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ASSESSING RELATIONSHIP BETWEEN SELECTED CLIMATE VARIABLES, HUMAN DISEASES AND CROP PRODUCTION USING ARDL APPROACH – THE EXAMPLE OF ONDO STATE, NIGERIA

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Abstract

This study was designed to investigate the relationship between crop production and selected climatic variables and human diseases in Ondo State, Nigeria. Time series data spanning 32 years (1982 to 2013) were used for this study. The analytical tools employed for this study were descriptive statistics and auto-regressive distributed lag (ARDL) model. The results confirmed the presence of long run equilibrium between crop production and temperature, rainfall, incidence of malaria and incidence of pneumonia. The results of long run estimates showed that rainfall and pneumonia coefficients were significant but negatively affected crop production in the long run, while all the variable except temperature were also significant but negatively affected crop production in the short run. The error correction model (ECM) value of -0.142 which was significant at 5% level showed that about 14% of disequilibria from the previous year's shock converge to the long run equilibrium in the current year. Therefore, disease prevention and environmental sanitation under the framework of the primary health care programme that can reduce human exposure to climate–related health risks should be strengthened by the government.

Key words: *Climate change, crop, diseases, health, production*

INTRODUCTION

Many evidences in the literature [10][6][9][7] reported that climate change will hit developing countries the hardest. Its effect in terms of higher temperatures, changes in rainfall patterns, rising sea levels and frequent occurrence of weather-related disasters which cause great threats to agriculture, food and water supplies. At stake are recent gains in the fight against poverty, hunger and diseases, and the lives and livelihoods of billions of people in developing countries, Nigeria inclusive [11]. It has been reported by WHO that climate change affects social and environmental determinants of health such as clean air, safe drinking water, sufficient food and secure shelter. Extremely high air temperatures contribute directly to deaths from cardiovascular and respiratory diseases in which over 70,000 deaths were recorded in the heat wave of summer 2003 in Europe [29]. It was also documented that pollen and aeroallergen levels as a result of extreme heat has increased asthma, affects about 300 million people while urban air pollution causes about 1.2 million deaths every year. Since the 1960s, weather-related disasters have been accounted for over 60,000 deaths, mainly in developing countries. With the rising sea levels and increasing weather disasters, many homes, farms, properties/assets and other essential services have been distrupted and destroyed most especially in the rural communities even here in Nigeria.

According to [20] and [30], extreme weather events amplifies the spread of pests and diseases, and increased in ailments such as meningitis, measles, chicken pox, malaria, dengue, asthma, cryptospordiosos, giardiasis, typhoid fever and other infections. There is no doubt from the literature that the changes in global climate patterns will affect all people and countries but what will be the fate of developing countries such as Nigeria and the farmers who depend mainly on rain-fed agriculture and as well referred to as most vulnerable in the struggle? Nigeria depends solely on agarian farming/agriculture who can not but practice activities that will provoke the ill consequence of climate change.

Recent evidences revealed that climate change will exacerbate the burden of climate sensitive diseases such as heat-related illnesses, injuries from extreme events, respiratory diseases, vector-borne diseases and other infections [16][21] and [22]. In Nigeria and other Sub-Saharan countries, the incidences of climate sensitive diseases have been on the increase [30]. According to [13], over 200 people were killed by meningitis within one week in the early 2009 in Nigeria and Niger Republic. There were outbreaks in 76 areas, 25,000 suspected cases and 1,500 deaths in the first quarter of 2009.

According to [31], about 3.3 billion people – half of the world's population – are at risk of malaria. In 2010, there were about 219 million malaria cases (with an uncertainty range of 154 million to 289 million) and an estimated 660,000 malaria deaths (with an uncertainty range of 490,000 to 836,000). Malaria is said to be responsible for about 66 per cent of all clinic visits in the country [14] and 30 percent of hospital admissions. It also accounts for 25 per cent of deaths in children under one year old; and 11 per cent of maternal deaths —a heavy burden on Nigeria's families, communities, health system, and workforce including farmers. Respiratory diseases are a major cause of mortality and morbidity worldwide especially in most developing countries including Nigeria [2][19]. Amongst these respiratory diseases, pneumonia is the leading cause of death worldwide. It was reported that it causes death of an estimated two million children every year, even more than AIDS, malaria, and measles combined [28]. Approximately 150 million new cases of pneumonia occur annually among children younger than 5years worldwide accounting for approximately 10 to 20 million hospitalizations [12] and [14].

Therefore, the researchers deem the study important by expanding the frontier of knowledge about the effect of climate change and variability on the productivity of crop farmers by the inclusion of disease factors. It will profer likely ways to abate the negative impacts of climate change to crop production and farmers' health. The study examines the relationship that exists among selected climatic variables, human diseases and crop output spanning from 1982 to 2013.

MATERIALS AND METHODS

The Study Area

This study was carried out in Ondo State, Nigeria. The State is located in the Southwestern part of Nigeria. It has 18 Local Government Areas (LGAs) as shown in Figure 1, with a population of about 3,440,000 of which the rural population constitutes about 1.7 million and land area of 14,606 km^2 [15]. The State is situated between longitudes $4^0\ 15^1$ E and $6^0\ 00^1$E of the Greenwich meridian and latitudes $5^0\ 45^1$N and $7^0\ 45^1$ N. It has a tropical wet-and-dry climate with average annual rainfall of about 1500mm and 2000mm in the derived savannah and humid forest zones respectively [18] with a high daily temperature of about 30^0C. The climate of the area is highly favoured for the agrarian activities of her teeming population. About 75% of the population is engaged in farming who grow both cash and food crops. The main cash crops are cocoa, oil palm, rubber, cashew and kola nut, while the food crops are maize, cassava, yam, plantain and vegetables

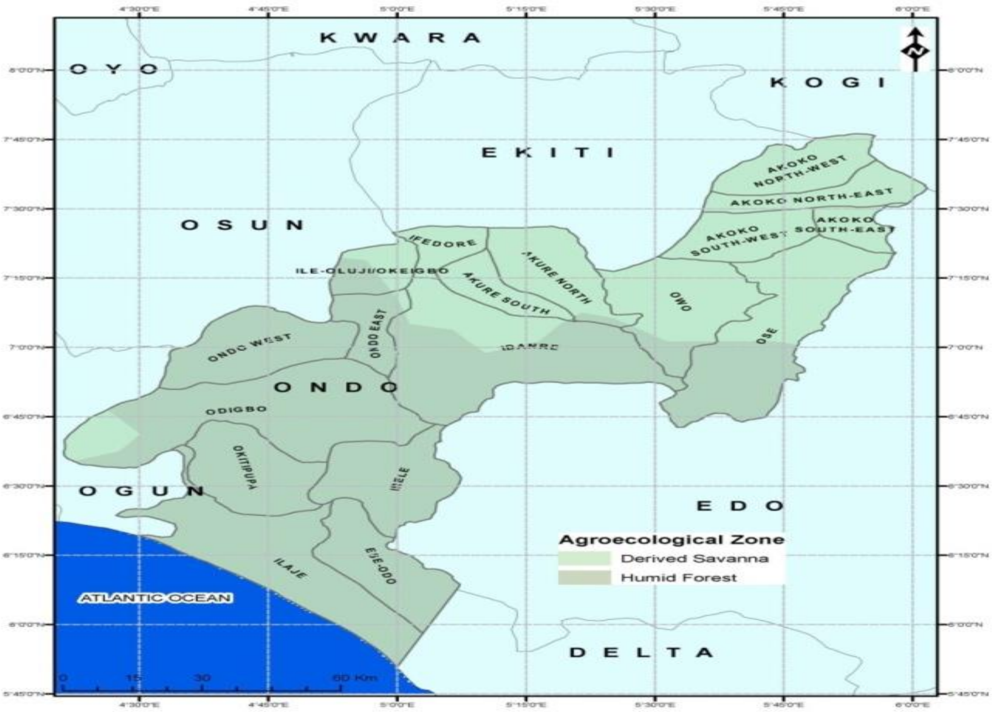

Figure 1. Agro-ecological Zones in Ondo State
Source: Adopted from [18].

Data sources and Description

Secondary data were collected on climate variables (temperature and rainfall), selected climate sensitive diseases (malaria and pneumonia) and crop production spanning the time period 1982 to 2013. The climatic variable data were sourced from the National Bureau of Statistics (NBS) and Agro-Climatological and Ecological Department, Ondo State Ministry of Agriculture. Also, data on crop output/production were sourced from the National Bureau of Statistics (NBS) and Ondo State Agricultural Development Programme (ADP). Data on climate sensitive diseases (malaria and pneumonia) were sourced from the National Bureau of Statistics (NBS) and Ondo State Ministry of Health.

Data Analysis and Model Specification

This study employed the autoregressive distributed lag (ARDL) bounds testing approach to cointegration proposed by [26]. Despite the fact that this technique can avoid unit root test, it is also germane to perform stationarity test to make sure that the assumption of ARDL (i.e. regressors are integrated of *I(1)*, *I(0)* or mutually) is not violated. This is because the model will crash in the presence of *I(2)* series. Therefore, the stationarity status of all the variables was determined by Augmented Dickey Fuller (ADF) test. The model is as follows:

Constant term: $\Delta P_{it} = \alpha_1 + \varphi P_{it-1} + \sum_{i=1}^{n} \theta_i \Delta P_{it-1} + \varepsilon_{it}$ …………………(1)

Constant term and Trend: $\Delta P_{it} = \alpha_1 + \alpha_{2t} + \varphi P_{it-1} + \sum_{i=1}^{n} \theta_i \Delta P_{it-1} + \varepsilon_{it}$ .... (2)

where Δ is the first difference operator; P_{it} is variables being investigated for stationarity; α, φ, θ are parameters to be estimated; n is number of lag of the variables to be included; ε_{it} is the error term.

The null hypothesis of the ADF unit root test is $H_0: \delta = 0$ which implies that the series is not stationary and the alternative hypothesis is $H_a: \delta < 0$ which indicates that the series is stationary. If the absolute value of calculated ADF statistic is higher than the absolute value of the critical values, we reject the null hypothesis which indicates that the series is stationary. However, if this value is lower than the critical values, we cannot reject the null hypothesis which indicates that the time series is not stationary [8].

Furthermore, unrestricted vector autoregression (VAR) by lag selection criteria was used to determine the optimal lag for the model. Akaike Information Criterion (AIC), Schwarz's Bayesian Information Criterion (SBIC) and Hannan-Quinn Information Criterion (HQIC) were used for the VAR models. The model with the lowest value of estimated standard errors was chosen for the study. Their formula is stated as:

$AIC = \ln(\epsilon^2) + {2K}/{T}$ .... (3)

$SBIC = \ln(\epsilon^2) + {K}/{T}\, lnT$ .... (4)

$HQIC = \ln(\epsilon^2) + {2K}/{T}\, lnT$ .... (5)

Where ln is the natural log; ϵ^2 is the variance of the estimated residuals; K is the sample size; T is the number of parameters.

Finally, the study employed the autoregressive distributed lag (ARDL) model (bounds testing procedure) to examine the cointegration (long run) relationship between crop production and its determinants (Temperature, Rainfall, Malaria and pneumonia) as well as the short run dynamics. The bound test is basically computed based on an estimated error correction version of autoregressive distributed lag (ARDL) model, by Ordinary Least Square (OLS) estimator [26].

An F-test of the joint significance of the coefficients of the lagged levels of the variables was used to test the hypothesis of no cointegration among the variables against the presence of cointegration among the variables. The null hypothesis of no cointegration (no long-run relationship) among crop production, temperature, rainfall, malaria and pneumonia were given as:

$H_0: \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$

The alternate hypothesis (there is long-run relationship or cointegration exists) was given as:

$H_1: \beta_1 \neq \beta_2 \neq \beta_3 \neq \beta_4 \neq \beta_5 \neq 0$

The F-test has a nonstandard distribution irrespective of whether the variables are *1(0)* or *1(1)*. [26] put forward two sets of adjusted critical values that provides the lower and upper bounds used for inference. One set assumes that all variables are *1(0)* and the other assumes that they are all *1(1)*. If the computed F-statistics falls above the upper bound critical value, then the null of no cointegration is rejected. If it falls below the lower bound, then the null hypothesis is accepted. Finally, if it falls between the lower and upper bound, then the result would be inconclusive. The optimal lag length for the specified ARDL model was determined based on the SBIC.

Model Specification:

The relationship among crop production (*CP*), temperature (*TP*), rainfall (*RF*), malaria (*ML*) and pneumonia (*PN*) is expressed implicitly as:

$lnCP = f(lnTP,\ lnRF,\ ln\,ML,\ lnPN) \ldots..(6)$

The variables were transformed and measured in their natural logarithm (*ln*) for easy interpretation of coefficients in standardized form of percentage as equally observed by [3].

Following [26], the ARDL model specification of equation (6) was expressed as Unrestricted Error Correction Model (UECM) to test for cointegration between the variables under study:

$$\Delta lnCP = \beta_0 + \sum_{i=1}^{q} \beta_1\, \Delta lnCP_{t-i} + \sum_{i=0}^{q} \beta_2\, \Delta lnTP_{t-i} + \sum_{i=0}^{q} \beta_3\, \Delta lnRF_{t-i} + \sum_{i=0}^{q} \beta_4\, \Delta lnML_{t=i} + \sum_{i=0}^{q} \beta_5\, \Delta lnPN_{t=i} + \omega_1 lnCP_{t-1} + \omega_2 lnTP_{t-1} + \omega_3 lnRF_{t-1} + \omega_4 lnML_{t-1} + \omega_5 lnPN_{t-1} + e_t \ldots\ldots\ldots\ldots(7)$$

Once cointegration was established, the long run relationship was estimated using the conditional ARDL model specified as: $lnCP_t = \beta_0 + \omega_1 lnCP_{t-1} + \omega_2 lnTP_{t-1} + \omega_3 lnRF_{t-1} + \omega_4 lnML_{t-1} + \omega_5 lnPN_{t-1} + e_t \ldots\ldots\ldots (8)$

The short run dynamic relationship was estimated using an error correction model specified as:

$$\Delta lnCP_t = \beta_0 + \sum_{i=1}^{q} \beta_1\, \Delta lnCP_{t-i} + \sum_{i=0}^{q} \beta_2\, \Delta lnTP_{t-i} + \sum_{i=0}^{q} \beta_3\, \Delta lnRF_{t-i} + \sum_{i=0}^{q} \beta_4\, \Delta lnML_{t-i} + \sum_{i=0}^{q} \beta_5\, \Delta lnPN_{t-i} + \delta ecm_{t-1} + e_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (9)$$

Where:

CP = Crop production in metric tons ('000MT)

TP = Average Temperature in degree celcius (^{0}C)

RF = Rainfall in millimeter (mm)

ML = Malaria count/incidence (number)

PN = Pneumonia count/incidence (number)

ln = natural log

β_0 = Constant term

e_t = White noise

$\beta_1 - \beta_5$ = Short run elasticities (coefficients of the first-differenced explanatory variables)

$\omega_1 - \omega_5$ = long run elasticites (coefficients of the explanatory variables)
ecm_{t-1} = Error correction term lagged for one period
δ = Speed of adjustment
Δ = First difference operator
ln = Natural logarithm
q = Lag length

ARDL Diagnostic Tests: All the estimated ARDL model coefficients were subjected to diagnostic tests for their reliability under both the Langrange Multiplier (LM) version and F-version tests. Although both versions of the test have the same asymptotic distribution, the F version is preferred to the LM version in small samples on the basis of Monte Carlo simulations [25][3]. Following [3], the F version was employed in this study.

RESULTS AND DICUSSIONS

Summary Statistics of Variables Used in ARDL Model

Table 1 shows the summary statistics of crop output, incidence of malaria, amount of rainfall, pneumonia and average temperature from 1982 to 2013. All the variables were positively skewed expect temperature while the Jarque-Bera coefficients were significant under crop output, malaria count and temperature with 1%, 5% and 1% level respectively.

Table 1. Summary Statistics of ARDL Approach Variables

Statistic	Crop Output	Malaria count	Rainfall	Pneumonia	Temperature
Mean	359019.0	54565.33	119.9994	699.6406	25.82891
Median	236209.0	39664.21	117.7250	604.5000	26.09250
Maximum	896000.0	184253.0	151.7000	2015.000	26.90000
Minimum	205000.0	4724.000	90.10000	23.00000	21.51500
Std. Dev.	237286.5	45966.48	15.56421	623.7619	0.964390
Skewness	1.535793	1.215173	0.178692	0.544284	-3.031596
Kurtosis	3.542365	3.556185	2.804150	2.125019	13.82398
Jarque-Bera	12.97173	8.287894	0.221441	2.600761	205.2277
Probability	0.001525	0.015860	0.895189	0.272428	0.000000
Sum	11488609	1746091.	3839.980	22388.50	826.5250
Sum Sq. Dev.	1.75E+12	6.55E+10	7509.588	12061446	28.83149
Observations	32	32	32	32	32

Source: Computed from Field Survey Data, 2014.

Unit Root Tests Analysis

Despite the fact that ARDL cointegration technique does not require pre-testing of variables included in the empirical model for the order of integration [17], it has also been reported that macroeconomic time series may not exhibit stationarity over time [32]. Therefore, the implementation of unit root tests might still be necessary in order to ensure that the assumption of [26] is not infringed. [27] opined that in the presence of *I(2)* variables, the computed F-statistic provided by [26] is rendered invalid and as well caused spurious regression because the bounds test are based on the assumption that the variables are *I(0)* or *I(1)* or mutually cointegrated. A unit root test result would therefore provide important information to justify the choice of the ARDL framework for cointegration analysis as the appropriate technique of estimation. The standard Augmented Dickey-Fuller (ADF) unit root test was exercised to check the order of integration of these variables. The results obtained are reported in Table 2. Based on the ADF test statistic, it was observed that out of five (5) variables, three (3) (i.e., average temperature, malaria and pneumonia) were stationary at first difference, *I(1)*, while crop production and rainfall were stationary at level, *I(0)*. Expectedly, the mixture of both *I(0)* and *I(1)* variables would not be possible under the Johansen procedure. This gives a good justification for using ARDL model.

Therefore, since all the criteria were met, this analysis seems appropriate.

Table 2. Results of Unit Root (ADF) Test

Variables	Level [I(0)]		First Differences [I(1)]	
	Constant	**Constant and Trend**	**Constant**	**Constant and Trend**
LCP	-5.089109 (7)***	-4.377027 (7)**	-4.989620 (3)***	-5.062626 (0)***
LTP	-1.29903341 (3)	-2.340643 (0)	11.57289 (1)***	-6.733288 (1)***
LRF	-5.639295 (0)***	-5.627956 (0)***	-7.743035 (0)***	-10.52832 (0)***
LML	-2.429182 (1)	-2.386139 (1)	-13.47781 (0)***	-13.24107 (0)***
LPN	-0.690383 (2)	-1.005221 (2)	-10.63103 (0)***	-5.492622 (1)***

Notes:
1.***, **, * imply significance at the 1%, 5%, 10% level respectively.
2.The figures in parentheses for the ADF (Dickey-Fuller, 1979) statistic represents the lag length of the dependent variable used to obtain white noise residuals.
3.The lag length for the ADF was selected using Automatic-based on SIC, max lag = 7
4.LCP = log Crop production output; LTP = log Temperature; LRF = log Rainfall; LML = log Malaria; LPN = log Pneumonia
5.The null hypothesis is that the series is non-stationary, or contains a unit root, this was rejected based on MacKinnon (1996) critical values. The lag length was selected based on SIC criteria ranged from lag zero to lag seven
Source: Computed from Field Survey Data, 2014.

Lag Order Selection Criteria Analysis

Unrestricted Vector Autoregression (VAR) by lag selection criteria was modelled to the time series data in order to determine the optimal number of lags for the model. This was necessary to ascertain how many lags to be used in the equation.

The result in Table 3 revealed that the optimal lag length was one (1) as estimated by all the criteria i.e.

Table 3. VAR Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-15.15196	NA	0.225086	1.343464	1.576997	1.418173
1	20.01578	56.26839*	0.023126*	-0.934385*	-0.654146*	-0.844734*
2	20.63446	0.948645	0.023800	-0.908964	-0.582018	-0.804371

* indicates lag order selected by the criterion; LR: sequential modified Likelihood Ratio test statistic (each test at 5%level); FPE: Final prediction error; AIC: Akaike information criterion; SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Akaike Information Criterion (AIC), Schwarz's Bayesian Information Criterion (SBIC) and Hannan-Quinn Information Criterion (HQIC).

The model with the lowest value of estimated standard errors was chosen for the study, and the lowest value for each estimator falls under lag one (1).

Based on the result, SBIC criterion was chosen for the determination of optimum lag length of ARDL model. ARDL (1,0,0,1,0) model was selected as a common consequence of the SBIC criterion.

Cointegration Test Based on ARDL Bounds Testing Approach

In the first step of the ARDL analysis, the presence of long-run relationships was tested in equation (6), using equation (7). Using a general-to-specific modelling approach guided by the short data span and SIC respectively to select a maximum lag order of 1 for the conditional ARDL-VECM. An OLS regression was estimated from equation (7) and then tested for the joint significance of the parameters of the lagged level variables when added to the regression analysis. Moreover, [25] reported that an OLS regression results in equation (7) are of "no direct interest" to the bounds testing approach to cointegration test. The F-statistic tests the joint null hypothesis that the coefficients of the lagged level variables are zero (i.e. no long-run relationship exists between the variables in question). The F-statistic is estimated using Wald Test of coefficients in the ARDL-OLS regressions. Table 4 showed that the value of calculated F-statistic for F_{LCP}(LCP | LTP, LRF, LML, LPN) to be 4.38 which is higher than the upper bound critical value of 4.01 at the 5% level. Thus, the null hypothesis of no cointegration was rejected. This indicates that there is a long-run cointegration relationship among the variables when crop production is regressed against explanatory variables of average temperature, rainfall, malaria and pneumonia. The outcome of this study is similar to the findings of [4][24] who reported a long run association between climatic variables (rainfall and temperature) and crop productivity in Nigeria using Johansen test of cointegration.

Table 4. Results of Cointegration Test Based on ARDL Bounds Test Approach

	Critical Value Bounds of the F-statistic	
Critical value	**lower bound I(0)**	**Upper bound I(1)**
1%	3.74	5.06
5%	2.86	4.01
10%	2.45	3.52
Computed F – Statistic : F_{LCP}(LCP | LTP, LRF, LML, LPN) = 4.38		

Note: Critical Values are cited from Pesaran et al. (2001), Table CI (iii), Case 111: Unrestricted intercept and no trend, Number of regressors (K) = 4.

Analysis of Long Run Estimates

The long run coefficents of ARDL (1,0,0,1,0) were presented in Table 5.

The results demonstrated that rainfall and pneumonia had negative impact on crop production in the long run.

Statistically, the empirical findings demonstrated that 1% increase in amount of rainfall and pneumonia incidence led to 0.12% and 0.45% decrease in crop production respectively.

This implies that incidence of rainfall pattern that leads to storm, flood, uncontrollable erosion and leaching will reduce crop yield in the study area.

In the same vein, occourrence of pneumonia that leads to the absence of farmers from farm activities and as well make him incurred cost of treatment will cause a significant decrease in crop production.

Table 5. Estimated Long Run Coefficients using the ARDL Approach

Regressor	Coefficient	Standard Error	T-Ratio	Prob.
LTP	0.86350	4.2565	0.20287	0.841
LRF	-0.12010**	0.0604	1.98901	0.047
LML	0.11959*	0.0713	1.67727	0.089
LPN	-0.45513**	0.2160	2.10781	0.015
C	9.6817	4.8466	1.99762	0.039

Note: *, **, ***, significant at 10%, 5%, 1% respectively; ARDL (1,0,0,1,0) selected based on Schwarz Bayesian Criterion; LCP = log Crop production output; LTP = log Temperature; LRF = log Rainfall; LML = log Malaria; LTF = log Pneumonia;

Source: Computed from Field Survey, 2014.

Analysis of Short Run Estimates – Vector Error Correction Model (VECM)

The short run dynamic coefficients associated with the long-run cointegration relationships were obtained from the analysis of Error Correction Model (ECM) based on ARDL bounds test approach. The results of the short run coefficients of ARDL (1,0,0,1,0) model are presented in Table 6. The empirical findings demonstrated that there was short run relationship among the variables. Expectedly, rainfall, malaria incidence and pneumonia incidence had negative effect on crop output in the short run. The statistically significant negative coefficient of ECM(-1) verified the long run relationship among the variables. According to [32], ECM measures how quickly the endogenous variable adjusts to the changes in the independent variables before the endogenous variable converges to the equilibrium level. Negative and statistically significant ECM demonstrates that adjustment process is effective in restoring equilibrium. Negative but low ECM in absolute value points out a slow adjustment. Therefore, ECM in this study was statistically significant at 5% level and had a value of -0.142. This implies that an approximately 14% of disequilibria from the previous year's shock converge to the long-run equilibrium in the current year. Moreover, a 1% increase in rainfall, malaria and pneumonia incidence caused a 0.01%, 0.02% and 0.06% respectively decrease in crop output in the short run. Rainfall will have negative effect on crop production when it is rained heavily, causing over flooding thereby leading to erosion and leach [4] which have been the case in the previous years in the study area. In the same vein, malaria and pneumonia could reduce crop production when the farmers were incapacitated with diseases which make them to be absent from the farm activities and as well render them inefficient in actualizing their potentials. Moreover, [1] opined that diseases (such as malaria and pneumonia) affect agricultural systems by affecting the health of producers. Poor health will result in loss of work days or decrease worker capacity, decrease innovative ability and ability to explore diverse farming practices thus making farmers to capitalize on farm specific knowledge.

Table 6. Results of the ARDL Short-run Relationship

Regressor	Coefficient	Standard Error	T-Ratio	Prob
ΔLTP	0.12300	0.4489	0.2740	1.987
ΔLRF	-0.01711***	0.0061	-2.8316	0.001
ΔLML	-0.02632***	0.0109	-2.4113	0.003
ΔLTF	-0.06483*	0.03354	-1.9331	0.059
C	1.3791	2.0787	0.6634	0.513
ecm(-1)	-0.14244**	0.0683	-2.0855	0.012

ecm = LCP -.86350*LTP + .12010*LRF -.11959*LML + .45513*LTF -9.6817*INPUT.

****

R-Squared	.38461	R-Bar-Squared	.19732
S.E. of Regression	.11880	F-stat. F(6, 24)	2.3958[.059]
Mean of Dependent Variable	.042675	S.D. of Dependent Variable	.13261
Residual Sum of Squares	.32463	Equation Log-likelihood	26.6781
Akaike Info. Criterion	18.6781	Schwarz Bayesian Criterion	12.9421
DW-statistic	1.4129		

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R-Squared and R-Bar-Squared measures refer to the dependent variable dLNCP and in cases where the error correction model is highly restricted, these measures could become negative.

LCP = log Crop production output; LTP = log Temperature; LRF = log Rainfall; LML = log Malaria; LTF = log Typhoid fever

Source: Computed from Field Survey, 2014.

The outcome of this study is similar to that of [4] who reported a negative and significant effect of rainfall on agricultural productivity but contrary in the case of temperature using Johansen test of cointegration approach.

Again, [23] reported a bi-directional relationship between crop productivity and

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rainfall in Nigeria using granger causality test spanning from 1970 to 2008.

Analysis of ARDL Diagnostic Tests

At 5% significant level, the F-test accepts the null hypotheses of no serial correlation, homoscedasticity, normal distribution and functional form misspecification as depicted in Table 7. Furthermore, stability tests using the cummulative sum of recursive residuals (CUSUM) and cummulative sum of squares of recursive residuals (CUSUMq) plots of [5] for the ARDL model as shown in Figure 2 depicted the movement of the CUSUM or CUSUMq outside the critical lines of 5% significant level indicates parameter instability. From the Figure, CUSUM statistic lies within the 5% critical lines, meaning that the model cofficients are stable in the short run. On the other hand, CUSUMq statistic for the model coefficients cross the critical value line, indicating some instability in the ARDL model in the long run.

Table 7. Results of Diagnostic Tests

Test	χ^2 statistic	Probability
Breusch-Godfrey Serial Correlation test	2.5686	0.123
White Heteroskedasticity test	3.7987	0.161
Jarque-Bera test (Normality)	1.0658	0.583
Ramsey RESET Test (log likelihood ratio) – Functional Form	9.0061	0.711

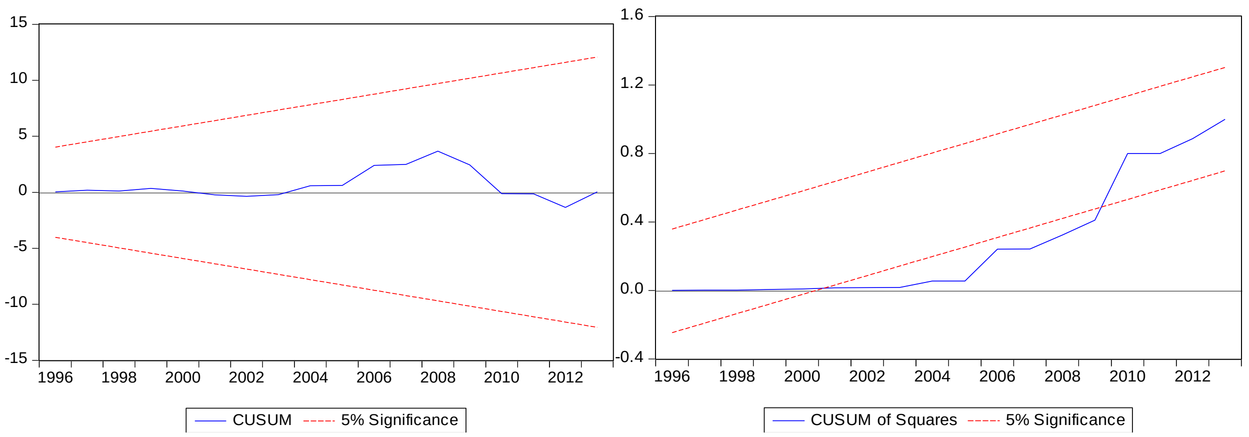

Fig. 2. Plot of the Cumulative Sum of Recursive Residuals (CUSUM) and Cumulative Sum of Recursive Residuals of Square (CUSUMq) Tests for ARDL Model
Source: Computed from Field Survey, 2014.

CONCLUSIONS

The study specifically looked into the relationship between crop production and selected climate and health variables (temperature, rainfall, malaria and pneumonia) in Ondo State, Nigeria. Secondary data were used for this study which were sourced from NBS, Ministry of Health and ADP spanning the period of 1982 to 2013. The analytical tools used were descriptive statistics (mean, standard deviation, frequency distribution and percentage) and auto-regressive distributed lag (ARDL) model (bounds testing approach to cointegration). The results of cointegration test using autoregressive distributed lag (ARDL) model revealed that crop production and rainfall data were stationary at level, while average temperature, incidence of malaria and pneumonia data were stationary at first difference using ADF test. ARDL results confirmed the presence of long run relationship between crop production and temperature, rainfall, malaria and pneumonia (F-value to be 4.38, $p < 0.05$). The results of long run estimates showed that rainfall and pneumonia were significant in affecting crop production negatively. On the other hand, the results of the short run estimates showed that all the variables except temperature were significant and negatively affected crop production in the short run. The long run relationship among the variables were further confirmed and verified by ECM (-1). About 14% of disequalibria from the previous year's shock converge to the long run equalibrium in the current year given an ECM value of -0.142.

Based on the findings of this study, it can be concluded that crop production was affected negatively by climate variability (such as changes in rainfall leading to drought, flooding, storm and heavy rainfall) and climate-sensitive diseases (e.g malaria and pneumonia leading to health poor vis-a-vis unproductive and inefficient farmers) both in the long and short runs in the study area.

The following policy recommendations were proffered based on the findings of this study:

(i)Government should provide safe drinking water, improved sanitation and adequate medical care that will prevent and control malaria and pneumonia incidences in the study area. This could be achieved by providing bole-hole or pipe borne water, modern healthcare centres and standard drainage to control erosion and flood that lead to extreme.

(ii)Early warning/meteorological forecasts and related information cum health surveillance programmes should be established especially among the most vulnerable groups. This can be channelled through radio and mobile phone.

(iii)Government should design holistic programme that will put the farmers at the frontline in order to reduce catastrophic health cases in the area most especially malaria and pneumonia.

This could be done through disease prevention and environmental sanitation under the framework of the primary health care programme.

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