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REMOTE SENSING TELLS KINSHIP: AGRICULTURAL LAND USE BASED STUDY IN RURAL BANGLADESH

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Abstract

Remote sensing senses the land cover, which is indirectly linked to social structure, economic condition, and environmental issues. For instance, collateral information from remote sensing can be used in certain economic conditions and social aspects such as kinship detection, family structure, economic condition, habitat fragmentation, biodiversity, and structure of the villages. The Manikdi *Mouza*, Netrokona, Bangladesh was chosen as a case study because of its homogeneous landscape. This study conducted a household questionnaire survey, involving 370 respondents with a 95% confidence level whereas the margin of error is 5%. CS, RS, and Worldview-3 images were used to map the agricultural boundary and interpret the associated family structure changes over the study period. Besides that, three primary methods such as cluster analysis, multiple regression modeling, and Fuzzy Cognitive Mapping (FCM) were employed to examine plot parcelization, identify the driving forces influencing land parcelization, and determine their respective weights. The results indicate that, over the study period from 1950 to 2023, the total number of plots increased from 359 to 1,048 due to land fragmentation, while 404 plots remained unchanged. Unaltered plots are associated with combined families, while fragmented plots correspond to nuclear families. From the Cadastral Survey (CS) to the Revisional Survey (RS), approximately 26.98% of plots remained unchanged, and from the RS to the present, 38.55% of plots have stayed unaltered. The study's investigation into agricultural land fragmentation and its effects on kinship dynamics in rural Bangladesh highlights crucial implications for local governance and national policy frameworks, advocating for informed, community-centric strategies in land management.

Key words: Remote sensing, Kinship, Plot fragmentation, Family structure and Agricultural plot size.

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Introduction

Kinship, a social bond formed through blood ties, is primarily concerned with future generations. Consequently, kin-based groups are also linked to their land possession (Dister, *et al.,* 1993). Therefore, this land possession is handed down from generation to generation. According to the Muslim Family Laws Ordinance, 1961 (Ordinance NO. VIII OF 1961)-"In the event of the death of any son or daughter of the propositus before the opening of the succession, the children of such son or daughter, if any, living at the time the succession opens, shall per stirpes receive a share equivalent to the share which such son or daughter, as the case may be, would have received if alive." On the contrary, the Muslim Family Laws Ordinance of 1961 also contains information on property ownership, which states that individuals can gain land ownership rights through purchase, inheritance, gift, or settlement by the government (Van schendel and Rahman, 1997). Therefore, in Bangladesh, the spatial orientation of landscape boundaries changes over time as family structures change (Mollah *et al.,* 2023). For example, when a combined family is divided into a single family, the land ownership is delineated as well. As a result, instead of farmland, an individual cropland notion is created (Abdullah, 1976).

Bangladesh is a developing nation with an emphasis on agriculture where more than 85% of the rural poor are directly or indirectly involved in agricultural activities (BBS, 2011). There are two distinct kinds of agricultural land such as farmland and scattered/fragmented agricultural land (Mollah *et al.,* 2023). These two types of land differ in terms of size, location, management techniques, and land use regulations (Mollah *et al.,* 2023). In Bangladesh, agricultural land that is scattered throughout an area is made up of smaller pieces of land because of its large population size (Hassan, 2017). Therefore, scattered agricultural land is operated by small-scale farmers in the rural areas of Bangladesh who grow crops for personal, local consumption and sometimes for large-scale agricultural operations (Rahman *et al.,* 2020).

The relationship between kinship and land fragmentation in Bangladesh is not a straightforward one (Wood, 1981). While kinship often plays a role in land ownership and distribution, land fragmentation can occur due to various socio-economic reasons, including population growth, economic pressure, or changes in livelihood options (Mollah *et al.,* 2023 and Siddik *et al.,* 2022). Hence, using kinship as a sole explanation for land fragmentation can be limiting and should be critically examined in relation to other potential driving forces. In general, remote sensing allows for direct dimensions of the earth's surface as well as the spatial distribution of its physical entities whereas social science is more interested in why things happen rather than where they happen (Turner, 1998). But both disciplines are connected through perceptions, concepts, and related spatial contextual information like area boundary, settlement distribution pattern, shape, size, and height of the buildings as well as vegetation and forest cover (Taubenbock *et al.*, 2009). This confluence of events paves the way to utilize remotely sensed data for distinctive socio-economic rural morphology that is strongly correlated with the characteristics of physical and human dimensions (National Research Council, 1998).

Through the reflection of the objects, remote sensing gives socio-economic information indirectly (Walker, 1994). For instance, the rural morphology in a satellite image is the physical reflection of a society which is influenced by the historical, social, cultural, economic, political, demographic, and natural variables, as well as their changes (Taubenbock *et al.*, 2009). However, these implicit variables have not yet been sufficiently studied. While remote sensing has been widely used to study land use and environmental changes, its application in assessing kinship is unprecedented (Rahman, 2022). Researchers have not previously discussed implicit aspects such as kinship. This interpretation of satellite data will aid in understanding socioeconomic conditions, land fragmentation, and land loss, among others. Thus, this study focuses on remote sensing to detect kinship in rural Bangladesh based on agricultural land use. To achieve this, a more nuanced approach is required, identifying specific kinship-related factors that drive land fragmentation. Therefore, this research has major three key goals. These are (1) know the family structure of the study site; (2) map the agricultural land boundary according to *Mouza* Maps and finally; (3) identify driving forces those are responsible for agricultural plot size fragmentation.

Materials and Methods

Selection of the study area: Manikdi *Mouza* is situated in the *Gohalakanda* Union, Purbadhala Upazila, Netrokona District, Bangladesh. Geographically it is situated between 24º43´2´´N to 24º43´36´´N Latitude and 90º 35´33´´E to 90º36´14´´E Longitude. The *Kulla Mouza* no. 165 and *Telihati Mouza* no. 169 are located in the southern and eastern parts of the Manikdi *Mouza* respectively (Fig. 1).

The total population of Manikdi *Mouza* is 7,507. Manikdi *Mouza* of Netrokona district is known for its homogeneous floodplains and scattered waterbodies. Agricultural practices of the area are extensive with rice, jute, wheat, and vegetables among the most common.

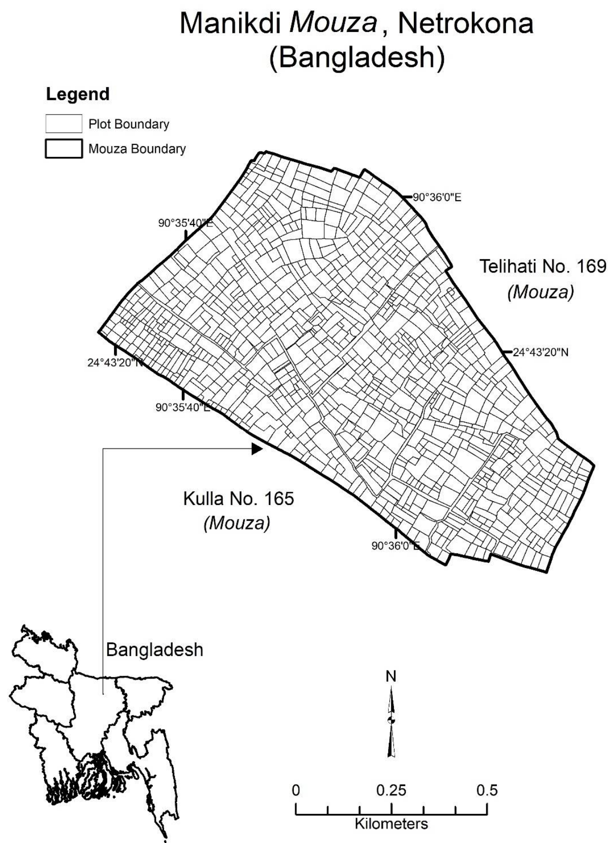

Fig. 1. The study area of Manikdi *Mouza*, Netrokona, Bangladesh.
Source: Compiled by authors, 2024 from CS, RS, and WorldView 3 satellite images.

Data sources: Primary data: To conduct this study, primary data were gathered from a variety of respondents through questionnaires and FGDs survey. Following is an explanation of the primary data gathering and requirements:

(a) Selection of local respondents: There are 370 questionnaires and 10 FGDs (each group consists of 7 to 8 respondents whereas male was 4 to 5 and female was 2 to 3) were conducted randomly with a 95% confidence level and 5% error margin for collecting data such as age, sex, education, earning sources or occupation, the total size of the family members, amount the of agricultural land acquired from the ancestor, the relationship among the family members, family status like combined or nuclear, driving forces that responsible for plot size fragmentation.

(b) KII: Key Informant Interviews (KIIs) were also conducted for data collection from the local experts and the Bangladesh Institute of Development Studies (BIDS) for identifying driving forces which are responsible for plot size fragmentation.

(c) Ground Control Points (GCPs): For accuracy assessment, Ground Control Points (GCPs) were used to geo-reference images and related *Mouza* maps like RS and CS. There are 9 GCPs were used for the datasets using the GPS survey.

(d) Error matrix was measured through GPS survey: There are 282 agricultural plots were surveyed for detecting error matrix.

Secondary data: In this study, secondary data were carefully collected from government as well as non-government organizations and used in figure 2. Listed below is a description of the secondary data collection:

(e) CS-1950 (Fig. 2a) and RS-1998 (Fig. 2b) *Mouza* maps were collected from DLRS (Department of Land Records and Surveys).

(f) The multispectral satellite image was collected through Maxar technologies, WorldView 3-November, 2023 (Fig-2c). The resolution of the image is 0.3m.

(g) Administrative/political maps were collected from the Center for Environmental and Geographic Information Services (CEGIS).

(h) Literature was reviewed from different national and international journals and books.

(i) Population data were collected from the Bangladesh Bureau of Statistics (BBS) in 2011.

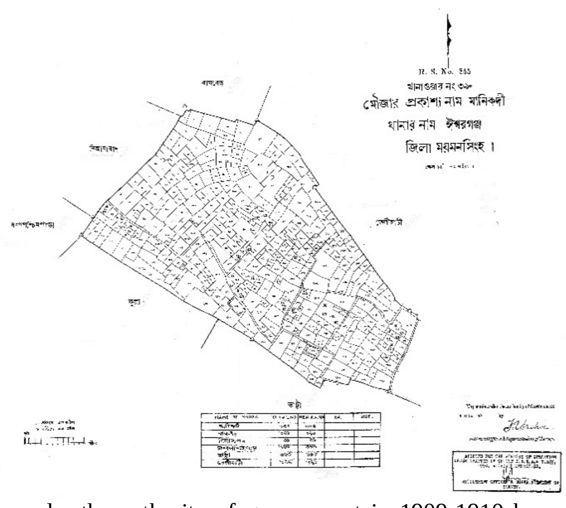

Fig. 2(a) Map made under the authority of government in 1909-1910 by settlement officer and superintendent of the survey which was adopted in 1950

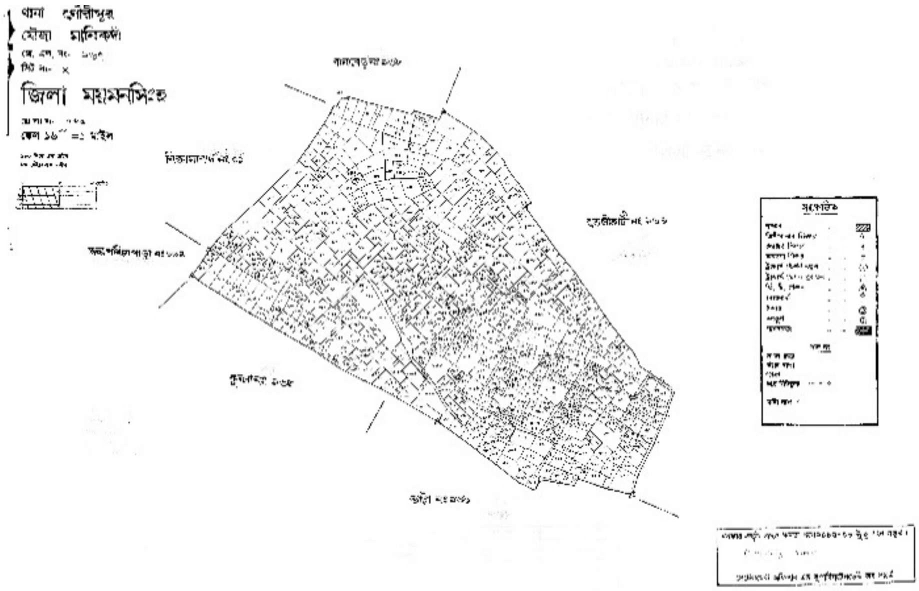

Fig. 2(b) Map made under the authority of government in 1984-1998 by settlement officer and superintendent of the survey which was adopted in 1998

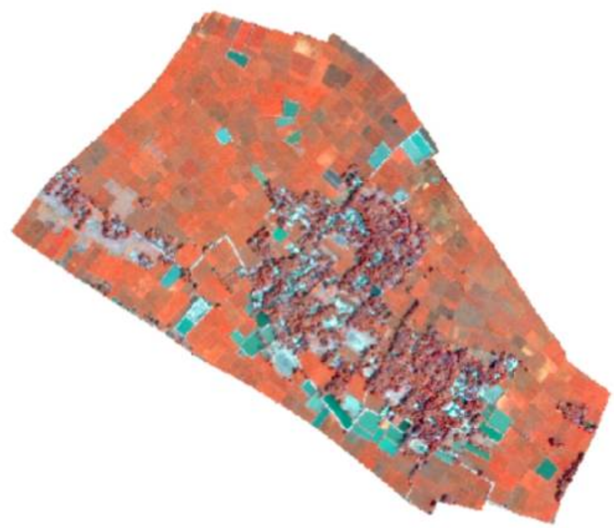

Fig. 2(c) Multispectral satellite imagery collected from Maxar technologies, WorldView 3; Nov, 2023, 0.3-meter resolution: Projection parameter: UTM N46

Fig. 2 (a-c). CS, RS, and Current WorldView-3 multispectral satellite imagery of the study area of Manikdi *Mouza*, Netrokona, Bangladesh.

Source: Compiled by authors, 2024 from CS, RS (collected from DLRS Bangladesh) and WorldView 3 satellite images.

Several methods were employed in this study to identify the relationship between plot size and family bonding. These methods include on-screen digitizing, multiple regression analysis, FCM (Fuzzy Cognitive Maps) and cluster analysis. Additionally, kappa statistics were utilized to measure the error matrix for nuclear and combined family data collected from agricultural plot boundaries in April 2024.

a. Georeferencing

Ground Control Points (GCPs) were collected through a field survey to georeference the CS and RS *Mouza* maps. The GCP data were processed and integrated into ArcGIS software for georeferencing purposes. Subsequently, the georeferenced maps were further adjusted using georeferencing tools to align with a WorldView satellite image, allowing for accurate plotting of boundaries.

b. On-screen digitizing

On-screen digitizing is an interactive technique used to generate vector data from previously scanned documents or raster information. In this study, the on-screen digitizing method was employed to digitize the CS map from 1950, the RS map from 1998, and satellite images from 2023, enabling the measurement of agricultural plot boundaries. Each digitized plot boundary is accompanied by metadata related to the landowners, including a unique plot number assigned to each plot on the map.

c. Cluster analysis

Cluster analysis is a statistical data processing technique that categorizes objects into clusters based on their degree of similarity. In this study, the hierarchical clustering algorithm was employed to analyze the fragmentation of agricultural plot sizes. Cluster analysis was utilized to identify similar groups within the dataset related to the parcelization of agricultural land.

d. Multiple regression model

According to Kutner, Nachtsheim, Neter, and Li (2005), the multiple regression model is expressed as: $Y = \beta 0 + \beta 1X1 + \beta 2X2 + ... + \beta p*Xp + \varepsilon$ Where, Y = Dependent variable, X1, X2, ..., Xp = Independent variables, β0, β1, β2, ..., βp = Regression coefficients (parameters), and ε = Error term (representing the Y variance that could not be explained by the set of independent variables).

The coefficients β1, β2, ..., βp show how much the dependent variable changes when the corresponding independent variable changes by one unit, while all other independent variables stay the same. The intercept term, β0, is the value of the dependent variable when all the independent variables are zero. Multiple regression aims to estimate the regression coefficient values that best suit the observed data by minimizing the sum of the squared differences between the actual and anticipated values of Y based on the independent variables. Ordinary least squares (OLS) regression is commonly used for this. Based on the values of the independent variables, the resulting model can be used to generate predictions about the value of the dependent variable.

e. *Kappa* statistics

In this study, the cross-validation method was used to validate data accuracy (Hussain *et al.,* 2022). Cross-validation was conducted through GPS Survey (Mishra *et al.,* 2020). From the evaluation samples, an error matrix was calculated. From the error matrix table, the producer's accuracy, user accuracy, overall accuracy, and the *Kappa* coefficient were calculated (Yesuph and Dagnew, 2019). The formula of Cohen's kappa coefficient (Hua, 2017): $K = \frac{PO-Pe}{1\ \ Pe}$, Where, *K*= Kappa Coefficient; *PO*= relative observed agreement among raters; and *Pe*= the hypothetical probability of chance agreement.

f. Fuzzy Cognitive Maps (FCMs)

In this study, the FCM was constructed to model the interactions between key factors influencing agricultural plot fragmentation. Each factor's influence was quantified through an adjacency matrix, where the weights w_{ij} indicate the strength and direction of influence from factor C_j to factor C_i. The activation values for each factor were updated iteratively using the equation $A_i^{(t+1)} - f\,(A_i^{(t)} + \sum_j^n w_{ij}\,.A_j^{(t)})$, where f is a threshold function ensuring the activations remain within a standard range (Kosko, 1986). This iterative process continued until the system reached a stable state, where activation values indicated the relative influence of each factor on land fragmentation.

g. GIS, Remote sensing, and statistical tools

This study employed several software applications, including ArcGIS 10.8, IDRISI Silva, JMP Pro 16, and Microsoft Excel. ArcGIS 10.8 was utilized for primary data preparation and map composition. The transition probability matrix, which analyzes land use gains and losses from the CS *Mouza* map (1950) to the WorldView satellite image (2023), was examined using IDRISI Silva. JMP Pro 16 was used for cluster modeling and multiple regression analysis. Microsoft Excel facilitated attribute generation, data table creation, and tabular data management.

Results and Discussion

Agricultural plot boundaries can be accurately mapped with the use of remote sensing. Agricultural field identification and delineation is made possible through the use of remote sensing and imaging techniques (Wang *et al.,* 2022). The distribution of land in Bangladesh is determined by kinship relationships and cultural norms. Land may be transferred and inherited in a variety of ways, including through ancestral systems (Wang *et al.,* 2022 and Tambiah, 1958). Therefore, land fragmentation techniques, such as the percelization and inheritance of agricultural plots within a family members, can be influenced by kinship as a significant social component (Tambiah, 1958; Yalcin and Gunay, 2016). Detailed findings and analysis are presented and discussed below:

*LULC changes from CS (1950) to the current year (*November, 2023*) with different dynamics:* This research investigates the use of geographic information system (GIS) and remote sensing techniques for mapping the percelization of agricultural land in order to ascertain the familial relationships among the family members. However, it also examines the use of GIS frameworks to precisely identify and map the physical boundaries of agricultural plots through the incorporation of high-resolution satellite images and field survey data. Figure 3 depicts the existing LULC divisions by area for the years 1950, 1998, and 2023. Comparative analysis of the shifting pattern of LULC revealed that the internal LULC categories diverged significantly. As a consequence, a massive transformation has been conceivable over the years as a result of one category LULC to others. The study was able to detect gain, loss, and net change for the three temporal periods 1950-1998, 1998-2023, and overall 1950-2023 by LULC category for a better understanding (Figure 3).

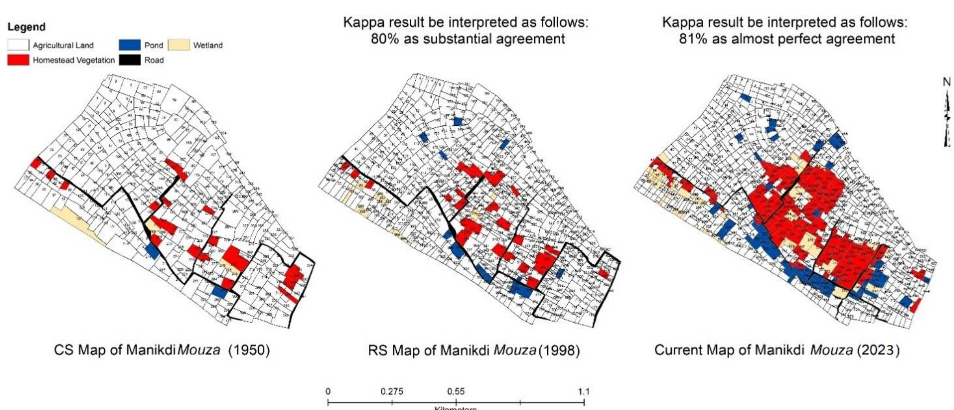

Fig. 3. Land use and land cover changes from CS (1950) to RS (1998) and RS to the Current Year (November, 2023) of Manikdi *Mouza*, Netrokona, Bangladesh.
Source: Compiled by authors, 2024 from CS, RS, and WorldView 3 satellite images.

A change area matrix was created for the aforementioned periods to examine the outcomes of land use/cover conversion. It displays the areas of change concerning other LULC categories during the specified periods. Figure 3 shows that agricultural land dominates the entire research region, with homestead vegetation taking up the majority of the area throughout each of the three study periods.

Table 1. Transition probability matrix derived from the land use maps such as CS, RS, and Landsat TM multispectral satellite imageries in HSCZ during 1950–1998

Changing from	Probability of changing by RS (1998) to:					Subtotals	
CS (1950)	Agricultural land	Homestead vegetation	Pond	Road	Wetland	Total	Loss
Agricultural land	0.7366	0.1473	0.0597	0.0079	0.0486	1	0.2635
Homestead vegetation	0.0162	0.9224	0	0.0037	0.0577	1	0.0776
Pond	0.0553	0.004	0.7426	0.0283	0.1698	1	0.2574
Road	0.2983	0.0941	0.0839	0.5153	0.0085	1	0.4848
Wetland	0.2222	0	0	0	0.7778	1	0.2222
Total	1.3286	1.1678	0.8862	0.5552	1.0624		
Gain	0.592	0.2454	0.1436	0.0399	0.2846		

*** Halgurd-Sakran Core Zone (HSCZ) of the Manikdi *Mouza* in the Netrokona district, Bangladesh;
*** CS (Cadastral Survey), 1950 land survey system used to establish and maintain land records in Bangladesh;
*** RS, 1998- A land surveying method known as RS (Record of Rights Survey) is used to establish and keep records of land ownership and use; and
*** *Mouza* Boundary- Smallest administrative units of Bangladesh.
Source: Compiled by authors, 2024 using CS and RS *Mouza* boundary.

The probability matrix for significant LULC conversions for all classes in HSCZ that occurred between 1950 and 1998 is summarised in Table 1. While agricultural land has a chance of 73.66% in 1998 to continue to be agricultural land, the likelihood of conversion from agricultural land to homestead vegetation is 14.73%. Other fields like agricultural land to the pond, agricultural land to the road, and agricultural land to wetland transformation probability are 5.97%, 0.79%, and 4.86%.

Homestead vegetation has a 92.24% probability of remaining as homestead vegetation, a 1.62% chance of becoming agricultural land, a 0% chance of being a pond, a 0.37% chance of turning roads, and a 4.86% chance of becoming wetlands. In comparison to other categories, homestead vegetation is less likely to alter under the impact of population increase and homestead expansion from 1950 to 1998. Pond-to-pond conversion is 74.26% likely, compared to 5.53% for the pond to agricultural land, 0.4% for pond-to-homestead vegetation, 2.83% for pond-to-road, and 16.98% for pond-to-wetland. Road has undergone the most alteration between 1950 and 1998. Road has a 51.53% chance of still being a road, compared to 29.83% for a road to an agricultural field, 9.41% for a road to homestead vegetation, 8.39% for a road to a pond, and 0.85% for a road to a wetland. Less change was made to wetland at that time. Wetland remained wetland 77.78% of the time, with transitions to agricultural land occurring just 22.22% of the time.

Table 2 shows the second scenario of transition probability from RS to WorldView 3 multispectral satellite imageries during 1998-2023. The classification categories remain the same as the scenario 1st from 1950-1998. For agricultural land, there is a 96.09% chance that it will continue to be unchanged. However, there is a 1.86% chance that it will be transformed into homestead vegetation, a 0.633% chance that it will become pond, a 0.51% chance that it will be road, and a 0.91% chance that it will become wetland.

The second least amount of change occurred on agricultural land among the various categorization groups. The likelihood that homestead vegetation will stay homestead vegetation is 71.37%, compared to the probabilities for homestead vegetation to be converted to agricultural land, ponds, roads, and wetland, which are all 0%. Pond categorization category had the least amount of change. Pond stayed a pond 96.48% of the time, changed into agricultural land 3.52%, changed into homestead vegetation 0%, changed into a road 0%, and changed into a wetland 0%.

Table 2. Transition probability matrix derived from the land use maps such as RS and WorldView 3 multispectral satellite imageries in HSCZ during 1998–2023.

Changing from	Probability of changing by the current year (2023) to:					Subtotals	
RS (1998)	Agricultural land	Homestead vegetation	Pond	Road	Wetland	Total	Loss
Agricultural land	0.9609	0.0186	0.0063	0.0051	0.0091	1	0.0391
Homestead vegetation	0.2634	0.7137	0	0.0228	0	1	0.2862
Pond	0.0352	0	0.9648	0	0	1	0.0352
Road	0.1744	0.0402	0.011	0.7743	0	1	0.2256
Wetland	0.5148	0.076	0	0.019	0.3902	1	0.6098
Total	1.9487	0.8485	0.9821	0.8212	0.3993		
Gain	0.9878	0.1348	0.0173	0.0469	0.0091		

*** Halgurd-Sakran Core Zone (HSCZ) of the Manikdi *Mouza* in the Netrokona district, Bangladesh;
Source: Compiled by authors, 2024 using RS *Mouza* boundary and WorldView 3 multispectral satellite imageries.

Road retained road 77.43% while experiencing the second-highest shifting. Road conversions to agricultural land, homestead vegetation, ponds, and wetlands total 17.44%, 4.02%, 1.1%, 0.1%, and 1.1%, respectively. Wetland underwent the greatest alteration of all for the final classification category. From 1950 to 1998, wetlands remained wetlands 39.02% of the time, but wetlands changed into agricultural land 51.48% of the time, the greatest likelihood of changing from wetlands to other classified categories. 7.6% of wetlands were converted to homestead vegetation, 0% to ponds, and 1.9% to roads. During the period, agricultural land had the biggest gains and wetlands saw the highest losses, which shows the intense pressure on land used for agriculture.

The spatial orientation of plot size boundaries changes over time: There are 1048 plots in total in November, 2023, and 684 of them are set aside for agriculture. Agricultural plot numbers grew from 1998 to 2023 from 646 to 684, with 299 plots fragmenting into 337 plots over this research period representing the nuclear family while 347 plots representing the united family stayed the same. The number of homestead vegetation plots was 20 in 1950; in 1998, it was broken into 31 plots, with 12 plots remaining the same as previously and 8 plots representing the nuclear family, adding 19 plots. The number of homestead vegetation plots rose from 187 in the previous research year (1998) to 215 between 1998 and 2023, with 28 plots remaining the same.

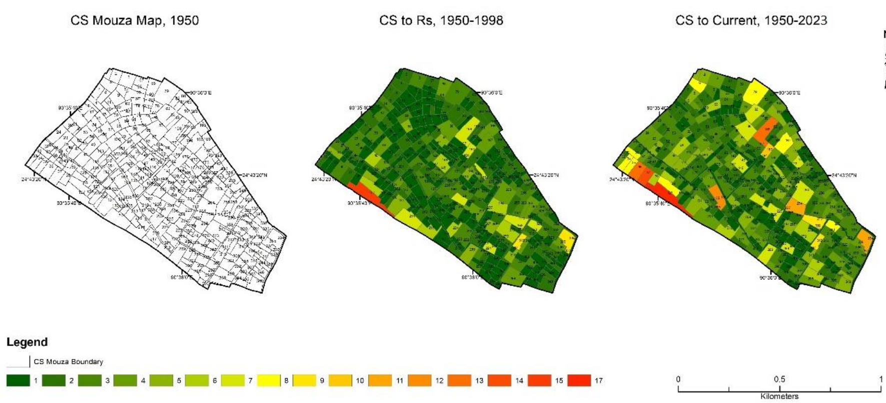

Fig. 4. The spatial orientation of plot size boundaries changes over time as family structures change from CS (1950) to RS (1998) and RS to Current Year (November, 2023) of Manikdi *Mouza*, Netrokona, Bangladesh.

Source: Compiled by authors, 2024 from CS, RS, and WorldView 3 satellite images.

Table 3. Identify the nuclear and combined family using CS, RS, and WorldView 3 multispectral satellite imageries during 1950–2023.

LULC/ Year	Total plot no- CS (1950)	Total plot no- RS (1998)	Nuclear family/LULC changes of plot numbers	No changes plot boundaries (RS-1998)	Total plot no. current (2023)	Nuclear family/LULC changes of plot numbers	No changes plot boundaries (Current-2023)
Agricultural land	327	646	471*	175**	684	337*	347**
Homestead vegetation	20	31	19*	12**	215	187*	28**
Pond	2	14	12	2	54	41	13
Road	7	7	3	4	8	6	2
Wetland	3	21	20	1	87	73	14
Total Plot No	359	719		194	1048		404

* Nuclear family in the Manikdi *Mouza*, Netrokona, Bangladesh from CS to the Current year of November, 2023; and

** Combined family in the Manikdi *Mouza*, Netrokona, Bangladesh from CS to the Current year of November, 2023.

Source: Compiled by authors, 2024 from CS, RS, and WorldView 3 satellite images.

Table 3 shows the total number of plots and how they were divided into nuclear and combined family groups over this study period. According to the CS map, there were 359 total plots in 1950. By combining the various categorization types of agricultural land, homestead vegetation, pond, road, and wetland, it fragmented into a total 719 number of plots. The two categorization groups with the greatest representation are agricultural land and homestead vegetation. The fragmentation of the entire plot number is shown by the fact that the overall plot number rose to 719 in 1998 from 359. According to this research, the number of agricultural plots expanded from 327 to 646 throughout the study period, while 175 plots stayed the same as they were in 1950, representing the combined family, and 152 agricultural plots are divided into 471 plots, which indicates the nuclear family.

Cluster analysis for plot size fragmentation: Cluster analysis is a statistical method for determining subsets of a dataset which have characteristics such as a high degree of similarity or close physical proximity. The use of cluster analysis allows for an investigation of temporal and spatial trends in the distribution of plot boundaries with the changes of family ties. Figure 5 displays the cluster analysis for plot size fragmentation over the research period. This diagram shows three clusters of plot fragmentation. Cluster 1 represents a plot that has been divided into 1-6 plots. Cluster 2 depicts the division of a plot into 7–12 plots, whereas Cluster 3 shows the division of a plot into 13–18 plots.

From CS until the present, there were a total of 359 plots, which were divided into 1,048 plots. Of them, 219 plots are part of Cluster 1, 37 plots are part of Cluster 2, and 103 plots are part of Cluster 3.

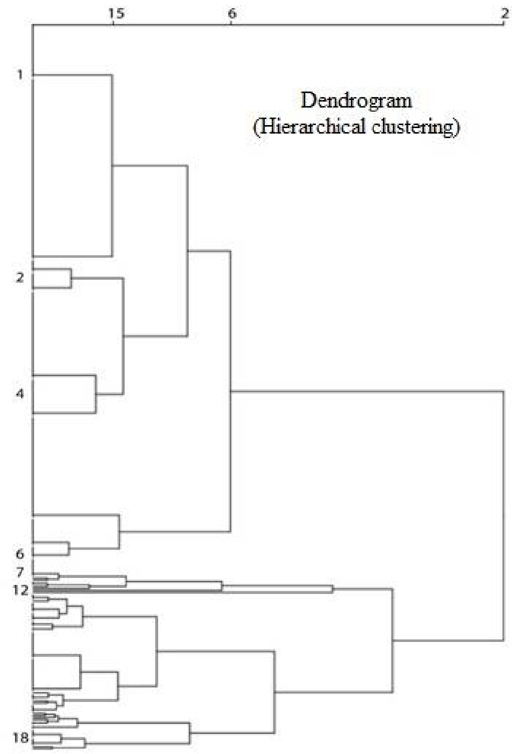

Fig. 5. Cluster analysis (Hierarchical clustering) for plot size fragmentation from 1950-2023. Source: Made by authors, 2024 from CS, RS, and WorldView 3 satellite images.

Driving forces that are responsible for agricultural plot size fragmentation using multiple regression model

Scenario-1: CS to RS (1950-1998)

There are a number of forces that directly influence parcelization of land. From 1950 to 1998, the primary propelling forces were economic development, demographic factors, social structure, resource scarcity, and land tenure systems. In this case, economic development plays the leading role, while demographic factors also play a significant role in land valuation. As the population development rate was high during that time period, particularly after independence, the rate of land fragmentation was also high. Social structure also influenced the fragmentation of the narrative. The tendency toward nuclear families determines the size of plots. With 12% and 8%, resource scarcity and land price systems play a less significant role.

Table 4. Driving factors for changing of land ownership between combined family to nuclear family from 1950-1998.

Contributing/influencing factors for changing of land ownership between combined family to nuclear family	Percentage according to multiple regression models
Economic development	35%
Demographic factors	25%
Social structure	20%
Resource scarcity	12%
Land tenure systems	8%

Source: Made by authors, 2024 using multiple regression models

Combined to Nuclear= 0.35Ed+0.25Df+0.20Ss+0.12Rs+0.8Lt

Here, Ed=Economic development, Df= Demographic factors, Ss=Social Structure, Rs=Resource scarcity and Lt=Land tenure systems

Scenario- 2: RS to Current (1998-2023)

For 2nd scenario, economic development, demographic factors, technological innovation, urbanization, land tenure systems, and resource scarcity are the main controlling factors of percelization of land. From 1998 to 2023, over 23 years, economic development and demographic factors influence the land fragmentation most having 40% and 30% contribution respectively.

Table 5. Driving factors for changing of land ownership between combined family to nuclear family from 1998 to 2023.

Contributing/influencing factors for changing of land ownership between combined family to nuclear family	Percentage according to multiple regression models
Economic development	40%
Demographic factors	30%
Technological innovation	15%
Urbanization	10%
Land tenure systems	3%
Resource scarcity	2%

Source: Made by authors, 2024 using multiple regression models

Combined to Nuclear= 0.40Ed+0.30Df+0.15Ti+0.10U+0.03Lt+0.02Rs

Here, Ed= Economic development, Df= Demographic Factors, Ti= Technological innovation, U= Urbanization, Lt= Land tenure systems and Rs=Resource scarcity

From CS to RS (1950-1998), the percentage of factors influencing the shift from combined to nuclear family land ownership found that economic development, demographic factors, and social structure were the most influential, while resource scarcity and land tenure systems had a relatively smaller impact.

The percentage change from RS to Current (1998-2023) shows that technological innovation and urbanization are the most important factors influencing the shift from combined to nuclear family land ownership. Resource scarcity and land ownership structures play a smaller role in this model.

FCM analysis

The FCM analysis highlights that economic development, with an activation value of 0.40, is the most influential driver of agricultural plot fragmentation, reflecting the strong role economic progress plays in driving land division. As economic growth increased land value, families divided their landholdings to capitalize on these rising values, marking economic development as the central force in plot fragmentation. Demographic factors, at 0.30, significantly contribute by intensifying land subdivision due to rapid population growth, particularly after Bangladesh's independence, which led to larger plots being split among more people. Social structure, with a value of 0.20, also plays an essential role, as the shift toward nuclear families increased the demand for individual landholdings, accelerating fragmentation. Technological innovation (0.15) and urbanization (0.10) add to this trend, with advancements in technology making smaller plots manageable and urban expansion pressuring rural areas. While resource scarcity (0.02) and land tenure systems (0.03) have lesser weights, they impose constraints that indirectly reinforce land division trends. Together, these factors underscore the cumulative impact of economic, demographic, social, and technological forces in reshaping agricultural land ownership in Bangladesh.

The discussion focuses on interpreting the results of this study, which analyzed land use and land cover (LULC) changes in Manikdi *Mouza*, Netrokona, Bangladesh, over the period from 1950 to 2023. Using remote sensing and GIS techniques, the analysis sheds light on the influence of family structures such as nuclear and combined families on agricultural land parcelization. The significant LULC transformations observed suggest that cultural shifts and evolving family dynamics have played a critical role in shaping

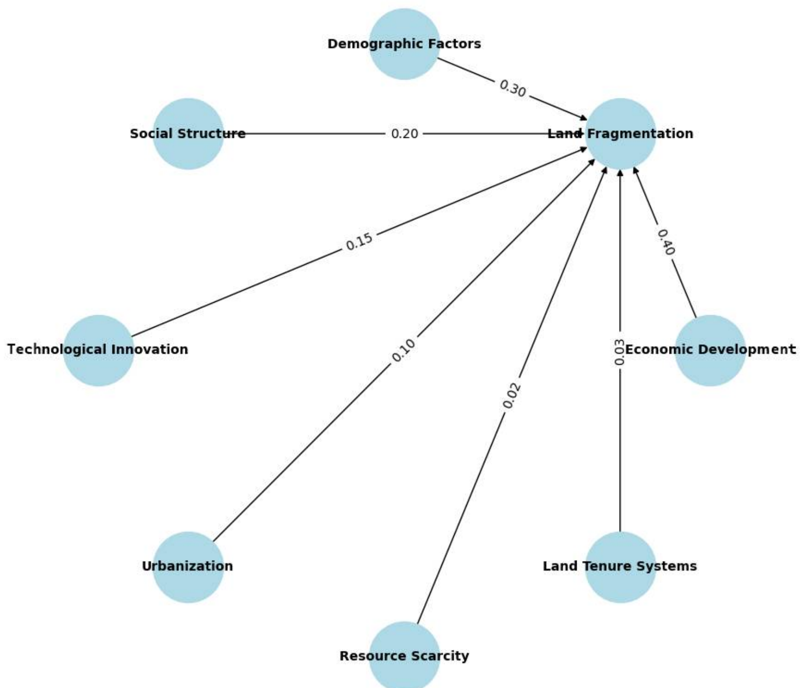

Fig. 6. The Fuzzy Cognitive Map (FCM) analysis using different driving forces that influences plot size fragmentation from 1950-2023.
Source: Made by authors, 2024 from surveyed data.

land fragmentation trends. These findings are examined in the broader context of rural development, economic impacts, and potential policy interventions to address the consequences of increasing land parcelization. The most significant changes were agricultural land and homestead vegetation. Agricultural land increased from 327 plots in 1950 to 646 plots in 1998 and further to 684 plots in 2023. Among these, 471 plots were fragmented into smaller plots representing nuclear families, while 175 plots remained unchanged and were associated with combined family units. By 2023, 337 of the total agricultural plots were associated with nuclear families, while 347 plots remained unchanged. Homestead vegetation, which initially consisted of only 20 plots in 1950, saw an increase to 31 plots in 1998, with 19 of these being associated with nuclear family units and 12 remaining unchanged. By 2023, homestead vegetation expanded dramatically to 215 plots, of which 187 represented nuclear family plots, leaving only 28 unchanged. The trend of land fragmentation in ponds, roads, and wetlands was also notable. Ponds expanded from just 2 plots in 1950 to 14 in 1998, and then to 54 plots by 2023, with the majority of this change attributed to nuclear family land use. Wetlands saw an even greater shift, increasing from 3 plots in 1950 to 21 in 1998, and then to 87 plots by 2023. Much of the wetland fragmentation occurred in nuclear family structures, with a significant portion of wetlands being repurposed for agricultural use. In total, the number of plots increased from 359 in 1950 to 1048 in 2023. This reflects the broader trend of land parcelization in Manikdi *Mouza*, as nuclear families sought to divide ancestral land among family members, leading to a significant increase in the number of plots, particularly in agricultural and homestead categories. The increase in nuclear family plots indicates the growing trend of land fragmentation in response to evolving family structures, with a shift from large, combined family landholdings to smaller, more fragmented parcels.

The multiple regression model reveals that from 1950 to 1998, economic development (35%), demographic factors (25%), and social structure (20%) were primary drivers of agricultural plot fragmentation, with resource scarcity (12%) and land tenure (8%) playing smaller roles. From 1998 to 2023, economic and demographic factors remained influential, while technological innovation (15%) and urbanization (10%) gained prominence. The FCM analysis corroborates these findings, highlighting economic (0.40) and demographic (0.30) factors as central, with social structure (0.20) and technology (0.15) reinforcing land fragmentation trends.

The spatial analysis demonstrates how kinship and cultural practices directly influence land use patterns, as seen in the breakdown of agricultural plots and homestead vegetation over time. This research highlights the significant socio-cultural factors driving land fragmentation and the implications this has for agricultural productivity, land management, and rural development in the region. The continued parcelization of land poses challenges for sustainable land use, particularly in maintaining agricultural productivity and addressing the increasing pressure on natural resources.

Accuracy Assessment/Validation: To evaluate the classification's accuracy, each LULC map was compared to reference data. Using ERDAS Imagine 9.1 software, a GPS field survey was used as ground truth data to confirm the categorization accuracy. The accuracy assessment process is a particularly effective approach to portray accuracy since it identifies the accuracies of each category as well as any inclusion- and exclusion-related mistakes (commission errors and omission errors) that may have occurred during the classification (Congalton, 1991). The image from 1950 and 1998 was found to have an overall accuracy of 85.98% and 82.13%, respectively, with matching kappa coefficients of 0.84 and 0.86. Both the accuracy of the producer and the user were over 82%.

Table 6. User's accuracy, producer accuracy, overall accuracy, and kappa statistics for Nuclear and Combined family from agricultural plot boundary, 2023.

Features	CS in 1950		RS in 1998		Current year-2023	
	User's accuracy	Producer's accuracy	User's accuracy	Producer's accuracy	User's accuracy	Producer's accuracy
Nuclear family	85.00%	81.73%	80.00%	83.33%	91.11%	95.35%
Combined family	82.00%	85.42%	85.00%	86.73%	92.22%	90.22%
Overall accuracy	85.98%		82.13%		89.52%	
Kappa statistics	84.90%		86.37%		82.50%	

Source: Compiled by authors, 2024 using Kappa statistics

Implications

This research introduces a novel cultural perspective on remote sensing by examining kinship detection and its impact on rural land use in Bangladesh, offering significant insights for local governance and national policies. By identifying familial connections, kinship detection can enhance various policy areas, including social welfare programs by validating family ties for benefit distribution, inheritance rights by clarifying family claims to prevent disputes, and public health by understanding genetic disease patterns. Additionally, it can support disaster response by reconnecting separated family members, inform socio-economic policies on wealth distribution and social mobility linked to familial land fragmentation, and improve census accuracy by identifying kin-based land use and hidden households in rural areas. The study suggests that integrating kinship detection with remote sensing can drive advancements in socio-economic policy, public health, and disaster management, expanding the applications of remote sensing in cultural studies.

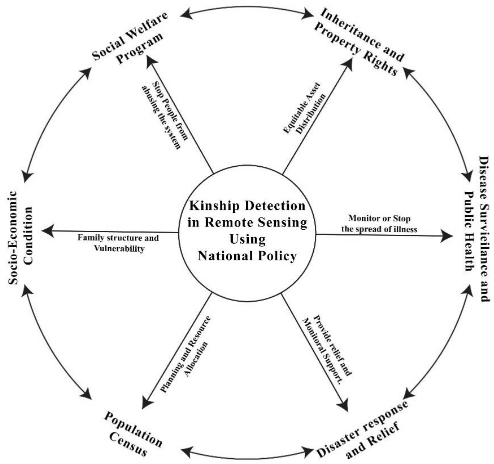

Fig. 7. Implications of kinship detection using remote sensing can indeed play a vital role in national policy in a number of ways.
Source: Made by authors, 2024 from KII, questionnaire survey and FGDs.

Conclusion

Land cover can be interpreted both implicitly and explicitly using remote sensing data. Through the use of remote sensing data, this study identifies the implicit aspect of kinship. From CS to RS, the rate of land parcelization was 73.02%, but from RS to the present day, it has decreased to 61.45%. High percelization of land from CS to RS indicates that the number of nuclear families increased between 1950 and 1998, despite the influence of population growth and economic development during this time period. Due to an increase in population, the agricultural land boundary changed significantly from CS to RS and then from RS to the present. Technical innovation and urbanisation were added to these factors, which essentially represent the kinship of Manikdi Mauza.

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