# Household livelihoods and conflict with wildlife in community-based conservation areas across northern Tanzania

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TABLE S1 Numbers of villages and households represented in wildlife management areas (WMAs) and control areas.

| Wildlife management area | No. of villages | No. of households |
|---|---|---|
| Burunge | 3 | 188 |
| Enduimet | 4 | 236 |
| Makame | 2 | 112 |
| Makao | 4 | 240 |
| *Total (wildlife management area)* | 13 | 776 |
| *Total (control)* | 27 | 1,723 |

TABLE S2 Descriptive measures of households in the WMAs of Burunge, Enduimet, Makame and Makao, and in the control sample: the proportion of households categorized as severely food insecure, mean household wealth index (Supplementary Material 2); mean household productive livelihood asset holdings (cattle, sheep/goats, poultry, land); and proportion of households that experienced one or more incidents of human–wildlife conflict (loss of livestock, cattle, sheep/goats, poultry, crops) in the 12 months prior to the survey.

| Wildlife management area | Severely food insecure | Wealth index | Productive livelihood asset holdings | | | | Experience of human–wildlife conflict | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Cattle | Sheep/goats | Poultry | Land (acres) | Livestock | Cattle | Sheep/goats | Poultry | Crops |
| Burunge | 0.38 | 1.50 | 3.98 | 11.50 | 3.60 | 4.52 | 0.39 | 0.02 | 0.10 | 0.34 | 0.48 |
| Enduimet | 0.75 | 0.57 | 4.77 | 13.60 | 0.94 | 1.79 | 0.67 | 0.36 | 0.60 | 0.10 | 0.50 |
| Makame | 0.88 | 0.63 | 10.80 | 14.00 | 1.30 | 4.57 | 0.62 | 0.46 | 0.39 | 0.15 | 0.25 |
| Makao | 0.34 | 1.20 | 14.80 | 15.10 | 6.00 | 8.25 | 0.51 | 0.05 | 0.21 | 0.46 | 0.53 |
| *Control* | 0.44 | 1.50 | 3.48 | 7.18 | 4.60 | 3.91 | 0.34 | 0.02 | 0.10 | 0.27 | 0.10* |

*Based on only 14 of the 27 control villages (Supplementary Material 2)

FIG. S1 Predicted relationships between productive livelihood assets and the log-odds of food insecurity, with 95% credibility bands. Observed values for productive livelihood assets are plotted above the x-axis. Estimates are from the top-ranked model with controls (m1; Supplementary Material 3).

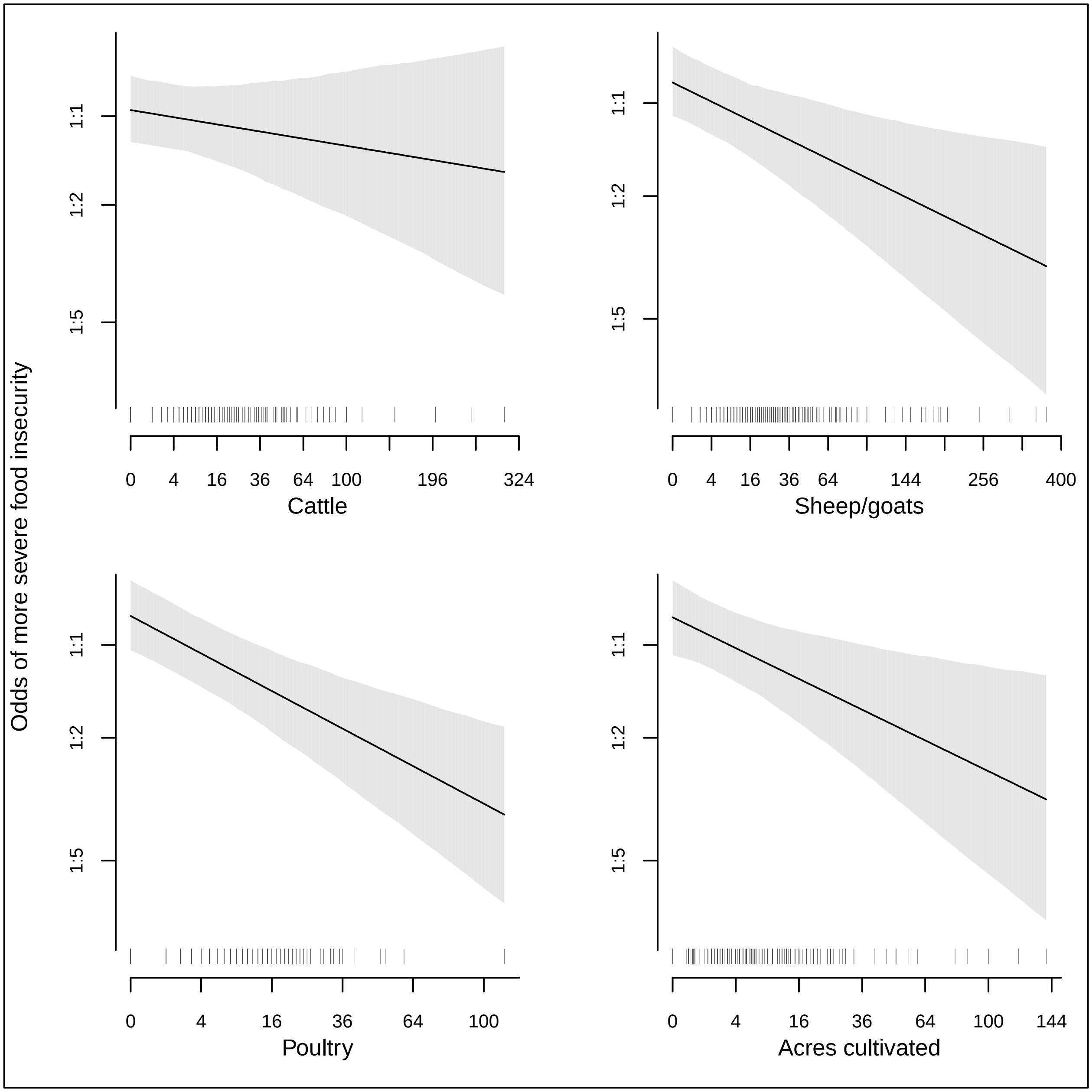
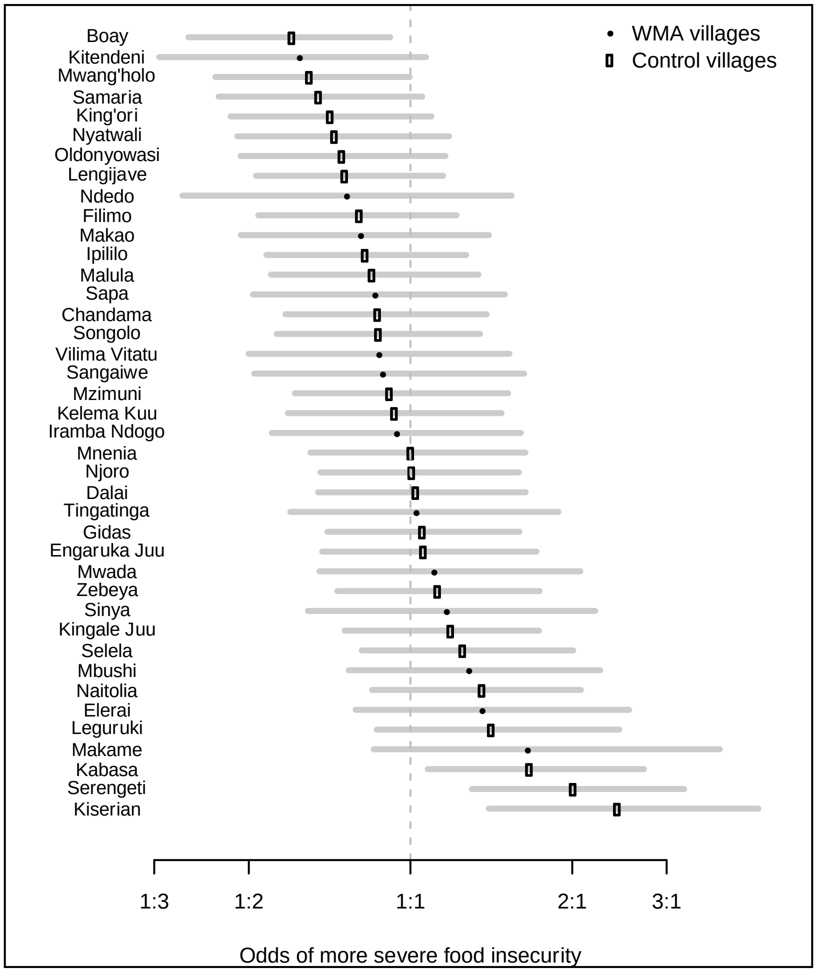


FIG. S2 Village-level effects predicting household food insecurity. Varying intercept estimates for villages in wildlife management areas (WMAs) and control villages, with 95% CI, are listed from least to most food insecure, top to bottom. Estimates are from posterior densities of the top-ranked model with controls (m1; Supplementary Material 3).



## Supplementary Material 1 Village site visits and household sample

### Whole Village Project site visits and institutional assessments

The Whole Village Project was funded primarily by the U.S. Agency for International Development to provide baseline data with which to evaluate rural development projects. In each of the 56 villages surveyed, meetings were held with elected and appointed leaders. Activities and objectives of the research were discussed and 60–75 households were selected at random from a complete list of residents. Village meetings also included a two-part institutional assessment. Firstly, leaders were asked about a number of village-level characteristics (e.g. recent in/out migration, religious composition, present facilities and social services). This part of the assessment included questions pertaining specifically to wildlife management areas and conservation efforts: communication of the village council with residents, recognized protected areas (including wildlife management areas) and their perceived costs and benefits, known village earnings from the protected areas, and known hunting and photography safari companies. Other informal interviews were completed (e.g. focus group interviews with the village health officer and female council members), but these were not considered in our study. Secondly, a group of randomly selected village residents were asked to list all active institutions and organizations in the village (including protected areas and wildlife management areas where applicable). Guided group discussion and debate (Chambers, 1992; Guijt & Pretty, 1992) produced numerical ratings of importance and effectiveness for each institution. For further information on the Whole Village Project, including site visit methodology and descriptive statistics, see Ritter et al. (2010) or contact MBM.

### Village participation in wildlife management areas

Village participation in wildlife management areas is voluntary. However, external organizations such as conservation NGOs or private interests typically facilitate the establishment of wildlife management areas through the formation and registration of the Authorized Association. Land use plans and boundaries are proposed based on a number of factors and can include villages that are not in favour of participation, either at the time of establishment or at a later date. Although each participating village typically contributes land to the wildlife areas, this is not always the case. Details of the participatory process are available in the report by Tetra Tech & Maliasili Initiatives (2013) and from the Government of Tanzania (2012).

### Household sample

Field teams conducted structured questionnaires in each of the 60–75 households selected randomly during meetings with village leaders. Household heads responded to questionnaire modules surveying the cultural, demographic, nutritional and socioeconomic characteristics of household members. In our sample of 40 villages adjacent to protected areas, Whole Village Project technicians completed 2,571 household surveys (Ritter et al., 2010). Seventy-two of these records were incomplete and therefore deleted (Supplementary Material 3).

## Supplementary Material 2 Household-level variables

### Food insecurity

Food insecurity was measured using the household food insecurity access scale. To produce the scale the Whole Village Project incorporated nine questions (assessing the extent to which households experienced problems accessing food during the previous 30 days) into one of the household survey modules. Responses to these questions were used to assign each household to one of four categories of food security. For details on the household food insecurity access scale and its implementation and validation see Coates et al. (2007) and, as applied in Tanzania, Knueppel et al. (2010).

### Wealth index

Table 1 and Supplementary Table S2 report a wealth index based on purchasable household items, excluding livestock and land holdings. This index was calculated by ordinary principal components analysis of 37 binary variables applied to household data from the first 14 villages visited (see also Lawson et al., 2014). We used this index only for descriptive purposes. In our modelling framework we omitted the index and instead selected a discrete set of controls (see below).

### Crop loss

Table 1 and Supplementary Table S2 report data on crop loss, which exist for only a subset of households. Questions pertaining to crop loss were omitted from surveys in 13 villages; this occurred in a particular phase of field sampling and exclusively in control villages. Because omissions were systematic or patterned in nature we did not impute missing values or include crop loss in our models. Where crop loss is reported in summary tables, means were calculated from the village subset where data existed.

### Productive livelihood assets

The majority of sample households engaged in mixed livelihood strategies; for example, traditionally pastoralist Maasai account for the largest ethnic group in our sample, yet approximately one-third of Maasai households identified farming as their primary livelihood activity. The effects of cultivated land and livestock holdings on food insecurity and overall household well-being may vary between households; for example, whereas additional cattle may strongly predict lower food insecurity for a poor livestock keeper without cultivated land, similar beneficial effects may not be evident in wealthy farming households that invest cash crop profits in larger herds. Although we endeavoured to account for the sources of variation that explain food insecurity, both at the household and village levels, we acknowledge the potential confound of differential livelihood asset effects.

### Control covariates included in models

A single set of household-level controls was selected to account for variation in wealth not captured by productive livelihood assets (livestock holdings and cultivated land). From variables recorded in the household surveys, we selected items that commonly indicate wealth accumulation in the study area. These were added to the basic model (Supplementary Material 3) and the most appropriate set was determined by model comparison of log-conditional predictive ordinates (logCPOs): bicycle, construction material of house (floor, walls and roofing), furnishings, mobile phone, motorbike, radio, sewing machine, and solar panel. This set was then included in all models.

## Supplementary Material 3 Modelling strategy

### Multilevel models

We refer to our approach throughout as multi-level or varying effects modelling (it is also known as hierarchical, random effects, or mixed effects modelling), inclusive of varying intercept and predictor effects. All models were fit using JAGS in *R* (Plummer, 2012; R Development Core Team, 2013). For simplicity, the main text specifies only the linear predictor $\mu$ of the basic model, a proportional-odds ordered logistic regression (Jackman, 2009). Here we specify the same model (m0), showing the cumulative logit link along with the linear predictor:

$$\Pr\left(y_{h,V,W} \leq c\right) = F\left(\tau_c - \mu_{h,V,W}\right),$$

where $y_{h,V,W}$ is the food insecurity level of household $h$ in village $V$ and wildlife management area $W$, $c$ is an arbitrary level on the food insecurity scale, $F$ is the cumulative distribution function of the logistic density, $\tau$ are cut points ($\tau_1 < \tau_2 < \tau_3$), and

$$\mu_{h,V,W} = \mathrm{A}_V + \mathrm{B}_W + \omega\chi_h.$$

We introduced focal predictors for livestock losses and their interactions with wildlife management area status, productive livelihood assets, and household level control covariates, aiming to build the simplest model (m1) that addressed our research questions. We then considered elaborations of m1 including, for example, additional interactions as well as varying predictor effects (m2–m4). All models containing ‘livestock loss’ included all three types of loss (cattle, sheep/goats, poultry), and those containing ‘productive livelihood assets’ included all four assets (cattle, sheep/goats, poultry, cultivated acres). All models except m0 contained an identical set of household-level controls (Supplementary Material 2).

TABLE S3 Varying effects, household-level effects, and logCPO values included in the linear predictor of models m0–m4.

| Model | Varying effects | Household-level fixed effects | logCPO |
|---|---|---|---|
| m0 | Village & wildlife management area intercepts | Wildlife management area status | –2,602 |
| m1 | Village & wildlife management area intercepts | Wildlife management area status, livestock loss, wildlife management area *loss, productive livelihood assets | –2,509 |
| m2 | Village & wildlife management area intercepts; livestock loss predictors by wildlife management area | Wildlife management area status, livestock loss, wildlife management area *loss, productive livelihood assets | –2,511 |
| m3 | Village & wildlife management area intercepts | Wildlife management area status, livestock loss, wildlife management area *loss, productive livelihood assets, wildlife management area *assets | –2,513 |
| m4 | Village & wildlife management area intercepts; livelihood asset predictors by wildlife management area | Wildlife management area status, livestock loss, wildlife management area *loss, productive livelihood assets | –2,512 |

We specified Gaussian priors with mean zero and variance 25 for fixed effects coefficients in the ordered logit model. The cut points $\tau_1 < \tau_2 < \tau_3$ were obtained by sorting independent Gaussian variables as in Jackman (2009). We specified Gaussian priors with mean zero and variance 100 for fixed effects coefficients in the Tobit model for imputation of acres cultivated (see below). We specified a uniform (0, 100) prior on the standard deviation of the Tobit outcome before truncation. All village and wildlife management area-level varying effects (both intercepts and slopes) were sampled from Gaussian distributions with mean zero and a uniform (0, 2) prior on the standard deviation.

Log-CPOs measure model quality by a cross-validation criterion (Gelfand, 1996) and are always negative; those closer to zero indicate more preferred models. Model m1 improves notably on m0 and is the best in the set of models we considered, although the more complex models, m2–m4, are only slightly less preferred than m1. As m1 is the simplest model among those including the focal predictors, as well as the top-ranked model, the results presented in the main text are based on m1 unless otherwise stated.

Village-level varying intercepts and variation in food insecurity

Village-level effects from model m1 adjust for variation in baseline food insecurity (apart from that explained by varying wildlife management area and household fixed effects) between villages. There is no apparent pattern in village-level effects when comparing wildlife management area and control villages (Fig. S2); we understand this to imply that variation attributable to wildlife management area-specific factors has been captured adequately by the wildlife management area effects of model m1. Food insecurity in control villages covers the sample range, and several control villages are noticeably food insecure, suggesting that our control sample is sufficiently variable. However, village-level effects are relatively small compared to the wildlife management area-level varying intercepts (the adjustments specific to unique wildlife management areas; Fig. 2) and household-level fixed effects (e.g. human–wildlife conflict, productive livelihood assets), and therefore villages appear to be less important sources of variation in food insecurity than household and wildlife management area-specific factors.

Missing data

Of the original dataset of 2,571 household surveys (Supplementary Material 1) 70 households were omitted because food insecurity, our outcome variable, was missing; two additional households were omitted because many of the other key variables were missing. The dataset for model fitting thus comprised 2,499 households. The productive livelihood asset variable cultivated acres was missing in 111 of these 2,499 household records, although there was no apparent pattern that indicated systematic omission. We therefore assumed an ignorable missing-data mechanism (Little & Rubin, 2002, Chapter 10) and included stochastic imputation of cultivated acres as part of Markov chain Monte Carlo estimation of m1–m4. Observed values of cultivated acres vary continuously and are necessarily greater than or equal to zero (with many zeros in the sample), so cultivated acres can be treated as a limited dependent variable (Tobin, 1958). We therefore used a Tobit regression model (with village and wildlife management area-level varying intercepts and the same household-level predictors and controls included in the main models) to impute missing values of cultivated acres at each Markov chain Monte Carlo iteration (Plummer, 2011). We then carried these imputed values forward in m1–m4. We understand the resulting estimates in m1–m4 for focal predictors (such as wildlife management area status and livestock loss) to be averaged over the possible values of cultivated acres in cases where this variable was missing.

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