Animal husbandry in Africa: Climate change impacts and adaptations

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Abstract

This paper uses a cross-sectional approach to analyze the impacts of climate change on animal husbandry and the way farmers adapt. The study is based on surveys of almost 5000 livestock farmers across ten countries in Africa. A traditional Ricardian regression finds that the livestock net revenues of large farms in Africa are more sensitive to temperature than those of small farms. Cross-sectional analysis also reveals that large farms (but not small farms) have fewer animals per farm in warmer places. Farmers tend to select beef cattle and chickens in cool climates and goats and sheep in hot climates. Using the Ricardian results and examining climate scenarios for 2060 and beyond, the net revenues of small farms are predicted to increase as much as 120% (+USD6 billion) but those of large farms are predicted to fall by 20% (-USD12 billion). The impact estimates in any given period also depend on the rainfall predictions. The results suggest that large livestock farms in Africa are more sensitive to temperature than small ones, primarily because of their dependence on cattle.

Keywords: Climate change; Livestock; Impact; Adaptation; Africa

JEL codes: Q12; Q25

Résumé

Cet article utilise une analyse transversale afin d'analyser les impacts du changement climatique sur l'élevage et la façon dont les fermiers s'adaptent. L'étude se base sur l'examen d'environ 5 000 éleveurs couvrant dix pays en Afrique. Une régression traditionnelle ricardienne montre que les revenus nets liés à l'élevage des fermes importantes en Afrique sont plus sensibles à la température que ceux des petites fermes. L'analyse transversale révèle également que les grandes fermes (mais pas les petites fermes) possèdent moins d'animaux par ferme dans les lieux plus chauds. Les éleveurs ont tendance à choisir les bovins à viande et la volaille dans les climats frais et les moutons et les chèvres dans les climats chauds. En se servant des résultats ricardiens et en examinant les scénarios climatiques de 2060 et au-delà, on prévoit une augmentation d'un maximum de 120% (+6 milliards USD) des revenus nets des petites fermes alors que l'on prévoit une chute de 20% (-12 milliards USD) pour ceux des grandes fermes. Les estimations en matière d'impact pour toute période donnée dépendent

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également des prévisions pluviométriques. Les résultats suggèrent qu'en Afrique les fermes pratiquant un élevage important sont plus sensibles à la température que les petites, parce qu'elles dépendent essentiellement de l'élevage.

Mots clés: *Changement climatique ; Élevage ; Impact ; Adaptation ; Afrique*

Catégories JEL : *Q12 ; Q25*

1. Introduction

This study investigates the effects of climate change on animal husbandry in Africa. Although the effects of climate change on crops have been studied frequently, there are very few analyses of its effects on livestock (Reilly et al., 1996; McCarthy et al., 2001). Yet livestock is important. Almost 80% of African agricultural land is grazing land. African farmers depend on livestock for income, food and animal products (Nin et al., 2007), and are known to keep cattle as an insurance policy for when droughts ruin annual crops (Fafchamps et al., 1998). A study of climate change impacts on agriculture must include an analysis of livestock impacts. The most careful economic analysis of animal husbandry completed to date used mathematical programming to examine the US livestock sector (Adams et al., 1999). It predicted that livestock in the US would be only mildly affected by warming because most livestock receive protection against the environment (sheds, barns, etc.) and supplemental feed. These results are not expected to generalize to Africa because African animals are exposed to the outside elements and depend largely on natural forage for nutrition. There is consequently every reason to expect that animal husbandry on farms in Africa will be sensitive to climate.

Climate can affect livestock both directly and indirectly (Adams et al., 1999, McCarthy et al., 2001). Direct effects from air temperature, humidity, wind speed and other climate factors influence animal performance such as growth, milk production, wool production and reproduction. Climate can also affect the quantity and quality of feedstuffs such as pasture, forage and grain, and the severity and distribution of livestock diseases and parasites. A decrease in mean annual precipitation in Africa is expected to have a negative impact on grassland. However, an increase in water use efficiency resulting from CO_2 doubling is estimated to increase grass production by 20–30%, which could offset this negative effect. A temperature increase is also expected to have a positive effect on the amount of grassland as forests shift to grassland. Another important factor is livestock diseases. African livestock productivity has been severely affected by vector-borne livestock diseases such as trypanosomiasis (nagana), theileriasis (East Coast fever), and Rift Valley fever (University of Georgia, 2007). For example, nagana is transmitted to people and animals by the tsetse fly and affects approximately 30% of Africa's 160 million cattle population and comparable numbers of small ruminants. These diseases are known to be climate sensitive (Ford & Katondo, 1977). Finally, the effect of climate on crops can also affect the desirability of livestock.

This study uses cross-sectional methods to estimate the sensitivity of African livestock to climate. Livestock net revenue per farm is regressed on climate, soils and other control variables. Note that this model is slightly different from the traditional Ricardian model (Mendelsohn et al., 1994) because African farmers rely on common land to graze livestock. Hence the amount of land used for livestock in Africa is not known and difficult to measure. We consequently also develop a two-equation model that controls for the size of the farm by first predicting the number of animals owned. The value of livestock owned per farm is regressed on a set of independent variables in the first equation of this model. Net revenue per value of livestock owned is regressed on a set of independent variables in the second equation. Both cross-sectional models detect whether climate affects net revenue per farm, but the two-equation model provides more details about what is changing on the farm. The Ricardian results are further explained by examining the underlying farmer decisions using a multinomial logit species selection model.

The models are estimated using economic survey data collected as part of the GEF/World Bank project that measured the impact of climate on African agriculture. Almost 5000 farms with livestock are analyzed from ten countries across Africa. The estimated model is then used to predict the impact of a set of climate scenarios from Atmospheric Ocean General Circulation Models (AOGCMs). We examine three scenarios that provide a likely range of future climate outcomes (IPCC, 2007). The estimated models are used to test the magnitude of the impacts on both small and large livestock farms in each scenario.

2. Theory

Farmers manage crops or livestock or both. Ideally, we would like to build a sophisticated joint model in which farmers maximize the combined profit from both crops and livestock. The focus of this paper is more limited. Here we present a simple model of the livestock sector alone. Because crops and livestock are likely to react to climate differently, it is important to understand how livestock behaves independently of how crops behave, before tackling the complex interactions between the two. Although it is not possible to fully understand these interactions without a joint model, the present model of livestock alone will help interpret the results from more complex models.

We assume that the farmer maximizes net income by choosing which livestock to purchase and which inputs to apply:

$$Max \quad \pi = R_{q_j}(\mathrm{P_q}, L_G, F, L, K, C, W, S) - P_F F - P_L L - P_K K \tag{1}$$

where π is net income, R_q is the gross revenue from the sale of both the animal and the animal products, P_{qj} is the market price of animal and animal products for animal q, L_G is grassland in the district, F is a vector of feed, L is a vector of labor (hired and household), K is a vector of capital such as barns and milking equipment, C is a vector of climate variables, W is available water, S is a vector of soil characteristics of grazing land, P_F is a vector of prices for each type of feed, P_L is a vector of prices for each type of labor, and P_K is the rental price of capital.

The farmer chooses the species q, F, L, K and the number of the animals that maximizes profit and the resulting net income will be a function of just the exogenous variables:

$$\pi^* = f(P_q, L_G, C, W, S, P_X, P_L, P_K) \tag{2}$$

The locus of profit maximizing solutions to equation (1) is the Ricardian function. It explains how profit changes across all the exogenous variables facing the farmer. The change in welfare, ΔU, resulting from a climate change from C_0 to C_1, can be measured using equation (2) as follows.

$$\Delta U = \pi^*(C_1) - \pi^*(C_0) \tag{3}$$

If the change increases net income it will be beneficial and if it decreases net income it will be harmful.

To understand what is behind the impact estimates, we analyze farmers' choice of animal species using a multinomial logit model (McFadden, 1981). This complementary analysis provides insights into farmers' underlying decisions as they respond to climate. Specifically, the model measures how they alter their choice of animals depending on climate conditions (Seo & Mendelsohn, 2008).

All the analyses in the paper assume that the farmer is an income maximizing entity. Although this paradigm clearly fits large farms that act as firms, there are two issues that must be addressed for the model to fit smaller household farms. First, households use their own labor and there is no observed wage for this. Although one might at first assume household labor and hired labor are perfect substitutes for each other, empirical evidence suggests that the implicit wage rate for household labor is less than the wage for hired workers (Bardhan & Udry, 1999). This result is supported by the economic data collected in this survey as well. A large fraction of small farms would earn negative profits if we assumed household labor is paid the wages of hired workers. Hired wage rates may overestimate annual wages because small farmers hire workers only during critical moments of labor shortage such as harvest times. Hence it is not obvious what wage rate to assign to household labor. Second, households often consume a large fraction of their output. In this study, we assume that own consumption is valued at the prevailing market prices. When households consume only a small fraction of their output, this is not a strong assumption. However, when households consume all of their output, one cannot be certain that they actually valued the output at the market price. For example, a remote household far from markets may place a higher price on the output than what they would get at the market.

We examine small and large farms separately in this analysis. Small farms tend to be household farms that rely on large amounts of household labor and use traditional methods. Large farms tend to be commercial farms although they can include pastoralists. They have access to more capital and operate on a much larger scale. We are interested in testing whether small farms are more vulnerable to warming than large farms because they tend to have less capital to use as a substitute.

A problem unique to African livestock is that farmers graze their animals off-farm on commons, so there is no way to determine how much land each farmer is using for livestock production. We therefore develop a two-equation model that explores two components that determine net revenue per farm. The first determines how much livestock a farmer owns, the second the annual earnings per livestock owned. Presumably, the higher the earnings per livestock, the more livestock a farmer might want. However, without knowing the amount of land available to each farm, it is difficult to accurately predict the number of livestock per farm. One of the advantages of the two-equation model, however, is that the regression of earnings per animal owned does a good job of controlling for farm size. We use the amount of grassland in a district to identify the number of animals a farmer will own. Note that this is a natural variable and not the result of manmade activity (land converted to pasture) and so can be treated as an exogenous variable.

3. Data

Temperature data in the study were directly measured by Special Sensor Microwave Imagers mounted on US Defense Department satellites (Basist et al., 1998). Precipitation data came from the Africa Rainfall and Temperature Evaluation System (ARTES). This data for each district was interpolated from weather stations throughout Africa by the National Oceanic and Atmospheric Administration (World Bank, 2003). In both cases we used long-term measures of climate, not weather. For monthly temperature, we use satellite data from 1988 through 2004. For monthly precipitation, we use weather station data from 1960–1990 (Mendelsohn et al., 2007).

Soil data were obtained from the FAO digital soil map of the world CD ROM and were extrapolated to the district level using a GIS (Geographical Information System). The dataset reports 116 dominant soil types, which we explore in the analysis.

The economic data come from a survey of over 9,000 farmers in ten countries across Africa: Burkina Faso, Cameroon, Egypt, Ethiopia, Ghana, Kenya, Niger, Senegal, South Africa and Zambia. Data from Zimbabwe had to be dropped because of erratic responses from farmers due to tumultuous conditions in that country in the year of the survey. Districts were selected to obtain observations from a wide range of climates within each country. Districts that could not support any agriculture (such as deserts) were not surveyed. In each country, 15 to 30 districts were selected. Within each district, 20 to 30 households were interviewed in clusters. Cluster sampling was done to control the cost of the survey. From this original sample of farmers, a total of about 5000 were found to have livestock. We examine solely these livestock farmers in this analysis. Although we do not examine their crop revenue, many of these farmers also grow crops.

The survey contains information on the number of livestock, transactions, livestock products and related costs. The eight major livestock sold are beef cattle, dairy cattle, breeding bulls, goats, sheep, pigs, oxen and chickens. Some farmers owned additional animals such as camels, duck, guinea fowl, horses, bees and doves. The major livestock products sold were milk, beef, goat products, sheep products, eggs, wool and leather. Other more minor livestock products include butter, cheese, honey, skins and manure.

Along with a large array of breeds,[1] the fragile market structure in Africa makes it difficult to obtain accurate prices for each animal. In our study, we used the median prices for each animal in each district in order to make our prices as robust as possible. When median district prices

[1] See *Breeds of livestock*, Department of Animal Science, Oklahoma State University (www.ansi.okstate.edu/breeds/).

were not available, we used provincial median prices, and if there were no provincial median prices we used the national median price. Generally the prices for animals in Egypt and South Africa were the highest. Cameroon, Egypt and Ethiopia had the highest prices for animal products.

Part of the problem with prices in the survey was measuring consistent units. For example, some households reported 'number of eggs sold' while others reported 'dozens of eggs sold'. Some households reported 'kg of beef per year' while others reported 'kg of beef per week'. By cleaning the data carefully, with the help of each country team, we were able to correct many observations but had to drop several cases that were unresolved.

4. Model specification

We estimate two econometric models. The first model is similar to a traditional Ricardian regression except that it is based on net revenue per farm not net revenue per hectare. Livestock in Africa is raised largely off-farm and it is not possible to measure the amount of land used by each farmer. Net revenue per farm is regressed on climate and other control variables:

$$\begin{aligned}\pi_i &= b_0 + b_1 \cdot T \cdot S + b_2 \cdot T^2 \cdot S + b_3 \cdot P \cdot S + b_4 \cdot P^2 \cdot S \\ &\quad + b_5 \cdot T \cdot L + b_6 \cdot T^2 \cdot L + b_7 \cdot P \cdot L + b_8 \cdot P^2 \cdot L + \sum_j b_j \cdot Z_j + e_i \end{aligned} \tag{4}$$

The dependent variable is annual net livestock income per farm, T and P represent temperature and precipitation variables, S is a dummy for small farms, L is a dummy for large farms, Z represents a set of relevant socioeconomic variables, and the b_i's are coefficients. The climate variables are introduced in a quadratic form because of earlier evidence that the relationships are nonlinear (for example, Mendelsohn et al., 1994). Although seasonal climate variables were tested, they were found to be insignificant. The livestock model consequently focuses on annual temperature and precipitation. By multiplying the climate variables by small and large farm dummies, we effectively estimate a separate climate response function for each farm type.

A two-equation model is also estimated using the Seemingly Unrelated Regression model (SUR) where the value of animals owned per farm is first regressed on climate and other variables and then the net revenue per owned animal is regressed on climate and other variables (Zellner, 1962) :

$$\begin{aligned}V_i &= \phi_0 + \phi_1 \cdot T \cdot S + \phi_2 \cdot T^2 \cdot S + \phi_3 \cdot P \cdot S + \phi_4 \cdot P^2 \cdot S \\ &\quad + \phi_5 \cdot T \cdot L + \phi_6 \cdot T^2 \cdot L + \phi_7 \cdot P \cdot L + \phi_8 \cdot P^2 \cdot L + \sum_j \phi_j \cdot Z_j + \mu_i \end{aligned} \tag{5a}$$

$$\pi_i / V_i = \gamma_0 + \gamma_1 \cdot T \cdot S + \gamma_2 \cdot T^2 \cdot S + \gamma_3 \cdot P \cdot S + \gamma_4 \cdot P^2 \cdot S + \gamma_5 \cdot T \cdot L + \gamma_6 \cdot T^2 \cdot L + \gamma_7 \cdot P \cdot L + \gamma_8 \cdot P^2 \cdot L + \sum_j \gamma_j \cdot Z_j + \upsilon_i \qquad (5b)$$

The first equation in (5a) is identified using the percentage of grassland (versus forest) in the district. This second model decomposes the climate effect per farm into what happens to the amount of stock versus annual net revenue per stock.

To understand the results from the net revenue changes, we examine the choice of the primary animal, defined as the type of animal that yields the highest total net revenue on the farm, using a multinomial logit model. We look at farms where a farmer has selected one of the five major types of livestock in Africa: beef cattle, dairy cattle, goats, sheep and chickens. With the assumption of an independent Gumbel error distribution, the probability to select a species j can be written as follows (McFadden, 1981):

$$P_{ji} = \frac{e^{Z_{ji}\gamma_j}}{\sum_{k=1}^{J} e^{Z_{ki}\gamma_k}} \qquad (6)$$

5. Empirical results

The ten-country survey provides some important background on African animal husbandry. Table 1 summarizes livestock ownership and sales by two different types of farms: small and large. Large farms are defined as those that own more than USD630 of livestock (approximately three beef cattle).[2] The large farms are different from the small farms because they are effectively commercial rather than household operations. Table 1 indicates that there is a huge divide between large and small farms. Although by definition a large farm owns more livestock than a small one, the average value (unweighted) of the number of animals on commercial farms is USD8,958, compared to USD243 on household farms. Large farms own over 95% of the market value of the livestock in the sample. Although this fraction varies across countries, large farms dominate livestock ownership in every country although there are more small farms than large ones in most countries. Because large farms own the most animals, they also have the greatest livestock gross revenue. Across the sample, large farms are responsible for 96% of all livestock gross revenue in Africa. This income comes from either direct sale of animals or livestock products, including meat, milk, cheese, butter and wool. Table 1 lists the income earned by small and large farms from selling both livestock and livestock products for each country. Note that selling livestock products is more important for the small farms in Egypt, Ethiopia, Senegal and Kenya, whereas direct sale of livestock is more important for large farms except those in Ethiopia.

[2] Although this definition is arbitrary, there is a substantial divide between large farms and small farms in our sample. Hence the overall results in this paper are robust to differing definitions of large farms.

Table 1: Descriptive statistics on livestock values and sales by farm size (USD/farm)

	Small farms			Large farms		
Country	Value of livestock	Revenue from livestock	Revenue from livestock products	Value of livestock	Revenue from livestock	Revenue from livestock products
Burkina Faso	281	28	11	2671	183	68
Egypt	311	143	247	7172	5340	1001
Ethiopia	349	12	59	2018	49	263
Ghana	202	30	1	3072	347	34
Niger	208	27	12	2123	142	127
Senegal	221	31	36	3326	238	83
South Africa	216	95	40	38770	14,258	4200
Zambia	92	10	3	10630	1086	1951
Cameroon	239	173	95	4017	1786	855
Kenya	315	32	179	15780	2280	3664

Table 2 shows the regressions of net revenue per farm, net revenue per livestock owned, and the value of livestock owned per farm. The net revenue is sensitive to the national percentage of the population that is Muslim, the percentage of grassland and the population density. The more grassland in a district, the higher the livestock net revenue per farm. This variable measures the scarcity of land for grazing. Countries with higher percentages of Muslim populations have a lower livestock net revenue per farm, but why this should be is not clear.[3] Higher population densities translate into higher net revenue because of higher net prices for output (lower transport costs to market). Household size is significant and negative. Large households tend to have lower livestock net revenues per farm. By contrast, households with electricity have higher net revenues. Electricity may be a dummy variable for higher technology or it may signify the farm is nearer major markets. Soil variables were also tested but were dropped because they were not significant. Household characteristics such as the age, gender and education of the head of the farm, whether the respondent was the head of the farm, and whether the head of the farm works off-farm were also tested but found to be insignificant. Regional dummy variables for Egypt, West Africa and East Africa were also tried but found to be insignificant. Water flow was also insignificant. Elevation does not seem to play a significant role either. The climate coefficients reveal that livestock net revenues are generally sensitive to climate variables. The climate effects vary for small and large farms. The regression shows that small farms are sensitive to temperature but large farms are not. Both types of farms are sensitive to rainfall changes.

The regression results for the two-equation model are also presented in Table 2. The coefficients in column 4 of Table 2 explain how the independent variables affect the value of livestock owned. Larger households have fewer livestock, perhaps indicating that they are more likely to be small farmers. Having electricity increases the number of livestock owned because of either more technology or better access to markets. Farms in places with higher population density have more livestock but the effect diminishes as it becomes too dense. Countries with a

[3] Egypt and Senegal, predominantly Islam countries in our collected data, did not report any ownership of pigs.

larger Muslim population have less livestock per farm. Farms in areas with more pasture have more livestock. Temperature has a discernible effect on the number of livestock for both small and large farms. Precipitation, however, has an effect on the stock of animals on small but not large farms.

The regression coefficients in column 6 of Table 2 explain how the independent variables affect the net revenue per value of livestock owned. To make the coefficients easier to interpret, we present the results in terms of USD/year per thousand dollars of livestock value. Household size does not influence net revenue per animal. However, electricity increases the net revenue per animal and higher population density increases net revenue per animal but at a decreasing rate. Farms in countries with higher Muslim populations get a smaller net revenue per animal, which partially explains why they choose to have fewer animals. The net revenues per animal of both small and large farms are highly sensitive to annual mean temperature and annual mean precipitation.

Table 2: Regressions on livestock performance (USD)

	Single equation model		Two-equation model with SUR			
	Net revenue per farm		Value of livestock owned		Net revenue per livestock value in USD1000	
Variable	Est.	T-stat.	Est.	T-stat.	Est.	T-stat.
Intercept	14410.	3.43	12460.	1.86	1424.	6.72
Temperature * small [1]	-1260.	-3.27	-1049.	-1.71	-49.9	-2.53
Temperature sq * small [1]	29.6	3.51	28.2	2.10	0.55	1.28
Precipitation * small [1]	-46.6	-2.14	-103.	-2.98	-13.41	-12.05
Precipitation sq * small [1]	0.20	1.79	0.47	2.60	0.07	13.17
Temperature * large [1]	-323.7	-0.82	1351.	7.15	14.90	2.43
Temperature sq * large [1]	-0.23	-0.03	-42.8	-7.21	-0.50	-2.59
Precipitation * large [1]	-99.0	-4.51	-7.62	-0.20	-2.67	-2.19
Precipitation sq * large [1]	0.28	2.26	-0.32	-1.47	0.01	1.07
Log household size	-1024.	-3.31	-2240.	-4.55	10.57	0.66
Electricity dummy	2469.	5.64	4960.	7.13	219.5	9.72
Population density	79.1	2.75	126.6	2.77	11.55	7.96
Population density sq	-1.16	-3.65	-2.13	-4.21	-0.12	-7.79
% Muslim	-2640.	-2.81	-4508.	-3.02	-31.75	-0.75
% grassland	9799.	7.18	22952.	10.58		
	Adj-rsq=0.20, N=4763				Adj-rsq=0.20, N=4763	

Note: Two regressions estimated using SUR (Seemingly Unrelated Regression). Correlation between errors was -.02.

[1] Climate variables were multiplied by farm size dummy. Interaction terms measure farm type specific climate impacts.

To interpret the quadratic climate coefficients in Table 2, Table 3 displays the marginal climate impacts computed at the African mean temperature and precipitation. Looking first at the Ricardian results, warming increases income on small farms by USD100 per degree. For large farms, warming reduces income by USD330 per degree. The temperature elasticity of small farms is about +24 whereas the temperature elasticity of large farms is -2.3. One reason why small farms have such large positive temperature elasticity is that they shift from crops to livestock as temperatures increase. Because large farms have access to more capital and technology, one might expect that they would be less vulnerable to warming. However, because they specialize in livestock they cannot use crops as a substitute. Further, the most profitable species for large farms is beef cattle, which do not do well at high temperatures. By contrast, small farmers find it relatively easy to shift to goats and sheep, which appear to tolerate high temperatures reasonably well. Thus, in the livestock example, small farmers appear to have more substitutes than large farmers and so they are less vulnerable to climate changes.

In the Ricardian regression, a marginal increase in precipitation reduces net revenue per farm for both small and large farms. Small farms decline by about USD20 per mm of monthly precipitation and large farms by about USD65 per mm, and both effects are significant. The precipitation elasticity is about -13 for small farms and -1.2 for large farms. Small farms have such a large elasticity because they shift from livestock to crops. All livestock farms have a negative elasticity with precipitation because natural ecosystems shift from grasslands to forests and there is an increased prevalence of animal diseases such as trypanosomiasis (University of Georgia, 2007). An alternative perspective on these same marginal results is that livestock net revenue increases as precipitation decreases. Farmers shift from crops to livestock, forests turn to grasslands, and diseases become less prevalent. For small farmers, livestock becomes a good alternative to crops if precipitation decreases, which is a well-known reason why many African farmers have both crops and livestock. As long as there is enough precipitation to support grassland, livestock incomes rise with less rainfall, especially for small households.

Table 3: Marginal climate effects and elasticities

TYPES	Current livestock income (USD/farm)	Marginal temperature impact (USD/°C)	Marginal precipitation impact (USD/mm)	Temperature elasticity	Precipitation elasticity
			Net revenue per farm		
SMALL	105	108.8*	-19.6*	24.0*	-12.5*
LARGE	3291	-334.2	-64.7*	-2.30	-1.20*
			Value of livestock owned		
SMALL	259	256.8*	-41.0*	22.9*	-10.6*
LARGE	7795	-357.9*	-93.0	-1.04*	-0.73
			Net revenue per livestock value		
SMALL	0.371	-0.024*	-0.004*	-1.51*	-0.63*
LARGE	0.394	-0.033*	-0.006*	-1.87*	-0.94*

* significant at 5% level

Table 3 also displays the marginal impacts of climate in the two-equation model. Small farms in warmer locations own more livestock but large farms in warmer locations own less. Both small and large farms own less livestock in wetter locations. The climate elasticity (percentage response) for small farms is considerably higher than for large ones, probably because of their ability to use crops as a substitute. Both small and large farms in warmer places have a lower net revenue per unit of stock. This lower profitability explains why large farms that specialize in livestock reduce their stock size. However, to understand what is happening on small farms one must compare the relative profitability of crops versus livestock. Although the profitability of livestock is less in warmer places, the profitability of crops in warm places has fallen even further for small farmers, making livestock a relatively more attractive option. The net revenue per stock for all farms is lower in wetter places, which explains why all farms in wetter locations have fewer animals.

The changes in farm income above resulted from the effect of climate on animals and numerous adjustments farmers made to cope with changing climate conditions. To understand how choices change with climate, we estimate a multinomial logit model of farmers' choice of livestock species. The results in Table 4 explain how exogenous variables affect farmers' choice of one animal from the five possible major animals in Africa. Chickens are the omitted choice. Farms in West Africa are more likely to choose goats and sheep, but less likely to choose beef cattle and dairy cattle. Large farms are more likely to choose beef cattle. Farms with electricity are less likely to choose chickens. Almost all the climate variables are significant. Note that in the species choice equation both winter and summer climate variables are significant. The quadratic summer temperature coefficient is negative for beef cattle but positive for goats and sheep.

Table 4: Multinomial logit species selection model

	Beef cattle	Dairy cattle	Goats	Sheep
Variable	Est.	Est.	Est.	Est.
Intercept	0.720	13.603*	4.478*	10.978*
Temperature summer	0.296*	-1.152*	-0.295*	-0.772*
Temperature summer sq	-0.0060*	0.0204*	0.0050*	0.0125*
Precipitation summer	0.033*	-0.0158*	-0.0061*	-0.0091*
Precipitation summer sq	-0.0001*	0.0000	0.0000*	0.0000
Temperature winter	-1.209*	-0.051	-0.378*	-0.432*
Temperature winter sq	0.032*	0.0084*	0.0146*	0.0184*
Precipitation winter	0.0239*	-0.0250*	-0.0064	-0.0087
Precipitation winter sq	-0.0001	0.0000	0.0000	0.0000
West Africa	-1.187*	-4.023*	0.585*	0.458*
Large farms	2.649*	2.238*	0.909*	1.410*
Electricity	1.462*	0.659*	0.343*	0.854*

Note: Omitted choice is chickens. Likelihood ratio test: P<0.0001, Lagrange multiplier test: P<0.0001, Wald test: P<0.0001. * denotes significance at 5% level.

Table 5 shows how the probability of selecting a specific animal changes as climate changes. As temperature rises, farmers shift from beef cattle, dairy cattle and chickens to goats and sheep. As precipitation increases, farmers shift away from dairy cattle and sheep to goats and chickens. Large farms specializing in beef or dairy cattle are especially vulnerable to warming. Commercial beef cattle are very sensitive to higher temperatures. This explains why large farms are especially vulnerable to warmer temperatures. By contrast, small farms can move to heat tolerant animals such as goats and sheep. This change in the portfolio of animals helps explain the farm level income changes as well as the differing vulnerabilities of small farms and large farms to climate change.

Table 5: Marginal effects on the selection of animals

	Beef cattle	Dairy cattle	Goats	Sheep	Chickens
Probability (%)					
Baseline	4.5%	15.4%	23.1%	15.0%	41.9%
Temperature	-0.5%	-0.1%	+1.8%	+1.1%	-2.3%
Precipitation	+0.1%	-0.3%	0.0%	-0.1%	+0.3%

6. Climate simulations

Based on the estimated parameters in the previous section and on a set of climate scenarios that predict a broad range of outcomes, consistent with the expectations in the most recent science (IPCC, 2007), we examine the effects of climate change on the dependent variables of the previous regressions. Specifically, we use the A1 scenarios from the following models: CCC (Boer et al., 2000), CCSR (Emori et al., 1999) and PCM (Washington et al., 2000).

Table 6 summarizes the average African mean climate scenario for each model and time period. The models provide a range of predictions. For example, by 2100, PCM predicts a 2°C increase in temperature, CCSR a 4°C increase and CCC a 6°C increase. The temperature projections of all the models steadily increase over time. The models also provide a range of rainfall predictions. For example, by 2100, PCM predicts a 4% increase in rainfall, CCC a 14% decrease and CCSR an 18% decrease. The rainfall predictions of the models do not steadily increase over time but rather have a varied pattern. CCC predicts a declining trend in rainfall; CCSR an initial decrease, then increase, and then decrease; PCM an initial increase, then decrease, and then increase again. Further, even though the mean rainfall for Africa might increase/decrease, the predictions for individual countries vary. Some of the models predict relative drying in certain regions and others predict relative increases in rainfall.

Table 6: AOGCM climate scenarios

	Current	2020	2060	2100
Temperature (°C)				
CCC	23.3	24.9 (+1.6)	26.9 (+3.6)	30.0 (+6.7)
CCSR	23.3	25.3(+2.0)	26.2(+2.9)	27.4(+4.1)
PCM	23.3	23.9 (+0.6)	24.9 (+1.6)	25.8 (+2.5)
Rainfall (mm/month)				
CCC	79.8	76.8 (-3.7%)	71.9 (-9.9%)	65.1 (-14.6%)
CCSR	79.8	73.9(-7.3%)	76.6(+3.6%)	62.4(-18.5%)
PCM	79.8	89.8 (+12.5%)	80.7 (+1.1%)	83.2 (+4.3%)

Table 7 presents the change in net revenue per farm for each climate scenario (three AOGCM models for the years 2020, 2060 and 2100). The CCC scenario predicts increasing revenues for small farms over the next century. The results suggest small farm livestock incomes will increase by 35% by 2020, 110% by 2060 and 300% by 2100. By contrast, the CCC scenario predicts that large farms will lose increasing amounts of livestock income over time. The PCM scenario predicts little change for small farms in 2020 because the harmful effects of increased rainfall offset the beneficial effects of warming. However, PCM predicts gains by 2060 that continue to increase through 2100. Large farms lose 20% of income by 2020 in the PCM scenario, but stabilize afterwards. Compared with the CCC predictions, the CCSR predictions lead to similar but smaller effects in 2020 and 2060. However, in 2100, CCSR predicts big gains for large farms because of the large predicted decrease in rainfall.[4]

Table 7: Change in net revenue per farm for each AOGCM climate prediction: Ricardian results (USD/farm)

Variable	Impact per small farm (USD/farm)	% of livestock income	Impact per large farm (USD/farm)	% of livestock income
2020				
CHANGE_CCC	+240.35	+35.8%	-205.77	-6.5%
CHANGE_CCSR	+435.53	+69.1%	-291.34	-9.3%
CHANGE_PCM	+2.66	+0.4%	-511.56	-16.3%
2060				
CHANGE_CCC	+750.48	+119.1%	-557.42	-17.7%
CHANGE_CCC	+381.03	+60.5%	-607.44	-19.3%
CHANGE_PCM	+111.28	+17.7%	-650.34	-20.7%
2100				
CHANGE_CCC	+2034.56	+322.9%	-830.62	-26.4%
CHANGE_CCSR	+1391.33	+220.8%	+142.55	+4.5%
CHANGE_PCM	+337.59	+53.6%	-720.25	-22.9%

Note: Small farms have a baseline income of USD623 per farm whereas large farms have a baseline income of USD3142 per farm.

[4] Although this result is not presented in this paper due to page limitation, small farmers increase the number of their livestock while large farmers reduce it. In addition, all the scenarios lead to a reduction in the net revenue per animal owned, regardless of whether the farms are small or large.

Table 8 reveals how the probability of choosing a specific animal is predicted to change for the five animals for each climate scenario. By 2020, the warming scenarios generally predict beef cattle, dairy cattle and chickens will decrease and goats and sheep will increase. The two exceptions are a decrease in the number of dairy cattle in the CCC scenario due to the reduction in rainfall and a reduction in the number of sheep in the PCM scenario due to the increase in rainfall. These changes in species continue and get stronger through 2100.

Table 8: Predicted change in the probability of selecting each animal from AOGCM climate scenarios

		Beef cattle	Dairy cattle	Goats	Sheep	Chickens
2020						
	CCC	-0.9%	+0.6%	+3.5%	+2.1%	-5.3%
	CCSR	-0.3%	-0.7%	+3.4%	+2.3%	-4.6%
	PCM	-0.2%	-3.1%	+8.2%	-0.1%	-4.8%
2060						
	CCC	+0.2%	-3.8%	+8.8%	+1.1%	-6.3%
	CCSR	-1.0%	+1.9%	+4.8%	+3.3%	-8.9%
	PCM	-1.2%	+1.0%	+5.2%	+8.4%	-13.3%
2100						
	CCC	-1.5%	+3.6%	+6.9%	+13.6%	-22.6%
	CCSR	-0.4%	-2.2%	+8.3%	+1.0%	-6.8%
	PCM	+0.2%	-3.0%	+12.0%	+0.9%	-10.1%

Table 9 presents the aggregate results for Africa. Using rural population estimates, the results from the sample of small and large farms are extrapolated to the whole of Africa. The results suggest that climate change will lead to gains for small farmers but losses for large ones. Because large farmers dominate the sector, the livestock sector will suffer losses of from USD2 to USD12 billion per year as climate change progresses.

Table 9: Aggregate change in livestock net revenue in Africa caused by each AOGCM scenario (billions USD/year)

Variable	Expected impact to small farms	Expected impact to large farms	Expected impact to all farms
2020			
CHANGE_CCC	+1.79	-3.9	-2.11
CHANGE_CCSR	+3.46	-5.58	-2.13
CHANGE_PCM	+0.02	-9.78	-9.76
2060			
CHANGE_CCC	+5.96	-10.62	-4.67
CHANGE_CCSR	+3.03	-11.58	-8.56
CHANGE_PCM	+0.89	-12.42	-11.54
2100			
CHANGE_CCC	+16.15	-15.84	+0.31
CHANGE_CCSR	+11.04	+2.7	+13.74
CHANGE_PCM	+2.68	-13.74	-11.06

7. Conclusion and policy implications

This paper examined the climate sensitivity of livestock management in Africa. The study is based on a large-scale survey of African livestock farmers. Net revenues per farm, livestock owned per farm, and net revenues per livestock owned are all regressed on climate and other variables to test their sensitivity to climate. Species choices are also analyzed using a multinomial logit model. The study found that livestock net revenues, the number of livestock per farm, and the earnings per livestock are all highly sensitive to climate. The climate sensitivity, however, varies according to farm size. The net revenue per farm for large farms decreases with higher temperature but increases for small farms. Both types of farms lose net revenue per animal owned. However, large farms reduce the size of their herds dramatically with higher temperature but small farms enlarge their herds. Small farms switch from crops to livestock and switch from temperate animals to heat tolerant animals. Large farms tend to specialize in livestock and especially beef cattle, for which there is no comparable substitute. The result is that livestock income rises for small farms as temperatures rise but falls for large farms.

The impacts of climate change also depend on how dry the scenario is. Although rainfall generally increases crop and grassland productivity, this study shows that increased rainfall reduces livestock net income. There are three plausible explanations. First, farmers shift to crops as rainfall increases; second, grassland shifts to forests as rain increases, reducing the quality and quantity of natural grazing for most animals; and third, increases in precipitation increase the incidence of certain animal diseases.

Evaluating the predictions of climate models, we find that warming generally leads to increased revenue for small farmers and reduced revenue for large farmers. These effects may be evident as early as 2020 and generally increase over time. For small farmers, livestock will provide some protection from the effects of warming as crops become less desirable. Livestock will also do well if rainfall decreases. From a portfolio perspective, this is excellent news for small

African farmers as it means that over the next century they will still have options to farm. Large livestock farms will have more trouble as temperatures rise. However, the damages foreseen are a small fraction of income so that they too are likely to be able to survive the next century, though with slightly lower incomes.

The results in this study contrast with the analysis of the climate sensitivity of livestock in the US (Adams et al., 1999), which found that American livestock were not climate sensitive. We believe this difference is due to the cooler average temperatures in the US and the capital intensity of American livestock management where many animals are in protected feedlots. With cooler initial temperatures in the US, warming does not at first reach a high enough temperature to reduce beef cattle use (except possibly in the southernmost reaches of the US). By contrast, most of Africa is already too hot for beef cattle. Further, African animals tend to live outdoors and depend largely on natural grazing. This direct exposure to the elements and reliance on natural ecosystems for sustenance makes African livestock far more climate sensitive (Seo & Mendelsohn, 2008).

Policy makers need to be aware that African livestock management is vulnerable to climate change. Global climate mitigation policies must reevaluate the estimated impact of climate change on agriculture. Aid programs to Africa must carefully consider how they can help African farmers adapt to climate change. Livestock farmers should know that they can substitute livestock for crops when climate gets hotter and drier. Large livestock operations must be made aware that cattle will be very sensitive to warming. Adaptation should vary across Africa depending on conditions. Government programs should help farmers adapt to the new conditions and become self-sufficient. Aid programs must be careful not to provide incentives for farmers to remain vulnerable and thus dependent on aid to survive.

There are several caveats readers should bear in mind. First, it was difficult to measure the land that was being used for livestock in Africa because many livestock farmers rely on communal lands. A dataset that measures the available land for each community and each community's livestock would increase the accuracy of the analysis. Second, the survey collected only limited data on the costs of raising livestock, so did not have a complete account of all these costs. Third, households sometimes used their own inputs (grain, labor) and consumed their own output. Although we tried to adjust for own consumption using market prices, there may be some remaining errors. Fourth, prices were difficult to collect since some farmers do not sell their products, some sell at the farm gate, some sell in local markets, and some process their products before sale. We relied on median prices in each district to control for this but this adjustment may have been imperfect. Further, we did not forecast how prices change with climate. This requires a general equilibrium model and assumptions about world trade that are beyond the scope of this analysis. If prices do change, price effects should be taken into account. Finally, in the forecasts, we have assumed that the only thing that changes over time is climate. In practice, many things will change over the next century, including population, prices, technology and institutional conditions. Future livestock owners may take advantage of new technologies that are not commonly used today in most of Africa, such as shade and sprinklers. Genetics and breeding may offer some new choices for farmers. Future papers should explore these many issues and develop ever more precise predictions of what may happen to livestock in Africa.

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