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Elia Machado
CUNY Lehman College

Helene Purcell
Fordham University

Andrew M. Simons
Fordham University

Stephanie Swinehart
Fordham University

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The quest for greener pastures: evaluating the livelihoods impacts of providing vegetation condition maps to pastoralists in Eastern Africa

Elia Axinia Machado, Lehman College, City University of New York
(elia.machado@lehman.cuny.edu)

Helene Purcell, Fordham University (hpurcell@fordham.edu)

Andrew M. Simons, Fordham University, 441 East Fordham Rd. Dealy Hall, Room E-506,
Bronx, NY 10458 (asimons5@fordham.edu) corresponding author

Stephanie Swinehart, Fordham University (sswinehart@fordham.edu)

Abstract:

The survival of millions of pastoral households in Eastern Africa has become increasingly at risk. Due to mounting socioeconomic and climatic stressors, pastoral households are faced with making migration decisions under increasing uncertainty about resource availability and limited coping strategies. We assess the potential of providing vegetation condition maps to support the migration decision of pastoralists in Ethiopia and Tanzania and the effect of map usage on their herd condition and size. The maps were generated from remotely sensed data using the Normalized Difference Vegetation Index (NDVI) as a proxy for vegetation condition and overlain with pastoralists' preferred grazing areas. The use of maps for migration decisions was low in both study areas, partly due to challenges in map distribution (26% and 2% in Ethiopia at midline and endline respectively; and 35% and 29% in Tanzania at midline and endline respectively). However, map adopters in both countries reported an overwhelmingly positive experience and found maps accurate and helpful. Map usage was associated with improved animal condition in Tanzania, but we find no causal evidence that map usage affected herd size.

Keywords: Pastoralism; Spatial Mapping; Climate Change; NDVI; Adaptation Strategies; Ethiopia; Tanzania

1. Introduction

Pastoralism constitutes the main livelihood of about 268 million people in Africa, contributing an estimated 10 to 40% of its GDP (African Union, 2013; FAO, 2018). In recent decades, the livelihoods of many pastoralists have become seriously threatened (IGAD and WFP, 2017; Williams et al., 2012; Williams and Funk, 2011). Rising climatic variability has altered the

seasonal distribution of water and forage upon which pastoralists rely (Butt, 2010; Luseno et al., 2003; Tierney et al., 2015), increasing the level of uncertainty in their migration decisions (Nkonya et al., 2017; Silvestri et al., 2012). Additionally, changes in land tenure systems and agricultural expansion have fractured pastoralists' production systems, amplifying their vulnerability to climate change and variability (FAO, 2018; Tsegaye et al., 2013).

Traditionally, migratory pastoralists receive information about pasture and make migration decisions in several ways. They may send scouts to evaluate conditions, rely on word-of-mouth and phone communication to verify conditions, or trust traditional knowledge of where and when they migrated in the past (Mapinduzi et al., 2003). We assess the potential of providing vegetation condition maps to enhance pastoralists' migration decision methods in Ethiopia and Tanzania and evaluate the effect of map usage on their herd size and condition.

In recent years, there has been a growing interest in using technology to assist pastoralist communities. These studies typically have focused on the impact of delivering climate-forecasting information. Our study contributes to this literature by focusing on the provision of relative vegetation condition information within pastoralists' traditional grazing zones. We provide an overview of antecedent studies and contextualize their differences with our study below.

Luseno et al., (2003) examined the impact of external climate forecasting (disseminated by the government primarily over the radio) of the timing and predicted amounts of seasonal rainfall for pastoralists in Kenya and Ethiopia. Overall, they found that pastoralists readily understood and could communicate the rainfall forecast information correctly, but the information was of limited value to them due to the coarse spatial and temporal scale. They

propose that the information most likely to be useful to pastoralists would be real-time, spatially explicit, and include forage conditions, consistent with Suliman and Ahmed (2013). In our study, the information provided to pastoralists attempted to meet all three of these conditions, albeit it is not “real-time,” with dissemination every ten days.

In the same setting, Lybbert et al., (2007) found that despite limited familiarity with computer-based forecasting approaches, pastoralists update their beliefs in response to climate forecasts. However, they seem to readily update below normal rainfall forecasts, generally ignoring above normal rainfall forecasts (Lybbert et al., 2007). We do not gather herdsman-level data on subjective belief formation, so we are not able to inform how beliefs are updated. However, we do examine pastoralist access, usage, and subjective understanding of the vegetation condition maps.

Rasmussen et al., (2015, 2014) emphasize the importance of providing information at an appropriate spatial resolution in their West African study and argue that information is most useful when it includes grazing conditions and coping strategies (e.g., suggested migration locations or advice to purchase supplementary fodder). In our study, pastoralists only received maps that showed the relative condition of vegetation in their traditional grazing areas; recommendations such as when to purchase supplementary feed or a specific migration location were not provided. Nevertheless, the visualization of decadal (every ten days), spatially explicit information on vegetation conditions seemed to provide pastoralists insights regarding several coping strategies.

In our study, pastoralists reported very high levels of satisfaction with the maps and that the maps accurately reflected the conditions on the ground. However, due in part to distribution

challenges, map use was lower than intended (26% and 2% in Ethiopia at midline and endline respectively; and 35% and 29% in Tanzania at midline and endline respectively). We did not find meaningful differences in herd size between control and intervention communities in Ethiopia, although suggestive evidence in Tanzania indicated that using maps was associated with improved animal condition.

Next, we provide a description of our data collection methods, analytical approach, and the results both from a randomized controlled trial and qualitative focus group discussions. The paper concludes with a discussion of the results in the context of scaling up the pilot and other implementation challenges.

2. Material and methods

2.1 Pilot Phase and Project Roll-out

The international NGO Project Concern International¹ (PCI) conducted a pilot project between July 2013 and July 2014 in which they distributed vegetation condition maps to assist pastoralists with their migration decision-making (PCI, 2014). In the pilot, maps were distributed in two woredas in the Afar region (Telelak and Megale).² Hoefsloot Spatial Solutions³ produced the maps using data from the satellite Meteosat to calculate the NDVI values.

¹PCI is a non-profit, humanitarian NGO headquartered in San Diego, CA founded in 1961. For additional details about the organization see: <https://www.pciglobal.org/our-work/>.

²In the pilot, Telelak received the vegetation maps while Megale did not. At the completion of the pilot, Megale was also given access to the maps.

³Maps were updated every ten days and posted at <http://www.hoefsloot.com/saparm/>. For other general information about Hoefsloot Spatial Solutions see <http://hoefsloot.com/new/>.

NDVI is calculated using the optical reflectance of sunlight in the red and near-infrared wavelengths of the electromagnetic spectrum and ranges from -1 to 1; higher values (typically over 0.2) are interpreted as more dense and vigorous vegetation (Tucker, 1979). The use of this index to monitor vegetation condition and environmental change is well established in the literature (Anyamba et al., 2018; Eastman et al., 2013; Fensholt et al., 2012; Menzel and Fabian, 1999), as well as to inform government policies and assistance programs such as the Famine Early Warning Systems Network (FEWS NET) and the Index-Based Livestock Insurance (Gandhi et al., 2015; Jensen et al., 2017; Sakamoto, 2016).

Figure 1 shows an example of the vegetation condition maps provided to the pastoralists. The maps show NDVI values classified into three broad classes (bad, average, good) for ease of interpretation by pastoralists, but there is variability within each class allowing map users to identify the best and worse areas within each category and differentiate intermediate values. Visualizing the distribution of different land use/cover or vegetation species (e.g., edible grasses vs. non-edible evergreen woody shrubs like *prosopis juliflora*) is also important, but it was not added to the maps to avoid impairing map readability and interpretation. This intervention attempts to overcome this limitation in several ways. First, areas with non-vegetative cover are shown in deep brown color (bad quality). Second, pastoralists' traditional grazing areas identifying areas with pasture cover are clearly marked on the maps. Third, pastoralists can use and share their knowledge of where patches of *prosopis* are located⁴ to avoid those locations

⁴For example, if pastoralists know that near the hills on the eastern edge of their grazing lands there has been a large patch of *prosopis*, and they see green in that location on the vegetation map, they may discount its value as grazing land, as they know that in years past that area was over grown with *prosopis*.

even if the map shows green conditions there. In addition, the program is designed to deliver maps every ten days, which allows users to differentiate areas undergoing seasonal cover changes (likely grasses useful for pasture) from areas with more consistent NDVI values year along (less likely to be pasture).

The main conclusions of the pilot report were: “Almost 80% of pastoralists received and used the maps for migration decision-making. All users found the maps to be accurate in identifying adequate grazing areas with 57% classifying them as very accurate. Over half the respondents asserted that the maps were now their most important information source for grazing decision-making, and all felt the maps could reduce livestock death and improve animal condition. Ninety percent of pastoralists felt [the vegetation maps] positively contributed to pasture management by allowing poor pastures to lay fallow while 43% also felt it could contribute to overgrazing in some areas. Most remarkable was that [self-reported] herd mortality rates dropped by nearly half (47%) after introduction of the maps, compared to the [self-reported mortality rate recalled from] previous three years in the intervention community. This drop was consistent across all species of animals” (PCI, 2014).

These positive results allowed PCI to secure additional funding to scale up and partner with an external academic group to evaluate map uptake, and the effect of providing maps on herd size and pastoralists’ migration decisions.

This larger intervention, carried out between 2015 and 2018, is the focus this paper. It was designed to include a cluster randomized control trial in Ethiopia (seven woredas received maps while another seven woredas did not receive maps) and a comparison of map users versus non-users in a non-randomized intervention in two districts in Tanzania. The two Ethiopian

woredas included in the pilot were not included in the subsequent randomized control trial. Randomization was not part of the research design in Tanzania due to logistical constraints and hesitation by the government to appear favoring certain groups over others. Table 1 shows the key project dates of this larger intervention and the household survey collection periods.

The maps provided to pastoralists showed their traditional grazing areas (delineated by communities in 2015 through participatory mapping sessions) and were updated to include permanent water sources, protected area boundaries, and improved zone borders based on community feedback over the course of the project. Figure 1 shows the traditional grazing areas overlaid on the vegetation condition data layer. PCI emailed the maps to key personnel in the woredas (Ethiopia) or district (Tanzania) government extension system every ten days. The maps were then printed and cascaded to pastoralists through existing government extension systems in each country. Maps were provided free of charge; however, using the extension system for dissemination does not guarantee equal access to all herdsmen in intervention areas. As a result, within intervention areas, some pastoralists saw and used the maps, some saw the maps but did not use them, and others never saw the maps. In some intervention areas, extension agents may have just delivered vegetation maps to key local traditional leaders and left it to them to further disseminate the information. Gathering data on the specific map distribution modality (i.e., through the extension system or through local leaders) was out of the scope of the project.

2.2 Survey Data Collection

We collected household surveys three times over the course of the project (Table 1) in the intervention communities of Afar, Ethiopia, and in two northern districts of Tanzania (Monduli and Longido). Figure 2 shows the intervention zones in both countries with the community-

delineated grazing areas, and the locations where surveys took place. Enumerators in Ethiopia surveyed approximately 12 households in each accessible kebele (kebele is the smallest administrative governmental unit in Ethiopia corresponding to a village/community) within the 14 woredas included in the study. In Tanzania, all rural, accessible villages located in the intervention zones were included in the survey. In each village, 12 households who met the eligibility criteria were interviewed.⁵ Criteria for survey inclusion were the same in both countries: (1) own livestock,⁶ (2) be a permanent resident of the community, (3) migrate their herds, and (4) be the primary migratory decision maker within the household. To facilitate data collection, leaders in each community were asked to mobilize herdsmen who met these criteria. In almost all communities more than 12 herdsmen were identified, so we randomly selected 12 herdsmen to be interviewed.

Enumerators asked qualitative and quantitative questions about migration decision-making, and collected user opinions regarding maps and how they were distributed. The map questions focused on how reliably individuals perceived the maps and their opinions on map ease of use, accuracy, and utility of the maps. Where respondents indicated the maps were helpful, they were prompted to provide additional details on how the maps were useful and how maps impacted their migration decisions.

⁵Smartphones programmed with the household questionnaires using CommCare were used to conduct the surveys. The survey added questions to the pilot phase survey and updated each round with additional relevant questions when necessary. The questionnaire was created through a collaborative process between PCI field office staff, PCI headquarters staff, and university researchers.

⁶“Livestock” is defined as cattle, camel (Ethiopia only), goats, and sheep.

Although assessing animal condition was not part of the initial focus of the evaluation, we believed it was important and we were able to add questions in this regard at endline in both countries. Respondents completed a retrospective proportional piling exercise to allocate ten stones for three animal conditions (good, average, poor) for each animal type at endline and were asked to recall this data for the previous survey periods. For example: a pastoralist distributing the ten stones as 2:5:3 for cattle indicates that 20% of cattle were in good condition, 50% were in average condition, and 30% were in poor condition). Survey enumerators recorded coordinates and elevation of the location where the interview with each respondent took place using GPS instruments.⁷

All animal holdings were converted into tropical livestock units (TLUs) to aggregate herd size over different types of animals into one measurement unit.⁸ Each round of data collection was a repeated cross section (we did not follow the same herdsman over time).

2.3 NDVI Standardized Monthly Anomaly Data

The condition of rangeland plays an important role in pastoralists' migration decisions since it determines where and when to migrate (Butt, 2010; Liao et al., 2017; Mapinduzi et al., 2003; Tsegaye et al., 2013). Staying closer to the household allows pastoralists to reduce costs and risks associated with moving animals, and is the preferred behavior, contingent on

⁷Due to the migratory nature of pastoralist households, the survey coordinates are most likely an approximation of the respondents' homestead, not their exact location.

⁸TLU calculations are based on rates used by the International Livestock Research Institute (ILRI) and the Food and Agriculture Organization (FAO) according to the following conversion: 1 camel = 1.4 TLUs, 1 cow = 1 TLUs, 1 sheep = 0.1 TLUs, 1 goat = 0.1 TLUs (Upton et al., 2016).

environmental conditions nearby. Thus, local conditions may serve as a useful indicator for triggering migration decisions.

To attempt to account for the effect of changing vegetation conditions in pastoralists' use of maps and migration decisions, we incorporate a measure of NDVI deviation from the prior 18-year mean monthly NDVI values as a variable in our regression models. Specifically, we use the NDVI standardized monthly anomalies (SMA) for the stated most frequent migration month at the community level (kebele in Ethiopia and ward in Tanzania) during the study period. All surveyed pastoralists were asked to list all the months in which they migrated in the past year. The most frequent migration month was calculated by tabulating responses by month for each community location.⁹

SMA values were calculated using the Moderate Resolution Imaging Spectroradiometer (MODIS) monthly vegetation index product at 0.05 degrees (approximately 5.5km at the equator) of spatial resolution (MOD13C2v6) for the base period May 2000 to April 2018 (Didan, 2015). First, we calculated the mean and standard deviation of NDVI values for each pixel and each month during this period (there were eighteen NDVI values per pixel and month). Then we calculated the SMA for a particular month, year, and pixel by subtracting the base period average for that month and pixel from its NDVI value and dividing the result by its corresponding base period standard deviation.¹⁰

⁹In the case of a tie, meaning more than one month was equally popular in a district, we choose the earliest month (as this would be when they made the first migration decision).

¹⁰For example, the SMA for a pixel (or point location) in January 2000 was calculated in two steps i) subtract the average of NDVI values in January during the base period (i.e., over the 18 years) from the pixel's NDVI value in

We note that the data source for the NDVI data used in this analysis differs from what was used (Meteosat) in the NDVI printed maps provided to the pastoralists during the project implementation. The vegetation product from MODIS was preferred in this analysis for its spatial and temporal consistency (Anyamba et al., 2018) over a time period exceeding the project duration.

Figure 3 and Figure 4 show how vegetation conditions change from the base period norm as SMA values, illustrating the contrast between the greener conditions in October 2014 and the drier conditions in December 2016. Greener areas correspond to higher NDVI values (i.e., more abundant/better vegetation conditions in a particular area) than the average for that month during the base period, while red areas indicate the opposite.

2.4 Specification of Regression Analysis

We use a standard approach (Duflo et al., 2007; Gertler et al., 2016) from the impact evaluation literature to measure the intent-to-treat (ITT) results of the randomized controlled trial (Equation 1) where access to maps was randomly assigned at the cluster level. The specification is:

$$Y_{t,i} = \beta_0 + \beta_1 Treat_i + \beta_2 Y_{t-1,i} + \beta_3 NDVI_{t,i} + X_i' \gamma + \varepsilon_i \quad (1)$$

where $Y_{t,i}$ is the dependent variable of interest (e.g., herd size expressed as TLUs) for respondent i at the time of survey, $Treat_i$ is a dummy variable indicating if the respondent was

January 2000, and, ii) divide the result by the standard deviation of that pixel's values in January during the base period.

in a woreda that received vegetation maps, $Y_{t-1,i}$ is the lagged variable of interest (e.g., herd size expressed as TLUs from 12 months prior to the survey), $NDVI_i$ is the SMA value for the most commonly noted migration month by an individual's community (kebele in Ethiopia and ward in Tanzania), X_i is a vector of socio-economic and household characteristics (gender, age, household size, livelihood strategy, cell phone ownership, etc.), and ε_i is the error term. We cluster the standard error at the level of randomization (woreda) for Ethiopia, and by village in Tanzania.

The ITT results reveal the community-wide average differences between those who lived in a community with (randomly assigned) access to the maps and those that did not. However, because there was low uptake of maps in intervention communities (meaning many in these communities did not actually use the maps), we also estimate the local average treatment effect (LATE), which would be interpreted as the effect of maps conditional on using them. To calculate this we use a standard instrumental variables approach with the random assignment of maps to certain woredas to instrument for using maps (Duflo et al., 2007; Gertler et al., 2016) (Duflo et al., 2007; Gertler et al., 2016). The first stage of this two-stage regression uses random assignment to estimate the predicted probability of using the maps. The predicted probability of using maps is then inserted in the second stage regression to estimate the local average treatment effects.

Because we do not have randomization in Tanzania, we simply compare map users versus non-users with the same specification as Equation 1, but replace $Treat_i$ with Use_i , which is a dummy variable indicating whether an individual used the maps in decision making. This

gives some indication of how outcomes are different between map users and non-users, but these differences should only be considered as suggestive evidence as the experimental design does not allow us to account for selection effects. For example, if only the most skilled herdsmen in finding good quality grazing areas seek out the additional information provided by the vegetation maps, they may have had better outcomes anyways due to being the most skilled even in the absence of the provision of vegetation maps.

3. Results

Map users in both countries had very similar responses about their experience using the maps. However, the analysis in Tanzania suffers from selection bias since conducting the randomized trial was only possible in Ethiopia.

3.1 Descriptive Statistics

Table 2 presents household characteristics using information gathered at baseline. The majorities of respondents in both countries were male and had little or no education. The negative SMA values in both countries indicate poorer vegetation conditions than normal at baseline in the surveyed communities. Notable differences between the two countries include the average household size (8.47 in Ethiopia, 12.60 in Tanzania), number of individuals engaged in agro-pastoralism versus pure pastoralism (11% in Ethiopia, 73% in Tanzania), cell phone ownership (32% in Ethiopia, 74% in Tanzania), and mean TLUs owned (12.79 in Ethiopia, 80.74 in Tanzania).

3.2 Map Access, Usage, and User Satisfaction

Table 3 shows a breakdown of the respondents in treatment areas that received vegetation maps and those who decided to use them. Clearly, cascading the paper maps was a challenge to universal access.

In Tanzania, about half (48.9%) of the respondents in the treatment area saw maps at midline (Table 3). Among them 71.5% choose to use the maps (Table 4). Interestingly, map access improved from midline (48.9% saw maps) to endline (70.3% saw maps, Table 3). However among those that saw the maps, the share of those that choose to use maps declined over the same period (71.5% vs. 41.1%, Table 4). This decline may be due to lower frequency of map distribution in Tanzania at endline compared to midline (Table 5). In sum, those that saw and used maps account for 35.0% and 28.9% of all the respondents in treatment areas in Tanzania at midline and endline, respectively (Table 3).

Overall, map usage was lower in Ethiopia, with 26.2% seeing and using the maps at midline (Table 3). Due to a tablet programming error, we did not collect information on map usage conditional on receiving the maps at midline. Map access at endline was very low; only 13.1% of respondents in treatment areas saw the maps (Table 3). Among them 16.8% choose to use the maps (Table 4), representing 2.2% of respondents in treatment areas (Table 3). We largely attribute low map access in Ethiopia and consequent low overall usage (Table 3) to a high level of unrest throughout the endline period, with two separate states of emergency issued between 2017 and 2018. A new prime minister was put into place in April 2018. The period leading up to this change in power was characterized by violence, cutting internet access throughout the country, and government officers being tasked with activities other than their

typical jobs (such as cascading maps for this intervention) (Schemm, 2018). Since the project almost collapsed at endline, we only report the baseline to midline regression results for Ethiopia.

The intent of the project was to provide pastoralists an updated map every ten days. Unfortunately, this was rarely achieved in practice. In both countries and both rounds, less than 21.0% of those who saw the maps saw them three times per month (Table 5). Most pastoralists saw the maps¹¹ once per month (midline) and twice per month (endline) in Ethiopia, and twice per month (midline) and once per month (endline) in Tanzania. Delays in map distribution decrease the accuracy of the map at the time of reception since they may not reflect actual ground conditions, which could discourage their use at the time of reception and in the future.

Despite the lower than expected rates of map adoption, reported rates of user satisfaction among maps adopters in both countries were very high. In both countries, map adopters overwhelmingly reported the maps as accurate and easy to understand (over 94.0% in all rounds and countries, Tables 6 and 7).¹² Map adopters, in both countries, noted time savings as the most common reason the maps were helpful across all rounds (Table 8). In Ethiopia (at midline), other reasons included better pasture management (32.4%) and reduced livestock deaths (32.1%). In Tanzania, other responses included reduced livestock deaths (69.2%) and improved livestock condition (60.1%) at midline, but by a smaller number of respondents at endline (28.8% and

¹¹This ignores the “I don’t know” and no response category, which was the most popular response in Ethiopia at endline. We suspect that the implementation struggles during the endline in Ethiopia are responsible for such high rates of “I don’t know” and no response.

¹²This is the respondent’s opinion of the maps’ accuracy and how well they felt they understood the maps. Note that the accuracy and understanding of the vegetation maps was not tested empirically.

17.6%, respectively, Table 8). Map adopters were also asked to list all the decisions they made that were influenced by the provision of the maps. Responses indicated that map adopters used the map for the intended purpose of making migration decisions. In Ethiopia (at midline), using the maps to make decisions on where to migrate was the most common response (80.4%), followed by when to migrate (33.8%), not to migrate (11.8%), and to coordinate migration with other community members (10.5%, Table 9).

In Tanzania, the most popular decisions that were assisted by the maps at midline and endline included: where to migrate (92.4% and 78.0%); when to migrate (67.8% and 28.3%); and coordination of migration with other community members (70.3% and 15.6%, Table 9). At endline, we added a question asking respondents who saw, but did not use the maps to list all the reasons why they did not use them. The most common responses in Tanzania were already having enough information (48.0%) and infrequent delivery (24.5%, Table 10). This underscores the importance of timing and consistency of map distribution. Also, while the vast majority of map adopters reported that the maps were easy to understand (Table 6), 22.6% (Ethiopia) and 10.9% (Tanzania) of those who saw but did not use the maps reported that maps were too confusing (Table 10). This confirms concerns mentioned in focus group discussions (detailed below) that more training on how to use the maps would have been beneficial.

3.3 Focus Group Discussions

We conducted focus group discussions in March 2018 with treatment communities in both countries. As with the midline and endline surveys (Table 8), respondents reported overwhelmingly positive feedback on the vegetation maps, in particular with regard to time savings, reductions in scouting costs, and allocation of grazing land and pasture management.

Additionally, some communities noted that the maps provided useful cues for coping mechanisms such as when to sell off portions of their herds or when to buy supplemental feed. Most pastoralists talked about the maps with what seemed like an obvious understanding of the information the maps were providing (though we note that we did not formally test their understanding). This aligns with the formal survey (in both countries at all survey periods) by more than 94% of map users reporting the maps were understandable (Table 6) and more than 96% of map users reporting the maps were accurate or very accurate in reflecting the conditions on the ground (Table 7). However, several issues with the map intervention were noted. Recurrent items mentioned in the focus groups included the severity of distribution challenges by the government extension systems, high turnover of government employees, political disruptions (Ethiopia only), and a lack of follow-up training on map usage.

3.4 Regression Analysis, Ethiopia

The regression results examining the effect of map access and usage on herd size are inconclusive in Ethiopia. The results from the ITT regression (Table 11, column 1) show an intent-to-treat estimate that on average, access to maps increases herd size by 0.32 TLUs ($p=0.89$) from baseline to midline in Ethiopia, however the coefficient is not statistically significantly different than zero. When adding an array of controls (column 2), the coefficient changes direction to -0.41 TLUs ($p=0.88$), but is not statistically significantly different than zero. In the specification with additional controls, the most significant determinant for current TLUs is prior year TLUs (at the time of the survey respondents recall the size of their herd one year prior), with a positive coefficient of 0.80 ($p<0.01$). This makes sense as changes in herd size would depend greatly on the original size of the herd. Additionally, owning a cell phone is

associated with owning 1.21 less TLUs ($p < 0.10$). It is unclear why owning a cell phone would be associated with fewer TLUs. On one hand, a cell phone is an asset, so we might expect higher assets to be correlated with higher levels of livestock ownership. However, it can also be indicative of economic activity outside of pastoralism (e.g., staying in touch with a potential outside employer) and therefore negatively correlated to livestock holdings.

Moving to the LATE two-stage regression (Table 12) using the selection of which woredas had randomly assigned access to the maps as an instrument for using the maps, we see larger coefficients (as expected), but the coefficients are still not statistically significantly different than zero. In column 1, using maps is associated with an increase of 1.50 TLUs from baseline to midline in Ethiopia ($p = 0.87$) and associated with a decrease of 2.34 TLUs ($p = 0.64$) when including the array of controls (column 2). In both the ITT and LATE regressions the signs of the coefficient of interest switch from positive to negative when adding controls (though in none of the cases is the estimate statistically significantly different from zero). We suspect the true estimate in both cases is most likely a zero effect with wide confidence bands, so the coefficient can move from slightly positive to slightly negative depending on the specification.

We also investigated whether the provision of maps affected one (or more) of these flow variables (deaths, births, acquisitions, and sales) over the preceding twelve months and if the effects were specific to a certain animal type. We ran additional ITT and LATE regressions separately for each animal type and the four flow variables as dependent variables. However,

none of the coefficients of the map intervention were statistically significantly different than zero in any of these regressions.¹³

3.5 Regression Analysis, Tanzania

We used the ITT framework to examine the average differences in herd size between map users and non-users in Tanzania (Table 13) acknowledging this specification suffers from selection bias. We find an intent-to-treat estimate that on average, seeing and using the maps increases herd size by 63.97 TLUs ($p < 0.01$) from baseline to midline in Tanzania. When adding an array of controls (column 2), the coefficient changes to 19.68 TLUs ($p < 0.01$). In the specification with additional controls, each additional TLU owned in the prior year increases current herd size by 0.99 ($p < 0.01$), each additional person in a household increases herd size by 2.20 TLUs ($p < 0.01$), being a pure pastoralist as opposed to agro-pastoralist is associated with having 17.63 more TLUs ($p < 0.01$), and owning a cell phone is associated with having 8.35 less TLUs ($p < 0.01$). Given the lack of randomization between users and non-users in Tanzania, we cannot claim that the relationship between map usage and herd sizes is causal.

3.6 Animal Condition, Tanzania

The proportional piling exercise performed at endline (Figure 5) compares the average rates of animals in good condition for each of the three animal types between map users and non-users in Tanzania (recall these were retrospective questions asked only at endline). These responses are consistent with those presented by respondents in Tanzania on how they found

¹³The regression results on the flow variables (deaths, births, acquisitions, or sales) or specific animal types (cattle, camels, goats, or sheep) can be provided if requested, but are omitted for the sake of space constraints.

vegetation maps helpful (Table 8), and suggest that maps may have been beneficial to improve animal condition. Improved animal condition is not only important for the economic wellbeing of the households, but also because it can contribute to better nutritional status of the families (animals in better condition produce more milk).

4. Discussion and Conclusion

Several studies have examined the assistance of pastoralists' migration decisions through the provision of information in Africa. Most of them have focused on providing weather forecasts, particularly rainfall (Luseno et al., 2003; Lybbert et al., 2007; Rasmussen et al., 2015, 2014). We contribute to this literature by evaluating the impact of providing decadal spatially explicit information on vegetation conditions within pastoralists' traditional grazing zones.

One of our most positive findings was the high rate of user satisfaction with the vegetation maps. Respondents overwhelmingly reported that the maps were accurate, easy to understand (consistent with the intervention described in Luseno et al., (2003) and Lybbert et al., (2007)), and provided useful information on where and when to migrate their herds (consistent with Butt, (2015)). These benefits, in addition to the reported improved community coordination, time savings, reduced herd mortality, and improved herd condition, were also consistent with Suliman and Ahmed's (2013) finding that technological information enhances traditional grazing practices. However, map adoption rates were lower than the pilot phase and lower than expected by the implementation partners.

We did not find causal evidence that map usage affected herd size (TLUs) in Ethiopia. Since the scope of our evaluation was focused on herd size (with additional questions on animal

condition at endline), it is very possible that we did not capture other effects. The most obvious effect would be improvements to the condition of livestock. In Tanzania the coefficient on the effect of the vegetation maps on livestock holdings (map-users versus non-users) was large and statistically significant, and there was also suggestive evidence that map adopters had animals in better condition. However, we are hesitant to put too much weight on these findings, as there is selection bias because there was no randomization in Tanzania.

The fact that the results related to herd size were not as promising as the pilot suggested, signals challenges in project implementation related to achieving the success of a pilot at scale. These challenges have been documented in the literature and range from spillovers and political reactions to site and pilot-selection bias (Banerjee et al., 2017). In our case, the selection of pilot areas could have unintentionally been biased towards areas with a high level of participants' interest and governmental support that was not matched in the scaled areas. The support of governmental staff that cascaded the maps was critical for the success of the project, since the maps were distributed in paper form. Banerjee et al., (2017) recommend practitioners address challenges of small-scale experiments and emphasize the utility of project replication before attempting larger scale-ups. In retrospect, a second small pilot study may have been appropriate before the larger randomized impact evaluation.

An interesting nuance we found was that reported high levels of map accuracy do not necessarily imply high levels of usability for migration decisions. This became apparent after conducting focus group discussions, where some potential map users mentioned not feeling adequately trained or comfortable using the maps. In retrospect, measuring how well pastoralists

understood the maps similar to how Lybbert et al., (2007) measured how beliefs about expected rainfall distributions changed, would have been useful.

Finally, an important implementation challenge of this project was map distribution. In both countries, the cascading structure of map dissemination resulted in low map access and delivery frequency in target communities. This was especially clear at endline, when political strife in Ethiopia from late 2017 through 2018 caused an almost complete shutdown of the cascading of maps amidst two government issued states of emergency and a mobile and broadband internet blackout outside the capital city. Additional distribution challenges included difficulties reaching the communities due to rough terrain and time constraints. In addition, the high turnover among extension agents, particularly in Ethiopia, impacted distribution throughout the course of the project.

To address the challenges in map distribution, PCI developed a mobile application in 2018 called AfriScout providing access to historical and decadal NDVI maps (PCI, 2018). AfriScout is an improvement over the static nature of paper maps, allowing the visualization of changes in vegetation conditions with additional functionality. However, it requires a smartphone and cellular data network, which is still very low in some pastoralists' communities. It is yet to be seen if AfriScout will address the challenges related to map access and interpretation and what its effect on pastoralists' livelihoods will be, but it is a promising distribution strategy that addresses many of the challenges faced in this study.

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Table 1
Timeline of Key Project Dates

	<i>Ethiopia</i>		<i>Tanzania</i>	
	Date	# Respondents	Date	# Respondents
Baseline Survey	October 2015	1,733	September 2015	734
Map Distribution Begins	November 2015	-	January 2016	-
Midline Survey	April 2017	1,887	January 2017	789
Endline Survey	April 2018	1,863	January 2018	710

Table 2
Baseline Survey - Tanzania and Ethiopia: Household Characteristics

	Ethiopia			Tanzania		
	Mean	SD	N	Mean	SD	N
<i>Household demographics</i>						
Age of respondent	35.91	11.78	1,733	43.47	12.84	734
Household Size	8.47	4.21	1,731	12.60	12.59	733
Male respondents (share)	0.83	0.38	1,733	0.93	0.25	734
Pastoralist	0.89	0.32	1,724	0.27	0.44	734
Agro-Pastoralist	0.11	0.32	1,724	0.73	0.44	734
No education (share)	0.80	0.40	1,733	0.37	0.48	734
Completed primary school (share)	0.06	0.24	1,733	0.54	0.50	734
Completed secondary school (share)	0.01	0.10	1,733	0.06	0.24	734
Owns cell phone (share)	0.32	0.47	1,733	0.74	0.44	733
Owns smart phone (share)	0.01	0.11	1,733	0.02	0.15	733
NDVI SMA	-0.28	0.44	1,107	-0.22	0.35	708
<i>Livestock ownership</i>						
Tropical livestock units owned, 2015	12.79	15.65	1,721	80.74	176.44	732
Household owns cattle (share)	0.54	0.50	1,733	0.98	0.13	734
Cattle owned, 2015	9.90	8.66	910	67.79	166.30	716
Household owns camel (share)	0.42	0.49	1,733	-	-	-
Camel owned, 2015	9.09	10.29	708	-	-	-
Household owns goats (share)	0.82	0.38	1,733	0.98	0.13	734
Goats owned, 2015	21.30	20.62	1,388	75.04	93.66	706
Household owns sheep (share)	0.39	0.49	1,733	0.97	0.17	734
Sheep owned, 2015	15.80	14.41	655	75.25	92.13	699

Note: The Tanzanian household size is calculated as the number of people supported by the herd, or the number of people in the “boma,” which may comprise multiple households. NDVI SMA stands for NDVI standardized monthly anomalies and is calculated as the monthly NDVI deviation from the prior 18-year mean monthly NDVI values. The NDVI SMA shown in the table is the average over the baseline period (November 2014 to October 2015 for Ethiopia, October 2014 to September 2015 for Tanzania). Herd sizes recorded at the time of survey (October 2015 for Ethiopia, September 2015 for Tanzania).

Table 3
Within treatment communities: Map access and usage

	<i>Ethiopia</i>				<i>Tanzania</i>			
	Midline		Endline		Midline		Endline	
	Number	(%)	Number	(%)	Number	(%)	Number	(%)
I never saw a map	-	-	991	86.9	403	51.1	211	29.7
I saw at least one map but did not use it	-	-	124	10.9	110	13.9	294	41.4
I saw at least one map and used it	296	26.2	25	2.2	276	35.0	205	28.9
Total (All Respondents)	1,129	-	1,140	100.0	789	100.0	710	100.0

Note: Due to a programming error in our tablet-based field data collection interface at midline in Ethiopia, we cannot differentiate those who saw the maps and didn't use them and those who did not see the maps. Therefore out of the 1,129 respondents at midline, 833 either did not see the maps or saw them and choose not to use them, but we can not differentiate what share is in each of these groups.

Table 4
Within treatment communities: Used map conditional on seeing map

	<i>Ethiopia</i>				<i>Tanzania</i>			
	Midline		Endline		Midline		Endline	
	Number	(%)	Number	(%)	Number	(%)	Number	(%)
I saw at least one map but did not use it	-	-	124	83.2	110	28.5	294	58.9
I saw at least one map and used it	296	-	25	16.8	276	71.5	205	41.1
Total (Conditional on Seeing Map)	-	-	149	100.0	386	100.0	499	100.0

Note: Due to a programming error in our tablet-based field data collection interface at midline in Ethiopia, we cannot differentiate those who saw the maps and didn't use them and those who did not see the maps.

Table 5
Times per month, saw maps

Response	<i>Ethiopia</i>				<i>Tanzania</i>			
	Midline		Endline		Midline		Endline	
	Number	(%)	Number	(%)	Number	(%)	Number	(%)
Less than once per month	84	28.4	15	10.1	111	28.8	93	18.6
Once per month	92	31.1	6	4.0	71	18.4	280	56.1
Twice per month	65	22.0	23	15.4	125	32.4	115	23.0
Three times per month	55	18.6	13	8.7	79	20.5	11	2.2
I don't know/no response	0	0.0	92	61.7	0	0.0	0	0.0
Total	296	100.0	149	100.0	386	100.0	499	100.0

Note: Includes those who saw the maps, regardless of whether or not they used them. Due to a programming error in the Ethiopia midline survey, we cannot separate those who saw maps but did not use them from those who did not see the maps. Therefore, the Ethiopia midline sample shows the times seen per month only for those who have seen and used maps.

Table 6
Were the contents of the maps understandable?

Response	<i>Ethiopia</i>				<i>Tanzania</i>			
	Midline		Endline		Midline		Endline	
	Number	(%)	Number	(%)	Number	(%)	Number	(%)
The maps were understandable	286	96.62	24	96.0	261	94.6	199	97.1
The maps were not understandable	10	3.38	0	0.0	14	5.1	4	2.0
I don't know	0	0.0	1	4.00	1	0.4	2	1.0
Total	296	100.0	25	100.0	276	100.0	205	100.0

Note: Conditional on receiving and using information from vegetation maps.

Table 7
How accurate were the maps in reflecting conditions on the ground?

Response	<i>Ethiopia</i>				<i>Tanzania</i>			
	Midline		Endline		Midline		Endline	
	Number	(%)	Number	(%)	Number	(%)	Number	(%)
The maps were very accurate	84	28.4	1	4.0	209	75.7	88	42.9
The maps were accurate	203	68.6	23	92.0	65	23.6	116	56.6
The maps were not accurate	9	3.0	1	4.0	2	0.7	0	0.0
I don't know	0	0.0	0	0.0	0	0.0	1	0.5
Total	296	100.0	25	100.0	276	100.0	205	100.0

Note: Conditional on receiving and using information from vegetation maps.

Table 8
How were the maps helpful (among map adopters)?

Response	<i>Ethiopia</i>				<i>Tanzania</i>			
	Midline		Endline		Midline		Endline	
	Number	(%)	Number	(%)	Number	(%)	Number	(%)
Saved time	225	76.0	23	92.0	259	93.8	153	74.6
Helped to better manage pasture	96	32.4	5	20.0	163	56.1	47	22.9
Reduced livestock deaths	95	32.1	6	24.0	191	69.2	59	28.8
Improved livestock condition	42	14.2	4	16.0	166	60.1	36	17.6
Improved community collaboration	-	-	1	4.0	-	-	18	8.8
Reduced amount of feed purchased	-	-	1	4.0	-	-	7	3.4
Reduced time spent scouting	-	-	5	20.0	-	-	14	6.8
Reduced cost of scouting	-	-	2	8.0	-	-	7	3.4
The maps were not helpful	0	0.0	0	0.0	3	1.1	1	0.5
I don't know	0	0.0	0	0.0	1	0.4	3	1.5
Total Respondents	296	-	25	-	276	-	205	-

Note: Conditional on receiving and using information from vegetation maps. Respondents were permitted to choose more than one response. Additional options added at the endline survey.

Table 9
What migration decisions did you make based on the vegetation maps (among map adopters)?

Response	<i>Ethiopia</i>				<i>Tanzania</i>			
	Midline		Endline		Midline		Endline	
	Number	(%)	Number	(%)	Number	(%)	Number	(%)
Where to migrate herd	238	80.4	19	76.0	255	92.4	160	78.0
When to migrate herd	100	33.8	5	20.0	187	67.8	58	28.3
Not to migrate my herd	35	11.8	4	16.0	106	38.4	13	6.3
Coordinate migration with community members	31	10.5	4	16.0	194	70.3	32	15.6
How many animals to move	28	9.5	3	12.0	164	59.4	26	12.7
To purchase supplemental feed	-	-	7	28.0	-	-	5	2.4
Total Respondents	296	-	25	-	276	-	205	-

Note: Conditional on receiving and using information from vegetation maps. Respondents were permitted to choose more than one response. The option "to purchase supplemental feed" was only provided during the endline survey.

Table 10
Why don't you use the vegetation maps

Response	Ethiopia Endline		Tanzania Endline	
	Number	(%)	Number	(%)
Have enough information	0	0.0	141	48.0
Maps delivered too infrequently	6	4.8	72	24.5
Maps don't show real condition	0	0.0	40	13.6
Maps too confusing	28	22.6	32	10.9
Don't trust the maps	0	0.0	6	2.0
Other	85	68.6	9	3.1
Total Respondents	124	-	294	-

Note: Conditional on being in the treatment community, and seeing but not using maps. Respondents were permitted to choose multiple responses.

Table 11
Ethiopia Regression Results
Intent to Treat

	Current TLU no controls (1)	Current TLU with controls (2)
Treatment	0.315 (2.083)	-0.410 (0.878)
Prior Year TLU (from recall)		0.800*** (0.071)
NDVI SMA		0.276 (2.332)
Gender (male=1)		0.519 (0.622)
Age of respondent		-0.035 (0.049)
Household size		-0.045 (0.105)
Pastoralist (pure pastoralist = 1)		1.348 (0.993)
Owns cell phone		-1.212* (0.565)
Constant	16.826*** (1.803)	2.651 (1.610)
Observations	1,861	1,700

Note: For Prior Year TLU, respondents were asked to recall livestock holdings from 12 months previous to the survey date. NDVI SMA stands for NDVI standardized monthly anomalies and is calculated as the monthly NDVI deviation from the prior 18-year mean monthly NDVI values. Clustered at the *woreda* level. Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12
Ethiopia Two Stage Regression Results
Local Average Treatment Effects

	Current TLU 2SLS no controls (1)	Current TLU 2SLS with controls (2)
Saw and Used Maps	1.499 (9.446)	-2.341 (4.987)
Prior Year TLU (from recall)		0.800*** (0.0684)
NDVI SMA		0.198 (2.436)
Gender (male=1)		0.635 (0.722)
Age of respondent		-0.039 (0.045)
Household size		-0.051 (0.105)
Pastoralist (pure pastoralist = 1)		1.219 (1.072)
Owns cell phone		-1.108* (0.613)
Constant	16.826*** (1.737)	5.427 (3.179)
Observations	1,861	1,700

Note: For Prior Year TLU, respondents were asked to recall livestock holdings from 12 months previous to the survey date. NDVI SMA stands for NDVI standardized monthly anomalies and is calculated as the monthly NDVI deviation from the prior 18-year mean monthly NDVI values. Clustered at the *woreda* level. Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13
Tanzania Regression Results
User versus Non-User

	Current TLU no controls (1)	Current TLU with controls (2)
Saw and Used Maps	63.970*** (6.224)	19.684*** (3.078)
Prior Year TLU (from recall)		0.989*** (0.034)
NDVI SMA		3.210 (7.833)
Gender (1=male)		-1.723 (2.839)
Age of respondent		-0.010 (0.0870)
Household size		2.200*** (0.510)
Pastoralist (pure pastoralist = 1)		17.625*** (3.387)
Owns cell phone		-8.352*** (2.637)
Constant	63.638*** (4.344)	-7.231 (6.763)
Observations	788	763

Note: For Prior Year TLU, respondents were asked to recall livestock holdings from 12 months previous to the survey date. The Tanzanian household size is calculated as the number of people supported by the herd, or the number of people in the “boma,” which may comprise multiple households. NDVI SMA stands for NDVI standardized monthly anomalies and is calculated as the monthly NDVI deviation from the prior 18-year mean monthly NDVI values. Clustered at the village level. Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 1
Examples of distributed NDVI vegetation condition maps: Monduli, Tanzania

Figure 2
Study areas, grazing areas, and survey locations in Ethiopia (A) and Tanzania (B)

Figure 3
NDVI standardized anomalies for October 2014 in Ethiopia (A) and Tanzania (B)

Figure 4
NDVI standardized anomalies for December 2016 in Ethiopia (A) and Tanzania (B)

Figure 5
Condition of animals, map users vs. non-users in Tanzania

(A) Cattle

(B) Goat

(C) Sheep