Post-Harvest Losses and Climate Conditions in Sub-Saharan Africa

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Abstract

Post–harvest losses (PHL) are particularly critical for developing countries. This is especially evident in Sub-Saharan (SSA) countries, where PHL are estimated to be about 37% of the total food production. Climate is a core determinant of cereal losses, as biodeterioration factors are sensitive to the temperature and humidity. In this paper we analyse to what extent climatic conditions affect PHL. The analysis considers Sub-Saharan countries and focuses on maize production over the period 2000-2020 period. Data on PHL are taken from APHLIS (African Postharvest Losses Information System), which represents a network of cereals and grain experts in SSA countries. Data collected by APHLIS are aimed at improving existing aggregated data on PHL (e.g. FAO data). PHL data quantify the percentage loss for each phase of the post-harvest chain. APHLIS has some unique characteristics, as it provides PHL at the province (Administrative 1 - ADM1) level over time. The main results of our analysis suggest that humidity is the most relevant determinant of PHL in this region. Our results are relevant, especially if we consider the future instability of the climate in this area.

Keywords Post-harvest Losses; Precipitation; Temperature; Sub-Saharan Africa

JEL code Q54, Q51, Q15

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Keywords: Post-Harvest Losses; Precipitation; Extreme Weather Events; Food Price; Sub-Saharan Africa.

1 Introduction

Despite the growing availability of foods over the last fifty years, which allowed an important reduction of worldwide hunger, more than one in seven person still does not have access to a sufficient protein and energy intake (Godfray et al., 2010). This critical situation is further exacerbated by the increase in global population, which will be estimated to reach 9 billion by 2050 (FAO, 2009). Almost all this growth is expected to occur in less developed countries (LDCs), where poverty and hunger are more diffused. The needs to improve food production is however complicated by the growing threats posed by climate change, and the simultaneous concerns on how the resulting mitigation and adaptation strategies will affect the food system (Godfray et al., 2010).

Notwithstanding this critical situation, food waste and losses are estimated to be, on average, about 32% of the global food production (FAO, 2010). If one considers cereals only, Post-harvest losses (PHL) are estimated to be on average 20.5% of the overall production (FAO, 2011). In this paper we analyse to what extent climatic conditions affect PHL. The analysis considers Sub-Saharan countries and focuses on maize production over the period 2000-2021. Our research question is relevant, as in the near future the high instability generated by climate change may further contribute to PHL growth, due to frequent changes in climatic conditions, which in turn may create unfavourable storage conditions and at the same time increasing the number of pests attacking stored cereal (Tefera, 2012). Climate is an important determinant of cereal losses, as bio-deterioration factors are sensitive to temperature and humidity. Climate and storage strategies are therefore correlated: hot and humid climates lead farmers to adopt open storage structure, while in hot and dry climates sealed storage are preferable. If climatic conditions do not guarantee the proper drying setting, PHL may increase substantially. This is especially true in SSA, where most of small farmers rely on sun drying to make cereals suitable for the storage. The drying phase is particularly important, because if grain is not sufficiently dried, this could promote the growth of moulds, and thus leading to massive product losses.

PHL are estimated to be, on average, about 37% of the total food production in Sub-Saharian countries (Kaminski and Christiaensen, 2014). This is clearly at odd with their widespread undernourishment, and the importance that agricultural sector cover in this countries, which contribute for more than 30% of their GDP, and about 15% of their exports (Tefera, 2012). PHL cause therefore a reduction of food supply in the market, which not only contribute to hunger, but also leads food prices to increase (Tefera, 2012). The latter in particular is often responsible of triggering political instability in several LDCs. The reduction of PHL should be thus considered a priority in the global political agenda, as any achievement in this direction can have important implications for improving the sustainability and resilience of the food systems, as well as reducing the environmental impact of agriculture (Stathers et al., 2020). Yet, from a socio-economic perspective, a more efficient agricultural production can also have positive effects on the income of small-size producers, and, in turns, on the role played by woman in this respect, who often are in charge of the different post-harvest activities.

The literature on this topic so far has mostly focused on the quantification of PHL and food waste along the food supply chain, or have analysed the determinants of PHL considering only a narrow number of cases (Kaminski and Christiaensen, 2014; Abass et al., 2014). This paper contributes to this literature by proposing a first attempt to analyse to what extent climatic conditions affect PHL, exploiting a large sample of countries and using data at the sub-national level over a 20-year period.

We use data from APHLIS (African Post-harvest Losses Information System), that provides comparable estimate of actual PHL at the regional (ADM1) level thanks to the help of a network of cereals experts in Sub-Saharan African countries (SSA). From a methodological perspective, we rely both on panel data and cross-section analysis.

This allows a deeper understanding of the causes of PHL, overcoming some limitations of the data (described in Section 4). The main results suggest that changes in the climatic conditions affect PHL. We find that humidity and other proxy for water vapour are detrimental for PHL, likely due to a favorable environment for pests. Higher temperature negatively affects PHL only in combination with humidity, otherwise it has a positive effect inducing better drying conditions. The size of the estimated effects are not irrelevant when considering the role played by humidity. An increase by one standard deviation in humidity (approximated by different variables) leads to a change in PHL from 0.42 to 1.2 percentage points.

The remainder of this paper is organized as follows. The next section introduces the background of the paper. In Section 3 we discuss the PHL measurement issue, and we present the data used in the analysis. Section 4 presents the empirical analysis, while the main results and conclusions are discussed in Section 5 and Section 6, respectively.

2 Background

Over the last 50 years, and especially after the food crises of the 2007-2008 period, the reduction of PHL has received increasing global attention (Stathers et al., 2020). This is proved by the fact that the reduction of PHL along the food supply chain is a specific target of Sustainable Development Goals (SDG), and specifically SDG 12.3. However, any improvement in the reduction of PHL can have positive socio-economic and environmental implication on many other SDGs. PHL is a sensitive issue especially for African countries. The African Union Member States have indeed set the ambitious target under the Malabo Declaration of reducing by 50% overall food PHL by 2025 (Stathers et al., 2020). Food waste and losses may occur at different stages of the food chain. FAO (2010) in particular suggests five main steps, along which food is lost: 1 - Harvesting phase, where food may incur in damages; 2 - Post-harvesting phase, including handling of harvested foods, drying, winnowing and storage; 3 - Processing phase; 4 - Distribution phase; 5 - Final consumer consumption, where food may be wasted for instance due to its poor quality or aspect. The first two stages are particularly critical for developing countries.

There is growing attention in the literature toward a better understanding of the causes of PHL. There are many reasons leading to PHL, as for instance crops left unharvested in the field, damages during transportation, or the action of pests and bacteria (Stathers et al., 2020). Delgado et al. (2021a) identify the following six main determinants of PHL: human capital; climate and environment; infrastructure; technology; economic incentives; market access. Our paper aims at contributing to the literature dealing with climate as potential determinant of PHL. Among the scarce number of contributions dealing with this issue, rainfall, temperature and moisture emerged as important determinant of PHL. Delgado et al. (2021a) analysing data from a survey on the determinants of PHL carried out in different developing countries for various crops, provide evidence that (self reported) adverse climatic condition increase PHL. Ambler et al. (2018) in analysing data gathered from a survey in Malawi find evidence of a positive relationship between PHL and rainfall during the post-harvest season for different crops. The same evidence is emphasized by Tefera (2012) in a review dealing with the main determinants of maize PHL in Africa. Arah et al. (2016) in a review concerning tomato postharvest handling practices in developing countries, provide evidence that high temperatures increase PHL. Similarly, Kasso and Bekele (2018) analysing data from a survey in an Ethiopian region, suggest that heat and humidity are important determinants of PHL for horticoltural crops.

Against this background Kaminski and Christiaensen (2014) in analysing data on self-reported maize losses in three African countries (i.e. Malawi, Uganda and Tanzania), make an attempt to provide a quantification of the effect of temperature on PHL. They show that is not high temperature *per se* that increase PHL, but is the combination of humidity and heat that is detrimental for PHL. The authors find evidence that a 2.3 C° increase in temperature during the wettest quarter of the year is associated with an increase of PHL of 0.95 percentage points, and 21 percentage point increase in the probability to incur in PHL. Conversely, average annual temperatures tend to reduce PHL, as higher temperature accelerate the maize drying phase, and so the probability to incur in PHL.

Most of the literature discussed in this section dealing with the relationship between climatic conditions and food losses is based on survey data, where often data on PHL are self-reported, and where the respondents are simply asked to answer whether or not the weather is a relevant determinant of PHL. These elements clearly make the quantification of this relationship quite problematic. Moreover, in many cases, survey data refer to a narrow context or refer to very few countries, and thus casting some doubt on the external validity of the results obtained through these analyses. In this paper we assess the effect of climatic conditions on maize PHL using data on PHL for a large number of Sub-Saharan countries at the sub-national level, and data on different weather indicators (e.g. temperature, precipitation, humidity, etc.). Our empirical analysis will therefore make an attempt to provide a quantification of the effect of climatic conditions on PHL. The main pros and cons of our approach are discussed in the next session.

3 Data

The design of successful strategies to reduce PHL is strictly related to an appropriate measurement of the extent to which this occurs, especially in low- and middle-income countries (Delgado et al., 2021b). Several studies have tried to quantify PHL as percentage of the total production, presenting estimations that vary considerably from one to another (Delgado et al., 2021b). This is due to several reasons. First, there is no consensus on what PHL and Food Waste are. This is especially evident if the objective is measuring food waste and losses in an international coherent way, as the boundaries between the two are not always clear (Fabi et al., 2021)[1]. Second, estimations may differ substantially if one relies on a macro or micro approach[2]. The first one considers aggregated data provided by national authorities, while the second one is often based on survey data that involve different actors within the food value chain. Each of these approaches has some disadvantage. The main drawback of the macro approach is the quality of the data, which are often missing for many regions of the worlds, and for different stages along the food value chain. The poor representativeness of some local realities especially in the low- and middle-income countries does not allow to fully capture the losses occurred in different stages of the food value chain. In contrast, the micro approach, being often based on survey, allows having a more comprehensive view of the losses occurring along the value chain. However, other than very costly, they are often context specific and the results are difficult to compare across various studies (Delgado et al., 2021b).

Examples of PHL measurement based on micro approaches in a comparable way across countries can be found in Kaminski and Christiaensen (2014) and Delgado et al. (2021b). In the former case, the authors rely on data from the Living Standard Measurement Surveys in three countries (i.e. Malawi, Tanzania and Uganda). The respondent were asked to indicate whether they incurred in any losses in the maize production, and, if so, to quantify the proportion of such losses. One of the main drawback of these

[1]For an in depth discussion on food waste and losses measure see Fabi et al. (2021) and Bellemare et al. (2017).

[2]for an extensive discussion on the different PHL estimation methodologies see Delgado et al. (2021b).

data is that very few farmers actually declared to have incurred in PHL, leading the estimated PHL in the overall sample to vary from about 1.4% to 5.9%. Delgado et al. (2021b) propose three different methods to quantify PHL, which all allow distinguishing between the total food that is loss and quality deterioration and allow distinguishing between losses at different production stages. Surveys were conducted in seven countries (Ecuador, Peru, Honduras, Guatemala, Ethiopia,China, and Mozambique) for 5 crops (potato, maize, beans, wheat, teff). While the proposed approaches trace a promising avenue toward a reliable and comparable quantification of PHL along the food value chain, these data have no time variation, which is an important element to understand the impact of change in climatic condition on PHL as in our case.

Against this background, our choice fell on the use of PHL data from the African Postharvest Losses Information System (APHLIS), which represents a network of cereals and grain experts in SSA countries that has the objective to provide accurate estimate of PHL in these countries at the regional level. These data are aimed at improving existing aggregated data on PHL (e.g. FAO data). APHLIS data are pooled considering data on the literature and data reported by scientists in the considered regions. APHLIS represents perhaps the most promising international attempt to collect, analyze and disseminate data on post-harvest grain losses in SSA. The data quantify the percentage loss for each phase of the post-harvest chain. APHLIS considers the net weight losses in dry substance occurred after a determined post-harvest activity. In some cases, APHLIS also considers quality losses: for instance, if the quality of the product is considered unsuitable for final consumption, this is then considered as an actual weight loss. One of the main value added of APHLIS is that missing data are replaced by interpolating existing data on production and weather information. We collect data at the highest level of disaggregation available, namely at the regional (Administrative 1 - ADM1) level.

Among different cereals, the analysis focuses on maize, as it represents the most important staple in SSA countries, thus being a fundamental source of food and income for million of people in this region (Tefera, 2012). It is worth mentioning that maize is particularly subject to aflatoxin contaminations, whose chronic exposure, as in many African countries, is correlated to malnutrition and fatalities. Aflatoxin contamination is exacerbated by insufficient crop drying and storage, which lead the moisture level to be well above the optimal level, and thus allowing insect infestations and damages (Román et al., 2020).
Our analysis considers diiferent weather variables: rainfall, temperature, humidity and

evaporation. These data are taken from the ERA5-Land dataset (Muñoz Sabater, 2019). It provides monthly gridded data at 0.1° x 0.1° resolution that we aggregate to match the administrative boundaries (ADM1). The monthly data have been then redefined using the harvest and post-harvest season, to be consistent with PHL data. Considering jointly temperature and precipitation is important to avoid biased estimates of their effects since the two variables are historically correlated (Auffhammer et al., 2013). However, to better represent the complexity of the climatic conditions, we also consider other weather variables, such as solar radiation, evaporation and humidity.

In Table I are presented the summary statistics. Our sample is formed by an unbalanced panel of 363 provinces (in 36 Sub-Saharan African countries) for 21 years (2000-2021). The yearly average percentage of the production being lost is about 17.6%, with a minimum of 13.5% and a maximum of 30.7% and a standard deviation of 2.1%. The weather variables refers to the harvest and post-harvest season. The average temperature in our sample is about 24 C°. The total precipitation has an average of 313 mm and it presents a large variability among the provinces (standard deviation of 317 mm). We extract from the ERA5-Land dataset two other variables, i.e. surface net solar radiation and total evaporation. The former is used as a control variable to proxy the cloud cover. The second one (expressed in absolute terms) represents the accumulated amount of water that has evaporated from the fields' surface. We use it in the analysis as an indicator of humidity and, given the high correlation with precipitation, we use them alternatively. With the same scope, we compute the relative humidity expressed in percentage using data on surface and dew-point temperatures. Finally, to consider the combined effect that temperature and humidity can have on PHL, we compute the Environmental Stress Index (ESI)[3] as showed in Moran et al. (2001).

[Table 1 about here.]

4 Empirical Strategy

The data described in Section 3 allow us to exploit the longitudinal structure over a large sample of sub-national units. This represents a unique opportunity given by APHLIS data on PHL. However, these data in some cases show low inter-annual variability within each ADM1 unit. To address potential biases related to this issue, we consider

[3]The ESI is a measure to approximate the Wet Bulb Globe Temperature (WBGT) and has been used to estimate the impact of heat stress on crop production in De Lima et al. (2021).

also as alternative methodologies to quantify the impact of the climatic conditions on PHL a cross-section analyses.

The first approach we employ is a panel data model. This method allows us to exploit the within unit weather variability to identify its short to medium-run effect on PHL. Specifically, we consider the following empirical specification:

$$PHL_{ijt} = \beta_1 X_{ijt} + \beta_2 X_{ijt}^2 + \gamma_j + \delta_t + \phi_{ixt} + \epsilon_{ijt} \tag{1}$$

where, PHL_{ijt} represents the percentage of maize post-harvest losses in country i, province (ADM1) j in the year t; X_{ijt} is a vector of weather variables, which includes average temperature, precipitation, humidity, evaporation and solar radiation. All these variables have been considered in the harvest and post-harvest season. The weather variables enter in our empirical specification as both linear and quadratic, to control for non linear relationship and, importantly, to allow the effect of weather deviation to change with their baseline level, i.e. the climate (see Mérel and Gammans (2021)). We control also for a large set of fixed effects: γ_j are province fixed effect; δ_t year fixed effects; we also introduce country specific time trends ϕ_{ixt} to control for potential unobservable time-varying country factors. Our fixed effects allow controlling for deviations in precipitation and temperature, which are likely to be randomly distributed (Damania et al., 2020). Standard errors are clustered at the Administrative 1 level. [4]

Our second approach is in line with the Ricardian literature that exploits cross-sectional variability of the climatic variables to quantify their relationship with the economic outcomes (e.g. land value in the first paper by Mendelsohn et al. (1994)). This method is traditionally considered able to provide an estimate of the long-run effect of the climate where full adaptation take place. Specifically, we consider the following empirical specification:

$$P\bar{H}L_{ij} = \beta_1 \bar{X}_{ij} + \beta_2 \bar{X}_{ij}^2 + \beta_3 \bar{\mathbf{Z}}_{ij} + \gamma_i + \epsilon_{ij} \tag{2}$$

where now the dependent variable $P\bar{H}L_{ij}$ is defined as an average over the analysed period, while the weather variables are defined as 30-years historical norms and computed over the period 1970-2000. $\mathbf{Z}_{ij}$ represents a vector of weather variables such

[4] Note that our main equation 1 is run using a fixed-effect panel data model. Other related articles in the literature (e.g. Kaminski and Christiaensen (2014) have instead used a censored Tobit model when dealing with a dependent variable expressed as percentage. We decided not to rely on this estimator as our dependent variable is not either left or right censored.

as solar radiation, elevation, access to cities and average GDP of the sub-national unit. Controlling for such variables is a key element to reduce the possibility of omitted variables bias. γ_i is a set of country fixed effects that account for national specific factors. Finally, ϵ_{ij} represents the error terms which is assumed not to be correlated with the climatic conditions.

5 Main results

In Table II we present the results from the panel data analysis. As a preliminary step, Column (1) shows the impact of temperature and precipitation on maize production. A 1°C rise in temperature during the cropping season reduces the output by 15% (the "Mfx" at bottom of the table shows the average marginal effect). In the case of precipitation, we find that an increase in the amount of water is beneficial up to a certain point (about 1230 mm) where a further rise would reduce the output. These results are consistent with previous literature and show how substantial is the impact of a temperature shock on sub-Saharan African crop production.

In columns from 2 to 4 we presents the results concerning the weather effect on PHL. In Column (2) we show the estimates of temperature and precipitation on PHL. In both cases, the average marginal effect is negative but the magnitude is considerably small. An increase in temperature by 1°C will reduce PHL of about 0.2 percentage points (pp). This is coherent with the fact that higher temperature allows a better drying of the seeds. Although the coefficients associated with precipitation are not significant, their signs are unforeseen, since we expect that higher level of precipitation would induce more PHL. Solar radiation presents significant coefficients but of negligible size.

To have a better understanding of these findings, we consider two alternative variables to precipitations. In Column (3) we show the effect of temperature and humidity on PHL. In the first case the average marginal effect is still negative but not significant (-0.03). Contrary, humidity shows a positive effect, indicating that a 1% (sd 17%) increase in relative humidity would increase PHL by 0.07 pp. A similar result occurs when considering the total evaporation (Column 4), where the associated coefficient is also positive and statistically significant. In this case, an increase of 1 m (sd 0.9%) in evaporated water from the fields would induce PHL to rise by 0.6 pp. The overall results suggest that higher level of humidity leads to a more pronounced deterioration of maize. This is likely due to the fact that humidity is a core determinant of the moisture content of maize (Tefera, 2012) and a key factor for biological activity (Coradi et al., 2020)). However the magnitude of this effect is considerably small, especially when compared with the weather effects on production.

[Table 2 about here.]

In Table III, we present the results from the Ricardian-style analysis. In Column (1) we observe that temperature does not have any significant effect on PHL. Contrary, the coefficients associated with precipitation are significant but the implied average marginal effect has a very low magnitude (0.001 pp). Column (3) and (4) show the impact that humidity and evaporation have on PHL, as an alternative to precipitation. Again, the associated coefficients for their marginal effect are positive and significant (0.02 and 0.39 pp) but their size is lower than the one previously estimated in the panel approach. Finally, in Column (4) we present an estimation of the effect of the Environmental Stress Index (ESI) on PHL. As mentioned in Section 4, this index allows us the consider the heat stress caused by the combination of both temperature and humidity. The associated coefficient for the average marginal effect is positive and significant (0.13) showing how the interaction between the two variable can translate into an higher detrimental effect on PHL (even if still a small one).

Looking at the control variables, solar radiation is never statistically significant. The coefficient associated with the access to cities always shows a positive sign, implying that the more time is needed to reach the closest town the higher is the PHL. However, the coefficient is not statistically significant at standard level. The elevation variable shows opposite coefficient and almost never significant. Potential yield has a positive coefficient, implying that the more suitable the land is to produce maize the higher would be also the consequent losses. Finally, the associated coefficient to GDP is always positive but not statistically significant.

Overall, these results are coherent with the ones estimated with the panel data approach. Temperature *per se* is not a determinant of PHL, although its interaction with humidity can translate into higher losses. Indeed, we find that humidity and other proxies for water vapour in the air are associated with higher PHL, even if these effects are considerably small.

[Table 3 about here.]

6 Conclusions

In the present paper we show the first attempt to empirically estimate the impact of climatic conditions on PHL for an extensive sample of countries using sub-national data. In particular we highlight the importance of climatic conditions, and humidity in particular, in affecting maize PHL in SSA. The results stress one more time the importance of developing more efficient post-harvest strategies in these countries. Effective post-harvest management practices may indeed not only improve food availability, but they could also reduce pressure on natural resources, which should be instead even more exploited to increase food production in response to the impressive population growth occurring in these countries.

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Table I: Descriptive Statistics

	N	Mean	SD	Min	Max
Total Production (t)	7583	121,046.31	280,867.00	1.00	4,819,206.00
Losses (t)	7580	22,669.26	53,063.57	1.00	1,083,961.00
Losses (%)	7580	17.62	2.07	13.49	30.73
Temperature (°C)	8463	23.99	4.51	2.89	33.35
Precipitation (mm)	8463	312.66	317.15	0.17	2,428.46
Solar Radiation (kJ m^{-2})	8463	16,223.41	1,696.57	9,026.95	20,246.60
Total Evaporation (m H20 equivalent)	8463	1.76	0.92	0.04	4.24
Relative Humidity (%)	8463	53.45	17.33	14.32	87.18
Environmental Stress Index (ESI)	8463	20.71	4.26	1.31	27.03
Countries	36				
Provinces (ADM1)	363				
Years	21			2000	2020

Table II: Impact of the Weather on Output and Post-Harvest Losses - Panel Data Approach

	(1) Log of Production	(2) Losses (%)	(3) Losses (%)	(4) Losses (%)
Temperature (°C)	-0.308*	0.051	0.245**	0.110
	(0.164)	(0.115)	(0.122)	(0.113)
Temperature^2	0.003	-0.005**	-0.006**	-0.004
	(0.003)	(0.003)	(0.003)	(0.003)
Precipitation (mm)	$4.29 \times 10^{-4***}$	-7.56×10^{-4}		
	(0.000)	(0.000)		
Precipitation^2	$-1.74 \times 10^{-7***}$	-2.41×10^{-7}		
	(0.000)	(0.000)		
Humidity (%)			0.092*	
			(0.047)	
Humidity^2			-2.31×10^{-4}	
			(0.000)	
Evaporation (m)				0.932**
				(0.379)
Evaporation^2				
Solar radiation (kJm^{-2})	$4.88 \times 10^{-4**}$	$9.77 \times 10^{-4***}$	0.001***	$7.61 \times 10^{-4**}$
	(0.000)	(0.000)	(0.000)	(0.000)
Solar radiation^2	$1.27 \times 10^{-8**}$	$3.68 \times 10^{-8***}$	$-2.64 \times 10^{-8**}$	$-2.45 \times 10^{-8**}$
	(0.000)	(0.000)	(0.000	(0.000)
Mfx Temperature	-0.154***	-0.200***	-0.030	-0.070
Mfx Solar Radiation	$7.52 \times 10^{-5**}$	$2.16 \times 10^{-4***}$	$1.78 \times 10^{-4***}$	-3.2×10^{-5}
Mfx Precipitation	$1.50 \times 10^{-4*}$	-0.001**		
Mfx Humidity			0.066***	
Mfx Evaporation				0.593***
Observations	7583	7580	7580	7580
R^2	0.944	0.479	0.480	0.479

Notes: Estimated model as Equation (1), with ADM1 and year Fixed Effects and country-specific time trend. Average Marginal Effect (Mfx) computed with Delta method. Standard errors are clustered at ADM1 level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table III: Impact of the Weather on Post-Harvest Losses - Ricardian Approach

	(1) Losses (%)	(2) Losses (%)	(3) Losses (%)	(4) Losses (%)
Temperature (°C)	-0.016	-0.108	-0.125	
	(0.151)	(0.154)	(0.163)	
Temperature^2	1.64×10^{-4}	0.003	0.002	
	(0.003)	(0.003)	(0.003)	
Precipitation (mm)	0.002***			
	(0.001)			
Precipitation^2	-1.06×10^{-6}***			
	(0.000)			
Humidity (%)		0.050		
		(0.038)		
Humidity^2		-2.3×10^{-4}		
		(0.000)		
Evaporation (m)			1.035***	
			(0.371)	
Evaporation^2			-0.169**	
			(0.083)	
ESI				-0.133
				(0.163)
ESI^2				0.006
				(0.004)
Solar radiation (kJm^{-2})	1.53×10^{-7}	3.25×10^{-7}	2.33×10^{-7}	1.01×10^{-7}
	(0.000)	(0.000)	(0.000)	(0.000)
Solar radiation^2	-3.77×10^{-15}	-8.36×10^{-15}	-7.08×10^{-15}	-3.77×10^{-15}
	(0.000)	(0.000)	(0.000)	(0.000)
Access Cities (min)	2.71×10^{-4}	2.96×10^{-4}	2.67×10^{-4}	2.16×10^{-4}
	(0.000)	(0.000)	(0.000)	(0.000)
Elevation (m)	-3.6×10^{-5}	2.02×10^{-4}	-1.57×10^{-4}	6.51×10^{-4} **
	(0.000)	(0.000)	(0.000)	(0.000)
Potential Yield	5.88×10^{-5}**	5.97×10^{-5}**	3.63×10^{-5}	7.68×10^{-5}***
	(0.000)	(0.000)	(0.000)	(0.000)
log GDP	0.106	0.063	0.077	0.101
	(0.069)	(0.067)	(0.071)	(0.069)
Mfx Temperature	-0.008	0.017	-0.029	
Mfx Sol Rad	3.18×10^{-8}	5.77×10^{-8}	6.14×10^{-9}	-2.02×10^{-8}
Mfx Precipitation	0.001***			
Mfx Humidity		0.024***		
Mfx Evaporation			0.394***	
Mfx ESI				0.127***
Observations	363	363	363	363
R^2	0.687	0.691	0.689	0.684

Notes: Estimated model as Equation (2), with country Fixed Effects. Average Marginal Effect (Mfx) computed with Delta method. Standard errors are clustered at ADM1 level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$