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Improved Spatially Disaggregated Livestock Measures for Uganda[*]

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Abstract: The objective of our study is twofold: on one side, to complement earlier analyses that estimate the spatial density of livestock holdings using different methods; on the other, to show that by combining different data sources—the 2009/10 Uganda National Panel Survey (UNPS) and the 2008 Uganda National Livestock Census (UNLC)—and applying the Small Area Estimation (SAE) technique, it is possible to provide a finer spatial disaggregation and representation of missing livestock measures in the census. First, we combine our livestock population and density figures with those from the UNLC. Second, we fit an estimation model of livestock income and share on the UNPS to generate an out-of-sample prediction of the missing information in the UNLC, mapping livestock income and share at the local level. Our results suggest that the integrated use of multiple data sources, such as household surveys, censuses, and administrative data, together with spatial analysis techniques, such as SAE, can provide reliable, coherent, and location-specific insights to guide policy and investment. This work shows a useful method that allows for a reliable spatial livestock analysis, whenever sectorial databases offer greater coverage of the population of interest, but more limited information than specialized surveys. This method can be applied in all countries where there is a similar livestock information system, and common support between livestock census and household surveys with detailed agricultural/livestock modules. Cross-validation across data sources provides clearer insights into livestock-related policy and a better springboard for effective poverty-reduction strategies.

Keywords: mapping, livestock, Uganda, Small Area Estimation
JEL Codes: R12, Q12

1. INTRODUCTION

Livestock ownership affects household welfare in a variety of ways, including possible direct effects on household's nutrition, disposable income, asset diversification, credit constraints, manure, traction power, savings and insurance, collateral for financial services, and consumption smoothing (Ayele and Peacock, 2003; Dore, Adair, and Popkin, 2003; Upton, 2004). The role of livestock and livestock products in household income and consumption is becoming increasingly important in developing countries as the level of development improves. The livestock sector is increasingly becoming so important that experts call the phenomenon a "livestock revolution"—a monotonic and sustained increase in livestock consumption—in

developing countries as the population increases, becomes wealthier, moves to urban areas, and changes its dietary preferences (Fischer, 2003). Despite the ongoing livestock revolution, widespread recognition of the importance of the livestock sector to a household's livelihood is yet to be achieved. Estimated returns to agricultural activities typically encompass livestock, although little analysis exists on distinguishing the independent contributions of crop versus livestock sources. Because of the relatively small contribution of livestock to household income, agricultural income is usually considered as being comprised mostly by returns from crop-marketing and own consumption. But in many agriculture-based economies, where agriculture contributes significantly to economic growth—such as those in sub-Saharan Africa,[1] livestock provides over half of the total agricultural output and over a third of total output across all developing countries (World Bank, 2008; Upton, 2004).

In this paper, we focus on livestock as a source of income and food. Our case study is Uganda, where agricultural data that includes livestock are relatively abundant and the proportion of rural poor holding livestock is higher (around 70 percent) than in most other Sub-Saharan African countries. While agricultural contribution to GDP has declined from 2004 to 2008 (from 20.6 percent to 15.6 percent), the livestock sector has grown due to the increasing demand for animal-source food (ASF) (UBOS, 2009). The fact that livestock production contributed only 1.6 percent to total GDP[2] in 2008 (UBOS, 2009) should be viewed as a lower bound on the overall benefits the sector can provide to small farmers. Besides income and consumption through production, livestock offers a variety of benefits to a smallholder's livelihood[3], such as cash income, food, manure, draft power and hauling services, savings and insurance, and social status and social capital. Indeed, many of the roles that livestock plays are not usually captured in standard household surveys and national accounts. A livelihood study in three districts of Uganda shows that while income from livestock provides only one of many sources of income for rural households, people typically rank livestock as their second or third most important means of livelihood (Ashley and Nanyeenya, 2005).

To build upon the existing literature on spatially disaggregated livestock measures in Uganda (Thornton et al., 2002; Kruska et al., 2003; Wint and Robinson, 2007; Robinson et al., 2011; Shaw et al., 2006; Ministry of Agriculture et al., 2010; Benson and Mugarura, 2013), this study employs the Small Area Estimation (SAE) method used in the poverty estimation literature (Elbers, Lanjouw, Lanjouw, 2003; Hentschel, Lanjouw, Lanjouw, and Poggi, 2000; Mistiaen at al., 2002; Alderman et al., 2002; Simler and Nhate, 2005) to combine survey and census data to extend and apply this method to livestock mapping. While multi-topic household surveys provide a wide array of information, their samples are not designed for disaggregation beyond the regional and rural/urban level. On the other hand, census data are usually very limited in scope but allow for disaggregation with the highest precision. Our primary objective is to provide a much finer spatial disaggregation of livestock measure than that obtained through the use of survey data alone, and to this end we combine data from the 2009/2010 Uganda National Panel Survey (UNPS) and the 2008 Uganda National Livestock Census (UNLC) to generate

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[1] The contribution is estimated at about 32 percent on average over the period 1993-2005.

[2] IGAD released a series of studies for some African countries where the role of livestock in GDP is re-estimated by rescaling the national accounts data (see Behnke, 2010; 2011). As an example, the study for Ethiopia concludes that the value of livestock's contribution to the Ethiopian Gross Domestic Product (GDP) and to the wider economy is 3.5 times higher than previous estimates.

[3] A smallholder is a family farm relying on a small piece of land.

small-area estimates of household income (and its share over total income) from livestock activities.[4] Those estimates are the core of this analysis, since information (livestock income and its share of total income) is not captured in the census but collected and fitted exclusively using survey data.

Our other purpose (and the novelty of our approach) is to show how SAE can be applied to livestock mapping to provide policy-makers with reliable and spatially detailed information on livestock in Uganda, given that small area estimates of poverty are being increasingly used to target anti-poverty programs both in developing (see Elbers, Lanjouw, and Lanjouw, 2003; Alderman et al., 2002; Simler and Nhate, 2005; Christiaensen et al., 2011 for examples) and developed countries (see U.S. Census Bureau, 2014; Giusti et al., 2014). As recognized by official sources, mapping and access to improved spatial information play important roles in informing government actors. Enhanced spatial information may empower citizens to demand appropriate livestock policies, advocate for alternative interventions, and exert pressure for better decision-making (Ministry of Agriculture et al., 2010). Livestock maps are used by agencies and government planners for a variety of reasons: to explore more profitable market opportunities in the livestock dairy sector, to assess the impact of livestock diseases (especially trypanosomiasis[5]), and to evaluate more intensive livestock production systems.

Beyond policy-decision support, the results of this paper demonstrate how integration of different data sets can greatly enhance spatial analysis. The latter is usually carried out by using a variety of spatial methods, while our approach takes advantage of microdata in a multivariate framework. Also, the particular livestock data environment causes the focus of this study to be Uganda, but the method can be applied to other countries with a similar livestock information system when agriculture or livestock censuses are conducted in concurrence with household surveys with detailed agriculture/livestock information. The crucial requirement is an extended base of common support between the two data sources so that the missing information in the census can be reliably proxied using statistical predictions from household survey data.

2. ANALYTICAL METHOD

A number of methods are used in the literature to spatially predict livestock numbers and densities, most of which are based on administrative or spatial data. The most widely used spatial and econometric techniques for livestock prediction and mapping, according to Wint and Robinson (2007), are:

- Interpolation method using Kriging techniques, which is used by some spatial software such as ArcGIS (by ESRI[6]), to interpolate intermediary values of a fitted Gaussian process;

- Logistic regression, which is used mainly to identify the presence/absence of livestock, but is not suitable for population prediction, given the underlying probabilistic process that does not model intensity;

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[4] Livestock income includes income from the sale and barter of livestock, livestock by-products (i.e., milk, eggs, honey, etc.), net of expenses related to livestock production and livestock purchases, plus the value of household consumption of own livestock and livestock byproducts. The values of own consumption are estimated based on the food expenditure section of the questionnaire.

[5] Trypanosomiasis is a pathogenic disease that could infect all species of domesticated livestock throughout many of the tropical and subtropical regions of the world.

[6] Environmental Systems Research Institute, a firm based in Redlands, California, is an international supplier of geographic information system (GIS) software, web GIS, and geodatabase management applications.

- Weighting techniques, which are used to allocate national figures at the subnational level, based on land and biophysical suitability;

- Methods linking domestic livestock and human densities in allocating national figures (population, production, commodities) within agro-ecological zones;

- Density prediction using raster (i.e., pixel) images of observed data and predictor variables (obtained from census reports, livestock surveys, data archives);

- Extrapolation or distribution modeling using known statistical relationships between the outcome variable (e.g., animal distribution) and a number of variables considered to proxy for the outcome.

We use micro-level data and extrapolate predictions from the survey at the spatial level at which the more precisely measured (bigger) data source (typically, the census) is representative, but when the dimension of interest is missing in the larger data source, although there are proxy variables of the missing characteristics present in the less precisely measured (smaller) survey. In these cases, a prediction model estimated on the smaller survey and predicted out-of-sample on the bigger survey through proxy variables could estimate the missing dimension of interest in the bigger survey. Among all the techniques cited above, the SAE is conceptually similar to extrapolation or distribution modeling, although it makes use of micro-level data instead of spatial/area information. Different micro-data modeling techniques are used in the present study for completeness and comparison purposes, and the SAE method appears to be the most suitable to answer our research question.

The SAE methodology for dataset-to-dataset prediction (survey-to-census in our case) comprises three steps or stages. Stage 0 (according to Mistiaen et al., 2002) involves the selection of comparable information—in terms of how the data was collected and the statistical distribution of variables—between the census and the survey. At this stage, means, standard deviations, and frequency distributions at the national and regional levels are compared across surveys and the census to check whether variables have similar distribution functions.

In stage 1, the dependent variable of interest is modeled as a function of the independent variables selected, using the equation

$$(1) \qquad \ln y_{ch} = E(\ln y_{ch} | X_{ch}) + \mu_{ch} = X'_{ch}\beta + \mu_{ch},$$

where y_{ch} is the outcome variable for household h in cluster c; X is the vector of independent variables in both the census and the survey; and μ is the error term.

One of the most important aspects of this stage is the specification of the error term. The model above is first estimated using OLS, weighted by survey sampling weights. Residuals from this regression serve as estimates of the overall disturbance, $\hat{\mu}_{ch}$. A portion of this disturbance is due to location-specific effects common to all households in a given cluster. Since not all clusters in the census are sampled in the survey, cluster fixed effects cannot be included in stage one. Location effects must be accounted for in the error term, and as such residuals must be decomposed into location (within-cluster means of overall residuals) and household (overall residuals net of location components) elements (Mistiaen et al., 2002).

In stage 2 the error term is decomposed, so that the linear approximation of the model becomes

$$(2) \qquad \ln y_{ch} = X'_{ch}\beta + \eta_c + \varepsilon_{ch},$$

where η is the cluster error and is applicable to all households in a cluster and ε is the household idiosyncratic error term. The two components of the error term are assumed to be uncorrelated with each other and independent of the regressors. The location component of the error term will allow for spatial autocorrelation and the possibility of heteroskedasticity of the household-specific error component (Simler and Nhate, 2005). Additionally, the μ error term—the unexplained location-specific component—is minimized, capturing as much variation as possible through the X vector by incorporating cluster-level means from the census into the survey. This is done through estimation of a Generalized Least Squares (GLS) model that takes heteroskedasticity of the household-specific error term into account.

In the final stage, parameter estimates of stage one and the decomposed error terms of stage two are applied to the census data. The disturbance term is accounted for by bootstrapping, re-sampling, and converting from logarithms to levels,[7] according to

$$(3) \qquad \widehat{y}_{ch} = e^{(X'_{ch} * \widehat{\beta} + \widehat{\mu_{ch}})} * E\left(e^{\widehat{\mu_{ch}}}\right).$$

In each of the n simulations run (in our case we set $n=100$), parameter estimates are drawn from the multivariate normal distribution while the variance-covariance matrix and the two disturbance terms are drawn from the distributions described by the same parameters estimated in the first stage.

It should be noted that there are two sources of error that arise from the use of this method. First, there is model error due to the parameter estimates. Second, there is idiosyncratic error from the deviation of the actual y from the expected y (Alderman et al., 2002). Crucial assumptions of the model are the presence of high spatial correlation between Enumeration Area (EA) and subcounty, and homogeneity of households within EAs. Yet, there could be unexplained effects that impact that error term at the subcounty level (for instance, livestock prices) and at the more local EA level (for instance, disease) that are unaccounted for in the X_{ch} vector. It is important to consider that the model estimated is assumed to hold for all levels of disaggregation.

These two sources for errors could substantially impact the standard errors of the estimates under certain conditions, as demonstrated by Tarozzi and Deaton (2009) through an empirical test using Monte-Carlo simulations. Nevertheless, if one is eager to accept the area homogeneity assumption, hence that "at least some aspects of the conditional distribution of income be the same in the small area as in the larger area that is used to calibrate the imputation rule," then the bias in the standard errors calculated by the version of the SAE method (Elbers, Lanjouw, and Lanjouw, 2003) used in this paper can be considered negligible, as in most empirical applications.

Despite some literature that has found that the SAE under a linear mixed model is not efficient in the case of zero-inflated outcome variables (see Chandra and Chambers, 2011; Chandra and Sud, 2012; Pfeffermann, Terryn, and Moura, 2008; Karlberg, 2000), in this paper

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[7] In the case of OLS and SAE, given the models estimated are in log-linear form to maximize their explanatory power, predicted values have been calculated according to the retransformation formula in Cameron and Trivedi (2010) and Duan (1983): $E(y_i|x_i) = \exp(x_i'\beta) E\{\exp(\mu_i)\}$. Under the assumption of an i.i.d. error term (weaker than normality), $E\{\exp(\mu_i)\} = \frac{1}{n}\sum_{i=1}^{n} \exp(\hat{\mu}_i)$. In the case of the Tobit model when the dependent variable has been log-transformed (in the case of per-capita income), the unconditional expected values have been computed according to Yen and Rosinski (2008), according to a Tobit model with two-part sample selection. We thank an anonymous referee for pointing out our mistake in an earlier version of the manuscript.

all the regressions have also been run on the positive part of the outcome variable distribution only, and results do not show any substantial difference.[8] Moreover, OLS and Tobit regression models are employed for comparison purposes, and Monte-Carlo simulations have been performed to assess the explanatory power and parameter accuracy of the SAE model estimated.

As in the case of SAE, the two models are estimated on the survey and fitted on the census. The resulting parameter estimates from the regressions are then applied to the census data to calculate the conditional mean of the left-hand-side variable given the predictors.

In the case of independently and identically distributed data, error terms with a conditional mean of zero, no extreme outliers, and homoscedastic error terms, OLS represents the best linear unbiased estimates. However, because our outcome variables contain a large number of zero observations (therefore, not normally distributed but censored), OLS does not yield consistent parameter estimates.

The second model, the Tobit model, is used when the dependent variable is only observed over some interval, such as corner solutions that are composed of positive values and a large number of observations with zero values. Our three dependent variables of interest (number of large ruminants, income from livestock activities, and share of income from livestock activities) show non-negative distributions, and have a significant number of observations with zero values, rendering their log-transformation intractable.[9]

The OLS model has the positive feature of being simple and easily interpretable, although it is not suitable when the response variable is discrete, with probability distribution mass at nonnegative integer values only. In our case, the outcomes of interest are also truncated, showing excess zeros. The Tobit model allows us to deal with censored variables, such as livestock holdings, share, and income, although it poses a restrictive assumption on the distribution of the error terms in the unobservable left tail.

3. DATA

Two datasets were used for this analysis. The 2009/2010 Uganda National Panel Survey (UNPS) collected information on 2,975 households from 322 EAs.[10] By sampling design, the survey is representative at the national level, plus the strata of (i) Kampala City, (ii) Other Urban Areas, (iii) Central Rural, (iv) Eastern Rural, (v) Western Rural, and (vi) Northern Rural. Data were collected in two visits, one for each cropping season, over a twelve month period. For the purpose of the analysis, the sample was narrowed to 2,375 households, of which 521 are urban. The sample was narrowed due to 45 households having incomplete questionnaires and 555 households that moved.

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[8] Those maps are not shown here for reason of space, but available from the authors upon request.

[9] When the dependent variable is a nonnegative count integer such as number of large ruminants, the Poisson model should be used. This regression model has the best fit for nonlinear, nonnegative count variables, and it relaxes the assumption of the normal distribution of error terms posed in the Tobit. However, it cannot be employed for non-count variables, such as net income from livestock and share of livestock over total net income, the outcomes of interest in this paper.

[10] The Uganda Bureau of Statistics conducted a Population and Housing Census in September 2002 that covered the whole country, and provided the sampling frame for the 2005/06 Uganda National Household Survey (UNHS) from which the UNPS 2009/10 used in this paper is drawn. For the purpose of census enumeration, the country was sub-divided into 34,068 Enumeration Areas, with an average of 140 households. An EA generally does not have its own name but is known by the name of the Local Council 1 (LC1) associated with it. The EA is the lowest administrative aggregation in the country.

The other dataset used, the 2008 Uganda National Livestock Census (UNLC), collected data from 964,690 rural holdings in all 80 districts of the country in a single visit during the month of February. The working sample under analysis excludes large commercial farms and is narrowed to households, consistent to the UNPS where the unit of analysis is the household, hence this analysis draws on 964,047 rural households. The census is not a full enumeration census but a sample-based one, and is representative at the district level. However, given that the average sample size at the subcounty level is adequately large (around 1,000 households), results are also reported at this lower geographic administrative level (see below).

Figure 1 shows the comparison of the share of households owning (or rearing/keeping) livestock[11] by region in the survey and the census. In each region, the average number of livestock owners is not statistically significantly different between the census and the survey. The figure also highlights the importance of livestock, as the prevalence of livestock owners in Uganda is relatively high in all regions, with a national average of around 70 percent.

4. RESULTS

Further exploring the importance of the livestock activities to the livelihoods of Ugandan households, Figure 2 displays the breakdown of income sources by consumption expenditure quintile. Despite a high prevalence of livestock owners, the share of net livestock income (including own-consumption of animal source food) at the national level is almost 12 percent.[12] This could signal that households rear livestock for scopes different than income generation, such as manure, draft power and hauling services, savings, and insurance, as well as social status and capital (Bebe et al., 2003; Moll, 2005; Upton, 2004).

**Figure 1: Share of Households Owning Livestock by Region,
from 2009/10 UNPS and 2008 UNLC (with 95 Percent Confidence)**

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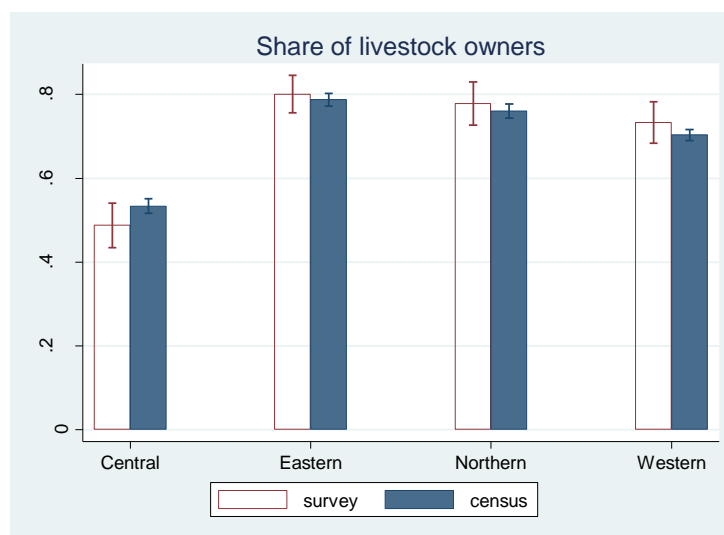
[11] In both the UNPS and the UNLC, the definition of livestock-owning households encompasses also households rearing, keeping, or taking care of livestock on behalf of the owners.

[12] Livestock income is defined as the value of sales and barter of livestock, plus the value of sales, barter and self-consumption of livestock products (such as milk, meat, eggs, honey, and so forth) minus the expenditures related to livestock production (e.g., feed, labour and veterinary services). Throughout the paper, income sources are computed and classified according to the FAO Rural Income Generating Activities (RIGA) definition and methodology (see http://www.fao.org/economic/riga/en/).

Figure 2: Income Decomposition by Region and Consumption Quintile
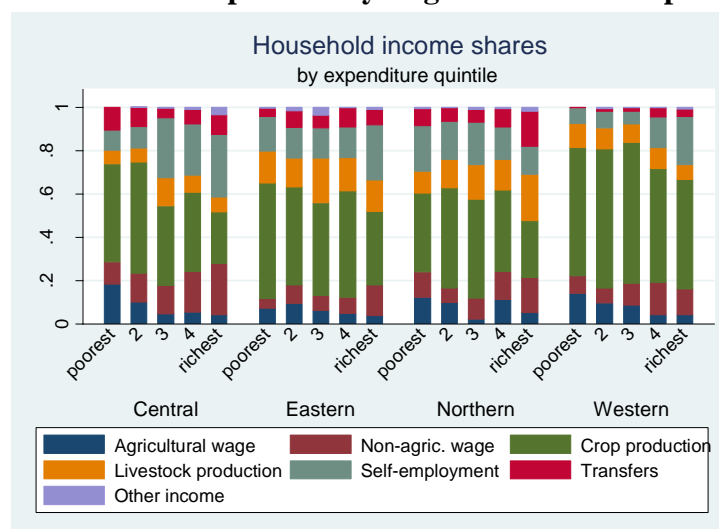
The figure shows that, overall, income composition is correlated with consumption expenditure level (a *proxy* of welfare), although for livestock income no stable association can be found. This finding is consistent to what the literature reports (among others, see Pica-Ciamarra et al. (2011) on a cross-country comparison of twelve developing countries). Income from crop production shows, instead, a larger share of total income in the poorest quintile, with a negative relationship with welfare. Livestock income shares differ markedly across regions, with the highest values found in the eastern and northern regions, which indeed show a greater percentage of livestock owners than the central and western regions. According to a study conducted in three districts (Mbale, Kamuli, and Mubende), livestock ownership does not seem to vary with welfare, although poorer households are more likely to have small stocks and the wealthier are more likely to own cattle. Wealthier households also keep proportionately more animals than poorer households (Ashley and Nanyeenya, 2005).

In the northern region, livestock income share seems to be positively correlated with welfare. Indeed, nomadic pastoralism constitutes the principal livelihood for many households in the northeastern part of Uganda (Benson and Mugarura, 2013). A possible explanation for this spatial pattern is due to the extremely important role of dairy cattle for children's milk consumption, especially in the Karamoja district (Stites and Mitchard, 2011). Krishna et al. (2006) show that income diversification through livestock is an important poverty-coping strategy for Ugandan households. They theorize that livestock provides an "asset stairway" out of poverty: first through investments in monogastrics, subsequently small ruminants, and finally local and then improved breeds of cattle. They also found livestock-related activities to have positively impacted the welfare of poor households.

Livestock also play a safety net role, increasing household resilience, as they are often sold in case of emergency or sudden income shortfall (Burke et al., 2007). Given that livestock play different roles, and pro-poor livestock breeds vary across regions, new research approaches providing a better understanding of spatial distribution of livestock and its contribution to livelihoods, such as the present paper, can effectively contribute to more targeted pro-poor livestock-related policy.

The use of the UNLC can therefore support a fine-resolution livestock analysis, although the limited amount of information collected is a constraint on the number of explanatory variables included in the model. The predictors used include: land size (separately by agricultural, pasture, and other land); number of livestock heads by type (disaggregated by indigenous and exotic bulls, cows and calves; poultry; small ruminants); average weekly egg and milk production; age and gender of the household head; whether the household hired agricultural labor; dummy variables by agro-ecological zone; and Normalized Difference Vegetation Index (NDVI).[13] Descriptive statistics for these variables are in Appendix A.

Three models are estimated on the 2009/10 UNPS, according to Equations (1) and (2), and are fitted on the 2008 UNLC, according to Equation (3). The first is used to test the reliability of the prediction method used. In this specification, the number of large ruminants owned are predicted and then compared to actual values in the census, both for all rural households and for those with livestock only, using different econometric models. Results of the GLS estimation are presented in Appendix B.

Figure 3 shows that the actual, as well as the predicted, spatial distribution of large ruminants from the census is very close to the predicted values using the models proposed.[14] This result offers a first insight as to how SAE can be a viable and reliable method to estimate the spatial distribution of missing information through prediction. The prediction of large ruminants offers an upper bound of the reliability of the prediction methods applied to livestock—whose accuracy is further deepened in Section 4 below, given that i) the UNLC contains variables considered to be a close *proxy* (hence, with high explanatory power) to the number of large ruminants; ii) it is possible to compare prediction results with actual values in the census, taken as benchmark; and iii) this model has the highest explanatory power among the models estimated on other outcome variables.

The prediction model for large ruminants has a relatively high explanatory power (adjusted R^2=.51), while those for the share of livestock income and the per capita income from livestock both suffer from low R^2 (.25 and .05, respectively) likely owing to omitted variables. Indeed, the major constraint in the SAE model is that regression explanatory power is bounded by availability of common information between survey and census. For this application, all the common variables between the two datasets are used, and the spatial specificity is also augmented by including the information on area covered by each agro-ecological zone and the NDVI at the subcounty level.

The northeast area of the country is ranked highest in the number of large ruminants by both actual and predicted models, although the comparison of actual versus predicted large ruminants for the whole northern region reveals substantial differences across districts. One emerging finding is that the number of large ruminants owned is not strongly correlated with livestock income and its share on household total income. While in the northeast and central areas the number of large ruminants, as well as livestock income and its share, are high, in the southern districts the latter two are both relatively low. This might occur because large ruminants

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[13] The NDVI assesses the degree of live green vegetation in the observed area. Negative values of NDVI (approaching -1) correspond to water. Values close to zero (-0.1 to 0.1) generally correspond to barren areas of rock, sand, or snow. Lastly, low, positive values represent shrub and grassland (approximately 0.2 to 0.4), while high values indicate temperate and tropical rainforests (values approaching 1). Here, the NDVI is expressed as a ten year average over the period 2000-2010 NASA (2011).

[14] Maps show the district distribution by quartile of actual large ruminants, so that in each category 25 percent of districts are represented. Ranges represented are the same in all maps, for ease of comparison between actual and predicted values.

Figure 3: Actual, and Predicted Number of Large Ruminants using SAE OLS, and Tobit

Large ruminants (actual)

Large Ruminants (predicted using SAE)

Large ruminants (OLS predicted)

Large ruminants (tobit precicted)
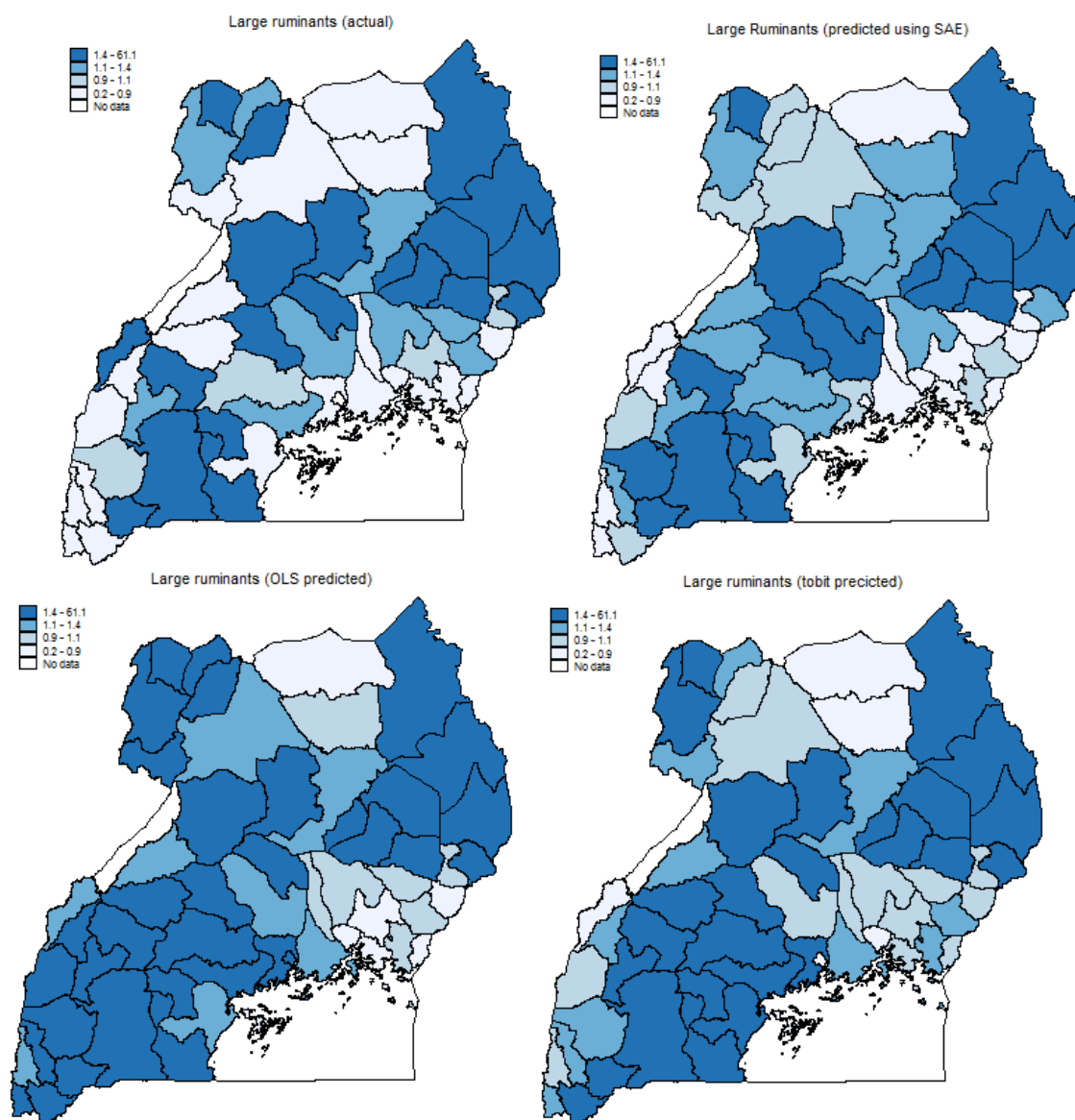
in Uganda are predominantly used by households as capital assets, and small ruminants, especially monogastrics,[15] are the livestock types mostly contributing to net livestock income, given the greater costs of rearing large ruminants (Kitalyi et al., 2005).

Lu et al. (2002) also found that in the district of Kapchorwa in the eastern region, cattle are the most common livestock kept by both poor and rich farmers. However, the percentage of rich farmers keeping cattle is about double that of poor farmers, 90 percent and 45 percent, respectively. The high concentration of livestock in the northeast area of the country is also confirmed by FAO (2014), as "2008 livestock population in Karamoja was estimated at about 6 million head, representing about 19.8 percent of the national cattle (2.3 million head); 16.3 percent of the goats (2.0 million head) and 49.4 percent of the sheep (1.7 million head)." Also, livestock density appears to be predominant in the region, given that "at an overall average of

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[15] Monogastrics are organisms with a simple single-chambered stomach, such as pigs, chickens, ducks, and rabbits.

Figure 4: Density of Large Ruminants: Actual from Survey and Census, and Predicted from Census

Density of Large Ruminants by region (actual from Survey)

52 – 53
47 – 52
31 – 47
19 – 31

Density of Large Ruminants by region (actual from Census)

56 – 65
44 – 56
41 – 44
41 – 41

survey

census

Density of Large Ruminants by district (actual from Census)

68 – 124
43 – 68
30 – 43
3 – 30
No data

Density of Large Ruminants by district (predicted using SAE)

68 – 124
43 – 68
30 – 43
3 – 30
No data

census (actual)

census (SAE predicted)

1.92 TLUs per hectare of grazing area, the stocking rates estimates are extremely high" (FAO, 2014).[16]

Figure 4 displays the actual densities (number of livestock per square kilometer) of large ruminants from the survey and the census, as well as the predicted densities from survey to the census using the SAE technique. Some important elements emerge. First, the survey map in

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[16]However, the same report warns that "livestock population estimates for 2014 are significantly lower than the UBOS 2008 estimates. The estimated reduction of about 70 percent conform to information from key informants and recent reports regarding the significant losses suffered by most herders during the protected *kraals* system. Accordingly, Mission's estimates of stocking rate reduction from 1.92 to 0.50 TLUs per hectare of grazing resources between 2008 and 2014 are consistent with the observation of abundant availability of pasture and good body condition of all livestock types and classes during Mission's transects."

Figure 4 (by region, the representative stratum of the UNPS) masks very different distributions once disaggregated to the district level through the census. Second, the density range is narrower in the survey than in the census, as in the former the range is just four values, one for each region. Indeed, these values are just the regional averages of district values of the right map. Third, and foremost, the census map is more meaningful for targeting purposes to policy-makers.

While the density of large ruminants in the census resembles the distribution from the survey, the model fitted on the log of per capita livestock income in PPP is less able to predict missing information into the census (see Appendix C). The low explanatory power of the livestock income model might be due to the fact that 46 percent of rural Ugandan households do not show any livestock income, despite 70 percent of rural households being livestock owners. Figure 5 shows maps from the survey and the census for the estimated model.[17]

It is interesting to note that while in the northeast region there is the highest number and concentration of large ruminants associated with high return from livestock activities, the same is less true in the central and southern areas of the country. Indeed, relatively higher income is associated with a low number and density of large ruminants in the central areas, something suggesting that households derive their income from other livestock types. Conversely, they do not seem to monetarily benefit from cattle in the Southern region, despite their high number and density. Here, two factors may be at play: the role of livestock as precautionary saving or social status, and the likely underreporting of livestock, especially in conflict-affected areas in the northern region, due to a variety of reasons (e.g., attempt to appear poorer due to fear of losing eligibility for public assistance or taxation and concern over possible retaliation or robbery).[18]

Figure 5: Per Capita Livestock Income (PPP): Actual from Survey (left) and Predicted to Census (left)

survey   census (SAE predicted)

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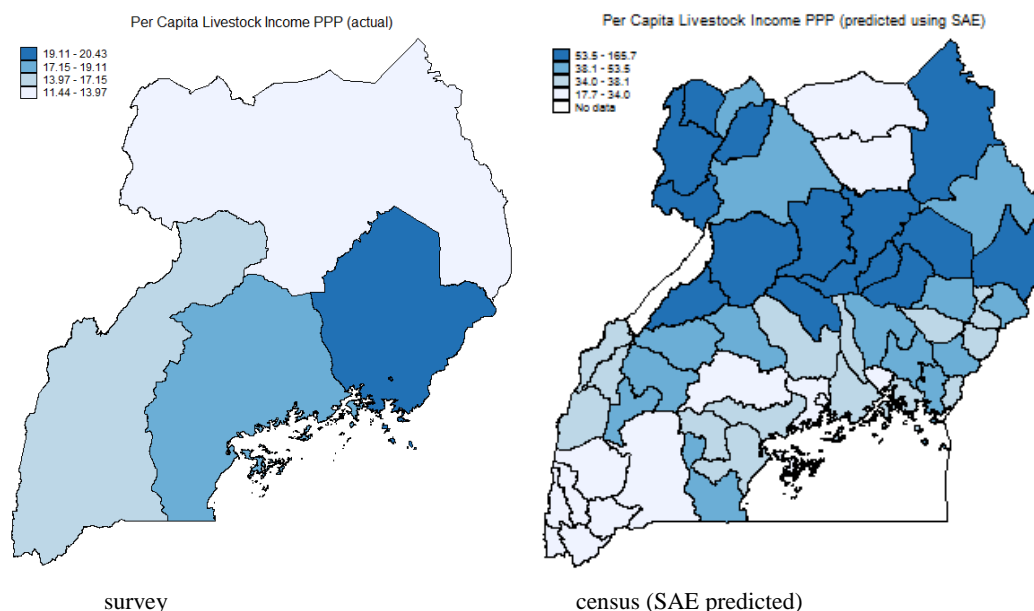
[17] See footnote 4 on the predicted value of a log-transformed dependent variable in linear models.

[18] Ashley and Nanyeenya (2005) point out that "rather than keeping livestock for the relative narrow contribution of income alone, most livestock-keepers in Uganda keep their livestock for the multiple contributions they make to their livelihoods", offering a comprehensive review of the most common strategies.

Figure 6: Share of Income from Livestock: Actual (left) and Predicted to Census (right)

survey   census (SAE predicted)
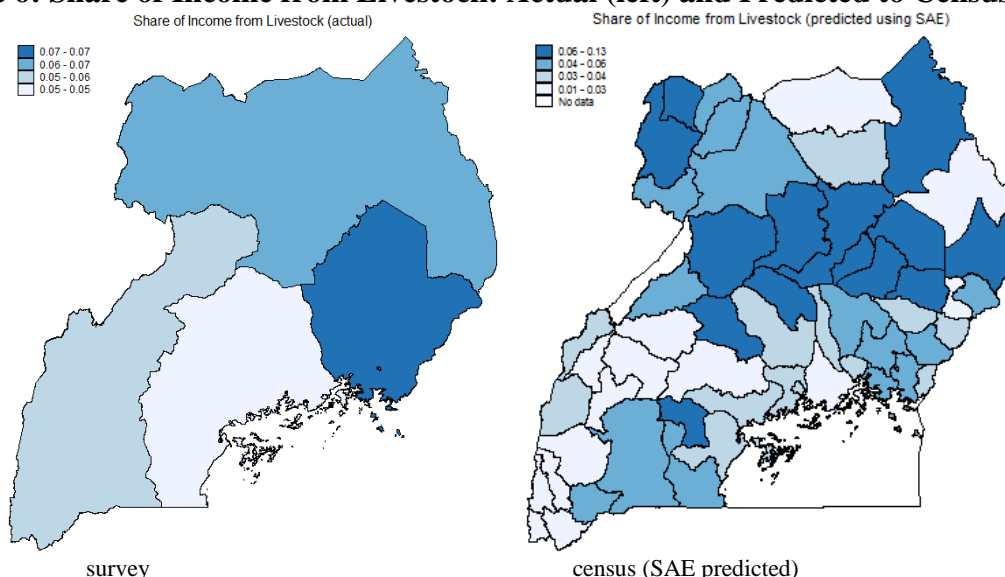
Finally, the analysis of the predicted income share from livestock at the district level yields unsurprising results in Figure 6, similar to those for income (see Appendix D for the model estimated). In almost all districts where livestock income is relatively higher, its share is also higher. Moreover, findings hold regardless of the method used,[19] and this reinforces the argument that it is the lack of timely, reliable, and comprehensive survey and census data that is the constraining factor in addressing policy at the local level more than advancement in spatial data analysis.

5. ACCURACY AND PRECISION

By construction, the approximated error of our estimates is proportional to the sampling error of the survey, that of the census, plus the simulation error of the bootstrapped predicted values (see Equation 3). In turn, the predicted values depend strictly on the explanatory power of the model, and this last factor bears the highest effect on the *accuracy* of the estimated values. Should the model be fitted using more explanatory variables (common to the survey and census) and on a sample with higher size, its goodness-of-fit would greatly increase.[20] As mentioned above, the specification in this paper uses the maximum number of common variables, and squared terms are also employed to maximize the portion of the variance explained by the model. To assess the explanatory power and the accuracy of the parameters of our SAE model, the actual and the SAE-predicted number of large ruminants based on the National Livestock Census are plotted in Figure 7. Treating the statistics from the NLC as the true distribution by subcounty, it is possible to realize how close the actual versus the predicted values are, as the linear fit (green line on the graph) is almost overlapping with the plotted 45° line. About 90 percent of the subcounties (those with less than five large ruminants) show an average number of two ruminants, and for them the error in the prediction is particularly low, increasing as the average number of large ruminants increases (similar correlation analysis can be found in You, Wood, and Wood-Sichra, 2009; You and Wood, 2005, 2006).

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[19] Maps using OLS and Tobit, are reported in Appendix E and F (for livestock income and it share on total income, respectively)

[20] Simulations were conducted using different numbers (*n*) of bootstrap replications, and results pointed to a statistical invariance of the average of the simulated values for *n>50*.

Figure 7: Actual and Predicted Number of Large Ruminants
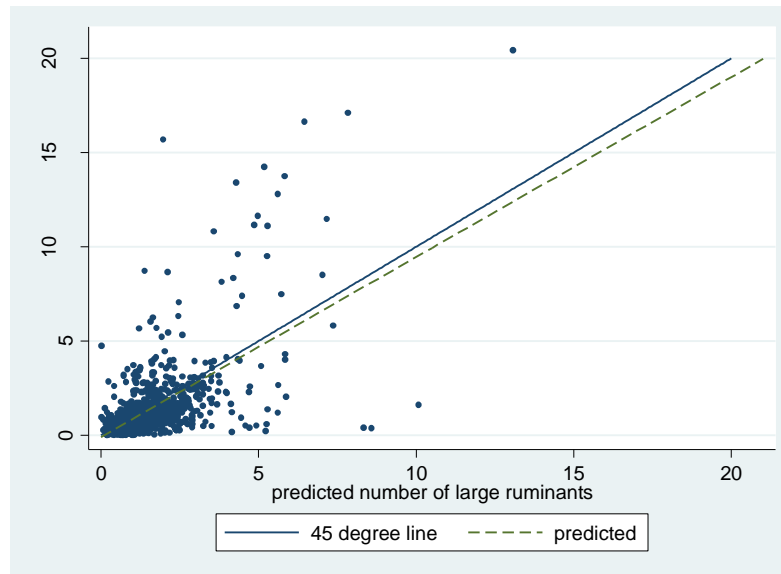
To look at the *precision* of the fitted values, for each value by district shown on the maps in Figure 5 and Figure 6, the corresponding value of the coefficient of variation (CV) was calculated in Figure 8.[21] Overall, the precision of the estimates is low in the northern regions, relatively higher in the western region for predicted large ruminants and livestock income, and in the eastern region for the share of livestock income. This pattern is fully consistent with the difference in the R^2 across regions and models: the higher the R^2, the lower the CVs.

Figure 8. Coefficient of Variation for the Two Predicted Variables
(Livestock Owners Only)
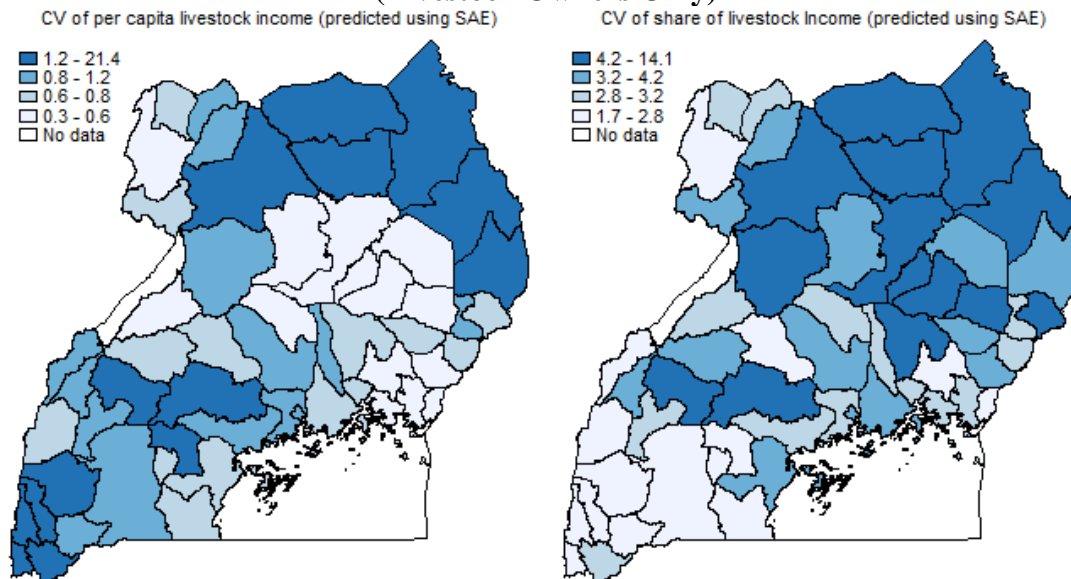
Maps thus far show district-level findings only, as this is the geographical stratification represented in the 2008 National Livestock Census. Maps at the subcounty level are also produced (see Appendix G), although they are not statistically representative of the subcounty, given the sampling design of the census. But, as mentioned above, the high average number of observations by subcounty in the UNLC (around 1,000) suggests the use of maps is possible at this lower geographical level.

As further corroboration to both *accuracy* and *precision* of our model, a set of Monte Carlo simulations has been performed. First, we test our estimated model on large ruminants against the true distribution using weighted OLS, using different simulated distributions of the error terms where the first simulation draws the residual value from a normal distribution with parameters:

$$\mu_h \sim N(\theta, \sigma) \text{ where } \theta = \frac{1}{n}\sum_{h=1}^{n} \mu_h \text{ and } \sigma = \sqrt{\frac{\sum_{h=1}^{n}(\mu_h - \theta)}{n-1}}$$

which are mean ($\mu = 0$) and standard deviation ($\sigma = 0.119$) of the original residual of the regression fitted using the survey. Then, we control for the data generating process (DGP) of the subsequent simulations, where parameters are simulated regardless of the structure assumed by the SAE method, that is without decomposing μ_h into cluster-effects and household-specific effects. Indeed, our aim is to show the difference in the parameters according to different DGPs, considering that OLS disregards the spatial autocorrelation of the error terms unlike the SAE estimator (Table 1). For this exercise, the number of Monte Carlo replications performed equals the number of observations in the National Livestock Census, thereby insuring each household in the NLC is associated a random residual drawn from different normal distributions of the residuals.[22]

Results show that the average values of the residuals in the OLS regressions are always higher than those using the SAE (closer to zero), for any σ^2. This points to a general inconsistency of the OLS regression. When the simulated error terms are used, the spatial distribution of large ruminants does not vary by district (see Figure 9 left panel compared to Figure 3's top right panel), although the unconditional simulated distribution is, overall, more dispersed than the actual empirical distribution. This finding could suggest that the OLS parameter estimates are indeed inconsistent when only a household-specific error term is simulated.

Table 1: Mean (μ) and Standard Deviation (σ) for Parameters Drawn from SAE and OLS Error Terms (Monte Carlo, *n*=964,047)

	OLS				SAE			
	σ^2				σ^2			
	0.0000	1	20	80	0.000	1	20	80
μ	0.219	0.220	0.227	0.244	-0.045	-0.046	-0.046	-0.054
σ	0.022	1.000	4.471	8.953	0.031	1.001	4.472	8.944

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[22] A different number of replications could be chosen, resulting in discarding replications obtained if n>sample size, or assigning the same value of the residuals to more observations in the NLC when *n* < sample size.

**Figure 9: Maps of Large Ruminants and Livestock Income per Capita
using Monte Carlo Simulations**
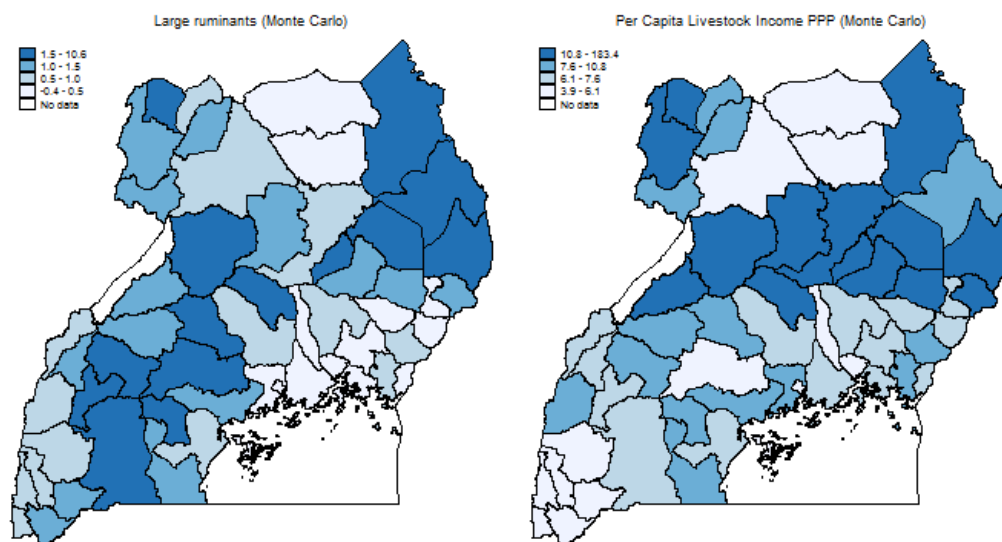
This result does not seem to vary substantially when replicating the same experiment using our preferred outcome of interest, livestock income per capita. For this case, the value of the residual assigned to each observation is the average of the 50 Monte Carlo replications drawn from a normal distribution, again with parameters equal to the original distribution of the error terms in the survey ($\mu = 0, \sigma = 0.119$). Again, the spatial ranking in Figure 9 (right panel) confirms the one shown in Figure 5 (right panel), although the distribution by district shows higher variability.[23]

6. CONCLUSIONS

By fitting prediction models on micro-data and using specific assumptions on the spatial distribution of the error terms, our novel approach is to apply the Small Area Estimation to a livestock census, whereby applications thus far have been focused on welfare, poverty, and nutrition prediction. Our paper shows that combining a relatively small, multi-topic household sample survey with a specialized, big livestock database could provide a promising approach to estimate the contribution of livestock to livelihood at the household level in Uganda. Among the various econometric models tested, the SAE technique could represent a valuable tool for informing livestock policy that governments should consider. We empirically show that, using two different databases and applying the SAE method, the spatial disaggregation of missing livestock measures in the census can be improved and used in policy targeting, as our survey-to-census imputation approach yields a finer geographical disaggregation than what is obtained using the survey data alone. This is particularly important for policy decisions as there is the constant need for various actors (e.g., donors, investment banks, policy-makers) to provide more spatially specific, tailored findings. Our results are also consistent with the literature and are stable regardless of the econometric model used, strengthening their reliability.

Estimation results show that the northeast area of the country is ranked highest in the number of large ruminants, although the comparison of actual versus predicted large ruminants

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[23] Maps at the sub-count level are reported in Appendix G.

for the whole northern region reveals substantial differences across districts. One important finding is that the number of large ruminants owned is not strongly correlated with livestock income and its share on household total income. While in the northeast and central areas the number of large ruminants, as well as livestock income and its share, are high, in the southern districts the latter two are both relatively low. Indeed, the relatively higher income is associated with a low number and density of large ruminants in the central areas, suggesting that households derive their income from other livestock types. Conversely, they do not seem to monetarily benefit from cattle in the southern region, despite their high number and density. Here, different factors may be at play: the role of livestock as precautionary saving or social status, the specific role of large ruminants as capital assets rather than income-generation resources, and the likely underreporting of livestock, especially in conflict-affected areas in the northern region, due to a variety of reasons.

This spatial pattern of our results confirms earlier studies that state the northeastern area of Uganda is characterized by extensive cattle-dominated farming systems, being part of the so-called cattle belt, stretching across the central region from the base of the highlands into the southwest through the area around Lake Kyoga. Our study underlines the importance of spatially explicit maps at the finest resolution level possible, here provided at region, district, and finally subcounty levels. A careful analysis of the maps at an increasingly finer disaggregation level can give important warnings about the costs due to miss-targeting. In fact, they can be remarkably high to the extent that livestock policy (such as veterinary campaigns, livestock extension services, investments in new breeds, and studies on market opportunities) targets whole regions or districts with apparently low shares of livestock. This eventual progressive misallocation (or leakage) could hit other districts or subcounties with undercoverage particularly hard, given the fixed level of funding and investments available for the sector.

The internal validity of our estimates has been tested using different econometric models and a set of Monte Carlo simulations, which suggest that OLS parameter estimates are indeed inconsistent when only a household-specific error term is simulated. The residuals in the OLS model are on average higher than those using the SAE method. This result seems to be stable regardless of the outcome of interest (large ruminants or our preferred livestock income per capita). While the spatial ranking across districts using the SAE approach confirms the method using Monte Carlo simulation, the distribution by district shows higher variability using the latter approach.

In terms of external validity and feasibility, our approach can be easily replicable and scaled to other countries with similar statistical agricultural and livestock data systems (e.g., Tanzania, Ethiopia). The crucial requirement is a relatively high common support between the survey and the census so that the missing information in the census can be reliably predicted using statistical inference from survey data, although our analysis shows that even with an agriculture-focused household survey it is possible to obtain granular and spatially robust results.

There are additional areas for potential exploration of SAE and mapping approaches for policy targeting. Mapping can be useful when combined with factors such as infrastructure, market access, land cover, soil quality, or environmental characteristics. Results of this paper suggest that national statistical agencies should aim to achieve greater coordination at the design stage between surveys and censuses so as to ensure higher common support between data sources for a more effective integration of different databases. Expanding the topics and the sample (ideally attaining full enumeration) covered in the census goes in this direction and would

greatly refine the results, provided information is collected using similar survey instruments and data collection protocols.

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APPENDIX A

Summary Statistics for Variables from Survey and Census

Variable	survey				census			
	Mean	Std. Dev	Min	Max	Mean	Std. Dev	Min	Max
Hired labor*	0.0692	0.2538	0	1	0.0361	0.1866	0	1
Agricultural Land	1.4297	1.7029	0	22.46	0.5448	1.1248	0	129.5
Pasture	0.3134	4.2924	0	133.55	0.5869	6.3135	0	404.69
Other Land	0.1324	2.8798	0	121.41	0.064	0.7186	0	242.81
Indigenous Bulls	0.3962	1.4853	0	40	0.6218	2.4312	0	78
Indigenous Cows	0.9094	3.5142	0	80	1.1522	4.6532	0	130
Indigenous Calves	0.4284	1.4868	0	23	0.4165	1.7483	0	50
Exotic Bulls	0.0525	0.4301	0	10	0.0301	0.4514	0	70
Exotic Cows	0.1877	1.3467	0	30	0.1148	1.573	0	121
Exotic Calves	0.1405	1.0278	0	22	0.0433	0.6247	0	52
Goats	2.083	3.6451	0	70	2.0117	4.7151	0	96
Sheep	0.4314	1.9538	0	33	0.696	4.1646	0	113
Pigs	0.4365	1.2419	0	15	0.4398	1.3278	0	64
Chickens	5.3391	8.3603	0	166	5.3873	10.735	0	562
Turkeys	0.0713	0.6038	0	10	0.0728	0.6739	0	40
Ducks	0.2005	1.3352	0	25	0.1865	1.2066	0	41
Other Birds	0.0987	1.0903	0	24	0.0962	1.0298	0	100
Rabbits	0.0606	0.6576	0	15	0.0419	0.5305	0	30
Donkeys	0.0123	0.2107	0	6	0.0419	0.5444	0	40
Bees	0.1319	1.5963	0	50	0.0898	0.8457	0	50
Eggs	1.63	54.001	0	2326.2	1.6134	10.718	0	1750
Milk	3.4793	18.777	0	346.15	2.6582	21.706	0	3780
Age of Head	47.295	15.162	14	100	41.925	15.365	12	99
Head is Female*	0.2863	0.4522	0	1	0.2729	0.4454	0	1
NDVI Mean	6439.9	804.68	3506.2	8169.5	6370.3	866.03	2950.7	8169.5
NDVI Standard Deviation	323.1	383.8	40.574	3061.5	319.19	400.83	0	3061.5
Tropic Cool Humid	46.26	91.116	0	832	40.073	101.63	0	832
Tropic Warm Humid	130.38	181.76	0	1823	136.82	246.43	0	3196
Tropic Cool Subhumid	38.912	116.96	0	815	39.557	144.47	0	1902
Tropic Warm Subhumid	14.27	76.471	0	770	18.098	109.07	0	1950
N=	1865				953455			

APPENDIX B

**Table B.1: Results of GLS Estimation of Number of Large Ruminants,
All Rural Households**

	National	Central	Eastern	Northern	Western
Household hired agricultural labor	3.7615***	5.2239***	1.0685**	1.0321	5.4623***
	-0.398	-0.7837	-0.4559	-1.0008	-0.64
Agricultural Land (Hectares)	0.2160***	-0.1233	0.4995***	0.1834*	0.0434
	-0.0579	-0.142	-0.0527	-0.1055	-0.1367
Pasture Land (Hectares)	0.2548***	0.8797***	-0.3264	1.0701	-0.1129***
	-0.0255	-0.0536	-0.2164	-1.1688	-0.032
Other Land (Hectares)	-0.1451***	0.9781	-0.1005***	0.3609	-0.0296
	-0.0339	-0.7347	-0.0221	-0.368	-0.692
Goats	0.2034***	0.2309**	0.246***	0.4083***	0.0236
	-0.0272	-0.0917	-0.0428	-0.0502	-0.0352
Sheep	0.7749***	0.5439***	0.2721***	0.3832***	0.6110***
	-0.0525	-0.1199	-0.0935	-0.0826	-0.1023
Pigs	0.1545**	0.4284***	0.2438***	0.0848	-0.2691**
	-0.0707	-0.1064	-0.0763	-0.4424	-0.1358
Chickens	0.0510***	0.0590*	0.0159	0.0418	0.0938***
	-0.0136	-0.0329	-0.0109	-0.0295	-0.0331
Turkeys	0.1215	0.4723	0.0384	0.2805	-0.1739
	-0.1543	-0.421	-0.0895	-0.7045	-0.6513
Ducks	-0.0502	-0.0547	-0.0029	-0.0616	-0.0297
	-0.0663	-0.0907	-0.0931	-0.1247	-0.2927
Other Birds	-0.0213	-0.7182	-0.0673	0.0935	----
	-0.0868	-0.5359	-0.0513	-0.1823	
Rabbits	-0.1049	-0.2926	-0.2129	-0.1287	0.0031
	-0.1492	-0.2718	-0.2299	-0.4299	-0.2003
Bees	0.0488	----	0.15541	-0.0043	-0.0577
	-0.0588		-0.1733	-0.0996	-0.0668
Average Weekly Egg Production	-0.0038***	-0.0051**	-0.0288	0.0738	0.041
	-0.0014	-0.0025	-0.0326	-0.1667	-0.037
Average Weekly Milk Production	0.0678***	0.0851***	0.1001***	0.1355***	0.0998***
	-0.0062	-0.0145	-0.0075	-0.0274	-0.0086
Age of Head	0.0079	-0.0019	0.0088	0.0182	0.0201*
	-0.0061	-0.0122	-0.0065	-0.0122	-0.0108
Head is Female	-0.3902*	-1.2453***	-0.2352	-0.6343	0.0789
	-0.2059	-0.4036	-0.2121	-0.4041	-0.3652
NDVI Mean	-0.0001	0.0001	0	-0.0001	0.0004
	-0.0001	-0.0004	-0.0002	-0.0004	-0.0003

Table B.1 (Continued): Results of GLS Estimation of Number of Large Ruminants,
All Rural Households

	National	Central	Eastern	Northern	Western
NDVI Standard Deviation	0.0001	0.0004	0.0005*	-0.0006	-0.0003
	-0.0003	-0.0008	-0.0003	-0.0013	-0.0006
AEZ-Tropic Cool Humid	0.0087***	0.0058***	0.0088*	-0.0082	0.0078***
	-0.0011	-0.0015	-0.0046	-0.0058	-0.0024
AEZ-Tropic Cool Subhumid	0.0037***	----	----	----	0.0042**
	-0.001				-0.0017
AEZ-Tropic Warm Humid	0.0014***	0.0014*	0.0007	-0.0031*	0.0020*
	-0.0005	-0.0007	-0.0016	-0.0018	-0.0011
AEZ-Tropic Warm Subhumid	-0.0012	----	0.0756	----	0.0013
	-0.0013		-0.0746		-0.0018
Constant	-0.6065	-1.1449	-0.7334	0.831	-4.3048**
	-0.982	-2.7509	-1.2242	-2.186	-2.0216
R^2	.5161	.7649	.6595	.3624	.6487
Adj R^2	.51	.7537	.6433	.3323	.6314
N	1865	440	487	467	471

Standard errors in parentheses. Significance levels: 90 percent*, 95 percent**, 99 percent***.

Table B.2: Results of GLS Estimation of Number of Large Ruminants,
Livestock Owners Only

	National	Central	Eastern	Northern	Western
Household hired agricultural labor	3.7841***	2.8035*	1.0420**	1.0451	5.7339***
	-0.4501	-1.4353	-0.4907	-1.1217	-0.7412
Agricultural Land (Hectares)	0.2439***	-0.6199**	0.5223***	0.2136*	0.0122
	-0.0702	-0.3066	-0.0578	-0.1237	-0.1703
Pasture Land (Hectares)	0.2434***	----	-0.3227	1.0345	-0.1197***
	-0.0289		-0.2326	-1.304	-0.0365
Other Land (Hectares)	-0.1419***	-0.4516	-0.1000***	0.3136	-0.0928
	-0.0383	-1.8199	-0.0238	-0.4143	-0.8039
Goats	0.1753***	0.9161***	0.2315***	0.3886***	0.0098
	-0.0318	-0.1642	-0.0477	-0.0593	-0.0408
Sheep	0.7518***	----	0.2674***	0.3542***	0.6196***
	-0.0595		-0.1006	-0.0936	-0.1171
Pigs	0.1158	0.4582**	0.2370***	0.0904	-0.2971*
	-0.082	-0.2258	-0.0824	-0.4944	-0.1572
Chickens	0.0451***	0.0343	0.0139	0.0376	0.0661*
	-0.0161	-0.0658	-0.0122	-0.0345	-0.0387
Turkeys	0.1288	1.0373	0.0278	0.2182	-0.2147
	-0.1743	-0.7443	-0.0965	-0.7966	-0.7459

Table B.2 (Continued): Results of GLS Estimation of Number of Large Ruminants, Livestock Owners

	National	Central	Eastern	Northern	Western
Ducks	-0.0554	-0.0143	-0.0176	-0.0745	-0.0335
	-0.082	-0.2415	-0.1004	-0.1393	-0.3437
Other Birds	-0.021	-0.9344	-0.0709	0.0905	----
	-0.0983	-1.1561	-0.0552	-0.2031	
Rabbits	-0.1093	-0.3638	-0.2268	-0.1407	-0.0204
	-0.1685	-0.433	-0.2473	-0.4792	-0.2296
Bees	0.0447	----	0.1744	-0.0061	-0.0598
	-0.0664		-0.1869	-0.1115	-0.0765
Average Weekly Egg Production	-0.0034**	-0.0033	-0.1221	0.0665	0.04
	-0.0016	-0.0055	-0.0909	-0.1857	-0.0421
Average Weekly Milk Production	0.0692***	0.2225***	0.0994***	0.1386***	0.0997***
	-0.007	-0.0251	-0.008	-0.0308	-0.0098
Age of Head	0.0107	0.0055	0.011	0.0234	0.0236*
	-0.008	-0.0269	-0.0081	-0.0163	-0.0139
Head is Female	-0.5239*	-1.5187	-0.3119	-0.7664	0.0746
	-0.2698	-0.9295	-0.2498	-0.5128	-0.4851
NDVI Mean	-0.0001	0.001	0	-0.0004	0.0005
	-0.0002	-0.0009	-0.0002	-0.0005	-0.0004
NDVI Standard Deviation	-0.0001	-0.0002	0.0006*	-0.0009	-0.0004
	-0.0004	-0.0019	-0.0004	-0.0016	-0.0008
AEZ-Tropic Cool Humid	0.0125***	0.0156***	0.0091*	-0.009	0.0093***
	-0.0015	-0.0033	-0.0053	-0.0071	-0.0031
AEZ-Tropic Cool Subhumid	0.0059***	----	----	----	0.0048**
	-0.0013				-0.0021
AEZ-Tropic Warm Humid	0.0025***	0.0033	0.0006	-0.0032	0.0028*
	-0.0008	-0.0021	-0.0018	-0.0022	-0.0016
AEZ-Tropic Warm Subhumid	-0.0009	----	0.0779	0.0054	0.0019
	-0.0016		-0.0859		-0.0023
Constant	-0.4283	-8.5973	-0.7333	2.1704	-5.2238*
	-1.2648	-6.5031	-1.4039	-3.0506	-2.783
R^2	.5099	.4805	.6505	.3407	.6488
Adj R^2	.502	.4471	.6311	.2999	.6258
N	1454	299	418	378	359

Standard errors in parentheses. Significance levels: 90 percent*, 95 percent**, 99 percent***.

APPENDIX C

**Table C.1: Results of GLS Estimation of Log of Per Capita
Livestock Income (PPP), All Rural Households**

	National	Central	Eastern	Northern	Western
Household hired agricultural labor	-0.1088	-0.0706	-0.6492	0.3667	-0.0515
	-0.1972	-0.4235	-0.4179	-0.4834	-0.3881
Agricultural Land (Hectares)	0.0555*	0.1172	0.0295	0.0474	0.1059
	-0.0284	-0.0729	-0.0564	-0.0499	-0.0769
Pasture Land (Hectares)	-0.0121	0.0569	-0.1628	-1.1341**	0.005
	-0.0186	-0.0562	-0.226	-0.5475	-0.0348
Other Land (Hectares)	0.0129	0.2811	-0.007	-0.0828	-0.4334
	-0.0165	-0.3777	-0.0236	-0.174	-0.3883
Indigenous Bulls	-0.0183	-0.0644	-0.0078	-0.0109	-0.2647
	-0.0356	-0.0894	-0.1004	-0.0926	-0.2089
Indigenous Cows	0.0554**	-0.0161	0.1391	0.1394**	0.0648
	-0.0257	-0.0615	-0.1074	-0.0674	-0.0604
Indigenous Calves	0.06	0.0214	0.1507	-0.0608	0.2834**
	-0.0463	-0.1364	-0.146	-0.0763	-0.1113
Exotic Bulls	0.1908	0.1918	0.0792	-1.1067	0.1994
	-0.1236	-0.5365	-0.3296	-1.0207	-0.1589
Exotic Cows	0.1544**	0.4357***	0.2815*	----	-0.1817
	-0.0635	-0.1577	-0.1622		-0.1464
Exotic Calves	-0.1221*	-0.2752	-0.1735	0.4448	0.2675
	-0.072	-0.2022	-0.1226	-1.7168	-0.221
Donkeys	0.5096*	----	0.9828*	0.3012	----
	-0.2665		-0.5771	-0.3033	
Goats	0.1183***	0.1996***	0.1223***	0.0997***	0.1084***
	-0.0131	-0.0483	-0.0394	-0.0248	-0.02
Sheep	-0.0452*	-0.0654	0.1492*	-0.0119	-0.0662
	-0.0269	-0.0642	-0.0864	-0.0458	-0.0597
Pigs	0.1729***	0.2356***	0.0937	-0.0532	0.1741**
	-0.034	-0.058	-0.0682	-0.2113	-0.0757
Chickens	0.0983***	0.0918***	0.0823***	0.0881***	0.1366***
	-0.0066	-0.017	-0.0099	-0.0143	-0.0186
Turkeys	0.1108	0.2329	-0.0019	0.3748	0.2824
	-0.0735	-0.2156	-0.0797	-0.3311	-0.3638
Ducks	0.0743**	0.0853*	0.1295	0.0442	0.2736*
	-0.0316	-0.046	-0.0828	-0.07	-0.1629
Other Birds	-0.0513	0.495	-0.0361	-0.0061	----
	-0.0417	-0.417	-0.0455	-0.086	

Table C.1 (Continued): Results of GLS Estimation of Log of Per Capita Livestock Income (PPP), All Rural Households

	National	Central	Eastern	Northern	Western
Rabbits	-0.0222	-0.1029	-0.1464	0.0666	0.0511
	-0.0711	-0.1379	-0.2049	-0.2013	-0.1112
Bees	-0.0312	----	0.1011	-0.1089**	0.0207
	-0.0283		-0.1551	-0.0485	-0.0373
Average Weekly Egg Production	-0.0064***	-0.0059***	0.0598**	-0.1136	-0.0052
	-0.0007	-0.0013	-0.0289	-0.0783	-0.0208
Average Weekly Milk Production	-0.0004	-0.0093	-0.0025	-0.0042	0.0079
	-0.0038	-0.0086	-0.0108	-0.0134	-0.007
Age of Head	-0.001	-0.0001	-0.0091	-0.0115**	0.0027
	-0.0029	-0.0062	-0.0058	-0.0058	-0.006
Head is Female	-0.1235	-0.3489*	-0.1805	0.0054	0.0016
	-0.0985	-0.2076	-0.1896	-0.1905	-0.2029
NDVI Mean	0	-0.0001	0.0001	0.0001	0.0001
	-0.0001	-0.0002	-0.0002	-0.0001	-0.0002
NDVI Standard Deviation	0	0.0001	0.0001	-0.0001	-0.0004
	-0.0001	-0.0004	-0.0003	-0.0006	-0.0003
AEZ-Tropic Cool Humid	-0.0003	0.0015*	0.0028	-0.0028	-0.0036***
	-0.0005	-0.0008	-0.0041	-0.0021	-0.0014
AEZ-Tropic Cool Subhumid	-0.0006	----	---	----	-0.0005
	-0.0005				-0.001
AEZ-Tropic Warm Humid	-0.0001	0.0006	-0.0009	----	-0.0006
	-0.0003	-0.0004	-0.0014		-0.0006
AEZ-Tropic Warm Subhumid	-0.0001	----	-0.1393**	----	0.0009
	-0.0006		-0.0668		-0.001
Constant	1.3307***	1.6296	1.6896	0.9782	0.6858
	-0.4696	-1.4027	-1.1151	-0.8642	-1.1322
R^2	.2587	.2555	.3308	.2361	.3436
Adj R^2	.2465	.2087	.2884	.1909	.302
N	1865	440	487	467	471

Standard errors in parentheses. Significance levels: 90 percent*, 95 percent**, 99 percent***.

**Table C.2: Results of GLS Estimation for Log of Per Capita
Livestock Income (PPP), Livestock Owners only**

	National	Central	Eastern	Northern	Western
Household hired agricultural labor	-0.2316	-0.236	-0.6735	0.1883	-0.2362
	-0.2042	-0.444	-0.418	-0.5087	-0.4313
Agricultural Land (Hectares)	0.0221	0.0908	0.0272	0.0265	0.0831
	-0.0317	-0.0908	-0.0582	-0.0551	-0.0907
Pasture Land (Hectares)	-0.0023	0.0365	-0.1271	-1.1527**	0.0175
	-0.019	-0.0607	-0.226	-0.5758	-0.0374
Other Land (Hectares)	0.0159	0.5349	-0.0097	-0.0607	-0.6568
	-0.0171	-0.537	-0.0236	-0.181	-0.4276
Indigenous Bulls	-0.0162	-0.0911	0.003	----	-0.2471
	-0.037	-0.1107	-0.1009		-0.2265
Indigenous Cows	0.0299	0.0013	0.1074	----	0.0241
	-0.0263	-0.0674	-0.1079		-0.0652
Indigenous Calves	0.0644	-0.0239	0.11833	0.0818	0.2792**
	-0.0475	-0.1412	-0.1462	-0.061	-0.1209
Exotic Bulls	0.1623	0.3548	0.1777	-0.6478	0.163
	-0.1279	-0.5516	-0.3299	-1.0752	-0.1707
Exotic Cows	0.1108*	0.3020*	0.2	----	-0.1677
	-0.0633	-0.1638	-0.1625		-0.159
Exotic Calves	-0.0575	-0.2429	-0.1448	0.0095	0.2801
	-0.0738	-0.2117	-0.1236	-1.8096	-0.2409
Donkeys	0.4534	----	0.8681	0.4446	----
	-0.2769		-0.581	-0.3209	
Goats	0.0812***	0.1539***	0.0690*	----	0.0841***
	-0.0139	-0.0523	-0.0406		-0.022
Sheep	-0.0525*	-0.044	0.1411	-0.0472	-0.0824
	-0.0278	-0.0667	-0.0864	-0.0481	-0.0643
Pigs	0.0986***	0.1764**	0.05	-0.0928	0.0842
	-0.036	-0.069	-0.0684	-0.2209	-0.0834
Chickens	0.0731***	0.0587***	0.064***	0.0751***	0.0970***
	-0.0071	-0.0195	-0.0103	-0.015	-0.0206
Turkeys	0.0804	0.2276	-0.0264	0.2836	0.2968
	-0.076	-0.2178	-0.08	-0.3472	-0.3964
Ducks	0.0502	0.0938	0.0981	0.0172	0.1466
	-0.0358	-0.0695	-0.0831	-0.0743	-0.1811
Other Birds	-0.0521	0.7892	-0.0276	-0.0233	----
	-0.0432	-0.6672	-0.0456	-0.09	
Rabbits	-0.0447	-0.1014	-0.163	0.0709	-0.0144
	-0.0734	-0.1252	-0.205	-0.2123	-0.1214

Table C.2 (Continued): Results of GLS Estimation for Log of Per Capita Livestock Income (PPP), Livestock Owners only

	National	Central	Eastern	Northern	Western
Bees	-0.0227	----	0.0864	-0.0567	0.0237
	-0.0292		-0.1556	-0.0497	-0.0407
Average Weekly Egg Production	-0.0048***	-0.0037**	0.1452*	-0.0959	-0.0053
	-0.0007	-0.0017	-0.0754	-0.0824	-0.0226
Average Weekly Milk Production	0.0002	-0.0091	0.0013	-0.0046	0.0066
	-0.0039	-0.0095	-0.0109	-0.0141	-0.0075
Age of Head	-0.0013	-0.0062	0.0003	-0.01	-0.0001
	-0.0035	-0.0078	-0.0067	-0.0072	-0.0074
Head is Female	-0.0763	-0.4415	-0.1166	0.0609	0.0559
	-0.1182	-0.2743	-0.2079	-0.2274	-0.2564
NDVI Mean	0	-0.0001	0	-0.0003	-0.0001
	-0.0001	-0.0003	-0.0002	-0.0002	-0.0002
NDVI Standard Deviation	0	-0.0001	0	-0.0001	-0.0003
	-0.0002	-0.0005	-0.0003	-0.0006	-0.0003
AEZ-Tropic Cool Humid	0	0.0013	0.002	----	----
	-0.0007	-0.001	-0.0045		
AEZ-Tropic Cool Subhumid	-0.0001	----	----	0.0004	----
	-0.0006				
AEZ-Tropic Warm Humid	0.0001	0.0011*	-0.0005	----	0
	-0.0003	-0.0006	-0.0015		-0.0007
AEZ-Tropic Warm Subhumid	-0.0004	----	-0.1979***	----	----
	-0.0007		-0.0717		
Constant	2.0206***	2.2451	2.0886*	3.9912***	2.2306*
	-0.5546	-1.8932	-1.195	-1.3766	-1.3481
R^2	.1434	.1571	.2502	.1023	.2151
Adj R^2	.1253	.0765	.1942	.0439	.1562
N	1454	299	418	378	359

Standard errors in parentheses. Significance levels: 90 percent*, 95 percent**, 99 percent***.

APPENDIX D

**Table D.1: Results of GLS Estimation of Share of Income from Livestock,
All Rural Households**

	National	Central	Eastern	Northern	Western
Household hired agricultural labor	-0.0478**	0.0092	-0.0806	-0.0706	-0.0298
	-0.0232	-0.0523	-0.0562	-0.0749	-0.0227
Agricultural Land (Hectares)	0.0024	0.0063	-0.0013	0.0021	-0.0053
	-0.0033	-0.0089	-0.0076	-0.0078	-0.0044
Pasture Land (Hectares)	-0.0016	0.0099	-0.0087	-0.1835**	-0.0039*
	-0.0022	-0.007	-0.0304	-0.0853	-0.002
Other Land (Hectares)	-0.0008	0.0017	-0.0013	0.0379	-0.0306
	-0.0019	-0.0466	-0.0032	-0.0273	-0.0227
Indigenous Bulls	-0.0032	-0.0128	-0.0058	0.0125	-0.011
	-0.0042	-0.0111	-0.0135	-0.0143	-0.0121
Indigenous Cows	0.0021	-0.0107	0.012	0.0012	0.0079**
	-0.003	-0.0075	-0.0144	-0.0102	-0.0035
Indigenous Calves	0.0124**	0.017	0.0204	0.0106	0.0242***
	-0.0054	-0.0169	-0.0196	-0.0118	-0.0065
Exotic Bulls	0.009	0.0317	0.0091	----	0.0157*
	-0.0145	-0.0658	-0.0443		-0.0093
Exotic Cows	-0.0019	0.0314	-0.0004	----	-0.004
	-0.0075	-0.0195	-0.0218		-0.0085
Exotic Calves	0.0032	-0.0281	0.0162	----	0.0064
	-0.0085	-0.0248	0.0165)		-0.0129
Donkeys	0.0572*	----	0.1413*	0.0668	----
	-0.0313		-0.0776	-0.0474	
Goats	0.0046***	0.0075	0.0035	----	0.0024**
	-0.0015	-0.006	-0.0053		-0.0012
Sheep	-0.008**	-0.0039	0.0047	-0.0145**	-0.0100***
	-0.0032	-0.0079	-0.0116	-0.0071	-0.0035
Pigs	0.0024	0.0051	-0.001	-0.0221	0.0092**
	-0.004	-0.0072	-0.0092	-0.0328	-0.0044
Chickens	0.0031***	0.0027	0.0018	0.0060***	----
	-0.0008	-0.0021	-0.0013	-0.0022	
Turkeys	-0.0025	-0.0135	-0.0054	----	-0.0007
	-0.0086	-0.0266	-0.0107		-0.0213
Ducks	0.0066*	0.0052	0.0194*	0.005	-0.0057
	-0.0037	-0.0057	-0.0111	-0.0092	-0.0095
Other Birds	-0.0092*	0.018	0.0003	-0.0285**	----
	-0.0049	-0.0516	-0.0061	-0.0134	
Rabbits	-0.0065	-0.0187	0.0018	-0.0001	-0.0033
	-0.0084	-0.017	-0.0275	-0.0314	-0.0065

Table D.1: Results of GLS Estimation of Share of Income from Livestock, All Rural Households

	National	Central	Eastern	Northern	Western
Bees	0.0114***	----	-0.0094	-0.0029	0.0202***
	-0.0033		-0.0208	-0.0073	-0.0022
Average Weekly Egg Production	-0.0002**	-0.0002	0.0003	-0.0106	0.0007
	-0.0001	-0.0002	-0.0039	-0.0121	-0.0012
Average Weekly Milk Production	0.0004	0.0005	-0.0009	0.0022	0.0005
	-0.0004	-0.0011	-0.0015	-0.0021	-0.0004
Age of Head	0.0005	0.0012	0.0002	-0.0005	0
	-0.0003	-0.0008	-0.0008	-0.0009	-0.0004
Head is Female	-0.0131	-0.0601**	-0.0084	0	-0.0211*
	-0.0116	-0.0256	-0.0255	-0.0295	-0.0118
NDVI Mean	0.0000***	0	0.0000**	-0.0001**	0
	0	0	0	0	0
NDVI Standard Deviation	0	0	0	-0.0001	0
	0	0	0	-0.0001	0
AEZ-Tropic Cool Humid	0	----	0.0002	-0.0001	-0.0001
	-0.0001		-0.0006	-0.0004	-0.0001
AEZ-Tropic Cool Subhumid	0	----	----	0	0
	-0.0001			-0.0001	-0.0001
AEZ-Tropic Warm Humid	0.0000*	----	0	0	0
	0		-0.0002	-0.0001	0
AEZ-Tropic Warm Subhumid	-0.0001	----	-0.0258***	----	----
	-0.0001		-0.009		
Constant	0.1812***	0.0628	0.3417**	0.4694**	0.0305
	-0.0552	-0.1684	-0.1499	-0.1889	-0.0655
R^2	.0699	.0613	.102	.0933	.2796
Adj R^2	.0547	.007	.045	.044	.2374
N	1865	440	487	467	471

Standard errors in parentheses. Significance levels: 90 percent*, 95 percent**, 99 percent***.

**Table D.2: Results of GLS Estimation for Share of Income from Livestock,
Livestock Owners Only**

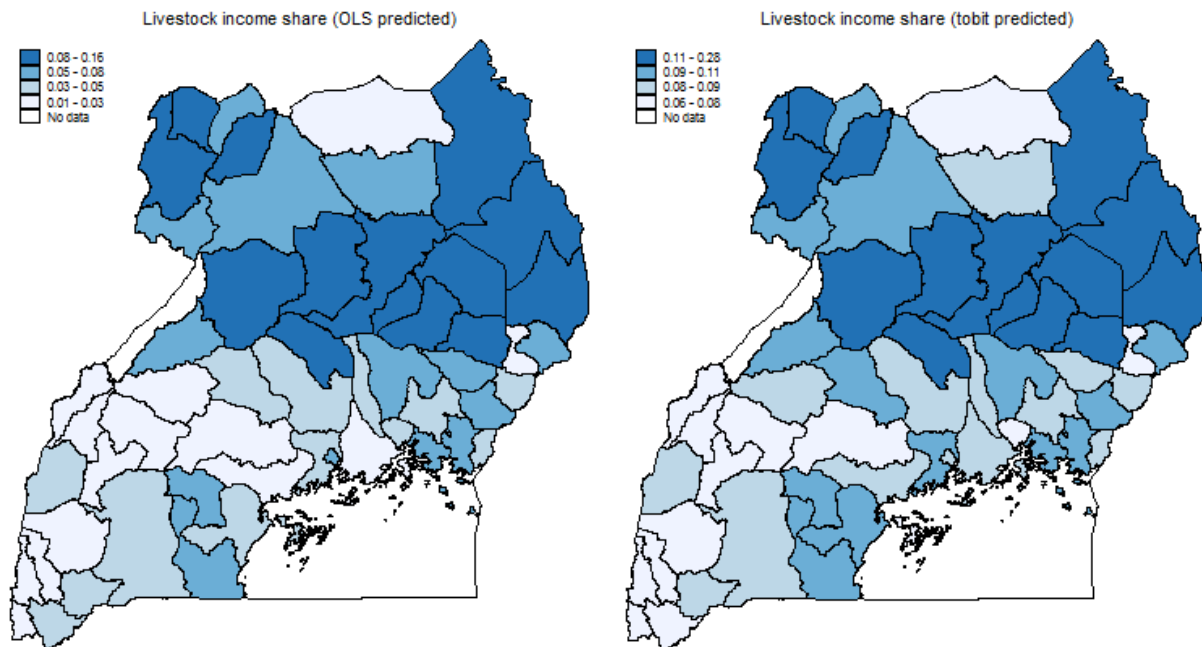|	National	Central	Eastern	Northern	Western
Household hired agricultural labor	-0.0503**	-0.0057	-0.0785	-0.0728	-0.0273
	-0.0255	-0.0587	-0.0606	-0.078	-0.0268
Agricultural Land (Hectares)	0	0.003	-0.0012	-0.0028	-0.0091
	-0.004	-0.0126	-0.0084	-0.0086	-0.0057
Pasture Land (Hectares)	-0.0011	----	-0.0092	-0.1732*	-0.0027
	-0.0024		-0.0328	-0.0885	-0.0023
Other Land (Hectares)	-0.001	----	-0.0015	0.0437	-0.0315
	-0.0021		-0.0034	-0.0284	-0.0267
Indigenous Bulls	-0.0031	-0.0035	-0.0062	0.012	-0.0127
	-0.0046	-0.0071	-0.0146	-0.015	-0.0141
Indigenous Cows	0.0012	----	0.0102	-0.0058	0.0058
	-0.0033		-0.0156	-0.011	-0.0041
Indigenous Calves	0.0126**	----	0.0194	0.0149	0.0255***
	-0.0059		-0.0212	-0.0124	-0.0076
Exotic Bulls	0.0076	0.006	0.014	----	0.0156
	-0.016	-0.073	-0.0478		-0.0108
Exotic Cows	-0.0026	0.027	-0.0022	----	-0.0069
	-0.0079	-0.0206	-0.0236		-0.0099
Exotic Calves	0.0058	-0.0155	0.0163	----	0.0103
	-0.0092	-0.0206	-0.0179		-0.015
Donkeys	0.0536	----	0.138	0.0607	----
	-0.0346		-0.0842	-0.0494	
Goats	0.0037**	0.0128*	0.0011	0.0067	0.0018
	-0.0017	-0.0073	-0.0059		-0.0014
Sheep	-0.0086**	-0.0006	0.004	-0.0181**	-0.0108***
	-0.0035	-0.008	-0.0125	-0.0075	-0.004
Pigs	0.0036	0.0088	-0.0025	-0.0243	0.006
	-0.0045	-0.0093	-0.0099	-0.0341	-0.0052
Chickens	0.0027***	0.0025	0.0011	0.0053**	0.0023*
	-0.0009	-0.0028	-0.0015	-0.0024	
Turkeys	-0.0028	-0.0133	-0.0063	0.0108	0.0019
	-0.0095	-0.0311	-0.0116		-0.0247
Ducks	0.0073	0.0079	0.0176	0.0033	-0.0064
	-0.0045	-0.0096	-0.012	-0.0096	-0.0113
Other Birds	-0.0093*	----	0.001	-0.0278**	----
	-0.0054		-0.0066	-0.0139	
Rabbits	-0.0068	-0.0187	0.0008	-0.0039	-0.0037
	-0.0092	-0.0179	-0.0297	-0.0326	-0.0075

Table D.2 (Continued): Results of GLS Estimation for Share of Income from Livestock, Livestock Owners Only

	National	Central	Eastern	Northern	Western
Bees	0.0113***	----	-0.0091	-0.0066	0.0193***
	-0.0037		-0.0225	-0.0078	-0.0025
Average Weekly Egg Production	-0.0002**	-0.0002	0.0019	-0.011	0.0004
	-0.0001	-0.0002	-0.0109	-0.0126	-0.0014
Average Weekly Milk Production	0.0004	----	-0.0008	0.0018	0.0005
	-0.0005		-0.0016	-0.0022	-0.0005
Age of Head	0.0007	0.0012	0.0007	-0.0001	-0.0002
	-0.0004	-0.0011	-0.001	-0.0011	-0.0005
Head is Female	-0.0111	-0.0762**	-0.006	0.0081	-0.026
	-0.0148	-0.0387	-0.0301	-0.035	-0.016
NDVI Mean	0.0000***	----	-0.0001**	-0.0001*	0
	0		0	0	0
NDVI Standard Deviation	0	----	0	-0.0001	0
	0		0	-0.0001	0
AEZ-Tropic Cool Humid	0	-0.0001	0.0002	-0.0002	-0.0001
	-0.0001		-0.0006	-0.0005	-0.0001
AEZ-Tropic Cool Subhumid	0.0001	----	----	0	0
	-0.0001			-0.0002	-0.0001
AEZ-Tropic Warm Humid	0.0001**	----	0	-0.0001	0.0001
	0		-0.0002	-0.0002	-0.0001
AEZ-Tropic Warm Subhumid	-0.0001	----	-0.0306***	----	0.0001
	-0.0001		-0.0104		
Constant	0.2169***	-0.0107	0.3983**	0.4977**	0.0521
	-0.0694	-0.0618	(0.1732	-0.2314	-0.0923
R²	.0644	.0487	.0998	.1168	.2857
Adj R²	.0446	-.0088	.0325	.0514	.2251
N	1454	299	418	378	359

Standard errors in parentheses. Significance levels: 90 percent*, 95 percent**, 99 percent***.

APPENDIX E

Maps of Livestock Income using OLS and Tobit

Livestock income (OLS predicted)   Livestock income (tobit predicted)
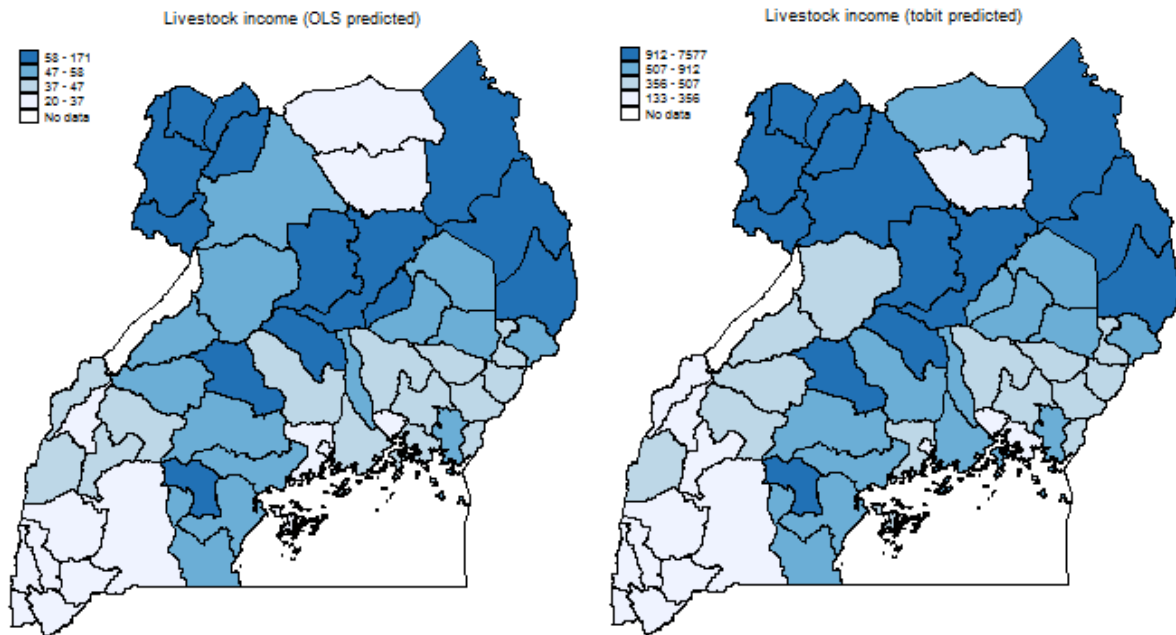
APPENDIX F

Maps of Livestock Income Share using OLS and Tobit

Livestock income share (OLS predicted)   Livestock income share (tobit predicted)

APPENDIX G

Maps at the Subcounty Level

Large ruminants (actual)

Large ruminants (OLS predicted)

Large ruminants (tobit precicted)

Large ruminants (predicted using GLS)

Density of Large Ruminants by Subcounty (actual)

■	19.7 - 146.9
■	9.5 - 19.7
■	3.9 - 9.5
■	0.0 - 3.9
□	No data

Density of Large Ruminants by Subcounty (predicted)

■	13.5 - 261.4
■	5.0 - 13.5
■	1.0 - 5.0
■	-64.3 - 1.0
□	No data

Per Capita Livestock Income PPP (predicted using SAE)

■	52.4 - 208.2
■	38.6 - 52.4
■	31.7 - 38.6
■	9.4 - 31.7
□	No data

Share of Income from Livestock (predicted using SAE)

■	0.06 - 0.53
■	0.05 - 0.06
■	0.04 - 0.05
■	0.01 - 0.04
□	No data

Large ruminants (Monte Carlo)

Per Capita Livestock Income PPP (Monte Carlo)