EFFECTS OF SPACE WEATHER PARAMETERS ON AGRICULTURAL PRODUCE

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ABSTRACT

Space weather is responsible for the time varying condition in the solar system. This variability in the solar system can lead to direct or indirect impacts on earth including Agricultural produce. It is important to understand the impact of space weather on agricultural produce as it reduces the risk associated with food shortage and low agricultural productivity. Previous studies have shown that extreme heat from solar radiation can cause reduction in crop yield. This study analyzed the effects of space weather parameters on agricultural produce. Vector Autoregressive package in R-programming statistical software was used to model cereal crop yield data for a period of 2006-2016. The VAR model was simplified to obtain yields for each crop: Rice, Millet, Sorghum and Maize. The results showed that crop yield increases with decrease in space weather parameters and vice-versa. This means that extreme space weather conditions can cause low crop yield leading to a negative impact on crop yield and vice- versa. The observed yields were compared with model fit and data gave crop yield values for years 2007(192.9400 Metric Tonnes), 2009(196.4600 Metric Tonnes), 2011(192.2600 Metric Tonnes) and 2012(196.6700 Metric Tonnes) for Sorghum, years 2008 (63.6600 Metric Tonnes), 2010(64.1800 Metric Tonnes), 2011(65.2200 Metric Tonnes) and 2014(64.4300 Metric Tonnes) for Millet, years 2008 (146.9500 Metric Tonnes), 2009 (149.9400 Metric Tonnes), 2015(174.4000 Metric Tonnes) and 2016 (175.3400 Metric Tonnes) for Maize and years 2006 (277.7300 Metric Tonnes), 2009 (289.6600 Metric Tonnes) and 2013(146.6800 Metric Tonnes) for Rice respectively. The comparisons between the obtained data and the model result suggest a good agreement, this means that the model accurately described the effects of space weather on crop yield.

Keywords: Agricultural produce, Space Weather, Crop yield.

INTRODUCTION

Space weather originates from the sun with different forms of solar activities. All solar activity is driven by the solar magnetic field. These activities include; Solar flares, coronal mass ejections, high-speed solar wind, and solar energetic particles and solar radio flux (Li *et al*., 2016). 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*et al*., 2007). 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 (Moldwin, 2008).

The sun's unceasing activity assures an impact on our planet far beyond the obvious light and heat from a constant stream of particles in the form of solar wind to the unpredictable bombardment from solar flares and coronal mass ejections, Earth often feels the effects of its stellar companions (Tsvetkov *et al*., 2018).

The sun goes through periodic variations (solar minimum and solar maximum) or cycles of high and low activity that repeat approximately every 11 years. Although cycles as short as 9 years and as long as 14 years have been observed. The Solar minimum refers to a period of several Earth years when the number of sunspots is lowest; solar maximum occurs in the years when sunspots are most numerous. During solar maximum, activity on the Sun and the effects of space weather on our terrestrial environment are high. At solar minimum, the sun may go many days with no sunspots visible. At maximum, there may be several hundred sunspots on any day (Schwenn, 2006).

Agriculture is a key activity of human being since it provides basic needs such as food, clothing and shelter (Tandzi& Shelton, 2009). A good understanding of dynamics involved in food production is critical for the improvement of food security. The world's population is expected to increase by 2 billion persons in the next 30 years, from 7.7 billion currently to 9.7 billion in 2050 (UN, 2019) and this will require an increase of about 70% in food production to meet the demand

(Tandzi&Shelton, 2009). *Extreme weather conditions could* have *significant* impacts on *crop* yields. An understanding of the effects of space weather events on agricultural produce is also vital for economic decision making and provides useful information for policy planners as well as government organizations.

Many researchers have used many methods to study the impact of space weather events on agricultural produce. In their study, the author in (Van *et al*., 2013) applied statistical model in carrying out study on global level of space weather scenarios to measure the effects of space weather events on agricultural region with diverse crops, using global grid-base and local point-based model. More, (Chen &Popovich, 2002) used geo-spatial cropmodeling at the 50 spatial resolutions to estimate the impact of weather extremes*event*(combined heat wave and *drought*) on maize yields across the USA. Results from these have been shown that weather extremes affect crop yield resulting to higher food prices and decreasing demand for industrial products. The biophysical analysis results suggest that the weather extremes*event* of 2012 that occurred in the USA increased food insecurity among poor communities where maize provides a substantial portion of daily calorie intake. Kindie*et al* (Kindie*et al*., 2014) used spatial bio-economic modeling toestimate the impact of an extended drought in China on foodsecurity in the nation. The studies highlighted the need toconsider trade effects in the economic analysis of extreme events. He concluded that the extreme weather event would have indirect secondary effects on food security in otherparts of the world where maize is a staple food. Also, Mechler*et al*. (2010) (Mechler*et al*., 2010), used a spatial bio-economic to quantifythe economic effect of a combined heat wave and drought inSpain. Their results revealed the need to consider trade effects in the economic analysis of space weather events which could have impacts on food security in Spain. More (Pustil'nik& Din, 2009), presented a conceptual model of possible modes for the 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 direct evidence of the causal connection between wheat price bursts and solar activity. Deepak et al. (Ray *et al*., 2012) used a global, high-resolution crop yield dataset which includes data of the top four global crops (maize, wheat, rice, soybeans) across ∼13 500 spatial units worldwide, spanning the years 1961–2008 to study the impacts of droughts and heat waves on yield anomalies of maize, soybeans, rice and spring wheat at the global scale using sub-national yield data and applying a machine-learning algorithm.The result suggests droughts and heat waves can lead to harvest failures and threaten the livelihoods of agricultural producers and the food security of communities worldwide. The research carried out by (Lesk& Corey, 2016) analyzed national agricultural production data from the United Nations' Food and Agriculture Organization for 16 different kinds of cereal in 177 countries. They also examined 2,800 international weather disasters from 1964 to 2007. They found that cereal harvests decreased due to both droughts and extreme heat, and production levels in North America, Europe and Australasia dropped by an average of 19.9 percent from droughts alone – roughly double the global average.Also, Steffen (2019) (Steffen *et al*., 2019) analyzed records that contained national food production of 16 different cereal crops in 177 countries. They compared space weather activities that occurred from 1964 to 2007. After evaluating their data, the team created a detailed snapshot of how space weather conditions affected global cereal harvests. (Trnka*et al*., 2007), studied the Effect of Estimated Daily Global Solar Radiation Data on the Results of Crop Growth Models. The research was conducted (i) at the eight individual sites in Austria and the Czech Republic where measured daily radius of gyration (RG) values with seven methods for RG estimation being tested, and (ii) for the agricultural areas of the Czech Republic using daily data from 52 weather stations, with five RG estimation methods. The RG values were estimated from the hours of sunshine using the Angstrom-Prescott formula. They concluded that even the use of methods based on hours of sunshine, which showed the lowest bias in RG estimates, led to a significant distortion of the key crop model outputs.

Despite the previous research done, the effect of space weather parameters such as solar wind and solar radio flux has not been well studied. It is for this reason that we analyzed space weather effects on agricultural produce using the VARs package in R-programming statistical software.

In this paper, we have modeled crop yield using space weather parameters and have compared the results with existing data to validate the model. The analyzed results were used to evaluate the effects of space weather parameters on agricultural produce and space weather was found to correlate with agricultural crop yields. It was found that extreme space weather conditions such as high-speed solar wind and high solar radio flux are responsible for decrease in crop yields.

AREA OF STUDY

Benue State is located along the lower River Benue basin in the middle belt region of Nigeria. The geographic coordinates of Benue State are 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. 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. 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. while 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. The vegetation of the State is typically that of the southern Guinea Savannah, characterized by sparse grasses and various species of trees.

Data

Yearly data of both Solar wind and solar radio flux were obtained from National Aeronautics and Space Administration (NASA, 2010) and Natural Resources Canada archive for a period of 2006-2016 respectively. In addition, cereal crop yield data cultivated for the period of 2006-2016 were obtained from Benue Agricultural and Rural Development Authority (BNARDA, 2007).

METHOD

The method used in this work is a theoretical method. Specifically, the Vector Autoregressive model (VAR) was used.

Vector Autoregressive (VAR) Model

VAR model is a Time Series multi-equation system. In this, model each variable has one equation (Olanrewaju, *et al*., 2015). The lagged values of each variable itself are all included. The model is used to capture the linear inter-dependencies among multiple time series. Vector Autoregressive (VAR) models generalize the univariateautoregressive model (AR model) by allowing for more than one evolving variable. In general, VAR encom-passes correlation information of the observed data and use this correlation information to forecast future movements or changes of the variable of interest (Hamilton &Susmelb, 1994). VAR model is one of the most successful and flexible models for the analysis of multivariate time series. The general form of Vector Autoregressive (VAR) model can be written as shown in equation (1) (Bernhard, &Kronbergim 2008):

$$y(t) = A_1 y(t-1) + e(t) \qquad (1)$$

Equation (1) in matrix notation is written as,

$$\begin{matrix} y_1(t) \\ y_2(t) \\ y_3(t) \\ \vdots \\ y_k(t) \end{matrix} = \begin{bmatrix} a_{11} & a_{12} & a_{13} & \cdots & a_{1k} \\ a_{21} & a_{22} & a_{23} & \cdots & a_{2k} \\ a_{31} & a_{32} & a_{33} & \cdots & a_{3k} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ a_{k1} & a_{k2} & a_{k3} & \cdots & a_{kk} \end{bmatrix} \begin{pmatrix} y_1(t-1) \\ y_2(t-1) \\ y_3(t-1) \\ \vdots \\ y_k(t-1) \end{pmatrix} + \begin{pmatrix} e_1(t) \\ e_1(t) \\ e_1(t) \\ \vdots \\ e_k(t) \end{pmatrix} \qquad (2)$$

where,

$$y(t-1) = \begin{pmatrix} y_1(t-1) \\ y_2(t-1) \\ y_3(t-1) \\ \vdots \\ y_k(t-1) \end{pmatrix}$$ = Vector of variables,

$$\begin{bmatrix} a_{11} & a_{12} & a_{13} & \cdots & a_{1k} \\ a_{21} & a_{22} & a_{23} & \cdots & a_{2k} \\ a_{31} & a_{32} & a_{33} & \cdots & a_{3k} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ a_{k1} & a_{k2} & a_{k3} & \cdots & a_{kk} \end{bmatrix} *$$

= Vector of coefficients of variables,

$$e(t) = \begin{pmatrix} e_1(t) \\ e_1(t) \\ e_1(t) \\ \vdots \\ e_k(t) \end{pmatrix}$$ Vector of residuals, t = 1, 2, 3 …k,

t= period (years).

There is thus one equation for each variable included in the model as dependent variable. All the equations have the same form and share the same right-hand side variables.

The VAR model was used to model the yields for the four crops each, one (Maize, Rice, Sorghum and Millet) at a time in relationship to two space weather parameters (solar wind and solar radio flux). For the sake of convenience, the following notations were used; $y_m(t)$ is the model yield for maize, $y_r(t)$, is the model yield for rice, $y_s(t)$ model yield for sorghum and $y_{mi}(t)$ model yield for millet respectively in equations (3)-(6):

$$y_m(t) = a_{11}y_m(t-1) + \cdots + a_{1k}y_m(t-k) + a_{51}y_{sw}(t-1) + \cdots + a_{5k}y_{sw}(t-k) + a_{6k}y_{srf}(t-1) + \cdots + a_{6k}y_{srf}(t-k) + e_m(t) \quad (3)$$

$$y_r(t) = a_{21}y_r(t-1) + \cdots + a_{2k}y_r(t-k) + a_{51}y_{sw}(t-1) + \cdots + a_{5k}y_{sw}(t-k) + a_{6k}y_{srf}(t-1) + \cdots + a_{6k}y_{srf}(t-k) + e_r(t) \quad (4)$$

$$y_s(t) = a_{31}y_s(t-1) + \cdots + a_{3k}y_s(t-k) + a_{51}y_{sw}(t-1) + \cdots + a_{5k}y_{sw}(t-k) + a_{6k}y_{srf}(t-1) + \cdots + a_{6k}y_{srf}(t-k) + e_s(t) \quad (5)$$

$$y_{mi}(t) = a_{41}y_{mi}(t-1) + \cdots + a_{4k}y_{mi}(t-k) + a_{51}y_{sw}(t-1) + \cdots + a_{5k}y_{sw}(t-k) + a_{6k}y_{srf}(t-1) + \cdots + a_{6k}y_{srf}(t-k) + e_{mi}(t) \quad (6)$$

$e_{m,}$, e_r , $e_{s,}\, and e_{mi\,,}$= symbolizes vector of residuals of Maize, Rice, Sorghum and Millet yield respectively. Also, t = period (years),y_{srf} andy_{sw} symbolizes solar radio flux and solar wind respectively as given in equations (3) – (6). All the four equations are lagged on the crop itself and the two space weather parameters (solar wind and solar radio flux) each (Bonett, 2008). The number of times each of the equations was lagged is an empirical matter and was only decided at the estimation stage of each of the models.

Method of Data Analysis

The data obtained for this study was analyzed using the VARs package in R-programming statistical software. The results obtained from this analysis is presented in Figures 1- 12.

Tests Analysis

In this study, both stationarity test and diagnostic test were employed to check the stationarity of the data for the analysis and model performance which are discussed below;

Stationarity Test

Stationarity is an important concept in time series analysis. The stationarity test is a property of time series which states that the value of the variable doesn't change with time that is, variation in time does not serve as a factor that brings changes in the value of a variable (Shay, 2019).

The stationarity test was conducted to know if the data was stationary or not. The Augmented Dickey-Fuller (ADF) test for unit root was employed to check stationarity. Unit roots are a cause for non-stationarity. The result of the Augmented Dickey-Fuller unit root test on the six variables considered in the model equation is presented in appendix 1. According to the stationarity test when p –values are less than 0.05 the variables were statistically significant and there was no unit root present in the original data, hence the series were stationary and suitable for the analysis. The result of this test is presented in Appendix 1.

The stationarity test was carried out using the VARs package in R-programming statistical software.

The model fitting procedure was continued and the VARSelect () in R programing was used in selecting an optimal lag-order for each of the four-crop model. The lag orders were determined using Akaike Information Criterion (AIC). AIC selected VAR (2) for Maize and Millet model while VAR (1) was selected for Rice and Sorghum, this is because both Millet and Maize model have the same minimum Akaike Information Criterion (AIC), while Rice and Sorghum model also has the same AIC (lag order selected must have minimum AIC value). However, the Akaike information criterion with the smallest criterion value evidences the most ideal lag length to employ. After selecting an appropriate lag order for all four models, the models were estimated including a constant term. The summary of each of the estimated coefficients of Maize, Rice, Sorghum and Millet model is presented in appendix 2, 3, 4 and 5 respectively.

The estimated coefficients of the models revealed that all lagged variables enter significantly into the equations of the VAR (2), VAR (1), VAR (1) and VAR (2) for Maize, Rice, Sorghum and millet respectively.

The Diagnostic Test

Diagnostic test are tests carried out on data which includes; the normality (Jarque-Bera normality) test and stationarity test to reveal model performance (Suniya, 2014). Normality is a condition in which the used variables follow the standard normal distribution. A normally distributed data set has a probability density (Suniya, 2014). The diagnostic test for all four crops revealed that the model performance was good.

The Jarque-Bera normality test on the model residuals each returned Chi-squared statistic of 2.8436, df = 6, p-value = 0.0364 for Maize VAR (2) model, 3.0215, df = 1, p-value = 0.04802 for Rice VAR (1) model, 2.1032, df = 1, p-value = 0.0014 for Sorghum VAR (1) model, and 1.9741, df = 2, p-value = 0.036802 for Millet VAR (2) model respectively. The test also revealed that the normal plots were neither negatively nor positively skewed and that the shape of the plot was platikurtic for the Maize and Sorghum models while a mesokurtic shape was returned for the Rice and Millet models respectively. The diagnostic check of all four models indicated that the residuals were completely random in nature and hence, confirming relatively good VAR (p) models. According to the diagnostic test when model residuals returned a very small chi-squared test statistic it means that observation data fits expected data extremely well. In other words, there is a relationship. A very large chi square test statistic means that the data does not fit very well. In order words, there is no relationship.The "critical"value of the chi-square statistic is 3.84. If the chi-square calculated is bigger than the critical value, then the data did not fit the model, which means you have to reject the null hypothesis (Johns *et al*., 1991). The diagnostic test was carried out using the VARs package in R-programming statistical software.

RESULTS AND DISCUSSION

Following a confirmation from the tests, data were fit into the model for all crops and the results are presented in Figures 1-4.

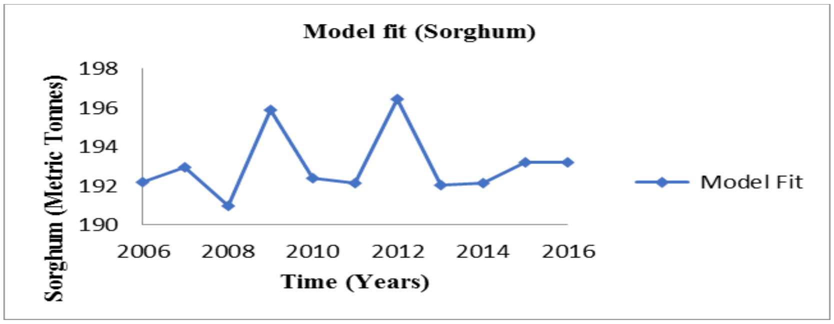

Figure 1: Graph of Model Result for Sorghum

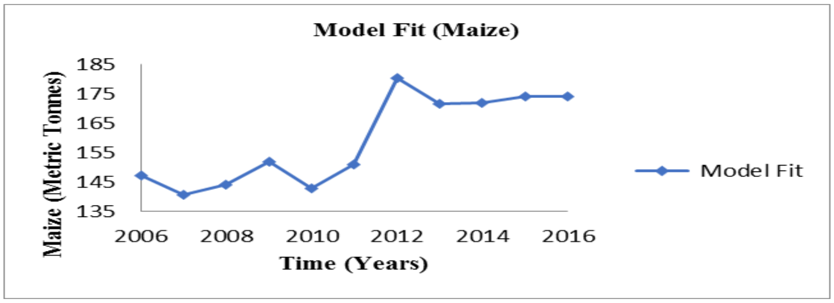

Figure 2: Graph of Model Result for Maize

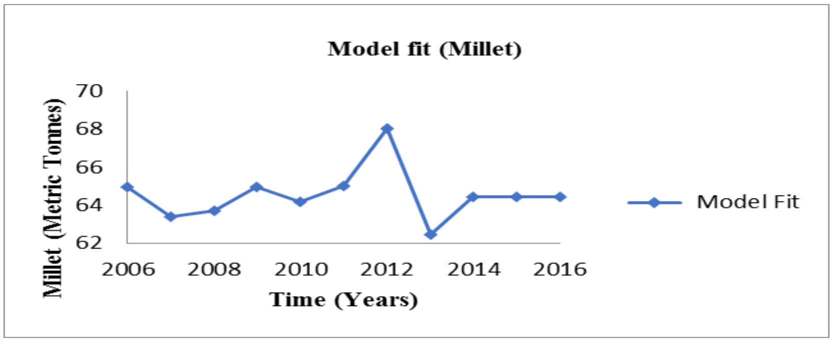

Figure 3: Graph of Model Result for Millet

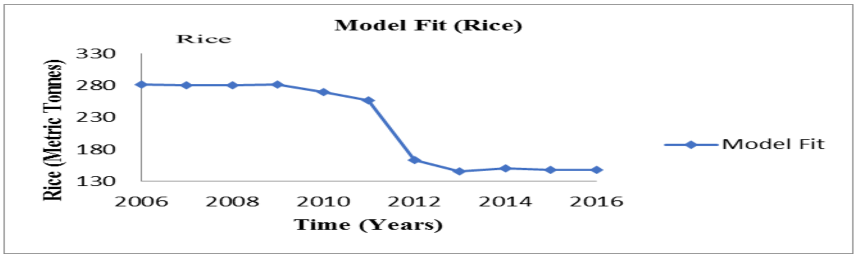

Figure 4: Graph of Model Result for Rice

The model results and observed yield data have been compared with space weather parameters, namely solar wind and solar radio presented in Figures 5 to 12.

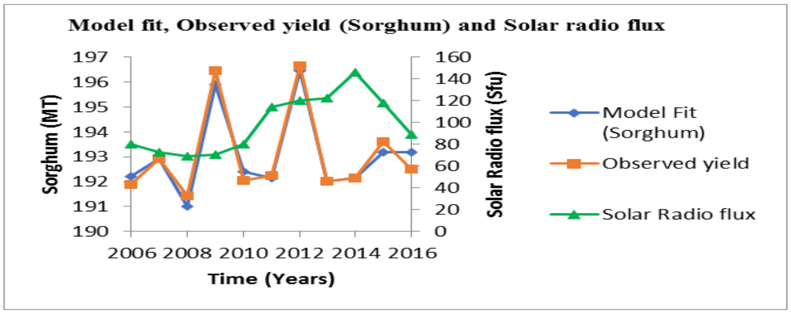

Figure 5: Model fit, Observed yield (Sorghum) and Solar Radio flux

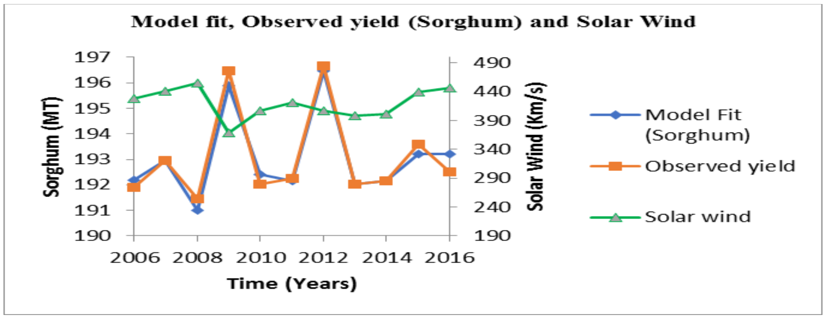

Figure 6: Model fit, Observed yield (Sorghum) and Solar Wind

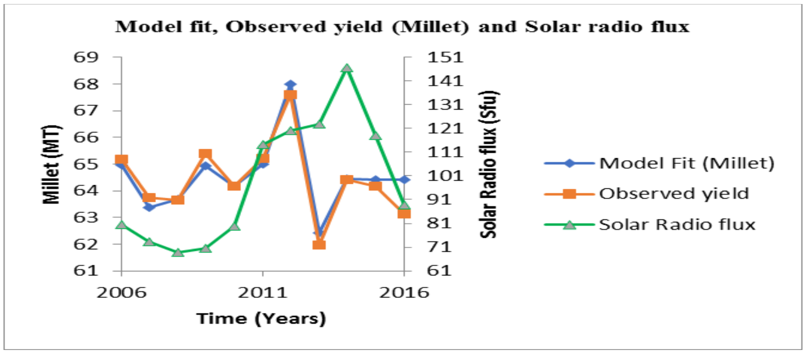

Figure 7: Model fit, Observed yield (Millet) and Solar Radio flux

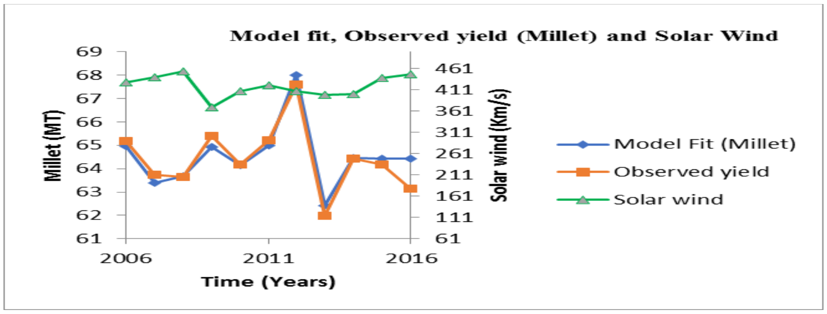

Figure 8: Model fit, Observed yield (Millet) and Solar Wind

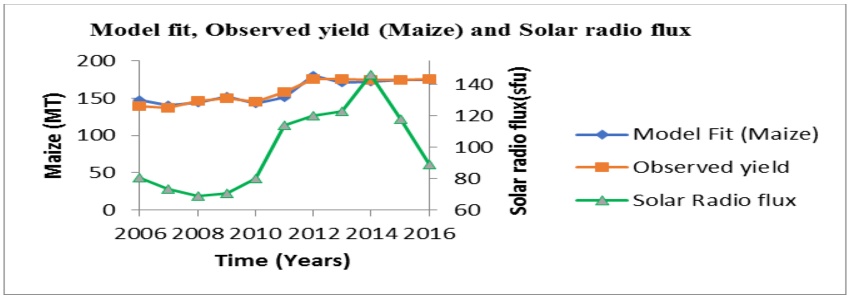

Figure 9: Model fit, Observed yield (Maize) and Solar Radio flux

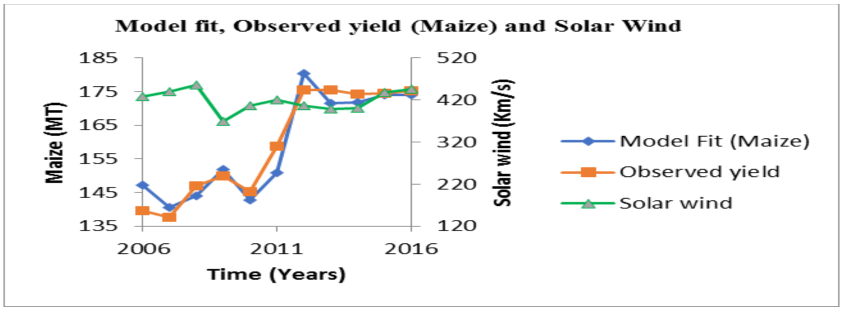

Figure 10: Model fit, Observed yield (Maize) and Solar Wind

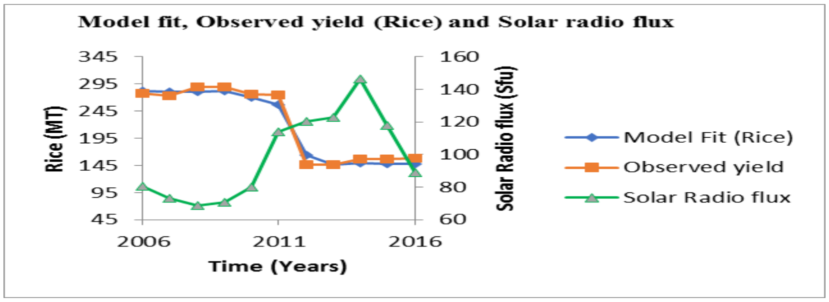

Figure 11: Model fit, Observed yield (Rice) and Solar Radio flux

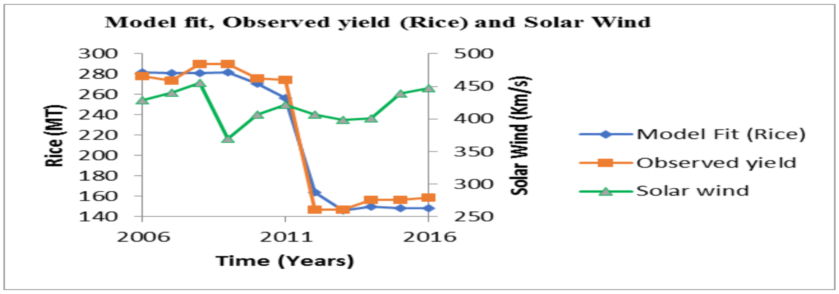

Figure 12: Model fit, Observed yield (Rice) and Solar Wind

Figure 1 shows the model fit for sorghum. It can be seen from the figure that the years 2008, 2010- 2011 and 2014 recorded low crop yield. This is due to high activities of the sun, during these years extreme conditions of the sun can give rise to extreme conditions that are not favorable to crops (Pustil'nik& Din, 2004). While the years 2009 and 2012 recorded the highest yield of Sorghum as shown on Figure 4.1 This suggests that low solar radio flux index and lower solar wind streams resulting from solar minimum conditions are more favorable to crops hence higher crop yield (Powell & Reinhard, 2016).

Figure 2 depicts the model fit for Maize. Low yields were recorded in years 2006, 2007 and 2008-2011. This can be attributed to the fact that sun's activity these years are very high giving rise to extreme conditions that are not be considered favorable to crops (Pustil'nik& Din, 2009). However, years 2012- 2016 recorded the highest yield of maize as shown in Figure 2. This suggests that the lower the solar wind streams and solar radio flux, the higher the crop yield and crops are favorable during solar minimum condition (Powell & Reinhard, 2016).

Figure 3 gives the model fit for Millet. Years 2007, 2008, 2010, 2013 and 2014- 2016 recorded low yield. This is ascribed to sun's activities at these years giving rise to extreme conditions that are unfavorable to crop yield. This means that extreme solar activities result to low crop yield (Powell & Reinhard, 2016).

The highest yield in millet was recorded in year 2012 in Figure 3. This showed that the lower the solar wind and solar radio flux the higher the crop yield (Pustil'nik, 2013).

Figure 4 shows the model fit for Rice. It can be seen that years 2012, 2013, and 2014- 2016 recorded low crop yield. This is due to high solar wind and solar radio flux. This suggests that the higher the solar wind streams and solar radio flux the lower the crop yield and vice-versa. However, in years 2006, 2007 and 2008-20011 recorded highest yield of Rice as shown in Figure 4. This implies that crops are favorable when solar wind streams and solar radio flux index are low (Pustil'nik, 2013).

To validate this model, the model results were compared with data and this is presented in Figures 5 to 12. The overall result showed a good agreement with data. For example, Figures (5) and (6) both model fit and data gave crop yield values for the years 2007 (192.9400 Metric Tonnes) 2009 (196.4600 Metric Tonnes), 2011 (192.2600 Metric Tonnes) and 2012 (196.6700 Metric Tonnes) for Sorghum, years 2008 (63.6600 Metric Tonnes), 2010 (64.1800 Metric Tonnes), 2011 (65.2200 Metric Tonnes) and 2014 (64.4300 Metric Tonnes) for Millet (Figures 7 and 8), years 2008 (146.9500 Metric Tonnes), 2009 (149.9400 Metric Tonnes), 2015 (174.4000 Metric Tonnes) and 2016 (175.3400 Metric Tonnes) for Maize (Figures 9 and 10) and years 2006 (277.7300 Metric Tonnes), 2009 (289.6600 Metric Tonnes) and 2013 (146.6800 Metric Tonnes) for Rice (Figures 11 and 12) respectively. In summary crop yield was found to decrease with increasing space weather parameters and vice-versa.

CONCLUSION

Space weather data was analyzed alongside crop data to understand the effects of space weather on crop produce. The analyzed results were used to evaluate the effects of space weather parameters on agricultural produce. Space weather was found to correlate with agricultural crop yields. It was found that extreme space weather conditions such as high-speed solar wind and high solar radio flux are responsible for decrease in crop yields. While periods with normal conditions such as low speed solar wind and low solar radio flux were found favorable to crops. For example, Sorghum in years 2009 (196.46 metric tonnes) and 2012 (196.67 metric tonnes), for Maize in years 2012 (175.38 metric tonnes) and 2013 (175.59 metric tonnes), for Millet in year 2012 (67.61 metric tonnes) and for Rice in years 2008 (289.72 metric tonnes) and 2009 (289.66 metric tonnes).

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