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Assessing the Suitability of the EPIC Crop Model for Use in the Study of Impacts of Climate Variability and Climate Change in West Africa

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ASSESSING THE SUITABILITY OF THE EPIC CROP MODEL FOR USE IN THE STUDY OF IMPACTS OF CLIMATE VARIABILITY AND CLIMATE CHANGE IN WEST AFRICA

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ABSTRACT

Scientists of the US Department of Agriculture developed the EPIC Crop Model for use in that country and it has been successfully applied in the study of erosion, water pollution, and crop growth and production. However, it is yet to be introduced for serious research purposes in other countries and other regions. This paper is designed to test the applicability of EPIC for the assessment of the potential impacts of climate variability and climate change on crop productivity in Sub-Saharan West Africa. Among the crops whose productivity has been successfully simulated with the crop model are five of West Africa's staple food crops: maize, millet, sorghum (guinea corn), rice, and cassava. Using the model, the sensitivities of maize, sorghum and millet to seasonal rainfall were demonstrated with coefficients of correlation significant at over 98 percent confidence limits. Validation tests based on a comparison of observed and model generated yields of rice and maize were conducted. In the case of maize, model simulated yields varied between 97 and 110 percent of observed yields. In the case of rice, model simulated yields varied between 109 and 117 percent of observed yields. 'Observed yields' in this context were the mean yields of several specified crop varieties in nationally coordinated experiments (trials). The main problems of validation are related to the multiplicity of crop varieties with contrasting performances under similar field conditions.

There are also the difficulties in appropriately representing, in the model, the microenvironments under which crops are produced in real life. Thus there is always some gap between observed and simulated yields resulting from data and/or model deficiencies. Attempts at closing the gaps between observations and predictions should be directed mainly at these deficiencies. Based on the results of the sensitivity and the validation tests, our conclusion is that the model could be satisfactorily employed in the assessment of impacts of, and adaptations to climate variability and climate change. The use of the model for estimation of production and for the assessment of vulnerabilities needs to be pursued in association with further field surveys and field experimentation.

Key Words: Crop Model; Climate Change, Climate Variability, Impacts, Adaptations, West Africa. .

INTRODUCTION

Crop growth simulation models are research tools usually applied in assessing the relationship between crop productivity and environmental factors. They have been shown to be efficient in determining the response of crop plants to changes in weather and climate. Examples of such models include EPIC (Williams et al, 1989), CERES (Ritchie et al, 1989), GAPS (Butler and Riha, 1989), SOYGRO (Jones et al, 1989) and IBSNAT (IBSNAT, 1989). In most cases these crop models have been developed in particular localities and they are not always applicable in other regions without modification. Therefore, when introducing such crop models into new regions, their applicability needs to be evaluated.

This paper is designed to assess the applicability of EPIC (Erosion Productivity Impact Calculator) Crop Model for use in the study of impacts of climate variability and climate change on crop productivity in Sub-Saharan West Africa. The effectiveness of EPIC as a research tool in West Africa will be determined largely by its capacity to simulate the sensitivity of the crop production systems to seasonal rainfall. This is because moisture is the main limiting factor on crop productivity in tropical ecological systems such as those characterizing West Africa. In the tropics, crop sensitivity to moisture is particularly keen during the stage of vegetative growth and also at the stage of grain infilling. In West Africa, as in the other parts of the low land tropics, the weather forecaster is seldom asked what the temperature will be, but everyone is greatly concerned about whether or not it is going to rain.

The data used for the study are for sites within Nigeria. What this implies, is that the country is being used as a case study for Sub-Saharan West Africa. The chief justification for this is that the country truly represents the climatic profile from the very wet to the semi-arid ends of the sub-continent. All the indicator vegetation types of the various climate types are present in the country. Thus, northwards from the very humid, eastern, coastal locations, to the drier margins, the vegetation profile includes Moist Evergreen Rain Forests, Dry Semi-Evergreen Rain Forests, Derived Savanna, Southern Guinea Savanna, Northern Guinea Savanna, Sudan Savanna, and Sahel Savanna. The crops used for the assessment include maize, rice, sorghum and millet. These are among the staple food crops of West Africa (Murdock, 1960) whose growths have already been simulated with EPIC.

Climate Change consequent upon increasing concentrations of greenhouse gases in the atmosphere is a topical contemporary environmental issue. The IPCC (Intergovernmental Panel on Climate Change) in its Third Assessment Report (IPCC, 2001a) has demonstrated that it is no longer in doubt that global climate changed significantly during the 20th Century, and that climate may continue to change more precipitously in the coming centuries. This change will continue irrespective of whether attempts at mitigation through implementation of the Kyoto Protocol to the UNFCCC (United Nations Framework Convention on Climate Change) are successful (IPCC, 2001). It had been concluded in the Second Assessment Report (IPCC, 1996) and reaffirmed in the Third Assessment Report that the magnitude and direction of change in the various climate elements will differ from one major region to the other. It was noted that climate change could be beneficial in certain regions and detrimental elsewhere. It was suggested that the less developed countries and regions are likely to experience the worst of the consequences of climate change partly because of negative changes in water availability in the tropical regions and partly because the communities concerned are poorly equipped to adapt. One of the sectors that will be exposed to the potential negative changes in climate is food production. It has therefore become imperative, while trying to roll back climate change through the implementation of the Kyoto Protocol, to formulate strategies for living with a changed global climate. Such strategies will require an understanding of the observed impacts of climate variability and the potential impacts of climate change.

ACQUISITION AND GENERAL FEATURES OF THE MODEL

The newest version of EPIC can be downloaded from www.tamu.edu at Blacklands Research Station (Temple). EPIC requires 446 items of input data; three hundred of which are the climatic characteristics of each modeled site. As downloaded from the web, the crop model comes with soil and climate data that could be used to create program files for any locality in the United States, including its associated islands. For example, soil files in EPIC format for about 900 soil series representing a great majority of soils characterizing every part of the USA are included in the downloaded package. Also included in the package are comprehensive climate data for more than six thousand weather stations. To load the climate data appropriate for any USA site only takes a few seconds. The first problem encountered in attempting to use EPIC for research in West Africa is that such data as are necessary for creating program files for experimental sites are not easily available. Where the primary data are available, weeks and sometimes months of computation are needed to convert them into the format required by EPIC. The first version of EPIC8120 as downloaded from the web could not respond when latitudinal locations were set at 15 degrees or less. We had to consult the originators of the model (Jimmy Williams of USDA Research Service) for trouble shooting the problem. While solving the problem it was admitted that they had limited experience in tropical environments and that the earlier versions might indeed have problems in areas outside the USA. Some modifications were made to the earlier versions that made them work. Versions subsequently downloaded did not have the latitude problem. We also had a problem simulating cassava growth, which was similarly attended to.

EPIC consists of a main data file created for each farm level site. The main data file incorporates program control codes, general site data, water erosion data, climate data, management information operations codes and management information operation variables. To run the model, three other files (daily weather, soil and operations schedule) are required. Each daily weather file gives details of weather including: rainfall, solar radiation, relative humidity, minimum and maximum temperature as well as wind speed. The daily weather file includes observed data when they are available. However, the model is capable of generating such data that are not available. Whenever the file is created for a specified ‘past’ period for example ‘1986’ observed data in respect of at least one parameter, must be used. Thus to simulate yield for 1986 growing season, the weather file for 1986, created with 1986 daily weather data, is fed into the model. To subsequently simulate yield for 1987, the 1986 file is withdrawn and replaced with another created for 1987. If, however, the simulation is for a future period, for example, 2010 to 2039, the model, based on projected climatic data, generates all the daily weather information required. The soil files provide details of the characteristics of the soil series found at the site. The ‘Operations Schedule’ files identify the specific crop or crops and include the details of farm operations such as timing, density of planting, tillage, type and amounts of fertilizer and pesticides applied, potential heat units, among others.

APPLICATION OF THE MODEL

There are five different ways in which EPIC Crop Model could be employed. These include:

- Estimation of crop productivity, that is, the yield of the crop per unit area of land planted to it;
- Estimation of total crop production within a given land area or territory;
- Assessment of the impacts of climate variability and climate change on crop yields and crop production (*impact* is defined as the change observed in the form or function of a biophysical or human system as a result of a change in the environment);
- Assessment of the vulnerability of crop production systems to climate variability and climate change (vulnerability is the probability that a human or a biophysical system falls into a state of disaster as a result of environmental changes);
- Assessment of adaptation options and strategies for managing the negative impacts of climate variability and climate change.

Crop productivity is the economic yield usually expressed as tons per hectare. It can be estimated for any unit area, starting from plots less than one hectare, and going up to local government areas, states within a country, nation states and major world regions. Yield is a measure of performance of the crop plant, enhanced by favorable environmental factors and reduced by constraining factors. Yield or productivity is the basic input for the computation of production and the assessments of impacts, vulnerabilities and adaptation options. For a crop model to be useful in estimating productivity, model yields need to be credible substitutes for observed yields.

Crop production is simply the total amount of seed, grain or tuber produced in specified areal units. For large regions, production figures represent the sum of farm outputs from all the farm units within them. As in the case of productivity, model performance is rated according to the closeness of model output to observed yields. In other words, yields per hectare from model output multiplied by area harvested must yield results close to the production figures as observed on individual farm plots and aggregated for each geographical region as a whole.

Impact is the change observed in the form or function of a biophysical or human system as a result of a change in the environment. Impact is measured as the difference between the situation before and after the environmental change occurred. In the specific case of the impact of climate change or variability on crop production, the impact is the difference between observed yield before and after the change or variation in climate occurs. The crop model allows us to hold constant all crop environment factors while changing the climatic factor. To simulate the yield of a crop for a given year, the daily weather file for that year is used. This file is withdrawn and replaced in order to simulate the yield of another year. Thus any change (in the yield) from one run of the model for a given year to another run for the succeeding year could be logically ascribed to the change in climate from the first to the second year.

Vulnerability expresses the probability that a human or a biophysical system falls into a state of disaster as a result of environmental changes. In this study, the system of interest is staple food crop production while the environmental change of concern relates to climate. The threshold to disaster is estimated as the point in the changing environment at which crop failure occurs. Crop failure could be defined in various ways. In one definition, the crop does not grow to produce any seed, grain or tuber and therefore no harvesting takes place. In another definition the crop grows to maturity but the value of the output in the form of grain, seed or tuber is as low as not to be worth the cost of harvesting. However, in our main research, we have adopted the technique of cost-benefit analysis. With this technique, the crop is assumed to have failed where the value of the farm output is less than the total costs of production. In this case vulnerability to climate variability is the probability that the value of the crop produced each year is less than the costs of production. If over a thirty-year period, the value of the crop produced is less than the costs of production in six years, then the vulnerability (probability) is expressed by an index of '0.2'.

Adaptations are the adjustments, which have to be made to crop production systems in order to live successfully with a changed climate. The probable adaptive responses are not new. They include farm level practices such as: change of planting dates, adoption of water conservation practices, change to early maturing varieties to mitigate shortened growing season, change to drought tolerant crop varieties, and change to high yielding crop varieties to take advantage of unusually favorable weather. Other adaptation strategies include: application of irrigation and adoption of multiple cropping to take advantage of longer growing seasons. Policy makers require an assessment of the benefits derivable from the adoption of the various adaptation options. Computation of such benefits would require knowledge of the pre- and the post-adoption yields in addition to the costs of the adaptation itself. In addition, a comparison of the net benefits derivable from the various adaptation options would be useful in making the choice among potential adaptation options. Some of the potential options cannot be integrated into EPIC. In such cases the crop model cannot be effectively employed in the assessment. However, in cases involving farm practices, such as irrigation, change of planting dates, crop substitution, multiple cropping, application of fertilizers, which can be incorporated into EPIC, the model could be extremely useful in assessing adaptation options.

To be able to successfully estimate production, the model must be able to accurately predict observed yields. In assessing vulnerability, the model must be capable of accurately estimating yields corresponding to various annual weather patterns and specifically the yields for the year when the climate is at a threshold between crop success or crop failure. Success in the assessments of impacts and adaptations does not depend on the accuracy of yield predictions as much as it depends on the extent to which the differences between pre impact (adaptation) and post impact (adaptation) yields are reflected. In other words, what is needed for the assessment of impacts of climate variability is the difference between pre- and post- impact productivity and production. Even if there are disparities between observed and simulated yields, the simulated differences could still truthfully reflect the observed differences in magnitude. Also in the assessment of adaptation options, it is the differences between pre- and post- adoption yields and production that are taken into account. In other words, model performance could be adjudged satisfactory once the model truthfully indicated such differences, not necessarily the actual productivity or production.

MODEL TESTING

For application in our area of study, a two-stage approach was adopted to evaluate EPIC. The first stage consisted of sensitivity analysis, while the second stage consisted of validation. In sensitivity analysis, changes in model output following changes in environmental factors were evaluated. The environmental changes introduced into the model may be arbitrary or may consist of real world observations. The evaluation will show whether model output is justified by the changes in the environmental factors. For example, application of fertilizer is expected to result in increased yields. Sensitivity is confirmed and model performance rated high when the model is successfully employed to demonstrate this. In other words, sensitivity analysis helps to determine whether the crop model could be used to test an *a-priori hypothesis*. Validation represents a more rigorous test of model performance involving the comparison of real world observations with the results of model outputs achieved with conditions similar to those prevailing at the time the real world observations were made. Attempts to create more accurate and realistic data files and thereby close the gaps between observations and predictions are usually described as model calibration. In this context, calibration should be conceived as any modification that could be effected to reduce the gaps between observed and predicted yields. Calibration is a continuing exercise requiring contributions from users especially in places other than where the model originated.

SENSITIVITY ANALYSIS

It is necessary to always bear in mind that the sensitivity tests are conducted on the model, not on the real world crop production systems. It is hardly in doubt that the real world systems are sensitive to changes in weather. The hypotheses in the current exercise are about whether the model could replicate the sensitivity of the real world systems. In conducting the sensitivity tests, archival weather data could be used where they are available. But they will not be available where the focus is on climate change, in which case artificial data is acceptable. Because of uncertainties associated with predicting climate change, researchers commonly use climate scenarios to estimate how climate affects a system (in this case agricultural production). "Scenarios derived from GCMs and arbitrary sensitive tests (e.g., +2^{o} C and +4^{o} C temperature changes, +/- 10% precipitation change) are recommended to estimate potential future changes in yield and other agronomically important variables." (U.S Country Studies Program, Version 1.0 p5-3). In the assessment of the impacts of climate variability, we used archival daily rainfall data, which are available for over 600 stations, more than 90 percent of which are limited in their observations to a single climatic element. For the study of the impacts of climate change in our main study (not reported here), we constructed scenarios with GCM (General Circulation Model) generated data for the respective time slices of 1961-90, 2010-2039, 2040-2069 and 2070-2099. For each of these time slices a different main EPIC file is created. Thus, even though all the daily weather data are model generated, they differ from one time slice to another since each set is based on the climate of the respective time slices.

Seasonal Rainfall

To test sensitivity to seasonal rainfall in the current exercise, we adopted climate and weather records for Maiduguri in the Sahel Zone in Nigeria. The main data file was created with the means of the records from 1961 to 1995. For the daily weather files, we employed the daily rainfall data for 1988 to 1999. The crops were: rice, millet, sorghum and maize. In our simulation exercises, the crops were planted on June 1, each year, and harvested on August 30. June 1 is the date of the climatic 'onset' of the rainy season and is the more likely date, in the calendar, for the farmers to plant their crops. The usual practice is for farmers to wait for the first heavy downpours before planting their crops. Further delay stands the risk of crop failure resulting from abrupt termination of the rainy season later in the year. Moreover, as the rainy season progresses, less solar radiation reaches the surface resulting in a reduction of both vegetative and reproductive growth, and therefore a decrease in yield. We opted to simulate for early-maturing varieties of the various crops as they have become popular with the local farmers in recent years. For example, some maize varieties mature after 120 days from planting while others mature within 90 days. The most recently introduced varieties in Nigeria belong to the latter group, which is usually described as "early maturing". It could be noted that while the weather records used were real world records, the model outputs were not real world outputs because at this stage our interests were not validation, but sensitivity. The outputs of the EPIC runs are depicted in Table 1. Also in the table are: the total rainfall for the first month, the first two months, the three months from sowing to harvesting, and the number of rain days.

The driest year with respect to the total for the three growing season months and the first two months was 1994. It was also the year with the lowest yield for the four crops modeled. The year with the next lowest yield for the four crops after1994 was 1992. It is also the year with the lowest June-July rainfall, that is, the first two months after planting. At the other end of the moisture regime, the wettest year, 1999, leads the other years in the yields of maize, sorghum and pearl millet. The year, 1999, came third among ten years in the simulated yield of rice. Table 2 depicts the sensitivity of the simulated yields of the various crops to rainfall parameters in terms of correlation coefficients. The sensitivities of simulated yields of maize, sorghum and millet to the rainfall of the first two months after planting are demonstrated with values of r significant at 99 percent confidence level. The corresponding values of r for the relationships with the total rainfall from planting to harvesting are significant at 98 percent confidence limits.

However, it is not only with respect to rainfall that EPIC Crop Model could be used to demonstrate sensitivity. In the following paragraphs, we demonstrate the sensitivities of model-simulated yields to temperature, radiation and carbon dioxide concentration, using incremental scenarios in anticipation of their use in climate change impact analysis. In this regard, we are following the suggestions of the U.S. Country Study, Version 1.0, on page 4.11, that "incremental changes in temperature and precipitation should be combined with the baseline climate data to create incremental scenarios".

Temperature

One way of testing model sensitivity to temperature is to increase artificially the minimum and maximum temperature for each of the growing season months. In Table 3, yield for the baseline situation as well as for three scenarios of increased temperature are depicted. The results indicate an increase in EPIC-simulated yield corresponding to the increases in temperature. The optimum temperature for the model maize variety as given in the parameter table is 25^{o} C. August minimum temperature at Ibadan, the experimental site, is lower than the optimum for maize. Thus there could be room for increased temperature to promote increased yield of maize before the cardinal maximum temperature begins to constrain yield. It is therefore conceivable that, an initial increase in temperature will bring about an increase in yield. However as temperature rises to higher levels, a decrease in yield may set in. But before then, there will be a stage during which the increases in yield will slow down. Table 3 seems to have captured this stage. Thus, as depicted in the table, "increases in yield seem to be decreasing with increasing temperature". We interpreted this observation "as evidence of model sensitivity to the upper limits of the range of temperature tolerance" In Southern Nigeria, the rainy season is the cooler part of the year. Temperature does not follow the sun but varies in response to cloud cover.

Solar Radiation
Solar radiation is the primary determinant of biomass yield from which the other yields are derived. One would therefore expect economic yields of crops to be related to the amount of incident solar radiation. Consideration of model sensitivity to this factor is called for when attempting to adapt a model developed for temperate latitude environment to a tropical region. Day length is longer in the temperate latitude than in the tropics during the growing season. However, the quantum of radiation received could be higher in the tropical environment than in the temperate latitude as a result of a higher angle of incidence. In the particular case of West Africa, the intensity of solar radiation depends more on the amount of cloud cover than on the angle of incidence of sunlight. Climate change projections by the various Global Climate Models for West Africa are for a higher level of solar radiation as a consequence of lower levels of cloud cover. Decreases in cloud cover with respect to the 1961-90 mean are projected to continue to the end of the 21st Century. (IPCC, 2001b)

Table 4 depicts the pattern of response of maize to different levels of solar radiation, according to EPIC simulations at a site corresponding to the weather station in Jos, north central Nigeria. The increases in solar radiation were introduced into EPIC while retaining the values of the other climatic parameters at the levels of the 1961-95 means. The resulting increases in yield were continuous, regular and considerable, more or less at the same percentage levels as the increases in solar radiation. It could be recalled that potential yield is determined in EPIC primarily by the amount of solar radiation received. The other climatic determining factors of yield play constraining roles, reducing potential to actual economic yields. This conforms to our observations in an earlier study to the effect that lower amounts of solar radiation characterizing the main growing season months in Nigeria tend to depress the yield of maize (Adejuwon, 2002). Maize planted in April, at the onset of the rainy season, when cloud cover was relatively low, produced significantly higher yields than maize planted in May or June, when the rainy season was well under way. It is therefore not surprising as depicted in the table, that there were increases in yield in response to increases in solar radiation. It is conceivable that the levels of solar radiation at the experiment site, during the growing season for the 1961-90 period, were sub-optimal for maize production. If changes in climate, as the 21st century progresses, turn out to be as they are currently being projected (IPCC, 2001b), West Africa may experience substantial increases in the yields of cereal crops, not as a result of increases in moisture supply or temperature, but in response to higher levels of solar radiation.

Carbon dioxide
Carbon dioxide and water are the main feedstocks for the processes of primary production, that is, photosynthesis, upon which life on the earth's surface ultimately depends. Carbon dioxide

input into photosynthesis comes from the atmosphere. One would expect an enhanced level of carbon dioxide concentration in the atmosphere to increase the gradient between the external air and the air spaces inside the leaves, thus promoting higher levels of diffusive transfer and absorption of CO_2 into the chloroplasts and higher levels of photosynthesis and of biological productivity. Higher concentrations of atmospheric carbon dioxide should also induce plants to be more economical in the use of water. Thus with higher concentrations of carbon dioxide, crops should be less subject to water stress in areas normally considered marginal with respect to precipitation. The sensitivity of maize to changes in the atmospheric concentration of carbon dioxide as depicted in Table 5 confirmed this. The location used is Jos in Central Nigeria. For each trial, the crop was planted on the first of June during a year with very high growing season rainfall. The 20-ppm change in CO_2 concentration (from 350 ppm to 370 ppm) resulted in yield increases of 80 kg/ha, while the much greater 150-ppm change in CO_2 concentration (from 500 ppm to 650 ppm) resulted in further yield increases of only 36 kg/ha. The model, in these results, confirmed the progressively smaller response of maize to higher carbon dioxide concentrations. This should be expected because maize is a *C4 plant* (Fischer et al., 1996).

VALIDATION

Once the crop model is adjudged capable of demonstrating sensitivity of the crop plant to climate variability and climate change, the next exercise in testing the model is validation. Validation seeks to establish the reliability of the outputs as possible substitutes for observed data in estimating production and assessing vulnerability. In the process of validation, observed yields of crops are compared with the model outputs for the same crop, the same sites and the same period. Ideally, for the model outputs to be considered reliable for the stated objectives, model outputs must be reasonably close to the observed yields.

Validation using the results of the 1986 Maize trial Experiments
Single field level data on yield are not available in Nigeria except on the research sites of the Agricultural Research institutes. Table 6 depicts the grain yields in tons/ha of early maturing, open pollinated maize varieties in the 1986 nationally coordinated trials in Nigeria, under the auspices of the International Institute for Tropical Agriculture (IITA, 1986a). The 15 varieties included in the table, consisted of cultivars either being used or being developed for adoption in the country. Observed yields in respect of the varieties were presented from row 3 to 17. In row 18 we gave the average yield of the varieties per location, while in row 19 we depicted the coefficients of variation. The latter is an expression of the standard deviation as a percentage of the mean yield of the varieties. In row 20, we entered the yield simulated by EPIC. In the last row we depicted the yield simulated by EPIC as a percentage of the mean yield of the varieties. The coefficients of variation among the yields of the 15 maize varieties fall between 8 and 17 percent. More important for validation purposes is the fact that yields simulated by EPIC fall between 97 and 110 percent of the mean yield of the varieties used in the trials. In other words, and it can be observed from the table, simulated yields in all locations fall within the bands set by the highest and the lowest observed variety yields. Except for the Kano station, there is virtually no difference between observed yields of the 8322-13 variety and the outputs from EPIC simulations. Also the observed yields of 8321-21, 8595-2, 8505-3, and 8322-13 varieties were generally closer to the outputs of model simulations than the mean yield of the varieties.

Although our immediate interests are in the differences between observed and simulated yields, it could be observed that there were substantial differences between the yields recorded at the various sites. Variation in yield from site to site was probably a result of differences in the amounts of solar radiation received. The amounts of solar radiation received are usually higher in the northern parts of the country than in the south (Davies, 1965). Following this, higher yields are recorded for northern than for southern stations. For example, the average yield for Benin, the most southerly location is 3.5 tons per hectare compared with 5.9 tons per hectare for Kano which is the most northerly location.

Validation with the results of the 1986 Rice Trial Experiments
In Table 7 we present the results of the 1986 nationally coordinated upland rice trials involving six varieties (IITA, 1986b). There is much contrast in yield among the varieties. In Ibadan, yields vary from 0.8 tons per hectare to 3 tons per hectare. Average yield is 1.72 t/ha; standard deviation is 0.84, while the coefficient of variation is 49 percent. At Ikenne (close to Lagos), coefficient of variation is 17 percent while the average is 1.38 tons. At Onne (near Port Hacourt), yields vary between 1.18 tons /ha and 3.07 tons /ha with a coefficient of variation of 27 percent. In all the stations, model simulated yields are higher than the mean observed yields. However, model simulated yields still fall between 109 and 117 percent of the means of the observed yields. At Ikene, model yield is higher than each of the observed variety yields whereas at Onne and Ibadan, model yields are respectively higher than one and two out of the six observed variety yields. Comparing observed and simulated yields at individual levels shows that the observed yields of variety Tox 1854 – 208 – 12 – 101 are consistently closer to the model simulated yields.

CALIBRATION

Notwithstanding the observations in the preceding paragraph, there will always be some disparity between observed and simulated yields resulting from model or data deficiencies. Attempts to close the gaps between observations and model predictions should therefore start with ensuring that the model truthfully reflects the determining environmental factors, the farm operational schedules as well as the forms and the functions of the crop plants.

Climatic Records:
For example, the type of climatic records required to run EPIC is kept at very few locations. Therefore models, in the best of circumstances are constructed with climate data gathered some distance away from the desired sites. With a land area of 923,000 square kilometers, there are fewer than 30 synoptic weather stations in Nigeria where the full complement of the data needed are observed. The usual practice is to adopt the data for the nearest weather station, which, in some cases could be more than 50 km from the experimental site. More realistic data could be provided through statistical or GIS-based interpolation. This procedure assumes minimum influence of topography. Using Arc View Spatial Analyst Extension, it is now possible to procure data through interpolation for unit areas as small as 1 km squared. Among the techniques commonly used in interpolating climate data are: IDWA (Inverse Distance Weighting Averaging); splinting and krigging (Hartkamp et al, 1999). However, all of these will involve another set of computationally demanding exercises.

Soil
At a given locality, there are several soil types, each with a different capacity to support crop growth. The choice of the appropriate soil type may be the only requirement to close the gaps between observed and simulated yields. In Table 8 we demonstrated the considerable differences in simulated yields that could result from the choice of soil at three locations: Ibadan, Benin and Jos. We used 1986 weather data for the simulations.

The three soil types used for the Ibadan site belong respectively to *Iwo* series, *Osun* series and *Apomu* series. *Iwo* is described as clayey, while *Osun* is poorly drained and *Apomu* is sandy. The clayey soils are usually rated higher in fertility status than either the sandy or the poorly drained soils. The respective yields of 3.739, 3.049, and 1.689 tonnes per hectare therefore conform to expectations. Because the planting date was April 1, at the beginning of the rainy season, poor drainage proved to be less of a constraint than anticipated. Hence the relatively high yield was recorded for *Osun* series. The lesson that could be learnt from these results is that the choice of appropriate soils is very crucial to ensuring minimum disparity between observed and simulated yields.

Crop Variety
Crop characteristics, however, cannot be fully truthfully reflected in the model for the simple reason that the model usually comes with a crop file that includes a single, unidentified variety, whereas there are tens and in many cases, hundreds of varieties of the same crop in real life situations. Some of the varieties bear distinguishing characteristics, while most of them cannot be separately identified either on the basis of form or function. However, planted with the same operations schedule and under the same environmental conditions, each variety is capable of vastly different levels of yield. Where the objective of the study includes estimation of production, field surveys are necessary to provide necessary ratios between observed yield of each variety and model simulated yields.

Three varieties of maize came with one of the EPIC8120 versions. These were used to run the model for a number of locations in Nigeria. The results are presented in Table 9. Planting dates at each location were selected to avoid the earlier parts of the rainy season when there could be inadequate rainfall. For all the stations in the forest belt, maize was planted on the 1st of April, and for the sites in the drier areas, planting took place on the 1st of June. It could be observed that EPIC recognized the different maize varieties as indicated in the significant differences in their yields. Average yield varied from 2.4 tons per hectare for M1, to 0.3 tonnes per hectare for M2 and 1.2 tons per hectare for M3. These results also suggest that each crop variety needs to be separately modeled. The disparities in yield could also be interpreted to mean that M1 is adapted to the environment in Nigeria while M2 and M3 are not. Thus while attempting to bridge the gap between observed and simulated yield, attempts should be made to ensure that the crop parameters in the model truthfully represent the actual cultivars in the field.

The authors of the model are only favorably disposed to users making changes to the program control codes, information operating codes and crop parameters on the basis of rigorous experiments. At the same time they have left two ends, accessible to users, in the forms of choices of PHU (potential heat units) and potential evapo-transpiration equations, which might be adopted to reduce the gaps between observed and simulated yields.

EPIC comes with five ET equations from which the user of EPIC has to make a single choice for a simulation exercise. The equations include: Penman-Monteith, Penman, Prietley-Taylor, Hargreaves and Baier-Robertson. For the same location, choice of potential ET equation could result in significant differences in yield. To demonstrate the relationship between yield of maize and the choice of ET equations, we adopted yields of maize observed in an agricultural experimental station, Ilora for 1996, 1997 and 1998 crop growing seasons. We then proceeded to conduct five EPIC runs, adjusting the data file to make use of Penmann-Monteith's, Penman's, Priestley-Taylor's, Hargraves' and Baier-Robertson's equations respectively. The results depicted in Table 10, show that simulations run with Penman-Monteith equation are nearest to the observed yields. One might be tempted to conclude from the results that Penman-Monteith's equation is the most appropriate to be used in simulating yields of the two particular maize varieties, specifically at Ilora. However, the appropriateness of the particular equation needs to be confirmed by field measurements of evapotranspiration or soil water extraction at the site.

Another parameter, which controls the magnitude of model yield, is potential heat units (PHU). Subtracting a crop specific base temperature from the average daily temperature derives the heat units. Whenever the average temperature is higher than the base temperature, heat units accumulate. In real life situations, phenological development of the crop is based on daily heat unit accumulation. Thus there should be a given amount of heat units required for the various stages of development and maturity of a given crop or crop variety. EPIC defines each crop by assigning values to about 50 crop parameters. However while the values for the other crop parameters were set and input in the crop parameter file, not to be tampered with by the user, that of the PHU is made to float within the Operations Schedule file, and adjusted for the proper cultivar or crop variety for a location. The choice of PHU is thus left to the user while creating an OPS (operations schedule) file. For example, in the USA, experiments conducted at various sites indicated that the PHU required for maturity by corn varies between 1000 and 2,900 (Williams et al, 1989: 506). Several varieties were involved but the emphasis was on site and geography. In situations where the crop variety is unknown or anonymous, one could reduce the gap between simulated and observed yields by adjusting the PHU in the Operations Schedule File, (Easterling et al, 1996). At the same time one would have provided phenological definition to the unknown cultivar. In Table 11, we attempted to demonstrate the relationship between observed yields of maize at Ilora, and the simulated yields corresponding to various values of PHU as adjusted in the 'Operations Schedule' file. These results show that simulated yields are closest to observed yields when PHU is set at 1000 and farthest when it is set at 1800. Our interpretation of the results is that they have helped to define the particular crop variety planted at Ilora. There in no doubt that such a definition will help increase the capacity of the model to predict crop yields. While some varieties require heat units as high as 2000 units, others need less than 1100 units.

CONCLUSIONS AND POTENTIAL MODEL PERFORMANCE

In conclusion, there is little doubt; that EPIC could be used to simulate the sensitivity of maize, sorghum and millet to seasonal rainfall. The model could therefore be satisfactorily employed in the assessment of impacts of and adaptations to climate variability and climate change, not only in site specific, but also in spatial analytic studies. The sensitivity capabilities are in giving measures of significance to the relationships between environmental factors and crop yield. Such measures could then be translated into indices or measures of impact.

The validation tests show that differences in yield among the cultivars used in the trials are generally greater than the average difference between the yield of each real world cultivar and the model simulated yield for each site. The inference that could be readily made from this result is that simulated yields and observed yields are sufficiently close for the former to be used as a substitute for the latter. However with respect to production estimates and vulnerability assessments with spatial analytical objectives, there is need for calibration based on more rigorous field experimentation. There is also need for improvement in the amount and quality of available data. It is possible that there are other crop models more suitable for crop-climate studies in the sub continent. This possibility should be explored. Meanwhile EPIC could be depended upon for impact and adaptation assessments and, subject to further field experimentation, for the estimation of production.

With the limitations expressed in the preceding paragraph, the paper confirms the potential suitability of the EPIC Crop Model for use in the study of the impacts of climate variability and climate change on crop growth in Nigeria. These observations are based on the fact that the data used in model testing have been collected at locations within the territorial limits of the country. The modeled sites (Fig 1) cover the climatic and ecological profiles from the coastal rainforest zone, though the sub-humid savanna and the semi arid Sudan and Sahel zones, to the southern margins of the Sahara Desert. These zones extend westwards to cover the entire West African sub-continent. They are also replicated in all the major regions of Sub-Saharan tropical Africa excepting the high altitude locations in East Africa. The Guineo-Congolian Rain Forests extend from coastal West Africa to the basin of the Congo River. The extensive Miombo (*Brachystergia*) woodlands of East and Central Africa are the ecological and floristic equivalents of the West African *Isoberlinia* woodlands. The Sahel and Sudan zones of West Africa also have ecological equivalents at the borders of the Kalahari Desert. Although not with the same intensity, the range of cultivation of West African crops extends to Central Africa. EPIC could thus be adjudged suitable for modeling crop growth not only in Nigeria, but also throughout lowland, tropical, Sub-Saharan Africa.

EPIC is credited with the capability to simulate the growth of many crops with the same data file. This represents an advantage over other crop models in simulating the productivity of tropical agricultural systems in which multi- and inter- cropping rather than mono- cropping is dominant. Thus the same run of the model could result in outputs including yields of both early and late crops, both major and minor crops, both heliophytic (light loving) and sciophytic (shade loving) crops, or both creeping and climbing crops. EPIC also provides for simultaneous modeling of changes in crop environment including those like moisture and nutrients, which constitute constraints on productivity of tropical agricultural systems

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Table 1: Sensitivity of simulated crop yield to rainfall in Maiduguri, Nigeria

	Rainfall Parameters				Simulated Yield of Crops in tons/ha			
Year	Jun-Jul-Aug Rain	Jun Rain	Jun-Jul Rain	Number of Rain Days	Maize	Sorghum	Millet	Rice
1988	516	87	270	39	2.808	2.294	0.775	0.790
1989	422	88	202	31	2.574	2.301	0.688	0.957
1990	367	47	230	26	2.430	2.134	0.654	0.842
1991	385	90	181	32	2.503	2.184	0.709	0.945
1992	450	41	154	35	1.706	1.493	0.427	0.685
1993	373	19	223	24	2.184	2.011	0.559	0.870
1994	285	50	117	33	1.339	1.204	0.353	0.526
1996	431	58	254	35	2.209	1.989	0.607	0.824
1998	461	60	239	32	2.992	2.504	0.836	0.888
1999	554	24	368	38	3.483	2.789	1.006	0.929

Table 2: Correlation of Rainfall parameters with Simulated crop yield based on Table 1

Rain parameters	Maize	Sorghum	Millet	Rice
Growing period rain	0.7759*	0.7121*	0.7633*	0.4560
First Month rain	0.0948	0.1144	0.1084	0.2029
First two months rain	0.8696**	0.8445**	0.8666**	0.5831+
No of rain days	0.2622	0.1420	0.3095	0.1655

** *r* is significant at 99 percent confidence level

* *r* is significant at 98 percent confidence level

+ *r* is significant at 90 percent confidence level

Table 3: Sensitivity of maize to temperature changes in Ibadan, Western Nigeria

Temperature changes	Yield tonnes/ha	Increase in Yiel tons/ha	Percentage Increase
A	2.607	---	---
B	3.998	1.391	53.3
C	4.384	0.386	9.6
D	4.865	0.481	9.7

A = mean min and mean max temp 1970 – 1999
B = A max temp plus 1^{o}C; A min temp plus 2^{o}C
C = A max temp plus 2^{o}C, A min temp plus 2^{o}C
D = A max temp plus 2^{o}C, A min temp plus 3^{o}C

Table 4: Sensitivity of maize to different levels of solar radiation in Jos, Nigeria

Solar radiation levels	Yield Tones/ha	Increase in yield	% Increase
A=mean 1961-99	2.607	-	-
B=A plus 5 percent	2.759	0.152	5.8
C=B plus 5 percent	2.904	0.145	5.2
D=C plus 5 percent	3.062	0.158	5.4

Table 5: Sensitivity of maize to different levels of CO_2 concentration in Jos, Nigeria

	Yield tonnes/ha	Increase over baseline Yield	Percentage increase over baseline Yield
350 ppm	2.607	----	----
370 ppm	2.687	0.08	3.06
500 ppm	2.835	0.228	8.71
650 ppm	2.871	0.264	10.1

Table 6 Grain Yield (tons/ha) of early maturing open-pollinated maize varieties in the 1986 Nationally Coordinated maize trial at locations in Nigeria {IITA Maize Research Programme 1986}

Stations-→	Benin	Ibadan	Makurdi	Kano	Mokwa
Varieties					
8321-18	4.4	6.4	4.5	8.0	4.9
8321-21	3.7	5.6	4.9	6.8	6.8
8595-2	3.8	5.2	4.2	7.0	5.1
8505-3	3.5	5.2	4.6	7.0	5.4
8346-3	3.0	5.1	4.7	5.1	5.4
8322-13	3.9	5.1	4.6	6.4	5.2
8428-19	3.3	4.9	5.5	6.6	4.8
8505-9	3.0	4.4	4.4	5.8	5.6
TZB Gusau	3.5	3.9	5.3	5.3	4.2
8505-1	3.6	5.2	4.9	5.1	4.4
8338-1	3.3	4.2	4.8	5.4	4.7
8505-5	3.4	4.8	4.3	6.0	5.1
8326-18	3.7	3.8	4.3	4.8	4.5
EV8443SR	3.8	4.4	4.5	5.7	4.1
FE27WSR	3.0	4.0	4.1	4.2	4.1
Mean	3.5	4.8	4.6	5.9	5.0
Coeff var	11	15	8	17	14
EPIC	3.8	5.3	4.7	5.6	5.1
EPIC/Mean %	107	110	102	97	.102

Table 7 Grain Yield (tons/ha) of upland rice varieties at three locations during 1986 wet season (IITA Rice Research Program; Annual Report 1986)

Locations	IBADAN	IKENNE	ONNE
Varieties			
Tox 955-212-2-102	3	1.4	3.07
Tox 1854-02-2-2	2.17	1.61	2.48
Tox 955-208-12-101	1.87	1.55	2.53
ITA 235 (check)	0.81	1.29	2.46
ITA 257 (check)	0.8	0.97	1.18
OS6 (check)	1.69	1.48	2.17
Standard Deviation	0.84	0.23	0.62
Mean	1.72	1.38	2.31
Coefficient of Var	49	17	27
EPIC	1.889	1.621	2.518
Epic/Mean			
%	110	117	109

Table 8 Variations in EPIC simulated yields on different soils at the same location.

Location	Parent rock	Soil Series	Soil main features	Yield/ha in tonnes
Ibadan	Igneous	Iwo	Clayey	3.739
Ibadan	Igneous	Apomu	Sandy	1.689
Ibadan	Igneous	Osun	Poorly drained	3.047
Benin	Sedimentary	Alagba	Clayey	5.906
Benin	Sedimentary	Agege	Clayey	4.011
Benin	Sedimentary	Kulfo	Sandy	3.306
Jos	Lava	Gwacl	Clayey	5.205
Jos	Lava	Gwasd	Sandy	4.070

Table 9: Differences in EPIC simulated yields between varieties of maize

Locations	Varieties of Maize Yields in tons/ha					
	Variety M1	Variety M2	Variety M3	Mean Yield	Stdev.	Coeff of variation (%)
Ibadan	1.72	0.04	0.06	0.60	0.99	160
Benin	1.38	0.04	0.05	0.49	0.77	157
Lagos	0.86	0.02	0.03	0.30	0.48	160
Ilorin	1.87	0.26	0.97	1.03	0.81	78
Lokoja	6.47	1.67	6.46	4.87	2.77	58
Enugu	3.00	0.48	1.84	1.77	1.26	71
Calabar	6.67	1.62	6.39	4.89	2.84	58
P.H	3.15	0.36	1.35	1.62	1.41	87
Maiduguri	0.76	0.03	0.07	0.28	0.41	141
Bauchi	1.75	0.07	0.18	0.66	0.94	140
Jos	2.47	0.06	0.09	0.87	1.38	159
Kano	0.97	0.04	0.11	0.37	0.52	140
Kaduna	2.11	0.07	0.11.	0.78	1.17	150
Sokoto	0.93	0,03	0.06	0.34	0.51	150
Minna	2.12	0.07	0.17	0.78	1.16	150

Coefficient of Variation is Standard Deviation divided by the Mean

Table 10: Yields based on different evapotranspiration equations

	OBSERVED YIELDS Varieties of maize		CROP MODEL OUTPUTS (Varying ET Equations)				
Year	Dmr.lsr.y	Suwan.1.sr	PenmanM	Penman	PriestleyT	Hargraves	BaierR
1996	1.569	1.440	1.734	2.176	2.607	2.651	2.778
1997	1.022	1.246	1.549	1.870	2.314	1.697	2.184
1998	1.220	1.397	1.559	1.842	2.245	2.530	2.990

Table 11: Yields based on different levels of 'Potential Heat Units'

	OBSERVED YIELDS (Varieties)		CROP MODEL OUTPUTS (Varying potential heat units)				
Year	Dmr.lsr.y	Suwan.1.sr	1000	1200	1500	1800	2000
1996	1.569	1.440	1.491	1.734	1.965	2.069	1.885
1997	1.022	1.246	1.391	1.549	1.706	1.983	1.821
1998	1.220	1.397	1.260	1.559	1.824	2.159	1.018