Socioecological determinants of dog ownership in Mara region, Tanzania

Abstract

Understanding domestic dog population dynamics is critical for rabies control, particularly in sub-Saharan Africa where domestic dogs are the primary virus reservoir. This study investigates demographic and environmental determinants of dog ownership in Tanzania's Mara region, a rabies-endemic area with ecologically diverse landscapes. Using a cross-sectional household survey (n = 27,400 households), we employed mixed-effects models to assess predictors of dog ownership, dog counts, and Human-to-Dog Ratios (HDRs).

Overall, 12,975 households (47%) owned dogs, with a mean of 2.2 dogs per dog-owning household. Logistic regression revealed key predictors of ownership: urban households had reduced odds of dog ownership (OR = 0.311, CI: 0.132-0.734, while ownership likelihood increased with larger household size (adults: OR = 1.151, CI: 1.134-1.169; children: OR = 1.160, CI: 1.140-1.180), and crop (OR = 1.502, 95% CI: 1.384-1.630), shrub (OR = 1.387, 95% CI: 1.269-1.515), or tree land cover (OR = 1.708, 95% CI: 1.260-2.314) compared to built areas. However, among dog-owning households, variables had minimal practical impact on dog counts with most households (85.6%) owning 1–3 dogs regardless of household size, location, or land cover. Urban districts exhibited significantly higher HDRs (18.3:1 vs. rural 7.1:1), further influenced by land cover (tree: 5.1:1 vs. built: 8.7:1).

These findings highlight a critical divergence: while contextual factors strongly predict dog ownership, they do not meaningfully influence the number of dogs owned. Consequently, effective vaccination programmes require strategies tailored to local dog density and ownership patterns.

Key Words

Dog demographics, Household survey, Human-animal interface, Rabies control, Spatial epidemiology, Zoonosis

Introduction

Rabies, a deadly zoonotic disease transmitted through the bites of infected animals, claims approximately 59,000 human lives annually, with over 95% of cases occurring in Africa and Asia (Hampson et al., 2015). Domestic dogs are responsible for over 99% of human rabies exposures, serving as the primary reservoir for the virus in rabies-endemic regions (Cleaveland, 1998; Cleaveland et al., 2006; Lembo et al., 2008). To eliminate dog-mediated human rabies by 2030, the World Health Organization (WHO), the World Organisation for Animal Health (WOAH), and the Food and Agriculture Organization of the United Nations (FAO) advocate for mass dog vaccination as the cornerstone strategy (FAO, 2025; WHO, 2018; WOAH, 2025). While dog vaccination is effective in reducing transmission, its successful implementation hinges on achieving high and uniform vaccination coverage (Cleaveland et al., 2006; Ferguson et al., 2025, 2015; Townsend et al., 2013). Higher and more geographically even vaccination coverage reduces transmission bottlenecks and increases the likelihood of sustained herd immunity (Fine, 1993), both important for rabies elimination. This in turn requires accurate dog population data enabling the calculation of vaccine requirements, identification of high-risk transmission zones, and adaptation of vaccination delivery strategies to local ownership practices and veterinary practices, all of which are critical for achieving the desired vaccination coverage. These data include ownership patterns, spatial distribution of households, and human-to-dog ratios (HDR), which remain poorly characterised in many rabies endemic regions within sub-Saharan Africa (Bouli et al., 2020; Fitzpatrick et al., 2012; Lembo et al., 2008; Sambo et al., 2018).

Despite being 100% preventable, rabies persists as a serious public health threat in East Africa, disproportionately affecting rural communities with limited access to human rabies post-exposure prophylaxis (Hampson et al., 2015, 2008; Knobel et al., 2005; Sambo et al., 2013). Dog vaccination has not yet been implemented at scale in most of sub-Saharan Africa, and where dog vaccination has been undertaken incomplete population data leads to vaccination coverage gaps (Butler and Bingham, 2000; Conan et al., 2015; Gibson et al., 2015; Gsell et al., 2012; Mancy et al., 2022; Monroe et al., 2021; Moran et al., 2022). These challenges are exacerbated in ecologically diverse regions like the Mara region in northern Tanzania, which comprises a mosaic of croplands, shrublands, and rapidly growing towns. This region exemplifies the complex interplay of ecological and socioeconomic drivers of dog ownership. Localised data on how household demographics and land use interact to shape dog populations will help planned vaccination campaigns avoid misjudging vaccination targets, which could fuel perceptions about the ineffectiveness of dog vaccination.

Current gaps in knowledge regarding the size and distribution of dog populations in rabies endemic settings such as East Africa limit the precision of rabies control strategies. While prior work has linked dog ownership to household size or socio-economic status, few studies have integrated environmental variables like land cover or examined how these factors influence dog ownership (Gsell et al., 2012; Knobel et al., 2008; Moran et al., 2022; Perry, 1993; Wallace et al., 2017). Furthermore, Human-to-Dog Ratios (HDRs) are often extrapolated from coarse population data aggregated to administrative boundaries rather than being derived from ecological or livelihood measures (Moran et al., 2022; Sambo et al., 2018, 2017; Sudarshan et al., 2001; Voupawoe et al., 2022). This oversight is problematic in regions undergoing rapid land use change, where shifting agricultural practices or urban expansion may affect the distribution of dog populations with equal rapidity, rendering previous estimates inaccurate.

This study investigates demographic, spatial, and environmental determinants of dog ownership and population size in the Mara region of Tanzania. Using household survey data, we analyse how household composition (including size and age structure), land cover, and urban-rural classification predict both the likelihood of owning dogs and the number of dogs per household. We further examine how household size itself varies across land cover types and urban-rural settings, reflecting underlying socioeconomic patterns. To contextualise these findings, we also assess HDRs at different administrative levels (ward and district), comparing urban versus rural areas and distinct land cover categories (e.g., croplands, shrublands) using negative binomial regression models. By integrating these predictors, this work advances frameworks for granular dog population estimation to inform mass dog vaccination for effective rabies control.

Methods

Study area

This study was conducted in the Mara Region, located in northern Tanzania identified in **Figure 1A**. Mara is one of the country's 31 administrative regions, covering approximately 30,150 square kilometres, of which about 10,942 square kilometres (36%) consists of water bodies, primarily Lake Victoria. According to the 2022 Human Population and Housing Census, the region has a human population of 2,372,015 (Tanzania National Bureau of Statistics and President's Office, 2024). The regional capital is Musoma Municipality.

Mara borders Kenya and Uganda to the north, Arusha Region to the southeast, Simiyu Region to the south, and Mwanza Region to the southwest. The region is known for its rich biodiversity and forms part of the Serengeti ecosystem, which includes Serengeti National Park, a globally recognised conservation area.

Administratively, Mara Region is divided into nine Local Government Authorities (LGAs): Musoma Municipal Council, Bunda Town Council, Tarime Town Council, Bunda District Council, Butiama District Council, Musoma District Council, Rorya District Council, Serengeti District Council, and Tarime District Council. Of these, Musoma Municipal is considered urban, while the others are rural. In this paper, the term "district" is used throughout this study to refer to councils. Rural districts are divided into wards, then wards are divided into villages, and villages are further divided into sub-villages (vitongoji), whereas urban districts are divided into wards and then into streets, which serve as the smallest administrative units. In this paper, the term "village" is also used to also represent "street" in urban areas. A map of the Mara region's wards coloured by the urban/rural split is shown in **Figure 1B**.

Agriculture, forestry, and fishing account for 72.2% of employment in the Mara region; other important economic activities include mining, tourism, and other professional activities that include trade, teaching, healthcare provision, and public service (Tanzania National Bureau of Statistics and President's Office, 2024).

Household survey and sampling procedures

Data was collected across the Mara region, through a cross-sectional survey conducted in November 2022. 104 of the Mara region wards were selected for the study, aligning with those chosen for an ongoing randomised controlled trial (RCT) of mass vaccination delivery strategies (ISRCTN registration number: 14813279). Within each ward the central-most village was then selected as the study village for the ward such that each study village was not in direct contact with another study village to avoid contamination within the RCT.

The household survey was carried out by sub-village leaders (or street leaders in urban areas) within the study districts. Each of the study sub-villages was assigned one enumerator who was familiar with the households and geographical boundaries of their respective sub-villages (or blocks/neighbourhoods in urban areas). Enumerators systematically visited each household in the sub-village and recorded demographic data on both humans and dogs. Data collection was conducted using the Open Data Kit platform (ODK, 2022). Prior to data collection, enumerators received training on the use of the data collection tool and on the standard operating procedures for conducting the survey. In each household, after obtaining verbal consent from the respondent, a questionnaire was administered to the household head or another family member over the age of 18 (Supplemental Table 1). Data was collected on the total number of people living in the household, specifying adults i.e., above 18 years of age, and children, as well as the total number of dogs owned (specifying adult dogs and puppies below 3 months) and the geo-location (latitude, longitude) and altitude of each visited household were recorded.

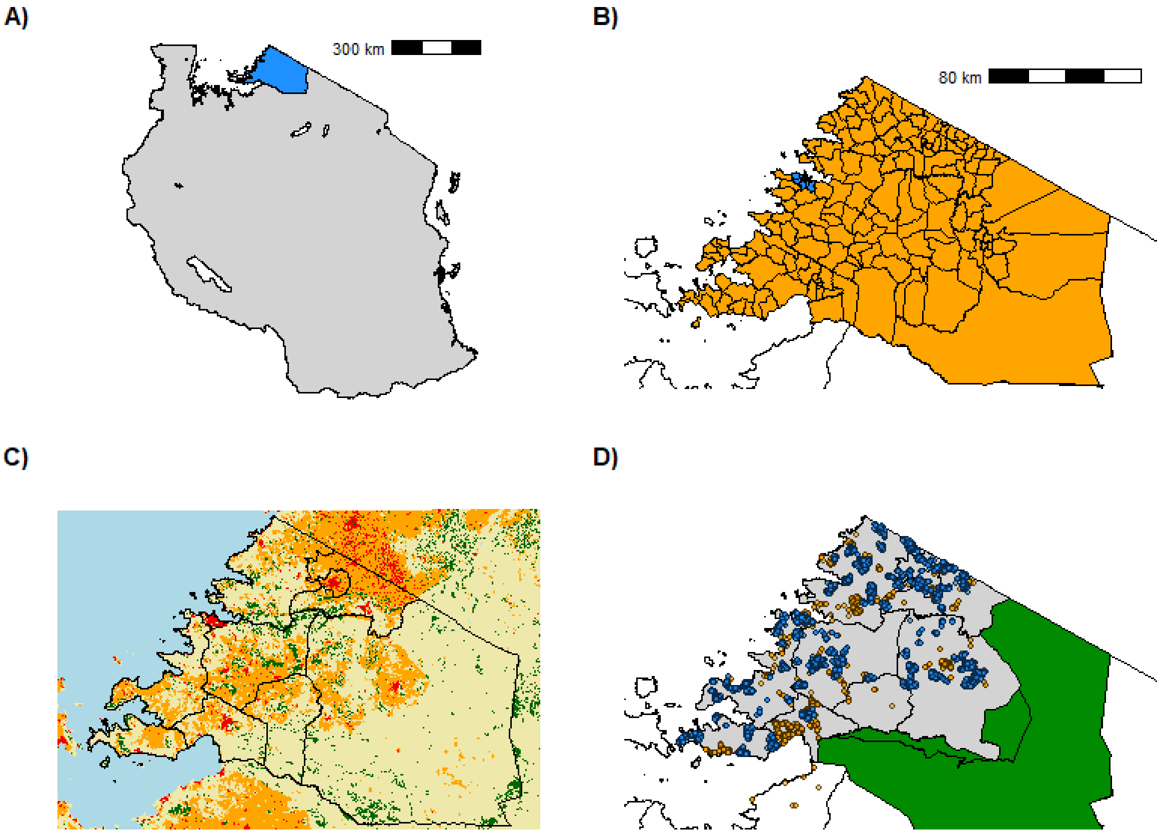

Figure 1. Spatial context and survey coverage of the Mara region, Tanzania. (A) Map of Tanzania with the Mara region highlighted in blue. **(B)** Administrative wards of the Mara region: rural wards (orange) and urban wards in the Musoma Municipal Council (blue). **(C)** Land cover, with district boundaries within the Mara region in black: shrubs (yellow), crops (orange), built (red), trees (green), water (blue). **(D)** Surveyed household distribution: retained households (blue circles), households excluded during data cleaning (orange circles), and protected areas/national parks (green).

Data cleaning of the household survey

Data cleaning was carried out prior to analysis to remove irregularities identified in the data. Both the data cleaning process and the later data analysis was carried out using R version 4.5.1 (R Core Team, 2025), and a link to a GitHub repository with these processes can be found in the supplemental information. A flowchart of the data cleaning process is provided in **Figure 2**.

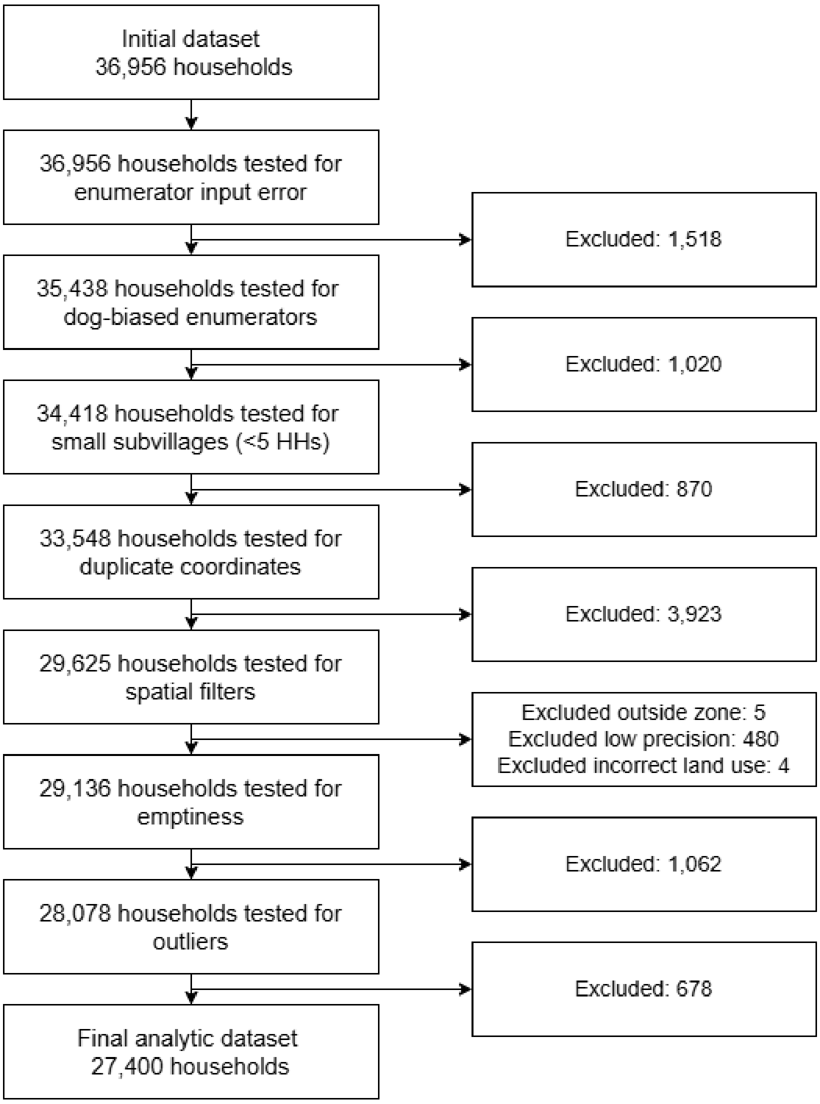

Figure 2. Data Cleaning Flowchart. Flowchart illustrating the sequential exclusion of households during data cleaning for a household survey in the Mara Region, Tanzania. The main vertical flow shows the number of households at the beginning of each step, while rightward branches indicate

excluded households. From the initial 36,956 households, 27,400 (74.1%) were retained for final analysis.

1,518 records associated with enumerators who recorded fewer than 10 households were excluded to mitigate inconsistencies arising from data entry errors (e.g., misspelled names fragmenting enumerator identities) and to ensure sufficient sample sizes per enumerator for reliable analysis. Additionally, 1,020 records associated with any enumerator name that only reported records from households that owned dogs were also removed as enumerators had mistakenly not also collected data from non-dog owning households (dog-biased enumerators, Figure 2), which would artificially inflate ownership rates. One survey question, intended to capture the total number of dogs owned by a household (adults and puppies) was misunderstood by some enumerators who mistakenly recorded only the number of adult dogs. For household records where the reported number of puppies exceeded the total number of dogs owned, we assumed that the enumerator had included only adult dogs in their assessment of the total number of dogs owned by a household. We also assumed that the enumerator had made this mistake for all other households that they collected data from. For the affected records, the total number of dogs owned by a household was used to represent the number of adult dogs, and the total number of dogs was calculated as the sum of this variable and the total number of puppies. 870, households belonging to a subvillage with less than five recorded households were also removed as these are unlikely to be representative of that area.

To align household locations with land cover data, GPS coordinates were first cleaned to address inaccuracies. A total of 3,923 households sharing identical coordinates (likely due to GPS signal errors or device limitations) were excluded to avoid spatial clustering artifacts.

Remaining households were then mapped to a Sentinel-2 land cover (Sentinel Hub, 2022) classification (Figure 1C) comprising five categories: built (areas dominated by closely spaced buildings), shrublands (low-lying woody vegetation), croplands (actively cultivated agricultural areas), trees (dense tree coverage), and water (natural or artificial water bodies). To ensure spatial reliability, 480 households with low-precision GPS recordings (>50 metres, as measured by the mobile survey application) and five households with coordinates outside the study area were removed. During data cleaning, four households were found to be erroneously geolocated within water bodies and were therefore excluded from the analysis as they were considered to be GPS errors.

During data cleaning, 1,062 households were excluded for being unoccupied (containing no adults or children). Additionally, it was noted that some households were atypical residences, such as schools or community centres, leading to abnormally high counts of people and dogs, while others exhibited extreme values, possibly resulting from data entry errors. To address these anomalies, z-scores were calculated for each variable (adults, children, dogs, puppies), and values exceeding three standard deviations from the mean were classified as outliers. A total of 678 households were removed through this process. Crucially, zero values (e.g., households without dogs or children) were excluded from z-score calculations to prevent skewing thresholds for non-zero entries. A map of all the surveyed households coloured by inclusion or exclusion is shown in **Figure 1D**.

Analysis of Household Composition and Dog Ownership

To assess variation in household size across ecological and administrative contexts, household composition (total humans, adults, and children under 18) was analysed using mixed-effects negative binomial regression with village as a random intercept to account for clustering effects. Predictor variables included land cover type (built, crops, shrubs, trees) and urban-rural classification. Model selection was performed using the dredge function in the *MuMIn* package to identify the best-fitting model through automated comparison of all possible subsets, with selection based on the lowest Akaike Information Criterion (AIC). Multicollinearity was assessed via variance inflation factors (VIF) from the car package, with all VIF values below 2.0, well under the conservative threshold of 5, indicating no problematic multicollinearity. We further examined bivariate relationships between predictors, finding expected associations that did not affect model stability (Supplemental Table 2a/2b).

Two mixed-effects regression models were developed to analyse dog populations. For dog ownership, a mixed-effects logistic regression model with village random intercepts was used, with dog ownership as the binary outcome variable. For the number of dogs owned, a mixed-effects negative binomial regression model with village random intercepts accounted for overdispersion in the count data. This analysis was restricted to households with at least one dog. Both models included the number of adults and children under 18 years in the household, land cover type, and urban-rural classification as predictor variables, and followed the same automated model selection procedure using dredge and multicollinearity assessment via VIF as described above. Model performance was evaluated using Nakagawa's marginal R^2 (variance explained by fixed effects) and conditional R^2 (fixed + random effects).

HDRs were analysed at multiple ecological scales using a hierarchical approach. The fundamental HDR for any given area (e.g., a village, district, or land cover class) was calculated as the total number of people (including children) from all surveyed households divided by the total number of dogs and puppies from those same households. Overall HDRs with 95% confidence intervals were calculated for urban-rural classifications and land cover types using village bootstrapping (10,000 iterations) to account for sampling variability. This method involved resampling villages with replacement within each category and recalculating the total human-to-dog ratio for each bootstrap sample, thereby generating a distribution of possible HDRs from which confidence intervals were derived. Village medians and interquartile ranges (IQR) were derived from village-aggregated HDRs after filtering villages with no recorded dogs to avoid infinite HDRs. Mixed-effects negative binomial regression models with village random intercepts assessed statistical differences between categories, with incidence rate ratios (IRR) and 95% Wald confidence intervals estimated for fixed effects. Model performance was evaluated using Nakagawa's marginal and conditional R^2.

District and regional dog populations were estimated by applying the survey-derived HDRs to 2022 National Census human population data (Tanzania National Bureau of Statistics and President's Office, 2024). For each district, the HDR was calculated from all surveyed households within its boundaries. District-specific HDRs were calculated from all surveyed households within the district, with 95% confidence intervals generated through village bootstrapping (10,000 iterations) for districts with less than three sampled villages. For districts with insufficient sampled villages (Bunda DC; n = 2), point estimates are reported without CIs due to limited sampling precision. The regional HDR was derived from all surveyed households across the Mara Region. Final dog population estimates and their confidence intervals were calculated by dividing the human population by the bootstrapped HDR distribution, with the upper HDR confidence bound yielding the lower bound for the dog population and vice versa, thereby propagating the uncertainty from the HDR estimate.

Ethical approval

This research was approved by the Ifakara Health Institute Review Board (IHI/IRB/No. 16-2021), and Tanzania's National Institute for Medical Research (NIMR/HQ/R.8a/Vol.IX/3701).

Results

A total of 36,956 households were surveyed from a total of 104 villages. The process of data cleaning removed 9,556 households (25.8%), leaving 27,400 households remaining (Supplemental Table 3, Figure 1D). These households were distributed across land cover types as follows: 13,857 (50.6%) in built areas, 7,288 (26.6%) in shrub areas, 6,028 (22%) in crop areas, and 227 (0.8%) in tree areas. From these households, 124,635 adults were recorded, as well as 84,838 children, totalling 209,473 people. Correspondingly, a total of 27,919 dogs were recorded in these households (22,049 adults and 5,870 puppies).

Household size

The median household size was 7 people (IQR: 5-10), with a median of 4 adults (IQR: 2-6) and 3 children (IQR: 2-4) per household. The distribution of people per household is shown in **Figure 3A**.

Using a multivariable mixed-effects model with village random effects to account for clustering, neither land cover nor urban-rural classification significantly predicted household size while village accounted for 19% of household size variance (Supplemental Table 4). Urban households showed negligible size differences compared to rural households (IRR = 1.001, 95% CI: 0.861-1.164, p = 0.990). Similarly, crop-dominated areas exhibited no significant difference from built areas (IRR = 0.999, 95% CI: 0.982-1.016, p = 0.899), nor did tree-dominated areas (IRR = 0.962, 95% CI: 0.900-1.028, p = 0.249). Households in shrub-dominated areas showed a marginal increase, though this did not reach statistical significance (IRR = 1.016, 95% CI: 0.997-1.035, p = 0.098).

Dog Ownership

Of the 27,400 households surveyed, 12,975 (47%) households reported owning dogs. Dog-owning households owned a median of 2 dogs (IQR: 1-3). Of the 27,400 households surveyed, 3,195 (12%) of these households owned puppies. Puppy owning households had a median of 1 puppies per household (IQR: 1-2). The distribution of dogs per household is shown in **Figure 3B**.

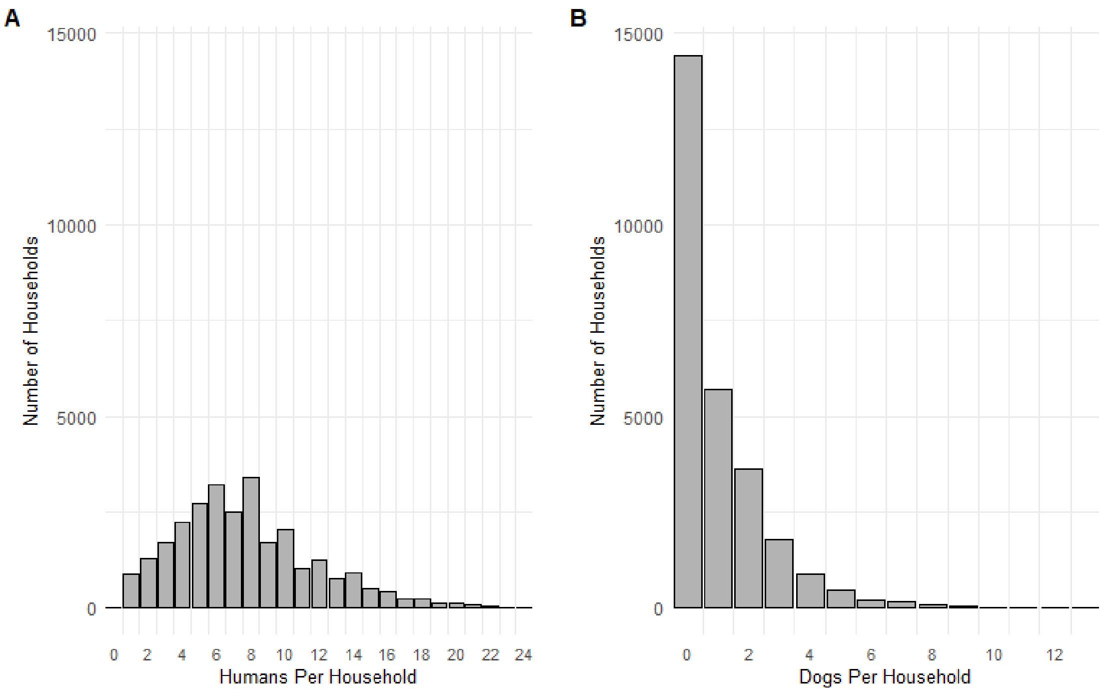

Figure 3. Distribution of household occupants and dog ownership in the Mara region, Tanzania. (A) Histogram of the number of people per household. Household sizes ranged from 1 to 23, with a median of 7 people per household. **(B)** Histogram of dogs per household. Dog ownership ranged from 0 to 1 3 dogs, with 14,425 households (53%) reporting no dogs. Data is based on 27,400 households surveyed (see Figures 1 & 2).

The multivariable mixed-effects logistic regression analysis identified several significant predictors of dog ownership (Supplemental Table 5). Households with more adults were more likely to own dogs, with each additional adult increasing the odds of dog ownership by approximately 15% (OR = 1.151, 95% CI: 1.134-1.169, $p < 0.001$). Similarly, the number of children under 18 years of age increased the likelihood of dog ownership, with each additional child raising the odds by approximately 16% (OR = 1.160, 95% CI: 1.140-1.180, $p < 0.001$).

Land cover was significantly associated with differences in dog ownership. Households located in areas dominated by crops had approximately 50% higher odds of owning dogs compared to those in built areas, i.e. the reference category (OR = 1.502, 95% CI: 1.384-1.630, $p < 0.001$). Similarly, households in areas characterised by shrub-dominated land had approximately 39% higher odds of owning dogs (OR = 1.387, 95% CI: 1.269-1.515, $p < 0.001$), while those in tree-dominated areas were approximately 71% more likely to own dogs compared to households in built areas (OR = 1.708, 95% CI: 1.260-2.314, $p < 0.001$). Households in the one urban district, Musoma Municipal were substantially less likely to own dogs compared to households in the other rural districts of the Mara region (OR = 0.311, 95% CI: 0.132-0.734, $p = 0.008$). **Figure 4** provides a summary of factors that influenced the number of dogs owned by dog-owning households. Model diagnostics confirmed no evidence of multicollinearity among the variables, with all variance inflation factors (VIFs) below 5. Model dredging to identify the most parsimonious model resulted in the same significant predictors as the initial analysis. The final model had a conditional R^2 of 0.402 and a marginal R^2 of 0.098.

Dog-owning households with more adult people were slightly more likely to own more dogs, with each additional adult increasing the expected number of dogs by 4% (IRR = 1.035, 95% CI: 1.029–1.041, $p < 0.001$). Similarly, households with more children under 18 years of age were also associated with an increase in the number of dogs owned, with each additional child raising the expected number of owned dogs by approximately 4% (IRR = 1.035, 95% CI: 1.027–1.042, p < 0.001). Dog-owning households in areas with crop land cover owned a mean of 2.2 dogs (SD = 1.48), which was significantly higher than the mean number of 2.1 dogs (SD=1.59) owned by households in areas with built land cover (IRR = 1.067, 95% CI: 1.031-1.103, p < 0.001). The households in shrub areas also owned a mean of 2.2 dogs (SD = 1.43) however this was not significantly different from the households in built areas (IRR = 1.031, 95% CI: 0.994-1.070, p = 0.097). Households from areas with tree land cover had a mean of 2.3 dogs (SD = 1.60) and this was significantly different from those from built areas (IRR = 1.127, 95% CI: 1.009-1.261, p = 0.035). Urban-rural classification was excluded from the best fitting model due to a lack of statistical significance (Supplemental Table 6a/6b). A summary of these factors influencing the number of dogs owned by dog-owning households are shown in **Figure 4**. Model diagnostics confirmed no evidence of multicollinearity among the variables, with all variance inflation factors (VIFs) below 5. The final model had a conditional R^2 of 0.147 and a marginal R^2 of 0.044.

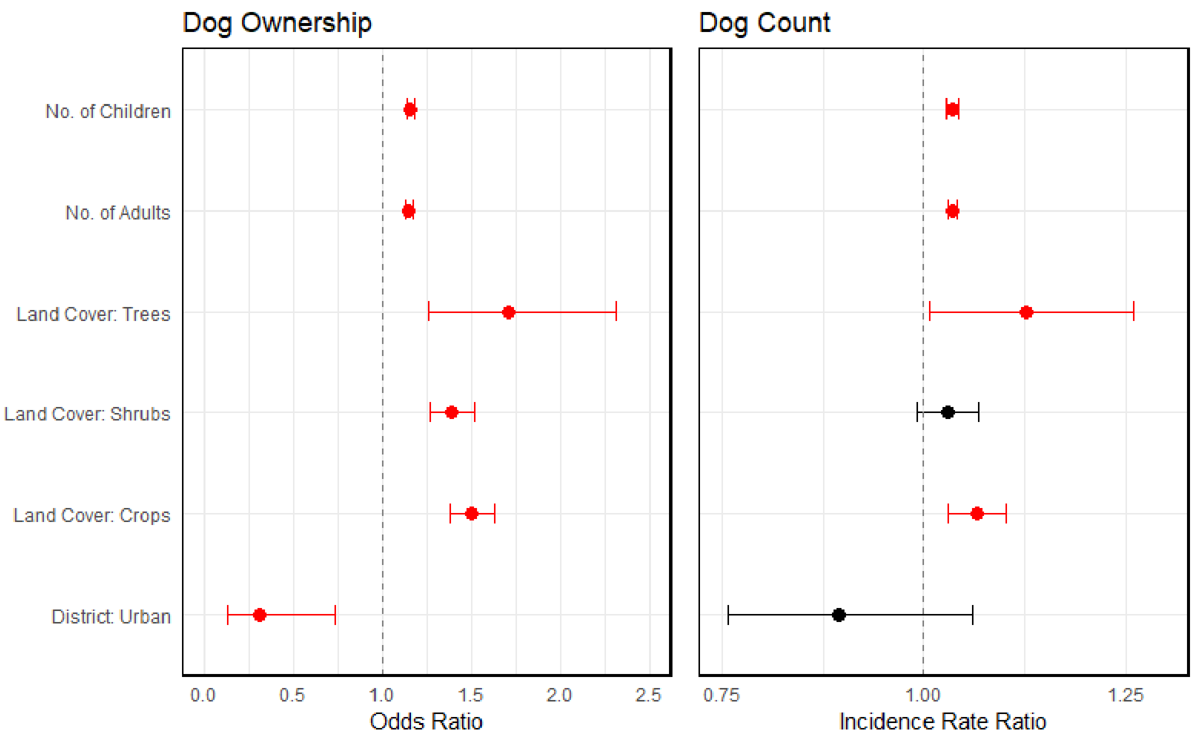

Figure 4. Forest Plots of Predictor Effects on Dog Ownership Outcomes. Effect sizes are shown as odds ratios (Dog Ownership model) and incidence rate ratios (Dog Count model) with 95% confidence intervals. Red markers indicate statistically significant effects (confidence intervals do not include 1, Wald Test). Predictors include the number of adults and children under 18 in the household, land cover classifications (crop, shrub, and tree) relative to the reference (built), and urban households relative to the reference (rural households). Dashed vertical line represents no effect (ratio = 1). Household counts were restricted to dog-owning households in the Dog Count model.

Human-Dog Ratios

With a total human population of 209,473 and a total dog population of 27,919, the region is estimated to have an overall HDR of 7.5 humans per dog. Analysis of village-level data revealed that rural areas showed a median HDR of 6.7 (IQR: 4.8-11.2) versus urban areas (20.9; IQR: 8.7-34.6). Mixed-effects modelling confirmed significantly higher Human-to-Dog

Ratios (HDRs) in urban settings (IRR = 2.49, 95% CI: 1.600-3.860, $p < 0.001$, **Figure 5A**) (Supplemental Table 7). This model had a conditional R^2 of 0.831 and a marginal R^2 of 0.151.

Land cover analysis of village-level data showed parallel patterns: built areas (median: 7.5, IQR: 5.1-14.9), shrubs (median: 6.4, IQR: 4.2-9.4), crops (median: 6.5, IQR: 4.2-9.3), and trees (median: 3.6, IQR: 2.4-7.3). All land cover types differed significantly from built areas ($p < 0.001$, **Figure 5B**) (Supplemental Table 8). This model had a conditional R^2 of 0.703 and a marginal R^2 of 0.064.

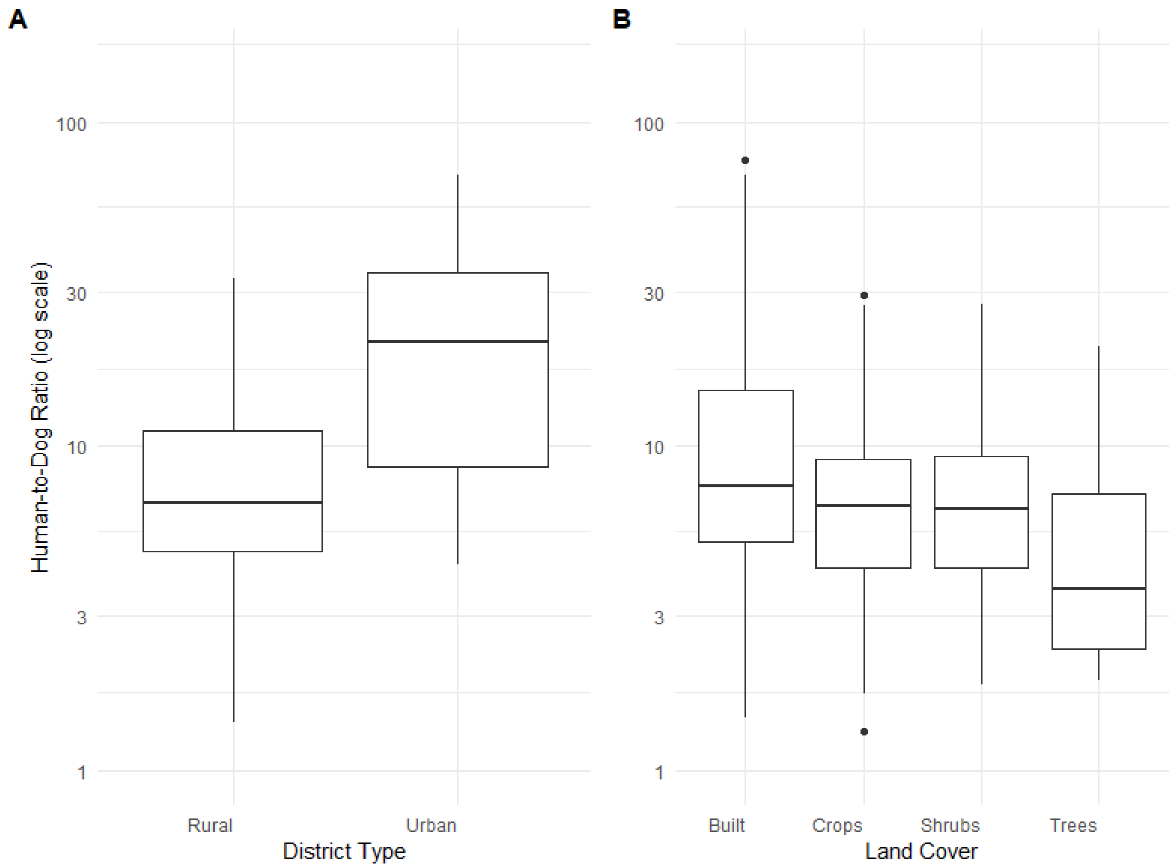

Figure 5. Predictors of the Number of Dogs Owned by Dog-Owning Households. (A) Distribution of village HDRs in urban versus rural districts. Rural districts had significantly lower HDRs (median HDR = 6.7) than urban districts (median HDR = 20.9). **(B)** Distribution of village HDRs across land cover types. Built areas show the highest HDRs (median = 7.5), followed by crop (median = 6.5), shrub (median =

6.4), and tree areas (median = 3.6). Each box represents the interquartile range (IQR), with the central line indicating the median village HDR. Y-axes are log-transformed to normalise skewed distributions.

Estimating the Mara region dog population

District-level dog population estimates revealed substantial heterogeneity across the Mara Region (Supplemental Table 9). Tarime DC had the highest estimated dog population (53,637; 95% CI: 51,673-55,591 dogs), while Musoma MC had the lowest (8,948; 95% CI: 8,103- 9,826 dogs). Summing district estimates yielded a regional total of 345,565 dogs, while extrapolation using the overall regional human-to-dog ratio (7.5; 95% CI: 7.4–7.6) gave 316,147 dogs (95% CI: 310,807–321,587), representing a difference of 29,418 dogs (8.5%) between the two estimation methods.

Discussion

Across the Mara region in northwest Tanzania, we found high levels of dog ownership with 47% of households owning dogs with a mean of 2.2 dogs per dog-owning household. More specifically, we identified household composition, land cover, and urban-rural classification as significant predictors of dog ownership in the Mara region. The odds of owning at least one dog were strongly associated with rural households and crop/tree-dominated land cover, while urban households had lower odds of dog ownership. Among dog-owning households, the number of dogs owned showed minimal variation across predictors, with relatively small effect sizes even for statistically significant factors. District-level HDRs revealed stark disparities (Tarime TC: 2.6:1 - Musoma Municipal: 18.3:1), informing two regional dog population estimates: 316,147 dogs using the overall regional HDR, and 345,565 dogs from summing district-level estimates.

The association between dog ownership and rural/agricultural settings reflects dogs' functional roles in agrarian livelihoods, specifically with dogs serving as guardians against wildlife predation of crops and livestock, a pattern documented across sub-Saharan Africa (Butler and Bingham, 2000; Czupryna et al., 2016; Knobel et al., 2008; Murungi et al., 2025; Sambo et al., 2018). Land cover reinforced this relationship, with elevated dog ownership in crop- and shrub-dominated areas where subsistence crops and livestock production prevail, while urban households had lower rates (OR = 0.31), possibly resulting from diminished agricultural utility and reduced household space. Notably, households in tree-dominated landscapes had the strongest association with dog ownership, but we acknowledge the limited sample size (0.8% of households) and so caution against overinterpretation. Future studies could target households in tree-dominated areas for more thorough investigation. Additionally, while these variables showed statistical associations, the model's low explanatory power (marginal R^2 = 0.098) indicates these variables alone cannot fully explain dog ownership patterns and unmeasured variables like cultural or religious preferences or economic constraints likely further contribute.

These ownership patterns directly shape Human-to-Dog Ratios (HDRs), manifesting in stark rural-urban disparities (mean: 7.1 vs 18.3). This aligns with broader African studies (Cleaveland et al., 2014; Sambo et al., 2018) and confirms that dogs are most common in agricultural zones where their protective functions are valued. While land cover (marginal R^2 = 0.064) and urban-rural classification (marginal R^2 = 0.151) were significant predictors, their modest explanatory power indicates livelihood practices alone cannot fully account for HDR variation. Nevertheless, these patterns have operational significance and vaccination campaigns could use this for prioritising areas where both dog ownership and rabies transmission risks peak.

While household composition variables were statistically significant predictors of numbers of dogs owned, their practical relevance is limited. For instance, each additional household resident only increased the expected dog count by 4%. These marginal increases suggest that, even in households with large families, the difference in dog numbers is negligible: a household with 10 residents would own approximately 1.4 dogs on average, compared to 1 dog in a household with 1 resident, a difference unlikely to translate to meaningful variation in rabies transmission risk or resource demands. Similarly, the land cover disparity in dogs owned per dog-owning household, though statistically significant, reflects only a modest difference. These findings imply that dog counts are largely decoupled from household demographics or land cover once ownership is established. The trend of 1–3 dogs per household, regardless of household size, was consistent with similar studies (Durr et al., 2009; Kitala et al., 2001; Murungi et al., 2025). This typical pattern of owned dogs may also reflect unmeasured variables such as economic capacity, dog utility (e.g., guarding, herding), or owner preferences. Future studies should incorporate qualitative methods to explore these latent drivers, as quantitative predictors alone are insufficient to explain these patterns of dog ownership.

Dog population estimates are critical for vaccination campaign logistics, informing vaccine procurement, resource allocation, and coverage assessment. Our study yielded two regional estimates: 345,565 dogs (district-aggregated) and 316,147 dogs (regional HDR-derived), a difference of 29,418 dogs (8.5%). This discrepancy reflects the methodological differences between the approaches; the district-summed estimate is sensitive to local HDR variation, while the regional estimate, using the survey-wide ratio, benefits from greater precision due to compensatory effects across districts. The notably small magnitude of this difference, despite these distinct methods, provides confidence in the robustness of the overall estimate. Both values provide actionable baselines, though their precision depends on representative sampling across ecological gradients. As land cover significantly influences ownership patterns, uneven sampling across these strata could bias HDRs, possibly affecting their accuracy. While valuable for regional planning, these estimates should not be extrapolated nationally as Tanzania's diverse cultural and ecological landscapes likely yield different human-dog dynamics than those in the Mara.

While this study provides critical insights into dog ownership patterns, several conceptual and contextual limitations warrant consideration. The analysis focused on household-level predictors but did not capture individual-level factors such as religious practices, cultural beliefs, income disparities, or owner perceptions of dogs as economic assets versus companions, all of which have been shown to impact attitudes towards dog ownership (Cleaveland et al., 2014; Conan et al., 2015; Knobel et al., 2008; Sambo et al., 2024, 2018). In the predominantly Christian Mara region (Tanzania National Bureau of Statistics and President’s Office, 2024), Islamic views of dogs as impure likely have limited impact, but religion remains an important consideration for broader Tanzanian studies. These unmeasured variables may explain residual variation in ownership rates, particularly in urbanising areas where shifting livelihoods could redefine human-dog relationships. Accounting for these variables in subsequent research would enhance predictive models for rabies vaccination planning.

The study's cross-sectional design precludes causal inference; longitudinal data are needed to assess how land use changes (e.g., urban expansion, deforestation, or shrubland being converted to cropland) dynamically influence dog populations over time. Geographic and temporal generalisability is also uncertain. Furthermore, the timing of the survey may introduce some temporal bias. While domestic dogs in sub-Saharan Africa generally lack a discrete breeding season (Gsell et al., 2012; Mutembei et al., 2002), their reproductive success can be influenced by seasonal resource availability (Ortega-Pacheco et al., 2007; Conan et al., 2015). As data collection occurred in November, immediately following the main dry season, the observed population may reflect seasonal fluctuations; however, due to the short study timeframe, we cannot determine the significance of this potential effect.

This study by design focuses on owned dogs as it was carried out in tandem with a rabies vaccination campaign focussing on owned dogs. Evidence suggests that unowned dogs are negligible within the Mara region (Kaare et al., 2009; Maganga et al., 2018) and neighbouring districts (Czupryna et al., 2016). However, as urbanisation accelerates, this assumption may require re-evaluation, as urban and peri-urban areas could develop transient dog populations. In other regions with different cultural contexts or less established vaccination programs, unowned dogs may represent a more substantial proportion of the dog population.

Methodological limitations emerged during data cleaning, primarily stemming from enumerator inconsistencies and technical challenges. A small number of enumerators demonstrated sampling bias by preferentially visiting dog-owning households, potentially inflating ownership rates in initial records. Similarly, misunderstanding of the questions regarding household dog ownership by some enumerators led to miscounted totals, while inconsistent enumerator name entries complicated quality control across survey days.

Additionally, GPS inaccuracies resulted in misaligned household coordinates, disproportionately affecting densely populated areas. These errors were spatially clustered, with certain wards exhibiting higher exclusion rates due to enumerator teams working in localised zones. Consequently, some high-error areas are underrepresented in the final analysis. Future studies could mitigate these issues through standardised enumerator identifiers for longitudinal tracking, real-time GPS validation tools to flag low-precision entries, and more comprehensive training of enumerators. Despite these limitations, the large sample size and robustness checks across ecological zones support the validity of our findings, which generally align with broader sub-Saharan African patterns (Butler and Bingham, 2000; Cleaveland et al., 2014; Conan et al., 2015; Knobel et al., 2008; Murungi et al., 2025; Sambo et al., 2024, 2018).

Understanding the spatial and demographic determinants of dog populations is critical for designing effective rabies vaccination programmes. This study highlights that dog distribution is not uniform but closely tied to land use and urbanisation. However, land use itself is heterogeneously distributed, and human settlement patterns do not align neatly with land classifications. These findings underscore the need for dynamic, iterative dog population mapping. Static estimates based on coarse administrative boundaries risk misrepresenting localised variation. Integrating land use trends (e.g., deforestation or urban expansion) into predictive models could help anticipate future shifts in dog populations, enabling proactive vaccination planning. Collaborative partnerships with local governments and agricultural extension services would further enhance data granularity, ensuring interventions align with both ecological and sociocultural realities.

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References

Bardosh, K., Sambo, M., Sikana, L., Hampson, K., Welburn, S.C., 2014. Eliminating rabies in Tanzania? Local understandings and responses to mass dog vaccination in Kilombero and Ulanga districts. PLoS Negl Trop Dis 8, e2935. https://doi.org/10.1371/journal.pntd.0002935

Bouli, F.P.N.O., Awah-Ndukum, J., Mingoas, K.J.-P., Tejiokem, M.C., Tchoumboue, J., 2020. Dog demographics and husbandry practices related with rabies in Cameroon. Trop Anim Health Prod 52, 979–987. https://doi.org/10.1007/s11250-019-02085-9

Butler, J.R.A., Bingham, J., 2000. Demography and dog-human relationships of the dog population in Zimbabwean communal lands. Veterinary Record 147, 442–446. https://doi.org/10.1136/vr.147.16.442

Cleaveland, S., 1998. Royal Society of Tropical Medicine and Hygiene meeting at Manson House, London, 20 March 1997. Epidemiology and control of rabies. The growing problem of rabies in Africa. Trans R Soc Trop Med Hyg 92, 131–134. https://doi.org/10.1016/s0035-9203(98)90718-0

Cleaveland, S., Beyer, H., Hampson, K., Haydon, D., Lankester, F., Lembo, T., Meslin, F.-X., Morters, M., Mtema, Z., Sambo, M., Townsend, S., 2014. The changing landscape of rabies epidemiology and control. Onderstepoort J Vet Res 81, ojvr.v81i2.731. https://doi.org/10.4102/ojvr.v81i2.731

Cleaveland, S., Kaare, M., Knobel, D., Laurenson, M.K., 2006. Canine vaccination--providing broader benefits for disease control. Vet Microbiol 117, 43–50. https://doi.org/10.1016/j.vetmic.2006.04.009

Conan, A., Akerele, O., Simpson, G., Reininghaus, B., Rooyen, J. van, Knobel, D., 2015. Population Dynamics of Owned, Free-Roaming Dogs: Implications for Rabies Control. PLOS Neglected Tropical Diseases 9, e0004177. https://doi.org/10.1371/journal.pntd.0004177

Czupryna, A.M., Brown, J.S., Bigambo, M.A., Whelan, C.J., Mehta, S.D., Santymire, R.M., Lankester, F.J., Faust, L.J., 2016. Ecology and Demography of Free-Roaming Domestic Dogs in Rural Villages near Serengeti National Park in Tanzania. PLOS ONE 11, e0167092. https://doi.org/10.1371/journal.pone.0167092

Durr, S., Mindekem, R., Kaninga, Y., Moto, D.D., Meltzer, M.I., Vounatsou, P., Zinsstag, J., 2009. Effectiveness of dog rabies vaccination programmes: comparison of owner-charged and free vaccination campaigns. Epidemiology & Infection 137, 1558–1567. https://doi.org/10.1017/S0950268809002386

Ferguson, E.A., Hampson, K., Cleaveland, S., Consunji, R., Deray, R., Friar, J., Haydon, D.T., Jimenez, J., Pancipane, M., Townsend, S.E., 2015. Heterogeneity in the spread and control of infectious disease: consequences for the elimination of canine rabies. Sci Rep 5, 18232. https://doi.org/10.1038/srep18232

Ferguson, E.A., Lugelo, A., Czupryna, A., Anderson, D., Lankester, F., Sikana, L., Dushoff, J., Hampson, K., 2025. Improved effectiveness of vaccination campaigns against rabies by reducing spatial heterogeneity in coverage. PLOS Biology 23, e3002872. https://doi.org/10.1371/journal.pbio.3002872

Fine, P.E.M., 1993. Herd Immunity: History, Theory, Practice. Epidemiologic Reviews 15, 265–302. https://doi.org/10.1093/oxfordjournals.epirev.a036121

Fitzpatrick, M.C., Hampson, K., Cleaveland, S., Meyers, L.A., Townsend, J.P., Galvani, A.P., 2012. Potential for rabies control through dog vaccination in wildlife-abundant communities of Tanzania. PLoS Negl Trop Dis 6, e1796. https://doi.org/10.1371/journal.pntd.0001796

Food and Agriculture Organization, 2025. One Health approach to rabies [WWW Document]. URL https://www.fao.org/one-health/areas-of-work/rabies/en (accessed 7.16.25).

Gibson, A.D., Ohal, P., Shervell, K., Handel, I.G., Bronsvoort, B.M., Mellanby, R.J., Gamble, L., 2015. Vaccinate-assess-move method of mass canine rabies vaccination utilising mobile technology data collection in Ranchi, India. BMC Infectious Diseases 15, 589. https://doi.org/10.1186/s12879-015-1320-2

Gsell, A.S., Knobel, D.L., Kazwala, R.R., Vounatsou, P., Zinsstag, J., 2012. Domestic dog demographic structure and dynamics relevant to rabies control planning in urban areas in

Africa: the case of Iringa, Tanzania. BMC Vet Res 8, 236. https://doi.org/10.1186/1746-6148-8-236

Hampson, K., Coudeville, L., Lembo, T., Sambo, M., Kieffer, A., Attlan, M., Barrat, J., Blanton, J.D., Briggs, D.J., Cleaveland, S., Costa, P., Freuling, C.M., Hiby, E., Knopf, L., Leanes, F., Meslin, F.-X., Metlin, A., Miranda, M.E., Müller, T., Nel, L.H., Recuenco, S., Rupprecht, C.E., Schumacher, C., Taylor, L., Vigilato, M.A.N., Zinsstag, J., Dushoff, J., Prevention, on behalf of the G.A. for R.C.P. for R., 2015. Estimating the Global Burden of Endemic Canine Rabies. PLOS Neglected Tropical Diseases 9, e0003709. https://doi.org/10.1371/journal.pntd.0003709

Hampson, K., Dobson, A., Kaare, M., Dushoff, J., Magoto, M., Sindoya, E., Cleaveland, S., 2008. Rabies Exposures, Post-Exposure Prophylaxis and Deaths in a Region of Endemic Canine Rabies. PLOS Neglected Tropical Diseases 2, e339. https://doi.org/10.1371/journal.pntd.0000339

Kaare, M., Lembo, T., Hampson, K., Ernest, E., Estes, A., Mentzel, C., Cleaveland, S., 2009. Rabies control in rural Africa: Evaluating strategies for effective domestic dog vaccination. Vaccine 27, 152–160. https://doi.org/10.1016/j.vaccine.2008.09.054

Kaneko, C., Omori, R., Sasaki, M., Kataoka-Nakamura, C., Simulundu, E., Muleya, W., Moonga, L., Ndebe, J., Hang'ombe, B.M., Dautu, G., Qiu, Y., Nakao, R., Kajihara, M., Mori-Kajihara, A., Chambaro, H.M., Higashi, H., Sugimoto, C., Sawa, H., Mweene, A.S., Takada, A., Isoda, N., 2021. Domestic dog demographics and estimates of canine vaccination coverage in a rural area of Zambia for the elimination of rabies. PLoS Negl Trop Dis 15, e0009222. https://doi.org/10.1371/journal.pntd.0009222

Kitala, P., McDermott, J., Kyule, M., Gathuma, J., Perry, B., Wandeler, A., 2001. Dog ecology and demography information to support the planning of rabies control in Machakos District, Kenya. Acta Tropica 78, 217–230. https://doi.org/10.1016/S0001-706X(01)00082-1

Knobel, D.L., Cleaveland, S., Coleman, P.G., Fèvre, E.M., Meltzer, M.I., Miranda, M.E.G., Shaw, A., Zinsstag, J., Meslin, F.-X., 2005. Re-evaluating the burden of rabies in Africa and Asia. Bulletin of the World Health Organization.

Knobel, D.L., Laurenson, M.K., Kazwala, R.R., Boden, L.A., Cleaveland, S., 2008. A cross-sectional study of factors associated with dog ownership in Tanzania. BMC Vet Res 4, 5. https://doi.org/10.1186/1746-6148-4-5

Lembo, T., Hampson, K., Haydon, D.T., Craft, M., Dobson, A., Dushoff, J., Ernest, E., Hoare, R., Kaare, M., Mlengeya, T., Mentzel, C., Cleaveland, S., 2008. Exploring reservoir dynamics: a case study of rabies in the Serengeti ecosystem. J Appl Ecol 45, 1246–1257. https://doi.org/10.1111/j.1365-2664.2008.01468.x

Lembo, T., Hampson, K., Kaare, M.T., Ernest, E., Knobel, D., Kazwala, R.R., Haydon, D.T., Cleaveland, S., 2010. The Feasibility of Canine Rabies Elimination in Africa: Dispelling Doubts with Data. PLoS Negl Trop Dis 4, e626. https://doi.org/10.1371/journal.pntd.0000626

Mancy, R., Rajeev, M., Lugelo, A., Brunker, K., Cleaveland, S., Ferguson, E.A., Hotopp, K., Kazwala, R., Magoto, M., Rysava, K., Haydon, D.T., Hampson, K., 2022. Rabies shows how scale of transmission can enable acute infections to persist at low prevalence. Science 376, 512–516. https://doi.org/10.1126/science.abn0713

Monroe, B., Ludder, F., Dilius, P., Crowdis, K., Lohr, F., Cleaton, J., Gamble, L., Blanton, J., Etheart, M., Pieracci, E.G., Natal Vigilato, M.A., Molina-Flores, B., Millien, M., Gibson, A.D., Wallace, R.M., 2021. Every Dog Has Its Data: Evaluation of a Technology-Aided Canine Rabies Vaccination Campaign to Implement a Microplanning Approach. Front Public Health 9, 757668. https://doi.org/10.3389/fpubh.2021.757668

Moran, D., Alvarez, D., Cadena, L., Cleaton, J., Salyer, S.J., Pieracci, E.G., Camposeco, L.R., Bernal, S., Wallace, R.M., 2022. Heterogeneity in dog population characteristics contributes to chronic under-vaccination against rabies in Guatemala. PLOS Neglected Tropical Diseases 16, e0010522. https://doi.org/10.1371/journal.pntd.0010522

Murungi, M.K., Thomas, L.F., Nicholas Bor, Masaku, I., Anyango, M., Munywoki, P.N., Glazer, C., Muloi, D.M., Fèvre, E.M., 2025. Demography of owned dogs across an East African continuum of high-low human density. Preventive Veterinary Medicine 239, 106518. https://doi.org/10.1016/j.prevetmed.2025.106518

Mutembei, H.M., Mutiga, E.R., Tsuma, V.T., 2002. An epidemiological survey demonstrating decline in reproductive efficiency with age and non-seasonality of reproductive parameters in German shepherd bitches in Kenya. J. S. Afr. Vet. Assoc. 73, 36–37. https://doi.org/10.4102/jsava.v73i1.546

ODK [WWW Document], 2022. URL https://getodk.org (accessed 3.25.25).

Ortega-Pacheco, A., Segura-Correa, J.C., Jimenez-Coello, M., Linde Forsberg, C., 2007. Reproductive patterns and reproductive pathologies of stray bitches in the tropics. Theriogenology 67, 382–390. https://doi.org/10.1016/j.theriogenology.2006.07.020

Perry, B.D., 1993. Dog ecology in eastern and southern Africa: implications for rabies control. Onderstepoort J Vet Res 60, 429–436.

R Core Team, 2025. R: A Language and Environment for Statistical Computing, Vienna, Austria. Available at: https://www.R-project.org/.

Ratsitorahina, M., Rasambainarivo, J.H., Raharimanana, S., Rakotonandrasana, H., Andriamiarisoa, M.-P., Rakalomanana, F.A., Richard, V., 2009. Dog ecology and demography in Antananarivo, 2007. BMC Veterinary Research 5, 21. https://doi.org/10.1186/1746-6148-5-21

Sambo, M., Cleaveland, S., Ferguson, H., Lembo, T., Simon, C., Urassa, H., Hampson, K., 2013. The Burden of Rabies in Tanzania and Its Impact on Local Communities. PLOS Neglected Tropical Diseases 7, e2510. https://doi.org/10.1371/journal.pntd.0002510

Sambo, M., Hampson, K., Changalucha, J., Cleaveland, S., Lembo, T., Lushasi, K., Mbunda, E., Mtema, Z., Sikana, L., Johnson, P.C.D., 2018. Estimating the Size of Dog Populations in Tanzania to Inform Rabies Control. Vet Sci 5, 77. https://doi.org/10.3390/vetsci5030077

Sambo, M., Hampson, K., Johnson, P.C.D., Johnson, O.O., 2024. Understanding and overcoming geographical barriers for scaling up dog vaccinations against rabies. Sci Rep 14, 30975. https://doi.org/10.1038/s41598-024-82085-4

Sambo, M., Johnson, P.C.D., Hotopp, K., Changalucha, J., Cleaveland, S., Kazwala, R., Lembo, T., Lugelo, A., Lushasi, K., Maziku, M., Mbunda, E., Mtema, Z., Sikana, L., Townsend, S.E., Hampson, K., 2017. Comparing Methods of Assessing Dog Rabies Vaccination Coverage in Rural and Urban Communities in Tanzania. Front Vet Sci 4, 33. https://doi.org/10.3389/fvets.2017.00033

Sentinel Hub, 2022. 10m Annual Land Use Land Cover (9-class) - Sentinel Hub Collections [WWW Document]. URL https://collections.sentinel-hub.com/impact-observatory-lulc-map/ (accessed 5.15.25).

Sudarshan, M.K., Mahendra, B.J., Narayan, D.H., 2001. A community survey of dog bites, anti-rabies treatment, rabies and dog population management in Bangalore city. J Commun Dis 33, 245–251.

Tanzania National Bureau of Statistics and President's Office, 2024. Mara Region - Basic Demographic and Socio-Economic Profile Report.

Townsend, S.E., Sumantra, I.P., Pudjiatmoko, Bagus, G.N., Brum, E., Cleaveland, S., Crafter, S., Dewi, A.P.M., Dharma, D.M.N., Dushoff, J., Girardi, J., Gunata, I.K., Hiby, E.F., Kalalo, C., Knobel, D.L., Mardiana, I.W., Putra, A.A.G., Schoonman, L., Scott–Orr, H., Shand, M., Sukanadi, I.W., Suseno, P.P., Haydon, D.T., Hampson, K., 2013. Designing Programs for Eliminating Canine Rabies from Islands: Bali, Indonesia as a Case Study. PLOS Neglected Tropical Diseases 7, e2372. https://doi.org/10.1371/journal.pntd.0002372

Voupawoe, G., Anthony, W., Hattendorf, J., Odermatt, P., Zinsstag, J., Mauti, S., 2022. Preparing liberia for rabies control: Human-dog relationship and practices, and vaccination scenarios. Acta Tropica 229, 106331. https://doi.org/10.1016/j.actatropica.2022.106331

Wallace, R.M., Mehal, J., Nakazawa, Y., Recuenco, S., Bakamutumaho, B., Osinubi, M., Tugumizemu, V., Blanton, J.D., Gilbert, A., Wamala, J., 2017. The impact of poverty on dog ownership and access to canine rabies vaccination: results from a knowledge, attitudes and practices survey, Uganda 2013. Infectious Diseases of Poverty 6, 97. https://doi.org/10.1186/s40249-017-0306-2

World Health Organization, 2018. Zero by 30: the global strategic plan to end human deaths from dog-mediated rabies by 2030 [WWW Document]. URL https://www.who.int/publications/i/item/9789241513838 (accessed 3.10.25).

World Organisation for Animal Health, 2025. Rabies control programmes [WWW Document]. URL https://www.woah.org/en/disease/rabies/ (accessed 7.16.25).