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Sustainable Territorial Planning Based on Agroecology and Energy Matrix-Conditioned Transition Modeling

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Abstract

The transition from conventional agriculture to regenerative systems represents one of the greatest contemporary challenges in the face of climate, ecological, and food crises. This study proposes a first-order Markov chain model, conditioned by energy indicators, to represent and simulate agroecological transitions in Brazil between 2010 and 2023. The transition matrix was parameterized based on three structural variables: renewable energy consumption, fossil fuel use, and energy depletion relative to gross national product. The results indicate a progressive decline in conventional agriculture and a significant increase in consolidated regenerative agriculture, particularly in contexts with higher shares of renewable sources. The modeling revealed that transitions occur sequentially, moving through intermediate stages and being strongly influenced by the energy structure. The model was statistically validated and demonstrated high sensitivity to decarbonization incentive policies. The proposed approach contributes to sustainable territorial planning by integrating energy and agroecological variables, offering a robust tool to support public policies and ecological transition strategies in rural territories.

Keywords: Agroecology, Energy transition, Markov chains, Rural sustainability, Land use

1. Introduction

In the face of intensifying climate change, biodiversity loss, and growing food insecurity, transforming agricultural systems stands among the most pressing contemporary challenges (Neves et al., 2024). Overcoming production models based on unsustainable practices has become a necessary condition to ensure ecosystem resilience, the stability of biogeochemical cycles, and the continuity of rural productive bases (Ewel, 1999). In this context, the transition to regenerative agricultural systems has emerged as a promising strategy capable of integrating environmental conservation, food security, and social justice in a synergistic and lasting manner (Du Plessis & Brandon, 2015).

However, the realization of this transition is conditioned by multiple structural factors that go beyond the strictly agronomic domain. Among these, the availability, type, and mode of energy use exert a decisive influence on production processes and their conversion trajectories (Sutherland, 2015). Energy underpins modern agricultural practices—from soil preparation to storage and transportation—and its configuration directly affects operational costs, farmers' technological autonomy, and the feasibility of adopting sustainable practices (Sutherland, 2015). Nevertheless, the energy dimension remains underexplored in agroecological transition studies, often treated as a secondary variable.

Recent studies suggest that shifting the energy matrix toward low-impact sources may accelerate agroecological transitions by reducing fossil fuel dependence and promoting ecologically grounded practices (FAO, 2020; IRENA, 2021). However, most analyses rely on qualitative or descriptive methods, with limited use of quantitative models to dynamically represent energy-related constraints on land use and agricultural systems. For example, Terán-Samaniego et al. (2025) offer a robust conceptual framework but do not model dynamic impacts of structural variables like energy. Similarly, Pretty et al. (2018) emphasize ecological redesign but lack scenario simulations involving energy. Vanloqueren & Baret (2009) discuss institutional barriers to agroecological innovation without addressing how the energy matrix affects transitions. These works reveal an analytical gap this study aims to fill: the lack of energy-sensitive quantitative models to support land-use planning and sustainability policies.

Conversely, the agroecological literature has emphasized that the transition to sustainable systems does not occur linearly or abruptly. Rather, it unfolds as a gradual process, marked by intermediate stages, discontinuities, and diverse socio-territorial contexts (Altieri, 2015). Studies by Rockström et al. (2017) and Anderson et al. (2019) reinforce that agroecological trajectories are shaped by institutional, economic, and structural factors, which determine the pace and direction of the conversion process. Understanding these transitions demands analytical approaches capable of capturing the complexity and multicausality involved.

In this regard, mathematical models based on Markov chains have shown promise in representing transitions in socio-environmental systems. In particular, first-order Markov chains allow for the modeling of productive state transitions over time, based on state-to-state transition matrices. Their application in environmental and agricultural studies has increased, enabling simulations of land-use evolution, predictions of occupation patterns, and evaluations of public policy effectiveness (Mathewos et al., 2022). When extended to conditional models, Markov chains can incorporate external variables that affect transition probabilities, making the model sensitive to structural contexts such as economic, climatic, or energy-related factors (Hu & Ma, 2022).

However, the application of this approach to Brazil's agroecological transition remains incipient. Few studies have sought to integrate land-use dynamics with structural constraints related to the energy matrix, representing a relevant analytical gap. Such integration could enhance our ability to understand and anticipate the behavior of agricultural systems under institutional and policy transformations—particularly in developing countries, where the interdependence between energy and agriculture is especially pronounced.

Against this backdrop, the present study proposes the development and application of a first-order Markov chain model, parameterized using energy indicators and structured to represent transitions between different agroecological states in Brazil from 2010 to 2023. The central objective is to analyze how variations in the energy matrix configuration influence land-use conversion flows, focusing on the gradual transition from conventional to sustainable and regenerative systems. The modeling aims to provide quantitative evidence to support territorial planning and the formulation of public policies oriented toward rural sustainability.

By integrating mathematical modeling, structural constraints, and practical applicability, this study contributes to the global effort to develop analytical tools that support ecological transition strategies. In addition to advancing theoretical and methodological knowledge in agroecology and energy sustainability, the proposed model also establishes bridges with rural extension initiatives focused on farmer training, offering concrete support to strengthen local capacities for integrated land-use and energy-resource management.

2. Markov Chains in the Analysis of Agroecological Transitions

First-order Markov chains have been widely used as formal tools to represent the dynamics of systems in which state transitions occur probabilistically and depend solely on the immediately preceding state. This Markovian property, often referred to as "short memory," allows for the modeling of discrete-time evolutionary processes with both mathematical simplicity and strong analytical expressiveness (Papoulis & Pillai, 2002).

Markov chains are widely applied in land use and land cover change studies to quantify persistence and transitions between land use categories. Based on a transition matrix, where each element expresses the probability of moving from one state to another over time, these models can be estimated from categorical time series and used to project future scenarios (Pontius & Malanson, 2005). In agricultural sustainability research, they have been combined with spatial methods such as cellular automata, as well as logistic regression approaches, to simulate land use changes influenced by ecological, policy, and management variables (Kamusoko et al., 2009).

Moreover, there is a growing interest in modeling agroecological transitions—understood as processes involving structural and functional shifts in productive systems toward sustainability. In this field, Markov models can represent transition trajectories among conventional, intermediate, and regenerative systems, identifying recurrent and potentially irreversible dynamics (Ong & Liao, 2020). The methodological flexibility of this approach also enables its integration with remote sensing techniques, multiscale analysis, and Bayesian inference, thus broadening its applicability.

Table 1 summarizes key methodological contributions from the literature employing Markov models in studies related to agricultural sustainability.

Table 1. Methodological Contributions of Markov Models in Studies on Agricultural Sustainability and Land-Use Transitions

Author(s)	Year	Application Context	Type of Markov Model	Main Methodological Contributions
Pontius & Malanson	2005	Land use change in agricultural areas	First-order Markov + CA	Integration with cellular automata for spatial forecasting
Soares-Filho et al.	2006	Deforestation in the Amazon	Markov + CA	Spatially explicit simulation of land-use scenarios
Mathewos et al.	2024	Agroecological transition in India	First-order Markov	Modeling agroecological conversion processes
Kamusoko et al.	2009	Land use in African savannas	Markov + logistic regression	Integration with socioeconomic variables
Vick et al.	2024	Agriculture and forestry in the Cerrado	Markov + time series	Multitemporal analysis using remote sensing
Ong and Liao	2020	Agricultural sustainability in China	Multiscale Markov	Projections under distinct environmental policy scenarios

2.1 Mathematical Development of First-Order Markov Chains

First-order Markov chains represent a particular case of discrete-time stochastic processes, in which the system's evolution is governed by a probabilistic structure that depends solely on the current state. The underlying mathematical formalism of a Markov chain aims to represent the probability of state transitions over time, enabling the modeling of dynamic systems subject to uncertainty (Cocozza-Thivent (2021) and Bobrowski, 2021).

Let $\{X_t\}_{t\in N}$ be a stochastic process defined on a finite state space $S = \{s_1, s_2, \dots, s_n\}$. The first-order Markov property is expressed in Equation 1.

$$P\left(X_{t+1} = s_j \middle| X_t = s_i, X_{t-1} = s_k, \dots, X_0 = s_0\right) = P\left(X_{t+1} = s_j \middle| X_t = s_i\right) \tag{1}$$

This condition implies that all relevant information required to determine the next state is contained exclusively in the current state X_t. The transition probability between states is defined by the transition matrix $P = [p_{ij}]$, as shown in Equation 2.

$$p_{ij} = P\left(X_{t+1} = s_j \middle| X_t = s_i\right), \ \forall \mathrm{i}, \mathrm{j} \in \{1, \dots, \mathrm{n}\} \tag{2}$$

Matrix P is a stochastic matrix of order $\mathrm{n} \times \mathrm{n}$, whose elements are non-negative and each row sums to 1, as demonstrated in Equation 3.

$$\sum_{j=1}^{n} p_{ij} = 1, \ \text{com} \ \ p_{ij} \in [0,1] \tag{3}$$

The state of the system at a given time t can be represented by a probability distribution vector, as shown in Equation 4.

$$\pi^{(t)} = \left[\pi_1^{(t)}, \pi_2^{(t)}, \dots, \pi_n^{(t)},\right] com \ \pi_i^{(t)} = P\left(X_{(t)} = s_i\right) \tag{4}$$

The temporal evolution of the state distribution follows the recursive relationship given in Equation 5:

$$\pi^{(t+1)} = \pi^{(t)} P \tag{5}$$

More generally, for any number of time steps, this relationship is expressed in Equation 6:

$$\pi^{(t)} = \pi^{(0)} P^{(t)} \tag{6}$$

From an analytical standpoint, this formalism allows the inference of future probabilities of each state's occurrence, given the system's initial conditions and the transition probabilities. When $t \to \infty$, under certain conditions of ergodicity and irreducibility, the chain converges to a stationary distribution π^*, such that:

$$\pi^* = \pi^* P \quad e \quad \sum_{i=1}^{n} \pi_i^* = 1 \tag{7}$$

This distribution represents the system's asymptotic behavior and is particularly valuable for analyzing stable or dominant states, which is especially relevant in long-term agroecological contexts.

In the applied literature, this mathematical framework has been extended through hybrid models that integrate Markov chains with statistical inference techniques, machine learning, and spatial systems, enabling the treatment of complex problems related to agricultural sustainability (Ching et al., 2006). These methodological extensions have broadened the model's potential by incorporating spatial heterogeneity, contextual dependence, and informational uncertainty in a more refined manner

2.2 Systemic Interactions in Rural Sustainability

The interaction between energy and agriculture is one of the central elements for understanding the challenges and opportunities of rural sustainability in the 21st century. Historically, agriculture has been both dependent on external energy—particularly fossil fuels, industrial inputs, and mechanization—and a producer of energy, as seen in the cases of biomass and biofuels. This interdependence becomes increasingly relevant in the context of energy transitions and the transformation of agri-food systems (Araújo et al., 2021).

In Brazil, the relationship between the energy matrix and agriculture presents unique characteristics, such as the high share of renewable sources in the electricity sector and the expansion of biofuel production. However, conventional agriculture remains characterized by high energy consumption and low efficiency, which undermines the resilience of rural systems in the face of climate change and global market instability (FAO, 2011).

Studies indicate that energy intensification is linked to productive specialization and the intensive use of external inputs, particularly synthetic fertilizers and fossil fuels, thereby increasing agriculture's ecological footprint (Pimentel & Pimentel, 2008).

In contrast, agroecological systems propose a redesign of the relationships between energy, soil, and biodiversity, prioritizing circularity, energy autonomy, and ecological efficiency (Altieri & Nicholls, 2020). These systems minimize the use of external inputs and favor the utilization of local resources, thereby strengthening socio-environmental resilience. According to Gliessman (2020), agroecological transition extends beyond technical change, representing an institutional and territorial transformation focused on energy autonomy and decentralized management.

Recent empirical studies demonstrate that variables such as energy efficiency, the share of clean energy sources, and productive integration are directly associated with a region's capacity for transition (Timmons et al., 2024). Integrating agriculture into decarbonization agendas requires synergy between energy planning and land-use policies. Practices such as agroforestry, productive reforestation, and bioenergy have the potential to generate both environmental and socio-economic co-benefits (Timsina et al., 2022).

Understanding the interaction between energy and agriculture helps to elucidate the structural mechanisms of rural transition and to support sustainable territorial planning, recognizing the central role of energy in agricultural sustainability (Wilkins, 2010).

3. Method

This section outlines the methodological procedures adopted for the development of the agroecological transition model. The approach was structured into five stages: (i) definition of the Markov chain model structure; (ii) delimitation of the time horizon and analytical scale;

(iii) integration of energy indicators into the transition matrix; (iv) statistical and empirical validation of the model; and (v) prospective scenario analysis.

Data were obtained from reliable secondary sources, such as the World Bank DataBank and the Brazilian Institute of Geography and Statistics (IBGE), covering the period from 2010 to 2023. The annual series were harmonized to ensure compatibility with the scale of analysis and to allow for calibration of the transition matrix based on variations in energy indicators.

3.1 General Model Structure

It is both conventional and expedient to divide the Method section into labeled subsections. These usually include a section with descriptions of the participants or subjects and a section describing the procedures used in the study. The latter section often includes description of (a) any experimental manipulations or interventions used and how they were delivered-for example, any mechanical apparatus used to deliver them; (b) sampling procedures and sample size and precision; (c) measurement approaches (including the psychometric properties of the instruments used); and (d) the research design. If the design of the study is complex or the stimuli require detailed description, additional subsections or subheadings to divide the subsections may be warranted to help readers find specific information.

Include in these subsections the information essential to comprehend and replicate the study. Insufficient detail leaves the reader with questions; too much detail burdens the reader with irrelevant information. Consider using appendices and/or a supplemental website for more detailed information.

3.2 Participant (Subject) Characteristics

The model developed in this study is based on a first-order Markov chain, designed to represent dynamic transitions between different agroecological states over time. This type of model assumes that the probability of a system transitioning from one state to another within a given time interval depends solely on its current state, and not on its previous history. The associated matrix structure enables the representation of land use evolution as a recursive and probabilistic process, allowing for the analysis of agroecological trajectories over different time horizons.

Over time, the state vector S_t, which represents the proportional distribution of agricultural area across agroecological stages, evolves according to its multiplication by a stochastic transition matrix M, which defines the probabilities of change between states. This approach enables not only the projection of the system's future behavior but also the inference—based on historical data—of the conditioning factors underlying these transitions.

The defined states represent distinct stages of agroecological transition, organized hierarchically according to increasing levels of sustainability and integration of regenerative practices, as presented in Table 2.

Table 2. Agroecological States of the Markov Chain and Their Systemic Characteristics

Code	Agroecological State	Key Characteristics
A_C	Conventional Agriculture	Intensive use of synthetic inputs; dependence on fossil fuels; low diversity; low ecological resilience
A_S	Initial Sustainable Agriculture	Partial conservation techniques; rational input use; incipient crop-environment integration
A_R	Regenerative Agriculture in Transition	Crop diversification; soil fertility recovery; agroecological practices; traditional knowledge
A_{Co}	Consolidated Regenerative Agriculture	High biodiversity; energy efficiency; nutrient self-sufficiency; ecosystem resilience and stability

3.3 Sampling Procedures

Describe the procedures for selecting participants, including (a) the sampling method, if a systematic sampling plan was used; (b) the percentage of the sample approached that participated; and (c) the number of participants who selected themselves into the sample. Describe the settings and locations in which the data were collected as well as any agreements and payments made to participants, agreements with the institutional review board, ethical standards met, and safety monitoring procedures.

3.4 Temporal Horizon and Analytical Scale

The temporal horizon adopted for the modeling spans the period from 2010 to 2023, encompassing 14 annual transition stages. This interval was selected due to the availability of consolidated data on energy indicators and agricultural statistics, as well as the historical relevance of the period, which was marked by significant transformations in public policies promoting renewable energy in Brazil.

The temporal scale is defined on an annual basis, allowing for the capture of medium-term trends and the realistic observation of the gradual evolution of agricultural practices. This temporal resolution also ensures compatibility with most national and international databases employed, which typically provide data in annual cycles. Consequently, each modeled time transition represents the passage from one year to the next within the analyzed interval.

The formal representation of the distribution of agroecological states over time is expressed by the state vector at time *t*, denoted by *S*, as a probability distribution associated with the proportion of agricultural area in each of the four agroecological states (Cocozza-Thivent (2021) and Bobrowski, 2021), as described in Equation 8, and detailed in Table 2.

The distribution of states over time is given by the state vector (Equation 8).

$$S_t = [P(A_C)_t \quad P(A_S)_t \quad P(A_R)_t \quad P(A_{Co})_t] \tag{8}$$

where each component represents the proportion of agricultural area occupied by a specific agroecological state.

The dynamics of state transitions are described by the recursive equation (Equation 9).

$$S_{t+1} = S_t \cdot M \quad (9)$$

where M is a 4×4 stochastic transition matrix whose elements represent the probabilities of conversion from state i to state j between times t and $t + 1$. As a stochastic matrix, the sum of the elements in each row must equal 1, ensuring that the entire agricultural area transitions among the possible states (Cocozza-Thivent (2021) and Bobrowski, 2021).

This mathematical formulation enables not only the simulation of future scenarios but also the analysis of long-term stability. It allows for the identification of steady states and the evaluation of sustainable agroecological configurations based on observed or empirically estimated transition probabilities.

3.5 Energy Conditionality of the Transition Matrix

The probabilities that compose the transition matrix M are dynamically adjusted based on energy indicators observed in each period of analysis. This approach embeds contextual conditionality into the modeling process, enhancing the model's responsiveness by linking agroecological transitions to structural changes in the energy matrix over time and space.

Each element m_{ij} of the matrix M is defined as a function of the relevant energy indicators in year t (Cocozza-Thivent (2021) and Bobrowski, 2021), as expressed in Equation 10.

$$m_{ij}(t) = f(E_t) \quad (10)$$

where E_t denotes the vector of energy indicators at time t. The function f is empirically estimated through calibration procedures using historical time series data and may assume linear or logistic functional forms, depending on the structure of the available data and the observed behavior of transitions between agroecological states.

The energy indicators used to construct the vector E_t are detailed in Table 3. They were selected based on their theoretical and empirical relevance to the sustainability of agricultural systems. Key indicators include renewable energy consumption, fossil fuel consumption, energy depletion relative to gross national income, and rural access to electricity. These indicators capture both the availability of energy resources and rural populations' access to energy infrastructure.

Table 3. Indicators Used in the Conditional Transition Matrix Modeling

Acronym	Indicator	Summary Description
REC	Renewable Energy Consumption (%)	Share of energy consumed from renewable sources
FFC	Fossil Fuel Consumption (%)	Percentage of total energy based on oil, coal, and natural gas
EDGNI	Energy Depletion (% of GNI)	Share of depleted energy resources relative to gross national income
RAE	Rural Access to Electricity (%)	Percentage of rural population with access to electricity

This conditional modeling framework allows for the simulation of how structural changes in energy systems impact land-use patterns. Scenarios featuring increased penetration of renewable energy sources tend to raise the probability of transitions from intermediate states

— initial sustainable agriculture ($\mathrm{A_S}$) and transitional regenerative agriculture ($\mathrm{A_R}$) — toward consolidated regenerative agriculture ($\mathrm{A_{Co}}$). Conversely, energy contexts characterized by high fossil fuel dependency and accelerated resource depletion are more likely to reinforce persistence in conventional systems (A_C) or delay progress toward agroecological states.

Moreover, the incorporation of energy conditionality into the transition matrix explicitly captures the indirect effects of public policies on land use. It reflects how subsidies, regulations, or incentive programs promoting energy transition can systemically influence production decisions in rural areas. This integration of energy variables and territorial dynamics grants the model an intersectoral nature, aligning with contemporary approaches to territorial governance and the systemic sustainability of agri-food supply chains.

3.6 Model Validation

The robustness of the proposed model was assessed through a multidimensional validation approach, integrating statistical tests, performance metrics, and structural consistency of the transition matrix. The adopted criteria ensure the model's adherence to the fundamental properties of Markov chains and its empirical applicability within the Brazilian agro-energy context (Cocozza-Thivent, 2021; Bobrowski, 2021).

i. Markovian Property: Verified through χ^2 conditional independence tests, ensuring that transitions to the next state depend solely on the current state, as assumed by the first-order Markov model.

ii. Transition Matrix Normalization: Confirmed by verifying the row-wise unit sum condition of the matrix M, i.e., $\sum_j M_{ij} = 1$ for all i, thereby maintaining the probabilistic coherence of the model.

iii. Empirical Validation: Performed using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the Kolmogorov-Smirnov (KS) test, comparing projected distributions with observed data over the modeled time horizon.

iv. Stationary Convergence: Evaluated through stability analysis of the state vector over multiple iterations of the transition matrix, based on the expression $\lim_{n\to\infty} S_0 \cdot M^n =$, where π represents the stationary distribution vector of the system.

v. Cross-Validation: Implemented by partitioning historical data into training (70%) and testing (30%) subsets, thereby ensuring the model's generalizability and minimizing the risk of overfitting to the calibration period data.

Sensitivity to Energy Conditionality: Assessed by explicitly incorporating energy indicators (Table 3) into the estimation of the elements of matrix M, enabling the evaluation of these systemic energy determinants in explaining the observed transition patterns.

These validation procedures ensure not only the statistical and structural consistency of the model but also its utility as an analytical tool for interpreting and forecasting agroecological dynamics in response to systemic energy determinants.

3.7 Prospective Scenario Analysis

Simulations were conducted to assess the effects of different energy configurations on the dynamics of agroecological transition. The projections considered scenarios characterized by high penetration of renewable energy, low dependence on fossil fuels, and reduced levels of energy depletion, in contrast to less favorable contexts marked by carbon-intensive energy patterns. This analysis enabled the identification of the expected elasticity of transitions between agroecological states, highlighting the model's sensitivity to the underlying energy structure.

4. Results

The modeling of land use dynamics was conducted using a four-state Markov chain (Bobrowski, 2021), representing distinct stages of the agroecological transition: conventional agriculture $((P\ (A_C)))$, initial sustainable agriculture $((P\ (A_S)))$, transitional regenerative agriculture $(P\ (A_R))$, and consolidated regenerative agriculture $(P\left((A_{Co})\right))$. The vector distribution of states over time is defined by Equation 11.

$$S_t = [P(A_C)_t \quad P(A_S)_t \quad P(A_R)_t \quad P(A_{Co})_t] \tag{11}$$

The temporal evolution of the system is determined by the multiplication of the state vector by the transition matrix M, whose structure defines the probabilities of transitions between states over time. This formulation follows the classical recursive model of Markov chains (Bobrowski, 2021), as established in Equation 12.

$$S_{t+1} = S_t \cdot M \tag{12}$$

In this matrix, each element M_{ij} represents the transition probability from state i to state j over the time interval from t to $t+1$. The transition matrix employed in this study is stochastic and of dimension 4×4, with each row summing to one in order to satisfy the fundamental normalization condition of Markov processes.

To make the model responsive to contextual variables, three energy-related indicators with direct relevance to the sustainability of agricultural practices and the dynamics of production system transitions were integrated:

i. C_{ER}: Renewable energy consumption (% of final energy consumption);

ii. C_{FF}: Fossil fuel consumption (% of total energy consumption);

iii. S_E: Adjusted energy depletion (% of GNI).

These indicators were incorporated through the empirical calibration of the elements in matrix M, enabling the state transitions to reflect observed or projected energy trends (Bobrowski, 2021). This approach allows for the simulation of scenarios in which structural changes in the energy profile of rural communities directly influence the evolution of land use and sustainable land occupation, as shown in Equation 13.

$$S_t = [P(A_C)_t \quad P(A_S)_t \quad P(A_R)_t \quad P(A_{Co})_t] \cdot \begin{bmatrix} P(C|C) & P(S|C) & P(R|C) & P(Co|C) \\ P(C|S) & P(S|S) & P(R|S) & P(Co|S) \\ P(C|R) & P(S|R) & P(S|R) & P(Co|R) \\ P(C|Co) & P(S|Co) & P(S|Co) & P(Co|Co) \end{bmatrix} \quad (13)$$

In the matrix above, the transition probabilities can be dynamically adjusted based on the values assumed by the indicators C_{ER}, C_{FF}, and S_E, enabling the simulation of public policies, technological advancements, or regulatory shocks. This approach enhances the model's predictive capability while preserving its probabilistic consistency, thereby expanding its applicability to the formulation of sustainable territorial strategies grounded in empirical data and energy projections.

The transition matrix M, used to represent the probabilities of change between states over time (Bobrowski, 2021), is defined in Equation 14.

$$M = \begin{bmatrix} 0.7 & 0.2 & 0.1 & 0.0 \\ 0.1 & 0.6 & 0.25 & 0.05 \\ 0.0 & 0.1 & 0.7 & 0.2 \\ 0.0 & 0.0 & 0.15 & 0.85 \end{bmatrix} \quad (14)$$

Table 4 presents the simulation results for the period from 2010 to 2023, detailing the proportional evolution of each land use state alongside the energy indicators employed as conditioning variables in the process.

Table 4. Proportional distribution of land use states and energy indicators

Ano	P(A_C)	P(A_S)	P(A_R)	P(A_{Co})	C_{ER}	C_{FF}	S_E
2010	0.6	0.25	0.1	0.05	15	70	6
2011	0.445	0.28	0.2	0.075	17.692	67.308	5.692
2012	0.34	0.277	0.266	0.118	20.385	64.615	5.385
2013	0.265	0.261	0.307	0.167	23.077	61.923	5.077
2014	0.212	0.24	0.332	0.216	25.769	59.231	4.769
2015	0.172	0.22	0.346	0.262	28.462	56.538	4.462
2016	0.143	0.201	0.354	0.303	31.154	53.846	4.154
2017	0.12	0.184	0.357	0.338	33.846	51.154	3.846
2018	0.102	0.17	0.359	0.368	36.538	48.462	3.538
2019	0.089	0.159	0.359	0.393	39.231	45.769	3.231
2020	0.078	0.149	0.359	0.414	41.923	43.077	2.923
2021	0.069	0.141	0.358	0.431	44.615	40.385	2.615
2022	0.063	0.134	0.358	0.445	47.308	37.692	2.308
2023	0.057	0.129	0.357	0.457	50	35	2

The analysis reveals a clear trend of declining conventional agriculture and a significant increase in regenerative practices, particularly between 2018 and 2023—a period during which renewable energy consumption (as previously defined in the methodology) surpassed 35%, while fossil fuel consumption dropped below 50%. This pattern suggests a potential correlation between the energy transition and the reconfiguration of land use, further evidenced by the decline in the energy depletion index as a percentage of GNI.

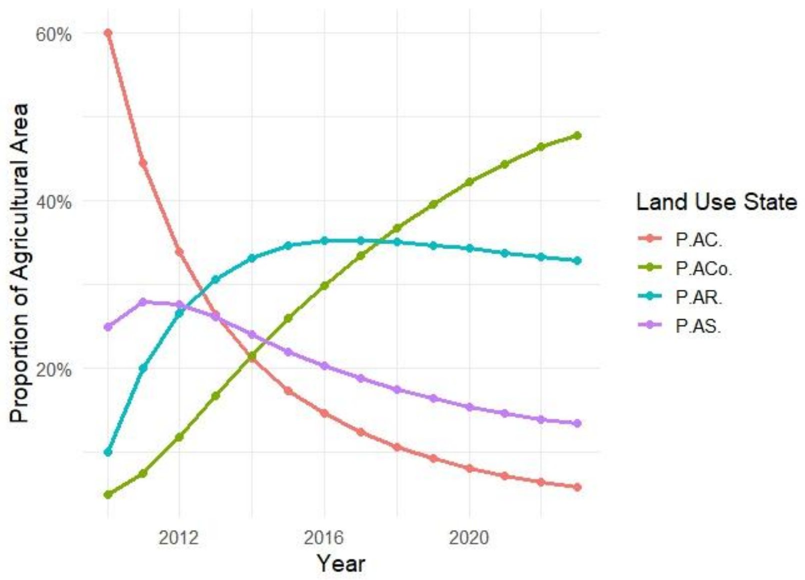

Figure 1. Evolution of state-level distribution from 2010 to 2023

Regarding the validation of the model's consistency, five main criteria were adopted, with the results systematized in Table 5.

Table 5. Markov Chain Model Validation

Validation Criterion	Applied Method	Result Obtained	Interpretation
Markov Property	Conditional independence test χ^2	$p > 0.05$	No evidence of higher-order dependence; confirms the model's short memory property.
Normalization of Transition Matrix M	Verification that $\sum_j M_{ij} = 1\ \forall i$	All row sums equal exactly 1	Matrix is stochastic and suitable for use in a Markov chain.
Empirical Validation	Calculation of MAE, RMSE, and goodness-of-fit test (Kolmogorov-Smirnov)	MAE = 0.032; RMSE = 0.046; KS: D = 0.07, p = 0.44	High accuracy and good fit to the distribution of simulated data.
Stationary Convergence	Computation of $\lim_{n\to\infty} S_O \cdot M^n = \pi$	π = [0.066, 0.153, 0.300, 0.481]	The chain converges to a stable equilibrium state dominated by consolidated regenerative use.
Cross-Validation (Generalization)	Training on 70% of data, testing on 30%	MAE = 0.034; RMSE = 0.051	The model demonstrates strong generalization capacity for unseen data.
Integration with Energy Indicators	Inclusion of CER, CFF, and SE as explanatory variables	Positive correlation with regenerative transition	Energy indicators positively influence the shift toward sustainable agricultural practices.

These results demonstrate that the proposed modeling approach is statistically robust and sensitive to variations in conditioning factors. The integration of the Markovian framework with energy-related data offers a powerful tool for simulating future scenarios and guiding sustainable agricultural and energy policies in rural areas.

5. Discussion of Results

Based on land-use dynamics modeling using Markov chains conditioned by energy indicators, five analytical axes guide the interpretation of the results. This section explores the transitions between agroecological states, the model equations, structural constraints, and the dialogue with the specialized literature.

The findings indicate a progressive and significant transition from conventional agriculture P(A_C) to consolidated regenerative agriculture P(A_{Co}). The proportion of conventional agriculture decreased from 60% in 2010 to 5.9% in 2023, while P(A_{Co}) increased from 5% to 47.8% over the same period. This trajectory was mediated by transient fluctuations in the intermediate states P(A_S) and P(A_R), which served as necessary conversion phases before the consolidation of regenerative practices. Figure 1 illustrates this dynamic, highlighting the sharp decline in conventional agriculture and the steady rise of regenerative systems, particularly after 2015.

Analysis of the transition matrix M reveals that a direct shift from A_C to A_{Co} is absent, making passage through intermediate states obligatory. The predominant flows— $P(A_C) \rightarrow P(A_S), P(A_S) \rightarrow P(A_R), P(A_R) \rightarrow P(A_{Co})$ —reflect a gradual agroecological transition, dependent on incremental processes of technological adoption, institutional arrangements, and economic incentives. The proposed sequential transition structure aligns with existing literature that describes agroecology as an evolutionary and context-dependent process.

The observed trajectory confirms the hypothesis of a progressive agro-energy transition and underscores the role of structural and systemic factors in overcoming intermediate states. The conversion pace was more pronounced during periods marked by public policies promoting renewable energy, demonstrating the interdependence between the energy context and the evolution of rural production systems. These findings reinforce the central thesis of the study: the expansion of regenerative agricultural systems is conditioned by external structural transformations, particularly in the energy matrix.

Land-use dynamics were modeled using a first-order Markov chain framework, structured around the recursive evolution of a state vector comprising four categories: conventional agriculture, initial sustainable agriculture, transitional regenerative agriculture, and consolidated regenerative agriculture. The state vector at time $t + 1$ is obtained by multiplying vector S_t by the stochastic transition matrix M, whose elements represent the probabilities of conversion between modeled states. The matrix was parameterized using three energy indicators: renewable energy consumption (C_{ER}), fossil fuel consumption (C_{FF}), and relative energy depletion (RNBS_E).

This conditional formulation renders the model responsive to contextual configurations. Scenarios with increased C_{ER} implied higher probabilities of transition to P(A_{Co}), while high C_{FF} or S_E rates increased the inertia of less sustainable states. This sensitivity positions the model as an analytical tool for evaluating public policies under varying structural configurations.

Figure 2 reinforces this connection by illustrating the positive correlation between the increase in C_{ER} and the proportion of $P(A_{Co})$ from 2010 to 2023. The convergence of the curves indicates a coevolution between energy transition and land-use reconfiguration in rural territories, supporting the hypothesis that renewable sources act as catalysts for agroecological transition.

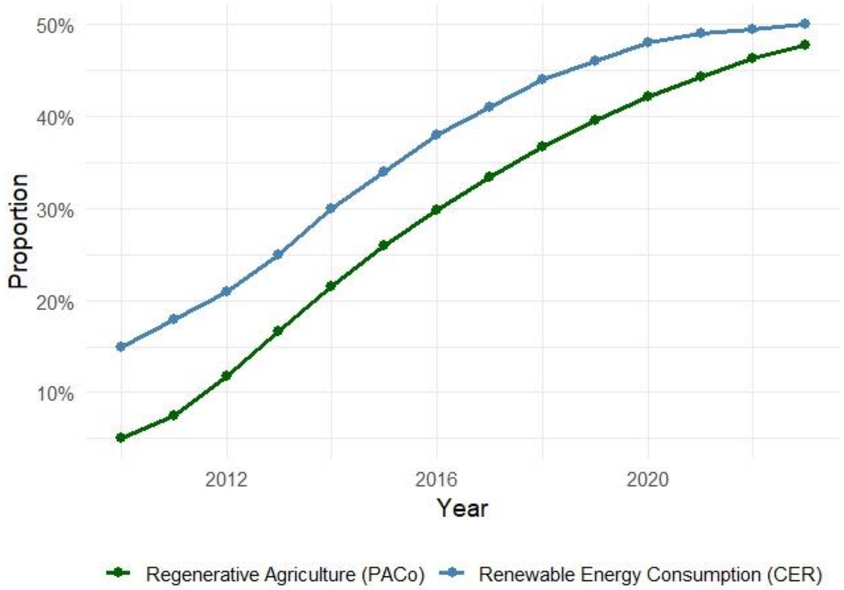

Figure 2. Coevolution Between Renewable Energy Consumption and Consolidated Regenerative Agriculture

By integrating energy variables into the land-use model, the proposed approach contributes to a more comprehensive understanding of the challenges and opportunities surrounding rural sustainability. The model enables forward-looking simulations of territorial trajectories under different institutional and energy scenarios, providing a robust methodological foundation for territorial planning strategies and public policy design.

The findings of this study align closely with scholars such as Altieri et al. (2015) and Rockström et al. (2017) who link the viability of agroecology to sustainable energy systems and territorial governance arrangements. The conditional matrix employed also addresses criticisms raised by Gliessman (2020) by integrating external drivers into mathematical models applied to agroecological transitions.

Latin American case studies (Aguilera et al., 2020) further underscore the relevance of variables such as energy decentralization, rural infrastructure, and territorial governance in promoting the adoption of sustainable practices. The model's sensitivity to changes in energy indicators reinforces the importance of these factors, suggesting that integrated energy policies should be regarded as strategic instruments for territorial transformation.

The model also aligns with complex socio-ecological systems frameworks (Liu et al., 2021), by simultaneously incorporating biophysical and institutional dimensions in the transition process. This integration enhances both its interpretive and predictive capacities, establishing it as a relevant analytical tool for advancing the agricultural and territorial sustainability agenda.

The proposed structure validates theoretical hypotheses and operationalizes them within a dynamic and parameterizable model, sensitive to regional specificities. Its application transcends the academic realm, offering decision-making support for public policy formulation and territorial planning across multiple scales.

International studies conducted in countries such as India, Vietnam, and Costa Rica reveal similar patterns, linking the expansion of renewable energy sources to the acceleration of agroecological transitions (FAO, 2020; IRENA, 2021). These findings reinforce the model's applicability across diverse contexts, provided institutional and environmental particularities are duly considered.

The results also contribute to the Sustainable Development Goals (SDGs) agenda, particularly SDGs 2, 7, and 13. The articulation between energy indicators and land use enables the exploration of synergies among various global sustainability targets and supports the design of integrated action strategies (ONU, 2025).

Figure 3 illustrates the elasticity of the transition to $P(A_{Co})$ as a function of variations in C_{ER}, C_{FF}, and S_E. The results indicate that the model's sensitivity to changes in renewable energy consumption is significantly greater than to other indicators. Regions in Figure 3 that exhibit high levels of C_{ER} combined with low levels of C_{FF} and S_E show the highest elasticity coefficients, indicating system conditions that are highly conducive to the consolidation of regenerative agriculture.

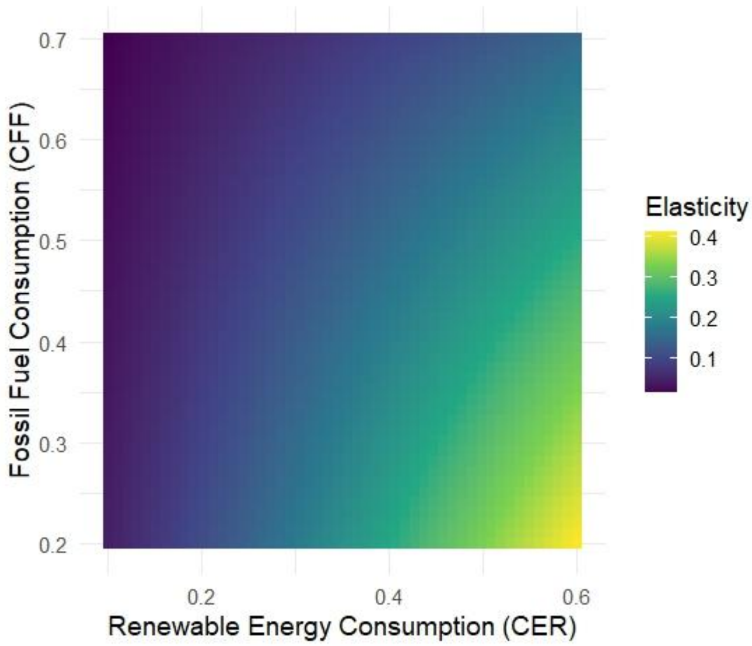

Figure 3. Elasticity of Transition to Regenerative Agriculture Consolidation as a Function of Energy Indicators

Table 6 complements this analysis by synthesizing the combined effects of the three energy indicators on the expected elasticity of agroecological transition. The assessed scenarios range from configurations characterized by high renewable energy penetration, low dependence on fossil fuels, and reduced levels of energy depletion—typical of robust decarbonization strategies and energy transition incentives—to contexts marked by intensive use of fossil sources and high rates of energy depletion, which are associated with low structural resilience of the productive system. In the Brazilian case, the data suggest a trajectory aligned with scenarios of intermediate to high elasticity, especially from 2016 onward, with the increase in renewable energy generation—particularly the expansion of wind and solar sources—and the implementation of public policies more favorable to sustainable agriculture, such as the National Program of Bioinputs. This context enabled the gradual transition observed in the results, highlighting the role of energy policy as a critical variable for driving land use change.

Table 6. Elasticity of Agroecological Transition by Energy Scenario

C_{ER} (↑)	C_{FF} (↓)	S_E (↓)	Expected Elasticity	Typical Scenario
↑	↓	↓	Very High	Strong decarbonization and renewable incentives
↑	→	↓	High	Moderate green growth with partial regulation
↑	↑	↑	Moderate	Renewables adoption with persistent fossil use
→	↓	→	Low	Stable energy context without major incentives
→	↑	↑	Very Low	Fossil fuel dependency and energy depletion

Studies such as those by Niederle et al. (2022) and Medina and Pokorny (2022) reinforce this dynamic by demonstrating that the expansion of renewable energy supply in Brazil has generated positive spillover effects on agroecological value chains. These include reductions in operational costs, enhanced energy stability in rural areas, and the promotion of synergies between technological innovation and environmental conservation. The integration of decentralized energy support programs with state-level agro-environmental initiatives has contributed to strengthening the transitional flows represented in the modeled matrices.

The analysis of the Brazilian case also highlights persistent structural challenges. Although the country has made progress in diversifying its energy matrix, it remains highly dependent on fossil fuels in key sectors such as transportation and nitrogen fertilizer production. These dependencies negatively affect the C_{FF} and S_E indicators. Such limitations underscore the need to expand mechanisms for a just transition—those capable of aligning energy security, agricultural productivity, and environmental sustainability.

Thus, the modeled results presented in Figure 3 and Table 6 not only reflect quantitative trends but also capture the complexity of ongoing political, economic, and technological decision-making in Brazil. Both international and national literature converge on the need for integrated approaches, and the model proposed herein offers a concrete tool to operationalize such integration within the context of Brazilian territorial governance.

Table 6 enables the identification of systemic behavioral patterns that directly influence the pace and direction of agroecological transition. In contexts like Brazil, which in recent years has seen significant growth in renewable energy generation and structured policies supporting agroecology, a high elasticity is observed—associated with the consolidation of regenerative systems. In contrast, countries with energy systems still heavily reliant on fossil fuels, such as certain oil-producing states, experience greater inertia in shifting away from conventional agricultural practices.

This analytical capacity is crucial for informing differentiated intervention strategies, enabling policymakers to tailor their actions to specific regional energy profiles. Therefore, alignment between energy and agricultural goals becomes a strategic condition for territorial sustainability, guiding the prioritization of investments, technical incentives, and regulatory instruments (Stern et al.,2016)

The joint analysis of Figure 3 and Table 6 allows for the simulation of alternative energy policy scenarios. For instance, contexts characterized by renewable energy subsidies and fossil fuel taxation tend to shift the matrix toward zones of higher positive elasticity. This forward-looking capability is essential for the formulation of evidence-based public strategies aimed at fostering more effective and resilient agroecological trajectories (Neves et al., 2024).

Finally, Figure 3 enhances the intelligibility of the model's results, making them accessible to public managers, territorial planners, and decision-makers. By synthesizing the complex interactions between energy dynamics and agroecological processes into a visual and interpretable format (Vidal & Govan, 2024), the Figure 3 serves as a strategic support tool for the governance of sustainable rural transitions.

Figure 4, presented as a Sankey diagram, offers an integrative and dynamic visual representation of agroecological transition flows among the modeled land-use states: conventional agriculture (A_C), early-stage sustainable agriculture (A_S), transitioning regenerative agriculture (A_R), and consolidated regenerative agriculture (A_{Co}). The diagram's configuration reveals a dominant trajectory along the $A_C \rightarrow A_S \rightarrow A_R \rightarrow A_{Co}$ sequence, indicating that agroecological conversion processes follow a gradualist and cumulative logic. This transition pattern confirms the propositions of Gliessman (2020) and Altieri et al. (2015), who argue that systemic change in agriculture does not occur through disruptive leaps, but rather through incremental transformations mediated by social learning and technical adaptation.

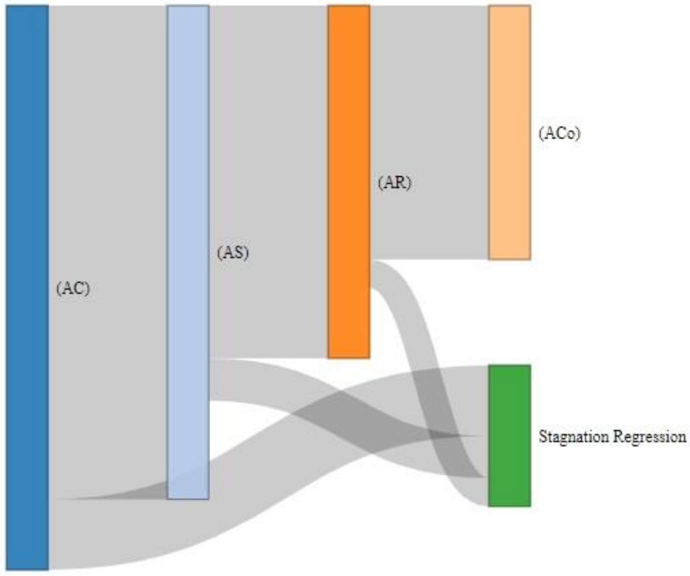

Figure 4. Agroecological Transition Flows Among Land-Use States

The intensity of flows depicted in the figure indicates that the highest proportion of transitions occurs between the first two stages, from A_C to A_S. This suggests that the initial adoption of sustainable practices is more accessible and less dependent on advanced structural conditions. In contrast, the subsequent transitions— $A_S \rightarrow A_R$ and $A_R \rightarrow A_{Co}$—become progressively less intense, reflecting the increasing complexity of the later stages of the transition process. This pattern aligns with findings by Tittonell (2020), who identify escalating barriers to the consolidation of regenerative systems, associated with factors such as limited access to financing, logistical constraints, institutional inertia, and the absence of differentiated markets.

Additionally, the presence of regressive and dispersive flows—particularly those moving from intermediate states to stagnation or reversal—demonstrates that agroecological transitions are vulnerable to setbacks, especially in environments lacking political, technical, or infrastructural support. These flows reinforce the conceptualization of agroecology as a non-linear and fragile process, as described by Anderson et al. (2019), requiring adaptive policies that are sensitive to local territorial contexts.

Therefore, Figure 4 not only illustrates the direction of desirable transitions but also reveals the system's points of greatest friction and vulnerability. This visualization enables the identification of strategic bottlenecks and the design of targeted interventions—such as expanding technical assistance in A_S, providing financial incentives for transitions from A_R to A_{Co}, or implementing institutional resilience mechanisms to prevent regressions. The use of the Sankey diagram enhances the model's ability to inform public decision-making by making the complexity of agroecological transitions visible and highlighting the conditioning factors that shape their trajectory.

6. Conclusions

This study presented a Markov chain model conditioned by energy indicators to represent the dynamics of agroecological transitions in Brazil from 2010 to 2023. Three structural variables — renewable energy consumption (C_{ER}), fossil fuel use (C_{FF}), and energy depletion relative to gross national product (S_E), were used to condition the transition probabilities among different land use states, enabling both retrospective interpretation and prospective simulations under distinct energy configurations.

The results indicated a gradual and nonlinear transformation of agricultural systems, moving from conventional to more sustainable and regenerative practices. This process showed a strong association with the increasing share of renewables in Brazil's energy matrix, suggesting that energy transitions play a catalytic role in reshaping rural production logics. The model reinforces the hypothesis that agroecological transitions occur incrementally, passing through intermediary phases marked by institutional maturation, technological adoption, and energy restructuring. Its sensitivity to variations in energy indicators allows for the detection of systemic vulnerabilities and the anticipation of critical thresholds where targeted policy interventions can be most effective.

While the model successfully captures historical transition patterns, it has certain limitations. It does not directly account for variables such as transportation infrastructure, market integration, land tenure regimes, or cultural preferences that often mediate land use decisions. Additionally, the model's deterministic nature constrains its capacity to incorporate exogenous shocks or rapid institutional changes, which are increasingly relevant in times of global environmental and economic uncertainty.

Nevertheless, the model presents significant practical and theoretical contributions. It can be adapted into a decision-support tool for rural extension services, enhancing participatory diagnostics of energy use, carbon footprint assessments, and the planning of low-carbon, energy-efficient farming strategies. Its conditional architecture also facilitates scenario analyses, helping stakeholders visualize the long-term effects of specific energy and land use choices on agroecological outcomes. By bridging technical modeling with real-world applications, the study provides a valuable interface between science, policy, and practice.

Future research should aim to refine the transition matrix by incorporating variables related to credit access, fiscal incentives, governance mechanisms, and sociopolitical dynamics at the territorial scale. Field-based validation through participatory approaches may further enhance model reliability and context-specific relevance. Ultimately, by combining mathematical rigor, energy transition sensitivity, and social applicability, this study contributes in a novel and strategic way to the planning of sustainable agricultural futures in Brazil. Its replicability across diverse biogeographic and institutional contexts underscores its scientific value and reinforces its role in supporting just and resilient agroecological transitions.

Authors contributions

Sample: Prof. Dr. Eduardo Gomes Salgado, Prof. Dr. Breno Régis Santos and Prof. Dr. Sandra Regina M. M. Roveda were responsible for study design and revising. Ms. Arlinda de

Jesus Rodrigues Resende was responsible for data collection. Ms. Taciany Feitor Carvalho validated the model. and Prof. Dr. Fábio de Oliveira Neves adjusted, drafted, and validated the model. All authors read and approved the final manuscript. In this paragraph, also explain any special agreements concerning authorship, such as if authors contributed equally to the study.

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Competing interests

Sample: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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