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IFPRI Discussion Paper 00843

December 2008

Climate Variability and Maize Yield in South Africa

Results from GME and MELE Methods

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IFPRI's research, capacity strengthening, and communications work is made possible by its financial contributors and partners. IFPRI receives its principal funding from governments, private foundations, and international and regional organizations, most of which are members of the Consultative Group on International Agricultural Research (CGIAR). IFPRI gratefully acknowledges the generous unrestricted funding from Australia, Canada, China, Finland, France, Germany, India, Ireland, Italy, Japan, Netherlands, Norway, South Africa, Sweden, Switzerland, United Kingdom, United States, and World Bank.

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Notices

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[2] IFPRI Discussion Papers contain preliminary material and research results. They have not been subject to formal external reviews managed by IFPRI's Publications Review Committee but have been reviewed by at least one internal and/or external reviewer. They are circulated in order to stimulate discussion and critical comment.

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ACKNOWLEDGEMENT

The authors are very grateful to an anonymous reviewer for their thoughtful comments, to Charles Nhemachena for assisting in the data compilation, to Siwa Msangi for providing the software for the estimation, and to James Benhin for his comments and assisting with the necessary information on the data. Financial support from CEEPA and IFPRI is gratefully acknowledged.

ABSTRACT

This paper investigates the impact of climate variability on maize yield in the Limpopo Basin of South Africa using the Generalized Maximum Entropy (GME) estimator and Maximum Entropy Leuven Estimator (MELE). Precipitation and temperature were used as proxies for climate variability, which were combined with traditional inputs variables (i.e., labor, fertilizer, seed, and irrigation). We found that the MELE fits the data better than the GME. In addition, increased precipitation, increased temperature, and irrigation have a positive impact on yield. Furthermore, results of the MELE show that the impact of precipitation on maize yield is stronger than that of temperature, meaning that the impact of climate variability on maize yield could be negative if the change increases temperature but reduces precipitation at the same rate and simultaneously. Moreover, the impact of irrigation on yield is positive but with a lower elasticity coefficient than that of precipitation, which supposes that irrigation may only partially mitigate the impact of reduced precipitation on yield.

Keywords: yield function; maize; generalized maximum entropy; maximum entropy Leuven estimator; climate variability

1. INTRODUCTION

Research has estimated that farming, which is mainly supported by rain in Africa, provides employment for over 70 percent of the labor force. In addition, about a third of the population live in drought-prone regions (Fleshman 2007). On the other hand, the scientific community, through extensive research, has established that there is a statistically significant increase in the global mean state of the climate or in its variability, and further increases are expected if carbon dioxide and greenhouse gas emissions are not controlled (IPCC 2007). In South Africa, between 1960 and 2003, the mean temperature increased by 0.13 degrees Celsius (Kruger and Shongwe 2004), and mean rainfall is expected to decrease 5–10 percent within the next 50 years (Hewitson 1999; Durand 2006). The expected reduction in rainfall would have significant impact on South Africa's agriculture because a large portion of the country is semiarid and experiences varying and low mean rainfall of 464 millimeters annually, relative to the world average of 857 millimeters (BFAP 2007).

Maize constitutes about 70 percent of grain production and covers about 60 percent of the cropping area in South Africa. It is a summer crop, mostly grown in semiarid regions of the country, and is highly susceptible to changes in precipitation and temperature (Durand 2006; Benhin 2006). Although the maize plant is quite hardy and adaptable to harsh conditions, a drier or warmer climate and lower precipitation could have detrimental effects on its yield (BFAP 2007). In addition, maize is the main staple in Southern Africa, and maize production in the country constitutes about 50 percent of the output within the Southern African Development Community (SADC) region (Durand 2006). Consequently, maize is one of the key drivers of food inflation in South Africa (BFAP 2007). It is noteworthy that although a decrease in maize production may result in increased total revenue because of its inelastic demand, it would increase food insecurity within the Southern African region.[1]

A considerable number of studies have been done to investigate the impact of climate change on yields of grain crops such as maize under controlled experiments (e.g., Du Toit et al. 2002; Kiker et al. 2002; Durand 2006). To simulate the water requirement for optimum yield, these studies require parameter values for precipitation, temperature, crop, and soil. One noticeable limitation of this approach is that it assumes for simplicity that other inputs (such as labor, seed, and fertilizer) are utilized optimally. Other studies employed the Ricardian approach of Mendelsohn, Nordhaus, and Shaw (1994) to investigate the impact of some climate variables on net revenue from commercial and subsistence farming in South Africa (e.g., Deressa, Hassan, and Poonyth 2005; Gbetibouo and Hassan, 2005; Benhin, 2006; Maddison, Manley, and Kurukulasuriya 2006; Kurukulasuriya and Mendelsohn 2006). Although these studies have generated interesting results, they do not address the direct impact of climate variability on crop yields, specifically maize yield, in South Africa.

This paper addresses this shortcoming by directly estimating a yield function for maize with the two relevant climate variables, that is, temperature and precipitation, together with the other traditional inputs (labor, seed, fertilizer, and irrigation). Due to the limited data available and high correlation between some of the variables, to improve the reliability of the results, the yield function was estimated using two different semiparametric methods, and the results were compared. These methods are the Maximum Entropy Leuven Estimator (MELE) and the Generalized Maximum Entropy (GME).[2] The plot of the actual and estimated values of yield depicts that the MELE fits the data better than the GME. Moreover, comparing the elasticity coefficient of irrigation with that of previous studies clearly shows that the GME grossly overestimates its effect on yield (see Durand 2006). Furthermore, the estimated results show that a rise in the mean summer temperature and precipitation, all other things being equal, would increase maize yield in South Africa. In addition, mean precipitation had the highest overall impact on yield. The corresponding elasticity coefficients of temperature and precipitation are 0.383 and 0.416,

[1] A study on maize demand in South Africa by Mabiso and Weatherspoon (2008) estimated price elasticity of -0.42 (P value<0.074).

[2] As noted by Golan, Moretti, and Perloff (1998), the GME is a robust, semi-parametric estimation method because it uses minimum distributional assumptions. The method performs well with small and possibly ill-behaved, noisy data.

respectively. Moreover, irrigated farms had higher yield than dry-land maize farms, with an elasticity coefficient difference of 0.356.

The rest of the paper is organized as follows: The analytical framework is presented in Section 2. Section 3 contains the data description and the results of our estimations. Finally, Section 4 presents the conclusions and limitations of the paper.

2. THE ANALYTICAL FRAMEWORK

In this section, the production function and the two estimation methods, GME and MELE, are presented.

The Production Function

Suppose the behavioral model of interest, which is the yield function for maize, is[3]

$$\log Y_i = \beta_0 + \beta_1 \log L_i + \beta_2 \log F_i + \beta_3 \log S_i + \beta_4 \log T_i + \beta_5 \log P_i + \beta_6 D_i + u_i \, , \tag{1}$$

where Y_i is yield (i.e., output per hectare) for farm $i = 1,...,n(=25)$; L_i is labor hours per hectare; F_i is fertilizer application per hectare; S_i is the quantity of seed cultivated per hectare (measured in kilograms); T_i is mean summer temperature (measured in degrees Celsius) that is experienced by farm *i* from October to May; P_i is mean precipitation (measured in millimeters per month) that is experienced by farm *i* between October and May; D_i is a dummy variable that takes the value of 1 if farm *i* is irrigated and 0 otherwise; β_k is the vector of the $k = 0,...,6$ parameters to be estimated; and $u_i \sim N(0,\sigma^2)$ is a normally distributed error term. Note that since all the variables but D_i are in logarithms, the coefficients are elasticities and the coefficient of D_i is a shift parameter. Furthermore, if, for example, $\beta_1 \in (0,1)$, then $\left(\partial Y_i / \partial L_i\right) > 0$ and $\left(\partial^2 Y_i / \partial L_i^2\right) \leq 0$ (i.e., there are diminishing returns to labor). Moreover, the yield elasticity of irrigation is $\beta_6 D_i$, where D_i is the dummy for irrigation evaluated at $D_i = 1$. It is expected that the coefficients of all the inputs should be positive and between 0 and 1. Due to the limited number of observations (i.e., 25) and the high correlation among some of the inputs, the results obtained from the application of standard parametric estimation techniques such as the ordinary least square may yield inconsistent and biased estimates (see Golan, Judge, and Miller 1996a). The pairwise correlation coefficient tests indicate that the climate variables (i.e., temperature and precipitation) and labor and fertilizer are significantly correlated ($p - \text{value} < 0.01$). We therefore estimated these coefficients using the MELE and GME, presented below.

Generalized Maximum Entropy

As noted previously, due to the data inadequacy and potentially high correlation among the climate variables (temperature and precipitation), for this study, conventional econometric methods may not give reliable estimates. To address similar shortcomings, a number of studies applied the GME method, which in principle could compute the parameters of a model even if the model has more parameters than the number of observations. The GME is a semiparametric estimator that belongs to a class of those used in engineering and physics. Research has shown that these estimators yield low mean-square errors in small samples and are particularly good at dealing with multicollinear regressors in behavioral models (e.g., Golan, Judge, and Miller 1996a; Paris and Howitt 1998; Lence and Miller 1998; Howitt and Msangi 2006). To present the GME estimator, let

$$\beta_k = \sum_s z_{ks} p_{ks} \, , \tag{2}$$

[3] Due to data constraints, the production function is limited to a Cobb-Douglas type specification.

where $p_{ks} \geq 0$ are unknown probabilities, and $\sum_s p_{ks} = 1$; z_{ks} constitutes a predetermined discrete support space (s) for the parameters, and β_k is as defined in Equation 1. Furthermore, define the error term in Equation 1 as

$$u_i = \sum_g V_{ig} w_{ig} , \tag{3}$$

where $w_{ig} \geq 0$ are unknown probabilities, $\sum_g w_{ig} = 1; V_{ig}$ constitutes an a priori discrete support space (g) for the errors, and u_i is also as defined in Equation 1. The GME estimator is specified as

$$\max \ H(p_{ks}, w_{ig}) = -\sum_s p_{ks} \ln(p_{ks}) - \sum_g w_{ig} \ln(w_{ig}) , \tag{4}$$

subject to Equation 1, but with the coefficients and the error term substituted with Equations 3 and 4.

The results obtained from this estimation using the General Algebraic Modeling System (GAMS) are reported in Table 2. Note that the GME method requires making an assumption that the parameters of the production function (i.e., Equation 1) are obtained as expected values, which depend on some chosen support values (Equation 2). Thus, different support values chosen a priori may generate different parameter estimates, even if a moment constraint (i.e., $\sum_i^{n=25} u_i \Big/ n = 0$) is imposed. Policy recommendations are therefore sensitive to the choice of these values, which is a strong limitation.

Maximum Entropy Leuven Estimator

Motivated by the theory of quantum electrodynamics, Paris (2001) extended the GME method to what he called MELE. The MELE does not require support values. According to the theory, the probability that a photomultiplier is hit by a photon reflected from a sheet of glass is equal to the square of its amplitude. As a result, if the parameter to be estimated in Equation 1, and for that matter any behavioral model, has amplitude or is normalized in a dimensionless manner, then the square of the amplitude will define the probability. Define the sum of the coefficients in Equation 1 as

$$L_\beta = \sum_k \beta_k^2 . \tag{5}$$

By dividing each parameter to be estimated by Equation 5 (i.e., $\beta_k \Big/ \sqrt{L_\beta} = \beta_k \Big/ \sqrt{\sum_k \beta_k^2}$), a unit-free or amplitude of each k is obtained. Consequently, Paris (2001) defined the probability for each k as

$$p_{\beta_k} = \frac{\beta_k^2}{L_\beta} . \tag{6}$$

Note that the three unknowns in Equations 1, 5, and 6 are β_k , p_{β_k} and u_i . Using these three equations as constraints, the following entropy function is maximized

$$\max H(p_{\beta_k}, L_\beta, u_i) = -\sum_i p_{\beta_i} \ln(p_{\beta_i}) - L_\beta \log(L_\beta) - \sum_i u_i^2 \tag{7}$$

with $p_{\beta_k} \geq 0$. As noted by Paris (2001), the term $L_\beta \log(L_\beta)$ prevents L_β from taking very large values.

The results for this nonlinear optimization program were also obtained using GAMS and are reported in Table 2. The following section presents the data for the study and the results obtained.

3. DATA DESCRIPTION AND RESULTS

The data for the study were extracted from a survey conducted by the Centre for Environmental Economics and Policy in Africa (CEEPA) in collaboration with the International Food Policy Research Institute (IFPRI) in the Limpopo Basin of South Africa during the 2004–2005 farming season. From the data, maize is the single most highly cultivated crop, but there are several missing observations in the yield and input variables. The problem of unwillingness of farmers in South Africa to freely give out information about yields and inputs usage due to the land reform act has also been noted by earlier studies (see Durand 2006). The traditional production variables include yield (per hectare of farm), labor, fertilizer, seed, and irrigation. The climate variables considered in this study are mean precipitation and mean temperature.

The climate data were obtained from the weather services in South Africa and are matched to farms that are within the neighborhood of each station. From the survey data, the mean monthly temperature and precipitation for the analysis were computed for October to May, the maize cultivation period. In Table 1, the mean values of 21.4 degrees Celsius for temperature and 71.0 millimeters for precipitation are not very different from the corresponding 30-year average values of 20.74 degrees and 86.38 millimeters, as reported by Kurukulasuriya and Mendelsohn (2006).

The majority of the maize farms were rain-fed, and the few farmers who complement this with irrigation could not provide information on flow rates and the depth of the water. Consequently, a dummy variable, which takes the value of 1 if the farmer irrigates and 0 otherwise, was used to capture the impact of irrigation on yield. The subsample for this study includes seven (28 percent) irrigated farms. This is close to the corresponding figure of 24 percent computed from the total sample of farmers in the Limpopo Basin survey. However, our figure is significantly higher than the national average of 5–11 percent reported by Durand (2006). The descriptive statistics of the data for the analysis are presented in Table 1.

The total number of complete observations used for the estimations is 25 farms. To show that the ordinary least square estimation with small sample and high correlation between some explanatory variables may be unreliable, we have estimated and presented the results in the second column of Table 2.[4] The results erroneously show that only labor and irrigation are significant in explaining the variation in yield, at 10 percent level of significance. It is important to note that the GME and MELE are semiparametric methods and therefore do not generate standard errors of the parameter estimates. As noted earlier in the section on the analytical framework, a Cobb-Douglas type specification was employed, but with no restriction on the parameter values for the maximum entropy estimations. The results from both methods show that all the inputs, including temperature and precipitation, are important in explaining variation in maize yield. Moreover, as noted earlier, Paris (2001) has shown that because the estimates of the GME are sensitive to the choice of support values (even if moment constraints are imposed, as we have also observed), the MELE is consistent and preferred. Moreover, if the results are compared with those obtained from earlier studies (e.g., Durand 2006), the GME overestimates the impact of irrigation on the yield.

[4] Note that the correlation coefficient between labor and fertilizer is 0.635 (P value <0.01), and that of temperature and precipitation is -0.938(P value<0.01).

Table 1. Descriptive statistics of production variables

Variable	Observations	Mean	SD
Yield (Kg/ha)	25	1237.186	1055.226
Labor (hrs)	25	448.750	561.369
Seed (kg)	25	25.568	30.755
Fertilizer (kg)	25	159.452	198.231
Mean Temperature (ºC /month: Oct–May)	25	21.396	2.969
Mean Precipitation (mm/month: Oct–May)	25	70.964	25.105
Irrigation (=1)	25	0.280	0.458

Since MELE is a semiparametric estimation method, we bootstrapped the estimated coefficients to obtain some pseudo statistics. To do this, we drew 120 random data sets, each with the same number of observations and variables as in the original data. For each data set, the MELE was used to obtain the set of coefficients from which the standard deviations were computed. Using the critical values of ±1.645 for 10 percent, ±1.965 for 5 percent and ±2.585 for 1 percent levels of significance, all the coefficients are significantly different from zero at 1 percent level of significance. In addition, we present the plots of the actual and fitted values of the yield for the GME and MELE in Figures 1 through 3 to compare the overall goodness of fit of the estimates. The plots clearly show that the MELE fits the data better than the GME. Moreover, a pseudo R^2 of the MELE indicates that about 64 percent of the variation in yield is explained by the right-hand-side variables.

Figure 1. Actual and fitted values of log (Yield)

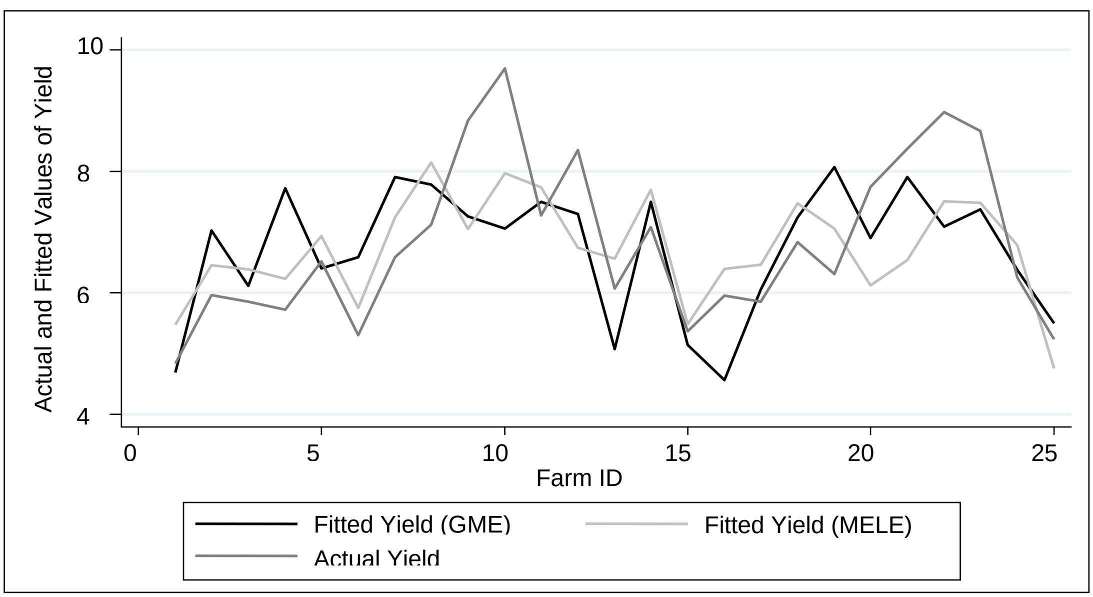


Figure 2. Actual and fitted values of log (GME Yield)

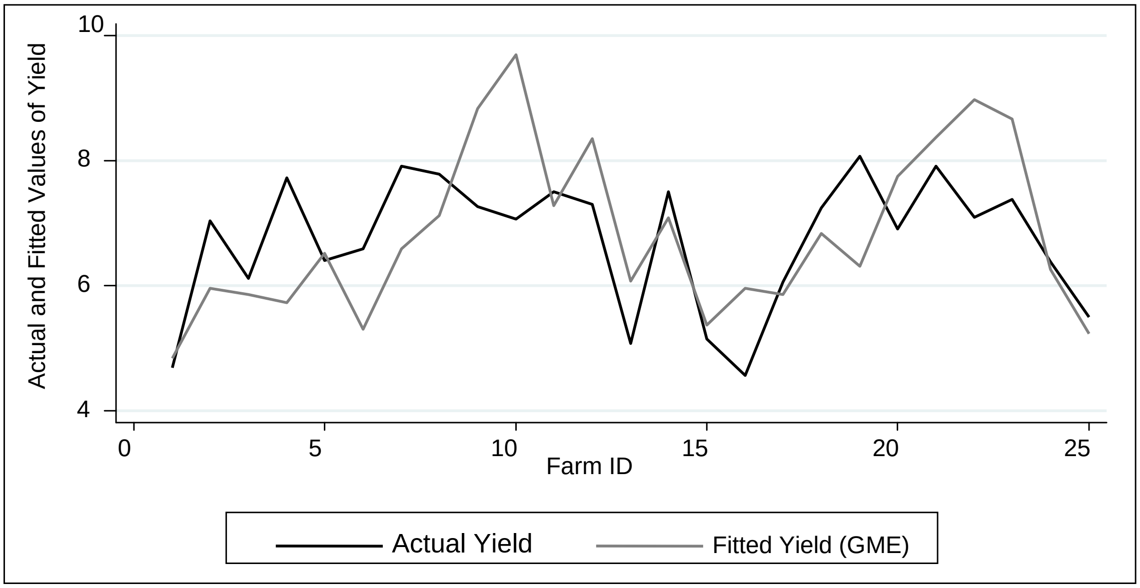


Figure 3. Actual and fitted values of log (MELE Yield)

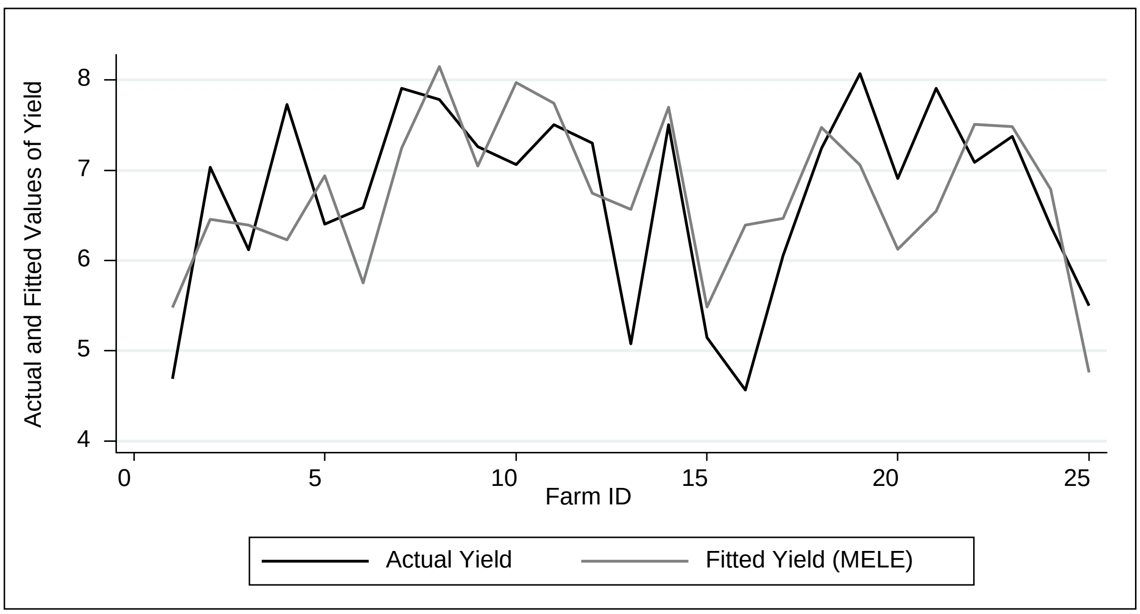
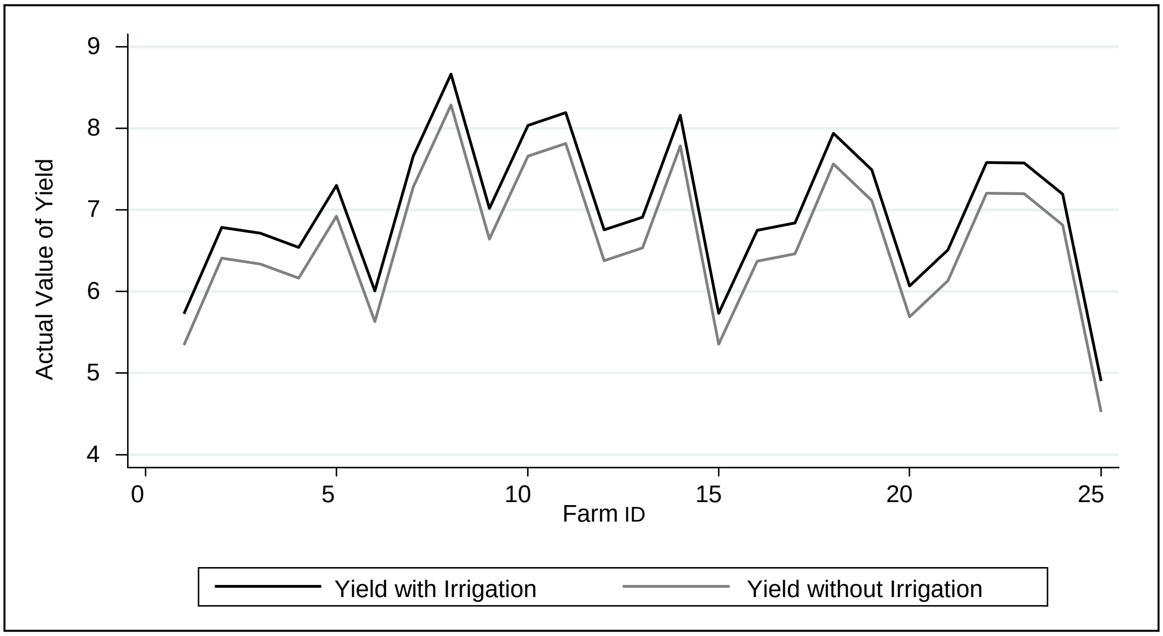


Figure 4. Estimated log (Yield) with and without irrigation



The results from the MELE, which are reported in Table 2, show that all the input variables are significant in explaining the variation in yield across the 25 farms, and show high t-statistics for all the variables. Moreover, the impact of irrigation and mean precipitation on yield is positive, with precipitation having the overall highest impact on yield. A 10 percent reduction in mean precipitation, all other things being equal, will reduce yield by approximately 4.2 percent. As noted by Durand (2006), precipitation is the most important driver of maize production. The high-yield elasticity coefficient with respect to precipitation indicates that marginal reductions in precipitation that may result from climate variability could affect maize production significantly. It is therefore important that farmers be encouraged to irrigate their crops to mitigate approximately 86 percent of the impact, all other things being equal. Figure 4 depicts the impact of irrigation yield.

Table 2. Estimated yield function of maize using ordinary least square (OLS), generalized maximum entropy (GME), and maximum entropy Leuven (MEL) estimators

Variable	Ordinary Least Square		Maximum Entropy Estimators		
	OLS (Elasticities)	**OLS (t-stats)**	**GME (Elasticities)**	**MELE (Elasticities)**	**MELE (Pseudo t-stats)**
Labor (in hours)	0.360	1.92*	0.102	0.256	3.582***
Seed (kg/ha)	0.302	1.61	0.449	0.321	7.652***
Fertilizer (kg/ha)	-0.009	-0.04	0.179	0.256	4.279***
Precipitation (mm)	-1.188	-0.78	0.170	0.416	9.603***
Irrigation (=1)	0.868	1.76*	2.306	0.356	9.761***
Temperature (ºC)	-5.207	-1.40	0.440	0.383	10.786***
Observations (25)	$\bar{R}^2 = 0.37$			$Pseudo\ R^2 = 0.64$	

Note: The standard deviations of the MELE were obtained from bootstrap estimates based on 120 replications.
*,**, *** indicate significantly different from zero at 10% (critical value ±1.645), 5% (critical value ±1.96), and 1% (critical value ±2.585), respectively.

Furthermore, Figures 5 and 6 have been drawn using the mean values of all the inputs except temperature and precipitation, respectively. Both figures show that an increase in temperature and precipitation from the current average value would increase yield but at a diminishing rate. In addition, the graphs show that yield from irrigated farms is higher than nonirrigated farms, irrespective of the levels of precipitation and temperature. The marginal yield obtainable from increased temperature (evaluated at the mean temperature of about 21 degrees Celsius) is much lower than the corresponding yield from increased precipitation (also evaluated at the mean of about 71 millimeters). Thus, concerning temperature, a 1 percent increase in mean temperature (i.e., from about 21.4 degrees Celsius to 21.6 degrees Celsius) would increase average yield by about 0.4 percent. This is not surprising since 21.4 degrees Celsius is below the mean temperature of 23 degrees Celsius that is necessary for optimum maize yield (BFAP 2007).

The positive relationship between the climate variables (summer mean temperature and precipitation) and revenue from agriculture has been found in the literature (see Mendelsohn, Nordhaus, and Shaw 1994 for the United States; Kurukulasuriya and Mendelsohn 2006 and Benhin 2006 for Africa). This finding is therefore consistent with the conclusion in Mendelsohn, Nordhaus, and Shaw (1994) that climate change could be beneficial under some conditions, and in our case, to maize production in the summer in South Africa. Perhaps very important is the fact that if climate change decreases mean precipitation but increases mean temperature marginally and simultaneously, the overall impact on yield will be negative since the coefficient of the mean precipitation is higher.

Figure 5. Declining marginal yield benefit from rising temperature

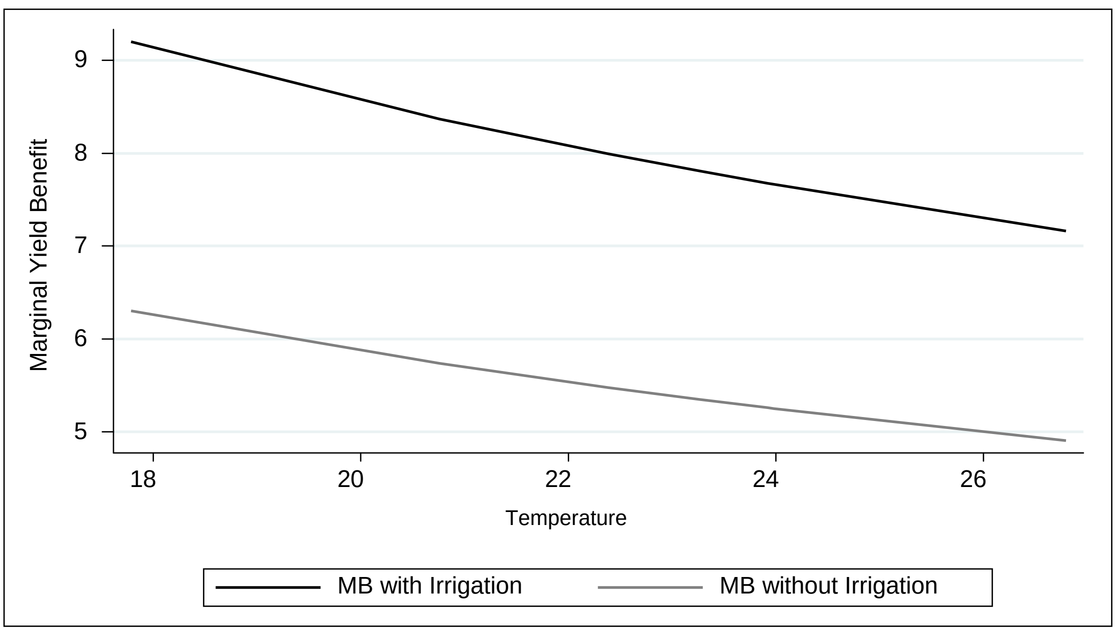
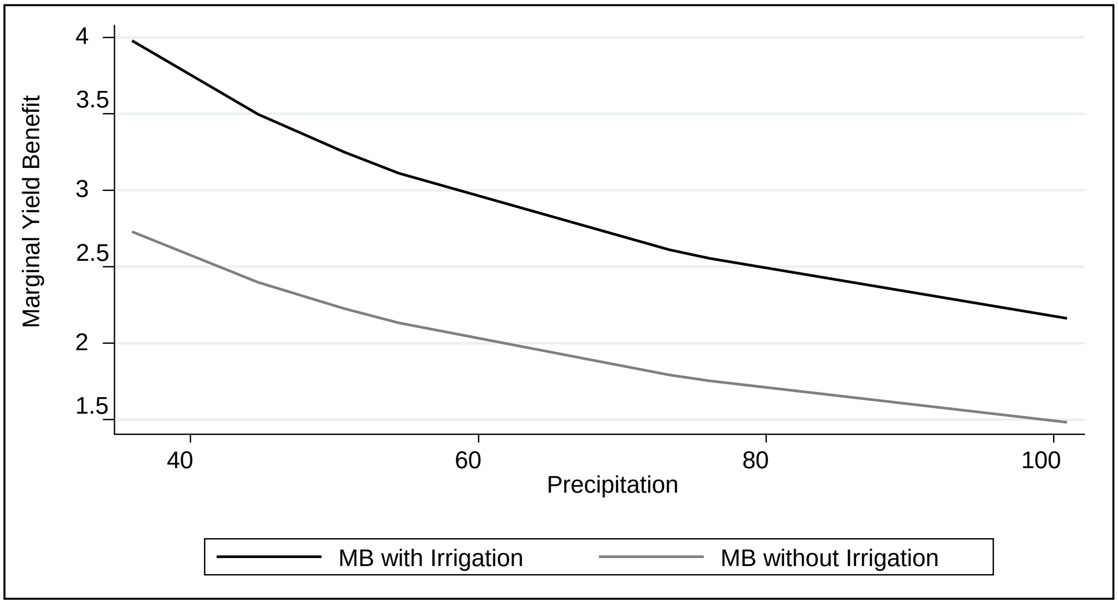


Figure 6. Decreasing marginal yield benefit from rising precipitation



4. CONCLUSIONS

This paper presents and discusses the results of the impact of climate change on maize yield in South Africa, using the GME estimator and MELE. The results from the MELE, which fit the data better, point to the fact that a percentage reduction in mean precipitation could have greater negative impact on maize yield vis-à-vis the gain from an equal percentage increase in mean temperature due to climate change. The corresponding elasticity coefficients of temperature and precipitation are 0.383 and 0.416, respectively. There is enough evidence that shows that the mean temperature has increased. On the other hand, mean rainfall is expected to decrease, and its variance is expected to increase in South Africa. This would impact negatively on maize yield and consequently pose a serious threat to food security within South Africa and the countries within the entire Southern African region that, in total, obtain about half of their maize from South Africa. This study also found that the impact of irrigation on yield is positive but with a lower elasticity than that of precipitation. Irrigated farms had higher yield than dry-land farms, with an elasticity coefficient difference of 0.356. This indicates that irrigation may partially mitigate the impact of decreased precipitation on yield, all other things being equal.

This study, however, suffers from some limitations. First and most important is the limited number of observations. Although the maximum entropy estimators are developed to address this constraint, large data points would have enabled a flexible functional form of the yield function to be specified and consequently increased the robustness of the results. Second, the farmers did not provide farm-level data on precipitation and temperature, so these data from the weather stations were matched to the farms. This is not without problems. The most obvious is that we have assumed that farms within the same district experience the same levels of precipitation and temperature. Furthermore, farms in three out of the seven districts in the study were matched to weather stations in districts that were the next closest to these farms because data from the weather stations in those districts where the farms were actually located were not available. Moreover, the weather stations have marked some of the observations as unreliable.

Notwithstanding the preceding limitations, our results are quite consistent with the findings in the literature and provide a starting point for further research in South Africa and other developing countries on the impact of climate change on crop yield. Moreover, to the best of our knowledge, this study is the first to employ the MELE technique to actual data in South Africa.

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