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Crop Yield Prediction Using Solar Activity

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Abstract:*The yields of tuber crops were predicted in this work. Parametric analysis was carried out to obtain historical coefficients for solar activity index and crop yield data, using observed yields with time, Sunspot Number, and cultivated area as input variables. Multiple polynomial regression of 2nd degree was used to model the yields of yam and cassava in Benue State-Nigeria. The model explained 73.9 % of yield variance for yam and 69.9% of yield variance for cassava, and it showed increment in yields for two years (2018 and 2019) for both crops, corresponding to minimum solar activity. The model was testedfor accuracy using Willmott's d-value,and the accuracy test gave* $\mathbf{0.92}$ *for yam and* $\mathbf{0.87}$ *for cassava on a scale of 0.0 to 1.0. In addition to this, the model was validated using observable data and a good agreement was found between the observed and the predicted yields.*

Keywords:*Crop yield Prediction, Food security, Polynomial Regression,Solar Activity*

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I. Introduction

It is estimated by Food and Agriculture Organization (FAO) that 868 million people worldwidestill live without adequate food supply (FAO, 2015), and that by 2050 there will be two billion more people to feed (FAO, 2015). Ending hunger and improving food security are primary goals in the 2030 Agenda for Sustainable Development of the United Nations (United Nations, 2015).Estimating the yields of crops before harvest is one of the greatest concerns in modern era, as deviations in crops yield on a yearly basis could affect food supply and local market prices or even international trade (Jeong*et al*., 2016). Crop yield prediction is vital for substantial land use, making economic decisions, and identifying effective adaption strategies to solar variability (Doraiswamy*et al.*, 2003; Pustil'nik& Din, 2004; Pustil'nik& Din, 2013; Verma*et al.*, 2015; Jeong*et al.*, 2016). It provides useful information for policy planners as well as Government organizations as it aids in the inspection of annual market status, specifically those allocated to exportation.A significant decrease in crop production caused by extreme weather conditions arising from the output of the sun can be perilous for a State where the economy is partially or entirely dependent on Agriculture.

The output of the sun in all forms; electromagnetic radiation, magnetic fields and energetic particles varies with both time and position of the sun (Usoskin, 2016). The dynamo processes in the sun's convection zone creates a magnetic field that gives rise to solar flares, coronal mass ejections, and other types of magnetic activity (De Jager&Usoskin, 2006; Moldwin, 2008; Schrijver& George, 2010), such as sunspots-collectively termed solar activity.Solar activity is regulated by the sun's dynamo, which is a non-linear system with deterministic chaotic elements (Giampapa*et al.*, 2010).

In connection with the above, the sun periodically changes its magnetic field, as the polarity is reversed, the overall structure transforms over time (Liou, 2002; Moldwin, 2008;Ihongo, 2016). This give rise to two extreme conditions, known as the solar maximum and solar minimum corresponding to the number of sunspots (Liou, 2002; De Jager&Usoskin, 2006; Moldwin, 2008).The full dynamo cycle takes two Schwabe cycles (the so-called Hale cycle of ~22 years) since the polarity of the solar magnetic field is reversed approximately every 11 years (Liou, 2002;De Jager&Usoskin, 2006; Moldwin, 2008;Usoskin, 2016).

One indicator of the activity level of the sun is the number of sunspots on the surface of the sun (Moldwin, 2008; Usoskin, 2016).The Sunspot Number (SSN) is a very useful parameter in quantifying the level of solar activity (Hathaway, 2015; Usoskin, 2016) as such it offers substantial information on the state of the Sun. A number of other forms/indicators of solar activity including the 10.7 cm radio flux, total solar irradiance, solar flares, radioisotopes in tree rings and ice cores have been observed to vary in association with sunspot numbers (Moldwin, 2008; Usoskin&Krivova, 2011; Pustil'nik& Din, 2013; Hathaway, 2015).

The climate of a region or an area is not static; it changes with time, and can be influenced by solar activity primarily through changes in the intensity of solar radiation (Palencia *et al*., 2013; Usoskin, 2016; Utomo, 2017). Solar activity apparently affects terrestrial climate (Shaviv, 2003). The Earth's climate heats and cools as solar activity rise and falls (Hiremath&Mandi, 2004; Hiremath, 2006; Haigh, 2007; Hathaway, 2015). Increase in solar activity could sufficiently magnify the sun's effect on Earth's temperature most especially at points normal to the sun (Shaviv, 2003), where there is intense heating. Conversely extreme change in temperature in turn may potentially affect crops and account for a wide yield variation. Predicting crop yield responses to such variability is usually done using Process-based modeling (Artificial Neural Networks) or statistical modeling (Michel &Makowski, 2013; Paswan& Begum, 2013). Process-based modeling can automatically approximate any nonlinear mathematical function. They simulate physiological processes of crop growth and development in response to environmental conditions and management practices. The features of neural networks are particularly useful when the relationship between variables is not known or is complex and hence difficult to handle statistically.

However, the determination of various parameters is not straightforward and finding the optimal configuration of neural networks is a very time consuming process (Paswan& Begum, 2013; Jeong*et al*., 2016). This makes the use of detailed process-based crop models for timely predictions of crop yield at regional or global scale challenging (Michel &Makowski, 2013). Statistical models clearly stands out in this regard, as it allows interpretation of historical coefficients of individual variables; and due to their parametric assumptions, inferences could be drawn regarding the significance of certain variables in crop yield prediction provided that sufficient and reliable data were used for model training (Michel &Makowski, 2013; Paswan& Begum, 2013).

The area of cultivation of crops, factors of their growth, their distribution and yield are analyzed with reference to space and time (Balasubramanian, 2014). Core predictive analysis relies on capturing relationships between explanatory variables from past occurrences, and exploiting them to predict the unknown outcome. Statistical modeling estimates direct relationships between predictor variables and crop yield in a given data set without considering the underlying processes in crop physiology and ecology (Michel &Makowski, 2013; Paswan& Begum, 2013).

A schematic representation of the conception of a system isreferred to as model (Murthy, 2002).A model represents the behavior of a system and its purpose is usually to aid in explaining, understanding or improving the performance of a given system.Theselection of anappropriatecrop model is extremely important as it reflects the underlying structure of a data. A fitted model in turn is useful for future prediction. It is expected that the average yield will be static over time if the factors that influence the yield also move in a cyclic pattern(Choudhury& Jones, 2014).Likewise, variations in yield would be similar also if the factors themselves affecting the yield remain constant. However, extreme changes in weather via solar activity during specific period of crops' cycle can influence crop yield adversely and widen the yield variance (Choudhury& Jones, 2014). Thus, a crop yield prediction model that accounts for higher percentage of yield variations is a preferable prediction model.

The purpose for which a crop model is developed may rely on the scientific understanding of crop growth (mechanistic models), or the provision of support to decision making processes (Predictive models). Unlike dynamic models which describe the effects of external changes, statistical models rather build predictions on historical basis.Statistical models are less dependent on field calibration data and may provide measures for commonly used performance assessment for uncertainty analyses at regional scale (Michel &Makowski, 2013; Paswan& Begum, 2013). This allows for model validity and good crop yield predictions. In what follows,this research work aimsat early prediction of crop yields in Benue State as it may perhaps improve crop production, as a consequence, drive the State's economy and at large, the nation's quest for an efficient agro-economy in the light of climate change due to solar activity.

Crop yield prediction is a formidable task.Predicting the yield of crops involves the use of available historic data (Shastry*et al.,* 2017). However, the accuracy of results depends largely on the level of data analysis and the quality of assumptions. Such predictions before harvest are required by the national and state governments for several policy decisions relating to storage, distribution, pricing, marketing and import-export (Pustil'nik& Din, 2004; Pustil'nik& Din, 2013; Verma*et al.,* 2015). Consequently, researchers have being working hard on this subject. For instance,Jayaram and Marad (2012), developed fuzzy inference systems for crop yield prediction. A huge database (around 1000 records) of physio-morphological features of Sorghum such as days of 50 percent flowering, plant height, panicle length, were considered for the development of the their model. In order to find out the sensitivity of parameters, one-to-one, two-to-one and three-to-one combinations of input and output were considered. The results obtained by this team clearly showed that panicle length contributes for the yield as the lone parameter with almost one-to-one matching between predicted yield and actual value. On the other hand the parameter for panicle length and panicle weight in combination played a significant role in contributing for the yield with the prediction accuracy reflected by very low Root Mean Square error (~3.9).

According to Harrison (1976), both the single and double sunspot cycles may give useful information in predictions of yield deviations. The hypothesis that crop yields at the State level are related to various phases of the sunspot cycle was tested in his publication ''Do Sunspot Cycles Affect Crop Yields?'' The Crops and States considered were wheat in Texas and Kansas, corn in Illinois and Nebraska, rice in Louisiana, and cotton in Texas. Data from 1866-1973 was analyzed statistically. The outcome of the research suggested that lower than average yields are associated with low sunspot activity and higher than average yields are associated with high sunspot activity.

Garnett *et al.* (2006)examined the impact of sunspot activity and large-scale atmospheric features on regional seasonal weather, as well as implications for crop yield and agronomy. The atmospheric variables analyzed were the stratospheric quasi-biennial wind oscillation (QBO), El Niño/Southern Oscillation (ENSO), and North American snow cover (NAS) on Canadian summer rainfall. The analysis was based on 55 years of atmospheric, crop yield and climatic data for more than 50 weather stations over the Canadian Prairie region. The findings of the study revealed that high (low) sunspot activity, easterly (westerly) phase of the QBO, persistent La Niña (El Niño) conditions and heavier (lighter) than normal NAS in seasons leading up to the summer months are associated with low (high) summer rainfall.

Pustil'nik and Din (2013), presented the results of the study of a possible relationship between the space weather and terrestrial markets of agricultural products. They described four possible scenarios of the market response to the modulations of local terrestrial weather via solar activity along with the behavior of 22 European markets during the Maunder minimum (1650–1715). Their analysis of the statistics of depopulation in the eighteenth and nineteenth century Iceland, induced by the famine due to a sharp livestock reduction and lack of foodstuff due to the local weather anomalies found a high statistical significance of temporal matching of these events with the periods of extreme solar activity.

Pustil'nik and Din (2004), presented a conceptual model of possible modes for sensitivity of wheat prices to weather conditions, caused by solar cycle variations. The database of wheat prices in England in the Middle Ages, was used to search for a possible influence of solar activity on the wheat market. A comparison of the statistical properties of the intervals between wheat price bursts during years 1249-1703 with statistical properties of the intervals between minimums of solar cycles during years 1700-2000 was made. The comparison revealed that the statistical properties of these two samples were similar, both for characteristics of the distributions and for histograms of the distributions. The authors analyzed a link between wheat prices and solar activity in the 17th Century and showed that for all 10 time moments of the solar activity minimums, the observed prices were higher than prices for the correspondent time moments of maximal solar activity. These results were considered as a direct evidence of the causal connection between wheat prices bursts and solar activity by the authors.

However, the aforementioned studies carried out little or no work at all on crop yield prediction using solar activity parameters, which is why in this research, parametric analysis of data on solar activity and crop yield was carried out, and the historical coefficients obtained from the analysis were used in a modeled equation to predict the yields of tuber crops in Benue State.

Study Area

Benue State is located along the lower river Benue basin in the middle belt region of Nigeria, and is regarded as the *Food Basket of the Nation*. The geographic coordinates of Benue State is between latitudes 6° 25'N and 8° 8'N of the equator and between longitudes 7° 47'E and 10° 00'E of the Greenwich meridian (NBS, 2012). The State shares boundary with Nasarawa State to the north, Taraba to the northeast, in the south by Cross River, while in the southwest is Enugu, Ebonyi and Kogi State to the west. The State has 23 Local Government Areas with a total land area of 30,800 sq. km and a total population estimated to be 4,253,641 (NBS, 2012). Based on the Köppen Classification Scheme, Benue State falls within the AW-climate-a Tropical Climate with two typical wet and dry seasons. The rainy season lasts from April to October, with annual rainfall ranging from 100mm-200mm. The dry season begins in November and ends in March. Temperatures are continually high all through the year, with average temperatures fluctuating between 21°C - 37°C (Ivande, 2006). The vegetation of the State is typically that of the southern Guinea Savannah, characterized by sparse grasses and various species of disseminated trees. About 75% of the working population (15-49 years) engages in agriculture, making it the main occupation and essentially the driver of the State's economy (NBS, 2012).

II. Theory

Quantum mechanics has it that, only certain configurations of electron orbits are permitted within each atom and only certain vibrations and rotations may be associated with a particular energy level. The energy transmitted by electromagnetic radiation exists in discrete entities known as photons$(h\nu)$, and an isolated molecule can only absorb and emit energy in discrete amount corresponding to the allowable changes in energy levels, so in theory, it can only interact with radiation with certain discrete wavelengths(λ). As a consequence, absorption and emission properties of an isolated molecule can be described in terms of line spectrum comprising of infinite number of extremely narrow absorption or emission lines separated by gaps whereby the absorption or emission of radiations are not possible (Wallace & Hobbs, 2006).

Solar activity brings energy to the metabolic process of plants. The reason being that the heat and light required by all growing crops are supplied by solar radiation. The main process is the photosynthetic assimilation that makes synthesize vegetal components from water (H_2O), carbon dioxide (CO_2) and light energy possible (Campillo*et al.*, 2012). Visible radiation with wavelengths of about 0.43μm and 0.66μm is required in photosynthesis (Wallace & Hobbs, 2006). The production of oxygen (O_2) by photosynthesis is closely linked with biological process, since CH_2O monomer produced in biological process is the basic building block for carbohydrate molecules that forms the cells in crops. Thus;

$$h\nu + H_2O + CO_2 = [CH_2O] + O_2 \qquad (1)$$

Photosynthesis reaction

Photosynthesis involves the absorption of energy in the form of visible light at wavelengths near 0.43 μm (blue) and 0.66 μm (orange). The respiration and decay reaction releases of an equivalent amount of energy in the form of heat (Wallace & Hobbs, 2006).

$$[CH_2O] + O_2 = H_2O + CO_2 + Heat \qquad (2)$$

Respiration and decay reaction

For instance, Palmer stated that, (Palmer, 1920); sunshine, directly through radiation, and indirectly through its effect upon air temperatures, influences the distribution of crops. This energy is required for chemical activities within growing crops, but it also promotes evaporation from the foliage. The quality and the quantity of the sun-light transmitted to growing crop are both dependent upon atmospheric conditions, as well as upon the season of the year. They vary from place to place and from month to month around the globe.

Interception of radiation also known as the interception of light (LI) by a canopy gives the difference between the solar incident radiation and reflected radiation by the soil surface (Purcell, 2000). This is a determining factor in crop development since it provides the energy needed for fundamental physiological processes such as photosynthesis and transpiration. At the surface of the earth, solar radiation can be separated into direct and diffuse components, with the latter due to scattering of light as it travels through the atmosphere. Both components of incident light are necessary for photosynthesis (Purcell, 2000; Campillo*et al.*, 2012). Crops intercept direct and diffuse sunlight. The upper leaves receive both types of radiation, while the lower leaves intercept a small portion of direct radiation. Diffuse radiation therefore, becomes more significant in the lower leaves due to radiation transmitted and reflected from the leaves and the soil surface. (Campillo*et al.*, 2012).

Ample of amount of sunshine is required of most crops. A part of this energy is used in the evaporation process inside the different organs of the crop, and also in the transpiration through the stomas. The effect of light intensity (irradiance) and temperature on the rate of carbon assimilation has been studied extensively by a number of researchers. Campillo*et al.*, (2012) in a study revealed that photorespiration makes plants increase the oxygen consumption when they are illuminated by the sun, and this is very important for crop growth. On a hot day with no wind, the CO_2 concentration in crops decreases considerably.

Crops deplete their carbon (C) reserves during cellular respiration, and replenish C stores from atmospheric carbon dioxide through their stomata during photosynthesis (de Villiers, 2017). As ambient temperature increases, stomata close to minimize water loss. This cuts off the supply of atmospheric CO_2, resulting in the levels of C-based molecules such as carbohydrates to plummet. High temperatures over prolonged periods therefore results in retarded crop growth (Campillo*et al*, 2012; de Villiers, 2017).

The possible relationship between solar activity and the yield of crops can be modelled. Nonlinear phenomena such as the growth rate and distribution of crops can be described by polynomial regression.The relationship between an independent variable x and a dependent variable y is modeled as an n^{th} degree polynomial in *x.* (Bremer, 2012). Although polynomial regression fits nonlinear data, statistically it is linear in the sense that the regression function $E(y|x)$, is linear in the unknown parameters to be estimated (Montgomery *et al.*, 2008; Vining *et al.*, 2012).

A basic choice in modeling is between parametric and non-parametric models. Parametric models such as polynomials may be quite difficult to fit, but the loss function can be expressed concisely.Polynomial regression models are usually fit using the method of least squares. This method minimizes the variance of the unbiased estimators of coefficients under the conditions of Markov theorem. Although polynomial regression is technically a special case of multiple linear regression, the interpretation of a fitted polynomial regression model requires a somewhat different approach. It is often difficult to interpret the individual coefficients in a polynomial regression fit, since the underlying monomials can be highly correlated. Even though, the correlation can be reduced using orthogonal polynomials, it is generally more informative to consider the fitted regression function as a whole. Point-wise or simultaneous confidence bands can be used to provide a sense of the uncertainty in the estimate of the regression function (Vining *et al.*, 2012).

The idea of fitting a function to a set of data in terms of least squares has received considerably more attention in physics, mathematics and other related fields. Curve fitting provides the opportunity to stress fundamental ideas about linear, exponential, power, logarithmic, logistic, and polynomial functions to situations from all walks of life. Fortunately, these capabilities are built into all graphing calculators and spreadsheets of a number of softwares.

The standard derivations of the formulas for the regression coefficientstypically require multivariable calculus to minimize the sum of the squares of the deviations between the data values and the equation of the mathematical model. Polynomial regression model is generalized (Montgomery *et al.,* 2008; Vining *et al.,* 2012) as

$$y = a_0 + a_1 x + \cdots + a_k x^k + \varepsilon \qquad (3)$$

It can be expressed in terms of a design matrix X, a response vector $\vec{y}$, a parameter vector $\vec{a}$ and a vector $\vec{\varepsilon}$ of random errors serving as a reminder that the polynomial will typically provide an estimate rather than an implicit value of the dataset for any given value of x. The *i-th*row of X and $\vec{y}$ will contain X and y values for the *i-th*data sample. Then the model can be written as a system of linear equations:

$$\begin{vmatrix} y_1 \\ y_2 \\ \cdot \\ \cdot \\ \cdot \\ y_n \end{vmatrix} = \begin{vmatrix} 1 & x_1 & x_1^2 & . & . & . & x_1^k \\ 1 & x_2 & x_2^2 & . & . & . & x_2^k \\ . & . & . & . & & & . \\ . & . & . & & . & & . \\ . & . & . & & & . & . \\ 1 & x_n & x_n^2 & . & . & . & x_n^k \end{vmatrix} \begin{vmatrix} a_0 \\ a_1 \\ \cdot \\ \cdot \\ \cdot \\ a_k \end{vmatrix} \qquad (4)$$

Which when using pure matrix notation is written as

$$\vec{y} = X\vec{a} + \vec{\varepsilon} \qquad (5)$$

The vector of estimated polynomial regression coefficients using least square estimation is

$$\vec{a} = (X^T X)^{-1} X^T \vec{y} \qquad (6)$$

Assuming $k < n$ which is required for the matrix to be invertible, then since X is a vandermonde matrix, the invertibility condition is guaranteed to hold if all the x_i values are distinct. This gives the unique least-square solution.

III. Materials and Methods

Data on total annual cultivated area with production of yam and cassava from 1995 to 2017 were obtained from the Department of Planning, Monitoring and Evaluation (PME), Benue State Agricultural and Rural Development Authority (BNARDA), Makurdi. In addition, online data on yearly mean total Sunspot Number was retrieved from WDC-SILSO, Royal Observatory of Belgium, Brussels from 1995 to 2017.

Again, estimated annual cultivated area of yam and cassava for 2018 and 2019 was obtained from BNARDA. The Predicted values of Sunspot Number were obtained from Space Weather Prediction Centre-National Oceanic and Atmospheric Administration (NOAA) for 2018 and 2019 as well. We used second-order multiple polynomial regression model with interactions that best represented the relationship between solar activity and crop yield variables to predict the yield of tuber crops. Observed yields with time, Sunspot Number, and cultivated area as input variables were carefully studied and prepared for analysis. We carried out Polynomial regression analysis using Minitab to obtain coefficients for the parameters under consideration. The analysis yielded parametric coefficients and these coefficients were inputted into the modeled equation for each study crop as expressed in equations (7) & (8). The equations were used to generate predicted outputs for yam and cassava respectively. The model used in this work to predict the yields of yam and cassava is given in equation (7) & (8).

$$YIELD_{\mathrm{YAM}} = -13110706 + 13199(\mathrm{t}) + 127.7(\mathrm{SSN}) - 1340(\mathrm{A}) + 0.0012(\mathrm{t} \times \mathrm{SSN}) + 0.5963(\mathrm{t} \times \mathrm{A}) - 0.5918(\mathrm{SSN} \times \mathrm{A}) - 3.318(\mathrm{t}^2) + 0.02544(\mathrm{SSN}^2) + 0.3748(\mathrm{A}^2) \qquad (7)$$

$$YIELD_{\mathrm{CASSAVA}} = 1215131 - 1900(\mathrm{t}) + 1952.6(\mathrm{SSN}) + 4640(\mathrm{A}) - 0.9899(\mathrm{t} \times \mathrm{SSN}) - 2.181(\mathrm{t} \times \mathrm{A}) + 0.1442(\mathrm{SSN} \times \mathrm{A}) + 0.637(\mathrm{t}^2) - 0.04654(\mathrm{SSN}^2) - 0.4532(\mathrm{A}^2) \qquad (8)$$

where*t*, *SSN*, and *A* symbolizes time, sunspot number and cultivated area respectively.

The Willmott'sd-value(Jeong, 2016), was used in evaluating the efficiency of the model, which is stated in equation (9)

$$d = 1 - \frac{\sum_{p=1}^{n} (y - \hat{y}_p)^2}{\sum_{p=1}^{n} (|\hat{y}_p - \bar{y}| + |y - \bar{y}|)^2} \qquad (9)$$

where, y represents the observations in the test data set, $\hat{y}_p$is the predictions, and $\bar{y}$ is the observation mean in each test dataset. The Willmott'sd-value is an index of agreement used in crop model systems for model performance evaluation and inter-comparison. It gives the measure of deviations between the observations and the model predictions ranging from 0.0 (poor model) to 1.0 (perfect model) (Jeong, 2016).

IV. Results

The fundamental driver of the polarity reversal of solar magnetic field is the solar dynamo; this gives rise to solar activity (Baumann, 2005; De Jager 2008). Solar activity is a process that is basically magnetic in nature, and its main features are characterized by the emergency and deterioration of active regions and as such far from stable, so to speak. A natural consequence of this instability is evident in the phase deviance of the solar activity cycle. Solar activity is known to be the main energy for metabolic processes of plants/crops, such as photosynthesis through solar radiation (Shaviv, 2003; Pustil'nik& Din, 2004; Wallace & Hobbs, 2006; Pustil'nik& Din, 2013). This could be that the heat and sunlight required by crops for development is by solar activity through solar radiation. This is evident in the results from this model, as it is observed for yam, (Fig. 1) the increase in yield at periods of solar minima. Also as in the case of cassava (Fig. 2) corresponding to periods of solar minima, relatively high yields were observed.

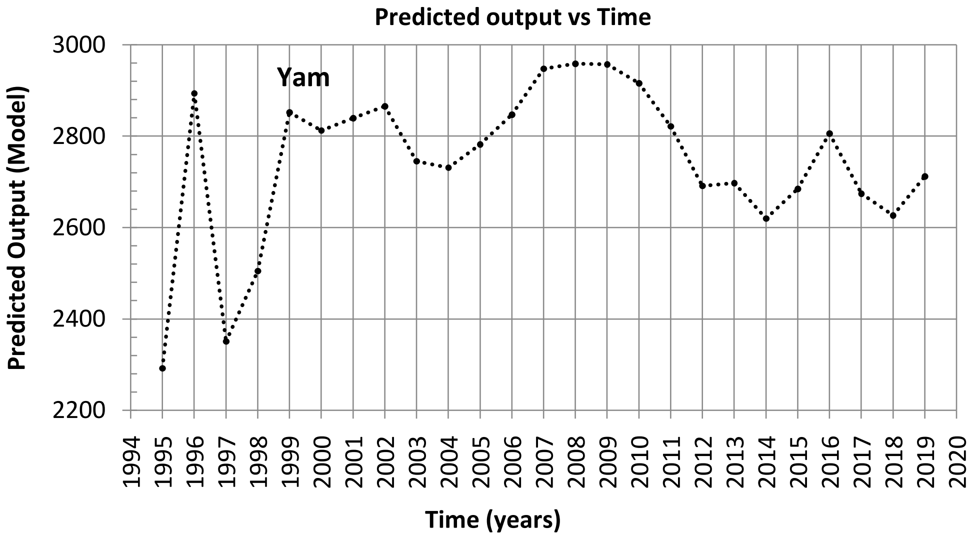

Fig. 1: Model Results for Equation (7)

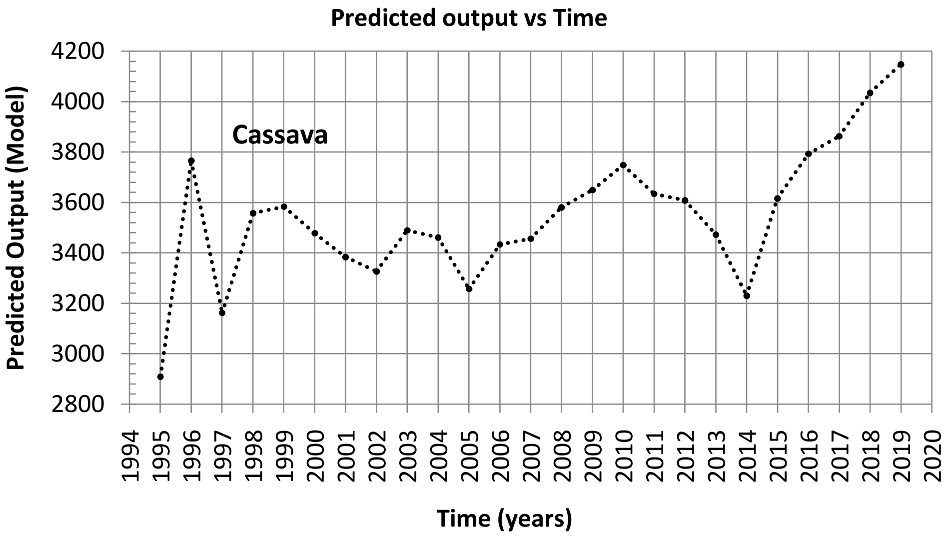

Fig. 2: Model Results for Equation (8)

This consistency could be attributed to solar radiation. The magnification of the effects of solar activity through solar radiation is most noticeable in regions of direct thermal circulation (Shaviv, 2003), as it is in the location of this study. Corresponding decrease in yields at periods of solar maxima may be as a result of intense heating at this location. Comparison between the observed and predicted yields of both study crops (Fig. 3 &

Fig. 4)suggests a good agreement. This is evident in the deviations between observed and the predicted yields for yam ($R^2 = 0.7386$) and cassava($R^2 = 0.6992$).

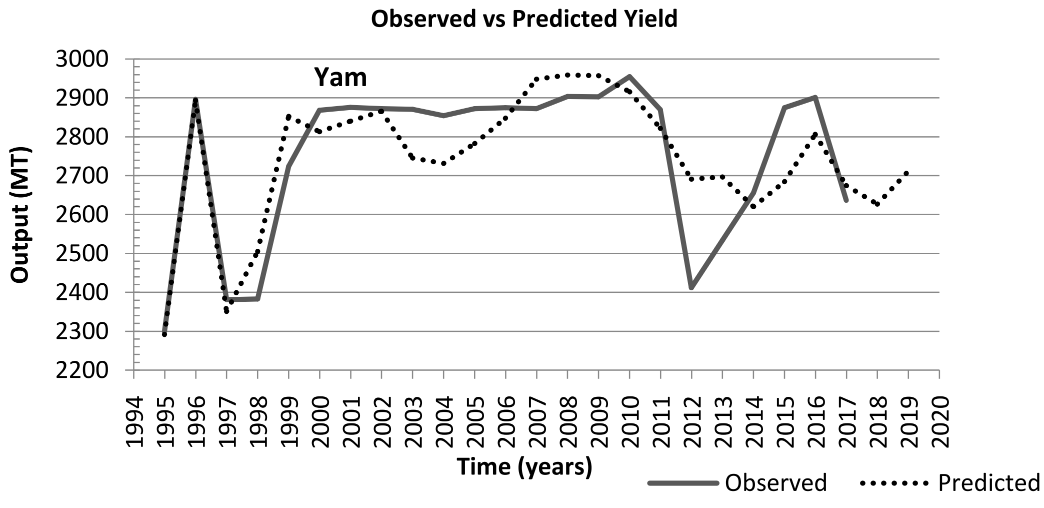

Fig. 3: Model Validation for yam

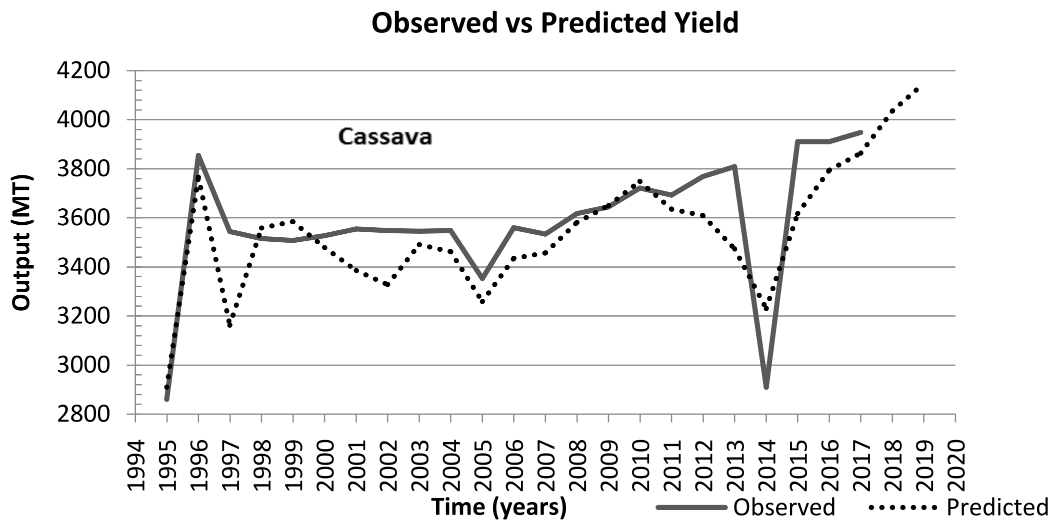

Fig. 4: Model Validation for cassava

In line with this, the model explained 73.9 % of yield variance for yam and 69.9% of yield variance for cassava. Nevertheless, for such an empirical study, the performance evaluation of such design is customary.The efficiency test of the model, on a measure of $0.0 - 1.0$ for a poor model to a perfect model, yielded results for yam with a value of 0.92 and 0.87 for cassava. The model performed considerably well for the two crops, as the values almost converge towards 1.0.

V. Conclusion

Unusual yields were revealed in connection with solar activity cycle. Notable decrease in yields for both crops was recorded at periods of maximum solar activity (2000, 2012, 2014), while significant increase in yields for the crops at periods of minimum solar activity (1996, 2008, 2016) was detected. The predicted yield for the year 2018 and 2019 is 2626.41 MT and 2711.94 MT for yam, while cassava is 4035.05 MT and 4147.71 MT.

Prospects

Yield variability is a significant risk factor in agricultural production systems, and the ability to predict yield and reduce such risk would have several benefits for both farmers and institutions that rely on these predictions, for investments, in providing capital, or for policy making. The availability and validity of key crops yield data is of great importance in yield prediction. Area cultivated has shown in this study to be a good input variable in crop yield prediction. However solar activity as reflected in the peak and troughs of its cycle gives an indication for future crop yields.The use of solar activity index as to the conventional weather/climate parameters has shown that the activity level of the sun can also be employed as a predictor in predicting the yield of crops in retrospect and the future on a short term basis. This research offers fore-knowledge of when to cultivate tuber crops bountifully as a way of mitigating yield losses due to solar variability.

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