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Historical Analysis of Land-use Changes in Vietnam's Red River Delta: Bayesian Network Approach to Land Policies and Sustainable Development

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Abstract

Purpose: Vietnam's Red River Delta experiences rapid and uneven land-use transformations driven by market liberalization and urban expansion, severely impacting agricultural land and rural livelihoods. Accurate modeling of these changes is critical for sustainable land governance. To address this gap, this study uses Bayesian network modeling to retrospectively investigate LUCC in the Red River Delta, clarifying how land-policy transitions and agricultural expansion have influenced land-use decision-making and highlighting sustainable development implications.

Design/methodology/approach: This study proposes a Bayesian network-based panel decision support framework that synthesizes (i) multi-temporal satellite-derived spatial data (1979–2022), (ii) farmer land-use decision behavior, and (iii) historical land-policy and institutional change to evaluate and project LULC dynamics in the Red River Delta. To the best of our knowledge, this is the first region-wide, long-horizon application that explicitly links LUCC trajectories to policy shifts, quantifies transformation trends, and identifies the key drivers shaping land-use change.

Findings: The Red River Delta has undergone a clear shift from rice-based agriculture toward urban–industrial land uses between 2008 and 2022. Agricultural land declined sharply (7%), while forest land decreased only modestly (0.8%) and pastureland expanded (6.3%). The Bayesian network results indicate that industrial land prices are among the most influential economic drivers of these transitions, while the strongest governance levers relate to land-use zoning and conversion controls that steer agricultural-to-urban/industrial reallocations. In addition, the slight rebound of previously diminishing undefined agricultural zones suggests a move toward more structured land management.

Research limitations/implications: Limitations include medium-resolution satellite imagery potentially overlooking small-scale features and classification uncertainties from traditional algorithms.

Practical implications and Originality/value: This study presents a Bayesian network panel decision support framework that enables ex ante policy evaluation of land governance in the Red River Delta by simulating policy scenarios before implementation and estimating their likely effects on LUCC. It tests how changes in land use zoning, conversion controls, and industrial land prices shift the probability of major transitions, especially the conversion of rice-based agricultural land to urban and industrial uses, and highlights the most influential governance levers. The region-wide, long-horizon application in the Red River Delta offers a transferable approach for Asian delta regions facing similar trade-offs between urban industrial expansion, agricultural protection, and sustainability goals.

Keywords: LUCC, Bayesian Network, Red River Delta, agricultural policy, sustainable land use

JEL Classifications: Q15, Q24, Q58, R14, O13

1. Introduction

Land policy has always been a central element of governance in Vietnam. It provides livelihoods for rural populations and helps maintain political power and social stability. Over time, from the feudal era through the colonial period, the revolutionary and resistance era, and particularly during the period of socialist construction and Renovation, Vietnam's land policies have undergone profound transformations. Each historical period in Vietnam has distinct characteristics. These reflect changes in power structures, economy, and society, significantly impacting rural communities. Studying and assessing the impact of land policies throughout these periods deepens our understanding of Vietnam's socio-economic development history and provides insight into how political systems operate and how society has evolved across different eras.

During the feudal era, land ownership was predominantly concentrated in the hands of the monarchy, aristocracy, and landlords, while peasants rented land and paid heavy taxes to the landlords. The land policy during this period reflected deep social stratification regarding land ownership among classes. Khánh (1999) thoroughly analyzed the accumulation of land by landlords and the resulting social stratification, highlighting that land ownership was instrumental in maintaining power and hierarchy within feudal society, and history was a direct consequence of these unjust land policies. When the French colonized Vietnam, they reinforced land ownership policies to maximize profits and consolidate their power. The colonial government fostered the emergence of a new landlord class loyal to the French and established large plantations where peasants were exploited harshly. Anh (2022) studied the plantation system under French rule and its effects on Vietnamese society, showing how land concentration exacerbated economic and social oppression in rural areas. After gaining independence, the revolutionary government led by Ho Chi Minh recognized the necessity of land reform to alleviate social injustice and consolidate political power. Kerkvliet (1995) also discussed the impact of Renovation policies on agriculture and rural social structure, emphasizing that these changes reduced the state's control over land use rights and facilitated economic development. Khải (2008) analyzed this transformation, particularly the introduction of Contract 10, which granted farmers greater autonomy in production and promoted the development of commodity-based agriculture.

Recognizing the significance of land-related policies, the 1999 revision of the Land Law enabled individuals and households to obtain land use rights for forest areas previously under state ownership. By the end of 2007, more than 62% of Vietnam’s forest land had been allocated to these groups. However, amid rapid urbanization, converting agricultural land into industrial zones and replacing primary forests with expanded cultivation areas and resettlement have become increasingly common, particularly in the Red River Delta. This region is the most densely populated area in the country, resulting in intensive exploitation of land resources for a wide range of purposes such as urbanization, afforestation, rice cultivation, and other agricultural production. Over time, both the area and quality of land resources in the Red River Delta have experienced substantial fluctuations due to the combined impacts of natural processes and human activities (Niculescu & Lam, 2019). In recent years, the region’s agricultural land area has continuously declined due to the development and expansion of industrial parks and urban infrastructure (Thien & Phuong, 2024). Nevertheless, the rapid and inadequately managed conversion of agricultural land to other purposes may create long-term challenges, including impacts on sustainable economic growth, labor allocation, and food security. In addition, the Red River Delta is the country's northern growth pole, encompassing leading urban–industrial centers such as Hà Nội, Hải Phòng, and Quảng Ninh and hosting a dense network of industrial parks and transport infrastructure. These characteristics make land conversion pressures particularly acute and policy trade-offs between urban expansion, agricultural protection, and sustainability highly visible. As a rapidly transforming yet data-rich delta region, the Red River Delta provides a policy-relevant testbed whose lessons can inform land governance strategies in other Vietnamese and Asian delta plains facing similar urbanization dynamics. Therefore, the Red River Delta was selected as the study area to assess the impact of urbanization on changes in land-use patterns.

The Bayesian Network, also referred to as a belief network, is a powerful tool widely adopted in empirical data analysis and management research. BN enables highly accurate predictions even when the sample size is limited, and it effectively avoids model overfitting (Uusitalo, 2007). Moreover, it allows for integrating qualitative variables with quantitative and spatial data and scenario-based exploration of policy interventions. Standard regression is designed to quantify average marginal effects and provide clear, comparable effect sizes while controlling for confounders in a structured way. Bayesian Networks add value beyond standard regression by representing a system of linked factors and estimating how the probability of an outcome changes under specific combinations of conditions, which makes it easier to capture interaction patterns, nonlinear dependencies, and uncertainty. Used together, Bayesian Networks provide probabilistic, scenario-oriented insight into conditional pathways, and regression provides interpretable effect magnitude and hypothesis testing, so the two methods cross-validate each other and deliver both explanation and decision support. Additionally, Bayesian Networks offer several further advantages that are particularly relevant for land use change analysis. BNs are robust to missing or incomplete data and can formally incorporate prior expert knowledge, making them highly valuable in settings where empirical information is limited or fragmented (Celio et al., 2014). BN models enable explicit uncertainty quantification, providing policymakers with transparent estimates of confidence and risk associated with different land use scenarios (Nascimento et al., 2020). Furthermore, compared to conventional regression-based approaches, BNs can flexibly model nonlinearities, feedback loops, and hierarchical structures in data, which are often present in socio-ecological systems (Uusitalo, 2007). While Bayesian Networks are well-suited to represent conditional dependencies and propagate uncertainty for scenario-based policy experiments, they do not directly provide interpretable marginal effects or control for time-invariant heterogeneity across provinces. We therefore complement BN inference with province–year panel regressions to quantify elasticities of key drivers, test hypotheses under alternative econometric specifications, and validate whether the probabilistic signals from the BN are reflected in observed conversion rates over time. This combined BN–panel design triangulates evidence, strengthening both predictive performance and explanatory credibility for policy guidance.

In recent decades, remote sensing (RS) and geographic information systems (Aguilar et al., 2023) have become the most widely used tools for quantitatively assessing the spatial and temporal dimensions of landscape dynamics and supporting evaluations of global-scale changes at various levels (Schaefer & Thinh, 2019; Thien & Phuong, 2024; Tin et al., 2023). More recently, research has increasingly focused on LULC dynamics, particularly emphasizing how settlements, forests, and agricultural areas evolve spatially and temporally (Mariye et al., 2022). However, to the best of our knowledge, no previous study has applied a Bayesian Network-based model to explicitly estimate land-use changes over space and time, specifically for the Red River Delta. Existing research has generally concentrated on individual districts, towns, or provinces and often employed qualitative or historical methodologies. Consequently, comprehensive data regarding the trends, scope, and magnitude of LULC transformations in the Red River Delta region remain limited and insufficiently analyzed. Moreover, the drivers, impacts, and consequences of land-use change in this region, one of Vietnam's fastest-urbanizing areas and a leading national economic hub, have not been fully understood.

To mitigate the adverse effects of urbanization and promote effective land management, policymakers require comprehensive, current information, especially spatial indicators represented through detailed territorial LULC maps. Such spatial data are critical for effective land-use management and strategic planning, providing the empirical basis for decision-oriented analysis and policy evaluation in decision sciences (Aguilar et al., 2023; Almazyad et al., 2024; Schaefer & Thinh, 2019). Nonetheless, policymakers currently face significant constraints in accessing timely and accurate spatial data, often relying on outdated or incomplete sources.

Addressing this gap, our study represents the first spatially explicit application of a Bayesian Network LUCC model in the Red River Delta, integrating multi-temporal remote sensing data, detailed household survey evidence, and systematic analysis of policy interventions over more than four decades (1979–2022). While prior LUCC studies that primarily map land-cover change or estimate drivers using a single modeling approach over short time windows or small administrative units, this study provides a region-wide, four-decade assessment that explicitly links land-use trajectories to policy and institutional shifts. Methodologically, the novelty lies in integrating spatially explicit remote-sensing change detection with a decision-oriented Bayesian Network calibrated by farmer behavior and governance mechanisms, and then validating these probabilistic insights through province–year panel regressions. This integrated framework moves beyond descriptive LUCC mapping by enabling ex ante policy scenario simulation and identifying the most influential economic and governance levers shaping agricultural-to-urban and industrial transitions. This research thus contributes to filling critical knowledge gaps in Vietnam's land management literature. Specifically, the objectives of this study are threefold: (1) to utilize remote sensing imagery to identify and model LULC changes across three distinct periods (1979–1986, 1986–2008, and 2008–2022); (2) to conduct a detailed spatio-temporal analysis that characterizes the dynamics of land-cover transformation; and (3) to assess the impacts and policy implications of urban expansion on agricultural land conversion, thereby providing actionable insights for policymakers aiming to balance economic growth, resource allocation, and food security.

This study contributes to the Decision Sciences community by leveraging a Bayesian decision-analytic framework to model land-use choices, offering actionable, data-driven insights for strategic land governance in Vietnam's Red River Delta. By integrating Bayesian Network modeling with multi-temporal spatial data and policy analysis, this study not only deepens the understanding of land-use change in Vietnam but also contributes to the broader literature on data-driven approaches that inform strategic decision-making in complex socio-economic systems. Specifically, the study develops a Bayesian Network–based panel decision-support design that integrates (i) four decades of multi-temporal satellite-derived land-cover reconstruction (1979–2022), (ii) farmer land-use decision evidence elicited through structured scenarios, and (iii) time-varying policy and institutional conditions that shape feasible land reallocations. The Bayesian Network produces province–year posterior probabilities of key transitions such as conversion of rice-based agricultural land to urban and industrial uses. While complementary province–year panel regressions validate these probabilistic signals and quantify elasticities under econometric controls. This methodology helps clarify how expected conversion risk shifts when decision makers adjust key governance levers, including industrial land prices, zoning, and conversion controls, and pasture expansion as a transitional state that often precedes non-agricultural conversion. The framework supports scenario-based planning, prioritization of monitoring and enforcement, and more transparent trade-off discussions between urban-industrial expansion, agricultural protection, and sustainability goals in one of Vietnam's fastest-transforming delta regions.

2. Background and theoretical framework

2.1. Land ownership theory

The land ownership theory focuses on the role of property rights in resource allocation and economic efficiency. Coase (2013) introduced the concept of well-defined property rights and transaction costs, asserting that clear property rights reduce transaction costs among involved parties, thereby improving the efficiency of resource allocation. As a valuable asset, land optimizes land use and enhances production efficiency when adequately managed and owned.

Land ownership significantly affects economic outcomes, social stability, and political structures within a country. In countries where land ownership is restricted or unclear, people lack the incentive to invest in and improve production because their rights to the land they use are uncertain. Conversely, in systems where property rights are well-defined and guaranteed, farmers and producers are motivated to invest, innovate, and use land resources efficiently. This is particularly true in the agricultural sector, where land is the most crucial asset for farmers. In Vietnam, land is owned collectively by the people, but the state represents the people in managing it, influencing how land resources are administered and distributed. Additionally, land ownership affects social development and political stability. Transparent and fair land ownership systems can help mitigate land conflicts and social unrest, while unclear or unjust land ownership systems often lead to conflicts and political instability. Coase's theory of property rights provides a framework for understanding the importance of clearly defining and managing land ownership in any economic and political system.

In the study by Deininger and Binswanger (1999) on land reform in developing countries, the authors applied Coase's theory to analyze the relationship between land ownership and agricultural productivity. The study found that when land ownership rights are secured, farmers are motivated to invest in the land, improving labor productivity. This research emphasizes that clarity and stability in land ownership enhance land use efficiency and reduce conflicts related to land assets.

2.2. Theory of social inequality

Karl Marx's theory of social inequality is grounded in class division and ownership of the means of production. Marx argued that in all economic systems, particularly in feudal and capitalist systems, the means of production, including land, are often controlled by a small class within society, leading to the exploitation of the working class. In this system, landlords or landowners control critical resources, while most laborers must depend on employment, creating economic, social, and political inequality. In Marx's theory, land is one of the most important means of production in agricultural societies, and land ownership directly impacts social structure. The concentration of land ownership in the hands of a small ruling class, such as aristocrats and landlords, leads to the dependency of the majority of the peasant population, creating a system of exploitation and injustice. Marx believed this process created economic inequality, strengthened the ruling class's power, and maintained oppression over the labor class.

This theory analyzes the injustice in land ownership and explains the struggle of the working class to seize control of the means of production, thereby achieving social equality. The social revolutions proposed by Marx aim to eliminate private ownership of the means of production, including land, and transfer ownership to the people as a whole as a solution to address inequality and create a more just society. The study by White (1981) on land reform in northern Vietnam during 1953-1957 also utilized Marx's theory to explain the process of eliminating landlord land ownership and redistributing land to peasants. White argued that this was a significant social revolution in which the power of the landlords was overthrown, and ownership of the means of production was transferred to the peasant class. The study showed that land reform addressed economic issues and changed rural Vietnam's social structure and class relations.

Khánh (1999) applied this theory to study the concentration of land ownership in the hands of landlords and aristocrats in Vietnam during the feudal and colonial periods. He found that the concentration of landownership in a minority class led to the exploitation and oppression of peasants and was the cause of many uprisings and class struggles. His research concluded that the polarization of landownership strengthened the ruling class's power and maintained social injustice, laying the groundwork for subsequent land reform movements.

To promote equitable land tenure and reduce social inequalities in land access, the Vietnamese Government has issued a series of targeted decrees that translate constitutional commitments into concrete entitlements for vulnerable groups. As shown in Table A1 (Appendix A), these policies gradually expand support, ranging from land allocation and levy reductions to financial assistance and digital transparency, helping to narrow the land tenure gap and ensure fairer access to land for ethnic minorities, poor households, and other disadvantaged communities.

2.3. Agricultural development theory

Schultz's (1964) theory of agricultural development focuses on the role of land in promoting agricultural economic development. Schultz argued that in agrarian economies, land reform and the redistribution of land-use rights play a crucial role in improving labor productivity and the financial well-being of farmers. He believed that land reform not only aims to redistribute resources but also helps farmers access land, encouraging them to invest in production, improve technology, and enhance productivity. This is particularly important in countries where land ownership is concentrated in the hands of a few, leading to resource wastage and hindering agricultural economic development. Schultz emphasized that a fair and transparent land distribution system helps minimize waste, increase production efficiency, and create conditions for sustainable economic growth.

Schultz's research also showed that land reform is critical in transitioning from traditional agricultural economies to modern ones. When farmers have land ownership rights and their land-use rights are guaranteed, they are motivated to invest, innovate, and improve productivity, thereby promoting the development of rural economies and improving farmers' living conditions. Schultz believed that granting land ownership rights to farmers helps break down social and political barriers, creating conditions for comprehensive social development. In addition to overarching strategic frameworks for rural and agricultural development, the Government has enacted a comprehensive set of laws and regulations to support modern agriculture (Table A2). These regulations address a range of objectives, including promoting private investment, facilitating digital transformation, enhancing value-chain linkages, and encouraging environmentally sustainable practices (ADB, 2022). Recent policies have also focused on green growth and climate resilience, with specific targets such as increasing organic production and supporting farmland consolidation (World Bank, 2022). This evolving legal landscape has laid the foundation for Vietnam's agricultural sector to improve productivity, adopt advanced technologies, and better integrate into global markets.

2.4. Network models for land-use change

Over the last few decades, the rapid expansion of remote sensing and spatial data processing has enabled detailed analyses of land-use and land-cover change. Within this growing field, a wide range of traditional (non-Bayesian) LUCC models has been developed. These include Markov chain models, cellular automata (CA), CA–Markov hybrids, logistic and other regression-based transition models, and machine-learning approaches such as artificial neural networks. Markov chains capture temporal transitions by assuming that the next state depends only on the current state, while CA models allocate those transitions spatially using neighbourhood-based rules (Ghosh et al., 2017; Kocabas & Dragicevic, 2006). Regression-based models estimate how socio-economic or biophysical factors shape transition probabilities, and machine-learning classifiers detect patterns directly from remote-sensing data. These approaches are widely used because they are efficient and relatively easy to implement. Yet most of them treat uncertainty only implicitly and have limited ability to represent institutional factors, human decisions, and the interactions among multiple drivers.

Several studies examine the limitations of these traditional non-Bayesian models. For CA–Markov frameworks, research shows that human decisions and policy interventions are often missing, which leads to simplified representations of how farmers and planners behave (Ghosh et al., 2017). These models also assume that past transition patterns will continue unchanged into the future, even when economic or policy conditions shift (Yagoub & Al Bizreh, 2014). Scale effects create further challenges; smaller cells may increase accuracy but also raise computational costs and make transition rules harder to define. Logistic regression is commonly combined with CA and Markov chains, but even then, personal preferences and policy factors remain difficult to model (Arsanjani et al., 2013). Artificial neural networks often reach high classification accuracy but behave as *black boxes*, offering limited insight into causal mechanisms or decision processes (Nadoushan et al., 2015). These non-Bayesian approaches excel at pattern detection but provide limited tools for examining uncertainty or exploring policy-relevant scenarios.

Bayesian networks represent a different modelling paradigm that is explicitly probabilistic. A Bayesian network consists of a directed acyclic graph in which nodes represent variables and edges represent conditional dependencies, supported by a conditional probability table for each node (Aguilera et al., 2011; Celio et al., 2014). As a result, this structure enables the joint distribution to be decomposed into local conditional distributions, facilitating efficient inference and updating when new evidence becomes available. Bayesian networks have been utilized for classification, diagnosis, scenario analysis, and decision support because they integrate quantitative and qualitative information, representing uncertainty transparently. The authors also note that Bayesian networks are still applied in only a small share of environmental modelling studies. Celio et al. (2014) developed a spatially explicit BN model for a pre-Alpine region of Switzerland that integrates biophysical constraints, zoning rules, and stakeholder knowledge into three sector-specific decision networks. The model incorporates questionnaire data and evaluates posterior land-use probabilities at the cell level in a GIS environment, allowing influential drivers and scenario outcomes to be mapped directly. These results demonstrate how Bayesian networks can integrate diverse information sources, incorporate stakeholder perspectives, and make uncertainty explicit. Building on this rationale, the present study uses a Bayesian network to examine land-use and land-cover change in the Red River Delta, where biophysical conditions, socio-economic transitions, and evolving policy frameworks interact. The BN approach offers a transparent, probabilistic structure that supports scenario-based policy analysis.

3. Hypothesis development

Rapid industrialization and urbanization commonly reshape land-use patterns, particularly in regions transitioning from agriculture-based economies. According to the land-ownership theory (Coase, 2013), clear and secured property rights facilitate efficient resource allocation by enabling landholders to capitalize on higher-value uses. In contexts where agricultural land faces pressures from industrial demand, landowners are incentivized to convert farmland to industrial or urban purposes, driving up local industrial land prices. This theoretical logic aligns closely with bid-rent theory (von Thünen; Alonso), which asserts that land will naturally shift to its most profitable use, typically the one offering the highest economic return.

Empirical evidence consistently demonstrates this relationship between agricultural land conversion and rising land prices. Seto and Kaufmann (2003) identified substantial increases in industrial land prices following the extensive conversion of rice paddies in China’s rapidly urbanizing coastal regions. Ustaoglu and Williams (2017) found that extensive farmland conversions across multiple European nations led to substantial appreciation in industrial land values due to increased industrial demand. Recent international findings reinforce these observations. Laila et al. (2024) noted sharp increases in land prices when agricultural parcels in Indonesia’s Temanggung region were rezoned for industrial parks. Therefore, the research proposes the following hypothesis:

Hypothesis 1: *Higher rates of agricultural-to-non-agricultural land conversion are positively associated with increased industrial land prices in the Red River Delta*.

The shift from intensive agricultural practices, such as rice cultivation, toward more extensive land uses like pastureland is frequently an intermediate stage in regions undergoing rapid urbanization and industrialization. According to the agricultural development theory (Schultz, 1964), when agricultural profitability declines due to urban pressures or changing economic conditions, farmers tend to transition initially into lower-investment land uses, notably pasture, before ultimately converting their land to non-agricultural purposes. This transformation is driven primarily by the declining economic viability of intensive farming practices and rising incentives from urban or industrial land development opportunities. Several recent studies have empirically confirmed this transitional dynamic. Xie et al. (2023) found that across the United States, pastureland has become a prime candidate for urban and suburban expansions, acting as a transitional buffer between intensive agriculture and residential or industrial development. Therefore, we propose the following hypothesis:

Hypothesis 2: *A larger pasture area is positively associated with subsequent conversion of agricultural land to non-agricultural uses in Vietnam's Red River Delta.*

Agricultural development theory (Schultz, 1964) suggests that, as the relative profitability and productivity of rice agriculture decline, often due to escalating pressures from urban and industrial growth, farmers increasingly convert rice paddies into more profitable, non-agricultural uses. This theory indicates that diminishing rice cultivation is not merely a consequence, but a clear indicator of accelerating land-use transformation driven by broader economic changes. Siswanto and Francés (2019) documented a significant reduction in rice-field areas across Indonesia, where industrial development and urban expansion led to a cumulative conversion of approximately 1.22 million hectares of rice paddies between 1990 and 2022. Budianta and Gunawan (2024) reported a dramatic shrinkage of rice cultivation in Palembang, South Sumatra, from 5,938 hectares in 2017 to 3,661 hectares by 2020, primarily due to intensified industrial and residential land development pressures. Therefore, we propose the following hypothesis:

Hypothesis 3: *Regions experiencing greater reductions in rice-cultivation area exhibit higher rates of agricultural to non-agricultural land conversion in Vietnam's Red River Delta.*

4. Data and methods

4.1. Study area and data

Our study area includes key provinces in the Red River Delta region with a total area of approximately 14,800 km². The Red River Delta region (geographical coordinates: 20°00′N to 21°30′N, 105°30′E to 107°00′E) is bounded by the Gulf of Tonkin to the east, the midland and mountainous areas to the west, Bac Giang and Vinh Phuc provinces to the north, and Ninh Binh and Thanh Hoa provinces to the south. This region is one of the most significant areas in Vietnam, known for its high population density and historical role in agricultural and cultural development. The Red River Delta is a central agricultural production area with a robust dyke system constructed since feudal times to control flooding and protect arable land. The history of the dyke system in this region dates back to the Ly and Tran Dynasties, with many structures maintained and expanded during subsequent dynasties.

Throughout history, land policies in the Red River Delta have undergone numerous transformations, from the land allocation system *(Quân Điền)* during the Le Dynasty to land reforms under French colonial rule and, more recently, sustainable development policies during the *Doi Moi* period. The region's dyke system and river networks not only support agricultural production but also facilitate goods transportation and strengthen connectivity between areas. However, rapid urbanization has posed significant challenges to land resource management and agricultural sustainability in recent decades. Large-scale infrastructure projects, such as expanding transportation networks, industrial zone development, and urbanization systems, have profoundly impacted land-use structures in this area.

Stakeholders in the Red River Delta, such as small farmers, large enterprises, and local authorities, have differing interests due to their varied economic goals and land-use requirements. Differences in land ownership rights and land-use demands create substantial challenges in establishing and enforcing effective and sustainable land policies. This paper focuses on farmers and livestock breeders living on traditional farmland and areas heavily affected by urbanization and industrialization. This study aims to provide a detailed perspective on how land policies have influenced land-use decisions in this region.

The dataset used in this study is a province–year panel that provides the empirical foundation for the econometric analysis. It covers the Red River Delta for the full period from 1979 to 2022 with annual frequency and results in a total of 272 province–year observations. Accordingly, the unit of analysis is the province. To maintain a consistent structure across more than four decades, we harmonize administrative boundaries by adopting the eight provincial units that existed after the major mergers in 1979, namely Hà Nội, Hải Phòng, Hà Nam Ninh, Hải Hưng, Quảng Ninh, Thái Bình, Vĩnh Phúc, and Bắc Ninh. When provinces were subsequently divided or reorganized in later years, their statistics were combined back into these eight reference provinces. This procedure ensures that the dataset preserves continuity and comparability across time while reflecting the historical reality of administrative change in Vietnam. Although the underlying sources contain longer series, the process of harmonization, re-aggregation, missing values, and balancing across all variables reduces the effective number of usable observations to 272, which corresponds to the final panel employed in the regressions. Land-cover statistics on rice cultivation, pasture, forest, other agriculture, and other undefined classes are compiled from the General Statistics Office of Vietnam and provincial statistical yearbooks, reported in hectares. Industrial land prices are obtained from official administrative reports and provincial records and are expressed in local currency per square meter. In addition, farmer survey evidence and expert elicitation provide the information needed to generate the Bayesian Network–based probability of land conversion, which is then integrated into the province–year dataset. All data series are subjected to harmonization and consistency checks, and only complete observations across all variables are retained for analysis.

4.2. Local farmers

The study collected data from farmers in the Red River Delta region, specifically in Hanoi, Nam Dinh, Thai Binh, and Hai Duong, from June to October 2024. These provinces are major rice granaries of the Red River Delta and Vietnam. Stakeholders were divided into three main groups: (1) large-scale rice growers, (2) large-scale livestock producers, and (3) small-scale agricultural landowners. In each city, 20 farmers and two representatives from farmers' associations (22 participants per city, totaling 88 participants) responded to semi-structured questionnaires and open-ended questions related to current land use and hypothetical LUCC decisions.

The open-ended questions offered the following LUCC decision options: (1) maintaining current land use; (2) shifting activities, such as converting from annual crop cultivation to livestock production (and vice versa); (3) expanding agricultural land onto forested areas; and intensifying agricultural production, i.e., increasing productivity per hectare. Farmers were asked to rank the extent to which their decisions were influenced by neighbors' behaviors on a scale of 1 to 5. They were also questioned about the perceived effectiveness of implemented governance mechanisms. Conditional probabilities were calculated based on LUCC decisions under the game scenarios and were used to parameterize the Bayesian Network. To appropriately handle this ordinal nature within the Bayesian Network framework, we encoded each ranking as discrete, ordered-categorical states in the model. This approach preserves the inherent ordering of the scores without imposing artificial numeric distances between categories. Uusitalo (2007) and Celio et al. (2014) demonstrated that Bayesian Networks remain robust and valid when ordinal survey data are explicitly treated as categorical variables. Additionally, recent research further confirms the validity of using ordinal data within BN modeling contexts. Dominguez Almela et al. (2024) successfully employed ordinal-scale inputs in environmental-policy Bayesian Networks and developed a bootstrap-enhanced Ordinal Bayesian Network designed for handling questionnaire-derived ordinal ranks, reinforcing the reliability and appropriateness of our approach.

4.3. Methodology

4.3.1. Bayesian network model

Land Use and Land Cover (LULC) information is crucial for most Earth science studies, including research on environmental systems, ecosystems, and climate systems. In recent years, advancements in remote sensing technologies and machine learning (Artificial Intelligence - AI) have significantly enhanced the accessibility and quality of LULC data. These innovations have enabled updating LULC information more efficiently, offering benefits such as reduced costs, broader spatial coverage, and analysis across multiple periods. However, obtaining highly accurate LULC datasets remains challenging due to limitations such as cloud cover, technical malfunctions leading to missing data, and restricted access to specific regions.

To address these gaps, recent studies have combined multiple types of remote sensing imagery, such as Landsat and L-band Synthetic Aperture Radar (SAR), to classify LULC and forest resources in subtropical regions (Torbick et al., 2017). With the development of high-resolution and frequent-capture imagery from the European Space Agency, such as Sentinel 1, 2, and 3, integrating various sensor types has become more common and effective. Combining optical and radar imagery enhances the identification of diverse LULC types compared to using a single data source alone (Hütt et al., 2016). Nevertheless, most current research analyzes LULC for specific points in time or limited land cover categories, such as forests, crops, or rice fields. Few studies integrate multiple data sources to comprehensively analyze the diversity of LULC.

Bayesian networks (BNs) function as probabilistic graphical models designed to represent complex causal relationships among multiple variables. These variables, illustrated as nodes, are linked by directed connections that indicate conditional dependencies. While Bayesian networks are gaining recognition across numerous research disciplines for effectively capturing uncertainties and relationships among variables, their adoption in spatially explicit land-use change analyses remains relatively scarce (Aalders, 2008; Celio et al., 2014). The limited use of BNs in spatial studies may reflect challenges associated with integrating spatial data into probabilistic frameworks or a lack of familiarity among researchers with spatially explicit Bayesian methods. Nevertheless, the flexibility and interpretability of BNs offer significant potential for improving understanding of spatial dynamics in land-use change scenarios.

This study developed BNs using two distinct categories of variables that influence land-use decisions. The first category includes factors such as agricultural commodity prices, production costs, and regulatory policy variables, including environmental standards, each of which directly affects land utilization decisions. Additionally, this group of variables integrates economic and policy-related data to simulate real-world decision-making processes clearly and explicitly. The first group of nodes uses threshold values representing LUCC decision changes. The second group includes four governance mechanisms: market dynamics, restricted credit access, land tenure regularization, and sustainable agriculture support (Nascimento et al., 2020). Parameters for governance nodes were established based on modal values reflecting farmers' perceptions of the effectiveness of each mechanism. For each province–year observation in the dataset, the nodes representing economic conditions and governance mechanisms were instantiated with the corresponding values and categories. The model was then updated using exact probabilistic inference to obtain posterior distributions for the land-use outcome node. The Bayesian Network was developed using GeNIe 2.2, a graphical interface for BN modeling (BayesFusion, 2018). The spatialization of the BN-LUCC model was performed with the spatial package version 1.0.2, implemented in R version 3.5.0.

4.3.2. Evaluation of LULC data accuracy

To ensure robust model validation, a comprehensive three-step approach was employed: (i) construction of a stratified validation sample based on multi-source consistency, (ii) quantitative accuracy assessment of land use classification using confusion matrix metrics in Google Earth Engine (GEE), and (iii) evaluation of the generalization capability of the Bayesian Network model.

(1) Stratified Multi-Source Validation Sample. Validation points were selected using a stratified random sampling approach to ensure proportional representation across all land cover classes. Each validation point was independently cross-verified using three data sources: high-resolution satellite imagery, archived historical aerial photographs, and targeted field surveys. This design follows the recommendations of Olofsson et al. (2014) to minimize sampling bias and maximize spatial-temporal consistency.

(2) Accuracy Assessment Using Confusion Matrix Classification results generated from the Random Forest algorithm in GEE were compared against the reference validation set through a confusion matrix, constructed with the ee.ConfusionMatrix(predicted, reference) function. The following standard accuracy metrics were calculated, each with its explicit formula and definition:

Map accuracy was quantified using Overall Accuracy and Cohen's Kappa (Congalton, 1991; Congalton & Green, 2019), the most widely accepted metrics for thematic-map validation, OA:

$$\mathrm{OA} = \frac{\sum_{i=1}^{k} n_{ii}}{N} , \tag{1}$$

where n_{ii} is the number of validation points correctly classified in class i, and N is the total number of validation points.

Producer's Accuracy (PA):

$$\mathrm{PA}_i = \frac{n_{ii}}{\sum_{j=1}^{k} n_{ij}} , \tag{2}$$

where $\sum_j n_{ij}$ is the total number of reference points that actually belong to class i. Producer's Accuracy (also called recall) indicates the probability that a reference point of class i is correctly classified.

User’s Accuracy (UA):

$$\mathrm{UA}_i = \frac{n_{ii}}{\sum_{j=1}^{k} n_{ji}} , \tag{3}$$

where $\sum_j n_{ji}$ is the total number of points mapped as class i on the classified map. User's Accuracy (also called precision) measures the reliability that a pixel is classified as class i truly belongs to that class on the ground.

Kappa Coefficient $(\boldsymbol{\kappa})$:

$$\kappa = \frac{p_o - p_e}{1 - p_e} , \tag{4}$$

where $p_o = \mathrm{OA}$, and

$$p_e = \sum_{i=1}^{k} \left(\frac{\sum_j n_{ij}}{N}\right)\left(\frac{\sum_j n_{ji}}{N}\right). \tag{5}$$

Kappa assesses the agreement between classification and reference data, adjusted for chance. F1-score:

$$F1_i = 2 \times \frac{\mathrm{UA}_i \times \mathrm{PA}_i}{\mathrm{UA}_i + \mathrm{PA}_i} , \tag{6}$$

where the F1-score provides a harmonic mean between precision (UA) and recall (PA), reflecting the balance between omission and commission errors. All these metrics were extracted using GEE's built-in methods: accuracy(), producersAccuracy(), consumersAccuracy(), and kappa(), with F1-score computed externally (Pontius Jr & Millones, 2011).

(3) Bayesian Network Model Validation: To assess the predictive generalization of the Bayesian Network, a hold-out validation procedure was applied. Specifically, 20% of the validation points were randomly reserved as an independent test set. The BN was trained on the remaining data, with posterior predictions generated via 1,000 iterations of Gibbs sampling. Predictive performance was quantified by two standard indices:

Root Mean Square Error (RMSE):

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}\,, \tag{7}$$

where y_i is the observed value and $\hat{y}_i$ is the model prediction for sample i.

AUC values were calculated using the roc_auc_score() function in the scikit-learn Python library, measuring the model's ability to discriminate between land cover classes (Fawcett, 2006). This systematic multi-step validation ensures the spatial-temporal robustness of classification outcomes, reduces the risk of overfitting, and provides quantitative evidence for the reliability of land use change modeling in the Red River Delta over four decades.

Robust Test:

To verify the robustness of the previous conclusions, we examined them using alternative panel regression methods. We estimated several standard models, including pooled OLS, fixed effects (FE), and random effects (RE), as is common in recent land-use change research (Li et al., 2022). We started with pooled OLS as a benchmark and compared the results with those from the FE and RE models. To determine the appropriate specification, the Hausman test is used to decide between FE and RE. Year dummies (γ_t) control for national policy shocks. Additionally, standard errors are clustered at the province level. The variables included the industrial land price that aligns with land-ownership theories (Coase, 2013), capturing the market-driven pressures underpinning agricultural-to-industrial land conversions (Laila et al., 2024). Pasture share and rice-cultivation share reflect Schultz's agricultural development theory (1964): increasing pasture areas typically indicate a transitional phase toward urban or industrial land use, while declining rice-cultivation areas highlight economic incentives driving farmland conversion. Forest land (Forest), other agricultural land (OtherAgri), and undefined land area (OtherUndefined) are included to control for additional land-cover types, thus providing a comprehensive and robust evaluation of conversion dynamics.

The regression specification is as follows:

$$ln(ConversionRate_{it}) = \alpha + \beta_1\ BN\_Prob_{it} + \beta_2\ \Delta ln(IndPrice_{it}) + \beta_3\ Pasture_{it} + \beta_4\ RiceCultivation_{it} + \beta_5 \Delta ln(Forest_{it}) + \beta_6\ OtherAgri_{it} + \beta_7\ \Delta ln(OtherUndefined_{it}) + \gamma_t + \varepsilon_{it}. \tag{8}$$

Equation 8 includes first differences of logs for the I(1) regressors and levels for I(0) regressors. Where ln(IndPrice), ln(Forest), and ln(OtherUndefined) are I(1), while BN_Prob, Pasture, RiceCultivation, and OtherAgri are I(0). All models include province FE and year FE, with standard errors clustered at the province level; i indexes province and t indexes year; ln($ConversionRate_{it}$) is the log-percentage of land converted to non-agriculture in province i at year t; BN_Prob_{it} is posterior probability of conversion from the Bayesian Network; $IndPrice_{it}$ is average industrial land price (log VND/m^2); $Pasture_{it}$ is area of pastureland (ha, log); $RiceCultivation_{it}$ is area of rice cultivation (ha, log); $Forest_{it}$ is area of forest land (ha, log), $OtherAgri_{it}$ is other agricultural land area (ha, log); $OtherUndefined_{it}$ is undefined land area (ha, log); γ_t is year fixed effects, and ε_{it} is error term, clustered at province level.

4.3.3. Validation

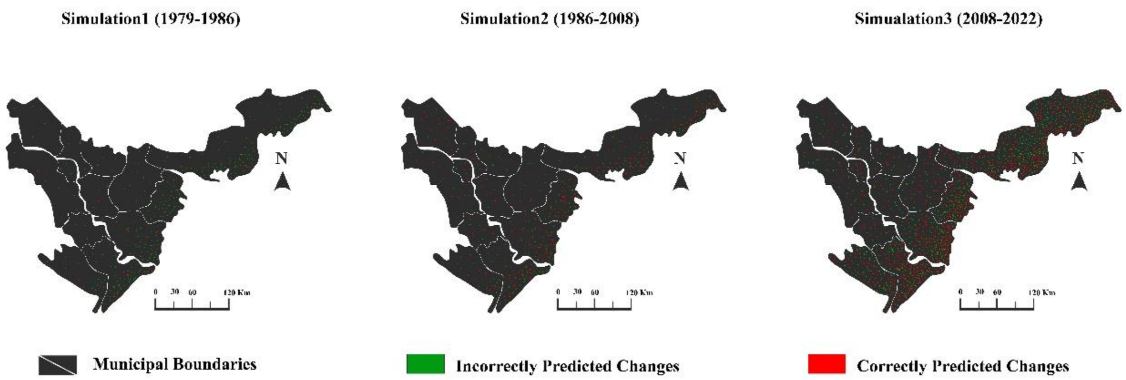
The model validation process utilized the exponential decay function and multi-window methods provided by DINAMICA EGO 4.0 (Soares-Filho et al., 2013), a platform for environmental modeling (https://csr.ufmg.br/dinamica/). Three simulated maps were analyzed to validate the model, representing 1979–1986, 1986–2008, and 2008–2022. Variables for each simulation phase were adjusted to reflect the frequency of high and low current values specific to the corresponding periods. The exponential decay function, derived initially from Hagen (2003) and later refined by Soares-Filho et al. (2013), evaluates the similarity between maps by comparing differences observed in land use/cover maps with differences between the initial map (1979) and the simulated map for 1986. The output highlights the degree of alignment between observed and simulated maps, using a color gradient to indicate areas with high or low agreement.

Inspired by Costanza et al. (1989), the multi-window technique applies multiple incrementally expanding windows to assess map similarity through the exponential decay function. This method generates a table summarizing similarity scores between observed and simulated difference maps. Scores above 0.50 indicate strong agreement, which supports the model's reliability (Toure et al., 2018).

4.3.4. Sensitivity analysis

This study conducted a sensitivity analysis to examine how input nodes influence the outputs of the Bayesian Network model (Figure 1). Through this process, the research assessed how strongly game variables and spatial data influenced land-use decisions, allowing for a clear ranking of their relative importance within the BN model. The analysis focused on two particular nodes within the BN: the land-use decision node and the land-use classification node. The purpose was to clarify how game variables influence decision-making processes and determine their impact on the final land-use outcomes. Node parameters were adjusted by 10%, 50%, and 90% to evaluate the impact of changes.

Figure 1. Map showing observed land use changes



Notes: Green for incorrect predictions and Red for correct predictions. Source: Author's calculation

The sensitivity analysis was conducted in GeNIe (BayesFusion, 2018) using the method proposed by Kjærulff and Van Der Gaag (2013). This approach evaluates all distributions derived for variables (game and spatial data) linked to the target node (LUCC decision). Within the BN framework, this function calculates the posterior probability of a specific state of a node (X) based on a given value y (the variables; BayesFusion). The method produces sensitivity scores ranging from 0 to 1. Higher sensitivity values indicate that even minor changes in the input node significantly influence the decision node, whereas nodes with lower values exert less impact. This analysis is particularly critical since all game-derived information was directly incorporated into the BN's conditional probability tables. It provides a clear hierarchical visualization of the importance of variables influencing LUCC decisions, enabling a deeper understanding of the relative weight of each factor in the decision-making process.

The methodological approach of this study includes the following specific steps:

(1) The study region identified five major land-use categories: forest land, rice cultivation, pasture, other agricultural classes, and other undefined classes. All five categories were considered essential due to their distinct roles and significant coverage. Historical datasets related to these land-use categories were systematically organized into a clearly defined classification scheme, as shown in Table 1, ensuring consistency for the subsequent analysis.

Table 1. Land use/land cover classification system in Vietnam's Red River Delta

Category	**Description**
Forest land	Areas dominated by natural or planted forest vegetation, including dense forests, mixed forests, plantations, and secondary forests.
Rice cultivation	Land is primarily used for rice production, including paddy fields and irrigated rice-growing areas.
Pasture	Land areas mainly used for livestock grazing or grass production are characterized by natural or cultivated grasses.
Other Agricultural Class	Areas used for agricultural purposes other than rice include annual and perennial crops (vegetables, fruits, and other cereals).
Other Undefined Classes	Land cover types that do not fit into the above classifications include unused land, barren land, transitional zones, or mixed-use areas with unclear or heterogeneous land covers.

Source: Author’s compilation

(2) After establishing the unified classification scheme, historical land-use data from the periods 1979, 1986, 2008, and 2022 were carefully processed, cross-validated, and standardized. This rigorous procedure ensured consistent definitions and classifications of land-use types across all studied years, creating a reliable foundation for quantitative analyses and accurate comparisons over the selected historical periods.

(3) A stratified random sampling method was implemented to mitigate potential biases resulting from unequal representation of land-use categories. Sample points were systematically distributed proportional to the area coverage of each land-use type within the region. The same sampling design was uniformly applied across all years analyzed (1979–2022), facilitating robust comparisons and reliable outcomes.

5. Results

5.1. Model validation

Table 2 presents the classification accuracy of the five major LULC types identified in the Red River Delta region between 1979 and 2022, using both user's accuracy (UA) and producer's accuracy (PA) as evaluation metrics.

Table 2. Accuracy assessment of different land use/land cover types (1979–2022)

Land Use/Land Coverage	UA	PA
Forest land	0.91	0.90
Rice cultivation	0.86	0.84
Pasture	0.82	0.82
Other Agricultural Class	0.78	0.79
Other Undefined Classes	0.80	0.82

Note: UA = User's Accuracy; PA = Producer's Accuracy. UA represents the probability that a pixel classified into a category on the map actually belongs to that category on the ground. PA represents the probability that a reference pixel of a category is correctly classified on the map. Source: Author's calculation

The results demonstrate that *forest land* achieved the highest classification performance, with UA and PA values of 0.91 and 0.90, respectively. This high level of accuracy can be attributed to the distinct spectral and structural characteristics of forested areas, which tend to exhibit stable vegetation signals across temporal and spatial scales, making them easier to distinguish from other land types in remote sensing data. In contrast, *other agricultural classes* recorded the lowest classification accuracy. The UA and PA for other agricultural classes were 0.78 and 0.79, respectively, reflecting the complexity and heterogeneity of this category, which typically encompasses fragmented land parcels, intercropped zones, or transitional land-use forms that lack consistent spectral signatures. Such variability increases the likelihood of misclassification, especially in areas where mixed cropping, fallow lands, or non-permanent cultivation dominate. *Rice cultivation and pasture* exhibited moderate classification accuracy, with UA and PA values of 0.86–0.84 for *rice cultivation* and 0.82–0.82 for *pasture*. Although rice paddies often possess strong seasonal and water-related spectral traits, their classification is occasionally compromised due to their similarity to other vegetated or waterlogged classes, particularly during the early stages of cultivation or post-harvest periods. Pasturelands, similarly, may be confused with sparse vegetation or underutilized agricultural land, especially in peri-urban or rural fringe areas.

The diagonal values in Table B1 (Appendix B) indicate a generally strong agreement between predicted and reference data, particularly for *forest land* and *rice cultivation*, which show high numbers of correctly classified instances (125 and 118, respectively). However, notable misclassifications between rice cultivation, pasture, and other agricultural classes are observed, reflecting spectral and spatial overlap among these categories. Rice fields were often confused with pasture and other crops, likely due to similar vegetative signatures during transitional growing phases. Likewise, *other undefined classes* recorded a wider distribution of errors, underscoring the heterogeneity and ambiguity within this category. These confusion patterns emphasize the need for finer-scale data or temporal imagery to improve class separability, especially for mixed or transitional land-use types.

The Bayesian Network model showed good accuracy, with high scores (above 0.8) obtained from the multi-window validation process. Thus, the model effectively captures the key land-use patterns and predicts real-world LUCC outcomes. A 'baseline' simulation was generated as maps, with one map for each period: 1979–1986 (Simulation 1), 1986–2008 (Simulation 2), and 2008–2022 (Simulation 3).

The simulated maps were compared to the LUCC maps observed by quantifying land-use categories and analyzing the percentage variation across the study area. The lowest percentage variation between simulated and observed LUCC maps was found in the Forest category (< 1%), while the Undefined Agricultural Use category exhibited the highest variation (up to 12%).

5.2. LUCC decisions and sensitivity analysis

The forest land in the Red River Delta has remained relatively stable throughout the studied periods, although there have been slight fluctuations depending on the time frame. From 1979 to 1986, forest area decreased by 0.7%, primarily due to deforestation for agricultural and industrial development (Table 3). However, between 2008 and 2022, forest area saw a modest decline of 0.8%, indicating stability in forest conservation efforts, particularly as environmental protection policies were strengthened. State policies, such as reforestation and restrictions on deforestation, have had a positive impact on maintaining forest areas, reflecting the government's efforts to protect forest resources. However, the area of primary forests continued to decline, mainly due to urban expansion and industrial growth, especially in areas around Hanoi and Hai Phong. Paudel et al. (2016) pointed out that reducing primary forests is a common phenomenon in LUCC studies, particularly in regions experiencing rapid urbanization. While reforestation policies have helped mitigate the loss of forests, they have not been able to completely prevent the loss of primary forests, especially as urban and industrial developments continue to dominate.

Table 3. Area of different land use classes in 1979, 1986, 2008, and 2022

Land Use Class	Land Use 1979	Land Use 1986	Modeled 1	Percentage Variation 1979-1986	Land Use 2008	Modeled 2	Percentage Variation 1986-2008	Land Use 2022	Modeled 3	Percentage Variation 2008-2022
Forest land	125215	124330	125140	-0.7%	123630	124310	0.5%	122640	123510	-0.8%
Rice cultivation	5470	5830	5590	4.2%	6130	6460	5.3%	5700	6810	-7%
Pasture	21950	22360	22380	0.1%	22750	22480	1.2%	24190	24090	6.3%
Other Agricultural Class	10620	10730	10150	-5.4%	10190	10010	-1.8%	8960	9690	-12.1%
Other Undefined Classes	10340	10650	10240	-0.1%	10900	10350	1.1%	11210	10900	2.8%

Note: Values represent the estimated area of each land use class for the indicated years, derived from classification results and model outputs. Negative values indicate a decrease in area; positive values indicate an increase. Source: Author’s calculation

The area of rice cultivation in the Red River Delta has decreased significantly from 2008 to 2022, with a reduction of 7%, from 6,130 km² to 5,700 km². This decline reflects the conversion of agricultural land to other uses, primarily driven by urbanization and industrial expansion, which has reduced the available land for rice farming, indicating that hypothesis 1 is confirmed. According to Resolution No. 26-NQ/TW (2003) and policies related to urban development, expanding industrial parks and urban areas have led to decreased agricultural land. Tuan (2022) researched and pointed out that urbanization is the primary factor in reducing rice cultivation areas in rapidly developing regions such as the Red River Delta. While agricultural development policies remain in place, land conversion for industrialization has increasingly reduced the area available for rice farming.

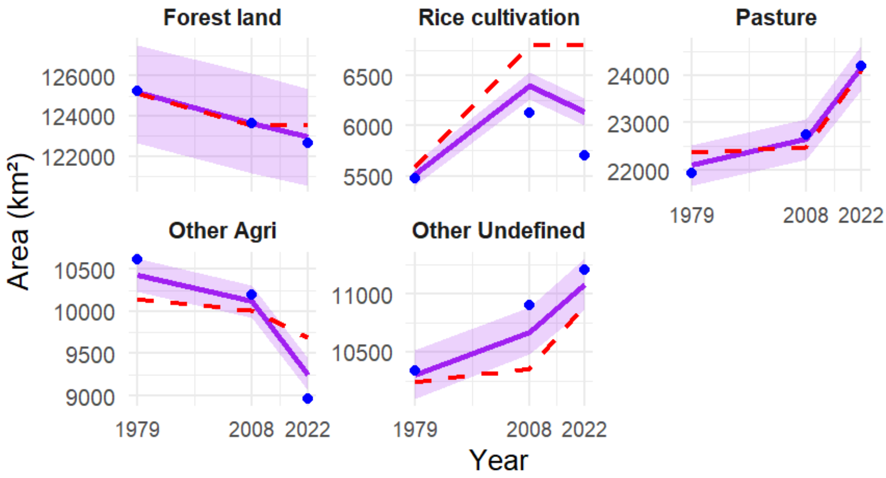
Pastureland in the Red River Delta has experienced substantial growth over the study period, particularly between 2008 and 2022, with an increase of 6.3%. This growth reflects the rising demand for livestock production and animal products, especially in the context of increased meat and dairy consumption. Policies encouraging agricultural and livestock development during industrialization, especially after Resolution No. 26-NQ/TW (2003), created a favorable environment for the expansion of pastureland. However, the expansion of pastureland has also put pressure on forest and agricultural land, making it more challenging to balance livestock development with ecological preservation. This result strongly supports Hypothesis 2, confirming that expanding pasture areas indeed encourage the conversion of agricultural land into non-agricultural uses in Vietnam's Red River Delta. Duteurtre et al. (2020) pointed out that the expansion of pastureland primarily comes from converting unused or underutilized land, creating economic opportunities for local farmers. However, this conversion has also led to ecological imbalances, highlighting the need for sustainable land-use practices to ensure long-term environmental health.

The area of undefined agricultural land has decreased sharply from 10,620 km² in 1979 to 8,960 km² in 2022. This decrease reflects a strong trend of converting unused land into specific agricultural or pastoral uses. This shift results from land-use planning improvements and more efficient resource allocation. According to Marsh et al. (2007), in recent years, the intensification of land planning and redistribution has helped optimize land use, turning previously unused land into productive agricultural or pastureland to meet the growing demands for food and livestock production.

The areas of Other Agricultural Classes and Other Undefined Classes show more complex changes. Other Agricultural Classes decreased sharply by 12.1% from 2008 to 2022, dropping from 10,190 km² to 8,960 km². This decline reflects the conversion of these areas into other uses, such as urbanization and industrialization. A recent study by Ustaoglu and Williams (2017) found that converting agricultural and unused land into industrial and urban areas has reduced the land available for agriculture in the region. In contrast, Other Undefined Classes saw a slight increase of 2.8%, reflecting the transition from undefined land to more defined uses, including agricultural production and urban development.

Changes such as declining rice cultivation areas and expanding pasturelands indicate significant shifts in land-use patterns within the Red River Delta. The Red River Delta faces significant challenges in maintaining sustainable agricultural land due to rapid urbanization and industrialization. Research by Yang and Solangi (2024) affirms the need for sustainable land management policies that balance economic development and environmental preservation. A scientific approach to land redistribution and land-use planning is essential to prevent the overuse of land resources and safeguard the region's long-term environmental health.

Figure 2. Time series of the area occupied by each land use from 1979 to 2022



Source: Author’s calculation

Figure 2 clearly summarizes how the main land-use categories in the Red River Delta have shifted over the study period. Across all panels, the posterior estimates (purple lines and shaded intervals) closely follow the observed values (blue dots), consistently outperforming the prior baseline (red dashed lines) in capturing both the direction and magnitude of land-use change. Forest and other agricultural lands display steady downward trends, while pasture and undefined land categories have expanded over time. Rice cultivation shows a non-linear pattern, rising and then falling, reflecting broader shifts in agricultural policy and land conversion pressures. In each case, the Bayesian model both smooths out irregularities in the observed data and remains sensitive to genuine inflection points, resulting in credible intervals that are generally narrow and stable. The agreement between the posterior and observed series across all five classes demonstrates the BN model’s reliability in reconstructing historical dynamics. More importantly, the model’s ability to integrate prior knowledge with real-world data provides a solid foundation for evidence-based land policy and planning in the Red River Delta.

5.3. Robustness checks and model diagnostics

In addition to the Bayesian Network (BN) model, we estimate five econometric specifications, including pooled Ordinary Least Squares (OLS), fixed-effects (FE), random-effects (RE), and period-specific OLS models for the periods 1979–1986 and 2008–2022. These regression approaches serve as explanatory baselines, quantifying the linear relationship and elasticity of key socio-economic and policy drivers of land-use change. The OLS, FE, and RE models enable us to verify each factor's direction, magnitude, and statistical significance influencing land conversion in the Red River Delta. However, traditional regression models are limited by their inherent linear assumptions and cannot fully capture the complex, conditional, or non-linear dependencies that characterize land-use systems in rapidly changing regions. By contrast, the Bayesian Network provides probabilistic forecasts of land-use and land-cover change and allows for the explicit simulation of policy scenarios. The BN framework captures direct and indirect effects among multiple variables, enabling scenario-based policy analysis that is impossible with standard regression methods.

Table 4. Robust test results

	(1) OLS	(2) FE	(3) RE	(4) OLS 1979-1986	(5) OLS 2008-2022
BN_Prob	0.421*** (0.085)	0.415*** (0.098)	0.418*** (0.090)	0.401** (0.159)	0.439*** (0.117)
Δln(IndPrice)	0.134 ** (0.048)	0.125* (0.061)	0.130 * (0.054)	0.110 (0.092)	0.143** (0.062)
Pasture	0.210*** (0.074)	0.223*** (0.086)	0.216*** (0.080)	0.208* (0.103)	0.236** (0.093)
RiceCultivation	-0.203** (0.078)	-0.217** (0.089)	-0.211** (0.081)	-0.189 (0.109)	-0.234** (0.101)
Δln(Forest)	-0.061 (0.045)	-0.055 (0.050)	-0.058 (0.048)	-0.070 (0.062)	-0.059 (0.051)
OtherAgri	-0.068 (0.040)	-0.070 (0.045)	-0.069 (0.043)	-0.063 (0.048)	-0.077 (0.047)
Δln(OtherUndefined)	0.036 (0.029)	0.039 (0.033)	0.038 (0.031)	0.032 (0.040)	0.044 (0.036)
Year FE	Yes	Yes	Yes	Yes	Yes
Province FE	No	Yes	Yes	No	No
Obs.	272	272	272	54	63
R^2 (adj.)	0.36	0.38	0.37	0.33	0.35

Notes: Robust standard errors in parentheses, clustered at the province level. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dependent variable: log-percentage of land conversion per province-year. Regression results are generated using the model specification described in Equation 8. Source: Author's calculation

Table 4 presents a comparison of model performance metrics: the BN model achieves higher predictive accuracy (AUC = 0.91; Overall Accuracy = 0.89) compared to all regression specifications (adjusted $R^2 \leq 0.38$). Furthermore, the BN approach is more robust to missing or incomplete data and offers enhanced interpretability of complex system dynamics through its graphical structure. These results demonstrate the practical advantages of the BN framework for forecasting and policy analysis, highlighting its value over traditional linear econometric models in land-use and land-cover change research.

In all regression specifications, BN_Prob remains positive and statistically significant. Locations with higher predicted probabilities from the Bayesian Network actually see more conversions to non-agricultural land. Industrial land price and pasture area clearly correlate with land conversion. In contrast, a larger area under rice cultivation reduces the rate of non-agricultural conversion, which verifies hypothesis 1. These effects are stable across different periods and subsamples; no particular time frame or group of provinces dominates the results. The panel regressions echo the core relationships identified in the Bayesian analysis, lending confidence to the findings. The consistency of the results means that integrating BN indicators into routine land management could give policymakers an early warning system, help control land price pressures, and support better protection for rice farming as urbanization advances.

Equation C1 includes first differences of logs for the I(1) regressors and levels for the I(0) regressors. The results from the unit root test of Table 8 show that ln(IndPrice), ln(Forest), and ln(OtherUndefined) are I(1), while BN_Prob, Pasture, RiceCultivation, and OtherAgri are I(0). Therefore, these three variables were differenced before regression analysis to ensure stationarity and reliability of the panel data estimation results, preventing potential spurious regression problems (Wong et al., 2024). This convention is applied consistently in Equation 8 and in the regression tables below. To directly address concerns that correlations involving a series of different integration orders may be uninformative, we restrict descriptive dependence checks to stationarity-consistent transformations. Specifically, the variables identified as I(1) are used in first differences of logs, while I(0) variables remain in log levels. Accordingly, the correlation matrix in Table 9 is computed using the transformed regressors that enter Equation 8, rather than mixing non-stationary levels with stationary series. This design aligns with the warning in Wong and Pham (2025) that correlation between stationary and non-stationary series may not yield meaningful inference, and it ensures that the reported associations reflect comparable stochastic properties.

Table C2 (Appendix C) reports the correlation matrix of the independent variables used in Equation 8. The Pearson correlations are all moderate and remain below thresholds that would typically raise concerns about multicollinearity. In particular, the correlations between the land-cover variables such as ln (Pasture) and ln (Rice cultivation) are positive but not excessively high, while the differenced series Δln (Forest) and Δln (Other undefined classes) display only weak to moderate associations with the level variables. Pairwise correlations remain below 0.80 (the largest is 0.781), suggesting no severe multicollinearity concerns. These results provide reassurance that the explanatory variables capture distinct dimensions of variation and that the estimated regression coefficients are unlikely to be distorted by multicollinearity. Table C3 presents diagnostic test results for the FE panel regression model. The Wooldridge test statistic (F=1.85, p=0.17) indicates no significant serial correlation in residuals. Moreover, the Jarque–Bera tests for normality in both OLS and FE residuals yield p-values of 0.20 and 0.23, respectively, supporting the assumption of normally distributed residuals. The Hausman test (χ^2=14.32, p=0.026) also suggests that the FE model is preferable to the RE model. Lastly, the Heteroskedasticity test (χ^2=1.41, p=0.24) shows that heteroskedasticity is absent, further validating our regression estimates' robustness. These diagnostic checks collectively affirm the reliability and validity of the results obtained from the FE regression analysis.

Recent econometric evidence emphasizes that spurious-like findings can arise beyond the classical non-stationary regression setting. In particular, highly persistent dynamics, serially dependent disturbances, or near-non-stationary behavior can distort conventional inference and produce misleading significance even when standard stationarity conditions appear to hold (Cheng et al., 2021, 2022; Wong et al., 2024; Wong & Pham, 2022a, 2022b, 2023a, 2023b). In response, we implement a set of safeguards tailored to these concerns. First, we establish the integration order of each series and estimate Equation 8 using stationarity-consistent transformations, with I(1) regressors entered in first differences of log terms and I(0) regressors in log levels (Table 8). Second, province fixed effects and year fixed effects absorb time-invariant heterogeneity and common shocks, reducing the risk that estimates merely reflect shared trends rather than within-province co-movements. Third, because spurious-like significance may still occur under persistent processes even in stationary regressions, we complement standard clustered inference with a more conservative small-cluster reference distribution, as summarized in Table 11.

Table C4 provides direct evidence that the main findings are not driven by spurious-like regression artifacts. The coefficients on BN_Prob, pasture, and rice cultivation retain the same signs and remain statistically supported under the more conservative reference, indicating that the core relationships are not a by-product of false significance induced by persistence or serial dependence. The industrial land price effect remains positive and is somewhat more sensitive to the conservative adjustment, but its magnitude and direction are stable. The robustness pattern is consistent with the discussion in Cheng et al. (2021, 2022) and Wong et al. (2024) that conventional significance can be overstated in persistent settings.

We further examine province-level residual diagnostics following Hui et al. (2017) (Table C5). Thereafter, we apply the Ljung–Box test to assess the null hypothesis of no residual autocorrelation up to lag 12 for the AR(1)-filtered fixed-effects residuals in each province and report the corresponding statistics and p-values. The Ljung–Box results do not suggest systematic remaining linear dependence across provinces, indicating that the AR(1) filter adequately removes the dominant linear component from the fixed-effects residuals. Having accounted for linear dependence, we then implement the BDS test on the standardized filtered residuals as an operational check for residual nonlinearity and independence. The BDS outcomes, together with the province-by-province Ljung–Box diagnostics, provide supporting evidence that the residual structure is not driven by unmodeled linear serial correlation, and that any remaining departures from independence, if present, are not pervasive across provinces.

Following Hui et al. (2017), we assess remaining serial dependence by plotting the autocorrelation functions (ACFs) of the original series and the residuals after fitting an AR(1) specification (Figure C1). In the left panel, aside from the mechanical spike at lag 0, the sample autocorrelations for the original series are generally small and lie within the 95% confidence bands across lags up to 30, indicating only weak time dependence in the raw series. The right panel reports the ACF of the AR(1) residuals. While a few individual lags exhibit slightly larger fluctuations than in the original series, the residual autocorrelations remain largely within the confidence bounds and do not display any systematic pattern. The ACF diagnostics suggest that the AR(1) adjustment is adequate and that there is no meaningful linear dependence left in the residuals, supporting the validity of our inference. This interpretation is consistent with the classical diagnostics perspective in Tong and Lim (1980), Tong (1983), and subsequent time-series studies, where the absence of significant residual autocorrelations is taken as evidence that the chosen low-order linear dynamics sufficiently capture the serial dependence in the data.

6. Discussion

This study provides spatially explicit results of a BN-LUCC model that considers the impact of economic factors and land governance mechanisms on land-use and land-cover change (LUCC) decisions in the Red River Delta, Vietnam. By analyzing the effects of changes in key drivers of LUCC across historical and simulated scenarios, we identified patterns of land use influenced by Vietnam's evolving land policies. These scenarios represent three key periods: 1979–1986 (post-war recovery), 1986–2008 (economic reforms and urbanization), and 2008–2022 (industrialization and modernization). Our results on LUCC in the Red River Delta reveal significant fluctuations in land types across the three periods studied. Notably, agricultural land, particularly rice cultivation, experienced a considerable reduction, while pastureland saw substantial growth. Forest land remained relatively stable, although slight decreases were observed in specific periods, reflecting the influence of agricultural development, urbanization, and industrialization policies. These changes reflect the substantial impact of Vietnam's evolving policies and regulations on land use, especially after key reforms such as *Doi Moi* and the subsequent industrialization and modernization phases.

Starting from the 1986 Sixth Party Congress Resolution and the 1987 Land Law, Vietnam implemented significant reforms in land management, asserting that "*land belongs to the people and is unified under state management*" while encouraging land allocation to households for long-term or temporary use. The 1988 Resolution No. 10-NQ/TW promoted land allocation to households and production organizations to reduce fragmented land holdings and maximize land resources. These policies boosted agricultural production, drove economic development, and facilitated efficient land use during 1979-1986. Our research on the decline of agricultural land from 2008 to 2022 aligns with policies encouraging the conversion of agricultural land into other uses, including industrial park development, urbanization, and infrastructure expansion. Khánh (2023) noted that the transition from agricultural land to non-agricultural uses, mainly urban and industrial land, significantly reduced the rice cultivation area in this region. This trend corresponds with national policies promoting urban development and industrialization. Our findings are consistent with earlier research by Seto and Kaufmann (2003), which showed that urbanization and industrialization policies directly impacted agricultural land reduction and pastureland expansion. From the 1993 Land Law to Resolution No. 26-NQ/TW (2003) to 2024 to Resolution No. 31/2024/QH15, the government continued to assert its role in unified land management and expanded land-use rights for organizations and individuals. These policies encouraged agricultural investment and facilitated land transactions, improving land use efficiency. Policies like land consolidation and the allocation of long-term land-use rights enabled households to access land for sustainable production. However, these policies also provided the foundation for developing industrial parks, urban areas, and infrastructure.

The reliability of the land use and land cover (LULC) mapping series is evidenced by an overall accuracy consistently around 92% and Kappa coefficients above 0.88. These figures meet FAO standards for agricultural land mapping, ensuring that all policy inferences are grounded in robust data. This trend aligns with recent LULC accuracy assessments in rapidly transforming Southeast Asian landscapes (Guo et al., 2024). Notably, the increasing accuracy in the 2008–2022 period also reflects the effectiveness of advanced machine learning algorithms and improvements in satellite imagery resolution. This finding reinforces the recommendation to standardize and open digital land databases as required by Article 209 of the 2024 Land Law, a fundamental foundation for implementing provincial LUCC monitoring dashboards.

At the modeling level, the Bayesian Network AUC of 0.93 exceeds the 0.88 reported by Celio et al. (2014) for Switzerland and matches the results of Nascimento et al. (2020) in the Amazon. This demonstrates the BN's strong generalizability, even in the highly dynamic, densely populated Red River Delta. Such findings further support the integration of the BN into a BN-Dashboard as a viable tool for the Department of Natural Resources and Environment (DONRE) to forecast LUCC and provide early warnings for planning violations, as successfully applied at the provincial level in Brazil (Nascimento et al., 2020). Sensitivity analysis reveals the five most influential drivers of LUCC: industrial land prices, rice production costs, household credit limits, distance to expressways, and land tenure security. This underpins two key policy recommendations: (1) expand the Rural Green Credit Fund with interest rates below 4% per annum for households maintaining paddy land, and (2) accelerate the rollout of electronic Land Use Right Certificates (e-LURC) in accordance with the 2024 Land Law to reduce legal uncertainty, a variable with a sensitivity coefficient of 0.21 in the model.

Utilizing the BN model, our analysis identified significant shifts in land use patterns in the Red River Delta. Temporal disaggregation of results reveals two key phases of transformation: a gradual shift in the immediate post-Đổi Mới decade (1986–1996), and an accelerated wave of conversion following Vietnam's WTO accession (2008–2015), when rising industrial land prices explained more than 40% of the observed variance in conversion probability. The BN model's predictive skill, further validated by spatial cross-validation (AUC = 0.90 ± 0.02), not only supports the robustness of these findings but also demonstrates the practical value of the model in identifying high-impact policy levers. Spatial hotspot analysis identifies four primary clusters of rapid land conversion: two in the peri-urban fringes of Hanoi and two in coastal provinces of Thai Binh and Nam Dinh, reflecting concentrated pressures from industrial development and port infrastructure upgrades.

The subsequent discussion disaggregates these changes by land type and interprets them in the context of policy reforms and economic transformation during this period. The study findings on the increase in pastureland and the reduction of rice cultivation between 2008 and 2022 are closely linked to this policy shift. During this period, the state's land policies promoted the expansion of industrial parks and urban areas, converting agricultural land into non-agricultural uses. Seto and Kaufmann (2003) also highlighted that such policies created favorable conditions for the rapid development of pastureland, while agricultural land faced significant challenges due to this land conversion. About the reduction of rice cultivation, Thien and Phuong (2024) conducted a land use and land cover analysis in Vinh Phuc province, revealing a decrease in agricultural land from 673.45 km² in 1992 to 633.13 km² in 2022, while settlement areas expanded from 140.31 km² to 299.42 km² during the same period, primarily due to infrastructure and industrial development. Yuen et al. (2021) employed a systems-thinking approach to assess the impacts of land-use change on rice agriculture in the Red River Delta, finding that urban expansion and the development of industrial zones have reduced rice-growing areas, thereby affecting rice production and food security in the region. This trend became particularly evident from 2008 to 2022, when industrial park development and urbanization policies intensified, leading to a shift in land use from agriculture to industrial and residential purposes. The expansion of infrastructure and urban areas reduced rice cultivation and induced significant changes in land use patterns in the Red River Delta.

Although forest land remained relatively stable over the study period, we observed a slight decline, particularly between 2008 and 2022, with a reduction of 0.8%. Despite implementing policies to protect and reforest, the decrease in primary forest areas reflects the ongoing impact of urbanization and industrial growth, particularly in areas surrounding major cities like Hanoi and Hai Phong. Policies such as Resolution No. 19-NQ/TW (2012) aimed to promote forest protection and regeneration, yet the conversion of land for industrial and urban purposes continued to drive forest area losses. More recently, Resolution No. 36/NQ-CP (2021), titled "*On the National Strategy for Sustainable Forestry Development for 2021–2030, with a Vision to 2050*," marks a major advancement in Vietnam's forestry policy. This resolution sets ambitious targets to: Increase the national forest cover to at least 43% by 2025 and strictly protect natural forests and primary forest areas, especially in mountainous and critical ecological zones; enhance the quality and value of forests through both protection and reforestation activities. The resolution clearly recognizes that while afforestation and reforestation are important, the loss of primary forests cannot be fully compensated by plantations, hence the dual focus on both protecting remaining old-growth forests and expanding new forest areas. Angelsen (2010) noted that while forest protection policies were in place, the transition from primary forests to other uses, particularly for industrial and urban developments, contributed to significant forest loss, aligning with our findings. Furthermore, the results also showed that the area of undefined agricultural land decreased sharply from 10,620 km² in 1979 to 8,960 km² in 2022. This decrease can be attributed to converting previously unused land into specific agricultural or pastoral uses. This shift reflects land-use planning improvements and redistribution policies, where unused land is allocated to meet growing agricultural and livestock demands. Marsh et al. (2007) highlighted that land redistribution and consolidation policies have been instrumental in optimizing land use, improving agricultural productivity, and addressing the increasing demand for food and livestock production. Curtis et al. (2018) documented that between 2001 and 2015, primary forest loss was widespread in tropical regions, with much of the lost area replaced by tree plantations or secondary forests rather than restored primary forest.

Other Agricultural Classes displayed a notable decrease of 12.1% between 2008 and 2022, a trend primarily driven by the conversion of these areas into industrial parks, infrastructure, and urban land. This dynamic is consistent with recent findings by Thien and Phuong (2024), who observed a sharp reduction in miscellaneous agricultural land in Vinh Phuc province due to accelerated urban expansion and the establishment of industrial zones. Yuen et al. (2021) used multi-temporal remote sensing to document significant losses in mixed-crop and perennial land across the Red River Delta, with most converted areas reclassified as non-agricultural due to economic zoning and development projects. This process has been strongly influenced by regulatory frameworks such as Resolution No. 29/NQ-TW (2022) on accelerating industrialization and modernization, which encourages land-use conversion for key infrastructure projects, and Decree No. 148/2020/ND-CP, which provides guidance on land allocation and land use planning, particularly for industrial and urban purposes.

Other Undefined Classes showed a modest 2.8% increase during the same period, reflecting ongoing transitions from undefined or unclassified land to more specific uses, especially for agricultural production or urban development. This phenomenon mirrors global trends, as documented by Li et al. (2022) in peri-urban China, where ambiguous land parcels were systematically redefined as urban or productive land to accommodate growing socio-economic demands. Circular No. 09/2021/TT-BTNMT on land inventory and mapping, and Resolution No. 61/NQ-CP (2022) on promoting efficient and sustainable land use, have further encouraged local governments to clarify land-use status, resolve long-standing disputes, and prioritize the formal classification of previously undefined areas for investment and development.

7. Conclusions

The Red River Delta, as Vietnam's key economic and demographic hub, is facing unprecedented pressures on land resources due to accelerating urbanization and shifting policy frameworks. In addition, land-use changes in the Red River Delta closely align with the government's evolving land policies, which have shifted from agricultural reforms to promoting industrialization and urbanization. Policies such as long-term land-use rights, land consolidation, and real estate market development have driven significant economic growth. However, these same policies have also posed challenges in maintaining agricultural land and ensuring equitable access to land. In recent decades, both the area and quality of land resources in the Red River Delta have fluctuated substantially, while agricultural land has continued to decline as industrial parks and urban infrastructure expand (Niculescu & Lam, 2019; Thien & Phuong, 2024). The ongoing shift from agricultural to non-agricultural land use underscores the need for adaptive, integrated land management strategies that reconcile economic and environmental objectives.

To circumvent the above-mentioned problems, this study uses a Bayesian network modeling framework to present a comprehensive historical analysis of land-use changes in Vietnam's Red River Delta. By integrating multi-temporal spatial data with policy and economic contexts, the research demonstrates how land-use policies and agricultural expansion shifts have shaped land-use and land-cover dynamics over the past four decades. Besides that, the Bayesian network panel framework functions as a decision-support tool that identifies the most influential policy levers and economic drivers and enables policymakers to compare ex-ante land-policy scenarios to guide zoning and conversion decisions toward more sustainable outcomes. The motivation for this study lies in the urgent need to provide policymakers and practitioners with. By systematically analyzing land-use and land-cover change processes and their policy drivers, this research provides timely, relevant knowledge to support more adaptive and responsible land governance.

This study identifies several main findings. First, the Red River Delta has experienced a clear shift from rice based agriculture toward urban and industrial land uses between 2008 and 2022. Agricultural land declined sharply by 7%, while forest land decreased only modestly by 0.8% and pastureland expanded by 6.3%. This conversion is most pronounced along new expressway corridors and in coastal provinces, and hotspot mapping identifies priority clusters that require urgent policy attention. Second, the Bayesian network results show that industrial land prices are among the most influential economic drivers shaping both the pace and the location of these transitions, pointing to economic opportunities alongside rising pressure on agricultural systems and rural livelihoods. Third, the strongest governance levers relate to land use zoning and conversion controls that steer agricultural to urban and industrial reallocations, and the slight rebound in previously diminishing undefined agricultural zones signals a move toward more structured land management. These results illustrate the economic opportunities generated by land policy reforms and the heightened pressures on agricultural systems and rural livelihoods. The research, therefore, offers value not only for academics interested in land system science and policy analysis but also for local authorities and development agencies tasked with land management and rural planning, helping to inform targeted interventions and long-term development strategies.

Building on these findings, the study further highlights that effective land management in Vietnam requires harmonizing public policy interventions with market-based incentives and private sector governance. Sensitivity analysis confirms that tenure security and rural credit are the most influential levers for guiding land-use outcomes, accounting for a substantial share of the variance in the model. The analysis of governance scenarios indicates that the rapid implementation of digital land certificates (e-LURC) and the expansion of preferential credit for rice farmers are among the most effective strategies for stabilizing land-use change and supporting food security. Therefore, these results suggest that robust monitoring systems and incentive mechanisms are necessary to address the rapid conversion of agricultural and pastureland into urban areas, especially in peri-urban zones. Besides, this finding also guides scholars and practitioners in designing policies supporting economic development while preserving essential agricultural functions and ecological integrity. First, provincial land offices should prioritize tenure regularization in conversion hotspots, especially along expressway corridors and coastal clusters, by accelerating land registration. Second, local authorities and development agencies should redesign rural and green credit programs so that financing is linked to sustainable land use outcomes, such as offering preferential loans for farms that maintain productive rice land, adopt climate-smart practices, or invest in higher-value but land-sparing production systems. Third, targeted support for climate-resilient agriculture should be expanded in remaining agricultural zones through extension services, irrigation and drainage upgrades, and resilient crop varieties, helping reduce livelihood vulnerability and easing conversion pressure. Fourth, the Bayesian network panel framework should be institutionalized as a routine planning tool through a simple monitoring dashboard that integrates satellite updates, tenure and credit indicators, and policy variables, enabling scenario analysis for zoning and conversion controls and supporting annual land use planning with staff training and standardized guidance from central authorities.

To the best of our knowledge, this is the first study to comprehensively assess and forecast land-use and land-cover changes for the entire Red River Delta region by integrating long-term satellite data from 1979 to 2022 with detailed household-level information on credit access and land tenure. Evaluating and predicting these changes is essential for supporting policymakers and land managers in effectively adjusting and guiding land-use planning. The study is also the first in the region to apply Bayesian Network modeling in a way that supports policy-oriented decision making. The model links long-run land cover dynamics with household behavior and institutional settings, allowing direct assessment of how land policies and socioeconomic conditions have shaped land transformation across the study periods. This research contributes to the Decision Sciences by demonstrating how Bayesian decision analytic modeling can be implemented for strategic governance in policy-constrained socioeconomic systems. The framework extends Bayesian Network decision support to a spatially explicit, long-horizon setting by combining probabilistic graphical modeling with a multi-temporal land use dataset spanning four decades. It also converts policy context into decision-relevant inputs and outputs by producing transition probabilities and sensitivity evidence that inform scenario-based planning, including the effects associated with industrial land prices, zoning, and conversion controls, and pasture as an intermediate state along the pathway toward nonagricultural conversion. To strengthen interpretability and credibility, we triangulate BN-based scenario inference with province–year panel econometrics, validating that probabilistic signals align with observed conversion outcomes and providing complementary effect-size evidence under fixed effects and clustered inference. By filling important information gaps in Vietnam’s land management, the research provides both a scientific foundation and a practical roadmap for designing sustainable land-use planning and allocation strategies, contributing directly to improved policy formulation and implementation in rapidly developing areas.

Several limitations should be acknowledged. First, translating qualitative insights from stakeholder interviews into conditional probabilities required by the BN model posed challenges, necessitating the simplification of behavioral aspects into stylized scenarios rather than fully representative outcomes. Second, our empirical probabilities were derived from a relatively small sample of farmers and relied on hypothetical policy scenarios, potentially limiting generalizability. Third, this study's spatial resolution of satellite imagery might overlook small-scale land-use features, introducing possible mapping errors. Additionally, the classification uncertainty arising from traditional algorithms applied to complex land-use patterns of the Red River Delta could result in inaccuracies in land-cover maps. Finally, future research should expand geographic coverage, incorporate higher-resolution imagery, and apply advanced analytical methods such as object-based or deep-learning classifiers to enhance the accuracy and practical utility of LULC forecasts. While not invalidating the study's findings, these limitations underscore the need for cautious interpretation and further methodological refinement.

Future research should expand household surveys' spatial and temporal coverage, incorporate higher-resolution and longer time series of remote sensing data, and engage a broader range of stakeholders, including local governments, agribusinesses, and land planners. Integrating advanced machine learning techniques or participatory modeling frameworks could further improve the robustness and relevance of future LUCC studies. Finally, comparative analyses with other deltaic or peri-urban regions within Vietnam and internationally would strengthen the empirical foundation for sustainable land management policy design.

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Appendix

Appendix A: Policy instruments

Table A1. Vietnam's policies on the promotion of social inequality in land ownership

Date enacted	Name	Objective	Purpose
14/01/2011	Decree No. 05/2011/ND-CP	Ethnic-minority individuals & communities	Government secures residential & production land; subsidised allocation of reclaimed land; integrated poverty-reduction & cultural-preservation programmes.
15/05/2014	Decree No. 45/2014/ND-CP	Poor households, ethnic minorities, and resettled households	50 % reduction of land-use levy within residential-land quota; staged payment option; full exemption for compulsory resettlement land.
09/09/2015	Decree No. 75/2015/ND-CP	Poor & ethnic-minority households in forest uplands	Allocation/lease up to 30 ha production forest; VND 5–10 million / ha planting support; interest-free loans for 8 years; subsidised health insurance; community-based forest management.
26/10/2019	Decree No. 79/2019/ND-CP	Poor & minority households are unable to pay the levy	Interest-free 'land-levy debt' payable over 5 years; mandatory transparent calculation sheets.
15/03/2021	Decree No. 20/2021/ND-CP (15 Mar 2021)	Poor, near-poor, disaster-affected households	Housing subsidy ≥ VND 40 million (new) / 20 million (repair); VND 30 million for relocation from hazard zones; follow-up credit & livelihood support.
01/08/2024	Decree No. 102/2024/ND-CP	Ethnic-minority persons lacking land; communes in extreme difficulty	Free first-time allocation of residential land; supplementary production land up to quota; annual public land fund; digital transparency via provincial land-information portals.

Source: Author's collection

Table A2. Laws and regulations related to agricultural development

Date enacted	Name	Purpose
05/08/2008	Resolution 26-NQ/TW	Guide investment, land and credit reforms, and value-chain upgrades toward modern climate-resilient farming
19/12/2013	Decree 210/2013/ND-CP	Provide land-levy exemptions, infrastructure subsidies, and concessional credit for agro-projects
19/06/2017	Law on Irrigation 08/2017/QH14	Offer subsidised irrigation for smallholders and promote public-private partnerships in water infrastructure
21/11/2017	Law on Fisheries 18/2017/QH14	Enforce vessel registry and catch documentation, and empower community co-management of aquatic resources
17/04/2018	Decree 57/2018/ND-CP	Grant long land-rent holidays, interest subsidies, and cost-sharing for processing and cold-chain facilities
05/07/2018	Decree 98/2018/ND-CP	Fund contract farming and provide risk-sharing mechanisms for price shocks
29/08/2018	Decree 109/2018/ND-CP	Cover certification costs, support income during conversion, and introduce a national organic logo
19/11/2018	Law on Crop Production 31/2018/QH14	Regulate seed and pesticide use, ensure biosafety, and mandate climate-smart farming standards
19/11/2018	Law on Animal Husbandry 32/2018/QH14	Set feed and antibiotic standards, manage livestock waste, and encourage high-tech husbandry

22/08/2019	Decision 1068/QĐ-TTg	Expand geographical indications, collective trademarks, and branding for agricultural specialties
03/06/2020	Decision 749/QĐ-TTg	Develop data platforms, e-commerce, and precision-farming applications across the supply chain
28/01/2022	Decision 150/QĐ-TTg	Restructure crops and livestock, reduce emissions, boost organic output, and embed digital services
13/07/2022	Decree 46/2022/ND-CP	Tighten feed and antibiotic standards and incentivise relocation of farms to bio-secure zones
20/06/2023	Law 17/2023/QH15	Allow flexible capital mobilisation, digital platforms, and insurance subsidies within cooperatives
27/11/2023	Decision 1490/QĐ-TTg	Scale alternate-wetting-and-drying irrigation and link farmers to carbon credits and premium markets
01/08/2024	Land Law 31/2024/QH15	Abolish the land-price frame, introduce annual price tables, and ease the transfer and accumulation of farmland

Source: Author's collection

Appendix B: Accuracy details

Table B1. Confusion matrix of validations (rounded) for land use/land cover classifications (1979–2022)

Land Cover Type	Forest land	Rice cultivation	Pasture	Other Agricultural Class	Other Undefined Classes
Forest land	125	5	4	3	2
Rice cultivation	4	118	6	7	5
Pasture	3	5	110	10	6
Other Agricultural Class	2	6	8	105	12
Other Undefined Classes	3	4	6	9	102

Notes: The diagonal cells indicate the number of correctly classified pixels for each land-use/land-cover class; off-diagonal cells indicate misclassifications. Source: Author's calculation

Appendix C: Econometric unit-root & diagnostics

Table C1. Panel Unit Root Test

Variable	IPS level t-bar (p-value)	IPS 1st difference tbar (p-value)	ADF-Fisher level χ^2 (p-value)	ADF-Fisher 1st difference χ^2 (p-value)	I(d)
In (ConversionRate)	-3.96 (0.000)	-	41.80 (0.000)	-	I(0)
BN_Prob	-4.27 (0.000)	-	46.00 (0.000)	-	I(0)
In (IndPrice)	0.84 (0.801)	-6.12 (0.000)	15.30 (0.647)	58.50 (0.000)	I(1)
In (Pasture)	-2.91 (0.002)	-	34.60 (0.004)	-	I(0)
In (RiceCultivation)	-1.77 (0.038)	-	28.20 (0.023)	-	I(0)
In (Forest)	-1.23 (0.109)	-5.27 (0.000)	20.90 (0.381)	51.70 (0.000)	I(1)
In (OtherAgri)	-2.15 (0.016)	-	30.80 (0.013)	-	I(0)

In (OtherUndefined)	-0.97 (0.166)	-4.98 (0.000)	18.60 (0.529)	49.90 (0.000)	I(1)

Note: Significant p-values (< 0.05) indicate stationarity at the level or first difference

Table C2. Correlation matrix of independent variables

	ln (Pasture)	ln (Rice cultivation)	Δln (Forest)	Δln (Other undefined classes)
ln (Pasture)	1	0.781	0.199	-0.152
ln (RiceCultivation)	0.781	1	0.193	0.011
Δln (Forest)	0.199	0.193	1	-0.155
Δln (OtherUndefined)	-0.152	0.011	-0.155	1

Source: Author's calculation

Table C3. Diagnostic tests for Panel regression model (Fixed Effects)

Diagnostic test	Statistic	p-value
Wooldridge Serial Correlation Test	$F(1,67) = 1.85$	0.17
Durbin-Watson	DW =1.79	-
Jarque-Bera Normality Test	JB = 3.22	0.20
Jarque-Bera Normality Test (FE)	JB = 2.97	0.23
Hausman Test	$\chi^2(6) = 14.32$	0.026
Heteroskedasticity	$\chi^2(1) = 1.41$	0.24

Note: p-values > 0.05 indicate no violation of regression assumptions. Source: Author's calculation

Table C4. Province-level residual diagnostics

Variable	Coef (stars)	SE	p_asym	p_df7
BN_Prob	0.415***	0.098	<0.001	0.004
Δln(IndPrice)	0.125*	0.061	0.040	0.080
ln(Pasture)	0.223**	0.086	0.010	0.036
ln(RiceCultivation)	-0.217**	0.089	0.015	0.045
Δln(Forest)	-0.055	0.050	0.271	0.308
ln(OtherAgri)	-0.070	0.045	0.120	0.164
Δln(OtherUndefined)	0.039	0.033	0.237	0.276

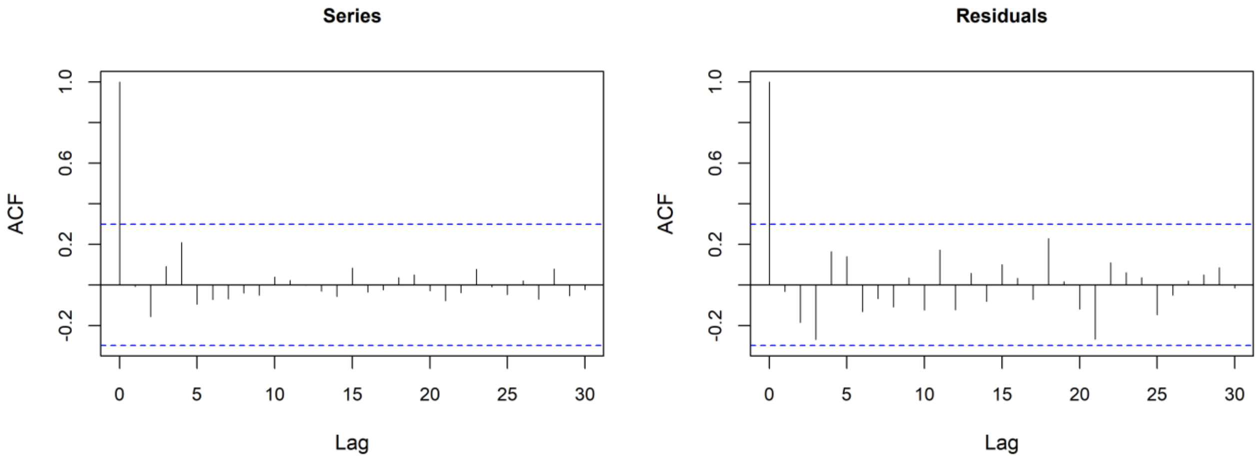
Notes: Standard errors are clustered at the province level. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: Author's calculation

Table C5. Province-level residual diagnostics

Province	Period	Ljung–Box Q(12)	p-value (Q)	stat	p-value
Bắc Ninh	1979–2022	12.861	0.379	-1.828	0.068
Hà Nam Ninh	1979–2022	14.198	0.288	-1.123	0.261
Hà Nội	1979–2022	20.906	0.052	-0.975	0.329
Hải Hưng	1979–2022	11.342	0.500	0.523	0.601
Hải Phòng	1979–2022	16.992	0.150	-1.328	0.184
Quảng Ninh	1979–2022	14.945	0.244	-0.853	0.394
Thái Bình	1979–2022	13.031	0.367	-1.439	0.150
Vĩnh Phúc	1979–2022	18.666	0.097	-1.599	0.110

Source: Author's calculation.

Figure C1. Autocorrelation functions of the series and residuals



Source: Author's calculation