The single scattering albedo (SSA, ω_0) can determine the sign of the aerosol radiative effects. Pure light absorbing carbon particles typically have a ω_0 of 0.2 (Bergstrom et al., 2007) while its value for scattering is close to unity (Moosmuller and Chakrabarty, 2011). The FMF values can vary from 0 (single coarse mode aerosol) to 1 (single fine mode aerosol), and provides quantitative information on the nature of the aerosol size distribution (Kedia et al., 2014)

4.3 Data Analysis

The aerosol optical properties data from MAPSS obtained for the study period are daily data. The large data density for the period makes it easier for monthly cycle and distribution trends of the parameters to be distinguished. The daily data were used to compute the monthly and seasonal averages over the entire period of study. Equation (3) can be used to estimate Angstrom parameters (α and β) (Boersma and de Vroom, 2006; Kumar et al., 2014; Tijjani et al., 2014)

$$\tau_{ext}(\lambda) = \beta \lambda^{-\alpha_{ext}} \quad (2)$$

The Angstrom exponent ($\alpha_{470-660}$) was calculated using Equation (3) (Hesham and Mansour, 2009; Tijjani and Akpootu, 2012; Tijjani et al., 2014)

$$\alpha = - \frac{\ln(\frac{\tau_1}{\tau_2})}{\ln(\frac{\lambda_1}{\lambda_2})} \quad (3)$$

where τ_1 is the aerosol optical depth (AOD) at 470 nm wavelength λ_1 and τ_2 is the AOD at 660 nm wavelength λ_2 . The RF, τ , α , Ncloud, ω_0 and FMF are required for evaluating the latent structure in the climate system. The EOT method aims at decomposing the multivariate data matrix into a set of independent, orthogonal eigenvectors, with the first eigenvector explaining the most variance, the second eigenvector explaining the most of the remaining variance, and so on. Here we consider it potentially useful in studying aerosol data primarily due to two reasons: (1) the composition of aerosols is rather complicated and different aerosol species have different mechanisms of generation and deposition. The EOT method may help isolate independent aerosol processes; (2) the aerosol data sets are comparatively noisy, due to uncertainties in surface reflectance, cloud screening, instrument calibration and retrieval assumptions. Ideally, much of the

Table 2 Component Correlation Matrix Component

Component	1	2	3	4
1	1	0.3	-0.227	0.212
2	0.3	1	-0.104	-0.013
3	-0.227	-0.104	1	-0.218
4	0.212	-0.013	-0.218	1

noise should be randomly distributed and EOT analysis will filter the noise into a series high order modes, while separating signals in the dominant modes.

5 Results and Discussion

5.1 EOT Results and Interpretation

The result of the direct oblique in rotation conducted on the aerosol parameters in Ilorin station to assess whether an oblique or orthogonal rotation is required, gives Table 2. From the Table 2, it can be seen that the highest correlation aside the diagonals are all less than 0.32 and this means that the best rotation for this dataset is an orthogonal rotation. The value of the determinant in this station is 0.192. The KMO measure is 0.589 and it is statistically significant. Varimax rotation gives the best description of this station. The four principal components extracted after rotation can be seen in Table 3. The first component accounted for 29.533% of the variance, the second component accounted for 25.712% of the variance, the third component accounted for 17.140% and the fourth component accounted for 16.733% of the variance. Table 4 displays the aerosol parameters and the components' correlation coefficients for the rotated components in Ilorin, after suppressing values less than 0.4. The first component is extracted most strongly on RF and Ncloud, with their regression coefficients in the first column. This indicates a rainy season because of the increase in cloud cover and rainfall. The second component is extracted on τ_{550} and $\alpha_{470-660}$, with their regression coefficients in the second column. This also indicate a rainy season because of the negative (inverse) correlation of τ_{550} (reduction of aerosols in the atmosphere) with the component. Besides, the two parameters show an inverse relationship. The third component is extracted on SSA with correlation coefficient in column 3. This indicates a dry and cold dry season because it is synonymous to scattering of electromagnetic radiation into space, thereby reducing the amount reaching the earth. The fourth component had only FMF with correlation coefficient in the fourth column. This indicates a dry and warm season because FMF is synonymous to absorption of electromagnetic radiation, thereby warming up the earth. The latent characteristics deduced from the parameters recorded in this station is that there are well pronounced rainy and dry seasons.

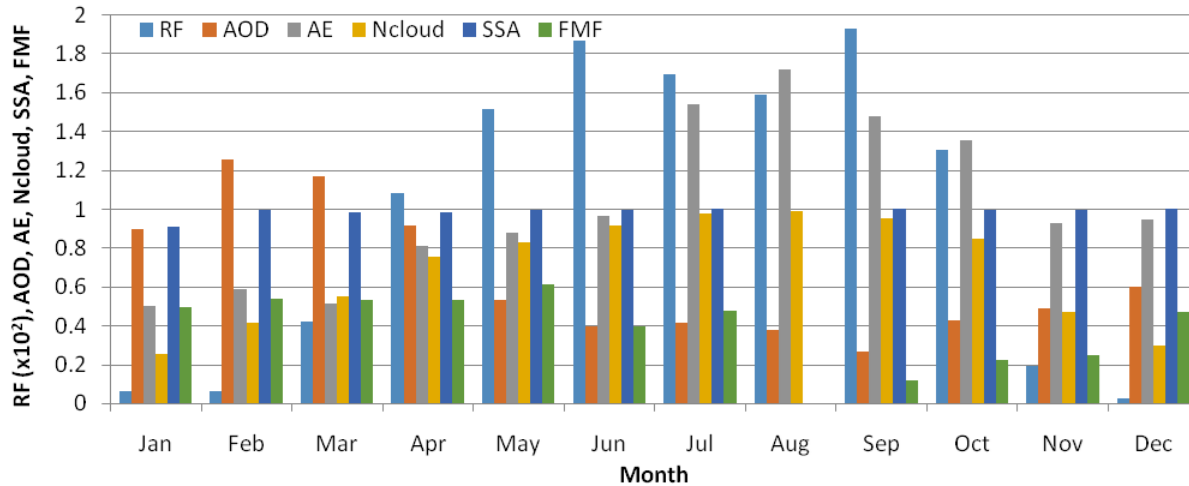
Table 4 Rotated Component Matrix for Ilorin (Nigeria) using Varimax rotation

Parameters	Component			
	1	2	3	4
RF	0.936			
Ncloud	0.904			
AE		0.887		
AOD		-0.813		
SSA			0.968	
FMF				0.973

As expected, the rainy season is characterized by a buildup of cloud and a reduction in aerosol load. The dry season is characterized by two phases; (1) hot dry season and (2) cold dry season (harmattan). The total rotated eigenvalues for rainy and dry season are 3.315 (55.245% of variance) and 2.032 (33.873% of variance) respectively. The eigenvalues (and the % of variance) for the two seasons show that the rainy season is longer than the dry season. Figure 1 shows the seasonal cycle of the MODIS aerosol loading (AOD, τ_{550}), Angstrom exponent (AE, $\alpha_{470-660}$), cloud fraction (Ncloud), single scattering albedo (SSA, ω_0) fine mode fraction (FMF) and amount of precipitation (rainfall, RF) averaged between 2000 and 2010 for Ilorin AERONET station. From Figure 1, it can be seen that the amount of rainfall (2.38 – 19.46 mm) received in Ilorin between November and February is very low. April to October has the highest record of rainfall (108.57 – 192.88 mm) as expected because they are rainy season months in Ilorin. Figure 1 also shows that the aerosol concentration is strongest between January and April with its peak in February (1.202) and the least was observed in August (0.378). This shows, as expected, that the aerosol loading trend of the station agrees with the two seasons (dry and rainy). April is the onset of rainy season in this station, and the loading of aerosols starts decreasing from this month up to September. This is due to the wet deposition of aerosols. The atmosphere in this station is a polluted one (i.e., $\tau \geq 0.05$). The mean τ present high values with the same trend pattern which are the traits of all high aerosol loading regions. The cleanest month is August. τ values start decreasing in wet season (April to August) and increases significantly during dry (November – March). Aerosol concentration begins to build up in the atmosphere in November; it increases continuously until its peaks in March (a transition month). This pattern of monthly cycle of τ (increase after wet season and decrease after Dry) is consistent during the 11 years of study. Comparing the monthly τ values obtained in this work with those reported by (Beegum *et al.*, 2012) where the authors used a 7-year (2002 – 2008) τ data from the Island of Port Blair in the Union territory of India. This current work has a similar value to what was obtained by the authors. We

Table 3 Total variance explained for Ilorin (Nigeria) using Varimax rotation

Component	Initial Eigenvalues			Rotation		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.354	39.236	39.236	1.772	29.533	29.533
2	1.424	23.728	62.964	1.543	25.712	55.245
3	0.865	14.425	77.388	1.028	17.14	72.385
4	0.704	11.73	89.118	1.004	16.733	89.118
5	0.438	7.296	96.414			
6	0.215	3.586	100			

**Figure 1** Histogram of the seasonal cycle of the parameters over Ilorin AERONET station averaged between 2000 and 2010.

found that in each month, τ_{550} over Ilorin is higher than those in the Iberian Peninsula based on 9-year (2000 – 2009) MODIS dataset (Granados-Munoz et al., 2011). Moreover, the mean τ_{550} values over this site are also greater than those in Penang but less than what was observed Kuching, both in Malaysia. The high τ values in Ilorin may be explained by the fact that it is located in a desert dust dominated region. The study area can be said to have poor air quality all year round for having the minimum monthly τ_{550} of 0.268. Additionally, Figure 2 shows the variation of $\alpha_{470-660}$ over the months. It can be seen that values of $\alpha_{470-660}$ decreases during dry season and increases during rainy season. This observed seasonal pattern can be associated with high concentrations of coarse mode aerosol ($\alpha_{470-660} \leq 1$) during dry. Similar conclusion was drawn by (Kaskaoutis et al., 2007). The transport of dust aerosol from the Sahara to the station by northeasterly dry wind during dry has been reported by (Balarabe et al., 2015). The seasonal dependence of τ has resulted in the corresponding seasonal feature of α discussed below. The lowest value of mean $\alpha_{470-660}$ observed in January is a signature of mineral dust (Ogunjobi et al., 2008). It increases from March until the peak is reached in August due to fre-

quent rainfall as a result of which significant amount of the larger particles are washed down from the atmosphere. This natural phenomenon causes the $\alpha_{470-660}$ to become larger. $\alpha_{470-660}$ remains considerably high in September and maintains a dip in value between October and January. In addition, variation of monthly Ncloud can be seen in Figure 1. It can be seen that values of Ncloud decreases during dry season and increases during rainy season. This seasonal pattern can be associated with the north-easterly and south-westerly winds. The increase in Ncloud during rainy season could be associated with the use of aerosol particles as cloud condensation nuclei (CCN). ω_0 is found to be ≥ 0.9 and does not exhibit any seasonal dependence over study area during 2000 – 2010. This indicates that during the study period, scattering aerosols are the dominant. FMF is found to be between 0.0 and 0.614. Its variation also shows a slight seasonal dependence over study area during the study period. This indicates high contribution of anthropogenic aerosols in the station during rainy season.

5.2 Conclusion

Studies of EOT analysis of aerosols' parameters in sub-Saharan Africa are very rare. Here, we look at the un-

derlying modes and effects of the parameters on this region. This study is an attempt to link the seasonal dynamics of the atmosphere and the aerosol parameters in the study area. We have studied the seasonal variability of the distribution of aerosols from their optical and physical properties. MODIS observations allowed us to show the predominant presence of Saharan dust in the atmosphere almost throughout the year. The EOT analysis, with Varimax rotation, indicates that the aerosol parameters obtained from Ilorin has four underlying characteristics because of the four (4) Principal components extracted (with a total of 89.118% variance explained). The remaining 10.882% are noises that had to be screened out. The extracted components translated into two types of rainy seasons and two types of dry seasons i.e., (1) a cloudy rainy season (29.533% variance), (2) warm rainy season (25.712% variance), (3) cold (harmattan) dry season (17.140% variance) and, (4) warm and dry season (16.733% variance). The climatology of Ilorin shows that the study area is polluted, has higher amount of coarse mode aerosols, has distinct rainy and dry seasons, and there is a significant contribution from fine mode aerosols.

Competing interests

The authors declare that they have no competing interests.

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