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Regression Models in Forecasting Crop Yield under Climate Change Scenarios

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Abstract:
This paper reviews documented regression models applied in simulating the future crop yields under uncertain climatic futures across different parts of the world. The paper also evaluates the appropriateness of regression models in forecasting wheat yields under different climate change scenarios in Kenya. Crop Yield in this case is considered as the final recorded harvest while climate change scenarios as Global Circulation Model (GCM) climate change scenarios based on Intergovernmental Panel on Climate Change (IPCC) approved modeled data. Even though linear regression models appear to dominate literature relating to climate-crop simulations, other forms of regression too have been used in different parts of the world and are appropriate for use in wheat yield prediction in Kenya given different projected future climates. The choices of regression model depend on the nature and number of climatic variables factored in the model for extrapolation of the grain yield. Further, for reliable results, regression models require evaluation in-terms of time, applicability under varied surface physiognomies of an area, and statistical strength to affirm their efficacy in specific studies.

Keywords: *Climate change scenarios, regression models, crop yield, simulation*

1. Introduction

Agricultural production is directly dependent on weather, which together with soil, determines the conditions for plant growth (FAO, 2015). Most literature suggests that the sector will be strongly affected by climate change while the extent of these effects varies by country and region (Mandelson *et al.,* 1994). Wheat is one of the most widely grown crops globally; cropped in approximately one sixth of the total world's arable land (Satorre & Slafer, 1999), thus its production response to changing climates would have a pronounced effect on global food security. In Kenya, the crop is ranked second in importance after maize (KARI, 1989). The process of crop production requires several considerations ranging from physical to management aspects. Among the physical factors, climate is perceived to be one of the most influential in the life cycle of crops. Temperature and precipitation are deemed more important in determining growth processes and final grain yield (Calderini *et al.*, 2001). With sustained rise in global surface temperatures, crop yields will be negatively affected. This is because, for example, a crop such as wheat is a cool season crop and increasing temperature shortens its growth period by accelerating phenological development (You *et al.,* 2005; Asseng *et al.,* 2011).

2. Climate Change Scenarios

Climate change is currently one of the most threating global environmental hazards. From the onset of industrial revolution in mid-17th Century, the world has experienced a sustained increase in greenhouse gas accumulation in the atmosphere. This has consequently led to the gradual rise in earth surface temperatures and accompanying effects on climatic regimes. Scientists have through time attempted to counter this through technological changes backed by policy structures that are binding to majority of world economies. Among the main technological advances is the use of models to predict the future levels of key greenhouse gas accumulation in the atmosphere and suggestions on how such gases can be lowered comparative to a set base period. Since 1992, different institutions and modelers have constructed climate change/greenhouse gas emission scenarios, based on demographics, energy consumption and economic projections of the future world, and calibrated estimates of key climatic parameters based on forecasted emission levels - referred to as Emission Scenarios.

In its Third Assessment Report (TAR3), Working Group II (WG2) of the IPCC explain scenarios as coherent, internally consistent, and plausible description of a possible future state of the world commonly used in climate change impact, adaptation, and vulnerability assessments to provide alternative views of future conditions considered likely to influence a given system or activity (IPCC, 2007). In the year 2014, the IPCC released the Representative Concentration Pathway (RCP) scenarios and accompanying data that were used in IPCC's Fifth Assessment Report (IPCC, 2014). This had been preceded by IS92 data released in 1992, and Special Report on Scenario Emissions (SRES) released in the year 2000.

IPCC also makes the data available to different sectoral experts for use in assessment of how the sectors would respond to future climatic changes; consumption of which is mainly synthesized through regional downscaling and input into prediction models. Examples of such applications is in The Fourth Assessment Report (AR4) of IPCC (2007), in which model estimates project an average global surface temperature increase of between 1.1^{0}C and 5.4 °C for the period 2001 to 2100 as would be triggered by the estimated varying trends in future fossil-fuel emissions (IPCC, 2007).

Regionally, Climate model simulations under a range of possible emissions scenarios suggest that for Africa, and in all seasons, the median temperature increase lies between 3°C and 4°C, roughly 1.5 times the global mean response (Christensen *et al.,* 2007). In main wheat growing regions such as Northern Europe, annual precipitation amount is very likely to increase across most parts while a decrease is expected in the Mediterranean basin (Christensen *et al.,* 2007). Africa as a continent has been warming through the 20th century at the rate of about 0.05°C per decade with slightly larger warming in the June-November seasons than in December-May (Nkomo *et al.,* 2016), indicating an existence of seasonal variation within the larger temporal climatic changes in the continent. In its Fifth Assessment Report (AR5), IPCC (2014) points towards a more worrying warming trend with a near-term (2016 - 2035) projected Global Mean Surface Temperature anomaly in the range of 0.3^{0}C to 0.7^{0}C at medium confidence. Tropical Africa and East Africa is expected to experience an increase in rainfall for the period running to 2100, with the frequency of extremely wet seasons projected to range between 9% and 24% in June-July-August and December-January-February respectively (Nkomo *et al.,* 2016). Across Kenya, under SRES emission scenarios of A2, A1B1 and B1, a rise in precipitation is simulated to a tune of between +5% to 48% by 2090s relative to 1970 – 1999 base period (McSweeney *et al.,* 2010). In the same period averages for the four SRES scenarios indicate projected rise in median temperatures of 1.15^{0}C by 2030s, 2.15^{0}C by 2060s and 3.07^{0}C by 2090s, all against 1970 – 1999 base period (McSweeney *et al.,* 2010). The two climate parameters are greatly important in agriculture and alterations in normal trend will highly likely affect the farming. In the Kenya's initial National Communication, it is reported that the two extreme climate events that would adversely impact on the agricultural sector are drought, which would result in crop water stress and hence yield reduction, and flooding resulting in water logging in both Arid and Semi-Arid Lands (ASALs) and high potential areas (UNEP & GOK, 2000).

3. Statistical Models in Crop Yield Forecasting

Plant models are calibrated to show how different crops respond to changes in physical and human factors that influence their performance. Crop growth models try to capture the relationship between the physiological processes within the plant and its environment. Steduto & Albrizio (2007) identifies three types of crop growth engines as: carbon-driven, water-driven and solar-driven. By simulating these processes, usually on set time steps, crop growth and development can be appraised and crop performance at harvest too can be forecasted. Similarly, crop simulation models are effective in climate change risk assessment and projecting yield as they produce faster survey results thus lowering the risk of adverse crop losses by enhancing risk detection thereby triggering swift intervention (Aparicio *et al.,* 2002). FAO (2015) classifies crop growth models into process-based models and empirical (statistical) models. Plant process-based models are simulation models that attempt to represent the key processes governing crop growth and yield formation (Lobell & Asseng, 2017). Such models operate on diurnal time step by calculating the dynamics of different soil and plant properties. In as much as process models have been used in several yield predictive applications, they have been frequently faulted in climate change studies and impact assessment in that they were not originally designed for such a purpose, and thus may be missing key processes related to extreme climate conditions (White *et al.,* 2011).

The second category are the *statistical models* that utilize recorded climatic data and plant yields to construct models that functionally relate the two and can as well be used to simulate future yields given fluxes in predictor parameters. *Regression statistical analysis* in particular is a predictive modeling technique which explores the connection between a predictor(s) and dependent variable(s). This technique is used for future likelihoods, time series modeling, finding the cause-effect relationship between/among the variables as well as the magnitude of the relationship. To achieve these in agriculture, regression models factor in historical crop and climate data in simulating future crop performance given changes in climatic conditions over time. Further, in order to make yield extrapolations if hypothesized to be a function of climate change, then data on projected future climatic constraints are run in models as the predictor variable. Among the common types of regression models are: Linear Regression, Logistic Regression, Polynomial Regression, Stepwise Regression and Ridge Regression (some represented in their basic/simple forms in equation 1- 4). Just like process-based models, statistical crop models have the advantage of generally being able to quantify the effects of changes in mean and variability of temperature and precipitation on crops with reasonable accuracy (Holzkämper *et al.,* 2013). Secondly, they are easier to work with since their validation and assessments do not need field and management data and are more suitable for larger spatio-temporal scale studies (Lobell & Burke, 2010). Regression models' main short coming is their difficulty in making extrapolations beyond historical extremes (Wenjiao *et al.,* 2013).

- Simple Linear Regression model: $Y_i = \beta_0 + \beta_1 X_1 + \mathcal{E}$ *(Eq. 1)*
- Multiple Linear Regression Model: $Yi = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots \beta_n X_n + \mathcal{E}$ *(Eq. 2)*
- Where: Y_i is the dependent variable, β_0 is the intercept, β_1, β_2 *and* β_n are the slope coefficients, X_1, X_2 and X_n are predictor variables while $\mathcal{E}$ is the random error term.
- Polynomial Regression: $Y = \beta_0 + \beta_1 X + \beta_2 X^2 + \beta_3 X^3 + \ldots .\beta_n X^n + \mathcal{E}$ *(Eq. 3)*
- Where y is the dependent variable and the betas are the coefficients for different nth powers of the independent variable x starting from 0 to n.
- Logistic Regression: $In\left(\frac{p}{(1-p)}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 \ldots \ldots + \beta_k X_k$ (Eq. 4)

Where ρ is the target variable, β_0 is the intercept, $\beta_1, \beta_2, \beta_k$ are coefficients, while X_1 and X_2, X_k are independent variables.

In agriculture, statistical models use historical data of growth at different stages, and final crop yield and climatic/weather parameters as input to construct regression equations. Wenjiao *et al.* (2013) identifies three main statistical methods applied in agro-climatology as time-series models, cross-section models and panel models. The output equations form models that are run over different spaces and at different times with relevant input adjustments for yield prediction. Vegetation change is affected by precipitation, temperature, and recurrent droughts, which can be the impacts of climate change and global warming (Brdar *et al.,* 2006), though temperature is singled out as the most important environmental factor affecting grain filling and grain weight (Brdar *et al*., 2006). At the global scale, studies on potential effects of climate change on both rain-fed and irrigated wheat have reported reduction of yield by 10%-40% and 20%-50%, respectively (Parry *et al*., 2004). In its Fifth Assessment Report (AR5), IPCC (2014) reported that model runs under A1F1 emission scenarios projects that maize cropped on higher altitude areas are the only cereal crop expected to yield positively across Africa (Niang *et al,* 2014); implying a high likelihood of an overall negative effect of climate change on yields of major cereal crops across the continent.

4. Discussion

Regression models have been used in extrapolation of yields of both cereals and non-cereal crops with varying results reported from crop to crop, and from region to region. In their studies across Uganda, Sabitii *et al.* (2018) used non-linear regression model to assess the impact of future changes in temperature on banana growth and concluded that there will be higher likelihood of banana suitability production across the country under RCP 2.6, RCP 6.0 and SRES A1B as compared to RCP 4.5, RCP 8.5 and SRES A2 which they observed will likely retard banana performance to the end of 21st Century. Sitienei *et al.* (2017) used a multiple linear model to predict tea yield using temperature and precipitation data and observed a weak response of tea yield to changes in climatic parameters. On cereal crops, Martin *et al.* (2000) reported a high correlation between maize water-stress time series and the ENSO indices in South Africa and Zimbabwe using linear regression techniques in forecasting seasonal maize yield. Details showed the study split in which a 4-month lead yielded a hindcast correlation of 0.67 over 17 seasons (1961–78) and a forecast correlation of 0.69 over 16 seasons from 1978 to 94 (Martin *et al.,* 2000). In this case the study applied the same technique in testing model performance through hindcasting. The limitation of such application of time series data on linear regression model is that it may over-fit in cases where randomness is assumed in the climate data. Mansouri *et al.* (2015) simulated future wheat yield under climate change in carbon dioxide enrichment and technological advancement in Iran's Azerbaijan region for three future time periods (2020, 2050 and 2080) compared to 2011 base year under SRES A2 and SRES B2 emission scenarios. They applied linear regression models to establish the relationship between wheat yield and historical year to investigate historical development effects in which a slope of the fitted regression between adjusted yield and time for East and West Azarbaijan were 0.065 and 0.084, respectively (Mansouri *et al.,* 2015).

Regression techniques have also been used to test the model fit of other crop simulation approaches. In predicting the effect of temperature and precipitation changes on maize yields simulated with CropSyst (a process-based model) under four climate change scenarios in Switzerland, Holzkämper *et al*. (2012) fitted multiple regression models using the forward and backward stepwise regression procedure on different sample sizes to explore the minimum data requirements for predicting the effect of different synthetic climate scenarios. Kumar *et al*. (2019) on their part recognizes stepwise regression procedures as essential in reducing data redundancy by eliminating independent variables with low impact on the predicted factor. Apart from predictor data reduction, step-up stepwise regression was also applied in Burkina Faso to building-up relevant variables (Nana, 2019).

Many interactions between weather and climate are non-linear (Semenov & Porter, 1994) calling for techniques that curve-fits trends by maximally reducing the squares of the residual errors - of which polynomial regression endeavors to accomplish well. Mathew-Penannen (2018) regressed multivariable fractional polynomials to model the nonlinear pattern of relationships between RCPs 2.6, 4.5, 8.5 data and other environmental parameters in assessing the potential changes in yields of cotton, maize, soybeans, and spring and winter wheat in Central United States of America. It is also practical to probabilistically determine the chances of yield performing above or below a set threshold by applying *Logistic Regression* method, a technique that factors-in binary or categorical independent data in qualitative/quantitative forecasting. This is mainly used in spatial determinations to map out shifts in crop availability as influenced by environmental factors over time. In their determination of rapeseed suitability under future RCP emission scenarios in Europe, Jaime *et al*. (2018) produced four maps - representing the combinations of two years (2050 and 2080) under two greenhouse gas emission scenarios (RCP4.5 and RCP8.5) - after summing five threshold projections to obtain an ensemble map with pixel values ranging from 0 to 5 according to the number of GCMs that predict the presence of the species within particular localities.

Regression techniques provide a wide range of methods depending on space, time and the number of variables. *Panel Regression* that works by pooling data across space/sites and over different times into a single model equation has been used to establish the relationship between yield and predictor variables especially over large areas. Its robustness in predicting yield response to temperature has been confirmed (Lobell, 2010) and (Nana, 2019). To estimate the potential impact of a 1°C increase in wheat growing season temperature all over China, You *et al.* (2009) regressed panel datasets over the period 1979–2000, returning results which pointed to a reduction in wheat yields by about 3–10%. Choudhury & Jones (2014) applied univariate time series methods to predict maize yield using seventeen years of data while conducting analyses separately to individual district for the five districts of Ghana. Such variation in yields for every site over time however can still be analyzed as pooled data under a single model run using Panel Regression tool (Lobell, 2010). After using panel data in Burkina Faso, Nana (2019) showed precipitation as having a significant and positive effect on the production of maize, millet and sorghum and a not significant but negative influence on the production of rice. He quantifies the results by considering a 1% increase in precipitation yielding 0.8%, 0.53% and 0.43%, in an increase in maize, millet and sorghum production respectively (Nana, 2019).

Ridge Regression Models are a prominent choice in studies where independent variables exhibit multicollinearity or when they exceed the number of observations. In predicting grain yield of different genotypes under three different water regimes using spectral reflectance data sets at anthesis or grain filling, Hermandez *et al*. (2015) confirmed the suitability of the technique to predict grain yield among different genotypes in high and low-yield environments after their experiment in which ridge regression generated model explained between 77% and 91% of yield variability in the three water regimes and phenological stages. Shastry *et al.* (2017) trained six regression models (linear, polynomial, quadratic, pure quadratics, interactions and Generalized Linear Regression Model) on experimental data of maize, wheat and cotton to predict their yields in India. Using R^2, Root Means Squared Error (RMSE) and Mean Percentage Prediction Error (MPPE), their result demonstrated that Generalized Linear Regression Model with highest R^2 and lowest RMSE and MPPE better predicts wheat yield than the rest of the models.

5. Conclusion

Regression tools are variedly used in simulating future reaction of crops to climatic variations and changes. Limited studies linking crop and climate change have been conducted in Kenya while the existing literature too is on maize while ignoring other cereal crops such as rice, beans, wheat etc. In reported studies, regression tools have been widely used in forecasting cereals yield in different parts of the world and can be a promising tool in predicting wheat yield under different climatic scenarios in Kenya as well. Given relief and other environmental diversity of the country as well as variations in yields over different localities and for different cultivars, it is appropriate to choose a regression tool (such as panel regression) that pools different site and different time data together in order to achieve higher robustness. The existence of diversities also present numerous numbers of physical predictor variables some of which may be redundant thereby requiring elimination through stepwise regression. However, in cases where multiple data are obligatory to be factored in making a prediction, establishing the relative hierarchy of importance of predictor data is recommended to avoid bias. For example, biases and multicollinearity issues are better addressed by running a ridge regression as compared to simple least square regression techniques. Where non-linearity in variables is expected, then polynomial regression appropriately applies for better curve fitting in constructing yield projection model.

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