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The Impact of Climate Change on Livestock Production in Mozambique

by
Nancy McCarthy
Romina Cavatassi
Giuseppe Maggio

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Abstract

This article incorporates climate variables into an impact assessment of the Value Chain Development Project in the Maputo and Limpopo Corridors (PROSUL) implemented by IFAD in two semi-arid provinces in Mozambique from 2013 to 2020. The paper focuses on project activities targeting improved pasture management, additional supplemental feed sources, and livestock value chain development. The study evaluates a number of climate variables from different satellite product sources to capture the impacts of historical rainfall conditions and current rainfall patterns, limiting the search by selecting variables and sources that accord with: (i) economic theory; (ii) empirical evidence from the agronomic and satellite product evaluation literature; and (iii) variables mentioned in early-warning systems documents covering the relevant survey time period. Results show significant impacts of current weather patterns and climate conditions on households' adoption of activities promoted by the project, as well as livestock productivity outcomes. A key finding is that project beneficiaries in drought-prone areas are more likely to provide supplemental feed in the dry season, though livestock birth rates are still lower in those areas. Additionally, while the project has positive impacts on cattle herd size, the proportion of goats in the herd is lower for treated households. Being located in a drought-prone area has no impact on the proportion of goats in the herd. Combined with evidence on potential overstocking, the project's emphasis on cattle may mean that households will be less resilient to droughts in the future. Overall, the analysis reveals how incorporating climate variables into impact assessments can provide clear and compelling evidence to guide future project design, as well as the design of future impact assessments.

1. Introduction

Mozambique is considered one of the most disaster-prone countries in the world, and the third most exposed to weather hazards in Africa (UNISDR, 2009). Since 1977, the country has suffered from major floods, droughts and cyclones, in some cases with multiple weather shocks occurring in the same year (RCRC, 2021). The south of the country is often affected by floods caused by weather events that occur in neighbouring countries, since nine major river systems drain through Mozambique (GFDRR, 2014). Droughts, however, are the most frequent weather shock and are especially common in the centre and south of the country (World Bank, 2010). Climate change is predicted to increase erratic rainfall associated with more frequent droughts, floods, cyclones and higher temperature spikes, especially inland in the central and southern regions (Neumann et al., 2013; World Bank, 2010).

At the same time, rainfed agriculture remains the main economic activity in the country, and 70 per cent of the workforce is employed in the agricultural sector (Delgado et al., 2021). This dependence on rainfed agriculture under current climatic conditions is a main reason why Mozambique is one of the poorest countries in the world, ranking 181st out of 189 countries and territories on the Human Development Index (UNDP, 2020). The combination of high rates of poverty and dependence on rainfed agriculture means that smallholders are very vulnerable to weather shocks. In this context, it is critical to gain empirical evidence on the impacts of climate variables on project outcomes, to better understand how future projects can increase their ability to generate climate-resilient outcomes.

This study focuses on evaluating the impacts of climate and weather variables on project outputs and outcomes, using the Value Chain Development Project in the Maputo and Limpopo Corridors (PROSUL) project implemented in Mozambique as a case study. This study is also the fourth in a series of reports that have incorporated climatic data into impact assessments, and the only report that looks at livestock-based project impacts (McCarthy et al., 2022a; 2022b; McCarthy, Cavatassi and Mabiso, 2022). The objective of this study is to broaden the empirical results to inform future project design in three specific ways: (ii) draw implications for using climate variables in selecting control sites; (ii) draw implications regarding the empirical methodology incorporating climate variables; and (iii) draw lessons from observed impacts of climate variables on project outputs and impacts for the design of future project activities that seek to increase resilience to climate change.

The study proceeds as follows: In section 2, we briefly outline the project's objectives, activities, outputs and outcomes. In section 3, we outline our empirical strategy and present descriptive statistics on key outcome and explanatory variables. In section 4, we present empirical results, while section 5 concludes.

2. Project overview

The PROSUL project began in 2013 and ended in 2020. It was co-financed by the International Fund for Agricultural Development (IFAD) and implemented through Mozambique's Ministry of Agriculture and Rural Development (MADER). The project focused on three value chains (horticulture, cassava and red meat), but in this study, we will focus on the red meat component; hereafter, we will refer to this as the livestock component. The livestock component was implemented in two districts of Maputo province (Magude and Manhica), and six districts of Gaza province (Mabalane, Massingir, Chókwè, Guijá, Mapai and Chicualacuala). These districts are considered semi-arid and subject to frequent dry spells and droughts (Southern Africa Drought Resilience Initiative, n.d.; FAO, 2004). Livestock (large and small ruminants, as well as poultry) forms a large part of the wealth of households in this area (Cunguara et al., 2011; Salite and Poskitt, 2019) – though this project focused mainly on large and small ruminants. More specifically, the project focused on cattle and goat production, as very few households held sheep. Most households raise animals for live sale, with limited production of livestock products such as milk (Njuki and Sanginga, 2013; Salite and Poskitt, 2019).

The objective of the livestock component was to improve animal productivity, animal husbandry practices, the sustainable use of environmental resources, and market linkages throughout the livestock value chain. There were three main sets of activities: (ii) improving the value chain environment; (ii) improving the production environment; and (iii) facilitating market linkages. Additionally, a fourth set of activities was financed by the Adaptation for Smallholder Agriculture Programme (ASAP) to increase resilience to climate change. Specific activities under each set are outlined below.

First set:

- Regional multi-stakeholder value chain and district-level innovation platforms established

Second set:

- Livestock Producer Organizations (LPOs) supported, primarily through animal health training and start-up kits for animal drugs and sprays
- Training of Animal Health Agents
- Farmer Field Schools held to improve smallholders' technical and management skills, animal health management, use of nutritional and salt blocks, and climate-resilient dry season practices such as production of hay and fodder banks, and increased access to water facilities

Third set:

- Livestock market fairs organized and held
- Construction of livestock holding and crush pens at cattle fairs

Fourth set:

- Development of community-based natural resource management plans (unclear whether implemented, and if so, whether in all or only a subset of communities)
- Increase fodder production and fodder banks (overlap with second set)
- Support to private network of veterinary pharmacies at district level
- Establishment of water storage and management activities (potential overlap with second set).

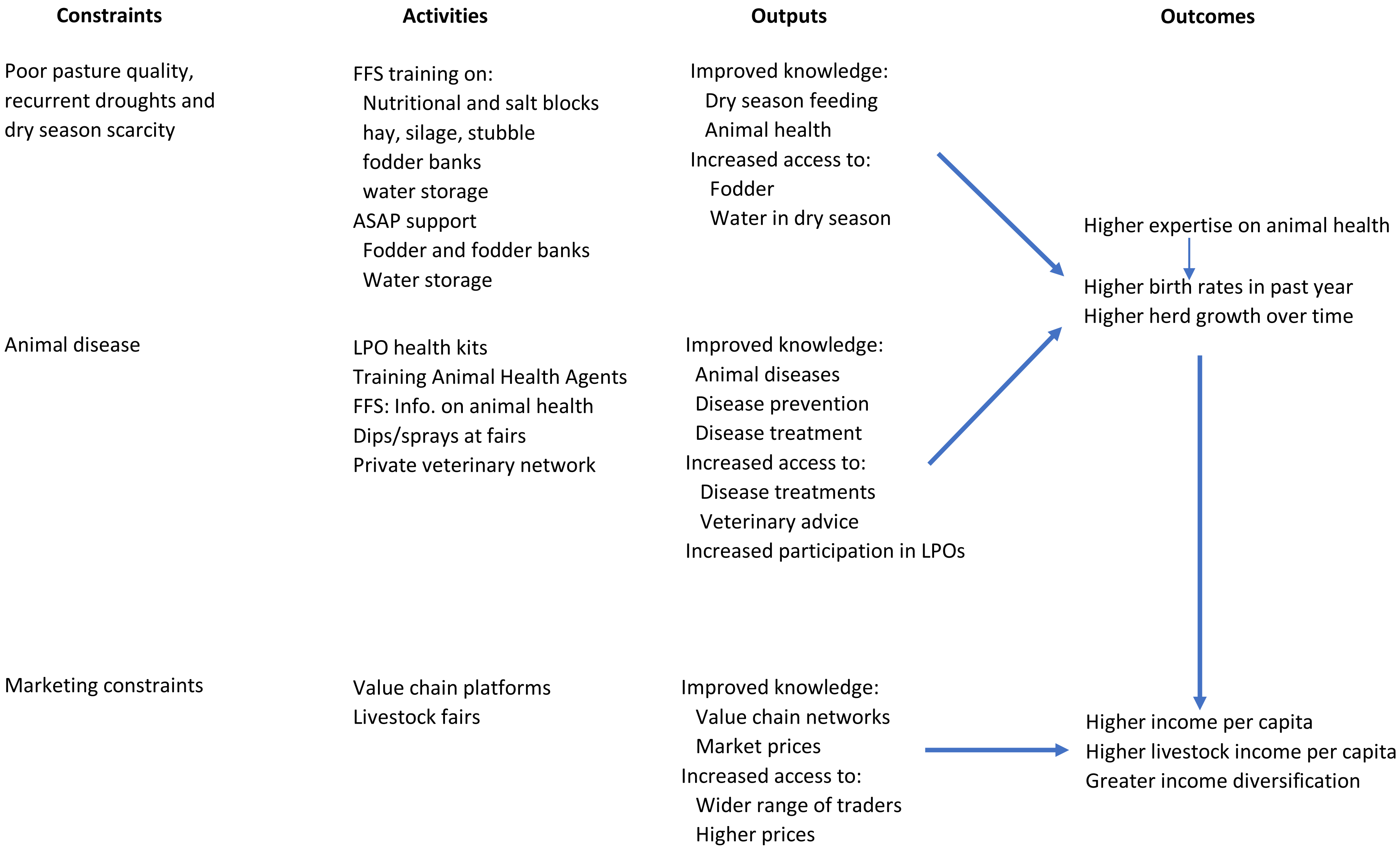
The theory of change underpinning the choice of activities is based on the observation that households in these semi-arid regions are largely dependent on income from livestock sales; that pastures are of poor quality and subject to periodic droughts; and that households often face poor feed and water availability in the dry season, are subject to animal disease incidence and have limited market connections. Proactive and coordinated grazing management on shared pastures is limited, which also exacerbates the preceding problems.

The theory of change is depicted in figure 1. The activities to address poor pasture quality, recurrent droughts and dry season scarcities should generate knowledge outputs, as well as increased access to resources in the dry season, though there may be limited impacts on overall pasture quality. The activities to address animal diseases should also generate knowledge outputs, as well as increased access to treatments and veterinary services, and should also increase participation in LPOs (which may also confer greater benefits for production, pasture management and marketing, in addition to livestock health, but we have kept it as an animal health output, given project documents). Combined, these two sets of outputs should lead to higher expenditures on animal health, and subsequently to higher animal productivity. The marketing activities should generate knowledge outputs, as well as increased access to a wider range of traders and higher prices from live sales. Finally, the animal productivity outcomes and marketing outputs combine to generate higher incomes per capita, higher livestock incomes per capita and greater income diversification. With respect to climate resilience, we expect that outputs associated with improved knowledge and use of dry season feeding, increased access to fodder and feed, and greater access to water would all be consistent with increased resilience to climate change.

Not considered in the project's theory of change is how current weather conditions and historical climate conditions might impact project outputs and outcomes, and this will be one of the main focuses of this study. With respect to dry season feeding, we expect that those households located in relatively dry areas with greater downside rainfall variability would be more likely to adopt feeding strategies promoted by the project. With respect to livestock diseases, our hypotheses on climate conditions are ambiguous, given evidence from the literature. For instance, Bett et al. (2019) show that vector-borne livestock diseases are more prevalent in wetter areas. A higher prevalence of ticks in wetter areas has also been documented for Gaza and Maputo provinces, where the project was located (Tembue et al., 2011). The project promoted the use of tick baths for both cattle and goats, and we expect this to be higher in areas with high rainfall. With respect to helminths (worms), Ouattara and Dorchies (2001) note high loads in both humid and semi-arid areas in Burkina Faso, noting that goats in the semi-arid regions were particularly susceptible during the rainy season. Atanasio-Nhacumbe and Sitoe (2019) also found prevalence of helminths to be highest in Mozambique in the semi-arid zones during the rainy season. Combined, the data suggest that animals in semi-arid areas with relatively high rainy season rainfall were more likely to be affected by worms. The literature also suggests that goats are relatively more susceptible to worms than cattle, though the data on deworming are not broken down by species in our analysis. Nonetheless, we expect deworming to be higher in drier areas with greater downside rainfall variability, but also positively correlated with current or previous period rainfall.

We also expect that historical climate conditions and current weather patterns will have different impacts on cattle versus goat production. Given that goat productivity is more resilient to low rainfall shocks, we expect that downside rainfall variability will have greater relative negative impacts on cattle productivity, while we hypothesize more muted impacts – if any – on goat productivity. Finally, we expect both cattle and goat productivity to be higher, as the percentage difference in current and previous period rainfall is higher, and that certain measures of goat birth rates may be relatively more responsive than those for cattle to current and previous period rainfall, because of the shorter gestational period.

Figure 1. Theory of change



Project output and outcome indicators following the theory of change

The survey obtained data on a number of outputs and outcomes related to livestock production, with less information on non-livestock activities and measures of well-being. For this analysis, we create the following variables for outputs and outcomes, where labels are included for each variable in parentheses and underlined.

Outputs

All outputs are dichotomous variables that capture whether the household engaged in a number of activities promoted by the household. These include: received information on livestock diseases (Disease Info.); received technical assistance on livestock diseases (Disease, Tech. Asst.); frequently bathe cattle in acaracides (Cattle Baths); frequently bathe goats in acaracides (Goat Baths); frequently deworm animals (Deworm); belongs to cattle organization (Cattle Org.); frequently provides supplemental feed to animals (Feed); has sold cattle in past year (Cattle, Sale); and has sold goat in past year (Goat, Sale).

Outcomes

Birth rates of cattle and goats, and average tropical livestock units (TLUs) (Jahnke, 1982) (Birth Rates: Cattle, Goats, AvgTLU). Birth rates are calculated as the number of animals less than one year old divided by the number of adult female animals.[1] All birth rates were winsorized at the upper 99th percentile.

Change in the number of cattle, goats and TLUs (Change in: Cattle, Goats, AvgTLU). Change is over the period from project inception through 2019 (four years). We transform these variables using the inverse hyperbolic sine function (IHSF), which performs in a similar way to the natural log transformation in reducing the influence of outliers but is more flexible in that it can handle negative values. Such a transformation also reflects underlying hypotheses of standard production theories, consistent with either constant or diminishing returns to scale. Finally, we look at the proportion of goats, measured in TLUs, in overall TLUs held by the household (Prop. Goats), primarily because goats are more resilient to droughts, which are likely to become more frequent and severe as the climate continues to change.

3. Empirical strategy

3.1. Conceptual framework guiding estimations

As noted in the introduction, this paper is the fourth in a series of papers that incorporate climate variables into a project impact evaluation. In the first two papers (McCarthy et al., 2022a; 2022b), we develop and present a theoretical model of decision-making by risk-averse producers subject to weather fluctuations to draw hypotheses on the relevant variables to include. Here, we summarize those hypotheses and refer interested readers to those papers for a more rigorous treatment. Assuming that farmers are risk-averse, maximizing expected utility given risky livestock production leads to the following hypotheses: (i) input choices at the beginning of the season will be a function of expected (average) weather conditions and the variance of those weather conditions; and (ii) actual outcomes at the end of the season will be a function of deviations of actual weather from expected weather. It is important to control for expected weather and variance of weather when estimating agricultural production outcomes because these expected conditions drive investment decisions and decisions that must be made at the beginning of the season, before weather conditions are known. Additionally, their inclusion is required in cross-sectional surveys to ensure that the current period weather deviations and shocks will be conditionally exogenous.

[1] This is our only option for constructing birth rates, which is likely to be somewhat noisy if female cattle that gave birth are no longer in the herd – for instance, due to death. Yet it is the only measure of animal productivity possible to construct with the survey data, so we include it despite this caveat.

To further restrict our evaluation of alternative climate variables, we turn to the agronomic literature and studies assessing the performance of satellite-based climate data products. First, we note that the agronomic literature documents that heat stress can have large negative impacts on animal productivity (Getu, 2015); however, given the limited area covered by the project, we do not observe sufficient variation in temperatures in the European Centre for Medium-Range Weather (ECMWF) ERA INTERIM reanalysis model data to include temperature as a predictor.

Second, we considered seasonal rainfall patterns. In the semi-arid regions covered here, rainy season crop productivity is low and variable, but crop residues and grasses grown in this period can be important to cover feeding requirements in the long dry season (Midgley et al., 2012; Vernooij, van Mierlo and dos Anjos, 2016). The dry season is indeed dry, with average rainfall of just 81 mm, ranging between 35 mm and 145 mm. Forage biomass and quality deteriorates throughout the dry season, as does water availability (Midgley et al., 2015; Maposse et al., 2003). Given the above, we consider three time periods over which to construct rainfall estimates: the rainy season, the dry season and the year as a whole.

Third, there is some evidence in the literature which suggests that UC Santa Barbara's Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) rainfall estimate data and the National Oceanic and Atmospheric Administration's Climate Prediction Center (NOAA-CPC) rainfall estimate data (RFE2) do a better job than other products at matching rainfall gauge precipitation in the Southern region (Toté et al., 2015). We thus collected data for CHIRPS, and NOAA-CPC African rainfall estimate data (ARC2) in place of the RFE. ARC2 uses a subset of inputs used to generate RFE2, and using this subset enables a consistent construction of the estimates over a much longer time range than RFE2, covering 1983 to current period (Novella and Thiaw, 2012).

Fourth, a wide range of studies also determine that decadal data are more closely correlated with rainfall gauge data than daily data (Ouma et al., 2012; Dembele and Zwart, 2016; Le Coz and van de Giesen, 2020; Logah et al., 2021), so we collected decadal data for CHIRPS and ARC2.

Fifth, we decided not to use normalized difference vegetation indices (NDVI), primarily because it is often difficult to tease out pasture quality when invasive, unpalatable species are present (Karnieli et al., 2013; Niphadkar and Nagendra, 2016; Weber et al., 2018). We note here that technological advances and more sophisticated data analytics may improve NDVI-based products to estimate forage availability in future studies (Akumu et al., 2021).

Finally, we turned to the early-warning documentation – specifically, the FEWSNET bulletins for Mozambique –for the relevant period covered by the survey. In those bulletins, FEWSNET noted that many areas of southern Mozambique received drier than average rainfall in 2018/19, but did not otherwise note other weather-related shocks.[2] Our own analysis of the CHIRPS and ARC2 data indicate that where rain shortfalls did occur, they were relatively modest relative to the long-term mean, with none being greater than 10 per cent below the long-term mean. However, according to FEWSNET, the 2017/18 rainy season was also below normal in many areas of southern Mozambique;[3] our observations indicate that the 2017/18 season low rainfall shocks were larger, with some households facing differences nearly 30 per cent below normal. Given that livestock production accumulates over years, we also evaluated deviations from mean rainfall in 2018 and 2019. In summary, to arrive at a feasible set of climate variables to evaluate as predictors of project outputs and outcomes, we relied on economic theory, empirical evidence from the agronomic and satellite-based rainfall products literature, and the documentation from early-warning systems that provide snapshots of weather conditions prevailing over the relevant period.

[2] See https://fews.net/southern-africa/mozambique/key-message-update/may-2019.
[3] See https://fews.net/southern-africa/mozambique/key-message-update/may-2018.

3.2. Estimation strategy

The estimation strategy comprises four stages. In the zero stage, we evaluate the performance of weather and climate variables as explanatory variables in project outputs, including variables created from CHIRPS and ARC2 and covering the rainy season, dry season and year, and percentage differences from means in 2018 and 2019. To capture underlying climate conditions, we calculated long-term yearly mean rainfall, the coefficient of variation of rainfall when rainfall is greater than the mean and the coefficient of variation of rainfall when rainfall is below the mean. Separating out measures of variability for high and low rainfall allows us to capture potentially different impacts on outputs and outcomes from exposure to low versus high rainfall shocks, which we expect to be important, given that households in these semi-arid regions have limited exposure to excessive rainfall. We also note that long-term mean rainfall is highly correlated with the coefficients of variation, and thus we chose to retain just the coefficients of variation to proxy underlying climate conditions in the final specification. In particular, higher mean rainfall is associated with a higher coefficient of variation for high rainfall. For ease of exposition, we will hereafter refer to this variable as favourable climate (Fav. Climate). On the other hand, mean rainfall is negatively correlated with the coefficient of variation for low rainfall, meaning those in low mean rainfall environments face greater low rainfall variability and thus greater exposure to dry spells and droughts. We hereafter refer to this variable as drought prone (Drought Prone).

For both CHIRPS and ARC2, the yearly rainfall measures performed better than seasonal or flowering period measures. The analysis also showed similar results when using either CHIRPS or ARC2, with CHIRPS performing somewhat better in terms of explanatory power. To summarize, from this zero stage analysis, we choose the following CHIRPS-based preferred set of weather and climate variables: (i) the percentage difference in yearly rainfall in 2019 from the historical mean (%Diff. Rain, 2019); (ii) the percentage difference in yearly rainfall in 2018 from the historical mean (%Diff. Rain, 2018); (iii) the proxy for favourable climate; and (iv) the proxy for drought prone.

In the first stage, we use our preferred set of weather and climate variables in the propensity score matching, and present results of matching diagnostics. The results from the propensity score matching are then used to generate the inverse probability weights (IPW), which are used in the output and outcome regressions. In the second stage, we run regressions on a range of output and outcome indicators, using regressions weighted by the IPW. In the third stage, we evaluate how results change when we either drop the climate variables from the matching procedure or exclude the weather and climate variables from the regressions, to probe for potential bias in results when these variables are excluded.

3.3. Propensity score weights

The logistic equation is specified as follows:

$$\ln\left(\frac{1}{1-P}\right) = \upsilon + \eta_c C_i + \lambda X4_i + \varepsilon_{Pi}$$

where P is the probability (or propensity) of being a beneficiary, C_i is a set of historical climate variables, $X4_i$ is a set of household characteristics obtained at the beginning of the project four years before the survey, and υ, η_c, λ, and ε_{Pi} are parameters to be estimated. We recover the probability using a logistic regression, and use the inverse weight in our output and outcome equations to ensure that households are matched.[4]

3.4. Output and outcome equations

Outputs associated with the project include knowledge transfers and changes in certain practices, such as investing in animal health and increasing feed availability in the dry season. We have outcomes that are captured by dichotomous variables, such as sale of goats and/or cattle. Adoption of these practices is captured by a dichotomous variable, where adoption is coded 1, and non-adoption 0. Adoption is predicated on expected net returns from adoption, which we can write as follows:

$$EA_{ij} = \alpha + \beta_T T_i + \beta_W W_i + \beta_C C_i + \beta_X X_i + \varepsilon_{ij}$$

where EA_{ij} is the expected return to farmer i from adopting the j-th practice, T_i takes a value of 1 if the farmer is a project beneficiary, W_i and C_i are the sets of weather and climate variables, respectively, X_i is a set of additional household explanatory variables observed in the current period, α, β_T, β_W, β_W, β_X, are parameters to be estimated, and ε_{ij} is the cluster robust standard error. Note that we include the weather variables in the adoption decision because, unlike many crop decisions, livestock inputs and management decisions can respond to actual weather realizations, as well as to long-term expected climate conditions.

Adoption, A_{ij}, occurs when expected returns are positive:

$$A_{ij} = \left\{ \begin{matrix} 1 & \alpha + \beta_T T_i + \beta_W W_i + \beta_C C_i + \beta_X X_i > 0 \\ 0 & \text{Otherwise} \end{matrix} \right\}$$

For continuous outcomes, a similar equation is specified as follows:

$$O_{ik} = \delta + \gamma_T T_i + \gamma_W W_i + \gamma_C C_i + \gamma_X X_i + \varepsilon_{ik}$$

where O_{ik} is k-th outcome realized by farmer i, T_i, W_i, C_i, and X_i are as defined above, and δ, γ_T, γ_{WC}, γ_X, are parameters to be estimated. All error terms, ε_{ik}, are assumed $\sim N(0, \sigma^2)$ after propensity score weighting and clustering standard errors at the village level.

3.5. Data and additional exogenous variables

Survey data were collected in all eight districts of two provinces (Gaza and Maputo) where the project operated. Both beneficiaries and non-beneficiaries were selected from members of farmer groups. Control group farmer organizations were selected outside the area of direct influence of

[4] Using the estimated probability weights in a two-stage procedure as here ignores error associated with this estimate, and may lead to standard errors that are biased downwards. We nonetheless follow this procedure, since it allows us to only evaluate certain interaction terms, instead of interacting all terms with treatment, which itself can lead to an upward bias in standard errors. As a robustness check, we ran all regressions using STATA's teffects iprwa command, and results were nearly identical for significant coefficients, but results are easier to interpret using the two-stage procedure, so that is what we present here.

project activities, though it is noted that some activities, such as the trade fairs[5] and training of animal health promoters, may have had impacts on non-beneficiaries. We cannot directly address potential spillovers given the dataset, but instead consider how spillovers may influence results if they occurred substantially. All farm households with at least one member participating in the farmer groups were enumerated, and a random sample was then selected from each organization, with the number of households per organization mainly ranging from 20 to 30. A total of 697 beneficiary and 669 non-beneficiary households were selected, for a total sample size of 1,366. Nine of these households held no livestock at the time of the interview. When examining the differences between treatment and control on matching variables, we also found that there are two high-density locations that include only control households, both with over 1.5 persons per square kilometre, while the median density for other locations was just 0.1. We do not include households located in these areas in the remainder of the analysis. Finally, as discussed below, eight treated households were not on common support, so these households were also excluded from the analysis. Thus, the estimation sample includes 1,215 households.[6]

In addition to the treatment dummy, we draw mainly from the livestock production literature to specify output and outcome regressors, to the extent possible given information collected in the survey instrument (McCarthy, 2004; Musemwa et al., 2010). For variables directly related to livestock production, we include: a dummy for whether the respondent has been involved in livestock production since before baseline (Dummy, Livestock>4 Years.); whether community pastures have been delimited, which potentially captures increased incentives to invest in such pastures (Comm. Pastures, Delim.); whether the community pastures are shared with neighbouring villages, which captures potentially lower incentives to invest in pastures, overstocking and higher incidence of diseases (Comm. Pastures, Shared); the distance from the household to the nearest community pasture in minutes from the homestead (Distance, Pasture); and the number of water sources for livestock to which the household has access (# Water Sources).

For variables related to crop and hay production, we use own land in hectares (Own Land); and an index of agricultural implements by the household, created using principal component factors (Ag. Asset Index). Crop production may either complement livestock production – for example, through the use of crop residues as feed – or compete with livestock production over scarce resources such as labour time. The impact of these variables is thus generally ambiguous.

Demographic and wealth variables include: a dummy for whether the household is headed by a woman (Dummy, Head Female); a dummy for whether the household head has no formal education (Dummy, Head, No Edu.); the age of the household head (Age of HH Head); the number of family members (HH Size); the dependency ratio (Dependency Ratio), defined as being the number of children under 11 and elderly people over 60 divided by the number of adults in the family; and an index of consumer durables created using principal component factors (Consumer Durables Index). We expect that female-headed households, those where the head has no education and those with lower wealth levels would be less likely to adopt livestock productivity-enhancing practices and have fewer livestock. Smaller households and those with more dependents per adult may find it difficult to undertake labour-intensive practices.

To capture location effects, we include the slope in degrees found at the village centroid (Slope), which is obtained from the SRTM 90m Digital Elevation database; and an index that measures the relative isolation of the village (Isolation Index), created using a principal components factor analysis of population densities in 2014 at the district level, distance from the village centre to the nearest primary road, and distance to the nearest health centre.

[5] However, just 4 per cent of control households said that they attended an animal fair.
[6] Observations differ by regressions. For instance, cattle birth rates are only run on the sample of households with cattle. Running regressions only on the intensive margin may give rise to selection bias if holding cattle is not controlled for by our included regressors and propensity score weights. We can evaluate this potential by looking at results for which all observations are used, such as outcomes for TLUs versus cattle or goats.

We include a number of baseline characteristics that are also used in the matching exercise, including the number of TLUs held at baseline (# TLU at Base); a dummy for whether the household had been raising livestock before the project began (Dummy, Live.>4 years); dummies for whether the household held goats at baseline or both goats and cattle at baseline (with cattle only at baseline being the omitted category) (Dummy, Goats at Baseline; Dummy, Goats & Cattle at Base); a dummy capturing whether the household believes their animals were in generally poor condition at baseline (Dummy, Poor Cond., Base); and an index of the number of meals a household typically ate per day in different seasons in the year (Meal Index, Base). Finally, we included enumerator dummies to control for potential differences in enumeration skills that may have led to systematic recording biases, given that the survey was paper-based.

4. Results and discussion

4.1 Propensity score matching

To match households, we use variables capturing climate conditions (Fav. Climate and Drought Prone); livestock production-related characteristics (# TLU at Baseline, Livestock>4 Years, and Dummy, Poor Cond., Base); baseline household characteristics (Dummy, Head Female; Dummy, Head, No Edu.; Meal Index, Base); and location characteristics (Slope and Isolation Index). As shown in table 1, few variables had significant marginal effects in explaining treatment, indicating that the project team did a good job in selecting controls. However, having more than four years' experience raising livestock and whether the respondent felt animals were generally in poor or very poor condition four years ago are significant predictors at the 10 per cent level.

Table 1. Logit results, marginal effects

Variable	Treat
Climate	
Fav. Climate	2.491
	(8.453)
Drought Prone	3.160
	(35.089)
Livestock production	
# TLU at Baseline	0.002
	(0.006)
Livestock>4 Years	0.343*
	(0.177)
Dummy, Poor Cond., Base	0.298*
	(0.164)
Demographics	
Dummy, Head Female	-0.018
	(0.132)
Dummy, Head, No Edu.	-0.073
	(0.145)
Meal Index, Base	-0.027
	(0.150)
Location	
Slope	0.121
	(0.228)
Isolation Index	0.128
	(0.273)
Constant	-1.082
	(2.857)
Observations	1,302

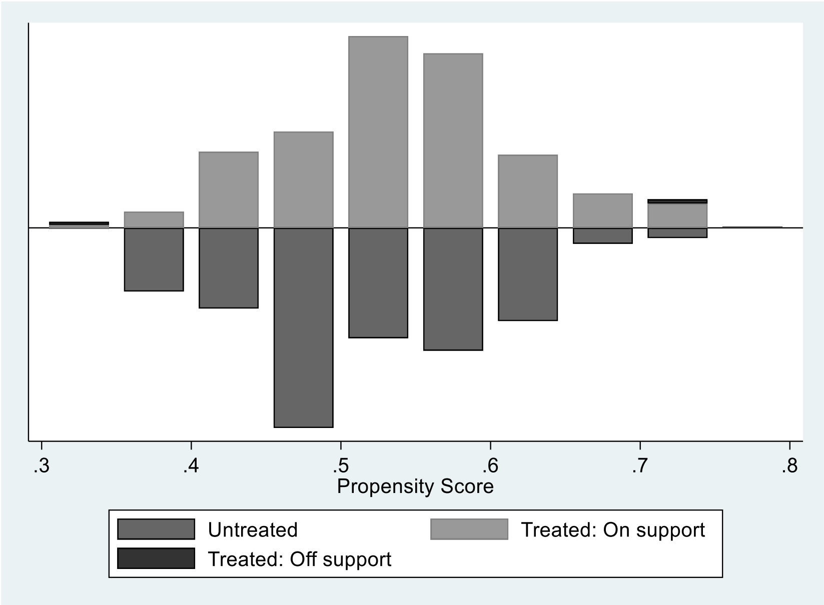
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

With respect to balance after matching, table 2 gives the standardized difference between treatment and control for the raw data and the differences after weighting in the second and third columns, respectively, and the variance ratio for the raw data and after weighting in the fourth and fifth columns. As can be seen, the weighting gives much closer standardized differences, and the variance ratios are close to 1. However, the isolation index still has a relatively large difference and a low variance ratio even after weighting, even though this variable was not a significant predictor of being treated. Nonetheless, as shown in figure 2, the balance plot indicates that overall matching on the propensity score shows good common support, with just eight treated observations not on common support. As noted above, these observations are excluded from the analyses that follow.

Table 2. Standardized differences and variance ratio, raw and weighted

	Standardized differences		**Variance ratio**	
	Raw	**Weighted**	**Raw**	**Weighted**
Climate				
CoV, High	0.139	0.003	0.880	0.881
CoV, Low	0.140	0.001	1.263	1.166
Livestock production				
# TLU at Baseline	0.061	0.005	0.845	0.858
Dummy, Live.>4 years	0.174	0.012	0.748	0.977
Dummy, Poor Condition, B	0.140	-0.015	1.248	0.980
Demographics				
Dummy, Head Female	-0.019	0.006	0.985	1.004
Dummy, Head, No Edu.	-0.010	-0.003	1.008	1.002
Meal Index at Baseline	-0.041	0.009	1.028	0.989
Location				
Slope	0.170	0.011	1.656	1.243
Isolation Index	0.093	-0.064	0.384	0.400

Figure 2. Propensity score histograms



4.2 Household output regressions

Select results for the household output regressions are reported in table 3. First, we note that being a project beneficiary (Treat) has a significant impact on receiving information and technical assistance on animal diseases, on frequently using cattle baths, deworming, and supplemental feed. However, there were no impacts on cattle or goat sales, or on participating in an LPO. These results are consistent with limited spillover impacts from training animal health workers, since we would expect coefficients to be biased downwards specifically for health-related outcomes, but differences are strongly significant on all health-related outputs except goat baths.

With respect to climate variables, we first note that neither participation in an LPO nor cattle sales are affected by current/recent rainfall patterns or by underlying climate conditions. Goat sales are in fact higher with higher differences in rainfall in both years, suggesting that the shorter gestation period for goats versus cattle may allow farmers greater flexibility to respond to positive rainfall shocks. Access to disease information and assistance is higher in areas with higher percentage differences, but also in drought-prone areas. Cattle baths are more likely in more favourable areas, consistent with the evidence that suggests ticks are more prevalent in such areas. However, underlying climate conditions have no impact on goat baths and in fact are lower in areas that experienced larger rainfall shocks. Deworming is lower in more favourable areas and higher in drought-prone regions, again consistent with the empirical evidence that suggests worms are particularly problematic in dry areas (though during the rainy season). Finally, supplementary feeding is positively related to rainfall shocks, negatively related to favourable climate and positively related to drought-prone conditions. The results on supplemental feeding are consistent with less demand for supplemental feed in areas with more favourable climate conditions and greater demand in drought-prone areas, but, controlling for those characteristics, also where farmers take the opportunity to use supplemental feed – including hay and other crop residues – when supply of these feeds is relatively more abundant due to more favourable rain in a specific season.

With respect to production variables, delimited community pastures are consistent with increased investment in livestock health, as we hypothesize. Shared pastures do not have negative impacts on most outputs. However, farmers are less likely to sell cattle when pastures are delimited, but more likely when pastures are shared. Since we do not observe stocking densities on the pastures, it is not clear what factors are operating to drive these results. A consistent interpretation would be that overstocking is occurring on shared pastures to a greater extent than on delimited pastures, and that greater stock levels are also associated with greater opportunities to sell. We return to evidence on overstocking when we present outcome results below.

Overall, farmers living in areas with more favourable rainfall in the current and previous season were more likely to adopt a subset of practices promoted by the project, with the exception of goat baths. The climate variables have different impacts depending on the specific practice, as we might expect, given different distributions of disease incidence. Supplemental feed is more likely in drought-prone areas, consistent with building resilience in livestock production. And there is some evidence to suggest that delimited pastures improve incentives to invest in animal health.

Table 3. Output variable probits, marginal effects for select variables

Those Variables	Livestock Org.	Cattle, Sale	Goat, Sale	Disease Information	Disease Tech. Asst.	Cattle Baths	Goat Baths	Deworm	Feed
Treat	0.028	0.033	-0.030	0.284***	0.261***	0.128**	0.031	0.034***	0.124***
	(0.035)	(0.034)	(0.032)	(0.044)	(0.063)	(0.052)	(0.021)	(0.011)	(0.022)
Climate variables									
% Diff. Rain, 2018	0.004	0.003	0.008**	0.011**	0.014**	-0.000	-0.005*	0.000	0.005**
	(0.004)	(0.003)	(0.003)	(0.004)	(0.006)	(0.005)	(0.003)	(0.002)	(0.002)
% Diff. Rain, 2019	-0.002	-0.000	0.013***	0.014***	0.009	-0.015	-0.009***	-0.002	0.005**
	(0.006)	(0.005)	(0.004)	(0.005)	(0.006)	(0.010)	(0.004)	(0.002)	(0.002)
Fav. Climate	0.097	0.821	0.889	-1.482*	-1.421	2.310**	0.528	-0.543**	-0.647*
	(0.696)	(0.606)	(0.586)	(0.882)	(1.120)	(0.994)	(0.419)	(0.240)	(0.343)
Drought Prone	2.442	2.948	2.594	11.122**	13.869**	-3.500	-1.635	1.805*	2.910*
	(2.287)	(2.058)	(2.793)	(5.059)	(5.406)	(3.966)	(2.356)	(0.952)	(1.741)
Livestock production									
Dummy, Live.>4 Years	0.038***	0.062***	0.003	0.028	-0.001	0.031*	0.006	0.007	0.004
	(0.013)	(0.024)	(0.014)	(0.020)	(0.018)	(0.017)	(0.011)	(0.008)	(0.007)
Comm Pastures, Delim.	0.066	-0.135***	0.008	0.168***	0.147**	0.114*	0.069***	-0.022	0.025
	(0.051)	(0.046)	(0.044)	(0.041)	(0.065)	(0.066)	(0.025)	(0.016)	(0.028)
Comm Pastures, Shared	-0.024	0.220***	-0.024	0.010	0.062	0.111	0.049	-0.026	-0.051
	(0.058)	(0.041)	(0.090)	(0.053)	(0.098)	(0.068)	(0.032)	(0.024)	(0.033)
Distance, Pasture	0.000	0.000	-0.000	-0.000	-0.000	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Baseline variables									
# TLU, Baseline	0.001**	0.007***	-0.002	0.001	0.002	0.006***	0.002***	0.000	-0.001**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.000)	(0.000)
Observations	1,215	1,215	1,215	1,215	1,215	1,215	1,215	1,138	1,215

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

4.1 Household outcome regressions

Table 4 gives select regression results for livestock birth rates and changes in herd size in the past four years for cattle, goats and TLUs, respectively, and the proportion of goats in TLUs. We first note that there were no impacts of the project on birth rates. We interpret impacts on birth rates with caution, because these rates are likely to be noisy given their construction, and project impacts may not have been large enough to detect with a relatively noisy variable. However, there are significant impacts of climate variables on birth rates. The larger percentage differences in 2019 increased both goat and TLU birth rates, while drought-prone areas had lower birth rates for cattle, goats and TLUs. We note that livestock production characteristics had limited impacts on birth rates, though the number of TLUs at baseline is a positive predictor, as we would expect.

With respect to changes in herd size, the project did increase the number of cattle and TLUs. The percentage difference in 2019 rainfall led to larger increases in numbers of cattle and TLUs; however, underlying climate conditions did not have any impacts on changing livestock numbers over time. With respect to the proportion of goats in the herd in terms of TLUs, the project had a significant negative impact, while the weather and climate variables had no impact. The fact that underlying climate conditions had no impact on herd composition and that treated households actually reduced the proportion of goats in the herd should concern the project team and be seriously considered in the design of future projects. Goats are better able to withstand longer dry spells and droughts than cattle, and projects should aim to increase incentives to expand the proportion of goats in the herd through productive feeding strategies and by supporting goat value chain development so that goat production is more valuable to farmers.

Finally, looking at changes in herd sizes, our results are consistent with a classic “commons” problem related to the higher likelihood of cattle sales observed in table 3. Changes in numbers of cattle and TLUs over time are greater where pastures are not delimited (lower land tenure security) and where pastures are shared (greater incentives to overexploit pasture resources). Combined, the evidence suggests that livestock projects need to address directly the incentives associated with land tenure insecurity and incentives to overexploit pastures, to achieve hoped-for gains in productivity in the longer term.

Table 4. Outcome regression results for select variables

	Birth Rates			Change in:			Prop. of Goats in TLU
Variables	**Cattle**	**Goats**	**AvgTLU**	**Cattle**	**Goats**	**TLUs**	
Treat	0.063	-0.000	0.035	0.351**	0.122	0.300*	-0.054*
	(0.041)	(0.037)	(0.034)	(0.166)	(0.174)	(0.153)	(0.027)
Climate variables							
% Difference Rain, 2018	-0.003	-0.002	-0.004	-0.006	0.016	-0.003	0.001
	(0.003)	(0.004)	(0.003)	(0.013)	(0.013)	(0.012)	(0.003)
% Difference Rain, 2019	0.005	0.011***	0.006*	0.086***	0.021	0.077***	-0.006
	(0.004)	(0.004)	(0.004)	(0.022)	(0.021)	(0.020)	(0.004)
CoV, High	-0.594	-0.429	-0.592	1.560	3.234	1.940	0.335
	(0.554)	(0.645)	(0.516)	(3.324)	(3.663)	(3.139)	(0.459)
CoV, Low	-4.313**	-5.000*	-4.467**	-21.104	10.729	-16.541	1.535
	(1.956)	(2.828)	(2.188)	(12.664)	(17.940)	(13.192)	(1.414)
Livestock production							
# Years Livestock Exp.	0.027	-0.017	0.013	-0.187***	-0.097	-0.186***	-0.052***
	(0.023)	(0.022)	(0.017)	(0.068)	(0.082)	(0.066)	(0.012)
Comm Pastures, Delimit.	-0.054	-0.049	-0.054	-0.703***	-0.199	-0.620***	0.014
	(0.049)	(0.051)	(0.044)	(0.211)	(0.197)	(0.199)	(0.032)
Comm Pastures, Shared	0.044	0.017	0.030	0.876***	0.274	0.816***	-0.130***
	(0.115)	(0.079)	(0.083)	(0.318)	(0.291)	(0.261)	(0.035)
Distance, Pasture	-0.001*	0.000	-0.000	0.001	-0.001	0.001	-0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
Baseline variables							
# TLU, Baseline	0.004**	0.004***	0.004***	-0.061***	-0.020**	-0.057***	-0.004***
	(0.002)	(0.001)	(0.001)	(0.011)	(0.008)	(0.010)	(0.001)
Constant	0.967***	1.005***	1.022***	1.664	-0.478	1.164	0.305
	(0.286)	(0.316)	(0.253)	(1.324)	(1.388)	(1.308)	(0.187)
Observations	903	876	1,157	1,215	1,215	1,215	1,215
Adj.R2	0.0895	0.119	0.108	0.349	0.150	0.368	0.492

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

4.1 Outcome regressions without climate variables

We next consider whether and to what extent results change if we first omit the climate variables from the matching procedure, and when we omit climate variables from the matching procedure as well as from the regressions. As noted in section 4.1 above, there were limited differences across treatment and control households in terms of baseline characteristics, indicating that the impact assessment team did a good job in selecting control villages, at least after removing those control households located in two localities with a very high population density from the sample. We thus expect that dropping the climate variables from the construction of inverse probability weights will have limited impact.

On the other hand, we would expect that excluding climate variables from the regression analysis might lead to biased estimates. In particular, we would expect the potential for bias due to omitted confounders to become more likely as we move further down the causal chain. Outcomes further down the causal chain may well give rise to confounding impacts of omitting climate variables - both through the adoption of different livestock practices (which are affected by both treatment and climate variables) as well as other pathways, such as labour reallocation.

Table 5 provides results for project outputs in Panel A, and project outcomes in Panel B. In each panel, there are three sets of results: The first two rows correspond to the results obtained in tables 3 and 4 while the third and fourth rows capture results when we do not use climate variables in the matching. The final two rows capture the results when climate variables are not used in both the matching procedure and the regressions.

Panel A shows that the estimated coefficients on treatment are indeed quite similar when significant, with the exception of deworming, where the coefficient when not controlling for climate in the matching and regression is lower than the other two specifications. However, the difference is not significant. Panel B also shows limited differences across the first two specifications, but here the change in the number of cattle and average TLUs is higher when climate conditions are not included in the matching and regressions. Not including climate conditions biases the coefficient downwards, and thus underestimates cattle and TLU herd sizes, which may also underestimate the threats to productivity gains from overstocking. At the same time, given the relatively large standard errors, the differences are not statistically significant.

Table 5. Results on estimated treatment coefficient when climate variables not used

Panel A: Project outputs

Variables	Livestock Org.	Cattle, Sale	Goat, Sale	Disease, Information	Disease Tech. Asst.	Cattle Baths	Goat Baths	Deworm	Feed
Table 3 results									
Treat	0.028	0.033	-0.03	0.284***	0.261***	0.128**	0.031	0.034***	0.124***
	-0.035	-0.034	-0.032	-0.044	-0.063	-0.052	-0.021	-0.011	-0.022
No Clim., Match									
Treat	0.026	0.035	-0.029	0.289***	0.269***	0.130**	0.031	0.033***	0.127***
	(0.034)	(0.034)	(0.033)	(0.043)	(0.061)	(0.053)	(0.021)	(0.011)	(0.022)
No Clim., Match and Reg.									
Treat	0.022	0.049	0.001	0.282***	0.258***	0.130**	0.032	0.024*	0.126***
	-0.039	-0.037	-0.042	-0.05	-0.068	-0.06	-0.025	-0.013	-0.021

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Panel B: Project outcomes

	Birth rates:			Change in:			Prop. of Goats in TLU
Variables	**Cattle**	**Goats**	**AvgTLU**	**Cattle**	**Goats**	**AvgTLU**	
Table 4 results	0.063	0	0.035	0.351**	0.122	0.300*	-0.054*
Treat	-0.041	-0.037	-0.034	-0.166	-0.174	-0.153	-0.027
No Clim., Matching	0.061	0.001	0.036	0.351**	0.132	0.300*	-0.056**
Treat	(0.041)	(0.038)	(0.034)	(0.170)	(0.175)	(0.156)	(0.027)
No Clim., Match and Reg.							
Treat	0.05	-0.006	0.03	0.467**	0.21	0.413**	-0.055**
	-0.04	-0.038	-0.034	-0.188	-0.184	-0.174	-0.025

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

5. Concluding comments

We have incorporated climate variables into an analysis of an IFAD livestock project, using climate variables that are grounded in economic theory and have empirical support in the agronomic and GIS literature, and prevailing weather conditions that might affect livestock production outcomes found in early-warning systems documentation. Given the number of different data sources for rainfall estimates and temperatures, and the different types of weather condition indices found in a rapidly expanding literature, researchers must determine the best ways to limit the search for climate variables to include in econometric analyses, and we suggest that these three sources – theory, empirical evidence of impacts of weather conditions on production outcomes using specific sources, and weather patterns observed during the relevant survey period – all provide useful ways to limit that search. It goes without saying that, in the future, more and more research will focus on machine learning applications that can evaluate thousands and thousands of variables to identify patterns, though it is unclear what the practical implications might be. Governments and project implementers need a better understanding of the impacts of weather events on production in order to gauge vulnerabilities and design projects to address those vulnerabilities. And these variables should be easily understood and monitored. The evidence provided here suggests that easily monitored and understood variables can be identified, with impacts on production largely as hypothesized. As noted in the introduction, this paper is the fourth in a series of publications that incorporates climate variables into impact assessments, and in each of those cases, the search for climate variables, using the methodology outlined above, yielded variables that explained outputs and outcomes, and with results that can directly inform future resilience-related project designs.

Results from the matching analysis showed that climate conditions had no impact on being treated, indicating that the impact assessment team did a good job of ensuring that treated and control households experienced a similar range of climate conditions. This result was serendipitous, as climate conditions were not explicitly considered in selecting controls; in the future, it would be better to use climate conditions, particularly when project outcomes are weather- and climate-sensitive, as is the case here. Project outputs were affected by both current and recent weather deviations, as well as underlying climate conditions. Those located in locations with a more favourable climate were less likely to obtain disease information, deworm and provide supplemental feed, while those located in drought-prone locations were more likely to access disease information and assistance, deworm and provide additional feed. Higher percentage deviations from average rainfall increased provision of feed, indicating that farmers took advantage of favourable supply shocks on crops due to higher relative rainfall. Neither weather nor climate conditions affected cattle sales, but positive shocks did spur more goat sales. Altogether, results indicate that livestock owners facing different weather shocks and climate conditions have different incentives to generate project outputs. This in turn suggests that projects need to explicitly incorporate climate conditions when deciding which activities need to be promoted to generate hoped-for outputs across these different conditions. In addition, project planners need to consider how shocks can affect outputs, and whether/how project activities can increase the ability to take advantage of positive shocks and reduce the impacts of negative shocks.

Given the survey design and implementation, we only have a limited number of outcomes associated with livestock productivity. The results show the positive impacts on productivity of a high percentage difference of rainfall from expected in the current period, in terms of livestock birth rates and increased herd size, and future projects should consider how project activities can further improve gains from positive shocks. On the other hand, those living in drought-prone locations had lower birth rates, indicating that more could be done to increase access to fodder and feed in these regions to enhance productivity. We also note that percentage differences in rainfall and climate conditions had no impact on the proportion of goats in the herd, and that treated households increased cattle holdings but not goat holdings vis-à-vis control households. This indicates that project activities may have favoured raising cattle over goats, which may in fact make households in this semi-arid area less resilient to future climate impacts. Given that weather conditions were relatively favourable during the production period covered by the survey, we cannot test this directly, but it remains concerning, and future livestock projects should directly address the question of optimal livestock mix for those more exposed to droughts versus less exposed.

Finally, we also found additional interesting results on the regressors included. In many econometric-based impact assessments, researchers focus narrowly on treatment effects, and are often not careful when specifying the regression equations. Such an approach does not allow project implementers to learn fully from the data collected. In this particular case, livestock owners rely heavily on common pastures, often shared with one or more other communities. This means there can be incentives to overstock on the common pastures – something not recognized in the theory of change. While we do not have the data to test directly this (we would need to observe stock densities on the commons themselves), the evidence does point to common property management problems, if not a tragedy. For instance, those who share pastures were more likely to increase cattle herd sizes and reduce the proportion of goats in the herd, consistent with incentives to overstock. On the other hand, those for whom common pastures were delimited were more likely to access disease information, increase the frequency of baths for both cattle and goats, and decrease cattle herd size – all indicating increased incentives to intensify livestock production, consistent with lower incentives to overstock. This finding is very important for future resilience to climate change, because overstocked pastures with a high proportion of cattle will be more vulnerable to a drought shock. These results need to inform future project design.

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