Do Neighboring Herd Sizes Influence the Incidence of Farmer-Herder Conflicts? A Case Study from Kilosa District, Tanzania

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Abstract

Farmer-herder conflicts had been widely studied in the Sub-Saharan region, with most literature emphasizing the causes and effects within the origins of these conflicts. However, the impact of neighboring herd sizes on the incidence of these conflicts received limited attention. This study aimed to address this gap by analyzing ward-level data on herd sizes and conflict presence in Kilosa District, Tanzania. Using Logistic Regression Models (LRM) and Geographically Weighted Logistic Regression Models (GWLRM), we estimated the spillover effects of neighboring herd sizes. Our findings revealed that farmer-herder conflicts remained a significant challenge in Kilosa District, with over 50% of the wards experiencing conflicts. Results from both spatial and non-spatial models indicated that neighboring herd size was a strong predictor of these conflicts. An increase in neighboring herd size significantly raised the likelihood of conflict occurrence. The GWLRM results further suggested that the spillover effect of neighboring herd sizes was location-dependent, showing significance in specific areas. The spatial variation in the impact of neighboring herd sizes highlighted the importance of considering local geographical contexts when addressing these conflicts. This study underscored the need for locally tailored strategies to mitigate the incidence of such conflicts effectively. Recommendations included implementing community-based conflict resolution mechanisms, promoting sustainable herd management practices, and enhancing communication between farmers and herders to foster mutual understanding and cooperation. It calls for context-specific interventions to develop effective and sustainable solutions in Kilosa District, Tanzania.

Keywords: *Farmer-herder conflicts; Neighboring herd sizes; Kilosa District; Spillover effects.*

Introduction

In Africa, access to vital resources such as land, water, forests, and wildlife reserves has long been pivotal for sustainable development (Rweyemamu, 2019); Saidu *et al.,* 2021). These diverse natural environments, including arid and semi-arid regions designated as biodiversity hotspots, contribute significantly to national economies through tourism revenues. They also provide conducive conditions for agricultural activities and grazing, which are essential for supporting the livelihoods of farmers and herders respectively (Reda, 2015; Roe, 2020).

Livestock plays a central role in pastoralist societies, serving not only as sources of production and labor but also as symbols of cultural pride and capital goods (Kileli, 2014). However, the relationships between farmers, who predominantly practice agropastoralism, and herders, who rely solely on livestock for sustenance, are often fraught with challenges that undermine human security. Nowhere is this more apparent than in Sub-Saharan Africa, where conflicts between these groups have been pervasive (UNDP, 2018).

The Sub-Saharan African region, celebrated for its rich cultural diversity and ecological complexities, has become a focal point for studying farmer-herder conflicts due to their profound social, economic, and environmental implications (Adugna, 2020). These conflicts arise at the intricate intersection of agricultural and pastoralist communities, exacerbated by historical land use practices, competition for resources, changing climatic patterns, and demographic shifts. Prior to the late 1960s, farmers and herders in East Africa maintained a sustainable coexistence through institutionalized and customary strategies that facilitated flexible access to resources such as pasture and water (Mtenga, 2019).

However, the colonial period (1885-1960) ushered in significant changes, with authorities and development organizations viewing farmers and herders as unproductive, nomadic, and environmentally damaging (Rweyemamu, 2019). National development policies favoring agriculture further marginalized pastoralist livelihoods, increasing vulnerability to shocks and intensifying farmer-herder conflicts in terms of both frequency and severity (Benjaminsen *et al.,* 2009; Saidu *et al*., 2021). Extensive research efforts have aimed to resolve the underlying causes and consequences of these conflicts, predominantly focusing on understanding localized dynamics. Numerous studies conducted in Tanzania and other African countries have identified competition over natural resources, particularly water and grazing lands, as primary drivers of conflicts between farmers and herders (Adano *et al*., 2012; Mwalyosi *et al*., 2017). Additionally, the proximity of herders to farmers' fields has been identified as a significant predictor of conflicts, as grazing activities near cultivated areas increase the likelihood of crop damage and ensuing disputes (Katani, 2016).

Kilosa District in Tanzania stands out among locations extensively studied for farmer-herder conflicts, driven by persistent tensions over scarce resources such as water and grazing lands. While previous research (Benjaminsen *et al*., 2009; Mtenga, 2019) has predominantly focused on proximate causes within conflict hotspots, this study seeks to broaden the perspective by investigating the influence of neighboring herd sizes on conflict occurrence. This approach is motivated by the recognition that spatial interactions between farming and herding areas, influenced by herd sizes, may significantly impact conflict dynamics across broader geographical contexts.

The study was grounded in Wilson's (1970) Theory of Spatial Interaction and Mamdani's (1996) Theory of Power and Inequality. Spatial interaction theory analyzed the relationship between herd sizes and conflicts, highlighting how geographic space shapes social interactions. Analysis of livestock and human movement identified conflict hotspots in Kilosa, where spatial arrangement of farming and herding areas, influenced by herd sizes, affected conflict likelihood. Spatial interaction theory posits that conflicts increase with proximity and herd size, intensifying competition over resources like water and grazing land (Wilson, 1970).

Mamdani's (1996) theory examined power imbalances and resource access, showing that in Kilosa, herders, with larger herds, held more power, causing tensions with marginalized farmers. The theory also noted scenarios where farmers had more resources, influencing land use and access to water, with herders relegated to marginal lands. Large herds exacerbate these power imbalances, intensifying conflicts as they strain resources (Mamdani, 1996). The application of both spatial interaction theory and theory of power and inequality was aimed at capturing the multi-dimensional nature of the farmer-herder conflicts. Spatial interaction theory explains the spatial patterns of movement, resource use and resultant conflicts between herders and farmers, however, it does not sufficiently account for the underlying structural and social power dynamics that shape access to and control over resources. The theory of power and inequality complements this gap by illuminating how historical and institutionalized power asymmetries such as the dominance of herders with large herds or farmers with privileged access to water exacerbate and sustain these conflicts beyond what spatial proximity alone can explain. Together, the two theories offer a more comprehensive analytical framework, integrating spatial processes with socio-political inequalities to provide a deeper understanding of the conflict dynamics.

Furthermore, insights from studies on neighborhood characteristics and human conflicts, including violent crime and incivilities, highlight the critical role of physical and social environments in shaping interactions and behaviors (Perkins *et al*., 1993; Lee &

Oropesa, 1999; Krivo & Peterson, 2000; Le Roux, 2019). Building on this premise, this paper aimed to investigate the extent to which geographical neighborhood characteristics, specifically neighboring herd sizes, influence conflict occurrence at the ward level in Kilosa District, Tanzania. Despite substantial progress in understanding the complexities of farmer-herder conflicts and their impacts on local communities, a critical knowledge gap persists regarding the role of neighboring herd sizes. Thus, by analyzing ward-level data encompassing herd sizes and conflict incidences, this study employs advanced statistical models such as Logistic Regression Models (LRM) and Geographically Weighted Logistic Regression Models (GWLRM). These models are crucial for uncovering spatial variations in the relationship between neighboring herd sizes and conflict likelihood, thereby informing targeted interventions and policies for conflict mitigation and sustainable resource management.

Methods

Description of the Study Area

The focus of this study was the Kilosa District, situated between the geospatial coordinates of 6° and 9° south of the Equator and 35° and 38° east of the prime meridian. Kilosa District, one of the eight districts of the Morogoro Region in the coastal zone of Tanzania, served as an intriguing setting for investigating the intricate dynamics of farmer-herder conflicts and their relationship with neighboring herd sizes.

Kilosa District exhibited a unique blend of geographical and climatic features that contributed to its significance within the broader context of farmer-herder conflicts. The district is characterized by a tropical climate with

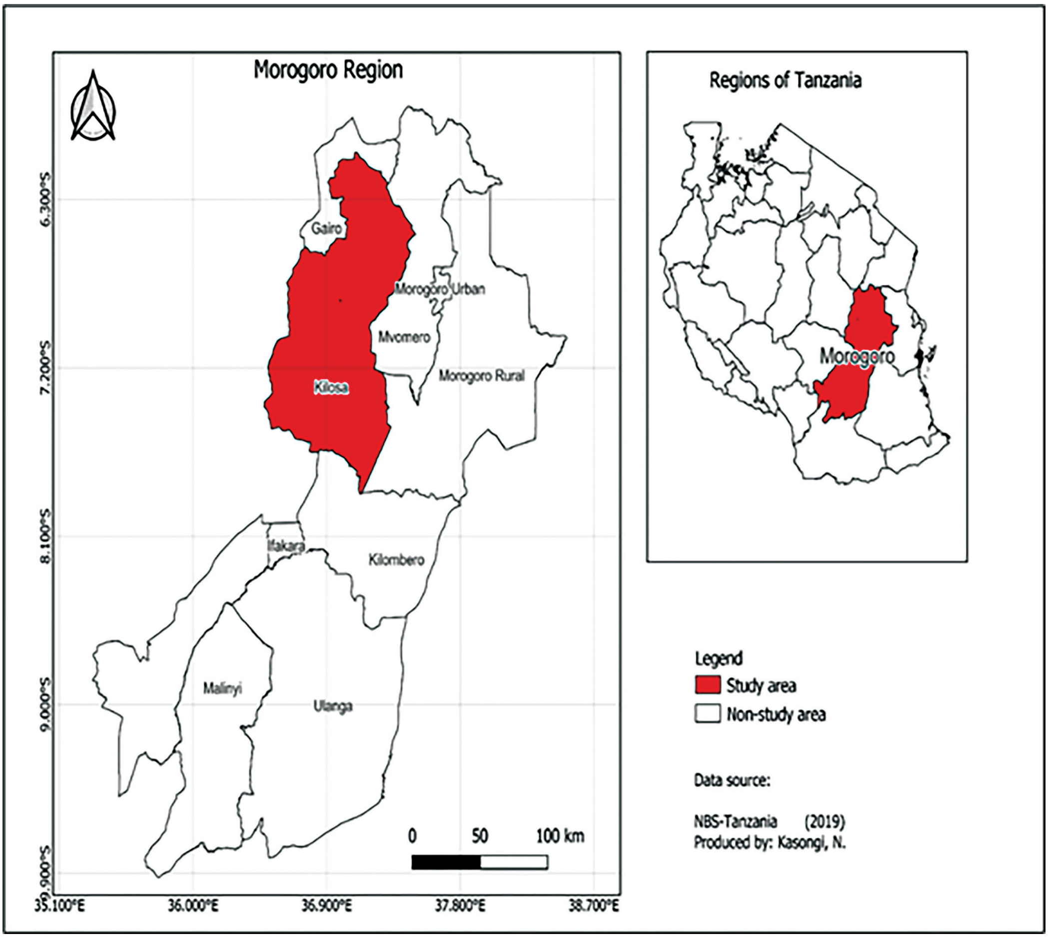

Figure1: Geographical location of the study area

temperature variations spanning a considerable range, influencing both agricultural and pastoral practices (Makota *et al*., 2019). This climatic variability played a pivotal role in shaping resource availability, livestock grazing patterns, and agricultural productivity, all of which were integral to the emergence and escalation of conflicts between farmers and herders.

Annual rainfall patterns within Kilosa District further underscored the complexity of its ecological dynamics. The district experienced a wide range of annual precipitation levels, with significant implications for water availability, forage resources, and crop cultivation. This diversity in climatic conditions shaped the distribution of resources critical to both farmers and herders, potentially influencing the frequency and intensity of conflicts.

the district level to gain in-depth insights into the nature of farmer-herder conflicts in the study area (Rweyemamu, 2019; Mtenga, 2019).

Definition of Variables

The dependent variable was conflict presence, indicating whether a ward had encountered farmer-herder conflicts. This binary variable was coded as 1 if the ward had encountered a conflict and 0 if it had not.

The independent variables were the herd size within the ward and the neighboring wards' herd sizes. Herd size was defined as the sum of cattle, goats, and sheep in each ward. Neighboring herd size was calculated as the average herd size of all neighboring wards, using the equation provided below. Table 1 provides details on the study variables (Adano *et al*., 2012; Mwalyosi *et al*., 2017).

Table 1: Key Variables

Variable	Indicator	Measurement Scale
Conflict	Farmer-herder conflict	Categorical
Ward herd size	Total number of herds (including cattle, goats, and sheep)	Continuous
Neighbors' herd size	Average of the total number of herds (including cattle, goats, and sheep) in the neighboring wards	Continuous

Data Types and Sources

We acquired farmer-herder conflict presence data from district authorities using a structured questionnaire. Due to the lack of detailed conflict incident records at local authority offices, we utilized a binary scale to capture conflict presence data. This involved identifying all wards that reported one or more farmer-herder conflicts in the past twelve months and coding them as conflict wards. Conversely, wards with no reported incidents in the same period were coded as non-conflict wards (Benjaminsen *et al*., 2009).

Herd size data were obtained from local authority offices, which conduct a livestock census every ten years. The herd size data comprised the total number of cattle, sheep, and goats in each ward, based on the latest livestock census conducted in 2022. Additionally, we conducted expert interviews with agricultural extension officers and social welfare officers at

Spatial Neighbors Characterization

To comprehensively characterize the geographical neighborhood of each ward within Kilosa District, a systematic approach was employed to ensure accuracy and relevance. The identification of spatial neighbors was based on the concept of contiguity, wherein neighboring wards were defined as those sharing direct borders, both at edges and corners (Anselin, 1995). This method, known as queen's contiguity, provided a comprehensive consideration of proximate areas.

To operationalize this concept, spatial relationships were established using the sf R-package, specifically the intersection function. This allowed for the accurate identification of neighboring wards for each ward polygon. The process facilitated the creation of a network of spatial neighbors, enabling a robust examination of the influence of neighboring herd sizes on the incidence of farmer-herder conflicts within

Kilosa District (Bivand *et al.*, 2013).

Figure 2 visually encapsulates the conceptualization of spatial neighbors as employed in this study. The central red box denotes the location of interest, while the surrounding green boxes represent neighboring wards that share contiguous borders, whether at the edges or corners. This representation underscores the meticulous attention to detail in capturing the spatial relationships essential for understanding the dynamics of farmer-herder conflicts.

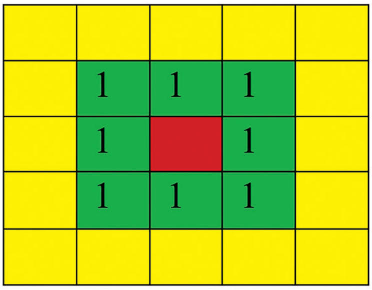

Figure 2: Conceptualization of Spatial Neighbours, *Source:* Author's own conceptualization of spatial neighbors

The process of obtaining the neighbors' variable, crucial for subsequent analysis, involved a rigorous computation. The central premise was to gauge the influence of the characteristics of neighboring wards on the occurrence of farmer-herder conflicts within a given ward. This was achieved by calculating the average of relevant observations across all neighboring wards, effectively encapsulating the collective attributes of the surrounding context. This computation was expressed through Equation (1), where *xi* represents the sum of observations of a specific variable across all neighboring wards, and ni denotes the number of neighboring wards contributing to the computation. This formula encapsulates the essence of harnessing the collective influence of spatial neighbors' attributes on the variable of interest, illuminating the interconnectedness of the study area below.

$$Neighbors' variable = \frac{\sum x_i}{n_i} \quad ....(1)$$

where the *xi* is the sum of observations of a variable of other wards about the ward and ni is the number of neighbors of the wards.

This formula encapsulates the idea that the attributes of a ward are influenced not only by its own characteristics but also by those of its neighbors, thereby offering a comprehensive view of the spatial dynamics at play in Kilosa District (Anselin, 1995; Bivand *et al.*, 2013). Building on this, conceptualization of spatial neighbors using queen's contiguity is grounded in the spatial interaction theory, which emphasizes the role of proximity and spatial arrangement in shaping interactions, such as farmer-herder conflicts. This neighborhood scheme operationalizes the potential for interaction between wards. The theory of power and inequality informs the interpretation of how unequal access to resources and power dynamics within and across these spatial units influence the observed conflict patterns.

Spatial Analysis

Spatial Autocorrelation

We conducted the spatial autocorrelation to check if the variables in the study were spatially autocorrelated. This spatial analysis helps to identify potential hotspots for conflict and spatial autocorrelation analysis of herd sizes to determine if there were any inherent clusters in the distribution. We used Global Moran's I because of our variable is in continuous scale.

Global Moran's I

We used global Moran's I to measure spatial autocorrelation. The Global Moran's I is computed by using the formula 2 below (Chen, 2013).

$$Moran's\ I = \frac{N\sum_{i=1}^{n}\sum_{i=1}^{n} w_i\,(x_i-\mu)(x_j-\mu)}{\sum_{i=1}^{n}\sum_{i=1}^{n} w_i \sum_{i=1}^{n}(x_i-\bar{x})^2} \quad ....(2)$$

Where *N* is the number of observations, μ is the mean variable, *xi* is the variable at location i, xj is the variable at location *j*, *wi* is the spatial contiguity matrix.

The value of Moran's I ranges between -1 and 1. If the value is greater than 1, it indicates positive spatial autocorrelation and -1 indicates negative spatial autocorrelation. The value of 0 indicates no spatial autocorrelation or random spatial pattern Furthermore, spatial autocorrelation test of the model residuals was used to confirm if residuals had a random spatial pattern. If the residuals are not spatially autocorrelated, we can confidently trust the results of the non-spatial logistic regression.

Statistical Modeling

We used binary spatial logistic and geographically weighted logistic regression model to measure the spillover effect.

Binary Logistic Regression Model

The binary logistic regression model was used to measure the effect of covariates on the likelihood of a binary outcome variable. We employed a binary logistic regression to assess the spillover effect, specifically investigating whether an increase in neighbors' herd size leads to a higher likelihood of conflict within wards. Our variable of interest was the herd size of the neighbors. A statistically significant result for this variable would allow us to reject the null hypothesis and conclude the presence of a spillover effect. This regression method assumes that the coefficients of the regression are constant over space (Hosmer *et al*., 2013).

$$ln\left(\frac{p}{1-p}\right) = \beta_0 + \sum_{i=1}^{p} \beta_i x_i + \varepsilon_i \qquad \ldots\ldots(3)$$

Where p is the likelihood of outcome to occur, $\beta0$ is in the intercept, xi is the i^{th} independent variable, βi is the i^{th} coefficient,εi is the error term, and p is the number of independent variables

The model's logarithmic transformation of the odds ratio (ln(p/(1-p))) allows for the linear relationship between the dependent variable and the independent variables. This approach is particularly useful for binary outcomes, providing insights into how each predictor variable influences the likelihood of an event occurring (Peng *et al*., 2002).

Geographically Weighted Logistic Regression Model

In the pursuit of refining our understanding of the influence of neighboring herd sizes on the incidence of farmer-herder conflicts within Kilosa District, a Geographically Weighted Logistic Regression (GWLR) model was employed. This approach allowed for a spatially differentiated analysis of the relationship between herd sizes and conflict occurrence, recognizing the spatial variability inherent in such complex interactions. The GWLR model was developed with a strategic omission, specifically, the exclusion of the herd size variable within individual wards. This decision was based on its non-significance as observed in the non-spatial regression model. This judicious selection aimed to enhance the model's predictive power by focusing solely on the influential variable, the herd size of neighbors.

The GWLR model extends traditional logistic regression by incorporating spatial heterogeneity in regression coefficients (Wu & Zhang, 2012). This approach is particularly suited for scenarios where relationships between variables vary across geographical locations.

The geographically weighted logistic regression model is formulated as:

$$ln\left(\frac{p_i}{1-p_i}\right) = \beta_0(u_i, v_j) + \beta_1(u_i, v_j)x_i + \cdots \beta_n(u_i, v_j)n_i + \varepsilon_i \qquad \ldots\ldots(4)$$

Where (β0(ui,vj), β1(ui,vj)) are geographically varying regression coefficients at location I with the coordinate (ui,vj) in the study area. The geographically weighted logistic regression produces estimates of regression coefficients for each covariate at each location i.

This model estimates regression coefficients that vary spatially, allowing for a nuanced understanding of how predictors influence outcomes across different locations within the study area.

We hypothesized that the increase of neighbors' herd size leads to an increase in the likelihood of conflict within the wards. Thus, the hypotheses of the study are as follows:

H0: Neighbors' herd size does not lead to the increase of likelihood of conflict within the wards.

H1: Neighbors' herd size leads to an increase in the likelihood of conflict within the wards.

Results

Incidence of Conflicts and Herd Size

The results indicate that most of the wards, 24 out of 40 (60%), have encountered farmer-herder conflict incidents, while 16 wards (40%) did not experience conflicts (Table 2). This suggests that farmer-herder conflict is a significant challenge, as more than 50% of all wards had encountered conflicts.

Table 2: Distribution of Farmer-Herder Conflict Incidents in Wards

Conflict Status	Number of Wards	%
Conflict Wards	24	60%
Non-Conflict Wards	16	40%

On average, wards that encountered conflict had larger herd sizes than those that did not encounter conflicts (Table 3). Surprisingly, the variance in herd size was much higher in the non-conflict wards, primarily due to the significantly large herd size in Parakuyo Ward. Additionally, the minimum and maximum values of herd size were higher in non-conflict wards than in conflict wards, with the maximum value in non-conflict wards attributed to Parakuyo Ward.

These results underscore the complex relationship between herd sizes and the incidence of farmer-herder conflicts, suggesting that larger herd sizes might contribute to the likelihood of conflicts. However, the high variance in non-conflict wards indicates that other factors might also play a significant role in the occurrence of these conflicts.

The spatial distribution of herd sizes and farmer-herder conflicts in Kilosa District is depicted in Figure 4. These maps illustrate the geographical patterns of herd sizes and conflict incidences, providing a visual representation of the areas most affected by farmer-herder conflicts.

Table 3: Summary Statistics of Herd Sizes in Conflict and Non-Conflict Wards

	Min	Max	Mean	Std. Dev
Non-conflict wards	250	74474	11524.25	18188.96
Conflict wards	202	38931	11902.00	11521.81

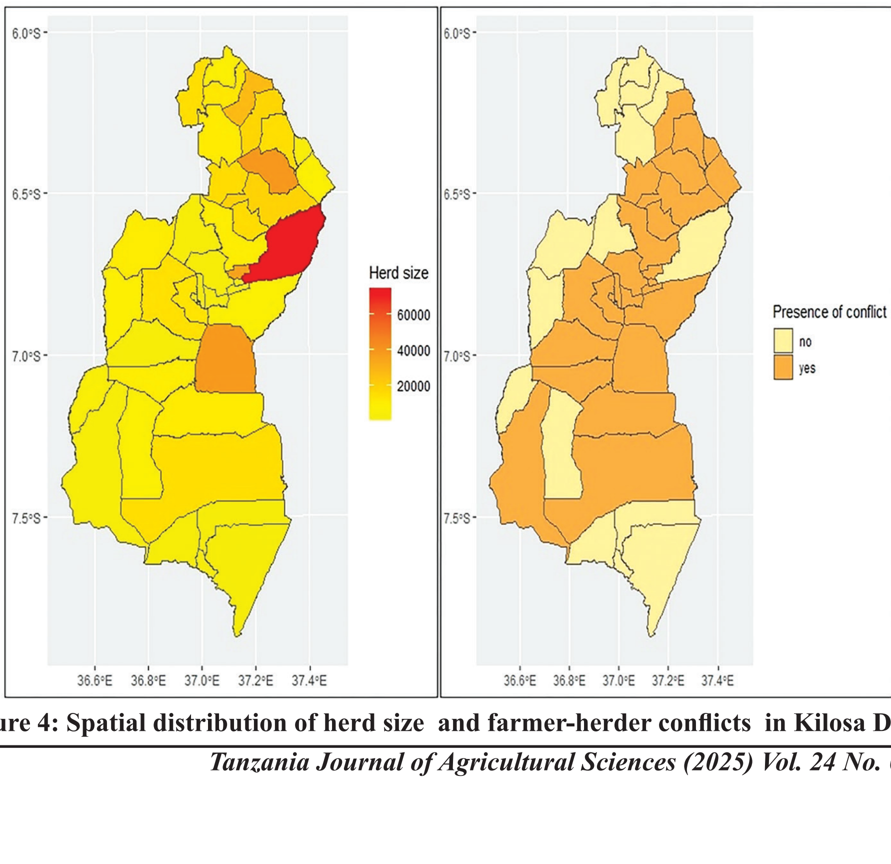

Figure 4: Spatial distribution of herd size and farmer-herder conflicts in Kilosa District

Spatial Patterns in Herd Size Distribution

The results of the global spatial autocorrelation indicated a non-significant spatial autocorrelation of herd size (Global Moran's I=0.1225, p-value=0.0505). This suggests that herd sizes follow a more random spatial pattern within the study area.

Table 4: Global Moran's I Test Result of the Herd Size

Moran I statistics	Expectations	Variance	Moran I p-value
0.1225	-0.0256	0.0082	0.0505

**Significance level at 5%*

The Moran's scatter plot (Fig. 5) illustrates the local pattern of spatial autocorrelation. According to the plot, the majority of wards (43%) are located in the bottom-left quadrant, indicating that both these wards and their neighbors have lower herd sizes than the mean herd size. The remaining 57% of the wards are distributed across other quadrants. This distribution suggests that the observed local clusters in the plot may occur due to chance.

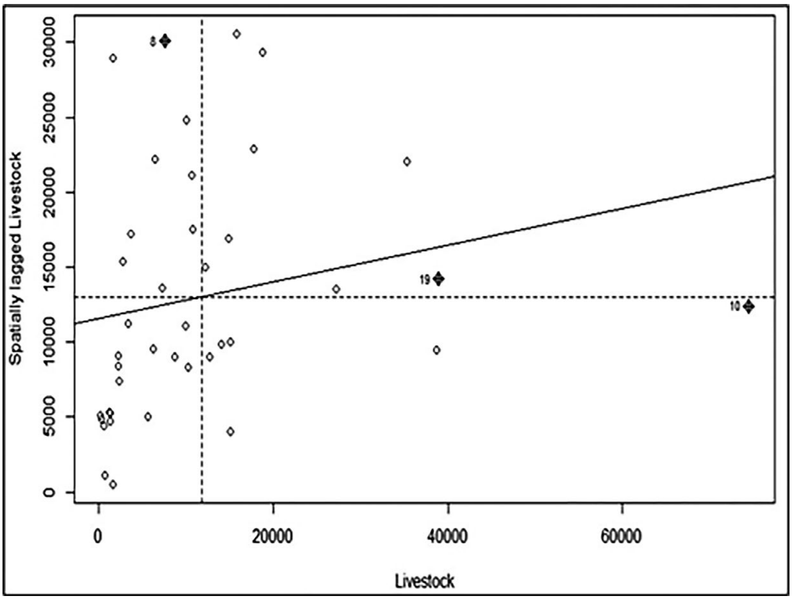

Figure 5: Moran Plot of Herd Size vs Lagged Herd Size

Conflict Spillovers from Neighbouring Herd Size within Wards

The logistic regression results (Table 5) indicate that the herd size of neighbors is statistically significant (p-value<0.05) in the model. Specifically, for each unit increase in herd size in the neighboring wards, the odds of a ward encountering a farmer-herder conflict increase by a factor of 1.000198. This finding suggests a spillover effect of herd size on the occurrence of farmer-herder conflict. Conversely, herd size within the ward was non-significant (p-value>0.05) in the model. However, we exercised caution regarding potential spatial patterns embedded within the data, which might not have been adequately captured by the non-spatial regression model. Non-spatial regression models may assume non-spatial stationarity of regression coefficients' effects (Anselin, 2005).

The findings of this study align with the complex and multifaceted nature of farmer-herder conflicts that have been documented in previous research. The spillover effect of neighboring herd sizes corroborates the notion that conflict dynamics transcend individual wards, echoing the interconnectedness of resource competition, land use practices, and socio-cultural factors. These results resonate with previous studies that have highlighted

Table 5: The Results of Binary Logistic Regression

Coefficient	Estimate (Log-odds)	Estimate (odds ratio)	Standard Error	z-value
Intercept	126.83387023	Infinite	92.10567938	1.377
Ward's herd size	-0.00002062	0.9999794	0.00002694	-0.765
Neighbors' herd size	0.00019778*	1.000198*	0.00008963	2.207
Akaike Information Criterion (AIC)	52.94			
Number of observations	40			

**p* < 0.05, ** *p* < 0.001, *Significance level at 5%*

the role of ecological and resource factors in shaping conflict patterns (Gebrehiwot *et al.*, 2020; Adekunle *et al.*, 2021b).

The significance of neighbors' herd sizes also underscores the potential for cascading conflict effects across localities, urging policymakers to consider a broader, region-specific approach to conflict mitigation. While the non-significance of ward-specific herd size within the model may be unexpected, it accentuates the complexity of conflict dynamics that transcend the boundaries of individual wards.

Evidence of Spatial Dependence in Residuals

The results of the global spatial autocorrelation test (Table 6) highlighted significant positive spatial autocorrelation within the model residuals derived from the non-spatial regression. The Global Moran's I value of 0.261, coupled with a p-value of 0.002, demonstrated the presence of discernible spatial patterns in the residuals. This finding indicated that the non-spatial regression model was not entirely capable of capturing the intricate spatial dynamics within the data (Anselin, 1995). Consequently, there was a compelling rationale to explore the use of spatial logistic regression, which inherently integrates the spatial pattern of the data for more accurate estimates (Anselin, 2002).

Figure 6 vividly illustrates the local spatial pattern of model residuals across the study area. The spatial distribution of clusters becomes evident, where distinct patterns of high and low residuals are discernible. Notably, clusters of low residuals are observable at the northern and southern extremities of the study area. Conversely, a distinct cluster of high residuals emerges in the central region. These local patterns underscore the complex interplay of factors that contribute to the spatio-temporal distribution of farmer-herder conflicts.

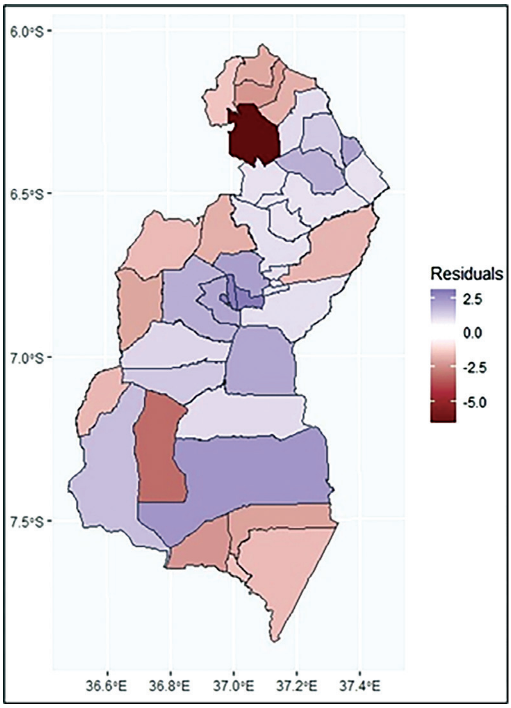

Figure 6: The Spatial Distribution of the Model Residuals

The finding of significant positive spatial autocorrelation in the model residuals highlights the inherent spatial dependency that

Table 6: Global Moran I Test Results of Residuals

Moran I statistics	Expectations	Variance	Moran I p-value
0.26133740	-0.02564103	0.01030357	0.002348

**Significance level at 5%*

characterizes farmer-herder conflict dynamics. This observation resonates with previous research that has emphasized the need to account for spatial interdependencies when studying conflicts (Gebrehiwot *et al.*, 2020).

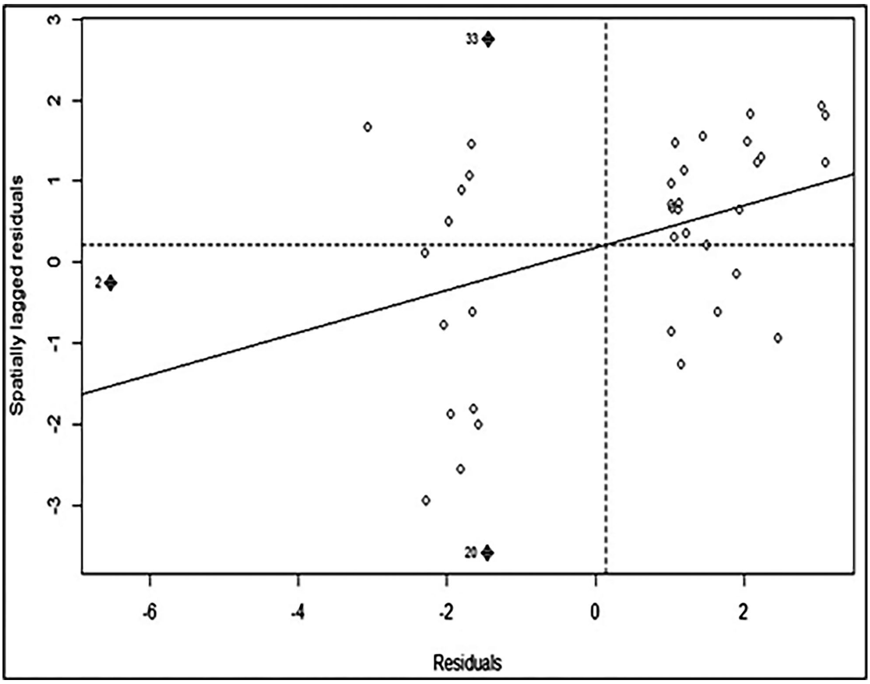

Figure 7: Moran Plot of Residuals

Furthermore, the presence of distinct local clusters of residuals, as depicted in Figure 6, echoes the heterogeneous nature of conflict dynamics within Kilosa District. The central cluster of high residuals indicates an area of elevated conflict incidence, possibly attributed to a convergence of factors such as resource scarcity, population density, and land use practices. These findings accentuate the importance of adopting spatially nuanced approaches to conflict analysis and management.

Relationship between Herd Sizes and Conflict Occurrence

The outcomes of the GWLR model (Table 7) introduced an intriguing perspective, namely, the varying effect of neighbors' herd sizes on conflict likelihood across the study area. This dynamic spatial variability contrasted with the uniformity assumption of non-spatial regression models. The p-values associated with the coefficient of herd size further elucidated this observation. Notably, a subset of wards (17.5%) exhibited significant herd size coefficients (p-value<0.05), while the majority (82.5%) demonstrated non-significant coefficients (p-value>0.05). This underscored that the spillover effect of herd size was pronounced in specific localized regions within the study area.

Table 7: The Results of Geographically Weighted Regression Model

	Min	Max	Average
Intercept	-2.680	-0.224	-0.857
Neighbors' herd size	0.000098684	0.0003	0.00012
AIC	47.12		
Pseudo-R^2	0.28		

The superiority of the spatial regression model over its non-spatial counterpart was substantiated through the Akaike Information Criterion (AIC). The spatial regression model achieved a lower AIC value of 47.12, indicative of its improved performance in comparison to the non-spatial regression model with an AIC of 52.94. This demonstrated the enhanced capacity of the spatial regression model to generate more accurate estimates of the spillover effect by accommodating the spatial intricacies inherent within the conflict landscape.

tailored conflict management strategies that consider the intricacies of each area.

Furthermore, the superior performance of the spatial regression model echoes the importance of incorporating spatial dependencies in conflict analysis. This aligns with the assertions of Anselin (2002), who emphasized the relevance of spatially informed modeling for capturing the true nature of phenomena influenced by geographical patterns.

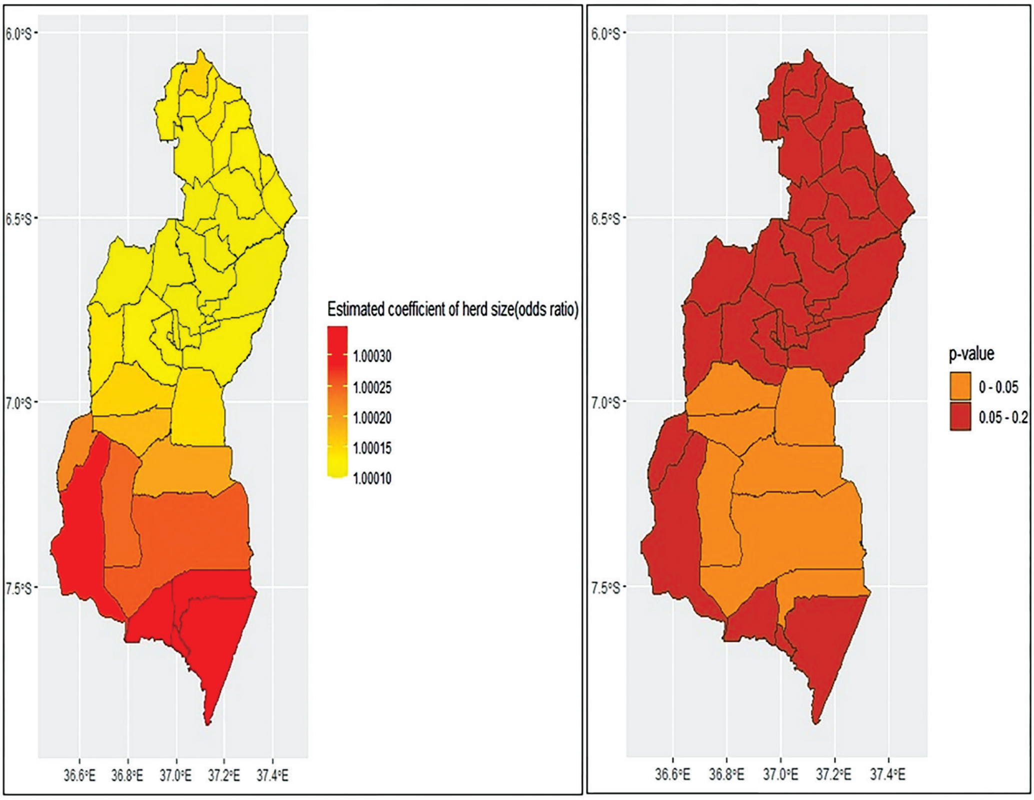

Figure 8: The Spatial Distribution of Estimated Coefficient of Herd Size and p-value of the Estimated Coefficient of Herd size

The findings of the GWLR model provide valuable insights into the nuanced spatial dynamics of farmer-herder conflicts. The spatial variability in the effect of neighbors' herd sizes aligns with the premise that conflict determinants are inherently location-specific, influenced by a myriad of local factors (Gebrehiwot *et al*., 2020; Adekunle *et al*., 2021a). This localization of effects underscores the need for contextually

Discussion

The analysis presented in this study underscores the complex and multifaceted nature of farmer-herder conflicts within Kilosa District. The results highlight significant findings across various statistical and spatial analyses, revealing complex patterns and dependencies that contribute to the occurrence and distribution of these conflicts.

Descriptive statistics showed that 60% of wards experienced farmer-herder conflicts (Table 2), underscoring the prevalence of these conflicts. Additionally, the average herd size was found to be larger in conflict wards compared to non-conflict wards (Table 3). This suggests a potential relationship between herd size and conflict occurrence, though the high variance in non-conflict wards, particularly due to the significantly large herd size in Parakuyo ward, indicates that herd size alone may not fully explain the conflict dynamics. These findings align with the work of Gebrehiwot *et al.* (2020) and Adekunle *et al*. (2021a), who have noted the complex interplay of ecological, socio-economic, and resource factors influencing conflict patterns. The spatial distribution maps (Fig. 4) further illustrate the geographical patterns of herd sizes and conflict incidences, providing a visual representation that helps identify potential conflict hotspots.

The Moran's scatter plot (Fig. 5) showed that 43% of the wards and their neighbors have lower herd sizes than the mean herd size, indicating that local clusters observed may occur by chance. This finding suggests that while herd sizes are variable across the district, they do not exhibit strong clustering tendencies. This randomness could imply that other local factors might be influencing herd size distribution, which do not necessarily lead to significant clustering patterns. This insight is crucial for understanding that while herd sizes are a factor, their spatial distribution does not solely determine conflict occurrences.

Spatial analysis techniques are valuable tools for understanding the distribution and clustering of animal health issues. Studies have employed various methods, including Moran's I, local indicators of spatial association (LISA), and spatial scan statistics, to assess spatial patterns in livestock depredation (Hoffmann *et al*., 2019), conflict hotspots (Khatiwada, 2014), and disease prevalence (Frössling *et al.*, 2008; Charoenlarp *et al.,* 2018). These analyses can reveal significant spatial clustering, as observed with Neospora caninum in Swedish dairy herds (Frössling *et al.*, 2008) and bovine viral diarrhoea virus in Northern Ireland (Charoenlarp *et al.*, 2018). However, spatial patterns may also be random, as found in carnivore depredation of livestock in Tanzania (Hoffmann *et al*., 2019). Identifying spatial patterns and associated risk factors can inform targeted interventions and policy decisions. For instance, socioeconomic factors were linked to conflict hotspots in Nepal (Khatiwada, 2014), while herd size and proximity to infected herds were risk factors for BVDV in Northern Ireland (Charoenlarp *et al*., 2018).

The binary logistic regression results suggests that an increase in neighbors' herd size slightly increases the odds of conflict within a ward. This finding underscores the importance of considering external factors and the interconnectedness of neighboring wards in conflict dynamics. Anselin (2005) cautions that non-spatial regression models might not fully capture spatial dependencies, which is why further spatial analysis was necessary.

Recent studies underscore the importance of spatial dynamics, regional heterogeneity, and economic factors in understanding conflict spillovers. Research by Bosker & Ree (2008), Balestri & Maggioni (2014), and Fetzer *et al.* (2021) reveals that conflicts tend to cluster geographically and spread to neighboring areas, with natural resources often driving diffusion. Tian (2015) highlights the negative economic impact of conflict spillovers on adjacent countries. Collectively studies advocate for incorporating spatial dependencies and economic considerations when analyzing conflict dynamics.

The spatial autocorrelation test of the model residuals revealed significant positive spatial autocorrelation (Table 6). This indicates that the non-spatial regression model did not adequately account for the spatial dynamics present in the data. The spatial distribution of residuals (Fig. 6) and the Moran plot of residuals (Fig. 7) demonstrated distinct local clusters, with high residuals in the central area and low residuals at the northern and southern extremities.

Spatial autocorrelation in residuals reveals the limitations of non-spatial models in representing spatially influenced phenomena, leading to biased tests and reduced precision (Mets *et al.*, 2017; Zhang *et al.*, 2009). Incorporating spatial dependencies, as advocated by Anselin (2002), improves estimate reliability. While spatial regression models address autocorrelation, they may not fully resolve heterogeneity, which more advanced methods like linear mixed models and geographically weighted regression can better capture (Zhang *et al.*, 2009). Moran's I and local Moran's I (Ellner & Seifu, 2002) help assess residual spatial patterns and inform model complexity. Additionally, the influence of spatial connectivity matrices and extreme residuals on global Moran's I, noted by Tiefelsdorf & Boots (2010), underscores the importance of properly accounting for spatial effects in regression analysis.

The spatial distribution of estimated coefficients (Fig. 8) aligns with the premise that conflict determinants are inherently location-specific, influenced by various local factors. Geographically Weighted Logistic Regression (GWLR) models have emerged as powerful tools for analyzing spatial variability in various contexts. These models offer advantages over non-spatial regression techniques by capturing local variations in relationships between variables (Mishra *et al*., 2021; Fathurahman *et al*., 2020). GWLR models have been applied to diverse fields, including remote sensing image classification accuracy assessment (Mishra *et al.*, 2021), multivariate logistic regression (Fathurahman *et al*., 2020), and fire risk assessment in urban-forest ecosystems (Guo *et al*., 2017).

The superiority of GWLR models over traditional logistic regression is demonstrated through improved prediction accuracy, goodness of fit, and model residuals (Guo *et al*., 2017). These models allow for the estimation of location-specific parameters and provide insights into spatial heterogeneity (Páez *et al*., 2002). The application of GWLR models has significant implications for developing targeted strategies in various domains, such as landscape mapping accuracy improvement and fire management in urban-forest ecosystems (Mishra *et al*., 2021; Guo *et al*., 2017).

Spatial interaction theory explains how proximity of wards and the size of neighboring herds create interaction spaces where conflicts are more likely, evidenced by positive association between neighboring herd sizes and conflict likelihood as well as spatial clustering of conflicts. However, herd size within a ward was not a significant predictor; indicating the influence of localized power dynamics. Mamdani's theory of power and inequality complements this by showing how institutionalized disparities in access to land, water and political influence exacerbate tensions beyond spatial factors alone. The two theories demonstrate that conflicts stem from both geographic arrangement of actors and entrenched inequalities, underscoring the need for policies addressing both dimensions.

Policy Implications

The study underscores several critical implications for conflict management and policy formulation in Kilosa District and similar regions. First and foremost, the spatial variability identified in conflict determinants necessitates localized interventions that are tailored to address specific local contexts and dynamics. As such, by recognizing that the factors contributing to farmer-herder conflicts vary across different wards and communities, policymakers can design targeted strategies that effectively mitigate tensions and promote sustainable coexistence. The study emphasizes critical implications for conflict management and policy formulation in Kilosa district and similar regions. It highlights the necessity for localized interventions that address specific local contexts and dynamics. Recognizing the variability in factors contributing to farmer-herder conflicts across different wards and communities allows policymakers to design targeted strategies effectively mitigating tensions and promoting sustainable coexistence (Saruni *et al.*, 2018; Falanta & Bengesi, 2018; Mwamfupe, 2015).

Second, policies focused on sustainable resource management are crucial for reducing conflict risks associated with resource competition, particularly over grazing lands and water sources. Implementing measures such as clear grazing land allocation, equitable access to water resources, and herd size regulation can help alleviate pressures that often exacerbate conflicts between farmers and herders. As such, by promoting responsible resource use and enhancing environmental stewardship, these policies not only mitigate conflict but also contribute to long-term socio-economic stability in rural areas.

Furthermore, integrating spatially explicit models into conflict analysis and management frameworks is essential for enhancing predictive accuracy and guiding effective interventions. The adoption of geospatial technologies and spatial regression models enables policymakers to map conflict hotspots, identify underlying spatial patterns, and predict future conflict scenarios with greater precision. This spatially informed approach allows for the implementation of preemptive measures and targeted interventions that address the root causes of conflicts before they escalate.

Therefore, by embracing localized interventions, sustainable resource management policies, and spatially informed strategies, policymakers can foster a conducive environment for peaceful coexistence between farmers and herders in Kilosa district and similar regions. These proactive measures not only address current conflict challenges but also lay the foundation for resilient communities capable of managing socio-environmental pressures effectively. As conflict dynamics continue to evolve, ongoing research and adaptive policy frameworks will be essential to ensure sustainable development and harmony in rural landscapes.

The study underscores the necessity of incorporating spatial analysis in understanding and managing farmer-herder conflicts. The significant spatial patterns observed in the residuals and the localized effects of neighbors' herd sizes highlight the complex interplay of factors influencing conflict dynamics. Policymakers and stakeholders should consider these spatial dependencies and localized patterns when designing interventions and policies aimed at mitigating farmer-herder conflicts in Kilosa District. Henceforth, by adopting spatially nuanced approaches, it is possible to develop more effective and contextually appropriate strategies for conflict prevention and resolution.

Conclusion

This study highlights importance of integrating spatial perspectives into the analysis and management of farmer-herder conflicts. By acknowledging complex interrelations among socio-economic, environmental and spatial factors; it provides a foundation for developing more effective and contextually appropriate interventions. Addressing these conflicts requires equitable and sustainable resource management policies and adaptive strategies that are sensitive to the specific conditions of rural communities. As conflict dynamics continue to shift in response to environmental and demographic changes, sustained research and the incorporation of spatially explicit approaches into policy frameworks remain imperative. Such evidence-based measures can promote peaceful coexistence, enhance resilience and support sustainable development in Kilosa District and comparable districts.

Study Limitations

The limitation of the study is that conflict presence and herd size data were obtain at the ward level because there is no record keeping system at the lower spatial unit (i.e., village). Thus, it could have affected the magnitude of the regression coefficients in the models.

Credit Authorship Contribution Statement

Tumaini Allan: Conceptualization, Methodology, software, writing - review & editing. Edwin Ngowi: Conceptualization, Methodology, software, writing - review & editing. Ng'winamila Kasongi: Conceptualization, Methodology, visualization, software, writing - review & editing. Justin Urassa: writing - review & editing. John Jeckoniah: writing - review & editing.

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