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Linking Climate Change, Pollinators and Cereal Yields in Kenya

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Abstract

Climate change episodes are increasingly complicating resource use, access and management in the majority of the developing countries. Parasitic weeds and crop diseases are hurting annual cereal yields. Application of agrochemicals to contain locusts, birds and insects that destroy produce have the propensity to kill pollinators such as bees. Essentially, pollinators play a critical role in ensuring ecological sustainability and food security. The study uses long-term historical data (1961 and 2017) to link climate change, pollinators and cereal yields in Kenya on a multivariate model. The findings revealed that a unit increase in the amount of rainfall will result in a proportionate increase in cereal yields but a unit increase in temperature will lead to varied increases in cereal yields. The findings also revealed that bees played a critical role in the pollination of maize, wheat and beans but not rice. It is recommended that future studies should consider monthly or quarterly climate data in determining future impacts of climate change and pollinators on cereal yields.

Subject Areas

Economics

Keywords

Bees, Temperature, Food Security, Farmers

1. Introduction

Nearly three decades after the formation of the United Nations Framework Convention on Climate Change (UNFCCC) in 1992 with the central aim of addressing climate change, progress has been made in containing the global challenge. Despite the progress, the climate change phenomena continue to escalate and are man's major threat multiplier, mainly in developing countries (Watts *et al.*, 2018) [1]. Climate change and variability have continued to complicate resource use, access and management (Ogada, Nyangena & Yesuf, 2010) [2]. In Kenya, scarcity of resources to meaningfully adapt and mitigate to the anticipated and unanticipated climate-related challenges has complicated cereal yields.

The recent wave of invasive locusts in 2019/2020 destroyed rangelands, led to exacerbation of climate change related crop diseases, intensified human-animal conflicts, and spread of opportunistic weeds that hurt quality and quantity of livestock, fisheries and crop yields (Yanda & Mubaya, 2011) [3]. This complicated the future of food security in the country. For instance, parasitic weed, *Cuscuta japonica* which is mainly dispersed by agricultural tools and machinery, wind, flooding, cattle and humans, relies on monocotyledonous and dicotyledonous plant families for survival. The weed is climate resilient and hurts crop yields (*see* Gaudet, 1977 [4]; Heide-Jørgensen, 2010 [5]; Jones, 2018 [6]; Kogan & Lanini, 2005 [7]; Nadler-Hassar & Rubin, 2003 [8]).

Bees are the major pollinators and play a critical role in ensuring ecological sustainability and food security. Worryingly though, efforts to contain destructive swarms of locusts by aerial spraying are also killing important communities of pollinators. Reliable lines of evidence suggest that the mean annual rainfall and temperature will continue to escalate and that this will be characterized by catastrophic environmental, health and economic risks (Cuni-Sanchez *et al.*, 2018 [9]; Kabubo-Mariara & Kabara, 2018 [10]; Nyangena *et al.*, 2019 [11]). According to the Food Security Information Network [NSIF] (2018) [12], climate-related risks are the main cause of food insecurity among 23 countries out of the 51 that were considered in a 2017 World Food Programme (WFP) survey.

If farmers know in time that it will not rain during a given planting season, they can adjust their planting dates and avoid losses. However, unreliable weather information impels them to count loses (ACRE Africa, 2019 [13]; KNAP, 2016 [14]; Slegers, 2008 [15]). Subsistence households, as Kabubo-Mariara and Kabara (2015) [16] have gleaned, lack proper planning mechanisms and inability to manage available natural resources, which are the main source of income, thereby, weakening households' resilience to climate-induced risks.

Certainly, the influence of climate change on maize production in Kenya has been explored (e.g. Hansen & Indeje, 2004 [17]; Mati, 2000 [18]; Bozzola, Smale & Di-Falco, 2018 [19]). However, explorations into how cereal crops like maize, beans, rice and wheat differ in their responses to the varying mean air temperature, rainfall and pollinators are erratic. An empirical understanding of this relationship, which the study sought to explore, is important in informing policy and enabling the country to feed her population, now and in the future.

Structure of the Paper

The rest of the paper is organised as follows: Section two presents the literature review, Section three details the methodology—under which the empirical model is specified. Section four provides data and variables used in the study while Section five presents the results and discussion. Section six details conclusions and recommendations. At the tail-end, authors' declaration of no conflict of interest is provided.

2. Literature Review

Various lines of literature reveal that climate change and variability is a problem with direct and indirect ramifications on agriculture (e.g. Kabubo-Mariara & Kabara, 2018 [10]; Ogada *et al.*, 2010 [2]; Yanda & Mubaya, 2011 [3]). However, due to differences in the physiology of monocots and dicots, it is probable that climate change affects different cereal crops differentially or as much as the effect is in the same direction, the magnitude is likely to be different. Varying mean air temperatures are likely to determine the presence or lack of pathogenicity of microbes in the rhizosphere as well as the PH level of the soil (Singh *et al.*, 2018 [20]).

It is projected that continued manifestation of climate change will add nearly 600 million people to the 815 million people that are chronically undernourished and worsen water accessibility for 1.8 billion people by 2080 (Kabubo-Mariara & Mulwa, 2019 [21]; World Health Organization [WHO], 2018 [22]). To overcome the challenge, Kabubo-Mariara and Mulwa (2019) [21] have observed that adoption of improved cereal crop varieties, diversification of crops and livestock alongside the improvement of water-harvesting technologies are among the most needed strategies that are needed most. Although their findings revealed that the mean air temperature and rainfall influenced food production, they assert that timing, soil and household characteristics are critical in determining the accretion or digression of yields. However, the duo did not hypothesize that the physiology of the cereal type can influence quantity of yields. Nonetheless, the study failed to account for the role of pollinators in crop production.

Across the globe, Wuebbles, Chitkara and Matheny (2014) [23] have detailed that the economic value of crop pollination is at €153 billion, annually. However, the trio warns that climate change threatens the pollination services derived, especially if temperature in the tropics will continue to escalate. They reveal that apiculture leverages on 11 out of the possible 30,000 bee species. The presence of climate change and biotic stress (as well as agrochemical use), could impel farmers to look for alternative pollinators.

A micro-perspective on the viability of adaption to climate change as a driver for food security reveals that adaptation increases food security and that if households affected by the harsh effects of climate change would adapt, a lot would be gained and losses minimized. Interventions that can provide farmers with extension services and access to finance, will enable farmers to overcome constraining household characteristics and incentivize their uptake of the tested adaptation options (Di-Falco, Veronesi & Yesuf, 2011) [24]. Di-Falco *et al.*, (2011) used a simultaneous equations model in their estimation but relied on interpolation to create spatial datasets [24]. Although spatial data interpolation is a novel statistical innovation to manipulate rainfall and temperature data, they claim that deterministic interpolation is a widely used technique. They assert that deterministic interpolation is credible, a claim that Bloschl and Grayson (2001) [25] strongly refute.

Bloschl and Grayson (2001) observe that interpolation as a technique involves data filtering and change of scale [25]. They have warned that, if due diligence is not observed, interpolation as a technique can be counter-productive. They further warn that the deterministic interpolation that is considered robust, is not explicit enough to account for measurement and estimation error. Whereas this observation does not undermine the findings by Di-Falco *et al.* (2011) [24], it is a pointer that climate data is stochastic and indeterminate.

Estimating stochastic data may not be feasible without worrying about margins of errors (Bloschl & Grayson, 2001) [25]. Most studies have amply used the Ricardian model (*see* De-Salvo, Raffaelli & Moser, 2013 [26]; Mendelsohn *et al.*, 2003 [27]), the computable general equilibrium models (e.g. Vargas *et al.*, 2018 [28]) or the semi-parametric smooth coefficient model (*see* Ogada *et al.*, 2020 [2]), among others. This study adopts the Alvi and Jamil (2018) [29] model, which is modified to encapsulate variates under consideration.

3. Methodology

This study adopted the Alvi and Jamil (2018) [29] model, which is adjusted to account to the variates under estimation. In this model, cereal farmers are economically (assumed to be) utility maximizing agents. Thus, the production function for a particular cereal crop is the form of the Cobb-Douglas. A utility maximizing Cobb-Douglas function equation is defined as:

$$Y_t = \mathrm{e}^{\beta t}\left(\prod_{j=1}^{k} x_{jk}^{\gamma j}\right)\mathrm{e}^{u_t} \tag{1}$$

where, Y_t is the quantity of a given cereal yield in time *t*, x_{jt} a set of climate estimate of temperature and other sets of parameters under estimation, whereby x_j is a series of x_k elements such that $x_j = \left(x_1, x_2, x_3, \cdots, x_k\right)$. In addition, γ are parameters whose composition of $X'_{jt}s$. Theoretical literature strengthens the idea that climate change leads to risk exposure that consequentially affects cereal yields. It also reveals that pollinators play a critical role in food security but that they are also affected by climate change. Instrumentally, it is assumed that pollinators have a dual outcome on food security (depending on how climate change influences on bees). These two probable scenarios are captured as shown:

$$Y_t^H = \mathrm{e}^{\beta_t^H}\left(\prod_{j=1}^{k} X_{jk}^{\gamma_j^H}\right)\mathrm{e}^{u_{it}^H} \tag{2}$$

$$Y_t^N = \mathrm{e}^{\beta_t^N}\left(\prod_{j=1}^{k} X_{jk}^{\gamma_j^N}\right)\mathrm{e}^{u_t^N} \tag{3}$$

where, Y_t^H and Y_t^N are cereal yields per hectare over time *t* accounting for the valuable contribution of pollinators or lack of it, respectively. By taking logs on

Equations (2) and (3), we respectively have:

$$y_t^H = \beta_t^H + X'_{jt}\gamma_j^H + u_t^H \tag{4}$$

$$y_t^N = \beta_t^N + X'_{jt}\gamma_j^N + u_t^N \tag{5}$$

where, y_t^H and y_t^N are the log(s) of given cereal yields per hectare over time *t*, X'_{jt} is log of the inputs. The gains from pollinators on a given cereal yield per hectare are given as a difference of potential gains and losses on yields as:

$$B_t = y_t^H - y_t^N = \beta_t^H - \beta_t^N + X'_{jt}\left(\gamma_j^H - \gamma_j^N\right) + u_t^H - u_t^N \tag{6}$$

where, B_{it} is the cereal yields when pollinators aid increase yields; yields under the two scenarios can be compared by:

$$h_t = 1; \text{if } y_t^H > y_t^N \tag{7}$$

$$h_t = 0; \text{if } y_t^H > y_t^N \tag{8}$$

Above Equations (7) and (8) provide a classical case when the influence of pollinators on yields is positive and negative, respectively. It is assumed that if pollinators are impaired due to climate change, $h_t = 0$, then s/he misses the comparative advantage that comes with pollinators *i.e.* $h_t = 1$. In order with Limieux (1998) [30] unobserved and uncorrelated "technological components" cum contribution of pollinators that affect the model can be instituted. These components are linear projections of the form θ_t^H and θ_t^N and this strengthens another assumption that pollinators have a positive influence on yields that when used as shown:

$$\theta_t^H = b_H\left(\theta_t^H - \theta_t^N\right) + \tau_t^H \tag{9}$$

$$\theta_t^N = b_H\left(\theta_t^H - \theta_t^N\right) + \tau_t^N \tag{10}$$

where, b_H and b_N are projected yields coefficients with $\left(\theta_t^H - \theta_t^N\right)$ being the ideal comparative advantage of pollinators. By the same token, the pollinators' comparative advantage, π, is given by:

$$\pi_t = \left(\theta_t^H - \theta_t^N\right) \tag{11}$$

It follows that by substituting Equation (11) into (10), we have an expression for the case of when it is assumed pollinators have a digressive role in yields is given as:

$$\theta_t^N = b_H \pi_t + \tau_t^N \tag{12}$$

Equally, yields projections case for when pollinators have an accretive role is given as:

$$\theta_t^H = b_H\left(\theta_t^H - \theta_t^N\right) + \tau_t^H \tag{13}$$

But $\theta_t^H - \theta_t^N = \tau_t^H$

$\therefore$

$$\theta_t^H = b_H \pi_t + \tau_t^H \tag{14}$$

By mathematically manipulating Equations (11) and (12), we have:

$$\mu_t^H = b_H \pi_t + \tau_t^H + \xi_t^H \tag{15}$$

$$\mu_t^N = b_H \pi_t + \tau_t^N + \xi_t^N \tag{16}$$

where, μ_t^H and ξ_t^H are standard error correlations in the model associated with the accretive role of pollinators. It is important to note that the three elements of ξ_t^H, ξ_t^N and $X'_{jt}s$ that are explained under Equation (5) are uncorrelated unlike θ_t^H and θ_t^N that are explained under Equations (9) and (10). By accounting for the standard errors, the unobserved components that are aggressive when discounted with the digressive ones, we have Equations (17) and (18) below where ξ_t^H and ξ_t^N are the respective transitory errors as:

$$y_t^H = \beta_t^H + X'_{jt}\gamma_j^H + b_t\pi_t + \tau_t^H + \xi_t^H \tag{17}$$

$$y_t^N = \beta_t^N + X'_{jt}\gamma_j^N + b_t\pi_t + \tau_t^N + \xi_t^N \tag{18}$$

By taking a generalized yield form, we have:

$$y_t = h_t y_t^H + y_t^N \left(1 - h_t\right) \tag{19}$$

By combining Equations (17) and (18) through substitution, we have:

$$\begin{aligned} y_t = {} & \beta_t^N + h_t\left(\beta_t^H - \beta_t^N\right) + X'_{jt}\gamma^N + X'_t\left(\gamma_j^H - \gamma_j^N\right)h_t \\ & + b_N\pi_t + \left(b_H - b_N\right)\pi_t h_t + a_t + \varepsilon_t \end{aligned} \tag{20}$$

$$y_t = X'_{jt}\gamma + \pi_t \oint_{jt} + \beta_t + a_t + \varepsilon_t \tag{21}$$

where, $\oint_{jt}$, pollination, is determined exogenously. Also as expressed in Equation (21), quantity of yield is mainly determined by pollination and climate estimates.

Empirical Model

Specifically, the model will adopt an econometric model that takes into account the climatic and non-climatic parameters. For purposes of completeness, let t be a time parameter for a given cereal yield in a given year. Further, the units of yields are quantified as tonnes. The mean annual temperature will be used as a climatic estimate in consistent with Southworth *et al.* (2000) [31] who have observed that mean annual temperatures are rising and affecting agricultural yields. Consequently, the total number of beehives produced in a year are used as a proxy variable for pollinators. The empirical model is thus specified as:

$$Y_t = \beta_0 + \beta_1 Tmp_t + \beta_2 Ptn_t + \beta_3 Pollinators_t + \varepsilon_t \tag{22}$$

where Y_t is the quantity of yields of a particular cereal crop (maize, rice, wheat and beans) produced over time t; β_0 is the intercept; β_1, β_2, β_3, β_4 are the coefficients; Tmp_t is the mean annual temperature; Ptn_t is the mean annual rainfall; $Pollinators_t$ are proxied by the number of beehives produced over time t; and, ε_t is the error term.

4. Data and Variables

Long-term historical data was used in this study. The data on the quantity of annual cereal crops (of maize and beans, rice and wheat) production was assembled from the Food and Agricultural Organization database over the period 1961 to 2017 while climatic data was assembled from the World Bank-Climate Change Knowledge Portal for the period 1961 to 2016. Using multivariate model, the data was analyzed to determine the influence of mean annual temperature, mean annual rainfall and pollinators on the aforementioned cereal yields. **Table 1** details key summary statistics for the estimated variable. On annual basis, the summary statistics indicated that under the observed period, the country produced a mean of 14.61 metric tonnes of maize. Data also indicated that the country produced 10.63 metric tonnes of rice, 12.33 metric tonnes of wheat and 12.39 metric tonnes of beans, in that order.

5. Results and Discussion

The study employed a multivariate approach. The approach is ideal when multiple variables are established on the right side of the model equation, that way, linking with a number of variables (Hidalgo & Goodman, 2013) [32]. In this model, endogeneity is assumed. The results are as detailed in **Table 2**.

Table 1. Summary statistics.

Variable	Unit	Mean	Std. Dev.	Min	Max
InMaize	Metric tonnes	14.61	0.34	13.75	15.16
InRice	Metric tonnes	10.63	0.56	9.47	11.84
InWheat	Metric tonnes	12.33	0.36	11.34	13.15
InBeans	Metric tonnes	12.39	0.80	10.92	13.65
InPtn	Milliliters	4.03	0.18	3.63	4.44
InTmp	Degrees Celsius	3.21	0.02	3.16	3.25
InPollinators	Number	14.15	0.61	13.12	15.30

Table 2. Multivariate regression results.

	Model One	Model Two	Model Three	Model Four
	Maize	Rice	Wheat	Beans
InPtn	0.366*** (0.0279)	0.137* (0.0590)	0.292*** (0.0378)	0.377*** (0.0589)
InTmp	9.776*** (0.277)	19.00*** (0.586)	5.064*** (0.376)	19.52*** (0.585)
InPollinators	0.0407*** (0.0101)	−0.162*** (0.0213)	0.248*** (0.0137)	0.209*** (0.0213)
Constant	−18.75*** (0.857)	−48.48*** (1.811)	−8.547*** (1.162)	−54.58*** (1.809)
Observations	1596	1596	1596	1596
R^2	0.5197	0.4077	0.3525	0.5300
F-Stat	574.2126	365.2018	288.8521	598.3496
P-value	0.0000	0.0000	0.0000	0.0000

Standard errors in parentheses $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

The results revealed that increasing amount of annual rainfall increases the yields of maize, rice, wheat and beans. It is further revealed that a unit increase in the amount of rainfall will result in a proportionate increase in cereal yields while a unit increase in temperature will result in varied increases in cereal yields. It is also revealed that a unit increase in the number of beehives (or increase in the number of bees—given that they are the world's major pollinators) increases maize, beans and wheat yields production to a tune of about 25 percent but has resultant reducing effects for rice. All coefficients were statistically significant across the three levels of significance (1%, 5% and 10%). As indicated by the coefficients of R^2, over 50% of the data fit the regression models one and four while 40% and 35% of the data under model two and model three fit the regression model, respectively.

6. Conclusions and Recommendations

6.1. Conclusions

This study may not be the first but there are few studies that have linked climate change, pollinators and cereal yields in Kenya. An empirical understanding of this linkage at the time when the world has continued to experience temperature escalations is important in informing policy and enabling food security in the country, now and in the future.

In this study, data interpolation would not have provided intended estimates (Bloschl & Grayson, 2001) [25]. For that, the number of observations for the long-term historical data used was not interpolated despite differences in length. As suggested in literature (see Singh *et al.*, 2018 [20]) due to differences in the physiology of monocots and dicots, climate change has different effects on potential yields. In this study, it was established that although the direction of effect was incremental, the magnitude differed from one crop to another. This makes it worthwhile to deliberate efforts to boost agriculture to ensure food security.

6.2. Recommendations

The findings revealed that a unit increase in the amount of rainfall resulted in a proportionate increase in cereal yields but a unit increase in temperature led to varied increases in cereal yields. This implies extensive use of extension services as observed by Di-Falco *et al.* (2011) [24] and Kabubo-Mariara and Mulwa (2019) [21] to inform farmers when and type of crops to grow to achieve maximum productivity and food security. Since agriculture in the country is heavily rain-fed, investments and explorations into avenues of broadening and strengthening resilience and coping mechanisms among farmers, especially small-scale farmers are critical. Such efforts will attenuate climate-related risks and minimize on-farm and post-harvest losses. Equally critical is the need to invest in agricultural research to continuously come up with climate-resilient seed varieties of maize, wheat, beans and rice.

Consistent with arguments posited by Wuebbles *et al.* (2014) [23], the findings revealed that bees played a critical role in the pollination of maize, wheat and beans but not rice. This necessitates continued research into ways of containing invasive insects and pests without killing bees, which play a critical in enabling food security. Long-term monitoring of agroecosystems and routine assessments on the impact of climate change on pollinators is critical. Beyond training, the National Beekeeping Institute should work on mechanisms that can enable data collection of pollinators and understanding of the environmental cues in controlling the phenology and distribution of bee species as they play a key role in ensuring food security. Future studies should investigate the viability of self-pollination for rice and employ cross-section data on monthly or quarterly basis. Importantly so, future studies should consider monthly or quarterly climate data including soil-surface temperature and humidity in determining the overall impact of climate change on cereal yields in the country.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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