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Downscaling and modelling climatic change projections with rainfall erosivity impact and wind velocity potential in the variability of tropical climate: a track towards space-earth sustainability nexus

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Abstract

The increase in atmospheric properties degradation including environmental polarization and ecosystem degradation has been linked with levels of climatic hazards posed by climatic change. The geographical location of the Federal Capital Territory of Nigeria in the North Central geo-political zone of Nigeria within the Savannah vegetation zone of the Wet African sub-region was x-rayed for her atmospheric-climatic-space property of wind, rainfall and the impact of the meteorological element of rainfall on the erosivity of the area. Downscaling of a thirty five (35) years climatic data was done. Modelling and simulation was undertaken using geo-statistical and physical science modelling and simulation packages including QGIS and Statgraphics centurion. Simulated and modelled data were subjected to statistical analysis using descriptive statistics including P-statistics. Result of the finding revealed that there exist a shift in the climatic behaviour of the Federal Capital Territory of Nigeria with projected data significant level at a P-value range at [P-value = 0.654638, P-value = 0.859967 and P-value = 0.859967] of the P-statistics at a 95% significant level (p > = 0.05), hence, validating a past (35 years) and future (12 years projection) change in the climatic behaviour of the area. Wind velocity impact in the area for the past 35 years has been huge, thus presenting a value range at 81.36km/h-12.6km/h which indicated high sea-land-atmospheric nexus impact towards the variability that exist in the climatic wellbeing of the area. Wind directional flux of the area ranges from 22°°-4.8 which also contributed to the change in climatic behavior of the area. There exist very minimal rainfall impact in the erosivity impact in the area, with a coefficient of Variation at CV=0.16%.

Keywords
Atmospheric wellbeing, Wind velocity, Wind direction, Climate projection, Sea-land-atmospheric nexus

Introduction

The increased in human suffering including ecological degradation and atmospheric imbalance, climatic fluctuation and subsequent environmental degradation, land pollution, eco-radioactivity flux, fragmentation and destruction of the potential of earth-system properties has been on a global scale years now (Adiaha et. al., 2022; Adiaha et. al., 2022 b; Adiaha, 2023) acting like a barrier to global sustainability. Projected climate change trend has shown that countries with geographical disadvantage including countries with inadequate adaptation and mitigation strategies will suffer bulk of the climatic hazards which has over the

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years debased humanity (Meza and Silva, 2009). According to the Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC), global surface temperature change for the end of the 21st century is highly likely to exceed 2°C for representative concentration pathways RCP6.0 and RCP8.5 (A mathematical model of the general circulation of a planetary atmosphere or ocean and based on the Navier-Stoke equations on a rotating sphere with thermodynamic terms for various energy sources) (IPCC, 2013). Like other parts of the world, northern and central Nigeria as well as the whole part of the country and West Africa in general has experienced monthly rainfall, temperature including wind flux variability trend which has being on a fluctuating frequency for years now (Giannini et. al., 2008). Climatic variation projections has indicated that the 21st century will have increased annual rainfall in West Africa (Giannini et. al., 2008). Current scientific evidence shows that climate change will continue into the future regardless of the effectiveness of mitigation (Tachie-Obeng et. al., 2012). Rain-feed agriculture is the main food production sources in Nigeria, so food availability and sustainability are mainly restricted by rainfall amount and distribution, making the need for reliable projections for Nigeria highly relevant. Wind direction generally report the direction of wind flux or point at which wind originates. Wind speed or wind velocity is one of three major characteristics of air movement on par with wind direction and wind gusts. Wind Speed (or Wind Velocity) has been described as air moving from high to low pressure (Quill et. al. 2019; Andrews, 2012). Air moving is usually due to changes in temperature that affects the horizontal movement of air specified by its speed and direction measured over the land surface at a height of 10 m above ground level. decline in the earth wind speed has been predicted to be impacted as carbon dioxide levels rise with the Earth's poles warm effect, the implication of this impact has a declining potential on wind energy production and plant growth including a resultant effect on Gulf Stream including other component of the earth-system properties. Various degradation processes that affect the sustainability of the earth-system properties including earth geological processes and atmospheric wellbeing has been linked with wind including rainfall (Adiaha et. al. 2020), hence, the variability of these atmospheric related properties remains critical for space-earth nexus sustainability.

Global Circulation Models (GCMs) are currently the tools most commonly used for climate projection. Due to their rough resolution, typically 300*300 km in the tropics, they cannot be used for projecting the local changes in scale required to assess impact and adaptation measures (Penlap et. al. 2004; Hewitson and Crane, 2006; IPCC, 2000). The use of empirical models in the forecast or predicting of future climate is based on local-scale weather. According to Hewitson and Crane (2006), empirical downscaling is one means of circumventing the problem of mismatch because it derives local climate response to largescale atmospheric states using more appropriate GCM attributes as required by impact assessment and adaptation. Many investigations into short-term variation in projected rainfall in many parts of the globe including West Africa has been based on GCMs outputs. Statistical forecast with downscaling thus plays a critical role and remains a keysone in the tropics for simulating projected local-scale climate change. Against the many challenges posed by the changing climate, the present research aim at the following objectives:

- Project climatic behaviour of Abuja over a 12 years future.
-Model wind velocity potential and its impact in Abuja over a 35 years.
-Period estimating decadal rainfall impact on the erosivity potential of the area.

Materials and Methods

Study Area

The Federal Capital Territory (FCT) (Fig. 1) is the seat of the Federal Government of Nigeria (Adiaha, 2019). The FCT holds a land area of about 8,000 square kilometres and located within latitude 7º25' North and 9º20' North of the Equator and longitude 5º45' and 7º39' (James et. al., 2013; Adiaha, 2019). The temperature of the area has being observed at 25°C–27°C. Annual rainfall of 1632mm and beyond has being observed in the area, while Highest relative humidity at 20% and above has being recorded in the area.

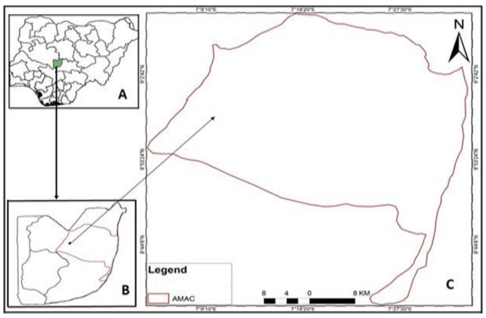

Figure 1
Study area location

A = Nigeria,
B = Abujawithin Abuja
C= Gwagwalada

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Climatic and Meteorological Data

Long-term daily rainfall dataset from 1983-2017 were obtained for Abuja, the Federal Capital Territory of Nigeria from Nigerian Meteorological Agency. The climate record was 100% complete (valid values).

Fournier Index

Fournier index (*F*) (Fournier, 1960) was used to assess the rainfall erosivity based on monthly average amount of Precipitation of the most rainy months (mm) and Average annual quantity of precipitation. The protocol was done according to the description of Fournier (1960), thus:

$$F = \frac{P^2_{max}}{P} \quad [1]$$

where: F = Fournier Index; P^2_{max} = Monthly average amount of Precipitation of the most rainy months (mm), *P* = Average annual quantity of precipitation.

Standardization of simulated, modelled and analytical output

All parameters determined in the study were compared with standardized ratings for tropical atmosphere and environment as presented in Table 1 and Table 2.

Table 1a. *The erosivity classes by Fournier index (F)* (Fournier, 1960)

Erosivity class	F
Very low	0 – 20
Low	20 – 40
Moderate	40 – 60
Severe	60 – 80
Very severe	80 - 100
Extremely severe	> 100

Table 1b *Coefficient of Variability (%)* (Wildings, 1985)

Coefficient of Variability	Class
Low	< 15
Moderate	16 - 35
High	> 35

Projected future climate change, modelling and statistical downscaling

Projected future climatic scenario. Climate scenario were projected based on a statistical downscaling technique. The procedure was done following the protocol as described by University of Loughborough (2021). The technique downscaled and modelled daily weather parameters using general circulation models (GCM) on the regional scale. A five years (12) years projecting period was undertaken. 2 season (raining and dry season) were taken into account (by computing such into the model) in the forecasting projection

Statistical downscaling. Statistical downscaling was done, where a statistical relationship was developed between the historical observed climate data and the output of the climate model for the same historical period of 1983-2017. The relationship was used to develop the future climate scenario (data) (as Presented in Table 3). The process of the statistical downscaling was combined with bias correction/adjustment procedure inother to present the best model and the modelled output.

Modelling. The following sixteen (16) projection models were tested:
(A) Random walk,
(B) Random walk with drift = 0.0171324,
(C) Constant mean = 33.7395,
(D) Linear trend = 43.4539 + -0.396507 t ,
(E) Quadratic trend = 23.3575 + 2.01506 t + -0.0492157 t^2 ,
(F) Simple moving average of 2 terms,
(G) Simple exponential smoothing with alpha = 0.9999,
(H) Brown's linear exp. smoothing with alpha = 0.8674,
(I) Holt's linear exp. smoothing with alpha = 0.312 and beta = 0.0001,
(J) Brown's quadratic exp. smoothing with alpha = 0.6473,
(K) Winters' exp. smoothing with alpha = 0.309, beta = 0.0001, gamma = 0.2179,
(L) ARIMA(1,1,2)x(2,0,2)2,
(M) ARIMA(2,1,1)x(2,0,2)2,
(N) ARIMA(2,1,2)x(2,1,2)2,
(O) ARIMA(0,0,1)x(2,1,2)2,
(P) ARIMA(2,0,1)x(2,1,1)2

The sixteen projection models were statistically evaluated against the local observed dataset of 1983-2017, and simulated climate change projection using was done using:
(1) the root mean squared error (RMSE),
(2) the mean absolute error (MAE),
(3) the mean absolute percentage error (MAPE),
(4) the mean error (ME),
(5) the mean percentage error (MPE)
The five analytical procedure enhanced the evaluation of the selected model performance in fitting the historical data.

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Table 2. *Wind scale table.* Source: Government of Canada, 2017

Force	Wind speed Km/h	Wind speed Knots	Descriptive term	Effects observed at sea	Effects observed on land
0	Less than 1	Less than 1	Calm	Sea surface like a mirror, but not necessarily flat.	Smoke rises vertically.
1	1 - 5	1 - 3	Light air	Ripples with the appearance of scales are formed, but without foam crests.	Direction of wind shown by smoke drift, but not wind vanes.
2	6 - 11	4 - 6	Light breeze	Small wavelets, still short but more pronounced. Crests do not break. When visibility good, horizon line always very clear.	Wind felt on face. Leaves rustle. Ordinary vane moved by wind.
3	12 -19	7 - 10	Gentle breeze	Large wavelets. Crests begin to break. Foam of glassy appearance. Perhaps scattered whitecaps.	Leaves and small twigs in constant motion. Wind extends light flag.
4	20 -28	11 - 16	Moderate breeze	Small waves, becoming longer. Fairly frequent whitecaps.	Raises dust and loose paper. Small branches are moved.
5	29 -38	17 - 21	Fresh breeze	Moderate waves, taking a more pronounced long form. Many whitecaps are formed. Chance of some spray.	Small trees with leaves begin to sway. Crested wavelets form on inland waters.
6	39 -49	22 - 27	Strong breeze	Large waves begin to form. The white foam crests are more extensive everywhere. Probably some spray.	Large branches in motion. Whistling heard in telephone wires. Umbrellas used with difficulty.
7	50 -61	28 - 33	Near gale	Sea heaps up and white foam from breaking waves begins to be blown in streaks along the direction of the wind.	Whole trees in motion. Inconvenience felt in walking against wind.
8	62 -74	34 - 40	Gale	Moderately high waves of greater length. Edges of crests begin to break into the spindrift. The foam is blown in well-marked streaks along the direction of the wind.	Breaks twigs off trees. Generally impedes progress. Walking into wind almost impossible.
9	75 -88	41 - 47	Strong gale	High waves. Dense streaks of foam along the direction of the wind. Crests of waves begin to topple, tumble and roll over. Spray may affect visibility.	Slight structural damage occurs, e.g. roofing shingles may become loose or blow off.
10	89 -102	48 - 55	Storm	Very high waves with long overhanging crests. Dense white streaks of foam. Surface of the sea takes a white appearance. The tumbling of the sea becomes heavy and shock-like. Visibility affected.	Trees uprooted. Considerable structural damage occurs.
11	103 -117	56 - 63	Violent storm	Exceptionally high waves. Sea completely covered with long white patches of foam. Visibility affected.	Widespread damage.
12	118 -133	64 - 71	Hurricane	Air filled with foam and spray. Sea entirely white with foam. Visibility seriously impaired.	Rare. Severe widespread damage to vegetation and significant structural damage possible.

Wind modelling (Wind Flow Modelling)

Wind flow modelling was done through modelling the real-time data of the measurement of the speed and direction of the wind. The modelled computational output was recorded as wind velocity. The procedure for modelling was done following the outline of Mughal et. al. (2017), where the decadal flux of the wind velocity impact was modelled.

Statistical application and analysis

Modelling and simulation was undertaken using geo-statistical and physical science modelling and simulation packages including Statgraphics Centurion. Simulated and modelled data were subjected to statistical analysis using descriptive statistics including P-statistics. Various simulation and modelled analytical procedures with statistical approaches were applied to test, analyzed and validate all modelled and simulated data. All statistical approach was done following strategies as described by IPCC (1995) and IPCC (2016).

Results and discussion

Evaluation of climate change projections

Projected future climatic behavior. The result of the projection from downscaling as presented in Table 3 shows the forecasted values for 1983-2017, it also display the predicted values from the fitted model and the residuals (data-forecast).

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Table 3.. *Climate change projection, wind velocity and erosivity impact based Fournier Index. The Forecast Table is based on ARIMA(1,1,2)x(2,0,2)2 Model:for the dataset of 1983-2017. Fournier Index as presented in the table is done for a decadal sequence.*

Period 1983-2017		Climate Change Projection					Fournier Index
		Data	Forecast	Residual	Wind velocity (m/s)		$F = \frac{P^2_{max}}{P}$
					Wind speed (m/s)	Wind direction (°)	
	Jan	0.72	0.10433	0.33433	3.5	4.8	
	Feb	1.14	6.59235	-5.45235	18.5	17.5	
	Mar	10.12	17.7222	-7.60224	20.1	22.1	
	Apr	21.50	28.1104	-6.61042	17.2	16.7	
Decade 1	May	47.94	42.0453	5.89472	15.4	18.7	
1983-1992	Jun	64.28	67.4008	-3.12081	14.7	15.7	
	Jul	78.34	71.0983	7.24175	13.4	14.6	
	Aug	98.73	76.4950	22.235	15.6	16.7	
	Sep	89.53	91.4527	-1.92265	13.6	14.5	
	Oct	39.55	62.4756	-22.9256	20.2	21.3	0.08333
	Nov	3.65	-3.10641	6.75641	14.8	19.1	
	Dec	1.36	-15.7202	17.0802	22.1	18.7	
	Jan	0.00	3.30514	-3.30514	17.4	18.5	
	Feb	0.01	0.25963	-0.24963	16.7	21.3	
	Mar	6.61	14.5594	-7.94941	16.9	22.0	
	Apr	26.18	23.1984	2.98159	21.0	19.8	
Decade 2	May	47.43	53.4399	-6.00993	17.8	21.0	
1993-2002	Jun	62.53	65.6948	-3.1648	22.6	23.5	
	Jul	89.52	74.8806	14.6394	21.7	18.6	
	Aug	111.3	98.9816	12.3184	20.9	18.9	
	Sep	86.15	104.928	-18.7779	22.1	20.0	
	Oct	57.14	55.9998	1.14023	20.2	18.9	0.083325
	Nov	1.77	26.2212	-24.4512	18.7	14.6	
	Dec	0.17	-25.2177	25.3877	16.7	29.1	
	Jan	0.64	-2.08542	2.72542	18.6	18.7	
	Feb	4.55	10.1742	-5.62424	22.2	19.8	
	Mar	4.63	9.6935	-5.0635	22.8	21.3	
	Apr	20.88	22.1928	-1.31284	18.7	16.7	
Decade 3	May	46.99	39.8579	7.13214	19.9	15.5	
2003-2012	Jun	76.99	73.5593	3.43072	21.2	19.8	
	Jul	90.24	83.3386	6.9014	13.6	14.5	
	Aug	96.60	100.658	-4.05774	20.2	21.3	
	Sep	73.96	71.4048	2.55516	14.8	19.1	
	Oct	56.58	64.2022	-7.62221	22.1	18.7	0.083335
	Nov	6.25	21.1639	-14.9139	17.4	18.5	
	Dec	0.00	-11.2611	11.2611	16.7	21.3	
	Jan	0.19	-5.04845	5.23845	16.9	22.0	
	Feb	2.22	9.66918	-7.44918	21.0	19.8	
	Mar	9.14	13.9749	-4.83494	17.8	21.0	
5 years trend	Apr	15.35	21.6593	-6.30927	21.5	19.8	
2013-2017	May	27.10	38.3091	-11.2091	11.8	18.8	
	Jun	23.94	39.4309	-15.4909	10.9	11.5	
	Jul	23.88	31.0141	-7.1341	17.4	18.5	
	Aug	37.50	34.1446	3.35537	16.7	21.3	
	Sep	24.83	34.7054	-9.87542	16.9	22.0	
	Oct	23.72	23.7518	-0.03179	21.0	19.8	0.08336
	Nov	0.30	3.75268	-3.45268	17.8	21.0	
	Dec	1.73	-7.16102	8.89102	19.1	15.8	

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For time periods beyond the end of the series, it shows 95.0% prediction limits for the forecasts. These limits show where the true data value at a selected future time is likely to be with 95.0% confidence, with a statistical accuracy of the fitted model being appropriate for the data. The increase in the numerical output of the projected data indicate increased in the rainfall of the area over a 12 years projected timeframe , although with fluctuations which could be high to low, thus, indication a departure which could be explained as change in the climatic element of rainfall sequence in the area, thus proving a drift (or change) in the climatic behavior of the area. The assertion presented from the output of the 35 years climatic trend for the Federal Capital Territory of Nigeria is inline with the review report of Giannini et. al. (2008) where their report indicated fluctuation in climatic elements including rainfall. Result output presented by Cook and Vizy (2006) also align with the output of this findings, where the Scholars presented modelled simulation output that indicated a departure from the meteorological dataset used which indicated a change in the behaiour and nature of the climatic condition of West Africa. Findings of this research is also inline with the work of Eltahir and Gong (1996) where their research indicated dynamical change in meteorological data after modelling and projection as an indication of climatic fluctuation and change in West Africa.

S*tatistical significance of the terms in the forecasting model.* Outcome of the forecasting produced future values of 1983-2017 as presented in Table 4 showed that the data cover 35 years periods (modelled-coded as 48 time periods). Currently, an autoregressive integrated moving average (ARIMA) model has been selected. The ARIMA model assumes that the best forecast for future data is given by a parametric model relating the most recent data value to previous data values and previous fluctuation (regarded as noise by the model). Each value of 1983-2017 has been adjusted in the following way before the model was fit: (1) *A multiplicative seasonal adjustment.* The output presented in Table 4 and Table 5 summa-rizes the statistical significance of the terms in the forecasting model. Terms with P-values less than 0.05 are statistically significantly different from zero at the 95.0% confidence level. The P-value for the AR(1) term is less than 0.05, so it is significantly different from 0. The P-value for the MA(2) term is less than 0.05, so it is significantly different from 0. The P-value for the SAR(2) term is less than 0.05, so it is significantly different from 0. The P-value for the SMA(2) term is less than 0.05, so it is significantly different from 0. The estimated standard deviation of the input white noise equals 11.4102.

Table 4. *ARIMA model evaluation (Summary)*

Parameter	Estimate	Stnd. Error	t	P-value
AR(1)	-0.929713	0.07515	-12.3714	0.000000
MA(1)	-1.31945	0.131889	-10.0042	0.000000
MA(2)	-0.642115	0.126368	-5.08132	0.000009
SAR(1)	1.00888	0.0658126	15.3297	0.000000
SAR(2)	-0.938697	0.0580461	-16.1716	0.000000
SMA(1)	1.44607	0.0412646	35.0439	0.000000
SMA(2)	-0.918169	0.0445322	-20.6181	0.000000

Key: Backforecasting: yes - Estimated white noise variance = 130.192 with 40 degrees of freedom - Estimated white noise standard deviation = 11.4102 - Number of iterations: 19 Length of seasonality = 2

The output presented in Table 5 also summarizes the performance of the currently selected model in fitting the historical data. It displays:
(1) the root mean squared error (RMSE)
(2) the mean absolute error (MAE)
(3) the mean absolute percentage error (MAPE)
(4) the mean error (ME)
(5) the mean percentage error (MPE)

Statistic	Estimation Period
RMSE	11.2363
MAE	8.15085
MAPE	
ME	-1.0374
MPE	

Table 5 *Statistical model flows. Forecast model selected: ARIMA (1,1,2)x(2,0,2)2*

The output presented in Table 5 also summarizes the performance of the currently selected model in fitting the historical data. It displays:
(1) the root mean squared error (RMSE)
(2) the mean absolute error (MAE)
(3) the mean absolute percentage error (MAPE)
(4) the mean error (ME)
(5) the mean percentage error (MPE)
Each of the statistics is based on the one-ahead forecast errors, which are the differences between the data value at time t and the forecast of that value made at time t-1. The first three statistics measure the magnitude of the errors. A better model gave a smaller value. The last two statistics measured bias. A better model gave a value close to 0. Note: the MAPE and MPE (as indica-

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ted in Table 5) were not calculated because the smallest data value was less than or equal to 0. It could be stressed that there exit a shift in the tend of normal from projected and collected climatic behaviour, hence validating the view of a change in the climate of the area, this view confirms the research output of IPCC (2013) which express departure from normal in the global climatic behaviour.

The variability of the shift in the climatic behaviou of the area as indicated in Figure 2 and Figure 3 in indicated sequential variability in the climatic behaviour of the area over a 35 year trend. The research of Opoku-Ankomah and Cordery (1994) which present shift in the climatic behaviour of sea surface and rainfall variability in a West African state is also inline with the outcome of this findings.

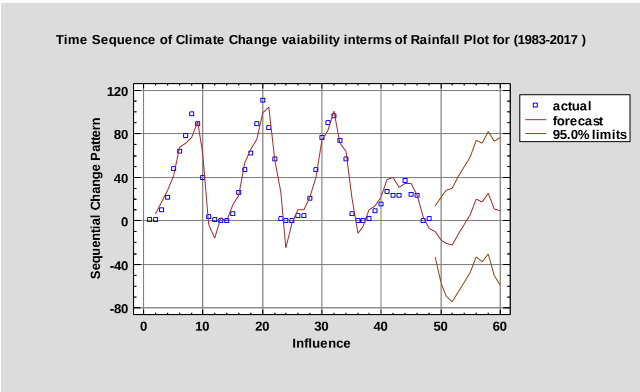

Figure 2. *Time sequence of climate change variability interms of rainfall over a 35 years time sequence*

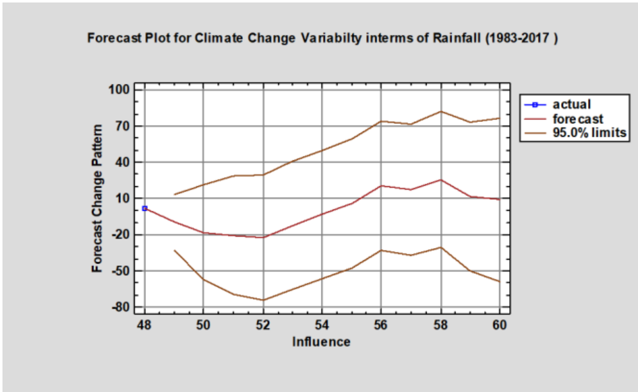

Figure 3. *Pattern of climatic change variability interms of rainfall over a 35 years time sequence*

Model comparison. Result output presented in Table 6 compares the results of fitting different models to the data. The model with the lowest value of the Akaike Information Criterion (AIC) is model L [ARIMA(1,1,2) x(2,0,2)2], which has been used to generate the forecasted climatic projections. Table 6 also summarizes the results of five tests run on the residuals to determine whether each model is adequate for the data. An OK means that the model passes the test. One * means that it fails at the 95% confidence level. Two *'s means that it fails at the 99% confidence level. Three *'s means that it fails at the 99.9% confidence level. *Note*: that the currently selected model, model L, passes 5 tests. Since no tests are statistically significant at the 95% or higher confidence level, the current model is probably adequate for the data. Analytical output presented in Figure 4 indicated about 99.9% increase in the projected shift expected in the climatic variability from normal in the area in the future 12 year interval. Views on the finding confirms the research of Willmott et. al. (1985) which indicated model fluctuation in stabilizing statistical data in model furcating. The outcome of this research is also in confirmation with the work of Akponikpe et. al. (2010) which indicated stability in using APSIM model in long term simulation

.Models

(A) Random walk

(B) Random walk with drift = 0.0171324

(C) Constant mean = 33.7395

(D) Linear trend = 43.4539 + -0.396507 t

(E) Quadratic trend =

23.3575+2.01506 t +-0.0492157 t^2

(F) Simple moving average of 2 terms

(G) Simple exponential smoothing with alpha = 0.9999

(H) Brown's linear exp. smoothing with alpha = 0.8674

(I) Holt's linear exp. smoothing with alpha = 0.312 and beta = 0.0001

(J) Brown's quadratic exp. smoothing with alpha = 0.6473

(K) Winters' exp. smoothing with alpha =

0.309, beta = 0.0001, gamma = 0.2179

(L) ARIMA(1,1,2)x(2,0,2)2

(M) ARIMA(2,1,1)x(2,0,2)2

(N) ARIMA(2,1,2)x(2,1,2)2

(O) ARIMA(0,0,1)x(2,1,2)2

(P) ARIMA(2,0,1)x(2,1,1)2

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Table 6
Estimation period

Model	RMSE	MAE	ME	AIC	HQC	SBIC
(A)	20.783	14.2482	-0.22327	6.10993	6.12467	6.14892
(B)	21.013	14.2438	-0.240434	6.17362	6.20308	6.25159
(C)	34.8159	29.5898	-0.116975	7.18348	7.21295	7.26145
(D)	34.7475	28.7402	-0.099923	7.22122	7.26541	7.33817
(E)	34.0351	27.9314	-0.099923	7.22145	7.28038	7.37738
(F)	27.7787	20.6104	-0.115306	6.73187	6.76133	6.80984
(G)	20.7839	13.9523	-0.218596	6.15169	6.18115	6.22966
(H)	22.051	16.2589	-0.387868	6.27005	6.29952	6.34802
(I)	33.5832	27.1534	-4.07284	7.15305	7.19725	7.27000
(J)	25.616	17.3189	-0.667758	6.56977	6.59923	6.64773
(K)	34.0453	27.1427	-0.734433	7.18038	7.22458	7.29733
(L)	11.2363	8.15085	-1.0374	5.12996	5.23309	5.40285
(M)	11.8903	8.44282	-1.07214	5.24311	5.34624	5.51600
(N)	11.8674	7.96368	-0.311221	5.28093	5.39879	5.59280
(O)	12.8534	9.93316	-1.28649	5.31556	5.38922	5.51047
(P)	12.9691	9.04041	-1.48312	5.37514	5.46353	5.60904

Length of seasonality = 2 - Years interval projected for =12

Table 7
Statistical significant test

Model	RMSE	RUNS	RUNM	AUTO	MEAN	VAR
(A)	20.783	OK	**	***	OK	*
(B)	21.013	OK	**	***	OK	*
(C)	34.8159	***	***	***	OK	OK
(D)	34.7475	***	***	***	OK	OK
(E)	34.0351	***	***	***	OK	OK
(F)	27.7787	**	***	***	OK	OK
(G)	20.7839	OK	***	***	OK	OK
(H)	22.051	OK	OK	*	OK	*
(I)	33.5832	***	***	***	OK	OK
(J)	25.616	OK	OK	*	OK	OK
(K)	34.0453	***	***	***	OK	OK
(L)	11.2363	OK	OK	OK	OK	OK
(M)	11.8903	OK	OK	OK	OK	OK
(N)	11.8674	OK	OK	OK	OK	OK
(O)	12.8534	*	*	OK	OK	OK
(P)	12.9691	OK	OK	OK	OK	OK

Key: RMSE = Root Mean Squared Error - RUNS = Test for excessive runs up and down - RUNM = Test for excessive runs above and below median - AUTO = Ljung-Box test for excessive autocorrelation - MEAN = Test for difference in mean 1st half to 2nd half - VAR = Test for difference in variance 1st half to 2nd half - OK = not significant (p >= 0.05) - * = marginally significant (0.01 < p <= 0.05) - ** = significant (0.001 < p <= 0.01) - *** = highly significant (p <= 0.001)

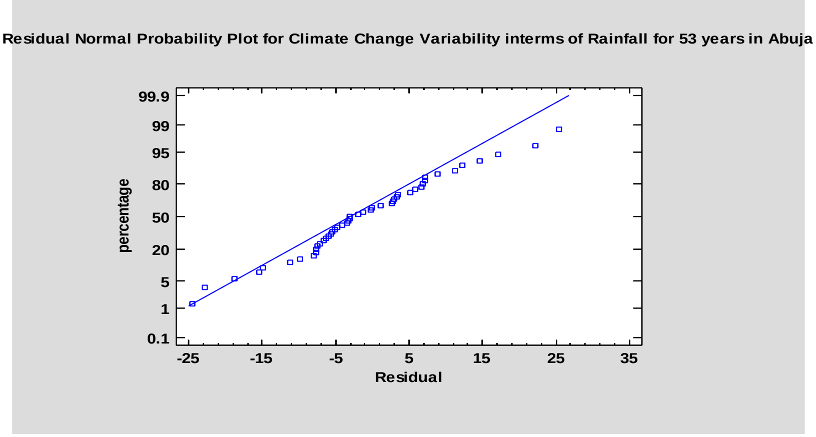

Figure. 4
ARIMA(1,1,2)x(2,0,2)2 performance indicating increasing trend in the residual normality of the projected climatic shift towards a 12 years future climate change.

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Estimated Autocorrelations for residuals. The finding result as presented in Table 8 shows the estimated autocorrelations between the residuals at various lags. The lag k autocorrelation coefficient measures the correlation between the residuals at time t and time t-k. Also shown are 95.0% probability limits around 0. If the probability limits at a particular lag do not contain the estimated coefficient, there is a statistically significant correlation at that lag at the 95.0% confidence level. In this case, there was no autocorrelations coefficients that was statistically significant, implying that the time series may well be completely random (white noise). Expression presented in this findings is inline with the research out of Willmott et. al. (1985) which presented variability in the statistics for the evaluation of models. Research output of Akponikpe at. al. (2010) also align with this finding where the Scholar indicated variation in the modelling with APSIM model.

Lag	Autocorrelation	Stnd. Error	Lower 95.0% Prob. Limit	Upper 95.0% Prob. Limit
1	-0.0789195	0.145865	-0.285891	0.285891
2	-0.20065	0.146771	-0.287666	0.287666
3	-0.124449	0.152495	-0.298886	0.298886
4	0.0872082	0.154641	-0.303092	0.303092
5	0.0671263	0.155684	-0.305136	0.305136
6	-0.0174314	0.156299	-0.306340	0.306340
7	0.0839226	0.15634	-0.306421	0.306421
8	0.0817443	0.157296	-0.308294	0.308294
9	-0.200644	0.158197	-0.310061	0.310061
10	-0.201543	0.163522	-0.320497	0.320497
11	0.0635477	0.168724	-0.330694	0.330694
12	0.258509	0.169233	-0.331690	0.331690
13	0.0500284	0.177436	-0.347768	0.347768
14	-0.172082	0.177735	-0.348356	0.348356

Table 8
Estimated autocorrelations for residuals.
Model: ARIMA(1,1,2)x(2,0)

Estimated partial autocorrelations for residuals. Analytical output presented in Table 9 shows the estimated partial autocorrelations between the residuals at various lags. The lag k partial autocorrelation coefficient measures the correlation between the residuals at time t and time t+k having accounted for the correlations at all lower lags. It can be used to judge the order of autoregressive model needed to fit the data. Also shown are 95.0% probability limits around 0. If the probability limits at a particular lag do not contain the estimated coefficient, there is a statistically significant correlation at that lag at the 95.0% confidence level. In this case, none of the 24 partial autocorrelations coefficients is statistically significant at the 95.0% confidence level. Outcome of this finding also confirms the research of Akponikpe at. al. (2010) which expressed variation in statistical output of the research statistical outcome in the in using APSIM model.

Lag	Partial Autocorrelation	Stnd. Error	Lower 95.0% Prob. Limit	Upper 95.0% Prob. Limit
1	-0.0789195	0.145865	-0.285891	0.285891
2	-0.208175	0.145865	-0.285891	0.285891
3	-0.168307	0.145865	-0.285891	0.285891
4	0.0137574	0.145865	-0.285891	0.285891
5	0.0199757	0.145865	-0.285891	0.285891
6	-0.00557118	0.145865	-0.285891	0.285891
7	0.125456	0.145865	-0.285891	0.285891
8	0.125882	0.145865	-0.285891	0.285891
9	-0.154528	0.145865	-0.285891	0.285891
10	-0.20555	0.145865	-0.285891	0.285891
11	-0.0554854	0.145865	-0.285891	0.285891
12	0.133777	0.145865	-0.285891	0.285891
13	0.0874988	0.145865	-0.285891	0.285891
14	-0.0432294	0.145865	-0.285891	0.285891
15	-0.174132	0.145865	-0.285891	0.285891

Table 9
Estimated partial autocorrelations for residuals

Model: ARIMA(1,1,2)x(2,0,2)2

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Periodogram for residuals. Data presented in Table 10 shows the periodogram ordinates for the residuals. It is often used to identify cycles of fixed frequency in the data. The periodogram was constructed by fitting a series of sine functions at each of 24 frequencies. The ordinates are equal to the squared amplitudes of the sine functions. The periodogram can be thought of as an analysis of variance by frequency, since the sum of the ordinates equals the total corrected sum of squares in an ANOVA table.Ouput of this finding analysis is inline with the scientific report of Adiku and Stone (1995) which expressed fluctuation in statistical sequence while modelling and predicting southern oscillation index for improving rainfall predictions. Further, the scientific output by Akponikpe at. al. (2010) which expressed fluctuation in data modelling and prediction also validate views of this research.

i	Frequency	Period	Ordinate	Cumulative Sum	Integrated Periodogram
0	0.0		2.26923E-29	2.26923E-29	4.53884E-33
1	0.0212766	47.0000	158.291	158.291	0.0316608
2	0.0425532	23.5000	181.865	340.157	0.0680369
3	0.0638298	15.6667	10.2936	350.45	0.0700957
4	0.0851064	11.7500	4.34344	354.793	0.0709645
5	0.106383	9.40000	148.607	503.401	0.100688
6	0.12766	7.83333	91.2909	594.692	0.118948
7	0.148936	6.71429	172.949	767.641	0.153541
8	0.170213	5.87500	844.416	1612.06	0.322438
9	0.191489	5.22222	85.7766	1697.83	0.339594
10	0.212766	4.70000	41.0087	1738.84	0.347797
11	0.234043	4.27273	304.466	2043.31	0.408695
12	0.255319	3.91667	706.134	2749.44	0.549933
13	0.276596	3.61538	397.562	3147.0	0.629452
14	0.297872	3.35714	33.7311	3180.73	0.636199
15	0.319149	3.13333	217.397	3398.13	0.679682
16	0.340426	2.93750	66.6175	3464.75	0.693006
17	0.361702	2.76471	309.445	3774.19	0.754900
18	0.382979	2.61111	84.3316	3858.52	0.771768
19	0.404255	2.47368	295.057	4153.58	0.830784
20	0.425532	2.35000	221.949	4375.53	0.875178
21	0.446809	2.23810	81.9683	4457.5	0.891573
22	0.468085	2.13636	329.563	4787.06	0.957491
23	0.489362	2.04348	212.528	4999.59	1.000000

Table 10
Periodogram for residuals i=frequency count, Model: ARIMA(1,1,2)x(2,0,2)2

Tests for randomness of residuals

Hypothesis

1. The residuals are random at the 95.0% or higher confidence level
2. The series is random at the 95.0% or higher confidence level
3. The series is random at the 95.0% or higher confidence level.

Result. Since the P-value for this test is greater than or equal to 0.05, we cannot reject the hypothesis that the residuals are random at the 95.0% or higher confidence level.

1. The second test counts the number of times the sequence rose or fell. The number of such runs equals 32, as compared to an expected value of 31.0 if the sequence were random. Since the P-value for this test is greater than or equal to 0.05, we cannot reject the hypothesis that the series is random at the 95.0% or higher confidence level.
2. The third test is based on the sum of squares of the first 24 autocorrelation coefficients. Since the P-value for this test is less than 0.05, we can reject the hypothesis that the series is random at the 95.0% confidence level.

Determination. Since the three tests are sensitive to different types of departures from random behavior, hence, the tests for randomness of residuals of hypothesis 1 and 2 are completely random indicating that [ARIMA(1,1,2)x(2,0,2)2] model capture all of the structure in the data.

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Key. -A sequence of random numbers is often called white noise, since it contains equal contributions at many frequencies. The first test counts the number of times the sequence was above or below the median.

(1) Runs above and below median
Median = -3.12081
Number of runs above and below median = 26
Expected number of runs = 24.0
Large sample test statistic z = 0.447324
P-value = 0.654638

(2) Runs up and down
Number of runs up and down = 32
Expected number of runs = 31.0
Large sample test statistic z = 0.17641
P-value = 0.859967

(3) Ljung-Box Test
Test based on first 15 autocorrelations
Large sample test statistic = 19.1513
P-value = 0.0140709

The output of the three tests ran to determine whether or not the residuals form a random sequence of numbers are completely random and if the model [ARIMA(1,1,2)x(2,0,2)2] used capture all of the structure in the data indicated a significant potential at P-values, hence, the are completely random and captured all of the structure in the dataset. Output of this finding is inline with the research of Akponikpe at. al. (2010) which expressed stability including fluctuation in dataset prediction and modelling. The outcome of this finding as indicated in Figure 5 also indicated residual impact in the periodic change in the climatic behavior of the Federal Capital Territory of Nigeria over a 35 years flux of climatic behavior and variability of the area. This output also align with the work of Akponikpe at. al. (2010). Further, the finding of this work also align with the views of IPCC (1995) which stressed modelling output testing with variation to validate climatic projections.

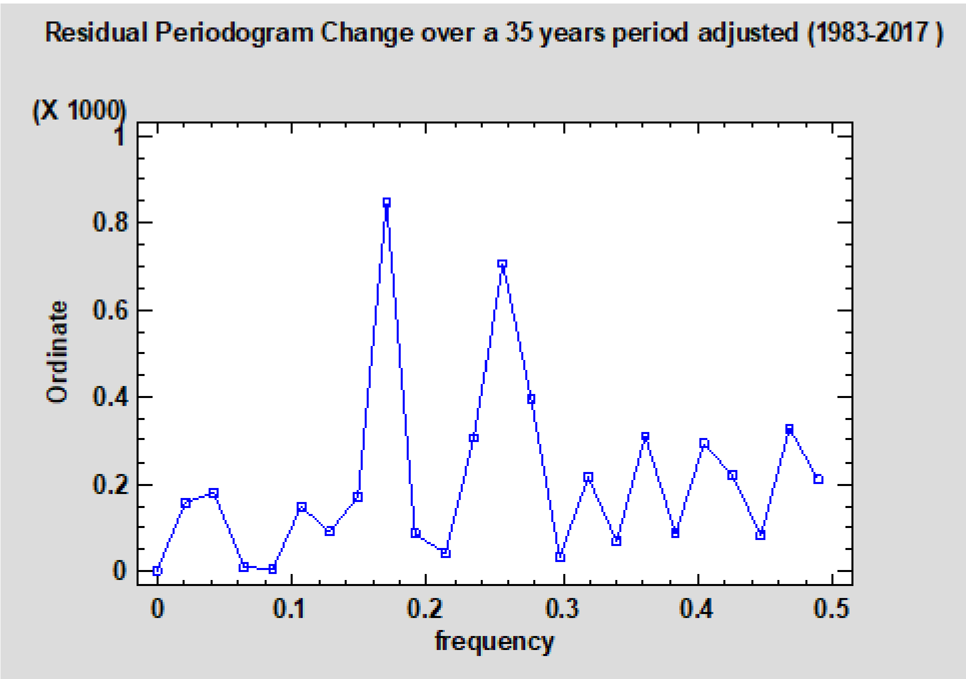

Figure 5
Residual impact in the periodic change in the climatic behavior of the Federal Capital Territory of Nigeria over a 35 years flux of climatic behavior and variability.

Wind velocity potential and impact on the area over a 35 year period

Result outcome of the trend of wind velocity in the Federal Capital Territory of Nigeria as indicated in Figure 6, 7, 8 and in Figure 9 has indicated that the direction of flux ranges from North East (NE) from the decadal sequence of 1983-1992 with an average direction of 16.70° NE with an average of 25.20 from 1993-2002, North (N) at an average of 16.70° from 2003-2012 and North direction for 2013-2017 with an average flux directional flux at 11.50°. The analytical output presented in Table 3 indicated that for the decade of 1983-1992 22.1 m/s was recorded in the wind speed sequence at the month of December while the least speed of wind was recorded in January with a figure of 3.5 m/s. The directional flux indicated a figure

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of 22.1° which presents the month of March of the decade 1983-1992 with the highest wind directional impact. The month of June with 22.6m/s of the impact in the wind speed flux, while the least wind speed was observed at 16.7m/s for the month of February and December respectively for the decadal impact of the range 1993-2002. The wind direction was observed at a potential highest flux of 29.1° for the month of December and the least flux of wind directional potential at 14.6° for the month of November at decadal flux wind directional impact for a decade 2003-2012. Wind speed highest impact of the decade 1993-2002 at 22.8m/ was recorded in February, while the least impact was recorded in the month of July at a value of 13.6m/s. Wind directional impact flux at a potential with value of 21.3° was recorded as the highest in the month of December and March respectively at a decadal range of 2003-2012, however, the least decadal impact was recorded at 14.5° in the month of July for the wind directional impact in the area..

A five (5) years impact on the wind speed potential in the area revealed 21.5m/s in the month of April which was the highest wind speed recorded, while 10.9m/s was the least value obtained for wind speed in the area. The highest directional flux of the area for 5 years period of 2013-2017 was obtained at 22.0° for the month of September and January respectively, while the least wind directional value was obtained at 15.8° in the month of December of the year range at 2013-2017. Outcome of the recorded behavior of wind speed and wind direction in the area is inline with the output of the projected findings of Quill et. al. (2019) who recorded climatic shift with wind impact while modeling wind direction distributions. This research findings confirms the work of Andrews (2012) where the Scholar reported wind variability in speed and directional flux. The outcome of this research also aligns with the work of Belcher et. al. (2012) who recorded variability in the frequency impact.

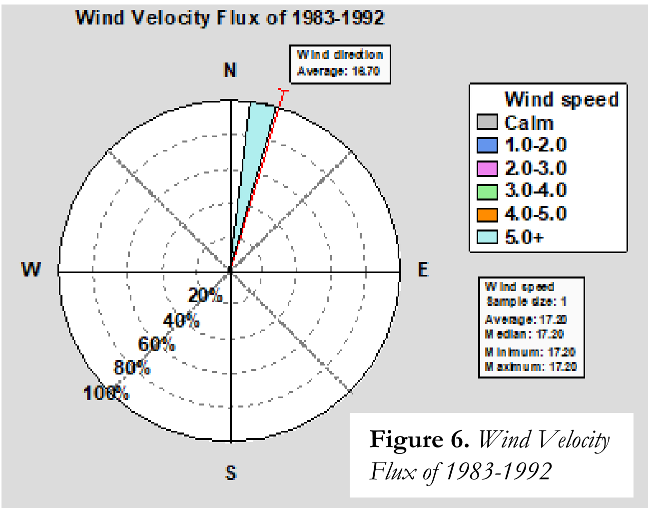

Figure 6. *Wind Velocity Flux of 1983-1992*

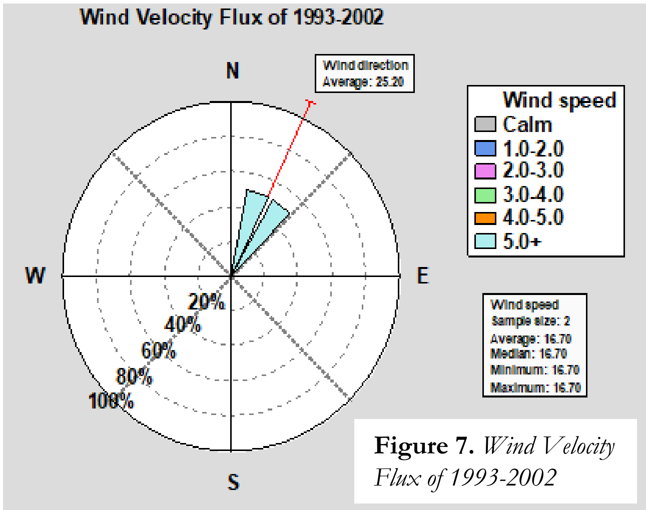

Figure 7. *Wind Velocity Flux of 1993-2002*

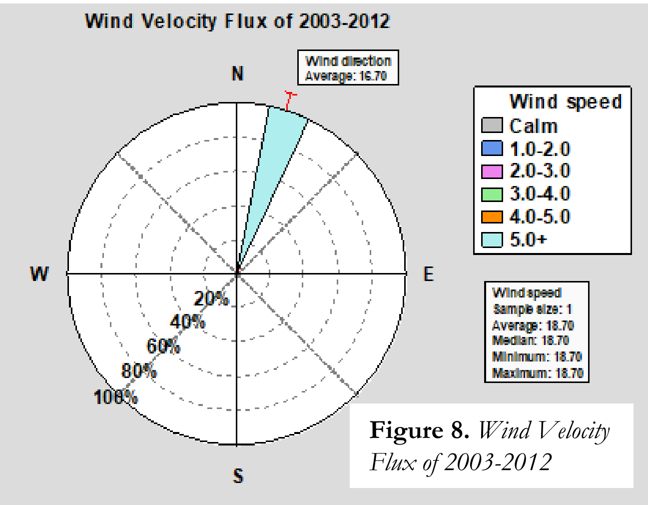

Figure 8. *Wind Velocity Flux of 2003-2012*

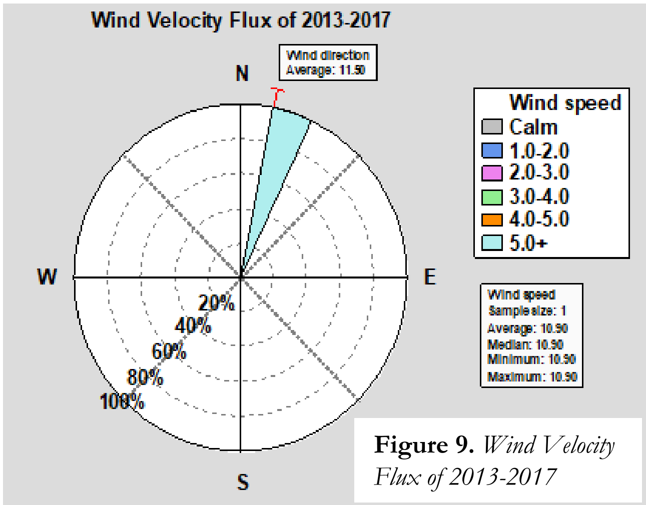

Figure 9. *Wind Velocity Flux of 2013-2017*

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Assessing the implication of the behavior of the wind speed to sea and land sustainability

Result of the output for wind velocity in the area over a 35 years period as presented in Table 11 indicated that 79.56km/h of wind flux hit the area in the decadal month of December at 1983-1992, this wind velocity flux could be said to have had a strong gale impact with tendency of causing a high wave that could have toppled the sea balance while causing crests of wave in sea with human-animal visibility impediment. The 79.56 km/h flux could have also accounted for land surface-space variability due to lifting and deposition of materials and gases, this view is inline with the expression in wind velocity potential ranking prescribed as presented by the Government of Canada as presented in Table 2b. However, the month of January in the decade of 1983-1992 witnessed 12.6 km/h of wind velocity which indicated that the month in the ten years interval contributed heavily to the gentle breeze profile of the area while producing large wavelets in the sea and small twigs in the land surface of the area.

The trend of wind velocity observed for the decade of 1993-2002 indicated that the decadal month of June produced 81.36 km/h volume of wind velocity which also contributed to variability in sea-climate abnormality through toppling and tumbling with slight structural and in environmental imbalance , however, the decadal months of April, June, July, August, September and Octeber produced wind velocity flux at 75.6 km/h, 78.12 km/h, 75.24 km/h, 79.56 km/h and 72.72 km/h respectively indicating a view that these decadal months had high significance in the climatic shift in the area. The decadal month of March in year range of 2003-2012 produced 82.08 km/h of wind velocity impact indicating a view that the decadal month had impacted on the climate of the Federal Capital Territory. f Nigeria through high wave flux, sea tumbling and topping including causing land degradation through slight structural damage in land surfaces and in human-animal settlement However, it could be stated that the decadal month of February (79.92 km/h), May (71.64 km/h), June(79.32 km/h), August (72.72 km/h and October (79.56 km/h) also falls in the range of being destructive, thereby had impacted heavily in the climatic shift of the area. The five (5) years trend in the wind velocity impact in the area indicated that the decadal month of April had a high impact in the wind velocity of the area, where 77.4 km/h of wind velocity had contributed to the climatic shift of the area in terms of sea-atmosphere de-

Decadal Period of 1983-2017		Wind Speed (Wind Velocity) m/s	km/h
Decade 1 (1983-1992)	Jan	3.5	12.6
	Feb	18.5	66.6
	Mar	20.1	72.36
	Apr	17.2	61.92
	May	15.4	55.44
	Jun	14.7	52.92
	Jul	13.4	48.24
	Aug	15.6	56.16
	Sep	13.6	48.96
	Oct	20.2	72.72
	Nov	14.8	53.28
	Dec	22.1	79.56
Decade 2 (1993-2002)	Jan	17.4	62.64
	Feb	16.7	60.12
	Mar	16.9	60.84
	Apr	21	75.6
	May	17.8	64.08
	Jun	22.6	81.36
	Jul	21.7	78.12
	Aug	20.9	75.24
	Sep	22.1	79.56
	Oct	20.2	72.72
	Nov	18.7	67.32
	Dec	16.7	60.12
Decade 3 (2003-2012)	Jan	18.6	66.96
	Feb	22.2	79.92
	Mar	22.8	82.08
	Apr	18.7	67.32
	May	19.9	71.64
	Jun	21.2	76.32
	Jul	13.6	48.96
	Aug	20.2	72.72
	Sep	14.8	53.28
	Oct	22.1	79.56
	Nov	17.4	62.64
	Dec	16.7	60.12
5 years trend (2013-2017)	Jan	16.9	60.84
	Feb	21	75.6
	Mar	17.8	64.08
	Apr	21.5	77.4
	May	11.8	42.48
	Jun	10.9	39.24
	Jul	17.4	62.64
	Aug	16.7	60.12
	Sep	16.9	60.84
	Oct	21	75.6
	Nov	17.8	64.08
	Dec	19.1	68.76
Total		858.80	3091.68
Mean		17.89	64.41
STD		3.60	12.98
SE		0.52	1.87
CV (%)		20.15	20.15

Table 11. *Decadal wind velocity flux*

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stabilization impact and land degradation potential. However, the decadal month of October (75.6 km/h), February (75.6 km/h) also falls into the decadal months that impacted greatly on the climatic departure from normality in the area. A coefficient of Variation (CV%) at CV=20.15% obtained for a 35 years period in the area indicated a moderate contribution towards the departure from normal in the climatic behaviour of the area. The output of this findings confirms the research report of IPCC (1995) which express change in the fluctuation and variability in meteorological and climatic elements as contributor to the global changing climate. Outcome of this findings is also inline with the views presented by Andrews (2012); Abimbola and Falaiye (2016); Abimbola et. al. (2017) where they expressed wind fluctuation and variability being a factor in modulating space-land atmospheric potential. Research outcome of Belcher et. al (2012) also align with the outcome of this findings, where the Scientists reported wind flux variability with terrain impact. The findings of this research further confirm the work of Forthofer (2007) which expressed variability in wind behavior.

Estimating the rainfall impact with Fournier Index

The result outcome of the Rainfall Erosivity Impact presented in Table 12 indicated that the rainfall impact for soil and environmental degradation in the area is very low. The Coefficient of Variability (%) of the erosion potential of the area fall at 0.016 for a 35 years period, which indicated the area as being low at a CV class of < 15 which indicated that the rainfall in the area is capable of having low impact on the erosivity status of the area, hence contributing less to possible environmental degradation potential of the area. Outcome presented in this findings confirms the work of Mohtar et. al. (2015) which presents views that fluctuations in climatic variable like rainfall not necessarily being an hazard to environmental sustainability. Views presented in this study further confirms the view raised by Fournier (1960) which points to many factors leading to the erosivity potential or impact in the soil system.

Decadal Range	Fournier Index
1983-1992	0.083330
1993-2002	0.083325
2003-2012	0.083335
5 years trend (2013-2017)	0.083360
Mean	0.083
CV (%)	0.016

Table 12 *Estimated rainfall erosivity impact with Fournier Index*

Conclusions

Projected data presents a P-value range at [P-value = 0.654638, P-value = 0.859967 and P-value = 0.859967] of the P-statistics at a 95% significant level, hence, validating a past and future change in the climatic behaviour of the area. This then indicate a view that there exist a shift in the climatic behaviour of the Federal Capital Territory of Nigeria over a 35 years period. The forecast of the area into a 12 years outlook has revealed that the climate of the area will continue to change with variability in climatic and meteorological elements of rainfall fluctuation, wind fluctuations and climate-environmental impact nexus posed by these elements. The wind velocity of the Federal Capital Territory of Nigeria has over a 35 years period fluctuate at a range of 81.36km/h-12.6km/h which indicated a high sea-land-atmospheric nexus impact toward the variability that exist in the climatic condition of the area. Wind directional flux of the area ranges from 22-4.8 which also contributed to the change in the climatic change in the area.The erosivity flux of the area over a 53 years period has indicated that the rainfall in the area contributes to minimal land disturbance at a Coefficient of Variation of CV=0.16%.

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Declaration of Competing Interest. The authors declare that they have no competing interest

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