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The impact of climate change on agricultural net revenue: a case study in the Fouta Djallon, West Africa

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ABSTRACT. Continental-scale economic analysis suggests that changes in climate conditions are associated with lower agricultural net revenue in sub-Saharan Africa. Specific locations, however, may not reflect this overall trend due to variation in baseline climate, soils, and socioeconomic factors that are difficult to model at large scales. The economic effect of changes in climate conditions on agricultural revenue in particular places in sub-Saharan Africa remains largely unknown. To test this effect, we study an area of West Africa with high climate variation over a small geographic area. We find that higher temperatures and precipitation lower agricultural revenues in the more important rainy season but increase revenues in the less important cool, dry season.

1. Introduction

Climate change poses a serious threat to agricultural production because of its potential impact on yields (Reilly *et al.*, 2003; Lobell and Field, 2007;

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Lobell *et al.*, 2011a, b; Gourdji *et al.*, 2013). Yield losses could lead to large losses in revenue, impacting human wellbeing (Butt *et al.*, 2005). However, farmers may be able to mitigate these effects by switching crops and farm management (Wood *et al.*, 2014). Understanding the net effect of climate on agriculture thus requires capturing farmer adaptation (Mendelsohn and Dinar, 1999).

One approach that takes adaptation implicitly into account is the Ricardian method (Mendelsohn *et al.*, 1994). The Ricardian method estimates climate impacts by comparing the net revenues of farmers in different climates across space. Because farmers in each place have adjusted to their particular conditions, the Ricardian approach implicitly captures adaptation. Although early research using the Ricardian method focused on the United States (Mendelsohn *et al.*, 1994; Mendelsohn and Neumann, 2004), there are now many Ricardian studies of developing countries (Deressa *et al.*, 2005; Gbetibouo and Hassan, 2005; Kurukulasuriya *et al.*, 2006; Molua, 2008, 2009), where the effects of climate change on agriculture are expected to be greatest (Mendelsohn *et al.*, 2006). These developing country studies have identified a significant, negative relationship between warmer temperatures and net revenue, mostly at the continental or large-country scale.

One concern about such large-scale studies is that they may be biased by omitted variables (Deschênes and Greenstone, 2011). Over such vast spaces, hidden variables may explain the effects ascribed to climate. We test this hypothesis by exploring climate impacts across a small homogenous space that happens to exhibit sufficient climate variation. We follow a few other small-scale studies that have explored small spatial scales (Seo *et al.*, 2005; Kurukulasuriya and Ajwad, 2007; Fleischer *et al.*, 2008; De Salvo *et al.*, 2013). We test whether the same negative impact of higher temperature is still evident across a more similar set of farmers.

In this study, we examine the Fouta Djallon area of West Africa (figure 1). This site spans from low to high elevation over a small area, generating large differences in climate (figures 2 and 3) without large changes in biophysical (such as underlying soils) and socioeconomic conditions. This study area is thus well suited to estimate the impact of climate on agricultural revenue at a small scale and to test our hypothesis. Following the earlier literature, we use a Ricardian method.

2. Material and methods

2.1. Study site

The Fouta Djallon highlands form a mountainous ecosystem that straddles the countries of Senegal, Guinea, Mali and Sierra Leone, between latitudes 6°00′ and 12°20′ N and longitudes 7°00′ and 15°00′ W. The highlands cover an area of 80,000 km^2 and rise to an average of 1,000 m above sea level, with the highest point reaching 1,600 m (Hillers *et al.*, 2008). Combined with the lowlands, the region comprises 378,500 km^2 (Kamara *et al.*, 2002). The Fouta Djallon makes up one of the most ecologically important zones of West Africa, harboring perhaps the highest level of biological diversity in

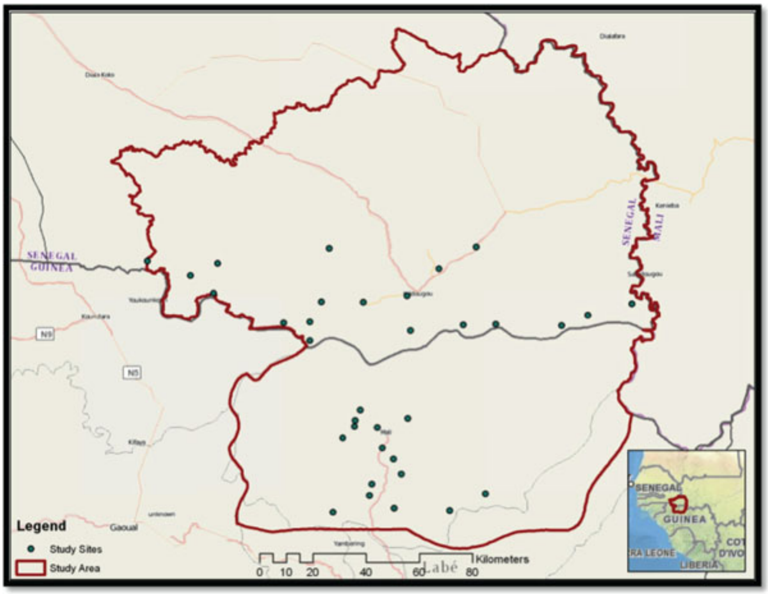

Figure 1. *Map of study area. Red line indicates the boundary of the two political districts in which the surveys were conducted. The points indicate survey villages*

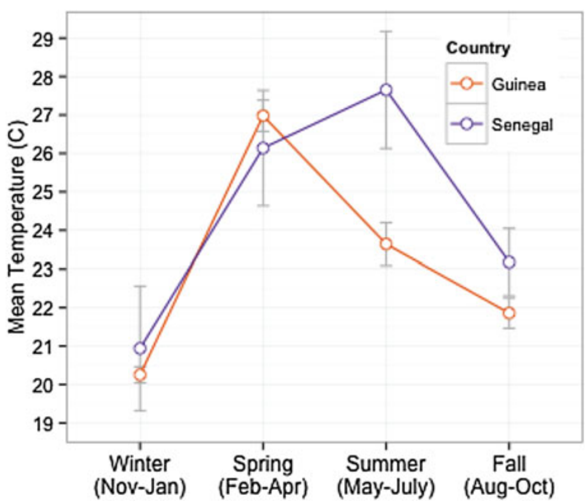

Figure 2. *Mean seasonal temperature (C), as measured by the SSMI satellite*

the Upper Guinea zone (Schnell, 1968) and also serving as the headwaters for West Africa's most economically important rivers: Gambia, Senegal and Niger (Porembski *et al.*, 1994; Lebbie, 2001). Climatically, the Fouta Djallon is thought to have been a refuge of climate stability during unfavorable periods in the rest of the region (Maley, 1987; Porembski *et al.*, 1994). The

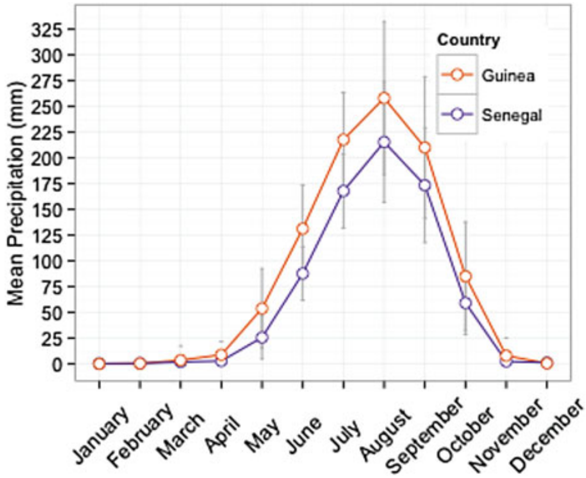

Figure 3. *Mean monthly precipitation (mm), using ARTES data*

highlands part of the region receives significantly higher rainfall than the lowlands, resulting from interactions among topography, oceanic proximity and prevailing warm, wet, southwesterly winds (Kamara *et al.*, 2002). The rainy season lasts from May to October and annual rainfall is mostly below 2,000 mm, with lower precipitation in the northern part of the zone (figure 3). Geologically, the area is dominated by sandstone with the highland mountains being sandstone and dolomite ingersolls in a savannah landscape (Porembski *et al.*, 1994). As a result, soils are generally considered to be infertile and slightly acidic, favoring indigenous crops such as *Digitaria exilis* (fonio) (Morton, 1986).

Most of the Fouta Djallon is undergoing significant anthropogenic pressure and change (Porembski *et al.*, 1994; Lebbie, 2001). The Guinean highlands are densely populated, with up to 120 inhabitants per square km, with around 80 per cent of the local population dependent on agriculture, agroforestry and animal husbandry. The main crops cultivated are peanuts, rice, maize, cassava, *fonio* and potatoes. Also in abundance are oil palm trees, cashew, pineapple, banana, mango and avocado. The dominant ethnic group in the region is the Fulani (table 1), but with other, smaller ethnic groups such as Sousou, Djallonké, Malinké, Bassari and Bedik.

2.2. Model

Early crop production models of the impact of climate on agriculture were inappropriate for estimating economic impacts because they did not incorporate farmer adaptation strategies such as crop switching and, thus, likely overstated the economic impacts of climate (Mendelsohn *et al.*, 1994). To account for adaptation, Mendelsohn *et al.* (1994) developed the Ricardian model, which incorporates farmer adaptation by measuring changes in agricultural revenue (either land values or net revenue) as a function of climate variables (and other socioeconomic controls) that vary across space. This approach employs a space-for-time substitution approach, which

Table 1. *Summary statistics for key covariates in the study zone, by country*

	Senegal				*Guinea*			
	Mean	*SD*	*Min*	*Max*	*Mean*	*SD*	*Min*	*Max*
Time to closest market (min.)	92.37	57.31	10	240	89.62	38.06	0	150
Road quality (0–5)	2.63	0.83	1	5	2.68	1.15	1	4
Is Fulani	0.42	0.50	0	1	0.98	0.13	0	1
People in household	13.85	7.77	3	50	11.64	4.70	5	36
Farm area (ha)	0.79	0.65	0.15	4.00	1.85	3.02	0.08	15.00
Net revenue (1,000 CFA)	265.08	293.45	−221.25	1363.40	288.99	216.27	47.16	979.27
Observations	71				56			

Notes: Country corresponds roughly to endpoints of climate conditions, with Senegal being warmer and drier and Guinea being cooler and wetter. 1,000 CFA is equal to approximately US$2. Road quality is ranked from lowest to highest.

treats changes in properties at different spatial locations as analogous to similar differences that could occur through time. Regressing agricultural revenue on climate and other control variables quantifies the importance of climate factors to agricultural net revenue.

The first application of the Ricardian model used land values as a response variable (Mendelsohn *et al.*, 1994). In cases in which countries do not have strong markets for land, such as in most of sub-Saharan Africa, net revenue is used as a proxy for land rent (Kurukulasuriya *et al.*, 2006), an approach we adopt in this paper. Net revenue is calculated as gross revenue (production for each crop multiplied by the price for that crop) minus costs (the monetized cost required to produce the given amount). Each farmer is assumed to maximize net revenue given various exogenous constraints on his or her farm, such as climate, soils and socioeconomic conditions. Farmers will choose the particular crop, land use and inputs that maximize net revenue for their land. This is given as:

$$\max R = \sum \int P_{qi} Q_i(X_i, C, S) - \sum \int P_x X_i$$

where R is annual net revenue, P_{qi} is the market price for crop i, Q_i is a production function for crop i, for which X_i is a vector of inputs chosen by the farmer, such as seed, fertilizer and pesticides, C is a vector of climate variables, and S is a vector of exogenous variables such as soil, socioeconomic and geographic variables.

In this analysis, we choose a set of control variables that reflect the important social, economic and ecological conditions of agriculture in the study zone (table 1). To measure the connectedness of a household to markets we use a measure of reported road quality and distance to local market. To control for underlying biophysical differences in soil on farms, we use a dummy variable for whether there was lowland soil anywhere on a farm. There are two main soil types among farms: upland soils and lowland soils. Lowland soils are exclusively used for rice while upland soils are used for maize, *fonio*, millet, potatoes and other crops. We did not use conventional soil classifications, such as the Food and Agriculture Organization soil map, because they do not vary at the narrow spatial scale of the study. We also include farm size (cultivated area) and the number of people in the household as controls. We also tested the square term of farm size, but found it insignificant. Irrigation has been identified as a potentially confounding variable since it modifies local climate (Schlenker *et al.*, 2005), but is not an issue in this study since all agricultural production in our study site is rain fed.

If a farmer chooses each output to maximize net revenue, and chooses each endogenous input to maximize net revenue, the resulting net revenue will be a function of the exogenous variables (Mendelsohn *et al.*, 1994; Seo and Mendelsohn, 2008; Wang *et al.*, 2009):

$$R^* = f(P_q, C, S, P_x, P_l)$$

The goal of the Ricardian technique is to assess changes in net revenue of agricultural land across climate gradients. Previous studies

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(Mendelsohn *et al.*, 1994; Kurukulasuriya *et al.*, 2006; Seo and Mendelsohn, 2008; Wang *et al.*, 2009) used a quadratic model of climate that includes both a linear and quadratic term for temperature and precipitation:

$$R = \alpha + \sum b_i T_i + c_i T_i^2 + \sum d_i P_i + e_i P_i^2 + \sum m_k Z_k + \varepsilon_n,$$

where R is net revenue per hectare, T is temperature, P is precipitation, Z is a vector of socioeconomic and other control variables, and is an unobserved error term. Although we tested quadratic climate terms in our model, they were insignificant. The resulting model is consequently linear in climate. We found that all models exhibited heteroskedasticity under the Breusch–Pagan test ($p < 0.05$). We corrected for this using robust standard errors.

2.3. Data

We used a spatially explicit data set of 126 farmers collected from 38 villages in northern Guinea and southern Senegal. Sixteen villages are from the prefecture of Mali, region of Labe in northern Guinea (figure 1). Twenty-one villages were selected from the region of Tambacounda, around the town of Kedougou, the southeastern-most town in Senegal (figure 1). Most farmers were of the Fulani ethnic group (table 1). The surveys were conducted in 2010 between the months of June and September. Although access to villages was difficult at this time due to rains, this was an optimal time to collect data on the previous year because it allowed for information on the entire sale from the previous harvest, which would have been impossible in the dry season. The timing of the survey also allowed for the collection of information on the goods sold to buy materials and inputs for planting early in the rainy season.

The villages surveyed span a topographical, ecological and climatic gradient, ranging in elevation from sea level to 1,300 m, in mean annual temperature from 17°C to 30°C, and in precipitation from 400 mm per year to 2,000 mm per year. The study zone was stratified into two zones along this ecological gradient. The Kedougou region lies in southern Senegal and is mostly flat, although there is a range of cliffs and hills that reach 500 m, and has a near Sahelian climate. The prefecture of Mali in northern Guinea reaches an altitude of 1,300 m and has much higher precipitation and lower temperatures than in Kedougou (figures 2 and 3). The low-elevation villages are located in Senegal and the high-elevation villages are located in Guinea. For simplicity, we refer to villages across this gradient by their national affiliation. Given high distances, travel times and costs to the rest of Senegal and Guinea, these communities are more similar to each other in culture and agricultural practices than they are to the rest of their countries.

The surveyed villages were selected at random from regional village lists provided by local health workers and agricultural extension agents. These lists are more thorough and up-to-date than the existing government lists, which exclude smaller villages and seasonal farming communities. In each community, the chief of the village was asked to identify two high-productivity farmers and two low-productivity farmers as well as one average farmer to be surveyed. Farmers were surveyed as long as a minimum of three identified farmers were available in each community. If the minimum number were not available, the surveyors returned later in the day or at another date. The survey included quantitative questions on household production levels, inputs, demography, local infrastructure, soil, environmental change, wage rates and other socioeconomic variables (see online Appendix A, available at http://journals.cambridge.org/EDE). In a few cases, key observations were missing from the data set (e.g., sorghum yield). These values were imputed by regressing available data on strong predictors for similar farmers (e.g., land area cultivated, fertilizer use) and using the relationship to impute missing values for similar farmers. Free-form questions were also asked to get a qualitative sense of farming practices (see online Appendix A).

Surveys were implemented with two professional survey administrators who come from the region. The survey was first tested in five villages in the region that were not included in the final study. Because all identified farmers chose to respond, there was no non-response bias in the survey. A potential source of bias identified in the survey test was that the best farmers were most often not at home because they were in their fields. We revisited communities until we found the farmer at home, even though this added greatly to survey time and reduced possible sample size. Interviewers were trained so that they understood the objectives of the survey. In cases where farmers did not understand a question, interviewers explained the question in greater detail. However, interviewers were trained not to lead farmers into possible answers in the process of questioning. All the interviews for the first two villages were conducted as a team to standardize the interview process. The survey results were discussed at the end of each day.

Local measurements of area and volume had to be converted to a standard hectare unit. The local units were either given in ropes (quarter of a hectare), *sariyaare* (a unit of volume that is measured in half gourds) and kilograms. Conversion rates are based on the expertise of local agriculture extension agents. For *sariyaare* and kilograms, the conversion to hectares varies by crops and standard crop spacing. This conversion allowed us to express production as CFA (the local currency) per hectare. The soils data collected in the survey are local measures of soil quality assessed by the farmers. These measures may be based on color but they are strongly correlated with the amount of soil organic matter content and fertility (Barrera-Bassols and Zinck, 2003). Alternative measures of soil quality were checked from the FAO, but the soils in this region were judged to be all of the same type.

We used three sources of climate data: continental-scale interpolations of precipitation from the African Rainfall and Temperature Evaluation System (ARTES) (World Bank, 2003), local weather station precipitation and temperature data, and satellite temperature data measured using Special Sensor Microwave Images (SSMI) (Basist *et al.*, 2001). The local weather station data was collected over the course of the rainy season from 2000 to 2009 for precipitation and from 2003 to 2009 for temperature. The ARTES precipitation data were collected from 1978 to 2000 (figure 3). The SSMI data were collected from 1988 to 2000 (figure 2). The ARTES and SSMI data have data per month for the whole year and are aggregated into four seasonal measures. Winter is defined as November through January; spring is February through April; summer is May through July; Fall is August through October.

A shortcoming in this analysis that is common in the development literature is that there is no observed wage rate for household labor. Most of the labor on small farms is provided by household members or close relatives, except during peak labor periods. One of the main challenges of estimating net revenues in sub-Saharan African farms is determining the wage rate that should be used for household labor. This study attempts to overcome this problem by including the financial costs of hosting work parties, in which community members come together to provide labor in exchange for a meal and some small take-home items, throughout the season and not only at peak wage periods. Although this estimate is conservative since it does not account for the sense of social reciprocity that motivates participants in these work parties, it does provide an alternative measure of wage rates depending on when in the season the work party was held. These pseudo wage rates were the used in the estimation of net revenue.

This study captures variation in climate at a local scale: the climate zone shifts over a 100 km distance. This local-scale approach captures differences in climate with other important factors, such as agricultural traditions, social institutions, pest and weed type, held relatively constant, naturally. This study also includes crops that were excluded from the larger, sub-Saharan Africa-wide study (Kurukulasuriya *et al.*, 2006), such as *fonio* and *bissap*, but which are known to play an important role in local livelihoods. Although these crops are not frequently sold in traditional market settings, farm gate prices do exist and figure strongly in household conceptions of farm value. Moreover, many of these crops have evolved *in situ* and are, therefore, more likely than other crops to be resistant to environmental conditions, which is particularly important in this sub-Sahelian zone (Franke and Chasin, 1980).

Farmers were asked about travel time to market, but when this variable was fit as a model covariate it produced the counter-intuitive result that farms that are further away have higher net revenue. To double-check this result, we calculated a spatially explicit estimate of distance from each village to its market center based on the assumption that most travel paths in the area follow topographic contours. Using a digital elevation model, we compared each pixel's elevation to neighboring cells to calculate the slope at each cell. We then weighted Euclidean distance to market centers for each community by slope using the Path Distance and Cost Distance operations in ArcGIS (ESRI, 2011). The results of the spatially explicit model produced the opposite result from the farmer reports – that locations further away from markets had lower revenue. Because this fit better with our prior belief about how markets work, we included the modeled distance to markets. Choice of which model, however, did not significantly impact the directional relationship or magnitude between climate variables and agricultural revenue.

3. Results

This study measures the effect of climate on agricultural net revenue at a local scale in the Fouta Djallon area of northern Guinea and southern Senegal. We test whether net agricultural revenue is negatively affected by higher temperatures and rainfall during the hot rainy season yet positively affected by higher temperature and rainfall during the cooler dry season. We test these hypotheses using a Ricardian model, regressing net revenue on climate variables and socioeconomic controls. Three different specifications of the model were used with different climate data sets and different measures of seasonality (table 2). We also test a number of alternative specifications using quadratic climate variables, climate interaction terms and socioeconomic variables. Because these tests were negative, we put them in online Appendix B.

The best-fit model used the precipitation measure of ARTES (weather station) and the temperature measure of SSMI (satellite) for all seasons ($R^2 = 0.342$; table 2). This conforms to other large-scale results for Africa (Kurukulasuriya *et al.*, 2006). Different measures of seasonality had very similar fits, suggesting that how monthly measures of climate are aggregated does not matter a great deal.

Consistent with predictions from continental-scale studies (Kurukulasuriya *et al.*, 2006), the ARTES and SSMI models show a negative relationship between temperature and net revenue in the summer or rainy season. This relationship, however, varies by season; our results also show a positive relationship between temperature and net revenue in the winter or dry season. The relative balance of gains in the winter months and losses during summer months is approximately equal for both of the two different classifications of seasonality. This study also finds a significant negative relationship between precipitation and net revenue in the rainy season. Since rain events occur only rarely in the dry season, there is no relationship between precipitation and net revenue in that season. The magnitude of the negative relationship between rainy season precipitation and net revenue is similar for the two classifications of seasonality (table 2).

The sign and magnitude of included socioeconomic control variables accord with intuition across the models, although the coefficients are not always significant. Road quality is uniformly positively associated with revenues, which fits with the intuition that better market access increases net revenue. Similarly, distance from market, using our estimated slope-weighted distance variable, is uniformly negative, suggesting that farms that are further from markets earn less revenue. Larger farm sizes and larger households both have higher net agricultural revenue across all models.

The regression coefficients can be interpreted as the amount of change in net revenue, measured in the West African CFA, for a one-unit change in the independent climate variable. For the SSMI-ARTES all-season model, a one-degree increase in summer temperatures corresponds with approximately a CFA 475,000 decrease in net revenue, which is around US$975, not adjusted for purchasing power. This loss, however, is balanced out by gains in the three other seasons, such that the net balance is a gain of

Table 2. *Results from main regression*

	(1)	(2)	(3)	(4)	(5)
		All Seasons		*Rainy/Dry Season*	
	Station/Station	*SSMI/ARTES*	*SSMI/Station*	*SSMI/ARTES*	*SSMI/Station*
	Net revenue				
Temperature					
Mean station temperature	**−17,825****				
	(8,910)				
SSMI_Winter		**211,244****	**428,010****		
		(98,740)	(177,299)		
SSMI_Spring		91,399	−245,795		
		(64,293)	(177,991)		
SSMI_Summer		**−479,402**	**−67,203**		
		(289,780)	(97,949)		
SSMI_Fall		449,363	54,023		
		(470,538)	(310,466)		
SSMI_Rainy Season				**−305,554*****	**−28,781**
				(110,358)	(24,939)
SSMI_Dry Season				**457,133*****	**121,827*****
				(141,005)	(42,986)

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Precipitation					
Station precipitation	**−481.0***		**961.6***		**−83.85**
	(274.2)		(557.0)		(229.3)
ARTES_Summer		**−29,762***			
		(15,183)			
ARTES_Rainy Season				**−24,021****	
				(9,440)	
Other covariates					
Road quality	21,294	45,408*	43,075	46,058*	22,980
	(24,375)	(23,315)	(26,033)	(23,548)	(22,410)
Distance to market	−0.0972	−0.211	−0.448	−0.480	−0.389
	(0.462)	(0.599)	(0.554)	(0.434)	(0.435)
Lowland soil	119,273**	77,831	81,837	70,799	79,306
	(55,599)	(51,663)	(51,227)	(48,642)	(50,029)
# of people in HH	9,469*	8,695*	9,197*	9,350*	9,921*
	(5,537)	(5,119)	(5,075)	(5,000)	(5,113)
Farm area	6,560***	5,959***	5,727***	6,143***	7,265***
	(2,090)	(1,726)	(1,705)	(1,682)	(1,994)

(*continued*)

Table 2. *Continued.*

	(1)	*(2)*	*(3)*	*(4)*	*(5)*
	All Seasons			***Rainy/Dry Season***	
	Station/Station	*SSMI/ARTES*	*SSMI/Station*	*SSMI/ARTES*	*SSMI/Station*
Constant	1.102e + 06*	−1.189e + 06	−2.981e + 06	1.132e + 06	−1.897e + 06*
	(590,634)	(2.570e + 06)	(3.337e + 06)	(1.475e + 06)	(1.053e + 06)
Observations	91	91	91	91	91
R^2	0.239	0.342	0.335	0.337	0.301

Notes: Columns represent separate regression results based on which weather information is used. Station data were collected from local weather stations, SSMI are satellite-derived temperature data, and ARTES is a database of weather data for sub-Saharan Africa provided by the World Bank. Regression models were run using all possible combinations of data sources to test for consistency in results. Weather data were aggregated based on all four seasons or, as is more representative of conditions at the site, rainy and dry seasons. In some cases, variables were dropped because of collinearity (such as only one season of precipitation in ARTES models). Values in bold indicate key climate terms for the particular model.
Robust standard errors reported in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

around CFA 270,000, or approximately US$550 per year. For the rainy–dry season classification, the net benefit is around US$300 per year, with a negative effect of increasing rainy season temperature of around CFA 300,000 (US$630) and a positive dry season temperature effect of around CFA 450,000 (US$940). The losses associated with increased rainy season precipitation are CFA 30,000 (US$60) per year for all seasons and CFA 25,000 (US$50) per year for the rainy–dry season classification (table 2).

4. Discussion

Our results show that an increasing rainy season temperature in the Fouta Djallon area of West Africa is correlated with a loss of agricultural revenue, suggesting that crop yields are sensitive to increases in temperature. These results are qualitatively consistent with predictions for sub-Saharan Africa based on continent-wide assessments (Kurukulasuriya *et al.*, 2006). However, agricultural losses from increased rainy season temperature are more than balanced out by higher revenue associated with increased temperature in the cooler winter months.

Our results also suggest that precipitation in the rainy season is associated with a loss of net revenue. Results from an African continental-scale assessment, however, show a positive relationship with precipitation in the spring and summer and a negative effect in winter and fall. The finding that increased precipitation decreases revenue suggests that, on average, the study region receives adequate rainfall for crop production and further precipitation would, thus, be detrimental. The mechanisms, however, of the negative effect of precipitation are not clear and could come from direct physiological effects of moisture, greater cloud cover, or increased load of pests and pathogens. Our result indicates a negative impact of increasing mean precipitation, but global climate projections also predict a change in the variance, and not just the mean, of precipitation. Increasingly variable precipitation, in the form of extreme weather events, may override changes in mean values in the impact on agriculture. Further work needs to be done to understand the impact of changes in the variability of climate on agricultural revenue.

Because of the high dependence on agriculture in the study region – and in west and sub-Saharan Africa more broadly – our results suggest that this study region is vulnerable to directional changes in temperature and precipitation. Although some of our results conform with regional-scale results, we also show that whether particular areas within sub-Saharan Africa will benefit or be harmed by climate change appears context dependent and will be determined by how climate changes and the climatic starting conditions of the location (e.g., whether temperatures are too low for cold season horticulture, whether precipitation is too high for rainy season cereal production).

This study offers a unique insight into whether the economic effects of climate change at local levels are predicted by larger scale analyses or are context dependent. Local-level studies are uncommon because variation in climate conditions most often occurs across larger spatial scales.

This study exploits differences in climate that are driven by topographic change over a short distance to measure local effects of climate on agricultural net revenue. A methodological advantage of this study is that it is able to include a measure of wage rates, which has previously been excluded from other Ricardian studies. Unlike previously published local-scale studies, this work is conducted in a region represented by larger scale analysis, allowing direct comparison of local-level results with broader scale patterns of the aggregate region. Understanding the scale of analysis needed to predict the economic effects of climate change is needed to determine the appropriate scale at which policies to facilitate farmer adaptation should be targeted. One of the limitations of the Ricardian approach is that it is unable to identify the particular adaptation mechanisms used by farmers to optimize agricultural revenue under climate change. Understanding the mechanisms of farmer change, in addition to the scale of impact, will be necessary in determining relevant policy tools for adaptation.

Supplementary materials and methods

The supplementary material referred to in this paper can be found online at journals.cambridge.org/EDE/.

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