Health-related Climate Indicator across Four States in Nigeria: Respiratory Rate Prediction and Multivariate Analysis Approach

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Abstract

Respiratory rate prediction(RRP) is vital for human or animal medical check-ups for a good health and well-being (SDG 3) to be established. The RRP is one of the biometeorological indices adopted to determine health-related climate indication, which is categorised into normal: $\leq$85, warning: between 85 and 110, danger: between 110 and 133, and emergency: $\geq$133. The study obtained 32-year (1987-2018) data of temperature, relative humidity, wind speed and solar radiation from the archive of Nigeria Meteorological Agency, Abuja. The data were adopted to compute the RRP across four rain-fed States (Benue, Edo, Niger (Bida and Minna) and Ondo) in Nigeria and further subjected to multi variate analysis. The reliability test showed that the data had acceptable internal consistency with Cronbach's value of 0.773, and the monthly RRP significantly ($p<0.05$) varied across the study locations and their environs over 32years.ThePrincipal Component Analysis (PCA) categorised the rainy periods (April to October) under component 1 with a 49 % variance while the dry periods (January, February, November and December) except March under component 2 with a 17 % variance. Benue, Edo, Niger (Bida) and their environs had more prevalence of warning category of RRP (between 85 and 110) than Ondo, Niger (Minna) and their environs. The study deduced that the health-related climate indication prevailed more in the wet than the dry periods, necessitating inhabitants of the study locations to understand their thermal regime for climate change coping capacities.

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Introduction

Humans and animals in the environment pathologically suffer from climate change effects (CCE), and assessment of the effect can be predictable from the respiratory rate or frequency. The essence of respiratory frequency monitoring is acknowledged as one of the vitals conducted in every medical check on humans or animals. It is a premiere vital sign to assess pathological conditions and stressors not limited to cognitive load, cold, emotional stress, exercise-induced fatigue, heat and physical effort. It is a measurable way to assess occupational and healthcare settings to advance its application to foster interdisciplinary interactions[1].Its assessment avails the scientists of information on cardiac arrest prediction, severe pneumonia diagnosis and clinical deterioration[2]. It is necessary to know the extent to which ventilation regulates non-metabolic stressors[3] and is a physiological parameter whose deviation indicates deteriorated health defect, thereby calling for the development of different and efficient techniques for easy, accurate and reliablemonitoring[4].

Data gathering for respiratory rate prediction has been successful through sensor techniques and new measurements[4,5].Motinet al.[6] subjected the results of the respiratory and heart frequencies obtained from the photoplethysmographic signal to statistical interpretation using principal component analysis. Statistical interpretation of data (not sparing those of the climatic) informs the trio (scientists, decision-makers and concerned stakeholders) about the CCE on human's health. Climate change as a subject is affecting the human environment and all in it. The great efforts of the trio mentioned above have highlighted various indications through which humans can understand and observe the CCE. Everyone knows that CCE exists through understanding the qualitative or quantitative results. The qualitative result shows the gravity or extent of what is being experienced, not limited to intense hotness or coldness of the days. The

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quantitative result is by subjecting data to statistical analysis and interpreting their values either by visualisation or modelling, as typified by the work of Safo-Ado[7].

Respiration rate as a valuable physiological parameter has been adopted in the field of agriculture using ambient temperature(T °C),relative humidity (RH %)and solar radiation (SR wm^{-2}) to measure the thermal state of the domesticated animal[8,9].Another research added air wind speed(V, m/s)to evaluate man's respiratory rate[10].Eigenberget al.[11]innovatively adopted four climate (T, RH, V and SR) data, and the obtained respiratory rate predictions were categorised into four: normal (≤85), warning (between 85 and 110), danger (between 110 and 133), and emergency (≥133). Thus, objective of this research was to assess health-related climate indicators through respiratory rate prediction(RRP) across four selected (Benin, Edo, Niger and Ondo) States in Nigeria using 32-yeardata of climatic elements (temperature, relative humidity, winds peed and solar radiation) subjected to multi variate analyses.

Materials and Methods

Design of the Study

The research thought it out to assess health-related climate indication by using an established biometeorological index called respiratory rate prediction(i.e., RRP). The developed RRP formula requires four climate parameters (temperature, relative humidity, windspeed and solar radiation) for its computations. Thus, the research adopted secondary data of 32 years, which were acquired from the archival of the Nigeria Meteorology Agency, Abuja, where the weather stations across the nation are centralised by the government policy that established the agency. The computed RRP has four categories of values namely normal: ≤85, warning: between 85 and 110, danger: between 110 and 133, and emergency: ≥133which are used to indicate and predict different respiratory conditions making the research to be a mixed method/triangulation (qualitative and quantitative) in nature. The outcome would be well related to the Sustainable Development Goal 3: a good health and well-being, thereby assessing possible climate change effects or indications on the small-scale farmers across the chosen four states.

Study areas

Benue, Edo, Niger and Ondo States across Nigeria were selected because of their potential with high tons of crop yields each year. The states practise rain-fed agriculture, which climate change can affect. Benue and Niger states are in the derived savannah zones, while Edo and Ondo states are in the rainforest zones. Consideration of the four States was also thought from the views of UNDP sustainable development goals (SDGs) 2, 3 and 13. SDG 2 aimed to achieve Zero Hunger by promoting sustainable agriculture to improve nutrition with food security. SDG 3 aimed to ascertain good health and well-being of all including the farmers that strive to produce food for every nation. SDG 13 aimed to implement Climate Action to reduce climate change effects on various sectors, not sparing agriculture.

Climate data acquisition

Monthly data of temperature, relative humidity, solar radiation and wind speed for 32years (1987-2018) were obtained from the archive of Nigeria Meteorological Agency, Abuja for Benue, Edo, Niger (Bida and Minna) and Ondo states.

Data Pruning

The TRUC Function of the EXCEL spread sheet was adopted to prune the acquired four climatic data to avoid bias in the data set and ascertain they are in the same decimal places =TRUN (number,[digits])

The value to be pruned is the number; in the EXCEL-referencedcell.The optionally specified decimal places retained after pruning are thedigits. The TRUC function prunes everything after the decimal point in the cell if the argument is blank.

Indication of climate change effects: respiratory rate prediction (RRP)

Eigenberget al.[11] worked on the respiratory rate prediction (RRP) for no-shade conditions considering the combined influence of four meteorological elements: temperature (T), relative humidity (RH), wind speed (V), solar radiation (SR) and the adopted equation is

$$RRP=5.4T+0.58RH-0.63V+0.024SR-110.9 \quad \text{-------} \quad \text{(Equation)}$$

The obtained value was classified into four which are normal (RRP≤85), warning (RRP:between 85 and 110), danger (RRP:between 110 and 133), and emergency (RRP≥133).

Multivariate analyses

The calculated 32-yearRRPwas subjected to multivariate analyses (Reliability test, Pearson's Correlation, Multiple Regression and Principal Component Analysis) using IBM SPSS v23.

Results

In the Benin (Edo State) enviros, the year 2008 and a month (dry-break period: August) were observed to have the normal category of the RRP (≤ 85). The indication of the warning category was peculiar to five months (dry season period: February and March, early

Table 1: Comparison of monthly computed RRP across the five MetS and ANOVA

Reliability Statistics			Hotelling's T-Squared Test				
Cronbach's Alpha	Cronbach's Alpha Based on Standardised Items	N of Items	Hotelling's T-Squared	F	df1	df2	Sig
0.773	0.895	12	1366.056	116.376	11	149	**0.000**

	Descriptive Statistics (N = 32, 1987-2018)					ANOVA	
	Benin	Ondo	Bida	Minna	Markudi	F	Sig.
JAN	79.79±9.25	73.35±8.18	70.31±44.50	54.68±6.69	57.41±7.73	8.222	0.000
FEB	89.34±8.73	82.29±6.68	73.54±10.48	67.73±9.13	72.45±8.39	30.886	0.000
MAR	91.57±6.91	86.04±5.51	89.19±7.48	80.53±8.95	85.92±7.88	10.375	0.000
APR	89.57±6.98	84.53±4.05	90.91±6.36	87.41±6.89	87.00±6.42	4.996	0.001
MAY	87.40±5.23	82.02±3.26	85.29±5.84	82.56±5.52	82.51±4.92	6.763	0.000
JUN	83.37±3.77	78.43±2.89	81.31±3.83	76.63±3.69	78.21±2.93	19.644	0.000
JUL	78.94±3.11	74.76±2.77	79.09±4.38	74.75±4.12	75.90±3.11	12.017	0.000
AUG	77.10±2.63	72.25±2.75	77.96±3.53	73.52±2.87	75.93±2.78	21.589	0.000
SEPT	80.55±2.71	76.03±2.38	79.22±4.10	74.27±2.61	76.60±3.08	22.169	0.000
OCT	83.28±3.35	78.93±2.99	80.89±5.27	75.81±4.93	78.26±3.92	14.501	0.000
NOV	86.36±4.64	82.18±4.55	71.45±5.02	63.83±5.80	73.67±6.59	88.213	0.000
DEC	82.08±6.72	78.39±4.95	58.41±8.40	55.81±8.83	59.33±7.15	91.244	0.000

MetS: meteorological station, ANOVA: multivariate analysis of variance, RRP: respiratory rate prediction, normal (RRP=85), warning (RRP: between 85 and 110), danger (RRP: between 110 and 133), and emergency (RRP=133).

Table 2: Pearson's correlations of RRP (n=32, 1987-2018) across five MetS

Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
1											
348**	1										
208**	0.587**	1									
0.100	0.334**	0.581**	1								
0.026	0.364**	0.575**	0.783**	1							
0.151	0.555**	0.574**	0.668**	0.755**	1						
0.071	0.374**	0.543**	0.630**	0.668**	0.759**	1					
0.007	0.203*	0.360**	0.510**	0.531**	0.639**	0.739**	1				
).157*	0.366**	0.373**	0.380**	0.474**	0.632**	0.626**	0.755**	1			
0.092	0.421**	0.377**	0.444**	0.542**	0.618**	0.566**	0.631**	0.792**	1		
294**	0.567**	0.303**	0.074	0.253**	0.433**	0.259**	0.197*	0.452**	0.575**	1	
331**	0.550**	0.205**	-0.009	0.198*	0.335**	0.208**	0.038	0.301**	0.412**	0.778**	1

Correlation indicates significant at both 0.05 and 0.01 level (2-tailed), respectively.

MetS: meteorological station, RRP: respiratory rate prediction

wet season: April and May, and late dry season: November) (s-1). The Ondo(Ondo State) environs hadfive years (1994, 2008, 2016 to 2018) and 4 months (wet season periods: June-October) with normal category (RRP≤85). The highest indication of warning category (RRP is between 85 and 110) was observed in the dry seasons (early period: February and March, and late period: November) (s-2).The late dry season (November and December) of the year in Bida (Niger State) environs was observed with an indication of the normal category (RRP ≤ 85), while the early wet season (April and May) had the highest indication of warning category (RRP is between 85 and 110).There was no indication of an entire year with normal category (RRP ≤85)over the past 32-year period in the Bida(Niger State) environs, while January of 2013 and 2014 indicated emergency category (RRP≥133)(s-3).Normal category (RRP≤ 85) condition was indicated over 8 years (1989, 1990, 2004, 2010-2013, and 2018) and 7 months (except March to May, October and December) across the wet and dry seasons

Table 3: Multiple regression analysis of RRP across the 12-Month (N=32, 1987-2018)

Model Summary[b]						MANOVA	
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson	F	Sig.
1	0.808[a]	**0.653**	0.625	0.869	**0.687**	23.073	**0.000**[b]

a. Predictions: (Constant), Dec, Apr, Jan, Sept, Mar, Feb, Jul, Nov, May, Oct, Aug, Jun
b. Dependent Variable: MetSRRP

Coefficients[a]

Model		Unstandardised Coefficients B	Unstandardised Coefficients Std. Error	Standardised Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	11.556	1.603		7.208	0.000		
	JAN	-0.006	0.003	-0.096	-1.737	0.084	0.767	1.304
	FEB	-0.020	0.009	-0.165	-2.129	**0.035**	0.391	2.561
	MAR	-0.002	0.013	-0.012	-0.159	0.874	0.430	2.328
	APR	0.031	0.020	0.144	1.564	0.120	0.280	3.575
	MAY	-0.026	0.025	-0.098	-1.025	0.307	0.260	3.841
	JUN	-0.078	0.035	-0.229	-2.219	**0.028**	0.221	4.526
	JUL	0.012	0.033	0.035	0.377	0.706	0.276	3.623
	AUG	**0.126**	0.038	**0.320**	3.330	**0.001**	0.256	3.907
	SEPT	-0.112	0.037	-0.297	-2.996	**0.003**	0.240	4.168
	OCT	0.011	0.028	0.038	0.400	0.690	0.264	3.790
	NOV	-0.006	0.014	-0.041	-0.446	0.656	0.282	3.549
	DEC	-0.045	0.009	-0.419	-4.854	**0.000**	0.317	3.151

a. Dependent Variable: MetSRRP

RRP: respiratory rate prediction, MANOVA: multivariate analysis of variance, MetS: meteorological station, VIF: variation inflation factor

in the Minna(Niger State) environs. However, the early wet season was observed to havea warning category (RRP is between 85 and 110) (s-4). Seven (7) years (2005 and 2009 to 2014) and 7 months (except February to May and October) were observed with the normal category (RRP $\leq$85) in Markudi (Benue State) environs (s-5).

From the Table 1, reliability statisticsindicated a Cronbach's value of 0.773 to show internal consistency of the twelve-monthly data over the past 32-yearconsidered for this study. The Hotelling's t-squared statistic (t^2) of the different tests between the (multivariate) means of different populations (the five meteorological stations and their environs (MetS)) under study indicated that distributions of the variables were highly significant (F= 116.376, p<0.001). The ANOVA indicated that the obtained monthly RRP across the study environs was significantly (p< 0.05) different. The comparative monthly average of the RRP (N=32, 1987-2018) with indications of warning categories (RRP between 85 and 110) was observed in the order of Benin (Edo State)with 5 months: February to May and November, Bida (Niger State) with 3 months: March to May, Markudi (Niger State) with 2 months: March and April. The indications were peculiar to both early dry (February and March) and early wet (April and May) periods, when the health-related climate indications could be felt across the MetS.Pearson's correlation analysis showed strong correlations (0.06-0.79) between July and the other wet periods (April to October) and between the two late dry periods (November and December), showing that the health-related climate indicator (through the RRP across the study States) was strong among the wet (April to October) and between late dry (November and December) periods (Table 2).

From Table 3, the multiple regression model had an R-value of 0.808(i.e., a very strong association among the four adopted climatic elements: temperature, relative humidity, wind and solar radiation) with an R-squared of 0.653, implying that the model explained a 65.30 % variance of the four data that computed the RRP. The Durbin-Watson value of 0.687 < 2, which is a positive autocorrelation, implied that there was similarity in the health-related climate indication across the States under study. The MANOVA indicated a general significance (p< 0.05) in the model's fitness. Furthermore, the coefficient of multiple regression showed that RRP had significant impacts (p < 0.05) in five months (February, June, August, September and December)over the past 32years, while the Beta-value (under the Standardised Coefficients) established that the month of August actually had the highest health-related climate indication. Thus, for every unit increase in the computed RRP, the health-related climate indications would have influenced0.126 unit of RRP in August. The normal probability plot of the regression standardised residue showed that data of the four

Table 4: Principal Components Analysis of the 12-Month respiratory rate prediction

Kaiser Meyer Olkin(KMO) and Bartlett's Test			
KMO Measure of Sampling Adequacy.			0.853
Bartlett's Test of Sphericity	Approx. Chi-Square		1418.270
	Df		66
	Sig.		0.000

	Component		
	1	2	3
JAN	-0.008	0.620	-0.129
FEB	0.464	0.697	-0.240
MAR	0.709	0.285	-0.405
APR	0.864	-0.147	-0.239
MAY	0.869	0.027	-0.109
JUN	0.864	0.253	0.047
JUL	0.856	0.050	0.145
AUG	0.763	-0.102	0.474
SEPT	0.667	0.233	0.583
OCT	0.657	0.328	0.519
NOV	0.248	0.816	0.284
DEC	0.124	0.855	0.164
Total	5.867	2.091	1.157
% of Variance	48.894	17.424	9.645
Cumulative %	48.894	66.319	75.964

climate elements(temperature, relative humidity, wind speed and solar radiation) adopted for the RRP computation were well distributed along the diagonal axis to illustrate that the model was valid and established homoscedasticity (s-6).The computed RRP was meritorious (KMO= 0.853) and valuable ($\chi2$= 1418.270, $p< 0.05$) to be subjected to the factor analysis for Principal Component Analysis (PCA). The PCA showed that the rainy periods (March to October) had higher (5.867) eigenvalues than (2.091) dry periods (January, February, November and December), thereby categorising the rainy periods under Component 1 with nearly a 49% variance and the dry periods under Component 2 with nearly a 17% variance. However, the PCA still categorised the late wet periods (September and October) under Component 3 with a moderate health-related climate indicator nearly accounted for a 10% variance(Table 4).

Discussion

The adopted respiratory rate prediction (RRP) in this study had been the biometeorologists' efforts to scientifically present how climate condition impacts health of the inhabitants of a region. The RRP could be importantly viewed for the datasets that compute it come from the atmosphere that modulates what either human or animal inhales and exhales. Its scales (normal: RRP $\leq$85, warning: 85 to 110, danger: 110 to 133, and emergency: $\geq$ 133) qualitatively and quanitatively categorised the levels of health-relatedconditions influenced by the regional climate [11],thereby predicting health and well-being (SDG 3) of human from breathing. Drummond et al.[12]adopted repeated breathing recordings of some acutely ill-health patients for avirtual investigation of RRP. The study of Mudizukhi et al.[13] indicated that critical consideration of RRP is a beneficial effort and prevention against health deterioration of discharged patients from emergency section. Thus, the RRP long-term computationfor each of the four states from the monthly data of 32 years would have made the computed RRP precise and substantiated as a contribution of the biometeorology to the field of health.

The four biometeorological scales in this study could add strength to the clinical scales, which are being adopted in the health sector to predict the breath per minute for a medical check-up vital: 30-60, 24-40, 22-34, 18-30, 12-16 and 12-60 for someone in the age range of birth to a year old, one to three, three to six, six to 12, 12 to 18, and 18 beyond, respectively[14]. Adoption of the quantified RRP in this study is helpful as efforts are still being made to find accurate ways of detecting the respirate rate of ill-health patients, it is on this note that the study of Latten et al.[15] investigatedprecision and comparative agreement of respiratory rate measurements computed by healthcare personnel as well as the likely influence of improper quantifications on the scores of four familiar clinical diagnostic/ prediction rules. Outcome of their study indicated inaccurate with over- and underestimation of the RRP. So, the biometeorological index (i.e., RRP) estimated in this study can be helpful from the influence of climate change.

The order of monthly average of the RRP warning category (RRP: 85 to 110) was 5 months i.e., February to May and November in Benin and its environs; 3 months i.e., March to May in Bida and its environs; and 2 months i.e., March and April in Markudi and its environs. The study deduced therefrom that there had been health-related climate indications beyond the normal condition (RRP $\leq$ 85) over the indicated months every year for the used 32-year data from the combined influences of the four climatic elements (temperature, relative humidity, wind speed, solar radiation)which computed the RRP. So, health of the inhabitants across the study locations were prone to breathing issues for the indicated months while working in the sun and under no shades, especially in the tropical region. The study deduction was because wellness of human (SDG 3)is best clinically and biometeorologically monitored by their breathing using the RRP[3,4]; this upheld the assertion of Zhao et al.[16] which saw to the necessity of developing multifaceted and very precise models to assisting RRP thereby making them to adopt transfer- based (numerous algorithms and machine learning) models with data from both BIDMC and CapnoBase datasets. Nurdanet al.[17] also conducted sequential studies of various algorithms for RRP from clinical data and supplemented data provided from the publicly available data sets. The aforementioned studies[3, 4, 16, 17] proved that RRP is essential in human's health thereby requiring multidiscipline approaches for its quantification and investigation. The assertion could further be reiterated from the views of a group of researchers[18], who recently stated that computation of RRP is necessitated by the cardiovascular disease; a globally major killer whose factor is an abnormal respiration and needing evaluation technique development. Their outcome stands to be evaluation-aided method.

Conclusion

The four study States had been observed to have all the four categories of respiratory rate prediction (RRP). Benin (in Edo State), Bida (in Niger State), Makurdi (in Benue State) and their environs had more prevalence of health-related climate indications than Ondo (in Ondo State), Minna (in Niger State) and their environs.The reliability statistics indicated a Cronbach's value of 0.773 for internal consistency of the 12-month data over the considered 32 years of study. From the compared monthly average of the RRP, order of warning categories (RRP between 85 and 110) was 5 months in Benin, 3 months in Bida (Niger State), and 2 months in Minna (Niger State). Pearson's correlation analysis showed that the health-related climate indicator (through the RRP across the study States) was strong among the wet (April to October) and between late dry (November and December) periods. The health-related climate indication prevailed more in the wet than dry periods through the computed RRP from the Principal Component Analysis.

Conflict of interest: None.

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Supplemetary Materials-1 to s-6are available on the corresponding author's Research Gate (https://www.researchgate.net/profile/At-Towolawi/research) as either Add Suppletary Source or Data immediate after the critical review and acceptance of the manuscript for publication.

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