Multivariate and Confirmatory Factor Analysis of Vehicular Emissions in Some Parts of Benin City, Nigeria

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Authors' Contributions

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ABSTRACT

Decline in air quality over the years has been linked to the growing rate of urbanization as well as an increase in the number of vehicles occasioned by the increased purchasing power of the people. Most of the pollutants emitted from vehicular activities have been observed to have adverse effects on individuals as well as the atmosphere. The focus of this study is to employ multivariate and confirmatory factor analysis (CFA) based on maximum likelihood estimation, to study the incidence of vehicular emissions in some parts of Benin city metropolis. Seven (7) georeferenced points (University of Benin main gate, Ekosodin junction, Agen Junction, Super D junction, Nitel junction, Okhunmwun junction and Oluku market junction) were used for data collection. Pollutants from vehicular emission, namely; dinitrogen oxide (NO₂), carbon monoxide (CO) including the total radiation were monitored in the morning and evening for a period (7th July to 12th August, 2020) with the aid of portable toxic gas monitors and radiation alert meters. Other measured parameters of interest include maximum temperature and wind speed. To ascertain the quality of the data, selected preliminary analysis, namely; test of normality, test of homogeneity, outlier detection and reliability test were done. With a calculated partial Eta squared based on Pillai's trace of 0.325, it was concluded that; there exist about 32.50 % variability among the dependent variables. Based on the CFA results, it was concluded that the hypothesis formulated for multivariate analysis of variance fits the sample data. Therefore, the alternate hypothesis was rejected and it was concluded that; the difference in the concentration of vehicular emission was as a result of change in temperature occasioned by time of measurement.

1. Introduction

The authors in a study [1], opined that the majority of vehicles used today are mostly powered by using internal combustion engines that burn gasoline or other petroleum products, which consequently give rise to harmful greenhouse gases that have adverse effects on our immediate environment. Example of such greenhouse gases include carbon monoxide, which is emitted from vehicles due to incomplete combustion of fuel. In addition to carbon monoxide, there is also the emission of toxic compound of hydrogen and carbon from the exhaust of hydrocarbon powered vehicles. More also, the reaction of nitrogen and oxygen to form nitrogen oxides (NO_x) is critical to the concept of air pollution by vehicular emission. In the presence of sunlight, nitrogen

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oxides can react with fumes from the volatilization of hydrocarbon to form the soup of photochemical smog for which the bad ozone is a major component. This smog can combine with particulate matter, which is small particles of foreign substances in the air to form haze which can cause damage to the lungs. Their behavior is also similar to that of ammonia, lead and sulfur dioxide [2]. In addition to the soup of photochemical smog, anti-knocking agents such as tetraethyl lead and other types of lead, which are added to improve the overall performance of fuel in an internal combustion engine remain the main source of lead in ambient air. It is estimated that 70 to 75 percent of this lead is converted into inorganic lead in engines during combustion and are emitted to the atmosphere through the exhaust pipe in addition to the small quantity of organic lead that passes through the engine in its original state [3].

The concentration of pollutants in a given volume/quality of fuel is usually influenced by so many variables; namely, the ratio of air-fuel present in the cylinder during internal combustion, the geometry of combustion chamber including the engine parameters such as speed, load, and engine temperature [4]. In Africa and Nigeria in particular, vehicular emissions are significantly on the rise due to the dearth of good transportation systems, which consequently gave birth to the use of unworthy vehicles for both private and commercial purposes [5]. Worthy of mention is the poor maintenance culture exhibited by most drivers of these unworthy vehicles; thus, putting the life of the people in perpetual danger due to the aftermath of air pollution [6]. There is also the issue of occasional traffic jam on our highways, which has increased the concentration of gaseous air pollutants and suspended particulate matter (PM) of different sizes and composition. 30 % of PM_{2.5} and other gaseous pollutants related to road transport normally results from the emissions of primary particles such as those from re-suspended road dust including wear of tires and brake linings [1].

2. Methodology

2.1. Study Sites

The study area is limited to some parts of Benin city particularly Ugbowo and environs where serious traffic jam is experienced on daily bases. Benin City serves as the principal administrative and socio-economic center for both Oredo Local Government Area and Edo State in Nigeria. Benin city is located within latitudes 6°20'N and 6°58'N and longitudes 5°35'E and 5°41'E, broadly occupies an area of approximately 112.552 sq km. This extensive coverage suggests spatial variability of weather and climatic elements [7]. A description of the specific locations employed for data collection, as presented in Fig. 1, is available in [8].

Fig. 1 Map of Study Area [8].

2.2. Data Collection and Measurement

Seven (7) georeferenced points (University of Benin main gate, Ekosodin junction, Ageri Junction, Super D junction, Nitel junction, Okhunmwun junction and Oluku market junction) were used for data collection. Pollutants from vehicular emission, namely; dinitrogen oxide (NO₂), carbon monoxide (CO) including the total radiation were monitored in the morning (9 a.m. to 10 a.m.) and evening (5 p.m. to 6 p.m.) during the period (7th July to 12th August 2020) with the aid of portable toxic gas monitors and radiation alert meters. In addition, the maximum temperature was measured using infra-red thermometer. To ascertain the quality of the data, selected preliminary analysis using different statistical techniques, namely outlier detection using seasonal box

plot method as proposed by [9], test of homogeneity of data using the residual mass curve as proposed by [10], test of normality using Jarque-Bera method and test of reliability using one-way analysis of variance were done.

2.3. Analysis of Temporal Variability

To study the variation in the concentration of vehicular emission occasioned by temporal variability (time of measurement), multivariate analysis of variance (MANOVA) was employed. Analysis of temporal variability is needed to ascertain if the difference in concentration of gaseous pollutant measured at the early hours of the morning and that measured at peak hour is significant. To employ MANOVA, its suitability was first ascertained using the degree of multivariate alliance associated with the data. Multivariate alliance was calculated through a measure known as the Mahala Nobis constant. If the maximum calculated value of the Mahala Nobis constant is less than the critical value, then the assumption of multivariate alliance has not been violated. If multivariate alliance has not been violated, then the concept of temporal variability can be investigated using multivariate analysis of variance (MANOVA) [11], [12]. The following tools were used to justify the presence of temporal variability and account for the percentage variability: (a) descriptive statistics; (b) box test or covariance matrix; (c) the multivariate test; and (d) Levene test of equality of error variance.

2.4. Confirmatory Factor Analysis

Confirmatory factor analysis (CFA) is a multivariate statistical technique usually employed to test how well the quantitative variables represent the number of constructs. CFA and exploratory factor analysis (EFA) are similar techniques in the field of data analysis, used to justify and confirmed the presence of temporal variability. Apart from data exploration, EFA can also provide information about the number of factors required to represent the data. On the other hand, CFA technique is usually employed to confirm the factors and validate the model hypothesis. The usefulness of CFA is twofold, to: (a) confirm a hypothesized factor structure, and (b) validate the structural procedure in the measurement model. In this study, confirmatory factor analysis was employed to validate the hypothesis that the difference in the concentration of vehicular emission during the early morning hours and peak hours of evening is significant.

3. Results and Discussion

To ascertain the presence of temporal variability occasioned by change in the time of measurement and also determine the degree of variability, multivariate analysis of variance was employed. The first step in the assessment of temporal variability is to compute the Mahala Nobis constant and the descriptive statistics of all the dependent variables (air quality data). The maximum calculated value of Mahala Nobis constant based on MANOVA was observed to be 15.86648. With degree of freedom equals 4 (number of dependent variables), the critical value of Mahala Nobis constant was (20.52). Since $15.86648 < 20.52$, it was concluded that the assumptions of multivariate outliers have not been violated; hence, the use of multivariate analysis of variance to study the presence of temporal variability was justified. The descriptive statistics of the data is presented in Table 1.

Table 1 Descriptive Statistics of Air Quality Data.

Pollutants	Period	Mean	Standard deviation	N
Temperature	Morning session	30.549	1.3716	245
	Evening session	28.879	1.1788	245
	Total	29.714	1.5268	490
Nitrogen dioxide	Morning session	0.0181	0.01119	245
	Evening session	0.0230	0.01282	245
	Total	0.0206	0.01226	490
Carbon monoxide	Morning session	0.5428	0.36396	245
	Evening session	0.6169	0.32395	245
	Total	0.5799	0.34618	490
Total Radiation	Morning session	0.247	0.1285	245
	Evening session	0.281	0.1298	245
	Total	0.264	0.1302	490

From the results of Table 1, it is observed that there is a significant difference between the calculated mean and standard deviation of all the dependent variables as a function of sampling time (morning and evening sessions). For temperature, the mean $\pm$ standard deviation is observed to be 30.549 ± 1.3716 °C during morning session and 28.879 ± 1.1788 °C during evening season. For NO₂, the mean $\pm$ standard deviation during morning session was observed to be 0.0181 ± 0.01119 ppm and during evening season it was observed to be 0.0230 ± 0.01282 ppm. For CO, the mean $\pm$ standard deviation during morning session was observed to be 0.5428 ± 0.36396 ppm and during evening season it was observed to be 0.6169 ± 0.32395 ppm. For total radiation, the mean $\pm$ standard deviation during morning session was observed to be 0.247 ± 0.1285 $\mu\text{g}/\text{m}^3$ and during evening

season it was observed to be $0.281 \pm 0.1298 \mu\text{g}/\text{m}^3$. The difference in the mean and standard deviation suggests the presence of imaginative variance, which is temporal variation occasioned by change in sampling time (morning and evening).

In multivariate analysis of variance, the null hypothesis that observed covariance matrix of all the dependent variables (gaseous emission concentration) is set equal across group (morning and evening sessions). That is, there is no variation in the concentration of the measured parameters. If the calculated p-value is less than 0.05 ($p < 0.05$), the null hypothesis is rejected. Hence, the assumption of equal covariance matrices across group has not been satisfied; an indication that temporal variability exists among the group. The computed covariance matrix for the corrected model and season is presented in Table 2.

From the results of Tables 2, it is observed that the computed significant values (p-value) for both the corrected model and season were less than 0.05 ($p < 0.05$); hence, the null hypothesis was rejected and it is concluded that the covariance matrix assumption was not satisfied. This means that the covariance matrices of the dependent variables are not equal across group an indication that temporal variability exists. It was concluded based on the covariance matrix that the variation in the dependent variables is due to variation in time of sampling. Numerous statistical techniques for computing the F-value for multivariate analysis of variance are present in literature and they are: Roy's largest root, which is the most acceptable and also the most susceptible to deviation in the covariance matrix. The next is the Pillai's trace followed by Wilk's Lambda. Pillai's trace is the least sensitive to the violation of the assumption of covariance matrix hence it was selected for this study. Result of multivariate test statistics computed to study the effect of temporal variability is presented in Table 3.

Table 2 Computed Covariance Matrix for Corrected Model (Tests of Between-Subjects Effects).

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power ^a
Corrected Model	TEMPERATURE	341.891 ^a	1	341.891	209.055	.000	.300	209.055	1.000
	NITROGEN DIOXIDE	.003 ^a	1	.003	19.959	.000	.039	19.959	.994
	CARBON MONOXIDE	.674 ^a	1	.674	5.676	.018	.011	5.676	.662
	TOTAL RADIATION	.144 ^a	1	.144	8.629	.003	.017	8.629	.834
Intercept	TEMPERATURE	432634.057	1	432634.057	2.645E5	.000	.998	264540.998	1.000
	NITROGEN DIOXIDE	.207	1	.207	1.429E3	.000	.745	1429.228	1.000
	CARBON MONOXIDE	164.755	1	164.755	1.388E3	.000	.740	1387.909	1.000
	TOTAL RADIATION	34.172	1	34.172	2.048E3	.000	.808	2047.685	1.000
SESSION	TEMPERATURE	341.891	1	341.891	209.055	.000	.300	209.055	1.000
	NITROGEN DIOXIDE	.003	1	.003	19.959	.000	.039	19.959	.994
	CARBON MONOXIDE	.674	1	.674	5.676	.018	.011	5.676	.662
	TOTAL RADIATION	.144	1	.144	8.629	.003	.017	8.629	.834
Error	TEMPERATURE	798.082	488	1.635					
	NITROGEN DIOXIDE	.071	488	.000					
	CARBON MONOXIDE	57.929	488	.119					
	TOTAL RADIATION	8.144	488	.017					
Total	TEMPERATURE	433774.030	490						
	NITROGEN DIOXIDE	.281	490						
	CARBON MONOXIDE	223.358	490						
	TOTAL RADIATION	42.460	490						
Corrected Total	TEMPERATURE	1139.973	489						
	NITROGEN DIOXIDE	.074	489						
	CARBON MONOXIDE	58.603	489						
	TOTAL RADIATION	8.288	489						

Table 3 Result of Multivariate Statistics (Multivariate Tests ^c).

Effect		Value	F	Hypothesis df	Error df	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power ^a
Intercept	Pillai's Trace	.998	6.922E4 ^a	4.000	485.000	.000	.998	276887.663	1.000
	Wilks' Lambda	.002	6.922E4 ^a	4.000	485.000	.000	.998	276887.663	1.000
	Hotelling's Trace	570.902	6.922E4 ^a	4.000	485.000	.000	.998	276887.663	1.000
	Roy's Largest Root	570.902	6.922E4 ^a	4.000	485.000	.000	.998	276887.663	1.000
SESSION	Pillai's Trace	.325	58.497 ^a	4.000	485.000	.000	.325	233.986	1.000
	Wilks' Lambda	.675	58.497 ^a	4.000	485.000	.000	.325	233.986	1.000
	Hotelling's Trace	.482	58.497 ^a	4.000	485.000	.000	.325	233.986	1.000
	Roy's Largest Root	.482	58.497 ^a	4.000	485.000	.000	.325	233.986	1.000

a. Exact statistic

b. Computed using alpha = .05

c. Design: Intercept + SESSION

From the result of Table 3, it was observed that the computed significant value (p-value) based on Roy's largest root, Wilk's Lambda, Hotelling's Trace and the Pillai's Trace were less than 0.05 ($p = 0.00$). Hence, the null hypothesis that the air quality parameters are the same for the two groups (morning and evening sessions) was rejected and it was concluded that temporal variability actually exists. To calculate the percentage

variability that is accounted for due to temporal variation, the partial Eta squared value of the Pillai's trace was employed. From the result of Table 3, the calculated partial Eta squared of the Pillai's trace was observed to be 0.325, which indicates 32.50 % variability among the dependent variables occasioned by change in the period of measurement. In addition, when the null hypothesis of equal variance assumption is rejected, then the observed power function based on Pillai's trace must be between 0.9 - 1.00. Again, from the result of Table 3, it was observed that the calculated power function based on Pillai's trace is 1.00 for both intercept and session. This validates the initial claim that temporal variability exists between the dependent variables.

It is hypothesized that there is a significant variation in the concentration of vehicular emission occasioned by change in measurement time, temperature and wind speed. An exploratory factor analysis using multivariate analysis of variance (MANOVA) was done to study this hypothesis and it was discovered that there exist about 32.50 % variability occasioned by time of data collection. The confirmatory factor analysis is set out to validate the result of exploratory factory analysis and further reaffirmed that time of measurement and change in temperature is a major determinant that can influenced the distribution of vehicular gaseous emission in the environment. An initial conceptual model of the influence of temporal variability on vehicular emission is presented in Fig. 2. Model-fit statistics used to assess the model's overall goodness of fit was adopted from standard literatures and presented in Table 4.

Table 4 Fit Statistics of Model Measurement.

Fit statistics	Recommended
CMIN (Minimum discrepancy function)	-
DF (Degree of freedom)	-
CMIN Significance (Model probability value)	$p < 0.05$
CMIN/DF	< 5.0
GFI (Goodness of Fit Index)	> 0.80
AGFI (Adjusted Goodness of Fit Index)	> 0.80
NFI (Normal Fit Index)	> 0.90
RFI (Relative Fit Index)	> 0.90
CFI (Comparative Fit Index)	> 0.90
TLI (Tucker-Lewis Index)	> 0.90
RMSEA (Root-mean-squared error of approximation)	< 0.06

Fig. 2 Path Diagram for Influence of Temporal Variability on Vehicular Emission.

The path diagram presented in Fig. 2 was implemented with the aid of SPSS Amos. Confirmatory factor analysis based on maximum likelihood estimation was performed and results obtained are presented in Table 5. Using the recommended fit statistics of model measurement, overall result of model was generated and presented in Table 6.

Table 5 Result of Model Fit Statistics for Influence of Temporal Variability.

Model Fit Summary					
CMIN					
Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	9	26.568	6	.000	4.428
Saturated model	15	.000	0		
Independence model	5	29.611	10	.001	2.961
RMR, GFI					
Model	RMR	GFI	AGFI	PGFI	
Default model	.115	.884	.711	.354	
Saturated model	.000	1.000			
Independence model	.116	.858	.787	.572	
Baseline Comparisons					
Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.103	-.495	.129	-.748	.000
Saturated model	1.000		1.000		1.000
RMSEA					
Model	RMSEA	LO 90	HI 90	PCLOSE	
Default model	.223	.141	.313	.001	
Independence model	.169	.100	.240	.004	
AIC					
Model	AIC	BCC	BIC	CAIC	
Default model	44.568	46.282	64.804	73.804	
Saturated model	30.000	32.857	63.727	78.727	
Independence model	39.611	40.563	50.854	55.854	
ECVI					
Model	ECVI	LO 90	HI 90	MECVI	
Default model	.646	.467	.934	.671	
Saturated model	.435	.435	.435	.476	
Independence model	.574	.391	.868	.588	

Table 6 Fit Statistics of Model Measurement for Influence of Temporal Variability.

Fit statistics	Recommended values	Obtained values
CMIN (Minimum discrepancy function)	-	25.568
DF (Degree of freedom)	-	6
CMIN Significance (Model probability value)	$p \leq 0.05$	0.000
CMIN/DF	< 5.0 [13]	4.428
GFI (Goodness of Fit Index)	> 0.80 [14]	0.884
AGFI (Adjusted Goodness of Fit Index)	> 0.80 [14]	0.771
NFI (Normal Fit Index)	> 0.90 [13]	0.103
RFI (Relative Fit Index)	> 0.90 [15]	0.495
CFI (Comparative Fit Index)	> 0.90 [16]	0.000
TLI (Tucker-Lewis Index)	> 0.90 [17]	0.748
RMSEA (Root-mean-square error of approximation)	< 0.06 [18]	0.223

From the results of Table 6, it was observed that; although, the model P-value of 0.000 is significant at $p = 0.05$ and the chi square (CMIN) value of 25.568 for the default model is almost equal to the value of the

independent model of 29.611 and this support the proposed theoretical model being tested, but the statistical parameters of the model are indeed poor. Outside the fact the normal fit index (NFI) is far below the standard limit, it was also observed that the relative fit index (RFI), comparative fit index (CFI) and the root mean square error of approximation (RMSEA) were all below the standard values. To improve the parameters of the model, model re-specification was done. In the first phase of model re-specification, the modification indices of the model were generated and presented in Table 7.

Table 7 Modification Indices of Model Fit for Influence of Temporal Variability.

Modification Indices (Group number 1 - Default model)			
Covariances: (Group number 1 - Default model)			
		M.I.	Par Change
F1	<--> SESSION	13.571	-.392
e1	<--> SESSION	13.514	-.391
Variances: (Group number 1 - Default model)			
		M.I.	Par Change
Regression Weights: (Group number 1 - Default model)			
		M.I.	Par Change
TEMPERATURE	<--- SESSION	13.514	-1.563

Using the modification indices of model fit, a covariance relation was introduced between the unobserved variables e1 and the model factor variable F1 as presented in Fig. 3. Using the path diagram of Fig. 3, the model fit parameters were re-estimated and result obtained is presented in Table 8.

Fig. 3 Path Diagram of First Phase Re-Specified Model for Influence of Temporal Variability.

Using the recommended fit statistics of model measurement, the overall result of the first phase re-specified model was regenerated and presented in Table 9. From the results of Table 9, it was observed that the statistical parameters of the model, which include (CMIN/DF), normal fit index, relative fit index, comparative fit index, Tucker-Lewis index [17] and the root-mean-square error of approximation have improved considerably.

Table 8 Fit statistics of First Phase Re-Specified Model for Influence of Temporal Variability.

RMR, GFI				
Model	RMR	GFI	AGFI	PGFI
Default model	.371	.978	.916	.261
Saturated model	.000	1.000		
Independence model	28.506	.368	.052	.245

Baseline Comparisons					
Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.993	.981	1.000	.999	1.000
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

Parsimony-Adjusted Measures			
Model	PRATIO	PNFI	PCFI
Default model	.400	.397	.400
Saturated model	.000	.000	.000
Independence model	1.000	.000	.000

NCP			
Model	NCP	LO 90	HI 90
Default model	.167	.000	9.444
Saturated model	.000	.000	.000
Independence model	549.954	476.117	631.195

FMIN				
Model	FMIN	F0	LO 90	HI 90
Default model	.059	.002	.000	.133
Saturated model	.000	.000	.000	.000
Independence model	7.887	7.746	6.706	8.890

RMSEA				
Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	.024	.000	.182	.475
Independence model	.880	.819	.943	.000

AIC				
Model	AIC	BCC	BIC	CAIC
Default model	26.167	28.197	51.210	62.210
Saturated model	30.000	32.769	64.150	79.150

Table 9 Fit Statistics of First Phase Re-Specified Model Measurement.

Fit statistics	Recommended	Obtained
CMIN (Minimum discrepancy function)	-	25.568
DF (Degree of freedom)	-	6
CMIN Significance (Model probability value)	$p \leq 0.05$	0.000
CMIN/DF	< 5.0 [13]	4.428
GFI (Goodness of Fit Index)	> 0.80 [14]	0.978
AGFI (Adjusted Goodness of Fit Index)	> 0.80 [14]	0.916
NFI (Normal Fit Index)	> 0.90 [13]	0.993
RFI (Relative Fit Index)	> 0.90 [15]	0.981
CFI (Comparative Fit Index)	> 0.90 [16]	1.000
TLI (Tucker-Lewis Index)	> 0.90 [17]	0.999
RMSEA (Root-mean-square error of approximation)	< 0.06 [18]	0.024

4. Conclusion

Since the critical value of Mahala Nobis constant was less than the calculated value, it was concluded that the assumptions of multivariate outliers have not been violated which justified the use of multivariate analysis of variance to study the presence of temporal variability. In addition, with a calculated partial Eta squared based

on Pillai's trace of 0.325, it was concluded that; there exist about 32.50% variability among the dependent variables occasioned by change in the period of measurement. The general results obtained from confirmatory factor analysis showed an acceptable overall model fit and hence, the theorized model fit well with the observed data. It was then concluded that the hypothesis formulated for multivariate analysis and confirmed using CFA fits the sample data and thus the null hypothesis was accepted and it was established that; the difference in the concentration of vehicular emission was as a result of change in temperature occasioned by time of measurement. In addition, the preliminary analysis including the reliability test revealed that the data collected in the course of the study are adequate and fit well with the model.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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References

- [1] H. S. Huboyo, W. Handayani, and B. P. Samadikun, "Potential air pollutant emission from private vehicles based on vehicle route," *IOP conference series: Earth and Environmental Science*, vol. 70, no. 1, pp. 1-8, 2017.
- [2] A. A. Adeyanju, and K. Manohar, "Effects of vehicular emission on environmental pollution in Lagos," *Sci-Afric Journal of Scientific Issues, Research & Essays*, vol. 5, no. 4, pp. 34-51, 2017.
- [3] B. Onursal, and S. G. Gautam, "Vehicular air pollution: experiences from seven Latin American urban centers," World Bank technical paper no. 373, Washington, D.C.: The World Bank Latin American and the Caribbean Region Technical Department, 1997.
- [4] C. Zhou, S. Li, and S. Wang, "Examining the impacts of urban form on air pollution in developing countries: a case study of China's megacities," *International Journal of Environmental Research & Public Health*, vol. 15, no. 8, p. 2018, doi: 10.3390/ijerph15081565
- [5] U. G. Akpan, and P. N. Ndoke, "Contribution of vehicular traffic emission to CO₂ emission in Kaduna and Abuja," Federal University of Technology, Minna, Nigeria, 1999
- [6] R. Afroz, M. N. Hassan, and N. A. Ibrahim, "Review of air pollution and health impacts in Malaysia," *Environmental Research*, vol. 92, no. 2, pp 71-77, 2003.
- [7] N. M. Nwokediuko, O. R. Ogirigbo, and I. Inerhunwa. "Load-settlement characteristics of tropical red soils of southern Nigeria," *European Journal of Engineering Research & Science*, vol. 4, no. 8, pp. 107-113, 2019.
- [8] I. R. Ilaboya, E. A. Otuaro, "Emission dispersion modeling and geospatial analysis of vehicular emissions in some parts of Benin City, Nigeria," *Journal of Advances in Science and Engineering*, vol. 4, no. 1, pp. 24-35, 2021.
- [9] D. Raes, P. Willens, and F. Gbaguidi, "Rainbow - a software package for hydrometeorological frequency analysis and testing the homogeneity of historical data sets," Proceedings of the 4th International Workshop on Sustainable Management of Marginal Drylands, 27 – 30 January, Islamabad, Pakistan, 2006, pp. 41-55.
- [10] D. B. Levi, E. K. Julie, J. R. Olsen, R. S. Pulwarty, D. A. Raff, D. P. Turnipseed, et al. "Climate change and water resources management," A Federal Perspective, vol. 1331, pp. 1-72, 2009.
- [11] A. F. M. Alkarkhi, A. Ahmad, N. Ismail, A. Easa, and K. Omar, "Assessment of surface water through multivariate analysis," *Journal of Sustainable Development*, vol. 1, no.3, pp. 27-33, 2008.
- [12] S. Shrestha and F. Kazama, "Assessment of surface water quality using multivariate statistical techniques: a case study of the Fuji river basin, Japan," *Environmental Modeling & Software*, vol. 22, no.4, pp. 464-475, 2007.
- [13] P. M. Bentler, and D. G. Bonett, "Significance tests and goodness-of-fit in the analysis of covariance structures," *Psychological Bulletin*, vol. 88, pp. 588-600, 1980.
- [14] K. G. Jöreskog, and D. Sörbom, "LISREL 7: guide to the program and applications," 2nd ed., Chicago, IL: SPSS, 1988.
- [15] K. A. Bollen, "Sample size and Bentler and Bonett's non-normed fit index," *Psychometrika*, vol. 51, pp. 375-377, 1986.
- [16] L. T. Hu, and P. M. Bentler, "Cutoff criteria for fit indexes in covariance structure analysis: conventional criteria versus new alternatives," *Structural Equation Modeling*, vol. 6, pp. 1-55, 1999.
- [17] L. R. Tucker, and C. Lewis, "The reliability coefficient for maximum likelihood factor analysis," *Psychometrika*, vol. 38, pp. 1-10, 1973.
- [18] R. Cudeck, and S. J. Henly, "Model selection in covariance structure analysis and the "problem" of sample size: a clarification," *Psychological Bulletin*, vol. 109, pp. 512-519, 1991.