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ARTICLE

Chaotic Dynamics and Key Drivers in the Evolution of Tibetan Village Systems: A Case Study in Western Sichuan

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ABSTRACT

This study examines the spatiotemporal evolution of Tibetan villages in western Sichuan through state transition models and predictive simulations to understand their complex dynamics and key driving factors. Using a combination of multivariate time-series analysis and chaotic attractor identification, the research identifies forest cover, economic growth, employment rates, road density, and communication network coverage as critical determinants of village trajectories. For instance, Molo Village recovers rapidly with a 10% increase in regional economic growth, while Xisuo Village becomes unstable with employment rate fluctuations above 2%. Shenzuo Village benefits from improved road density, and Minzu Village's stability depends on forest cover. Jiangba Village relies on the growth of irrigated farmland and communication network coverage, whereas Kegeyi Village exhibits periodic dynamics and high sensitivity to employment variations. The findings underscore the inherent complexity and nonlinearity of rural systems, revealed through chaotic attractor analysis, which highlights the system's sensitivity to initial conditions and external shocks. The article provides actionable insights into resilience mechanisms and offers practical recommendations for the sustainable development of culturally and ecologically sensitive regions. Emphasis on tailored management strategies is essential to meet the challenges faced by these unique systems in the face of modernization and environmental change.

Keywords: Nonlinear Analysis; Chaotic Attractors; Tibetan Villages; Complex Systems; Dynamic Behavior

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1. Introduction

Traditional Tibetan villages in western Sichuan have experienced complex and dynamic evolution throughout history and the modernization process, shaped by social, economic, cultural, and ecological factors [1]. As vital cultural heritage components, these villages lie at the intersection of modernization and traditional culture [2]. Functioning as complex, large-scale systems, village spatial systems encapsulate geographic and social information while exhibiting pronounced nonlinearity and complexity [3]. However, most existing studies rely on linear models, which fail to adequately capture the nonlinear dynamics, critical turning points, and multifaceted interactions that characterize the long-term evolution of these systems. Such limitations hinder our understanding of how various internal and external forces drive the unique developmental trajectories of individual villages, particularly their resilience and adaptability to changing conditions [4–6].

This study addresses these gaps by employing nonlinear analysis and chaotic attractor identification techniques to explore the dynamics and driving factors of Tibetan village spatial systems in western Sichuan. By integrating spatial data from Geographic Information Systems (GIS) with socioeconomic datasets [7], the research applies multivariate time series analysis and Recurrence Quantification Analysis (RQA). These advanced methods surpass traditional linear models by uncovering the nonlinear and chaotic behaviors inherent in complex systems. These methods enable a detailed examination of dynamic changes across different developmental stages, the identification of critical turning points, and the detection of chaotic attractors within the village systems [8, 9]. Chaotic attractor analysis highlights the systems' inherent complexity and sensitivity to initial conditions, offering insights into their adaptability and potential instability under external shocks.

Through systematic sensitivity analysis, this study identifies key variables influencing Tibetan village systems' behavior, providing theoretical contributions and practical recommendations for their sustainable development [10]. The innovation of this research lies in its application of advanced nonlinear analytical tools, which bridge critical gaps in current scholarship and present fresh perspectives for understanding and managing the resilience of Tibetan village systems amid modernization pressures and environmental changes.

2. Literature Review

In recent years, nonlinear dynamic system analysis methods have gained prominence in studying rural spatial systems and ecosystems. These complex systems, shaped by multiple interacting factors, exhibit diverse and dynamic behaviors, including distinct patterns of fluctuation and stability across different developmental stages [11–13]. Techniques such as multivariate time series analysis and Recurrence Quantification Analysis (RQA) have proven particularly effective in identifying key turning points, evaluating system stability, and uncovering sensitivity to external shocks. This theoretical and methodological foundation provides the necessary background for this study's exploration of Tibetan village systems in Western Sichuan.

The application of chaos theory in nonlinear dynamic system research has further advanced our understanding of these systems. Chaos theory highlights their heightened sensitivity to initial conditions and the unpredictable behaviors that emerge from deterministic processes. Recent studies have demonstrated that chaos theory not only explains the emergence of seemingly random evolutionary patterns, referred to as chaotic attractors but also serves as a diagnostic tool for detecting system instability and predicting potential transitions under external pressures [14, 15]. It explains how seemingly random evolutionary patterns—chaotic attractors—can arise within structured systems. These insights have facilitated a deeper understanding of the long-term evolution of rural spatial systems, offering valuable perspectives on their resilience, adaptability, and responses to external perturbations [16–18].

Rural spatial systems are widely recognized as complex nonlinear systems whose evolution is influenced by a multitude of factors, including land use, population mobility, and infrastructure layout. With the acceleration of urbanization, these systems have become increasingly dynamic, exhibiting pronounced changes in spatial structure under the influence of rural-urban integration [19–21]. Geographic Information Systems (GIS) and spatial analysis tools have facilitated the quantification of dynamic features such as rural land use changes, village layouts, and functional transformations. These tools have also revealed evolutionary trajectories of rural systems shaped by external conditions, particularly social and economic changes introduced during urbanization phases [22]. However, such approaches often fail to account for the nonlinear dynamics and chaotic behaviors inherent in complex systems, making it difficult to identify sudden shifts and critical transitions.

Despite the growing adoption of nonlinear methodologies, much of the existing research continues to rely on traditional linear models. These models are limited in their capacity to capture the full range of dynamic behaviors and system diversity in rural areas [23–25]. For example, many studies focus on isolated time points, neglecting the cumulative effects of long-term disturbances on system evolution. Linear models are particularly inadequate in addressing complex interactions and stability shifts under strongly correlated noise, as highlighted by scholar [26], who demonstrated the critical role of nonlinear approaches in quantifying resilience and predicting regime shifts. This limitation is particularly evident in Tibetan rural areas, where cultural and environmental factors are deeply intertwined [27]. Moreover, existing literature lacks sufficient cross-regional comparisons and fails to address the diverse ethnic and ecological contexts of these systems, thereby restricting the generalizability of findings [28, 29].

To address these gaps, this study employs nonlinear dynamic models and chaotic attractor analysis to examine the spatial evolution characteristics of traditional Tibetan villages in western Sichuan. By focusing on the system's nonlinear and chaotic behaviors under the influence of diverse factors, the research identifies key turning points and complexities through the detection of chaotic attractors. This approach enables a more precise evaluation of resilience and adaptability, offering valuable insights into how Tibetan villages can achieve sustainable development within culturally and ecologically sensitive contexts. Furthermore, it enhances our understanding of the resilience mechanisms and sustainability of these unique village systems [10, 15, 30].

The primary innovation of this study lies in the application of advanced nonlinear dynamic analysis tools to the evolution of complex rural systems. By bridging gaps in existing research, this study provides empirical evidence to support the long-term development and sustainability of rural spatial systems, contributing both theoretical insights and practical recommendations.

3. Research Area and Method

3.1. Research Location

The study focuses on traditional Tibetan villages in western Sichuan—Molo, Kegeyi, Xisuo, Shenzuo, Minzu, and Jiangba (as shown in **Figure 1**). These high-altitude villages, situated between 1,200 and 4,500 meters above sea level, are home to diverse Tibetan communities, including the Kham, Jiarong, Amdo, Baima, and Ersu groups. Classified as ecologically sensitive and restricted development zones, these areas are characterized by unique cultural and environmental features. The majority of residents practice Tibetan Buddhism (primarily the Gelug and Nyingma schools) or the Bon religion, deeply embedding spiritual traditions into daily life. The local economy is predominantly based on agriculture and animal husbandry, which sustain the livelihoods of these communities. Cultural tourism has recently been introduced as a supplementary industry to promote economic growth, enhance social participation, and support community development. This initiative also aims to preserve traditional cultural practices while balancing modernization and cultural heritage.

3.2. Research Path

3.2.1. Data Collection

This study employed a random sampling method to select six representative village samples, aiming to minimize selection bias and improve the generalizability of the findings. The sampling process utilized the RANDBETWEEN and INDEX functions in Excel, ensuring equal probability of selection for each village from a predefined list of potential study locations [31].

The dataset spans 2015 to 2023 and encompasses variables related to the natural environment, socioeconomic factors, and cultural attributes. To address challenges in data collection, some variables were replaced with county- or township-level averages to maintain data reliability. Data sources include field surveys, experimental measurements, government databases, and existing literature, while spatial data were derived from 30-meter resolution Digital Elevation Models (DEM) and Points of Interest (POI). To ensure data completeness and consistency, missing values were imputed using mean substitution, text data were converted to numeric formats, and all variables were standardized [32, 33]. These rigorous data processing steps produced a comprehensive, high-quality dataset, forming a robust foundation for subsequent modeling and analysis (See **Figure 2**).

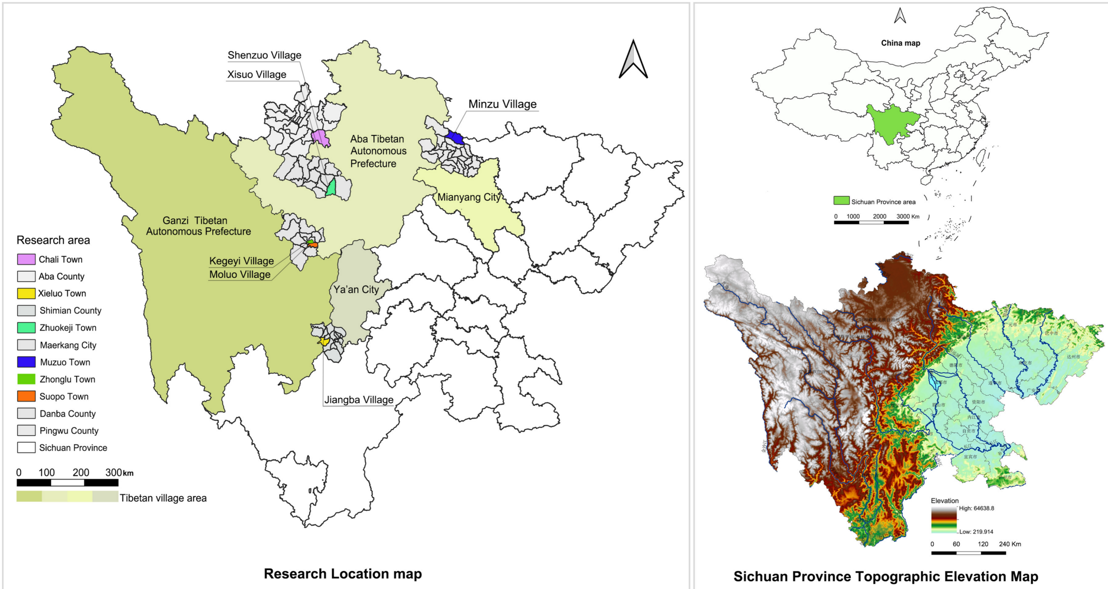


Figure 1. Research location.

Source: Self-illustrated.

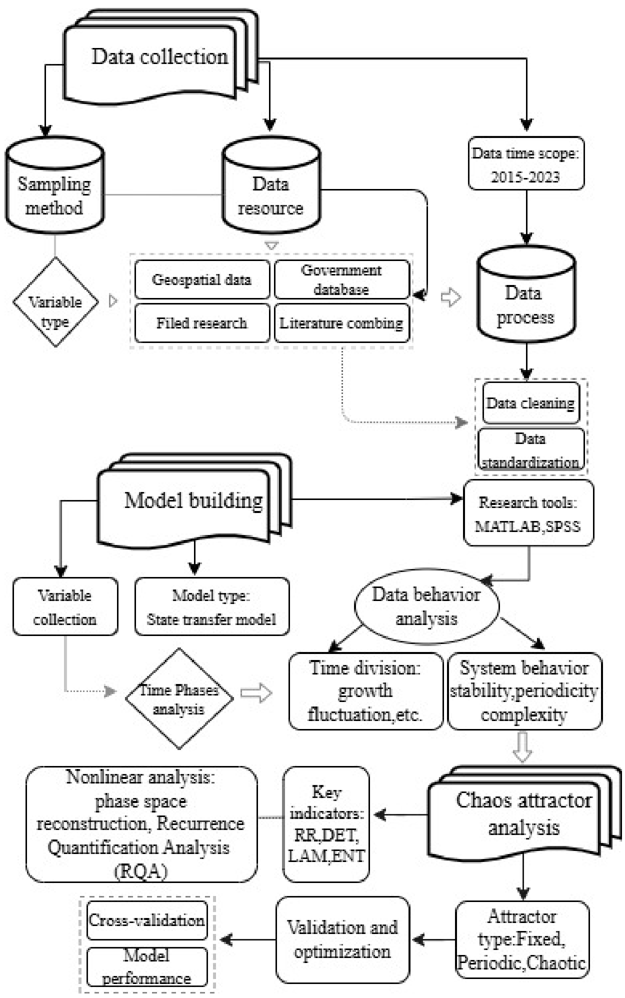


Figure 2. Research process flowchart.

Source: Self-illustrated.

3.2.2. Model Simulation and Analysis

The model simulation and analysis of the study are divided into three major steps: variable selection and state transition model construction, quantitative analysis, and multivariate nonlinear analysis, to capture critical socio-ecological dynamics unique to Tibetan village systems, such as environmental stability, infrastructure accessibility, economic drivers, and agricultural productivity. By incorporating these factors, the state transition model effectively simulates the dynamic behavior of village spatial systems across different developmental stages. The state transition process of the model is represented as:

$$S(t+1) = f(S(t), E(t)) \tag{1}$$

Here, $S(t)$ denotes the state of the system at time t, $E(t)$ denotes the external factors that affect the state of the system at time t, and f is a transition function that describes how the state changes over time [34].

Subsequently, SPSS statistical tools were used to analyze model outputs by calculating the mean, standard deviation, and autocorrelation of the system to evaluate its stability and periodicity. The mean provides insight into the system's typical behavior over its long-term evolution, while the standard deviation reflects stability, with lower values indicating greater system stability [35]. Autocorrelation assesses the dependency within the time series, aiding in the detection of periodic characteristics and memory effects in the system [36, 37].

To more accurately pinpoint key turning points within the system, the Top Entropy method was employed, calculating entropy values at different time points to quantify system uncertainty. Higher entropy values signify greater instability, and changes in entropy values reveal trends in system behavior across various stages. The equation is as follows:

$$H(X) = \sum_{i=1}^{n} P\left(x_i\right) log_2 P(x_i) \tag{2}$$

Here, H(X) is the entropy of the random variable X; $P(x_i)$ is the probability that the random variable X takes the value x_i; and n is the number of possible values of the random variable [34].

Finally, multivariate phase space reconstruction and Recurrence Quantification Analysis (RQA) were employed to perform nonlinear analysis, aiming to identify chaotic attractors and their key driving factors within the system. Phase space reconstruction maps the time series into a phase space, providing a visual representation of the system's dynamic behavior [38]. Recurrence plots were utilized to examine the system's periodicity and potential chaotic characteristics, with RQA metrics including the following: Recurrence Rate (RR), which quantifies the recurrence of system states over time and reflects overall periodicity; Determinism (DET), which measures the proportion of diagonal structures in the system and indicates determinism; Laminarity (LAM), which describes the proportion of laminar states and reveals intermittent characteristics; and Entropy (ENT), which reflects the system's complexity and chaotic behavior through the entropy of diagonal length distribution [39, 40]. Variables were progressively removed, and RQA metrics were recalculated to determine which variables most significantly influenced the system's dynamic behavior, thereby identifying the key factors driving chaotic behavior [41].

To ensure model robustness, we employed K-fold cross-validation and Lasso regression using MATLAB R2022b. Given the small sample size, the cvpartition function was used to divide the data into five folds (K = 5), and the crossval function was applied to perform multiple iterations of training and validation. This method produced more reliable average performance metrics [42] but also ensured that each subset contained sufficient data for meaningful evaluation, thereby improving the generalizability of the findings to similar datasets. Model performance was evaluated using Mean Squared Error (MSE) and the coefficient of determination (R^2). A lower MSE indicates reduced prediction error, while a higher R^2 reflects stronger explanatory power of the model [43].

Through this approach, we aim to uncover the dynamic characteristics and complex behaviors of village systems, constructing a reliable predictive model that provides a robust quantitative foundation for deeper insights into the nonlinear and chaotic properties of these systems.

4. Analysis and Results

This section utilizes a state transition model to analyze the dynamic evolution processes experienced by sample villages under the influence of environmental, social, economic, and cultural factors. The village spatial system is composed of material and immaterial subsystems, whose interactions shape the evolutionary characteristics of villages at different stages and reveal the system's complex diversity [44]. Using model predictions across various years, we analyzed the future dynamic trends of each village, supporting the assessment of system stability and periodicity [45].

By examining the volatility and recurrence of predicted values, this study identifies intrinsic behavioral patterns within the system, reflecting its sensitivity to external factors and its response characteristics. Additionally, using Recurrence Quantification Analysis (RQA) along with visualized recurrence plots, we identified key attractor types in the system and assessed the periodic and chaotic properties of each village under different conditions [41]. The results reveal core behavioral characteristics and primary driving factors in the system across various developmental stages, providing theoretical support and empirical evidence for a deeper understanding of the long-term evolutionary trajectories of Tibetan village spatial systems in western Sichuan [46].

4.1. Dynamic Behavior Analysis

4.1.1. Preliminary Stage Division

The dataset encompasses variables from four dimensions: environmental, social, cultural, and economic. State variables represent core characteristics of the village systems, such as village area, elevation, terrain features, building area, road density, and religious affiliation, while influence variables reflect external conditions driving system changes, including annual precipitation, urbanization rate, economic growth rate, and forest coverage[34].

To analyze the internal dynamic trends within village systems, the study preliminarily divided the period from 2015 to 2023 into four stages based on variable change characteristics: 2015–2016 (growth period), 2017–2019 (relative stability), 2020–2021 (fluctuation period), and 2022–2023 (reorganization period). This stage division, informed by time-series data trends and analysis of key events, lays a foundation for further examination of the dynamic behavioral characteristics of village systems across each stage.

4.1.2. Calculation and Evaluation of State Models

Based on the time series data, this study used a linear regression model to estimate the state of the village system at a future point in time[47], as follows:

$$S(t+1) = \alpha_0 + \alpha_1 S(t) + \beta_1 E(t) + \epsilon \qquad (3)$$

Where $S(t)$ denotes the current state variable, $E(t)$ denotes external factors, and α_0, α_1, β_1 are model parameters determined by data fitting. ϵ is the error term.

Using fitted calculations based on data from 2015 to 2023, we obtained predicted state values for each village system at future time points. Analyzing the differences and trends in these predictions allows us to further examine the distinct dynamic behaviors of various villages across different stages. This model analysis offers a quantitative basis for understanding the dynamic characteristics of each village over time, aiding in revealing each village's response mechanisms to changing external conditions (see **Figure 3**).

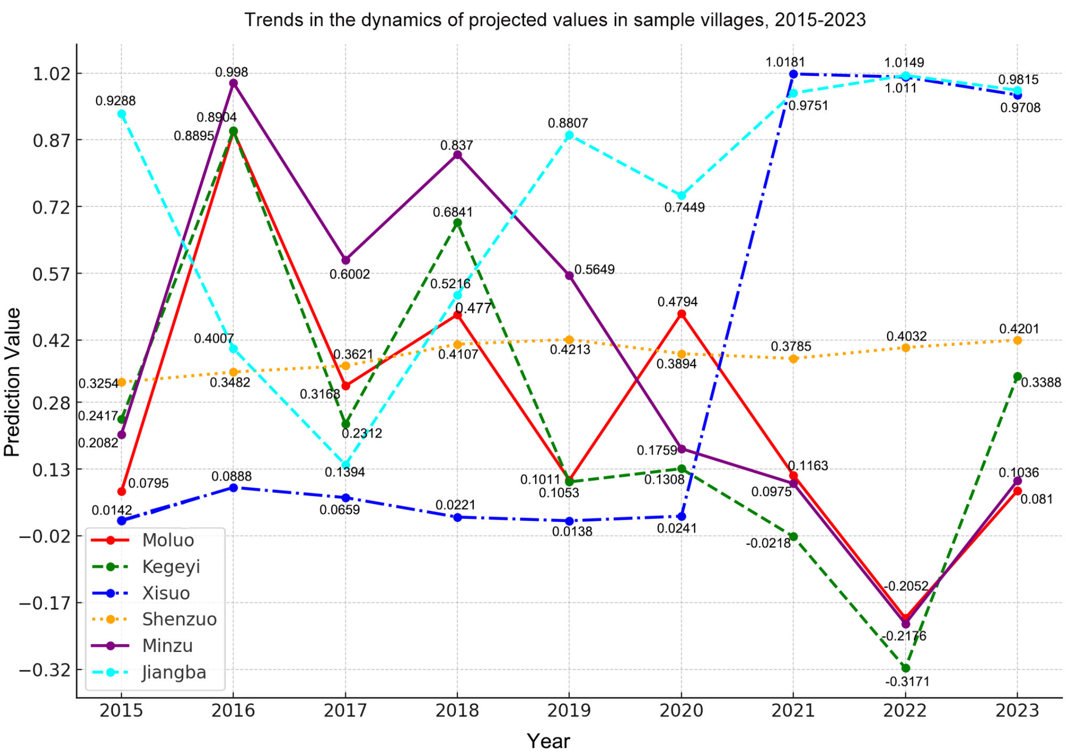


Figure 3. System dynamics process prediction value.

Source: Self-illustrated.

As shown in **Figure 3**, dynamic behavior analysis reveals distinct patterns in the evolution of village systems under varying external shocks and internal attributes. Key findings for each village system are summarized in **Table 1** as follows:

Table 1. Comparison of village system phases and key findings.

Village	Growth Phase	Release Phase	Reorganization Phase	Key Characteristic
Moluo	2015–2016: Steady growth.	2016–2022: Fluctuating decline	2023: Stable growth.	Highly sensitive to external shocks, showing prolonged instability during the release phase but stabilizing in 2023.
Kegeyi	2015–2019: Fluctuating decline	2019–2021: Declining trend	2022–2023: Gradual recovery.	Displays cyclical behavior with clear recovery in 2023 despite previous instability and external influences.
Shenzuo	2015–2019: Steady growth.	2020: Slight decline	2021–2023: Stable growth.	Exceptionally stable with minimal fluctuations, indicating strong resilience to external disturbances.
Xisuo	2015–2019: Slight decline.	2020–2021: Reached a peak	2022–2023: Gradual stable.	Maintains adaptability and recovers quickly after peak fluctuations, demonstrating consistent system recovery.
Minzu	2015–2018: Fluctuating decline.	2018–2022: Substantial decline	2022–2023: Starting to grow after continued downward adjustments	Experiences prolonged decline but shows signs of recovery and reorganization towards stability in the final phase.
Jiangba	2015–2017: Significant decline	2017–2021: Fluctuating growth	2021–2023: Gradual stable.	Marked by significant fluctuations but stabilizes gradually during the reorganization phase.

The table above visualizes and compares the distinctive patterns of the evolution of village systems in Tibet. Moluo and Kegeyi demonstrate pronounced sensitivity to external shocks, characterized by prolonged release phases followed by moderate recovery. In contrast, Xisuo and Shenzuo exhibit high stability and adaptability, with minimal fluctuations throughout the study period. Minzu and Jiangba display cyclical behaviors, marked by significant fluctuations during their release phases and gradual stabilization over time. These findings underscore the importance of integrating time-series data with system-specific attributes when managing village systems. Developing tailored strategies that account for each village's unique characteristics can significantly enhance resilience and adaptability to external disturbances [48–50].

4.2. System Dynamics and Attractor Identification

4.2.1. Stability, Periodicity and Turning Points of Systems

The pattern of predicted system values provides essential insights for analyzing periodicity and stability. When predicted values display a regular pattern of increases and decreases within a specific time frame, this suggests periodic behavior in the system [51]. Additionally, sharp fluctuations or trends toward stability in the predicted values reflect the system's volatility and stability [52].

This section calculates the mean to determine the system's central tendency and uses standard deviation to assess its volatility: a smaller standard deviation generally indicates greater stability, while a larger standard deviation suggests higher volatility and lower stability [53]. Furthermore, calculating autocorrelation evaluates the dependency within the time series, revealing whether the system exhibits significant relationships and periodic characteristics [47, 54]. Entropy analysis provides further insights into system order and uncertainty. Low entropy indicates a stable, orderly system with minimal internal changes and low uncertainty, while high entropy signifies a disordered, unstable system with substantial internal variation and lower adaptability [55]. Changes in entropy values over time also indicate adjustment trends within the system, serving as reference points for identifying potential turning points (see **Figure 4**).

An analysis of the dynamic behavior of each village's system reveals significant differences in stability, periodicity, and complexity. The systems of Moluo and Kegeyi villages exhibit moderate volatility, with standard deviations of 0.3202 and 0.3603, respectively, indicating relatively weak stability in their time series. Moluo village's negative autocorrelation (–0.0236) suggests a lack of significant periodicity, potentially even indicating countercyclical behavior. Additionally, its high entropy value (–10.3460) reflects considerable internal uncertainty, highlighting complexity and instability in response to external shocks [56]. Kegeyi village, while having positive autocorrelation (0.0619), only shows a weak cyclical trend, and its high entropy value (–2.6867), along with large extreme-value differences, further indicates system complexity and limited adaptability. These results suggest that Moluo and Kegeyi villages may lack sufficient resilience and stability to respond to external changes effectively.

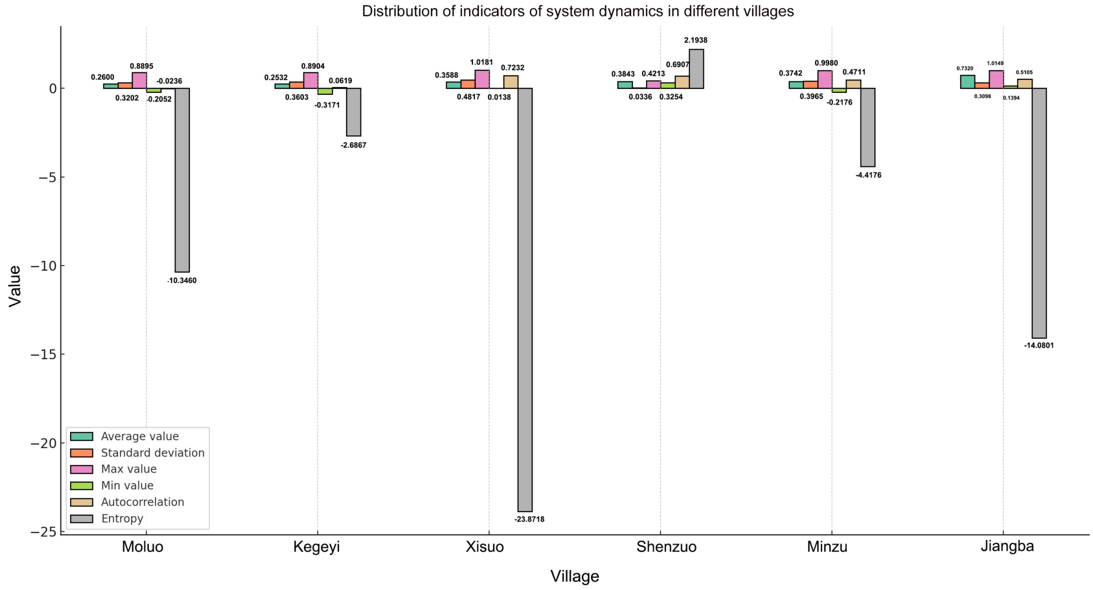


Figure 4. Comparison of metrics across villages.

Note: The mean value indicates the central tendency of the system, and the standard deviation assesses the volatility of the system; the larger the standard deviation, the higher the volatility. The autocorrelation is used to determine the periodicity and temporal correlation of the data, and the entropy value assesses the orderliness of the system; a low entropy value indicates stability, and a high entropy value indicates disorder and high uncertainty.
Source: Self-illustrated.

In contrast, the villages of Xisuo and Shenzuo demonstrate significantly different characteristics. Xisuo village has the highest standard deviation (0.4817), indicating the greatest volatility. Its autocorrelation of 0.7232 suggests strong periodic behavior, yet the extremely low entropy value (–23.8718) implies high internal complexity and extreme sensitivity to initial conditions, reducing the system's predictability [57]. Shenzuo village, by contrast, displays exceptional stability, with a standard deviation of only 0.0336 and minimal extreme-value differences, indicating low volatility and strong resilience. Its autocorrelation of 0.6907 reveals clear periodic behavior, while a positive entropy value (2.1938) suggests a high level of order, reflecting effective management strategies and strong resistance to external shocks.

In summary, Shenzuo village exhibits the best performance regarding system stability, periodicity, and order, suggesting that its management strategies are effective and possess strong system resilience. Xisuo village, while showing clear periodicity, has high volatility and complexity, indicating that the system is in an unstable dynamic state. The systems of Moluo and Kegeyi villages show high volatility and uncertainty, lack significant periodicity, and exhibit relatively poor stability. Minzu and Jiangba villages are intermediate in terms of periodicity and complexity, displaying some adaptability. The differences in dynamic behavior across villages reflect varying levels of management effectiveness and resilience to external shocks, offering valuable insights for further exploration of long-term village system development.

In the evolution of complex dynamic systems, identifying key turning points is crucial—not only for capturing transitions from one state to another but also for revealing the system's driving mechanisms [58]. To identify these turning points, we assessed the magnitude of dynamic changes each year by calculating the absolute change in the system, defined as $\Delta S(t) = |S(t) - S(t-1)|$. Assessing the magnitude of change in the dynamics of the system across years [38]. Larger absolute changes often indicate that the system underwent a significant dynamic shift during that year, potentially signaling the start of a new phase.

As shown in **Figure 5**, each village exhibits noticeable fluctuations in absolute change values in specific years, reflecting different sensitivities and response patterns to external influences. These changes are often closely associated with geographic environment, social structure, economic factors, and policy shifts.

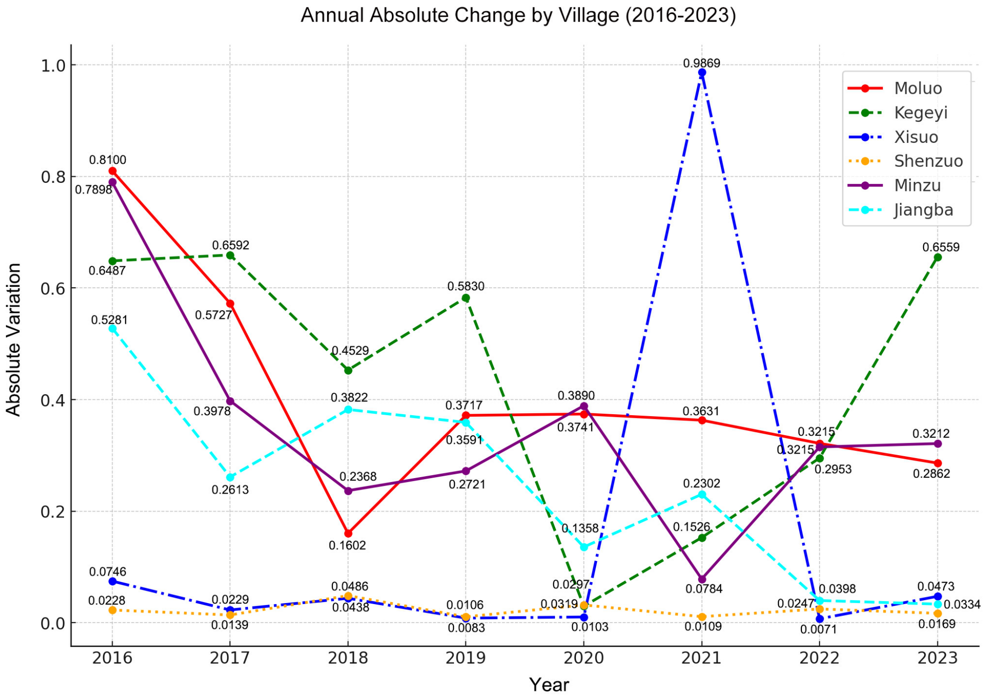


Figure 5. Absolute Annual Change and Identification of Turning Points.

Note: This figure shows the annual trend in the amount of absolute change in the system for each village from 2016 to 2023 and is used to identify system turning points. Years with higher amounts of change can be considered potential turning points, indicating that the system experienced a significant change or external shock in that year. Trends in change across villages reflect their differences in volatility and stability.
Source: Self-illustrated.

Specifically, Moluo village experienced significant fluctuations in 2016 and 2018, with a particularly high change value in 2016, suggesting that the village may have been impacted by substantial external influences or internal adjustments that affected its resilience. Similarly, Kegeyi village displayed high absolute change values in 2016 and 2023, likely due to environmental shifts, policy adjustments, or changes in management practices. Xisuo village's key turning point occurred in 2021, where the absolute change was far higher than in other years, potentially reflecting a sudden event or strong external shock. In contrast, Shenzuo village remained relatively stable throughout the analysis period, though minor fluctuations in 2018 and 2020 may indicate potential system change trends or the influence of external interventions. The key turning points for Minzu and Jiangba villages appeared in 2016 and 2020, respectively; notably, the fluctuation in 2016 may be associated with policy adjustments, environmental pressures, or shifts in economic development, revealing vulnerabilities in these villages when facing external shocks [59].

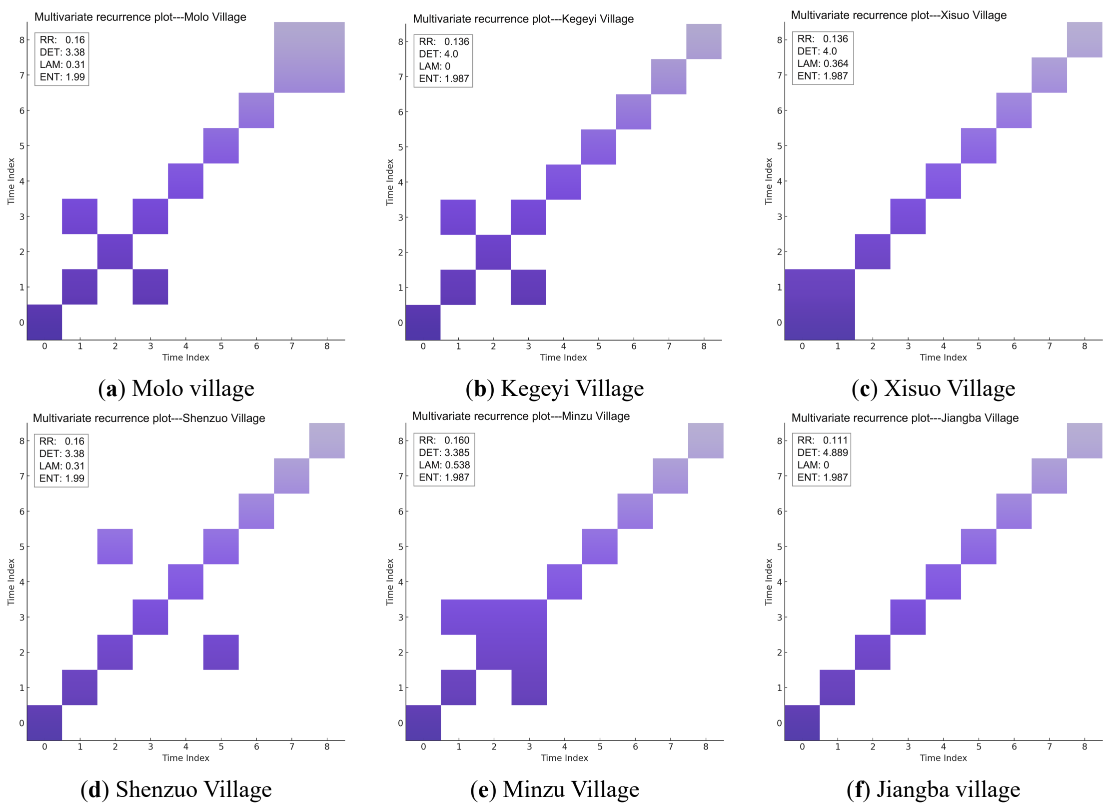
These turning points reveal that different villages display diverse response patterns when confronted with similar or distinct external factors. Identifying these turning points not only highlights significant changes in the system during specific years, but also provides valuable evidence for understanding dynamic system evolution and identifying key driving factors [43, 58]. These findings suggest that paying greater attention to turning points in management and decision-making can help develop more adaptive strategies, thereby enhancing the stability and resilience of village systems.

4.2.2. Attractor Identification and Verification

In complex dynamical systems, an attractor represents the long-term state toward which the system converges. Attractors are generally classified into three types: fixed-point attractors (where the system stabilizes at a specific state), periodic attractors (where the system follows a cyclical trajectory), and chaotic attractors (where the system exhibits complex, non-periodic, yet bounded behavior). Identifying attractors is critical for understanding a system's dynamic characteristics, particularly chaotic attractors, which reveal heightened complexity and sensitivity to initial conditions [60]. Insights into attractor types not only illuminate system behavior but also provide valuable guidance for controlling and optimizing complex systems. This section focuses on the identification of chaotic attractors to deepen understanding of the nonlinear dynamics underlying rural systems [61, 62]. Traditional linear analysis is insufficient to capture the full scope of a system's dynamic complexity. The identification of chaotic attractors offers critical insights into potential instabilities and sensitivities, which are essential for understanding and managing system behavior. Preliminary analysis of system periodicity and stability forms the foundation for attractor identification, with an emphasis on detecting chaotic dynamics to enhance our understanding of system evolution.

In this study, six key variables representing environmental, social, and economic dimensions were selected for multivariate nonlinear analysis. These variables include the "growth rate of irrigated farmland area", "forest coverage", "road density", "communication network coverage", "regional economic growth rate" and "annual growth rate of the employed population". Multivariate phase space reconstruction was employed, with principal component analysis (PCA) used to project the high-dimensional data onto a two-dimensional space for visualization. A multivariate recurrence plot (RP) was then generated (as illustrated in the accompanying figure), which highlights diagonal structures, scatter distributions, and empty regions indicative of the system's dynamics [63]. The diagonal structures, scatter distributions, and empty regions in the recurrence plot help determine whether the system exhibits periodic or chaotic characteristics.

Next, recurrence quantification analysis (RQA) was performed to calculate indicators such as recurrence rate (RR), determinism (DET), laminarity (LAM), and entropy (ENT), which quantify the recurrence behavior and complexity of the system. If RQA indicates a high entropy (ENT) and low recurrence rate (RR), the system likely has a chaotic attractor, reflecting high complexity and unpredictability. Conversely, a system with a high recurrence rate and determinism suggests a periodic attractor, indicating strong periodicity and stability [64]. This analysis offers deeper insights into the system's attractor characteristics and potential evolutionary trends (as shown in **Figure 6**).



(**a**) Molo village (**b**) Kegeyi Village (**c**) Xisuo Village

(**d**) Shenzuo Village (**e**) Minzu Village (**f**) Jiangba village

Figure 6. Identification of system dynamic attractors.

Note: This figure displays multivariate recurrence plots for each village, illustrating indicators such as recurrence rate (RR), determinism (DET), laminarity (LAM), and entropy (ENT), which help assess system complexity and periodicity. These indicators enable an assessment of each village system's dynamic behavior type, offering deeper insight into system stability and uncertainty.

Source: Self-illustrated.

The recurrence plot for Moluo village reveals an incomplete diagonal structure with some irregular scatter, suggesting periodicity and stability in certain periods but overall indicating high dynamic complexity and uncertainty [65].

In contrast, Kegeyi village's recurrence plot is relatively orderly, showing continuous diagonals, which implies high short-term predictability and stability, with lower uncertainty and chaotic tendencies. However, its entropy value (1.987) indicates that dynamic complexity may still be present over the long term.

The recurrence plots for Xisuo and Jiangba villages also show prominent diagonal structures, reflecting strong short-term periodicity and determinism. The high determinism (DET) in their RQA metrics further confirms this. Nonetheless, both villages exhibit high entropy values (1.987), suggesting that although stable in the short term, more complex dynamic behaviors or even chaotic tendencies could emerge over a longer timeframe [66]. Jiangba village's short-term stability and periodicity provide a basis for prediction and management, though more complex dynamics may appear in the long term [67].

Shenzuo village's recurrence plot shows strong periodicity and stability, but scattered points indicate the system is not entirely stable. Its entropy (1.99) and lower laminarity (LAM = 0.31) suggest a degree of complexity, with intermittent or irregular dynamic behavior in certain states. Overall, Shenzuo exhibits periodicity and predictability, though uncertainty may arise in specific situations.

Minzu village's recurrence plot and RQA metrics reveal mixed dynamic characteristics. The regular, continuous diagonals indicate predictability on certain time scales, while scattered points suggest complex and uncertain behavior in specific states. The high entropy value (1.99) supports the idea that the system may be influenced by external disturbances or changes in resource management, showing signs of chaotic behavior [68].

In summary, the dynamic behavior of each village system shows a certain degree of periodicity and stability in the short term yet exhibits varying levels of complexity and uncertainty over the long term. Identifying attractors should involve analyzing both short-term periodic characteristics and long-term dynamic complexity to gain a comprehensive understanding of each village system's behavior.

To further identify key "attractors," we screened, excluded, and compared the six key variables. The results reveal significant differences in how these variables affect the dynamic behavior of each village system, leading to the identification of chaotic attractors within the system [69]. As shown in **Table 2** and **Figure 7**:

Table 2. Key variables and dynamic indicators.

Village	GRRC	FLCF	RD	CC	EGR	AGREP
Molo	RR:0.2099 DET:2.5882 LAM:0.764 ENT:1.9874	RR:0.1605 DET:3.3846 LAM:0.3077 ENT: 1.9874	RR:0.165 DET:3.36 LAM:0.3077 ENT:1.9874	RR: 0.1605 DET:3.3846 LAM:0.3077 ENT: 1.9874	RR: 0.1605 DET:3.386 LAM:0.307 ENT:1.9874	RR: 0.2099 DET: 2.8235 LAM:0.4706 ENT: 2.1664
kegeyi	RR: 0.1852 DET: 2.9333 LAM: 0.6 ENT: 1.9874	RR: 0.1605 DET: 3.3846 LAM: 0.3077 ENT: 1.9874	RR: 0.1358 DET: 4.0 LAM: 0 ENT: 1.9874	RR: 0.1358 DET: 4.0 LAM: 0 ENT: 1.9874	RR: 0.1358 DET: 4.0 LAM: 0 ENT:1.9874	RR: 0.1852 DET: 3.2 LAM:0.2667 ENT: 2.1664
Xisuo	RR: 0.136 DET: 4.0 LAM: 0.364 ENT: 1.987	RR: 0.185 DET:2.933 LAM: 0.267 ENT: 1.987	RR: 0.136 DET: 4.0 LAM: 0.364 ENT: 1.987	RR: 0.136 DET: 4.0 LAM: 0.364 ENT: 1.987	RR: 0.235 DET: 2.526 LAM: 1.0 ENT: 2.166	RR: 0.210 DET: 2.824 LAM: 0.765 ENT: 2.166
Shenzuo	RR: 0.136 DET: 4.0 LAM: 0 ENT: 1.987	RR: 0.160 DET: 3.385 LAM: 0.308 ENT: 1.987	RR: 0.136 DET: 4.0 LAM: 0 ENT: 1.987	RR: 0.136 DET: 4.0 LAM: 0 ENT: 1.987	RR: 0.210 DET: 2.588 LAM: 0.588 ENT: 1.987	RR: 0.210 DET: 2.824 LAM: 0.529 ENT: 2.166
Minzu	RR: 0.210 DET: 2.588 LAM: 0.882 ENT: 1.987	RR: 0.235 DET: 2.737 LAM: 1.316 ENT: 2.324	RR: 0.160 DET: 3.385 LAM: 0.538 ENT: 1.987	RR: 0.160 DET: 3.385 LAM: 0.538 ENT: 1.987	RR: 0.210 DET: 2.824 LAM: 1.118 ENT: 2.166	RR: 0.185 DET: 2.933 LAM: 0.467 ENT: 1.987
Jiangba	RR: 0.160 DET: 3.692 LAM: 0 ENT: 2.166	RR: 0.160 DET: 3.385 LAM: 0 ENT: 1.987	RR: 0.160 DET: 3.385 LAM: 0.308 ENT: 1.987	RR: 0.111 DET: 4.889 LAM: 0 ENT: 1.987	RR: 0.136 DET: 4.0 LAM: 0.364 ENT: 1.987	RR: 0.136 DET: 4.0 LAM: 0.364 ENT: 1.987

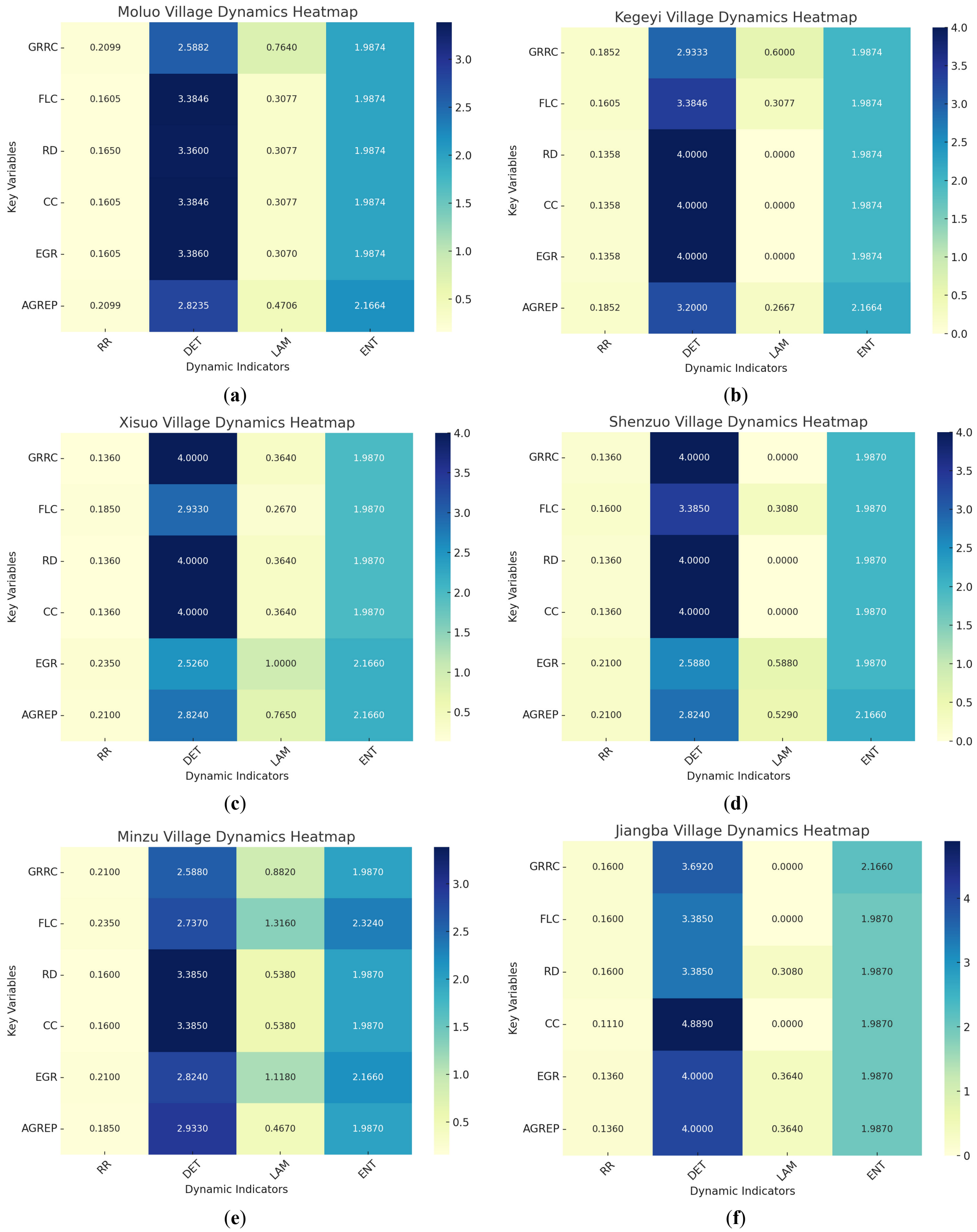


Figure 7. Villages attractor analysis heat map.

Note: List of abbreviations: GRRC Growth rate of irrigated cropland (%), FLC Forest land cover(%), RD Road density(km km–²), CC Communication coverage (%), EGR Economic growth rate in the region(%), AGREP Annual growth rate of employed population(%). (%), EGR Economic growth rate in the region (%), AGREP Annual growth rate of employed population (%).

Source: Self-illustrated.

The above maps (see **Figure 7a–f**) illustrate the reproducibility (RR), determinacy (DET), laminarity (LAM), and entropy (ENT) metrics of the six key variables in each village system. In each heat map, darker colors represent higher values, and lighter colors represent lower values. By excluding and comparing the key variables, the variables that significantly influence the dynamic behavior of the system can be identified and the chaotic attractor features in the system can be further extracted.

The figure shows that, after excluding certain variables, key system indicators (RR, DET, LAM, ENT) for each village display significant differences. Overall, the growth rate of irrigated farmland (GRRC) has a critical impact in several villages, particularly in Molo and Xisuo, where excluding this variable significantly affects the RR and LAM indicators. Road density (RD) plays a decisive role in Shenzuo's DET indicator, while the annual growth rate of employed population (AGREP) notably impacts the LAM and ENT indicators in Xisuo and Molo, highlighting its role in reducing system chaos and maintaining laminarity. This analysis suggests that different variables play distinct roles across villages, underscoring the need for tailored management strategies to meet the unique environmental adaptation needs of each village.

Specifically, the growth rate of irrigated farmland and the annual growth rate of employed population are key drivers of dynamic behavior in Molo and Kegeyi villages. Fluctuations in these variables directly affect the stability of the rural economic base and labor market, causing the system to display periodic or deterministic behavior at certain stages. However, when these variables fluctuate, system complexity and uncertainty increase, making dynamic behavior harder to predict[70]. In Xisuo and Shenzuo villages, the regional economic growth rate and annual growth rate of the employed population significantly influence dynamic stability, as shown by changes in recurrence rate and entropy. These variables drive the system to exhibit chaotic characteristics, indicating sensitivity to external economic and population changes[71]. In Minzu village, forest coverage and economic growth rate are the primary drivers of dynamic behavior. Fluctuations in these variables lead to an increase in recurrence rate and entropy, reflecting pronounced chaotic characteristics and high complexity[72]. In Jiangba village, the growth rate of irrigated farmland and communication network coverage are key drivers. The study finds that excluding these two variables reduces the system's recurrence rate and increases complexity, underscoring their importance in maintaining system stability.

In summary, forest coverage, economic growth rate, the growth rate of irrigated farmland, the annual growth rate of employed population, and communication network coverage are the primary drivers of chaotic behavior in the system, which play a key role in shaping the resilience and adaptability. Fluctuations and interactions among these variables likely contribute to the onset of chaos in the system. For example, changes in forest coverage not only affect environmental stability but can also have long-term impacts on agriculture and climate, leading to complex dynamic behaviors. Uncertainty in the economic growth rate directly influences resource allocation and economic activity, making the system more prone to chaotic states[16]. The economic growth rate is also a proxy for development pressures, which are particularly pronounced in transitioning rural economies. The growth rate of irrigated farmland, as a key indicator of agricultural production, affects food production and the rural economic base, with its fluctuations potentially destabilizing the system. Communication network coverage drives the system toward chaotic dynamics by influencing information flow and market connectivity in rural areas. The annual growth rate of the employed population reflects changes in the labor market; when population mobility is high, system uncertainty increases, resulting in unpredictable chaotic behavior[18]. Labor market dynamics are critical in these regions, where migration patterns and employment opportunities are closely tied to ethnic practices and economic stability.

Additionally, although cultural factors (such as religious beliefs, traditional festivals, and handicrafts) were included as state variables in the system, they did not show significant impact on attractor identification and key variable extraction. This may be because cultural factors remained consistent throughout the study period, making their effects difficult to capture in quantitative analysis. These factors may influence system dynamics indirectly rather than directly shaping the evolution process, an area that could be explored further in future research.

To further clarify the specific impact of each variable, **Figure 8** illustrates the performance of each village on four system dynamic behavior indicators (RR, DET, LAM, ENT) after excluding certain variables. The figure provides a comparative view that helps identify the critical role of different variables across villages, revealing the following key insights:

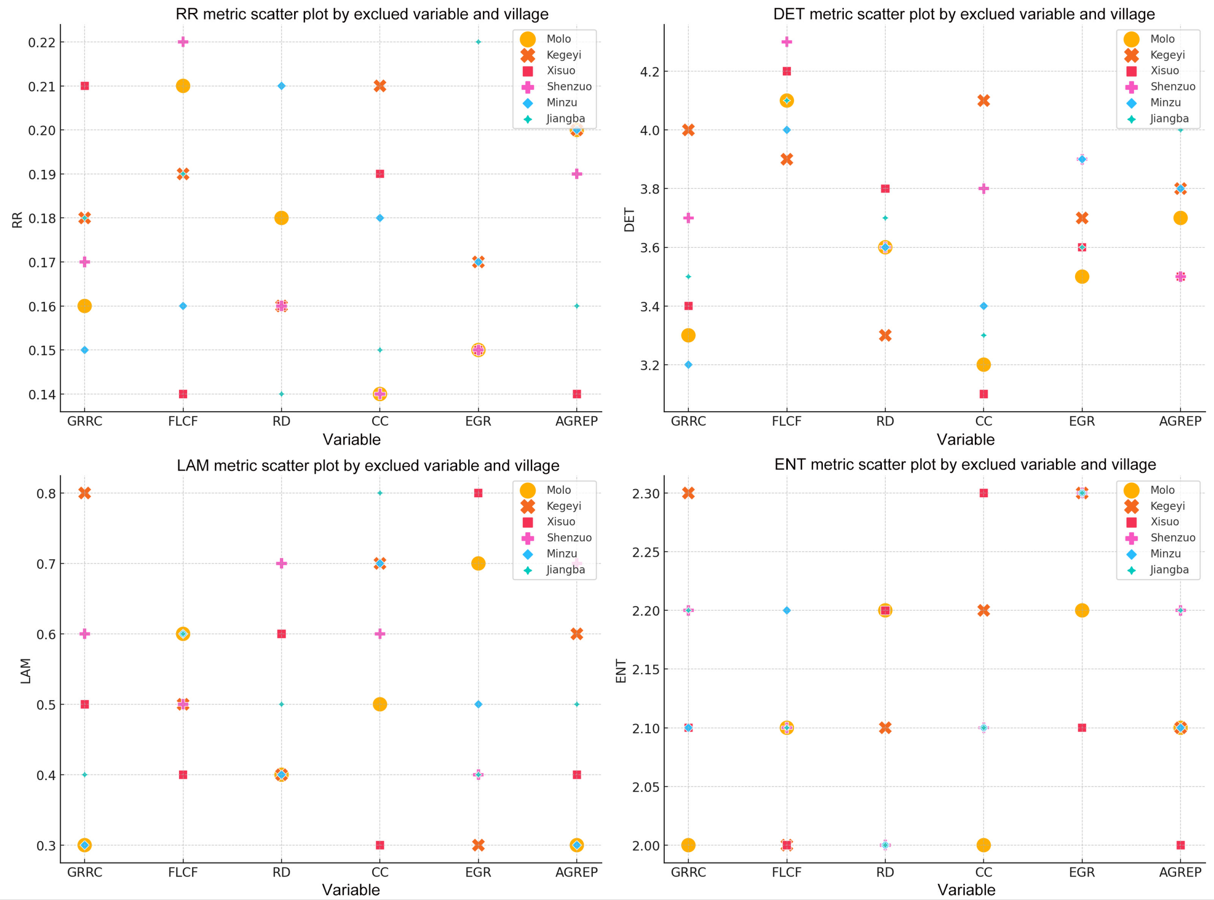


Figure 8. Differential effects of exclusion variables on system dynamics across villages.

Note: The figure illustrates the differences in the performance of the four behavioral indicators of system dynamics across villages after excluding specific variables. The scatter distribution of the indicators reveals the strength and variability of the impact of different variables on village system dynamics.

Source: Self-illustrated.

- Molo village, GRRC (growth rate of irrigated farmland), and AGREP (employment growth rate) are essential variables. GRRC maintains system periodicity and stability, while AGREP effectively reduces system chaos. This indicates that GRRC is crucial for stability, while AGREP significantly reduces system uncertainty.
- Kegeyi village, GRRC is the primary influencing variable. Excluding GRRC results in a significant increase in RR and LAM indicators, suggesting that GRRC strengthens system periodicity and coherence, enhancing stability. This makes GRRC a vital component for Kegeyi's system stability.
- Xisuo village, AGREP and EGR (regional economic growth rate) are primary drivers. AGREP positively impacts system laminarity and stability, while EGR enhances system determinism.
- Shenzuo village RD (road density) is the determining factor. After excluding RD, the DET index is significantly improved, indicating that the presence of road density increases the order and coherence of the system and improves the overall stability. Shenzuo village shows higher system coherence and anti-jamming ability under the effect of RD.
- Minzu village, FLCF (forest cover) and EGR significantly affect the stability of the system. The presence of FLCF and EGR reduces the uncertainty and complexity of the system, suggesting that these two variables play an important role in mitigating system fluctuations and supporting long-term stability.
- Jiangba Village, GRRC and CC (Communication Network Coverage) are the key variables. GRRC supports the periodicity of the system while CC helps to reduce the chaos and complexity of the system, which suggests that these two variables play an important role in maintaining the stability of the system and reducing the effects of external disturbances.

Combined with the overall trend analysis in **Figures 7** and **8**, although similar variables influence the dynamic behavior of the system in different villages, the specific roles of each variable differ significantly across villages. This variability provides data support for tailored village management and regulation strategies, which can help to take adaptive measures based on key drivers in each village to enhance system stability and improve resilience to external disturbances.

To validate the robustness of the model, we used MATLAB to perform 5-fold cross-validation and Lasso regression analysis. During validation, 5-fold cross-validation was applied to assess model performance under various parameter combinations. Specifically, each parameter combination was trained and tested across five different data partitions, with mean square error (MSE) and coefficient of determination (R^2) calculated as performance metrics (see **Figure 9**). From the cross-validation results, the parameter combination with the lowest MSE was selected as the optimal Lasso model. This optimal model demonstrated both high predictive accuracy and strong generalization across data partitions. Subsequently, the optimal Lasso model was used to train the entire dataset, and its MSE and R^2 values on the full dataset were re-evaluated to confirm the model's stability and predictive capability on a larger sample [73].

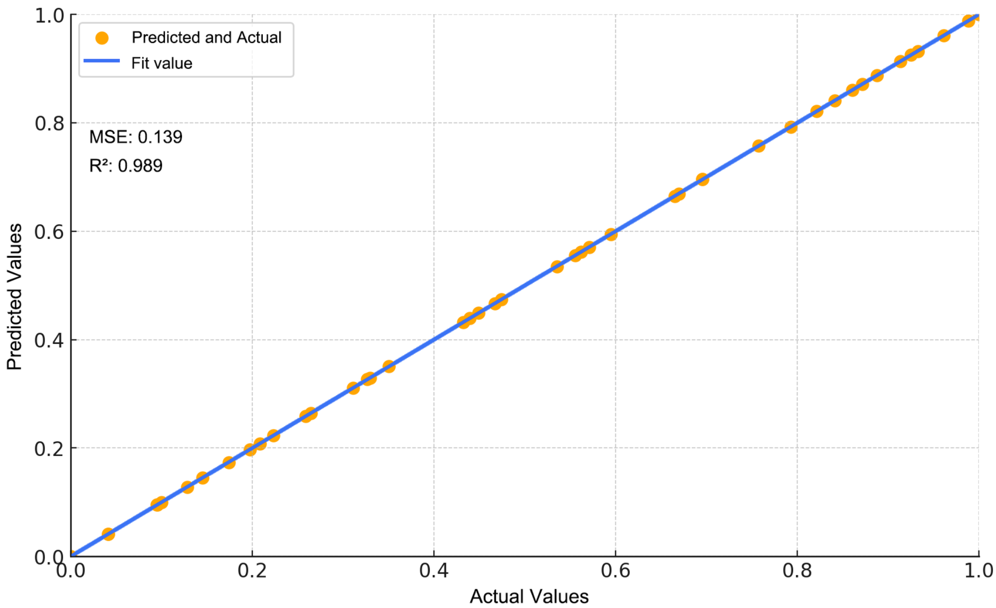


Figure 9. Model validation fit map.

Source: Self-illustrated.

The validation results show that the initial model had an average MSE of 1.14×10^{-22} and an R^2 of 1, indicating overfitting despite the extremely low error. After further tuning model complexity, the optimal model achieved an MSE of 0.139 and an average R^2 of 0.989, demonstrating exceptionally high predictive accuracy. The low MSE and high R^2 indicate that this model captures the variance within the data with high precision, resulting in an excellent fit [74, 75]. These findings suggest that the combination of cross-validation and Lasso regression effectively captures the relationship between features and target variables, demonstrating outstanding predictive capability. The validation results further indicate that this model is well-suited for understanding and predicting the dynamic behaviors of rural systems in this study.

5. Discussion

This study offers a comprehensive analysis of the evolutionary processes of six Tibetan villages in western Sichuan, uncovering significant differences in their developmental stages and dynamic mechanisms. Using nonlinear and chaotic attractor analysis, we identified key driving factors for each village's evolution and highlighted the high complexity and diversity of their responses to external environmental changes. These findings underscore the limitations of traditional linear models, which are unable to fully capture the nonlinear dynamics and intricate behaviors inherent in such systems.

Chaotic attractor analysis revealed the high sensitivity of village systems to initial conditions and their inherent uncertainty [16]. Villages were observed to reach turning points at different times when facing environmental pressures, reflecting their dynamic and complex evolutionary pathways. For instance, some villages rapidly entered an adjustment phase following external shocks, while others exhibited delayed recovery, illustrating the nonlinearity and diversity of system behaviors [71]. This analytical approach has practical implications for rural planning, emphasizing the importance of adaptive resource management strategies to address the unpredictability of village dynamics. Chaotic attractor analysis, particularly, serves as a diagnostic tool for detecting system instability, enabling policymakers to anticipate potential disturbances and implement preventive measures in culturally and ecologically sensitive areas.

Through multivariate nonlinear analysis, this study further highlights the distinct cultural and ecological contexts of Tibetan villages in western Sichuan, revealing significant differences in their responses to natural and social changes. Although all six villages share a Tibetan cultural background, their adaptive behaviors vary considerably. For example, Molo Village recovers quickly from external shocks, while Xisuo Village exhibits greater uncertainty and chaotic characteristics. These differences highlight the necessity of localized management strategies that consider the diversity of resource management practices and cultural traditions. The findings not only expand theoretical understanding but also provide a robust foundation for designing targeted policies.

Building on previous research, this study integrates nonlinear dynamic analysis with multivariate phase space reconstruction to investigate complex system behaviors. Through chaotic attractor identification and Recurrence Quantification Analysis (RQA), it uncovers hidden dynamic patterns and critical turning points, offering actionable insights for enhancing system resilience and adaptability. Unlike traditional linear models, nonlinear approaches enable a more nuanced understanding of dynamic interactions, providing a robust framework for localized rural governance and sustainable development strategies [23, 24]. By identifying chaotic attractors and analyzing multivariate interactions, this research reveals intricate dynamic behaviors and key turning points, advancing rural planning and cultural preservation [76]. For example, stabilizing the growth rate of irrigated farmland has significantly enhanced resilience in Molo Village, while managing fluctuations in employment growth has reduced uncertainty in Xisuo Village. These findings offer actionable recommendations for cultural heritage preservation and tailored rural governance strategies, addressing the distinct needs of each village.

While this study has achieved significant results, certain limitations remain. First, the limited sample size may restrict the generalizability of the findings, underscoring the need for future research to expand the sample scope to improve model robustness [77]. Additionally, comparing the study's results with similar research conducted in other regions is particularly important. Such comparisons not only validate the applicability of the findings but also reveal the uniqueness and commonalities of Tibetan village systems in coping with external shocks and adapting to environmental changes, offering a global perspective. Second, the relatively short study period limits the ability to capture long-term fluctuations and key turning points, suggesting that extending the timeframe in future studies could yield more comprehensive insights [78]. Furthermore, future research should aim to dynamically update research variables and model parameters to better reflect system complexity [18].

To address these limitations and further deepen the analysis, interdisciplinary collaboration integrating perspectives from sociology, economics, and ecology would be invaluable. Such collaboration could not only enrich our understanding of Tibetan village systems but also provide comparative insights into similar rural regions worldwide [79, 80]. Incorporating real-time data and dynamic variable analysis could further enhance model flexibility, enabling more precise identification of critical change points and long-term trends. An interdisciplinary approach would also offer stronger theoretical support for sustainable village development and cultural preservation [22, 81].

6. Conclusions

In conclusion, this study provides an in-depth exploration of the evolutionary processes of Tibetan villages in western Sichuan, revealing their high complexity and diversity within dynamic contexts. We identified critical turning points and key drivers in each village's adaptation to external shocks and internal changes by employing nonlinear analysis methods and chaotic attractor identification. This approach highlights the study's unique contribution to understanding how village systems evolve and adapt under environmental pressures.

The findings demonstrate that response patterns and key variables vary across villages, underscoring the importance of localized management strategies to enhance system resilience. Although the study faced limitations in sample size and study period, it offers valuable insights into the dynamic characteristics of Tibetan village systems. Future research should aim to expand the sample size and timeframe to validate and generalize these findings further. Additionally, integrating more flexible methods and fostering interdisciplinary collaboration will enable researchers to capture better the complexities of system evolution across diverse environmental conditions. A deeper understanding of each village's dynamics and key drivers can inform policies to enhance adaptability and resilience, supporting sustainable development in rapidly changing environments.

Author Contributions

Conceptualization, D.F., and N.Z.B.M.; methodology, F.D.; software, S.Y.; validation, D.F., N.Z.B.M., and S.Y.; formal analysis, D.F.; investigation, D.F., and S.Y.; resources, D.F.; data curation, D.F.; writing—original draft preparation, D.F.; writing—review and editing, S.Y.; visualization, F.D.; supervision, N.Z.B.M.; project administration, D.F.; funding acquisition, D.F., and S.Y. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement

This study was approved by the Administration Committee of the School of Art and Design, Leshan Normal University, Sichuan Province, China The experiments are related to urban space geographic information and do not involve human or animal rights. This study was approved by the Administration Committee of the School of Art and Design of Leshan Normal University.

Informed Consent Statement

There are no human subjects in this article, and informed consent is not applicable.

Data Availability Statement

The raw datasets collected for this study are available on platforms such as the Sichuan Provincial Statistical Yearbook (https://www.zgtjnj.org/navisearch-2-0-3-1-sichuan-0.html), Institute of Geographical Sciences and Resources, Chinese Academy of Sciences (https://www.resdec.cn/Default.aspx), and the Chinese Traditional Villages website (http://www.chuantongcunluo.com). The relevant platform's access procedure can access these datasets upon request.

Conflicts of Interest

The authors declare no conflict of interest, and we do not have any possible conflicts of interest within three years.

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