FUDMA Journal of Sciences (FJS)
ISSN online: 2616-1370
ISSN print: 2645 - 2944
Vol. 3 No. 1, March, 2019, pp 140 - 145

A MODIFIED LINEAR REGRESSION MODEL FOR PREDICTING AEROSOL OPTICAL DEPTH (AOD) IN ILORIN-NIGERIA

***[1]Balarabe, M. A. and [2]Isah, M. N.**

[1]Hassan Usman Katsina Polytechnic, Katsina, Nigeria
[2]Department of Physics, Al`qalam University Katsina, Katsina state

Corresponding author: mukhtarbalarabea@gmail.com +2348030701277

ABSTRACT

In general, aerosol measurements generated from the ground-based stations are some of the most trusted results; however, these measurements are limited in spatial density. The measurement is also affected by the presence of heavy cloud in the atmosphere which makes obtaining free cloud satellite image for atmospheric correction very difficult. The current study focuses on the development of a modified empirical regression models aiming to predict a local Aerosol Optical density (AOD) in the atmosphere that is cloud free using ground meteorological data in Ilorin-Nigeria. Ten years (January, 2007 to December 2017) of Aerosol robotic network **(**AERONET) AOD and National Oceanic Atmospheric Administration-National climate Data Centre (NOAA-NCDC) meteorological data were used to establish a quantitative relationship between AOD on one hand and visibility, relative humidity, sea level pressure, temperature and wind speed on the other hand. The highest correlated model was used to predict AOD values during overall (January-December), Harmattan (November-March) and summer (April-October). The analysis of 10 years overall AOD data was satisfactory, with coefficient of determination (R^2) =0.80 and root mean square error (RMSE) =0.07 with relatively low value of weighted mean absolute percentage error (wMAPE) <4% which indicates relative high accuracy of the model. Similarly, the prediction accuracy of the AOD model was high during summer ($R^2 = 0.85$, RMSE 0.05 and wMAPE =2%) and best during Harmattan ($R^2 = 0.90$, RMSE 0.03 and wMAPE =0.9%). This result is consistent with the results obtained in the previous literatures showing that, in as much meteorological variables will be used as input variables in AOD estimation; the model will always be more accurate during Harmattan than summer.

Keywords*:* AOD; Harmattan season; Ilorin; Visibility; Te

INTRODUCTION

An aerosol is a collection of airborne liquid or solid particles suspended in the atmosphere (Balarabe *et al.,* 2015). Atmospheric aerosols emanate from a variety of sources, ranging from natural to anthropogenic, and exhibit a wide range of sizes and chemical properties.

Dust aerosols are transported from the source in the Sahara towards Atlantic Ocean across Nigeria. The concentration of aerosols in Nigerian atmosphere is therefore governed by seasonally changed air mass (north-easterly trade wind and south-westerly trade wind) during Harmattan (November-March) and summer (April-October) seasons (Nwafor *et al.,* 2007). These two seasons not only reveal the variations in concentrations, but also types, and distributions of aerosols both spatially and temporally. Moreover, anthropogenic biomass burning activities for land and forest clearance (Field *et al.*, 2009) farming and need for warm weather as well as irrigation have increased dramatically in recent decades. These activities result in trans-boundary and long-range transport of aerosols in Nigerian atmospheric column.

Atmospheric aerosols cause disturbances to air quality, human health and solar radiation pattern which have both direct and indirect consequences on the earth climate. It also directly leads to visibility degradations (Balarabe *et al.,* 2015; Ogunjobi *et al.,* 2012) which in turn affect region's economy. The inconsistency in the chemical, physical and optical composition of the aerosol makes the assessment of their impact on both humans and the global climate difficult (Balarabe *et al.,* 2016a). Due to these uncertainties and their impact on both the environment and people's health, there has been rising research focus on these particles (Balarabe *et al.,* 2016b) in the recent years. Aerosol optical depth (AOD) has been recognised globally as one of the most important parameter for these researches (Balarabe *et al.,* 2016a). In general, aerosol measurements generated from the sun and sky scanning radiometer of Aerosol Robotic Network (AERONET) (ground-based stations) are considered the most trusted for local/regional aerosol study. However, these stations are limited in spatial density as there is only one in Nigeria. For a better monitoring and evaluation of aerosol, space-based observations (Satellite) which have the capability of providing global scale coverage of aerosol optical properties compare to AERONET (Tan *et al.,* 2015a) are necessary. However, aerosol observations using both the AERONET and satellite sensors are being affected by the presence of cloud in the atmosphere.

Ilorin (Southern) part of Nigeria hosts one of the most complex environmental and meteorological conditions. This couple with dust transport from Sahara and anthropogenic activities makes remote sensing difficult both for satellites and AERONET (Balarabe *et al*., 2016b). Cloud-contaminated data leave gaps in our remote sensing data record, and cause challenging tasks for scientists studying aerosols. Therefore, it is potentially valuable to develop a regional/local model which has not yet being applied over the region to enable detail aerosol studies.

Even though, it is documented in some studies that AOD and aerosol index (AI) are not always highly correlated to horizontal or surface measurements especially with the occurrence of an elevated transported dust or biomass burning (Barladeanu *et al.,* 2012; Chen *et al*., 2013; Toth *et al*., 2014). However, some research effort has been made to predict AOD values by using different ground meteorology data (Tan *et al*., 2014; Qin *et al*., 2010; Lin *et al.,* 2014; Balarabe and Koko 2018; Balarabe and Koko 2019) in different part of the world. Tan *et al* (2015b) and Cordero *et al* (2014) established that AOD is directly proportional to particulate matter (PM) but inversely proportional to visibility (Vis) (Tan *et al*., 2015a; Balarabe and Koko 2018) assuming uniform distribution of the aerosol in the atmospheric column (Balarabe and Koko 2018; Balarabe and Koko 2019). Tan et al (2015a and b) uses AOD in Penang Malaysia and their corresponding Ground-based measurements (i.e., visibility and air pollutant index) in their effort to obtain continuous AOD measurements in four monsoonal seasons from February 2012 to November 2013. The author revealed that, the proposed model efficiently predicted AOD data.

Balarabe and Koko, (2019) also obtained a significant correlation between AOD and relative humidity in their effort to develop a regression model for AOD retrieval. They found that the combined parameters of visibility and relative humidity were effective in predicting AOD data. The influence of meteorological parameters (Precipitation, temperature, relative humidity and wind speed) on air quality for a rural background site in Morogoro, Tanzania during 2005 and 2006 wet and dry seasons were investigated (Mkoma, 2009). This was carried out using meteorological data obtained from Tanzanian meteorological agency and AOD data from the Moderate Resolution Imaging Spectro-radiometer satellite (MODIS) for the study period and location. Aerosols concentrations (AOD) were correlated to meteorological parameters and a negative correlation between AOD and relative humidity, temperature and rainfall, and positive correlation between AOD and wind speed were observed. The author concludes that the aerosols response to changes in meteorological parameters was somewhat reasonable and the study can therefore be used to form basis for assessing the effect of meteorological factors on aerosols. Anuform *et al* (2007) obtained a significant correlations coefficient between the Total Ozone Mapping Spectrometer Aerosol Index (TOMS AI) and visibility (R = 0.92) on the one hand and TOMS AI and rainfall (R = −0.72) on the other hand in the Sahel zone of Nigeria. The author concludes that the TOMS AI and visibility can complement each other in dust monitoring. The need for more input parameters has been identified by Tan *et al* (2015b); Balarabe and Koko (2018); Balarabe and Koko (2019) to enhance the accuracy of the proposed models. Therefore, this work aimed at building on previous literature by developing an AOD prediction model based on five meteorological data namely: (i) Visibility (VSB) (ii) Relative humidity (RH) and (iii) Temperature (TEMP) (iv) Wind speed and (v) Dew point temperature (DEW). This will enable continuous record of AOD data irrespective of atmospheric conditions. These models are significant for climatological studies, providing continuous atmospheric columnar AOD data, and monitoring aerosol variation such as diurnal cycles of AOD.

DATA AND METHODOLOGY

AERONETAND METEOROLOGICAL DATA

The AOD data were obtained from the AERONET observation site located in Ilorin Nigeria on latitude 8˚32'N and longitude 4˚34'E. Detail description of thisAERONET site can be found in articles written by Nwafor *et al* (2007) and Ogunjobi *et al* (2008) while the instrument was illustrated in the work of Holben *et al*. (1998). The daily measured AOD data from level 2 (cloud screen and quality assured) (Smirnov *et al.,* 2000) at this station were obtained for the period of ten (2007-2017) years. The corresponding years of hourly meteorological data of Temperature, visibility relative humidity, dew point temperature and wind speed for the study location were dowloaded from the National Oceanic and Atmospheric Administration-National Climatic Data Centre (NOAA-NCDC) (htt://gis.ncdc.noaa.gov/).The station is found to keep at least 75% continue observations for the period under study in accordance with (Engelstaedter *et al*., 2003).

METHODOLOGY

The NOAA-NCDC data files were imported into Excel spreadsheet for further processing. The daily afternoon hourly observation wereutilised as the regular representative and converted to standard units for consistency. Daily average for each variable was computed from the hourly values. The daily AOD and meteorological variables were grouped in series of January–December each year. The datasets wereseparated into Overall,Harmattan and Summer based on the previous literatures of (Balarabe *et al.,* 2015; Balarabe and Koko, 2018; Anuforom *et al.*, 2007).

Development of Regression model

The procedure of (Balarabe and Koko, 2018) to generate predicted AOD data is adopted in this study as the data selection criteria. The existence and nature of the relationship between the selected meteorological parameters and AOD was identified using Pearson’s correlation. The predictive capability of the selected input parameters was tested using Back ward multiple regression analysis. Here, all the input parameters are implemented into the model (equation 1) after which the variables are removed from the model one after the other beginning with the least correlated variable and the new change in the R^2 and RMSE is observed.

In the backward regression, if a variable is removed from the model and R^2 drop by 5% or more then the variable is good for the model and will be selected as one of the input variable otherwise drop (Noor *et al.,* 2010). This is also applied to RMSE, if the decrease is not up to 5% , implies good parameter for the model.

$$AOD=a_o+a_1(SPD)+a_2(VSB)+a_3(TEMP)+a_4(RH)+a_5(DEW) \quad (1)$$

Where AOD is the aerosol optical depth, SPD is the wind speed, VSB is the visibility, TEMP is the temperature, RH is the relative humidity, DEW is the dew point temperature a_o, a_1 a_2 a_3 $a_4$and a_5 denotes the constant and the coefficients respectively.

Using this analysis it was found that Temperature and dew point temperature does not contribute significantly to AOD prediction. It is therefore suggested that TEMP and DEW, which are very moderate around in the study site, exerts less influence on AOD and therefore disregarded in this study.

The best subsets were generated for the selected parameters using Minitab statistical software based on high R^2 values and minimum standard error RMSE. The Minitab was also used in checking some basic assumptions of regression models such as Multicollinearity, Heteroscedasticity, autocorrelation and Normality.

The number of data points used for both the calibration and validation of the model varies depending on the available data in each month. After these checks and out layers successfully removed in each case (overall and seasonal), the remaining data points were divided into two for calibration and validation. For instance, if in the overall data there are n data points [D_1, D_2, D_3...D_n] arranged sequentially in years. This was divided inform of [D_1, D_2, D_4, D_5...] and [D_3, D_6, D_9...]. The first subsets were used to calibrate equation 2.

$$AOD = a_o+a_1VSB+ a_2 (RH) +a_3 (SPD) \quad (2)$$

Where AOD is the aerosol optical depth, VSB is the visibility, RH is the relative humidity, SPD is the wind speed, TEMP is the temperature and DEW is the dew point temperature, a_o, a_1 and a_2, and a_3,denote the constant and the coefficients respectively. The performance of the model was accessed by measuring the coefficient of determination (R^2) for the calibration (R_r^2), the root mean square error (RMSE) for calibration and weighted mean average percentage errors (wMAPE) at 95% confidence level between the measured and predicted AOD. The resulting coefficient for the calibrations were used in the second data set [D_3, D_6, D_9...] for cross validation and RMSE was calculated between the measure and predicted validation data.

RESULT AND DISCUSION

Statistical Model selection criteria and accuracy assessment

The multiple linear regression (backward) method was used to assess the combined effects of the selected meteorological parameters on the overall and seasonal AOD. The test procedure is revealed in Table 1 using the overall (Jan-Dec) data. The result of the backward regression is provided in equations (1) – (9) while equation (10) – (30) revealed the result of the sub setting using Minitab statistical package presented in Table 1.

Table 1: AOD model selection criteria

Model	Equation	RMSE	R^2
1	$AOD=a_o+a_1(SPD)+a_2(VSB)+a_3(TEMP)+a_4(RH)+ a_5(DEW)$	0.06	0.83
2	$AOD=a_o+a_1(SPD)+a_2(VSB)+a_3(TEMP)+a_4(RH)$	0.06	0.81
3	$AOD=a_o+a_1(SPD)+a_2(VSB)+a_3(TEMP)$	0.10	0.77
4	$AOD=a_o+a_1(SPD)+a_2(VSB)$	0.13	0.64
5	$AOD=a_o+a_1(SPD)$	0.20	0.52
6	$AOD=a_o+a_1(VSB)$	0.18	0.53
7	$AOD=a_o+a_1(TEMP)$	0.30	0.41
8	$AOD=a_o+a_1(RH)$	0.28	0.45
9	$AOD=a_o+a_1(DEW)$	0.30	0.41
10	$AOD=a_o+a_1(SPD)+a_2(TEMP)+a_3(RH)+ a_4 (DEW)$	0.13	0.78
11	$AOD=a_o+a_1(VSB)+a_2(TEMP)+a_3(RH)+ a_4(SPD)$	0.07	0.81
12	$AOD=a_o+a_1(VSB)+a_2(TEMP)+a_3(RH)+ a_4(DEW)$	0.13	0.79
13	$AOD=a_o+a_1(VSB)+a_2(SPD)+a_3(RH)+ a_4(DEW)$	0.08	0.81
14	$AOD=a_o+a_1(VSB)+a_2(TEMP)+a_3(SPD)+ a_4(DEW)$	0.07	0.79
15	$AOD=a_o+a_1(VSB)+a_2(TMP)+a_3(DEW)$	0.12	0.72
16	$AOD=a_o+a_1(SPD)+a_2(TEMP)+a_3(RH)$	0.14	0.68
17	$\mathbf{AOD=a_o+a_1(SPD)+a_2(VSB)+a_3(RH)}$	**0.07**	**0.80**
18	$AOD=a_o+a_1(VSB)+a_2(RH)+a_3(TEMP)$	0.11	0.68

19	$AOD=a_o+a_1(DEW)+a_2(TEMP)+a_3(RH)$	0.16	0.69
20	$AOD=a_o+a_1(SPD)+a_2(DEW)+a_3(RH)$	0.14	0.75
21	$AOD=a_o+a_1(SPD)+a_2(VSB)+a_3(DEW)$	0.12	0.78
22	$AOD=a_o+a_1(TEMP)+a_2(RH)$	0.17	0.57
23	$AOD=a_o+a_1(SPD)+a_2(TEMP)$	0.17	0.56
24	$AOD=a_o+a_1(SPD)+a_2(RH)$	0.14	0.61
25	$AOD=a_o+a_1(VSB)+a_2(TEMP)$	0.16	0.58
26	$AOD=a_o+a_1(VSB)+a_2(RH)$	0.11	0.65
27	$AOD=a_o+a_1(SPD)+a_2(DEW)$	0.18	0.55
28	$AOD=a_o+a_1(TEMP)+a_2(DEW)$	0.19	0.52
29	$AOD=a_o+a_1(DEW)+a_2(RH)$	0.17	0.54
30	$AOD=a_o+a_1(VSB)+a_2(DEW)$	0.17	0.55

From table 1, it was observed that TEMP and DEW do not contribute significantly to AOD prediction. However, these parameters appear to have an effect when combined with other variables in the models. It is obvious that all the models can effectively be use for modelling AOD except the single variables models (7)-(9).

The five variables model (equation 1) appears to be the best in terms of high R^2 value, even though with same RMSE values with four variable model, possibly due to variation in the range of values of one of the input variables. It is also obvious that the difference in the R^2 and RMSE between equation 1 and 17 (model 2) is not more than 5% in accordance with (Noor *et al.,* 2010) and the fact that since the difference does not worth complicating the model from three variables to five, it is suggested in this work that equation 17 (model 2) be used as the best model in all cases.

It is assumed that, the proposed linear model should show different level of accuracies between the overall and seasonal data respectively. Because, the sensitivity of the model is hypotheses to depend on the distribution pattern of the measured AOD and the selected meteorological parameters used as well as the season. It was observed in the previous literature of (Tan *et al.,* 2015b; Balarabe and Koko 2018; Balarabe and Koko 2019) that, the sensitivity of AOD model was low when the majority of the observed AOD clustered around small values. It was also observed in the same studies that the insensitivity of the models was low during clear atmospheric conditions (summer). It however improved during higher aerosol concentration (Harmattan).

The result of the current study is in agreement with the above mentioned hypothesis. The analysis of 10 years overall AOD data is satisfactory, with R^2 =0.80; RMSE=0.07 with relatively low value of wMAPE (<4%) which indicates relative high accuracy of the model. Given the criteria that a low wMAPE corresponds to good prediction (Tan *et al*., 2015b; Balarabe and Koko 2018; Balarabe and Koko 2019), the three variable model yields the least biased prediction on the overall data which means that the overall model can be interpreted as an effective and can predict AOD accurately. Similarly, the prediction accuracy of the AOD model is high during summer (R^2 = *0.85*, RMSE 0.05 and wMAPE =2%) and best during Harmattan (R^2 = *0.90*, RMSE 0.03 and wMAPE =0.9%). This observation is consistent with the previous observation of (Balarabe and Koko 2018; Balarabe and Koko 2019)

Table 2: AOD model performance evaluation

Model	Equation	RMSE	RMSEv	R^2	wMAPE (%)
1	Overall	0.07	0.04	0.80	3
2	Harmattan	0.03	0.01	0.90	0.9
3	Summer	0.05	0.02	0.85	2

During the summer season, the accuracy of the model showed some improvement compared to the overall data. It is however, less in comparison with the Harmattan period. This means that the model produces more successful result during Harmattan compared to summer even though, effective in all the seasons. In line with the previous studies of Balarabe and Koko (2018); Balarabe and Koko (2019) the low sensitivity of the AOD prediction during summer is likely due to the fact that, majority of the measured AOD values are low and occurs within a smaller range of values. However, the sensitivity increases as the aerosol concentration increases during Harmattan and occurs within a wider range of values. This is in agreement with the stated hypothesis in this work. The low root mean square errors (RMSE) and higher R^2 values suggest that the meteorological variables used in the models explain a greater percentage of the AOD variability in Ilorin-Nigerian. This is supported by the low value of wMAPE corresponding to high R^2 and lower RMSE.

Validation of the predicted AOD

The procedure to validate the AOD prediction model is revealed here. The coefficients and constants [ai] in equation 1(obtained from the data for subset 1) in each case were used to generate a set of "predicted AOD" values in the second data set that are directly compared with AOD values in subset 2 data. The correlation between the predicted and measured AOD were determined based on RMSE denoted as validated RMSE or RMSEv. These RMSEv revealed the performance of the predicted AOD compared to the measured AOD. The result shows that the RMSE for the validation is nearly the same pattern as that for the calibration data. This suggests that the measured AOD is equally correlated to the validation AOD as to the calibration AOD.

CONCLUSIONS

In this study, an AERONET AOD and meteorological data were used to develop a modified empirical model that can be used to effectively predict AOD in Ilorin-Nigeria. The results showed that TEMP and DEW do not contribute significantly to AOD prediction. It was also observed that all the models (1)-(6) and (10)-(30) can effectively be used for modelling AOD except the single variables models (7)-(9). It is also obvious that equation 17 is the best model and was used in both overall and seasonal data following the criteria of Noor *et al*. (2010) and the fact the model need not to be complicated.

The analysis of 10 years overall AOD data was found satisfactory, with R^2 =0.80 and RMSE=0.07 with relatively low value of wMAPE (<4%) which indicates relative high accuracy of the model. Similarly, the prediction accuracy of the AOD model was high during summer (R^2 = *0.85,* RMSE 0.05 and wMAPE =2%) and best during Harmattan (R^2 = *0.90,* RMSE 0.03 and wMAPE =0.9%). This observation was found consistent with the previous observation of Balarabe and Koko (2018); Balarabe and Koko (2019). Which means that in as much meteorological variables will be used as input variables in AOD estimation; the model will always be more accurate during Harmattan than summer.

ACKNOWLEDGMENTS

The meteorology data were provided by the NOAA/NESDIS/NCDC, the authors, for this reason, wish to thank Stuart Hinson a Meteorologist, NOAA-NCDC for providing the data. They also wish to thank, principal investigator of the Ilorin site Aeronet AOT used in this study.

REFERENCES

Anuforom, A., Akeh, L. Okeke, P. & Opara F. (2007). Inter-annual variability and long-term trend of UV-absorbing aerosols during Harmattan season in sub-Saharan West Africa", Atmospheric Environment, (41) 1550-1559.

Balarabe, M., Abdullah, K. and Nawawi M. (2015). Long-Term Trend and Seasonal Variability of Horizontal Visibility in Nigerian Troposphere. Atmosphere, (6) 1462-1486.

Balarabe, M,.Abdullah, K. &NawawiM. (2016a). Monthly Temporal-Spatial Variability andEstimation of Absorbing Aerosol Index using Ground-based Meteorological Data in Nigeria. Atmospheric and Climate Sciences (6) 13-28.

Balarabe, M., Abdullah, K. &Nawawi M. (2016b). Seasonal Variations of Aerosol Optical Properties and Identification of Different Aerosol Types Based on AERONET Dataover Sub-Sahara West-Africa. Atmospheric and Climate Sciences (6) 13-28. doi: 10.4236/acs.2016.61002.

Balarabe M.A. & Koko A. S. (2018). Simple Linear Regression method to Estimate aerosol optical depth (AOD) in atmospheric column in Ilorin-Nigeria", A paper presented at 3rdAfrica Biennual International Renewable Energy Conference (Solar Africa 2018): Renewable Energy promotion for the attainment of Sustainable Development Goals (SDGs), organised by Sokoto Energy Research Center, Energy Commission ofNigeria, Usmanu Danfodiyo University Sokoto, 18th – 20th , December, 2018 Sokoto, Nigeria.

Balarabe M.A. & Koko A. S. (2019). Multiple Regression model to predict aerosol optical
depth (AOD) in atmospheric column in Ilorin-Nigeria", Nigerian Journal of Basic and Applied Sciences, sokoto (article in press)

Barladeanu, R., Stefan, S., and Radulescu, R. (2012). Correlation between the particulate matter (PM10) mass concentrations and aerosol optical depth in Bucharest, Romania, Romanian Reports in Physics, 64, 1085–1096.

Chen, B. B., Sverdlik, L. G., Imashev, S. A., Solomon, P. A., Lantz, J., Schauer, J. J., Shafer, M. M., Artamonova, M. S., and Carmichael, G. (2013). Empirical relationship between particulate matter and aerosol optical depth over Northern Tien-Shan, Central Asia, Air Qual. Atmos. Health, 6, 385–396.

Cordero, L., Wu, Y. Gross, B. M. & Moshary F. (2012). Use of passive and active ground and satellite remote sensing to monitor fine particulate pollutants on regional scales, in: Advanced Environmental, Chemical, and Biological Sensing Technologies IX, Baltimore, MD" 2012.

Engelstaedter S., Kohfeld, K.E. Tegen, I. & Harrison, S.P. *(*2003). Controls of dust emissions by vegetation and topographic depressions: An evaluation using dust storm frequency data. *Geophy. Res. Letter3*1294–1294.

Field, R. D., Van der Werf, G. R. &Shen, S. S. P. (2009). Human amplification of drought- induced biomass burning in Indonesia since 1960. Nat. Geosci. (2) 185–188.

Holben, B., Eck, T. Slutsker, I. Tanre, D. Buis, J. Setzer, A. Vermote, E. Reagan, J. Kaufman, Y. & Nakajima T. (1998).

AERONET—A federated instrument network and data archive for aerosol characterization. Remote sensing of environment. (66) 1-16.

Kaufman, Y. & Nakajima, T. (1998). AERONET—A federated instrument network and data archive for aerosol characterization. Remote sensing of environment. 661-16.

Lin, N. H., Sayer, A. M. Wang, S. H. Loftus, A. M. Hsiao, T. C. Sheu, G. R. Hsu, N. C. Tsay, S. C. &Chantara S. (2014). Interactions between biomass-burning aerosols and clouds over Southeast Asia: Current status, challenges, and perspectives. Environ. Pollut. 195292–307, doi:10.1016/j.envpol.2014.06.036

Mkoma S.L., Maenhaut W., Chi X., Wang W. and Raes N, (2009). Characterisation of PM10 Atmospheric Aerosols for the Wet Season 2005 at Two Sites in East Africa. Atmospheric Environment. (43) 631-639.

Noori, R., Hoshyaripour, G. Ashrafi, K., &Araabi, B.N. (2010). Uncertainty Analysis of Developed ANN and ANFIS Models in Prediction of Carbon Monoxide Daily Concentration. AtmosphericEnvironment (44) 476-482.

Nwafor J. (2007). Global climate change: The driver of multiple causes of flood intensity in Sub-Saharan Africa. International Conference on Climate Change and Economic Sustainability held at Nnamdi Azikiwe University, Enugu, Nigeria, 12-14.

Ogunjobi, K., Ajayi, V. Balogun, I. Omotosho, J. & He Z. (2008). The synoptic and optical characteristics of the harmattan dust spells over Nigeria. Theoretical and Applied Climatology, (93) 91-105.

Ogunjobi, K. O., Oluleye, A. & Ajayi V. O. (2012). A long-term record of aerosol index from TOMS observations and horizontal visibility in sub-Saharan West Africa. *International Journal of Remote Sensing*, (33) 6076-6093.

Qin, S., Shi, G. Chen, L. Wang, B. Zhao, J. Yu, C. & Yang, S. (2010). Long-term variation of aerosol optical depth in China based on meteorological horizontal visibility observations. Chin. J. Atmos. Sci. (34) 449–456.

Smirnov, A., Holben, B. N. Eck, T. F. Dubovik, O. &Slutsker, I. (2000). Cloud-screening and quality control algorithms for the AERONET database. Remote Sens. Environ., 73337–349, doi:10.1016/S0034-4257(00)00109-7

.

Tan, F., Khor, H. W. Y. Hee, W. S. Choon, Y. E. San, L. H. & Abdullah K. (2015a). Investigation of aerosol distribution patterns and its optical properties at different time scale by using LIDAR system and AERONET", NATIONAL PHYSICS CONFERENCE 2014 (PERFIK 2015a), AIP Publishing, 130001.

Tan, F.,Lim, H. Abdullah, K. Yoon, T. & Holben B. (2015b). Monsoonal variations in aerosol optical properties and estimation of aerosol optical depth using ground-based meteorological and air quality data in Peninsular Malaysia. Atmospheric Chemistry and Physics (15) 3755-3771.

Toth, T. D., Zhang, J., Campbell, J. R., Hyer, E. J., Reid, J. S., Shi, Y., and Westphal, D. L. (2014). Impact of data quality and surface-tocolumn representativeness on the PM2:5 / satellite AOD relationship for the contiguous United States, Atmos. Chem. Phys., 14, 6049–6062, doi:10.5194/acp-14-6049-2014, 2014.