Sustainability **2015**, *7*, 2858-2870; doi:10.3390/su7032858

OPEN ACCESS

sustainability

ISSN 2071-1050

www.mdpi.com/journal/sustainability

Article

Effects of Weather Variability on Crop Abandonment

Kelvin Mulungu [1,*] and Gelson Tembo [2]

[1] International Center for Tropical Agriculture (CIAT)-HarvestPlus, C/O WorldFish Center, Lusaka 10101, Zambia

[2] Department of Agricultural Economics, University of Zambia, Lusaka 10101, Zambia; E-Mail: tembogel@unza.zm

* Author to whom correspondence should be addressed; E-Mail: K.Mulungu@cgiar.org; Tel.: +260-967-824-897.

Academic Editor: Marc A. Rosen

Received: 22 September 2014 / Accepted: 2 March 2015 / Published: 9 March 2015

Abstract: In Zambia, every year some parts of the maize fields are abandoned post-planting. Reasons for this are not clearly known. In this paper, we examine the influence of soil and climatic factors on crop abandonment using a six-year (2007–2012) panel data by modeling the planted-to-harvested ratio (a good indicator of crop abandonment) using a fractional and linear approach. Therefore, for the first time, our study appropriately (as supported by the model specification tests that favour fractional probit over linear) models the fractional nature of crop abandonment. Regression results, which are not very different between the two specifications, indicate that, more than anything, high rainfall immediately after planting and inadequate fertilizer are the leading determinants of crop abandonment. In the agro-ecological region where dry planting takes place, low temperature during planting months negatively affects the harvested area. The results have implications on the sustainability of farming systems in the face of a changing climate.

Keywords: crop abandonment; weather variability; fractional probit; Zambia

---

1. Introduction

Zambia has seen a steady increase in both agricultural production and productivity over the last six years. However, Crop Forecast Surveys (CFSs) conducted by the Central Statistical Office (CSO) and the Ministry of Agriculture have consistently revealed that smallholder farmers do not harvest all of their maize. Some of the maize fields are abandoned post-planting—a phenomenon we are calling crop abandonment in this study. The ratio of harvested-to-planted area—which best measures crop abandonment—has ranged between 0.52 and 0.97 in the last decade when aggregated by province [1]. Given that smallholder farmers spend about 50% of their family labor on land preparation and planting activities, addressing this problem does not only lead to production efficiency, but also to saving labor that is otherwise wasted in the initial activities. The cost of initial labor and inputs like seed that are wasted in the area that is never harvested make the enterprise look very unprofitable.

It is generally recognized that climate change has an impact on agriculture [2,3]. Most studies in developing countries have focused on measuring economic impacts of climate change [4,5] and much less on evaluating the impact on the production of specific crops, yet scientific evidence suggests that climate change is a reality [6,7]. Sub-Saharan Africa is often cited as one of the most vulnerable regions as it maintains the highest proportion of malnourished people with a large proportion of its population depending on agriculture for livelihoods [8]. Challinor *et al.* [9] have found increasing incidences of crop failures due to climate change. This is likely to worsen as the effects of global warming take root in the next half century, during which specifically maize yields have been projected to reduce by as much as 22 percent [8]. This will pose a serious threat to regions that are already food insecure [3]. As climate continues to vary annually, it has an impact on crop performance and ultimately on the decision that farmers make whether to abandon or not.

Crop failure and crop abandonment are differentiated in this paper. Crop failure, which is defined as the complete loss of crops on a farm [10] has received more attention from researchers. Crop failure happens more in catastrophic weather conditions in which the crops are wiped out by pests, floods or droughts, whereas abandonment is at a marginal level and is a decision made by the farmer to stop cultivation of the field or some part of the field post-planting even when it is still viable due to some poor performance of the crop and committing to other crops the limited labor and other inputs where the prospects of better yields are higher [11]. Crop failure can be part of crop abandonment in measurement sense, since the crop that failed could still be captured as an unharvested area, but crop abandonment does not always imply crop failure. If the weather is good enough to allow a farmer or an area to have good yields, then most likely the unharvested crop area is a result of crop abandonment and not failure. This difference is very important in our context as we use data for years in which Zambia received normal rainfall and there were no other catastrophes to wipe out crops.

Empirical evidence is scanty on the causes of crop abandonment and the role played by climate. Shipekesa and Jayne [12], in their descriptive study based on data from a 2008 Zambia smallholder farm household survey identify wilting due to drought, lack of fertilizer, flooding and a combination of these factors as some of the causes of abandonment. The ratio of harvested-to-planted area for one crop is influenced also by the total area that is allocated to other crops. Mendelson [10] estimates the influence of weather on crop failure rates, which is different from abandonment. Furthermore, the use of ordinary least squares (OLS) in his paper, as will be explained in Section 2, fails to handle the fractional nature of the response variable which was defined as proportion of failed crop.

This paper seeks methods to determine the influence of climatic and economic variables (temperature, rainfall and area not catered-for for fertilizer respectively) on the ratio of harvested-to-planted area in Zambia. It contributes to the literature on the interaction between climate variability and crop abandonment by determining the effect of rainfall, temperature and lack of fertilizer on proportion of crop area abandoned. It is also the first attempt, to the best of our literature search, to correctly model the fractional nature of crop abandonment. We also understand any differences in the effects, qualitatively, across the different agro-ecological regions by estimating fractional probit at sub-national level (agro-ecologcal level). The new knowledge generated through this study will help in designing better adaptation strategies that are agro-ecological region specific. The results are useful in sustainable land-use management and for environmental sustainability. Results indicate that rainfall in the early stages of maize crop development and proportion of the area that is catered-for for fertilizer are the main factors influencing the proportion abandoned. There are differences in the magnitude and variables affecting the harvested-to-planted ratio across the agro-ecological regions.

2. Methods

2.1. Theory

Conceptually, there are many factors that lead to crop abandonment. Weather is one aspect that may lead to a crop being abandoned as the farmer may see no hope and concentrate on another field. Changes in rainfall and temperature that adversely affect the crop may be another reason for abandonment. We hypothesize that abandonment happens during the early stages of the crop's development compared to mature crops when the cost of abandonment may be considered too high, and generally there may be more conviction of goods yields. Labor inadequacy could also lead to abandonment of crop areas as the household concentrates on certain fields or crops. However, our data does not allow us to include labor availability. Pest outbreaks are also often blamed for crop failure and abandonment. These are influenced by climate as well [9], and indirectly captured in the influence of weather variables.

Soils also have an influence on abandonment [10]. Poor soils may lead to more crop area being abandoned [13], especially in cases where fertilizer is not acquired. Fertilizer in Zambia is a major factor explaining yields of maize, especially in poor-soil regions. Because it is among the main inputs, farmers are more likely to abandon the area that is not catered-for for fertilizer and mainly concentrate on where they have applied.

The farmer's objective is to maximize the profit from different fields and hence allocate the available labor in a Pareto efficient manner among the fields and crops. The farmer abandons the crop and allocates his labor where he thinks there will be better returns. In short, the farmer's objective is to maximize the profit given the labor constraint that has to be allocated efficiently among the competing fields.

2.2. Analytical Framework

We measure crop abandonment using a proportion which is taken as the total planted area less the harvested area divided by the total planted area (harvested-to-planted area ratio). This transforms the response variable into a fractional one, and we devote the rest of this section to explaining the appropriateness of a model that takes into account the nature of this variable.

With a fractional (a fraction) dependent variable, OLS is inconsistent and biased while using the log-odds ratio approach does not help if the bounds (0 and 1) are part or can be part of the data. Moreover, our interest is in the partial effects of the expected value of the untransformed fractional responses, that is the ratio of the harvested-to-planted area, which are difficult to recover with transformed variables without strong independence assumptions under the log-odds ratio approach. Papke and Wooldridge [14] developed a model that was later named fractional logit that uses quasi-maximum likelihood estimation to obtain robust estimates of the conditional mean parameters with satisfactory efficiency properties that counter the problems faced with using OLS for fractional dependent variables. Wagner [15] uses the Papke and Wooldridge [16] approach of fractional probit model on panel data and allows for time constant unobserved effects to be correlated with the explanatory variables. This solves the problem that is faced by models like unconditional fixed-effects fractional logit that need all panels (*i.e.*, districts) in a population (*i.e.*, country) to be represented in the data.

Fractional probit is used in this study as it is better for panel data [16,17]. Strictly exogenous covariates (x_i) are assumed in the case of balanced panel data, but for unbalanced (which is our case) the assumption can easily be stated as: observing a data point in any time period cannot be systematically related to the idiosyncratic errors—which is a version of strict exogeneity of selection. With this version of strict exogeneity, the model is specified as;

$$E(y_{it} \mid x_i, c_i, s_i) = E(y_{it} \mid x_i, c_i), t = 1, \ldots T \tag{1}$$

where $0 \le y_{it} \le 1$ is the harvested-to-planted ratio, s_i is selection for observing unit *i* in time *t* and (c_i) is the unobserved effects. In this specification, serial correlation and heteroscedasticity is not modeled but rather the inferences are made robust. Let w_i be a vector of functions that we know; $\{(s_{it}, s_{it}x_{it}) : t = 1, \ldots, T\}$ that act as sufficient statistics for the model we specify (D) such that $D(c_i \mid \{(s_{it}, s_{it}x_{it}) : t, \ldots, T\}) = D(c_i \mid w_i)$. The simplest specification for $D(c_i \mid w_i)$ is the time average on the selected periods, $\overline{x_i}$ The time averages are constructed on the independent variables though not reported in the results tables. At minimum, the variance of the unobserved effects c_i can be allowed to change with *Ti*. If the assumption that $D(c_i \mid w_i)$ is normal is maintained, then the following is obtained:

$$E(y_{it} \mid x_{it}, w_i, s_{it}) = \Phi\left[\frac{x_{it}\beta + \sum_{r=1}^{T} x_i \xi_r}{\exp(\sum_{r=2}^{T} \omega_r)}\right] \tag{2}$$

ξ_r is the coefficient on the time averages; ω_r is the deviation from the base group (T_i = *T*) where observations are made for the whole range of the series.

The correlated random effects (CRE) approach is used mainly because, firstly, it is able take care of the unbalanced nature of the panel data we use; secondly, the CRE estimator provides an approach to allow for correlation between the unobserved (which may arise from unobserved soil characteristics within a broad soil group and institutional and managerial factors) individual omitted variable (c_i) and included explanatory variables provided the unobserved effect is time-invariant. This model includes, apart from the weather variables, an economic variable; the ratio of the unfertilized area, which was calculated as the area that is "unaccounted-for" for fertilizer divided by the total area planted. The total fertilizer applied to maize per district was divided by 400 kg (the recommended application rate per hectare (ha) in Zambia) and the area where fertilizer was applied was derived from this result as:

area fertilizer applied = total fertilizer applied/400 kg (3)

The area applied was subtracted from the total planted area to get the *un*fertilized area (area unaccounted-for), and the result divided by the total planted area to get the ratio of unfertilized area as below.

$$\textit{Ratio unfertilized} = \textit{(area planted} - \textit{area applied with fertilizer)/total area planted} \quad (4)$$

A ratio is more helpful compared to using absolute values of the area unfertilized. Take, for example, a small district that has planted a total of 50 ha and has not fertilized 25 ha, representing 50 percent (0.5 in ratio), and a big district that has a total area planted of 100 ha and has not applied fertilizer to about 40 ha, thereby representing 40 percent (0.4 in ratio). Using absolute values of area unfertilized, it will show that the small district had less area where fertilizer was not applied than the big district, but in ratio terms, a higher proportion of the planted area did not receive fertilizer application in the small rather than the big district. This distinction is very important especially since abandoning a section of the field or some field by the household incorporates in the decision-making process the total area under cultivation.

2.3. Data and Study Area

Climate data used was obtained from the Meteorological Department and the crop data from the Central Statistical Office and Ministry of Agriculture and Livestock. The climate data on rainfall and temperature is collected from 31 district weather stations across the country. However, some districts did not report in this period and hence were dropped from the data, leaving us only with a total of 17 districts. Though a longer panel could have been obtained, 2007–2012 is the period in which fertilizer use data, which is hypothesized to play a major role in crop area abandonment, was consistently collected. Districts with weather stations that reported rainfall and temperature in this period were matched to the district level yield, area planted, and area harvested variables. This brings all the data to district level. The observations, which are aggregated at the district, are made every year in a nationally representative sample and each farmer is asked questions pertaining to the area planted, area harvested, fertilizer use and other aspects of the farm. This covers all the three main agro-ecological regions (AERs). The agro-ecological regions are described in the Table 1.

Table 1. Agro-ecological regions of Zambia.

Agro-Ecoligcal Region	Average Rainfall (mm/year)	Elevation (Meters Above Sea Level)	Growing Season (Days)	Soil Productivity	Temperature Range (°C) (Min–Max)
I	<800	300–1200	80–129	Highly erodible	10.3–36.5
IIa	800–1000	900–1300	100–140	More fertile	6.3–33.6
IIb	800–1000	900–1200	100–140	Infertile coarse sands	17–18
III	>1000	1100–1700 (<1000 in Luapula)	120–150	Highly leached and acidic	5.7–32.1

Sources: [18,19].

2.4. Description of Variables

A description of the variables that were used in the estimation appears in Table 2. The average ratio of harvested-to-planted area is about 0.69 in AER I, 0.73 in AER II and 0.87 in AER III. More area is abandoned in AER I, while in AER III only about 13 percent of the planted area was not harvested on average in this six-year period. Region II has about a fourth (26 percent) of the total area that is planted not being harvested, or being abandoned along the way before harvest. For the ratio of the unfertilized area, the story is different. Region II has the highest area not accounted for in terms of fertilizer, with about 70 percent of the area planted not receiving fertilizer application, while region III has the lowest ratio with roughly about half receiving fertilizer and half not receiving.

October and November total rainfall was highest in AER II with about 183 mm received in two months on average and lowest in AER I, which recorded only about 108 mm for the two-month average. December and January as well as February and March rainfall also followed the same pattern as per the standard categorization of the agro-ecological regions.

Maturing months' temperature was lowest in AER III and highest in AER I and the planting months/early maturity was the same. The trend was the same for October and November's average temperature, where it is highest in AER I and average in AER II, while at its lowest in AER III. This is the reverse order of the rainfall trend for the same months.

Table 2. Descriptive statistics of the variables.

Variable	Mean	Std Dev.	Min	Max
Agro-Ecological Region I (*n* = 10)				
Ratio of *un*fertilized to total planted area	0.576	0.258	0.182	0.882
Harvested-to-planted ratio	0.692	0.230	0.250	0.925
October−November rainfall (mm)	108	36	70	182
December−January rainfall (mm)	486	244	184	947
February−March rainfall (mm)	280	116	180	494
October−November temperature (°C)	28	2	26	30
December−January temperature (°C)	26	2	23	29
February−March temperature (°C)	25	2	23	28
Agro-Ecological Region II (*n* = 34)				
Ratio of unfertilized to total planted area	0.693	0.230	0.035	0.999
Harvested-to-planted ratio	0.738	0.187	0.299	0.956
October−November rainfall (mm)	125	56	25	245
December−January rainfall (mm)	542	179	211	1,038
February−March rainfall (mm)	362	149	136	730
October−November temperature (°C)	25	1	23	27
December−January temperature (°C)	23	1	22	25
February−March temperature (°C)	23	1	21	24
Agro-Ecological Region III (*n* = 43)				
Ratio of unfertilized to total planted area	0.501	0.212	0.147	0.926
Harvested-to-planted ratio	0.872	0.123	0.276	0.998
October−November rainfall (mm)	183	87	24	425
December−January rainfall (mm)	510	148	268	875
February−March rainfall (mm)	370	144	111	657
October−November temperature (°C)	24	1	22	26
December−January temperature (°C)	22	1	21	24
February−March temperature (°C)	22	1	21	23

Author's own data from the Meteorological Department (2007–2012).

3. Results and Discussion

Results for the two estimations, one at the national level and another at the sub-national level, are presented and discussed. Two approaches—fractional probit and OLS—are presented in the national level estimations, whereas the sub-national uses only fractional probit which is favored by the model test statistics.

3.1. Regression Results at National Level

Fractional probit was fitted using a Stata programming approach. Ordinary least squares (OLS) was also used to fit the same model; given that the data in this case do not include the bounds, the estimation is relatively appropriate. The signs of the coefficients are consistent across the two models and so are the significance levels. The generalized linear model (GLM) (fractional probit) approach seems to have slightly higher estimates in absolute terms.

The estimates from the two models are consistent. The signs of the coefficients are the same across models, and the same variables are statistically significant in each model. When compared with the scaled fractional probit coefficients, OLS estimates seem to be somehow lower. This is in tandem with what others have found using this approach. For example, Papke and Wooldridge [14] also found lower estimates for the OLS model compared to their fractional logit results estimated using the same approach. Because of the nature of the response variable, fractional-heteroscedasticity is expected in this equation and robust standard errors are reported in both the fractional probit and OLS.

For both models, R-squared is reported to measure the goodness of fit. The R-squared is calculated as $1-(SSR/SST)$ where SSR (residual sum of squares) is from the unweighted residuals, $\hat{u}=y_i-\hat{y}_i$ and SST is the total sum of squares for the y_i. For OLS, R-squared is reported in the results while for fractional probit has to be calculated manually. As indicated by this measure, the fractional probit model fits better as it has a 9 percent higher R-squared (0.72) than for OLS (0.63): "Since only the conditional expectation is being modelled, with other features of the conditional distribution left unspecified, the R-squared is the most appropriate goodness-of-fit measure" [14]. Given that in the OLS $\hat{\beta}_s$ are chosen to maximize R-squared while the Quasi-Maximum Likelihood Estimation (QMLE) approach of fractional probit does not, a higher R-squared in the fractional probit is even more telling of how well fitting the model is. Weather and soil types explain only about 72 percent of the variation harvested-to-planted ratio or crop abandoned.

Ramsey's regression specification-error test (RESET) further adds support to the fact that fractional probit has a better fit than OLS. By its definition, OLS has a zero sample covariance between $\hat{u}$ and $\hat{y}$ [20]. Ramsey's RESET tests whether there is a correlation between $\hat{u}$ and the low-order-polynomials in $\hat{y}$ like the ones raised to the power of 2, 3 and 4 in this case.

The RESET statistic (0.23) shows that there is no misspecification in the fractional probit approach as indicated by the *p*-value (0.9731), unlike in the linear approach. With the *p*-value of 0.0301 in the linear, this means that the null hypothesis that there is no misspecification in the model is rejected at $\alpha = 0.01$ while in the fractional probit model, there is failure to reject the null hypothesis that there is no misspecification. This indicates that the fractional probit captures well the nonlinear relationship between the included independent variables and the harvested-to-planted ratio compared to the linear model.

Because the fractional probit has a better fit, the results from this model are the ones that were interpreted below. The marginal effects were computed and are shown in column four of Table 3. The marginal effects, considering it is a conditional expectation that was being modeled, are close to the coefficients of the OLS model.

Table 3. Estimates of the effects of weather on crop abandonment.

Variable	FP Coefficient	Marginal Effect	OLS Coefficients
Ratio of unfertilized to total area planted	−0.988 ***	−0.241 ***	−0.226 **
	(0.332)	(0.0804)	(0.0994)
Log of October−November rainfall	0.0356	0.00869	0.0106
	(0.0741)	(0.0180)	(0.0250)
Log December−January rainfall	−0.594 **	−0.145 **	−0.162 **
	(0.268)	(0.0659)	(0.0734)
Log February−March rainfall	0.0246	0.00600	0.00839
	(0.132)	(0.0321)	(0.0306)
Log October−November temperature	1.603	0.391	0.625
	(1.688)	(0.404)	(0.546)
Log December−January temperature	2.529	0.617	0.976
	(2.561)	(0.621)	(0.710)
Log February−March temperature	−2.053	−0.501	−0.500
	(2.945)	(0.715)	(0.906)
Agro-ecological Region I	−0.542	−0.131	−0.171
	(0.492)	(0.134)	(0.158)
Agro-ecological Region IIa	−0.577 ***	−0.142 ***	−0.133 ***
	(0.164)	(0.0431)	(0.0455)
Agro-ecological Region IIb	−0.942 **	−0.263 **	−0.314 **
	(0.415)	(0.132)	(0.131)
Constant	−2.537		−1.332
	(4.828)		(1.511)
Observations	93		93
R-squared	0.72		0.63
RESET	0.23		3.85
	(0.97131)		(0.0301)

, * indicate significance at α= 0.05 and 0.01 respectively. Numbers in parenthesis for the variables are robust standard errors and for the RESET statistic; numbers in parenthesis are the *p*-values. The model included time-averages that are not shown here. FP = Fractional probit.

Only two variables are significant across various specifications: the ratio of the unfertilized area to the planted area and the rainfall for December and January, and the dummies for agro-ecological regions. Because the classification into four agro-ecological regions is manly based on soil type, the AER dummies are proxies for soil type. All variables were converted to their natural logarithm.

The ratio of unfertilized area to total planted area has a negative marginal effect. For every 10 percent increase in this ratio, the ratio of the harvested to planted area decreases by 2.4 percent. This means that the area harvested decreases by 2.4 percent, or in opposite terms, the abandoned area increases by 2.4 percent, holding the planted area constant (henceforth, this interpretation will be followed). This relationship is significant at 95 percent confidence level. In the linear model, this is still the same when rounded to two decimal places. If rounded to three, the fractional approach shows that it is marginally higher by 0.004 percent compared to the linear model effect. Fertilizer application has been found to be a major factor in crop production in Zambia [1] and its lack thereof contributing to more area being neglected by the farmers, especially as most soils in Zambia are poor, is not surprising.

Total rainfall for December and January has a negative relationship with the ratio of harvested-to-planted area. This relationship is evaluated at the mean of 513 mm for the two months. The relationship indicates that high rainfall is not very beneficial to maize in its early maturity stage as this may lead to water logging and consequently a stunted crop that is abandoned by the farmers [21]. Once a field is abandoned in December and January, there is no opportunity for replanting as there remains only about two months in the growing season, which does not leave enough time for maize to be replanted and mature.

Moderate rainfall agro-ecological region II (AER IIa and IIb), despite having the most fertile soils, has a smaller ratio of hartested-to-planted compared to the high rainfall agro-ecological region III was used as a reference. More area is abandoned in all the three AERs compared to AER III, but more significantly for AER IIa and IIb. This indicates the importance of weather in crop abandoning compared to the soil type and fertilizer availability as AER IIb is more fertile but still has more area being abandoned than in III which has more stable weather but with acidic and highly leachable soils. Soil type differences generally explain only a small percentage of the variation in abandonment rates [10].

October and November rainfall did not significantly influence the area harvested. If the climatic conditions are not good in the early months of October and November, the farmers still have a chance of replanting in case the crop does not do well after planting; hence, any abandoned area can be corrected within the season. Replanting usually takes place in the months of December and early January [22]. The maturing months' rainfall (February and March) is not expected to have a major effect because, in this period, the crop will have matured to levels where abandonement is less likely, and as the results show, is not significant. However, the sign of the coefficient is positive, indicating that more rainfall is good during late maturity of maize crop.

3.2. Regression Results at the Sub-National Level

Fractional probit regression was further estimated by agro-ecological regions (AERs). Agro-ecological region IIa and IIb, where this further categorization is based on soil types, were grouped together and estimated as just AER II. In addition to helping understand if there are differences in the effect of climate on crop abandonment in the three agro-ecological regions, the result also helps to understand the magnitude of the effects when evaluated at different levels since the three agro-ecological regions had different means for rainfall and temperature. Only fractional probit was estimated, as it was the better model compared to OLS. The results of this regression are shown in Table 4 with coefficients (Coeff) and marginal effects (M.E) reported. Weather and proportion of *un*fertilized area explain about 90 percent of the variation in abandoned proportion in AER I, and about 84 percent in AER II, as compared to about 73 percent in AER II.

Table 4. Effect of climatic variables on area abandoned-by AERs.

Variable	AER I		AER II		AER III	
	Coeff	**M.E**	**Coeff**	**M.E**	**Coeff**	**M.E**
Ratio of unfertilized to total area planted	−2.358 ** (0.567)	−0.698 ** (0.153)	−1.417 * (0.647)	−0.408 * (0.181)	−1.225 * (0.489)	−0.227 * (0.091)
Log of October–November rainfall	−0.025 (0.455)	−0.007 (0.134)	0.037 (0.082)	0.011 (0.024)	0.303 * (0.150)	0.057 * (0.028)
Log December–January rainfall	0.881 (0.982)	0.261 (0.285)	−0.949 ** (0.263)	−0.273 ** (0.073)	−1.006 ** (0.285)	−0.186 ** (0.052)
Log February–March rainfall	0.769 (0.908)	0.228 (0.264)	0.029 (0.201)	0.008 (0.058)	-0.265 (0.222)	−0.049 (0.041)
Log October–November temperature	58.440 ** (4.732)	17.30 ** (1.026)	1.090 (1.799)	0.314 (0.519)	3.954 (2.547)	0.732 (0.471)
Log December–January temperature	9.423 (15.43)	2.789 (4.506)	2.931 (4.114)	0.843 (1.185)	0.418 (3.242)	0.077 (0.600)
Log February–March temperature	14.08 (13.83)	4.169 (4.183)	−1.630 (4.284)	−0.469 (1.235)	−0.838 (3.028)	−0.155 (0.561)
R-squared	0.90		0.73		0.84	
Observations	10		35		48	

*, ** indicate indicate significance at α= 0.1 and 0.05 respectively. Numbers in parentheses are robust standard errors. The model included time averages that are not shown.

The results indicate that for a 10 percent increase in ratio of the area unaccounted for in terms of fertilizer, the ratio of the harvested to planted reduces by about 24 percent in AER I, while it reduces by 14 percent in AER II (evaluated at 0.7) and about 12 percent in AER III (evaluated at 0.5). There is no perfect trend in terms of diminishing or increasing marginal effect that can be deduced from this. AER I seems to be more affected because of the poor soils in this region and the poor weather experienced in the period under review. Almost all major droughts and floods have been experienced in this region, implying it is more vulnerable to weather extremes. Region III may be able to buffer the effects of lack of fertilizer because of the good weather for crop production (high rainfall and average temperature) received in this region, while region II could be due to the fertile soils that characterize this region.

Rainfall for December and January, otherwise operationalized as early maturity rainfall, has no significant effect on ratio of harvested-to-planted area in region I, despite having a significant one in the overall model and the other two regions. Though not significant, the relationship is nevertheless positive. As indicated previously, it is the heavy rains that are not beneficial to crop growth at this stage, and given that this is the only region where this value is evaluated at the mean of less than 500 mm of rainfall, it means marginal increases from 500 mm are beneficial to the crop. Region II, which is evaluated at the mean of 541 mm of rainfall for December and January, has a marginal effect of −0.9, whereas region III, which is evaluated at the mean rainfall of 510 mm, has a marginal effect of −1. At higher rainfall, the marginal effect on the ratio of harvested-to-planted area is bigger in absolute terms. The ratio harvested-to-planted area is perfectly elastic in region II, as a percent increase in rainfall will result in a percent reduction in harvested to planted ratio.

The other variable that is significant is the temperature for October and November in AER I. There is a significant relationship between the ratio of area harvested to area planted and average temperature for the two months at 99 percent confidence level. This relationship is positive, thereby indicating that in AER I, increases in the planting and land preparation months are beneficial to the crop, and hence lead to less area being abandoned. In other words, reduction in temperature is not good for crop development at this stage. More farmers who have adopted conservation agriculture are found in this region than any other, and thus early/dry planting is expected to be high, meaning temperatures for October and November will play a key role in germination.

4. Conclusions

The objective of the study was to determine the influence of climatic and economic factors on the harvested-to-planted ratio (a measure of crop abandonment) using a 6-year panel data and evaluate which approach is better able to handle the fractional nature of the response variable. Model test statistics indicate that fractional probit is more appropriate than OLS. We estimated the model at national level using the whole sample and by each agro-ecological region to qualitatively determine if there are any differences in the effect of these variables on the planted-to-harvested ratio across regions. Results indicate that rainfall and fertilizer, or lack of, are the major factors explaining crop abandonment.

The study revealed that high rainfall in the months after planting is detrimental to the crop and leads to abandonment. Harmful rainfall during these months means there is no chance of replanting, unlike in the early months of October and November when the farmer can still replant in early December. Increase in rainfall in December and January leads to water logging and stunted crop that is abandoned by the farmers. Fertilizer, being a key input in maize production was also found to negatively affect the ratio of harvested-to-planted area. Farmers almost always abandoned a certain share of the area that was not fertilized. No major differences in terms of the effect of these on area abandoned was found between region II and III as shown by the coefficients that have almost the same magnitude and signs. Region I which is a low-rainfall region is affected differently from the two medium to and high rainfall regions.

Agricultural planners and policy makers need to fully understand the importance of certain months' rainfall on crop production to project better the expected yields. Farming systems that do not adapt to changing climate will see more abandonment and pose a risk to the sustainability of agriculture and sustainable land use. Climate modelers may also consider monthly variables instead of the annual variables to understand the effects of climatic variables on crop production as the monthly variables' effects differ depending on the stage of crop development.

Acknowledgments

We acknowledge support from the German Academic Exchange Service as a scholarship for Kelvin Mulungu.

Author Contributions

Kelvin Mulungu conceptualized and initiated the study as well as doing the analysis and write-up while Gelson Tembo ensured quality to this publishable version.

Conflicts of Interest

The authors declare no conflict of interest.

References

1. Burke, W.; Jayne, T.; Chapoto, A. *Factors Contributing to Zambia's 2010 Maize Bumper Harvest*; Food Security Research Project Working Paper No. 48; Ministry of Agriculture and Cooperatives: Lusaka, Zambia, 2010.
2. Deressa, T.; Hassan, R. Economic Impact of Climate Change on Crop Production in Ethiopia: Evidence from Cross-section Measures. *J. Afr. Econ.* **2009**, *18*, 529–554.
3. Knox, J.; Hess, T.; Daccache, A.; Wheeler, T. Climate change impacts on crop productivity in Africa and South Asia. *Environ. Res. Lett.* **2012**, *7*, Article 034032.
4. Deressa, T.T. *Measuring the Economic Impact of Climate Change on Ethiopian Agriculture: Ricardian Approach*; Policy Research Working Paper 4342; The World Bank: Washington, DC, USA, 2007.
5. Kabubo-mariara, J.; Karanja, F.K. The economic impact of climate change on Kenyan crop agriculture: A Ricardian approach. *Glob. Planet. Change* **2007**, *57*, 319–330.
6. Barker, T. Climate Change. An Assessment of the Intergovernmental Panel on Climate Change. *Change* **2007**, *446*, 12–17.
7. Freudenburg, W.R.; Muselli, V. Reexamining Climate Change Debates: Scientific Disagreement or Scientific Certainty Argumentation Methods (SCAMs)? *Am. Behav. Sci.* **2013**, *56*, 777–795.
8. Schlenker, W.; Lobell, D.B. Robust negative impacts of climate change on African agriculture. *Environ. Res. Lett.* **2010**, *5*, Article 014010.
9. Challinor, A.J.; Simelton, E.S.; Fraser, E.D.G.; Hemming, D.; Collins, M. Increased crop failure due to climate change: Assessing adaptation options using models and socio-economic data for wheat in China. *Environ. Res. Lett.* **2010**, *5*, Article 034012.
10. Mendelsohn, R. What Causes Crop Failure? *Clim. Change* **2007**, *81*, 61–70.
11. Chen, S.L.; Miranda, M.J. Effects of Insurance on Farmer Crop Abandonment. In Proceedings of the Annual Meetings of the American Agricultural Economics Association, Portland, OR, USA, 29 July–1 August 2007.
12. Shipekesa, A.M.; Jayne, T.S. *Why are Zambian Farmers not Harvesting all Their Maize*; Food Security Research Project Policy Synthesis No. 45; Ministry of Agriculture and Cooperatives: Lusaka, Zambia, 2011.
13. Xie, H.; Wang, P.; Yao, G. Exploring the Dynamic Mechanisms of Farmland Abandonment Based on a Spatially Explicit Economic Model for Environmental Sustainability: A Case Study in Jiangxi Province, China. *Sustainability* **2014**, *6*, 1260–1282.
14. Papke, L.E.; Wooldridge, J.M. Econometric methods for fractional response variables with an application to 401 (k) plan participation rates. *J. Appl. Econometrics* **1996**, *632*, 619–632.
15. Wagner, J. *Exports and Firm Characteristics: First Evidence Fromfractional Probit Panel Estimates*; University of Lüneburg Working Paper Series in Economics, No. 97; University of Lüneburg, Institute of Economics: Lüneburg, Germany, 2008.

16. Papke, L.E.; Wooldridge, J.M. Panel data methods for fractional response variables with an application to test pass rates. *J. Econom.* **2008**, *145*, 121–133.
17. Gardeazabal, J. *Vote Shares in Spanish General Elections as a Fractional Response to the Economy and Conflict*; Economics of Security Working Paper No. 33; EUSECON: Berlin, Germany, 2010.
18. Thurlow, J.; Zhu, T.; Diao, X. *The Impact of Climate Variability and Change on Economic Growth and Poverty in Zambia*; International Food Policy Research Institute: Washington, DC, USA, 2009.
19. Kunda, F. Status and Priorities of Soil Management in Zambia. In Proceedings of the Managing Living Soils, Rome, Italy, 5–7 December 2012.
20. Wooldridge, J.M. Fractional Response Models with Endogenous Explanatory Variables and Heterogeneity. In Proceedings of the Chicago Stata Users Group Meeting, Chicago, IL, USA, 14–15 July 2011.
21. Tadross, M.; Suarez, P.; Lotsch, A.; Hachigonta, S.; Mdoka, M.; Unganai, L.; Lucio, F.; Kamdonyo, D.; Muchinda, D. Growing-season rainfall and scenarios of future change in southeast Africa: Implications for cultivating maize. *Clim. Res.* **2009**, *40*, 147–161.
22. Langmead, P. *Hoe Conservation Farming of Maize in Zambia*; Conservation Farming Unit: Lusaka, Zambia, 2004.