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Mapping crop producer perceptions: The role of global drivers on local agricultural land use in Brazil

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A R T I C L E I N F O

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A B S T R A C T

Agricultural trade and climate change have altered land cover and land use worldwide. For example, the recent growth of international soybean demand has been associated with 1.3 Mha primary Amazon forest loss and up to 13-fold increase in double-cropping areas in Brazil. Many studies have tried to understand which and how global and local drivers affect deforestation and agricultural intensification processes at the landscape level, yet few have incorporated the direct perspectives of actual land users. Under the influence of a variety of social, economic, and cultural factors, producers are the ones who make decisions that will cause a significant impact on the environment. In this paper, we adopted Fuzzy Cognitive Maps (FCMs), a semi-quantitative modeling approach to represent complex decision-making systems, and we modeled land use and agricultural management perceptions of 27 crop producers from the three states - Mato Grosso, Goiás, and Tocantins - important soybean production and export areas in Brazil. We analyzed individual models and integrated them into aggregated regional models to compare individual and regional differences among the producers. In addition, we simulated how producers from the three states will make land-use decisions under more trade and extreme climatic events scenarios using the FCMs. Our results indicate that extreme climatic events are among the most important factors producers consider when it comes to the sustainability of their operations. Climate change scenarios have a stronger overall impact than trade scenarios on local land-use changes, causing a 12% reduction in total agricultural production. The improvement of technology packages can effectively mitigate climate change risks and has an overall positive impact on land-use intensification than expansion. On the other hand, sharing accurate climate information and socio-economic improvements such as credits have larger impacts on agricultural expansion than productivity itself. Moreover, the model complexity shows differences among the three states. Soybean trade has more weight in the perception of producers in Goiás and Tocantins than Mato Grosso. Based on the results, we discuss the importance of co-designing place-based, alternative policies and mitigation options for both agricultural intensification and environmental conservation, taken into consideration through the intertwined global and local forces.

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1. Introduction

In the first two decades of the 21th century, global drivers such as trade and climate change have drastically altered land cover and land use (LULC) worldwide. Over 314 Mha of forests were lost globally between 2001 and 2015, with a significant portion attributed to commodity-driven deforestation (Curtis et al., 2018). Brazil has been in the spotlight due to its agricultural land use, deforestation, and subsequent greenhouse gas emissions. In just three years, from 2001 to 2004, soybean expansion directly caused more than 5000 km^2 of deforestation in the state of Mato Grosso in Brazil (Morton et al., 2006). From 2001–2019, soybean area in Brazil has increased by a factor of 2.6, causing 1.3 Mha primary and 0.7 Mha secondary Amazon forest loss (Song et al., 2021). Despite implementing anti-deforestation measures, such as the Forest Code and the Soy Moratorium, deforestation in Brazil needs more effective policies and governance. As an alternative, agricultural intensification through increasing productivity per unit area (e.g., double cropping or two crop cycles per year on the same field), has emerged as a pathway for reducing deforestation and promoting more environmentally friendly agriculture (Helfenstein et al., 2020; Hu et al., 2020). As soybean demand continues to surge, it is strategically important to understand how to achieve the land-use pathway of intensification than expansion in the region (Stabile et al., 2020), given its role in both regional and global climate change, food production, ecosystem provision, and biodiversity conservation.

Extensive research on deforestation and soybean expansion has been carried out in Brazil. However, most of the research focus on mapping soybean productions with remote sensing (Kastens et al., 2017; Song et al., 2021) or quantifying the production using agricultural economics (Richards, 2015; Yao et al., 2018). Yet, our understanding of the underlying mechanisms of land-use change at the farm level is still incomplete. The linkage between local processes and various drivers at the local, regional, and global levels remains unclear, as does how farmers perceive anti-deforestation measures and make their land-use decisions (Gibbs et al., 2016, 2015; Lapola et al., 2023). Most previous efforts have taken a regional landscape approach to assess the impact of certain governance measures on deforestation ex-post (Diniz et al., 2015). For example, spatial regression has been applied to assess the direct and indirect land-use impacts of soybean land expansion, and determine the effects of market mechanisms and other socio-ecological drivers (such as elevation and precipitation) (Arima et al., 2011; Dou et al., 2018; Richards et al., 2014). While these analyses can identify important aggregated driving factors, they lack the ability to explain the heterogeneity of land actors and their land-use decision process. Some producers favor agricultural expansion, while others invest in intensification, because of differences in property size, timing of registration, previous deforestation, and access to extension agencies (Azevedo et al., 2017; Santiago et al., 2018). Trading with different partners and different contracts will also lead to different deforestation risks (Zu Ermgassen et al., 2020). Decisions of land-use actors can strongly determine the land-use outcomes of governance measures and global forces. However, current studies lack real insights from field observations and neglect stakeholders' engagement. Therefore, understanding individual land actors' decisions and upscaling results across a larger region is a crucial gap for leveraging policy-making to prepare for future risks with better land-use outcomes in agricultural development and conservation.

To address such a challenge (i.e., understanding farmers' land-use decision-making for regional assessment), we adopt the Fuzzy Cognitive Mapping (FCM) method. FCM is proven to be an effective tool to understand people's cognitive thinking, while incorporating multiple stakeholders' views and perceptions—i.e., accounting for heterogeneity and adding quantitative strength to decision-making analysis (Mehryar et al., 2019; O'Garra et al., 2021; Özesmi and Özesmi, 2004; Reckien, 2014). FCMs can be used to analyze the behavior of the system over time, under different scenarios or conditions (van Vliet et al., 2010). They can be particularly useful for exploring the potential impacts of policy interventions, technological innovations, or other changes to the system. Murungweni et al. (2011) drew FCMs with rural communities in southern Africa and visualized the effects on livelihoods from droughts and changes caused by humans. The conflicts between wildlife conservation and bush meat consumption were also explored using FCMs, and the current and alternative states of a resilience system were analyzed (Gray et al., 2015). Besides examples in rural communities, FCMs have also been used to compare urban case studies across Europe, which reveal the similarity and differences within complex drivers and the process of landscape changes in six cities from different environmental zones (van der Sluis et al., 2019). Like almost all other methods, FCMs do have some limitations such as adequate or unbiased knowledge from different participants (Malek, 2017). However, compared to other participatory approaches (e.g., causal loop diagrams, role-playing games), FCMs can provide a system causal overview from the stakeholders' perspective with conceptual quantification (Voinov et al., 2018). Based on FCMs results, detailed simulation methods such as agent-based models can be built to articulate system behaviors and state changes over time (Giabbanelli et al., 2017; Mehryar et al., 2019).

In this study, we used FCMs as a tool to investigate the decision-making processes of Brazilian soybean producers in the states of Goiás, Mato Grosso, and Tocantins, which are hotspots of agricultural expansion and intensification in the Brazilian Amazon and Cerrado biomes. Our aim of this study is to apply FCMs to gain insights into land-use change processes and provide answers to the following questions:

(1) How do decisions vary among producers and regions?
(2) How do global forces, such as soybean trade and climate change, affect local land-use changes among producers and regions within the current policy and governance framework?
(3) Which factors and channels can be used as leverage points by different soybean producers to achieve better land-use pathways and to cope with climate and trade uncertainties across regions?

The three questions require analyses covering three parts of the models: structure analysis, content analysis, and comparison between scenario simulations. To answer the first question, we constructed individual and regional models based on interviews with soybean producers in three Brazilian states; we then compared the structure and content of these models to reveal the differences in factors and relationships in land-use decisions. For the second question, we ran simulations on the aggregated regional models with trade and climate scenarios, to compare the affected factors and land-use outcomes. For the third question, we tested the extent to which improving a factor can contribute to land-use expansion and intensification, to compare which factors can be more effective as leverage points for governing better land-use outcomes. Results from this study can effectively guide soybean producers in addressing climate- and trade-related risks, and provide policy-makers with effective tools to foster a long-term outlook for agricultural development and environmental sustainability.

2. Methods and study site

2.1. Description of the case-study region

Brazil is the fifth largest country on Earth and an established agricultural powerhouse. The country encompasses 8.5 million km^2 and six terrestrial biomes. Two key biomes, the Brazilian Amazon and the Cerrado together cover approximately 73% of the country's territory. The states of Mato Grosso, Goiás, and Tocantins are located in this region (Fig. 1). Mato Grosso is the largest among the three, 903k km^2 and a population of 3.66 million in 2022. Goiás is one-third of Mato Grosso's area (312k km^2) and 66% of its population. Tocantins is the smallest among the three, with 277k km^2 and 1.51 million population. The three states are important for agricultural production, especially soybeans for

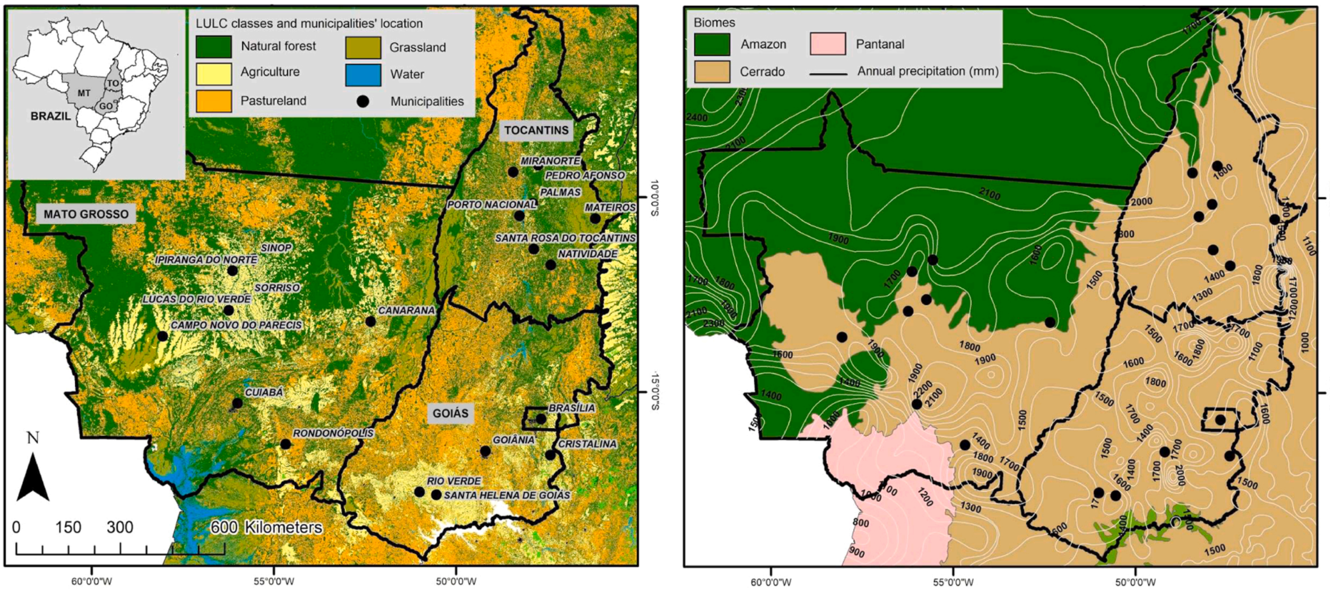

Fig. 1. Land use and land cover (left) and biomes (right) of Brazil and the locations/municipalities where interviews were held (shown by black dots). The location of the three states is shown in the imbedded figure. Individual farm locations were aggregated to the municipalities to keep information confidential.

exports. During the last decades, Brazil has increased its agricultural production exponentially to become a major global producer and exporter of food, feed, fiber and fuel (FAO, 2020). Although being neighboring states, they show specific trends of LULC changes and experience different human-environmental interactions (Souza et al., 2020). While Mato Grosso has the largest expansion and accounts for 28% of the national soybean production, Goiás produced 10% and Tocantins only produced 2.4%. However, Tocantins is the youngest agricultural frontier among the three states, and its soybean production increased from 144 Kt in 2000–3 Mt in 2020. The importance of agribusiness to the states is highlighted by their economic contribution (Martinelli et al., 2017). While Mato Grosso and Goiás contributed similarly (2.3% and 2.9% respectively) to the Brazilian gross domestic product (GDP) in 2020, Tocantins also has 0.5% GDP contribution given its size and history.

The three states exhibit different climatic conditions, such as annual precipitation (Fig. 1, right panel), with them spanning over three climate zones (Cordeiro et al., 2020). Tocantins has its territory between *Tropical Central Brazil* and *Tropical Equatorial*, with an average annual precipitation of 1372 mm. Goiás is entirely within *Tropical Central Brazil* (average annual precipitation of 1500 mm), and Mato Grosso spans its territory between *Tropical Central Brazil* and *Equatorial*. The average annual precipitation of Mato Grosso is 1700 mm, but ranging from 1200 mm to 2000 mm. Although different in magnitude and pace, all three states are adopting "double-cropping" systems (i.e., two crop cycles per year on the same field), when soybeans are planted at the beginning of the rainy season and maize or other crops are planted immediately after the harvest of soybeans through a no-tillage system. These follow-up crops endure less stable rainfall and more drought extremes, resulting in a more vulnerable and fluctuated production than the first growing season (Lathuillière et al., 2018; Spera et al., 2020).

Being the largest soybean and maize exporting country in the world, these agricultural commodities are identified as a major driver explaining agricultural expansion and intensification between 2001 and 2013 (Gusso et al., 2017). Climate change is also forcefully shaping agricultural production of the region. In the year 2015–2016, Brazilian farmers experienced a 50% soybean yield loss in the first growing season due to the abnormal El Niño, and may face more frequent and extreme events in the future with an average 28% yield reduction by 2040 (Hampf et al., 2020; Spera et al., 2020). Numerous environmental regulations (e.g., legal reserves) and supply-chain initiatives (e.g., soy moratorium) have slowed down the deforestation in the Amazon and Cerrado biomes (Gibbs et al., 2015; Kastens et al., 2017), but the rising deforestation rate (Fearnside, 2023; Qin et al., 2023) calls for urgent policy recommendations based on a comprehensive understanding of the land actors, as they directly promote the long-term agricultural suitability in the region. Soybean producers from the three states also differ in their own assets and characteristics. For example, in average, farms in Mato Grosso grow 1.5 Kha of soybeans, while this number is halved in Tocantins and further halved in Goias (Silva et al., 2020). Given the importance and the dynamic development of the agribusiness (i.e., soybean and maize production) in these three states, their intrinsic bioclimatic heterogeneity, land and development histories, we argue that this study offers a good case for the advancement of scientific knowledge on the understanding of land use decision-making processes taken by local actors.

2.2. *General approach: fuzzy cognitive mapping*

Fuzzy cognitive maps (FCM) are a graph-based knowledge representation method that was first proposed by Kosko (1986). Over years of theoretical and application development, Özesmi and Özesmi (2004) have developed and applied FCM for scenario analyses in complex social-ecological systems. We utilized FCM based on Ozesmi and Ozesmi, 2004. With the structure of a cognitive graph, FCM contains a set of concepts in a domain of interests and the links between nodes represent the causal relationships between them. The concepts can be any element, object, or entity of the system of interest. Concepts are represented as nodes in the map and the connections between nodes are assigned a weight based on the strength of the relationship. The connections can be positive or negative, with assigned values between "− 1.0" and "1.0". The bigger the absolute value, the more intensive the relationship. In each graph, the intensity of the relationship is shown by the width of the arrows. The connections are directional, indicated by the arrowhead in the graph. For instance, in a hypothetical FCM example as shown in Fig. 2, there can be two connections between two nodes A and B and they do not need to be reciprocal: from "farm credit" to "soybean production" the connection is 0.7 and the other way is − 0.3. This indicates a perceived strong positive relationship such as having farm credit largely boosts soybean production. On the contrary, having large soybean production will reduce the need for farm credit, but with weak intensity.

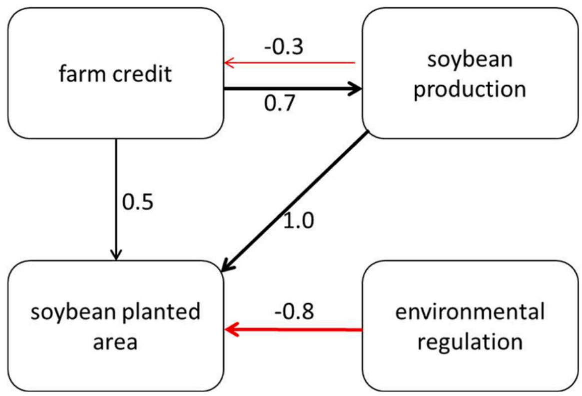

Fig. 2. Hypothetical Example of FCMs
Adapted from Gray et al. (2015).

FCM is easy to use because every FCM can be transformed into one adjacency matrix (Fig. 2 to Table 1). It can be used in a data-poor environment and aggregate individual perceptions to account for accumulated knowledge. We focused on the use of FCM as a means to reveal the complex driving forces and processes of land-use change in the selected agricultural region of Brazil. Furthermore, the semi-quantitative, dynamic nature of FCMs can be used to evaluate scenarios and factors ex-ante. Based on the cognitive graph and the adjacency matrix, the system's steady state can be calculated using neural network computational methods through iterations (Özesmi and Özesmi, 2004). The steady-state reveals the relative importance of all concepts in the system according to the perceived FCM under current conditions. It serves as a baseline that permits researchers to run "what-if" dynamic scenarios and compare the state that a given system will result in under hypothetical conditions. These scenarios can be used as a decision-support tool for planning anti-deforestation measures among farmers and regions.

2.3. *Target groups and methods: interviews and meetings with stakeholders to construct the models*

Different methods (e.g., semi-structured interviews, drawings, workshops) can be used to collect data and construct FCMs. For example, Reckien (2014) used semi-structured interviews to collect adaptation options to extreme climate events among different social-economic groups in India. Readings and drawings without direct interactions with interviewees were used by O'Garra et al. (2021). In this study, we used oral, face-to-face interviews to generate data and FCMs. Before contacting the interviewees, the authors of this article had meetings in Brasília (the federal capital) with representatives of the Brazilian Agricultural Research Corporation (Embrapa), the Soybean and Maize Producers Association (APROSOJA Brazil), and the National Company of Food and Supply (Conab). Additionally, the fieldwork team had meetings in Cuiabá (capital of Mato Grosso), Goiânia (capital of Goiás) and Palmas (capital of Tocantins) with state-level institutions such as APROSOJA (regional state branches), official state agencies and agricultural organizations (e.g., National Rural Learning Service (SENAR)/Mato Grosso division). These introductory meetings with the stakeholders from state officials, national agricultural associations, and large cooperatives allowed authors to develop a general understanding of the agricultural land use and production in the study areas, as well as define the current issues and gaps for the interviews with producers.

To conduct the interviews, Mato Grosso, Goiás, and Tocantins were stratified into different regions according to production characteristics (i.e., the quantity of production and planted area of soybean and maize as the second crop) and from each region we selected representative municipalities. The interviews were organized by a semi-structured questionnaire with open-ended questions (see Supplementary Material), recorded in audio files, and documented through mental models (Silva et al., 2020, 2017). Respondents were asked about:

(1) Their perception of current relations between major social, political, and climatic factors that may affect their soybean production.

(2) Their perception of the cause-effect relationship of how environmental regulation, climate, and trade would affect their soybean production and overall agricultural production.

(3) Their perception of the differences between their farms and other regions.

Fieldwork campaigns were conducted for two years, 2016 in Goiás and Tocantins and 2017 in Mato Grosso. From the producers identified in the introductory meetings with government officials, the fieldwork team used a snowball sampling approach (Atkinson and Flint, 2001) to reach out to more producers in the locations stratified regionally. For further information on the fieldwork design and application, see Silva et al., (2017, 2020). At the end of each interview, the authors summarized the whole model and checked with the participant producer to make sure that the research team did not misunderstand or misinterpret any aspect of their rationale. This validation process is common practice in participatory modeling processes and is vital to ensure a representative model (Gray et al., 2017).

This resulted in a total of 27 models with a total of 37 soybean producers, although more stakeholders were involved in the process. Depending on the purpose, it is often around 20–30 stakeholders involved to construct FCMs (e.g., 20 stakeholders in S. Targetti et al., 2019) given the time needed to construct a model. Our study adopted in-depth interviews with each participant, to compromise for the lower number of participants. Different to the 30 interviews in each of the five locations conducted by Reckien (2014) for small street vendors, our participants are large-scale producers who manage on average around 1000 ha of land. In addition, after every interview, we presented our draft model to the interviewee to validate it in real-time. Therefore, we argue that our samples are representative of the different soybean producers in the region.

2.4. *Modeling analysis and scenarios*

After interviews were conducted and raw data were collected, we first calibrated the models before data analysis on heterogeneity and scenarios (Fig. 3).

2.4.1. *Model calibration: common terminology and coding*

The constructed raw FCMs were in graph format. After returning from the field, we converted every model into an adjacency matrix in CSV file format. We went through all concepts that were mentioned in every model and put them one by one into one file as a meta code book.

Table 1
Converted adjacency matrix of the FCM example in Fig. 1.

	Farm credit	Soybean production	Soybean planted area	Environmental regulation	**Outdegree**
Farm credit	0	0.7	0.5	0	**1.2**
Soybean production	-0.3	0	1.0	0	**1.3**
Soybean planted area	0	0	0	0	**0**
Environmental regulation	0	0	-0.8	0	**0.8**
Indegree	**0.3**	**0.7**	**2.3**	**0**	

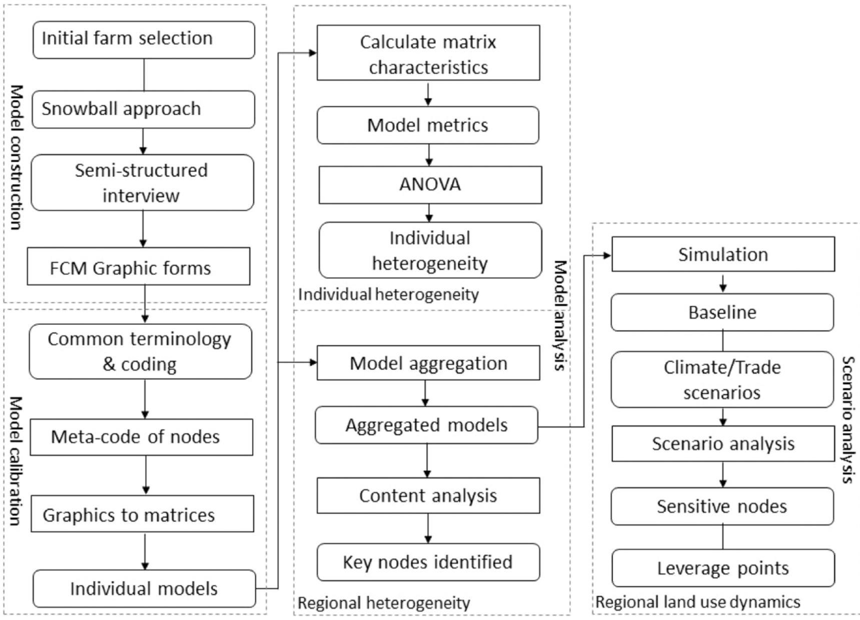

Fig. 3. Methodology: (1) Model construction through initial farm selection and interviews; (2) Model calibration through converting graphical networks to adjacency matrices and process common terminology; (3) Model analysis to answer Research Question 1: statistical comparison of individual heterogeneity and content analysis of regional heterogeneity. (4) Scenario analysis to answer Research Questions 2 and 3 by signifying trade, climate, and other leverage points to mitigate global change risks.

We then read through all concepts first and came up with a way to structure the concepts in order to compare them. Issues of extremely similar meanings were coded as one concept, for example, “storage space” and “silo for soybeans”; while specifically mentioned concepts were kept as they are, for example, “droughts” and “extreme climatic events” were kept as two separate impacts following Reckien (2014). In total, 50 interviews were completed (including government agents, associations, and producers). This resulted in 27 individual models that represent the 37 producers we interviewed, and three aggregated models representing the collective thoughts of producers from each selected state. Sample FCMs in graph format are shown in Fig. S2.

2.4.2. Model analysis: model aggregation

Consequently, we were able to aggregate individual models to collectively represent the regional cognitive perceptions of soybean production and land-use changes (see Fig. S1 for a detailed process). We aggregated individual models into one unified regional model for the three states, resulting in three state models (Fig. 3), we then used the matrix algebra function in the FCMapper library in R (Turney and Bachhofer, 2016). Every concept and connection of the aggregated model is the average of all individual models. This practice, although may lose some information regarding individual heterogeneity from different producers, can generate a representative understanding of the important drivers and processes of each region’s agricultural production. This aggregation process and comparison across three regional models allow us to identify the regional-specific factors and relationships, in consideration of individual heterogeneities and reduce the bias from individual farmers. Hereafter, we use “individual models” to indicate models representing individual producers, and “aggregated models” as the collective state models (Fig. 3).

2.4.3. Model analysis: metrics

We used the following metrics of FCMs to facilitate our understanding of individual and regional heterogeneity (Table 2), particularly on “centrality” and “complexity”. Concepts of FCMs can be divided into three categories: transmitters, receivers, and ordinary nodes. The **transmitters** are concepts that only show causing effect (i.e., indegree is zero, in the adjacency matrix the column sum of absolute values is zero). **Receivers** are concepts having solely indegree (i.e., in the adjacency matrix the row sum of absolute values is zero), which can be affected by others but have no causal effects themselves. **Ordinary nodes** are concepts that have both indegree and outdegree, indicating they can affect other concepts and be affected by others (i.e., neither row and column sum of absolute values is not zero). In the hypothetical FCM (Table 1), soybean planted area is a receiver concept because its outdegree value is zero, while environmental regulation is a transmitter concept because it only has outdegree but no indegree. All the concepts (i.e., transmitters, receivers, ordinary nodes) and metrics (i.e., indegree, outdegree, centrality, complexity) in Tables 1 and 2 are based on (Özesmi and Özesmi, 2004) and calculated using FCMapper in R (Turney and Bachhofer, 2016).

Centrality measures the relative importance of a variable for the system, which is determined by the strength of its incoming and outgoing connections and thus calculated as the sum of its indegree and outdegree. In the example case, the variable with the highest centrality is “soybean planted area” (centrality = 2.3) and the second-highest centrality is “soybean production” (centrality is 2.0) as the sum of indegree 0.7 and outdegree 1.3. The metric “complexity” is defined as the ratio of the number of receivers to transmitter variables. Complexity indicates whether this system has more outcomes and implications, or on the contrary, has more drivers to fewer receiving-ends in a top-down hierarchical system. A map with a larger complexity index suggests the system has a wide range of aspects that will be affected by the system’s dynamics, more than the number of factors that contribute to these changes. In the example, there is one receiver (“soybean planted area”) and one transmitter (“environmental regulation”) variable thus the complexity index is 1.0, which is a rather balanced causal network.

2.4.4. Model analysis: individual and regional heterogeneity

To show the individual and regional heterogeneity, we compared two aspects: model’s structural complexity and the concepts mentioned in the model (Fig. 3). It is likely that the number of nodes and their connections in a map reflect to some extent the complexity of driving factors and the relations that may affect soybean production in the region. Thus, the complexity of the models is indicative of the challenges and consequences that a producer relates to. To compare the structural complexity, we conducted a “meta-analysis” on the 27 individual models. First, we calculated five metrics of every individual model that can describe the model’s structure: the number of connections, the number of transmitters, the number of receivers, the number of ordinary factors, and complexity (Table S1). Based on the five metrics, we can get a general picture of the variation in the complexity of perceptions from

Table 2
Mathematical description and explanation of concepts and metrics used to describe FCMs.

Metrics	Equation	Variable explanations	Definition	Value in the example
Variable-level				**Farm credit**
Indegree	$id(v_i) = \sum_{K=1}^{N} \alpha_{ki}$	$id(v_i)$: indegree of node *I*; v_i: the *i*th node in the model a_{ki}: the connection from the *k*th node to this node (*i*th) N: number of nodes in the model	Indegree measures how strong this node is affected by other nodes in the model; If a node has zero indegree, it is a transmitter, only show causing effect on others but not affected by others.	0.3
Outdegree	$od(v_i) = \sum_{K=1}^{N} \alpha_{ik}$	$od(v_i)$: outdegree of node *I*; a_{ik}: the connection from this node (*i*th) to the *k*th node	Outdegree measures the cumulative strength this node has on all other nodes in the model; If a node has zero outdegree, it is a receiver, indicating it has no power to influence other nodes in the model.	1.2
Centrality	$c_i = od(v_i) + id(v_i)$	c_i: centrality of node *i*.		1.5
Model-level				
Complexity	$cp = R/T$	*cp*: complexity of the model; *R*: number of receivers in the model; *T*: number of transmitters in the model	the ratio of the number of transmitters to the number of receivers	Receiver: soy planted area; Transmitter: environmental regulation 1.0

different producers. We then conducted the analysis of variance (ANOVA) on the metrics of individual models grouped by the three states. ANOVA is a popular statistical test to study the effect of one single factor across more than two groups (Alkarkhi and Alqaraghuli, 2019), which is suitable for our analysis. We compared the number of transmitters and the number of receivers that indicate the range of driving forces and outcomes of the system. Our *null hypothesis* is that the FCMs in three states are the same in terms of structure and complexity, indicating that producers share a similar perception of the agricultural production systems. If the null hypothesis is rejected, then the individual producers show regional heterogeneity.

Furthermore, we identified and compared the top five transmitters, top five receivers, and top five ordinary factors in the aggregated state model, which indicates the concepts with the most importance.

2.4.5. Scenario analysis: how trade and climate affect land-use decisions with leverage points

FCMs can evaluate scenarios by analyzing the cumulative impact of model property manipulations over time through multiple iterations (van Vliet et al., 2010). Once the three aggregated state models were finalized, we used the FCMapper in R to establish a baseline state for each model. Scenarios were built on aggregated models instead of individual models in order to eliminate the differences across individual producers and to understand the possible trends of regional changes (Table 3).

(1) The baseline state signifies current conditions: the value of each node will stabilize and form an equilibrium pattern after a number of iterations. This describes the equilibrium state if the current concepts and relationships remain the same. All three models reached equilibrium states within 30 iterations, which is within the range compared to other FCMs of social-ecological systems (Giabbanelli et al., 2017; Reckien, 2014).

(2) Climate and trade scenario runs without improvement: This is to signify the challenges and uncertainty from global changes of trade and climate change, in order to understand which concepts and links are most affected. We used two sets of hypothetical scenarios similar to other evaluation studies (Diniz et al., 2015; Xu et al., 2020): (1) expanded soybean trade scenario by changing the value of trade nodes to 1.0, and (2) more extreme climatic event scenario by changing the value of extreme climate events to 1.0, to estimate the impacts of international trade and climate extremes on the land use changes in producers' current perspectives. In such hypothetical scenarios, we argue it is more likely to have more trade volume given the global population, economy, and consumption (Komarek et al., 2021), and stronger climatic events causing negative impacts on agricultural production trends (Spera et al., 2020). Therefore, we assumed more trade and climate change scenarios.

(3) Leverage points: We selected the top drivers from information, technology, and social dimensions in the three state models that potentially can be improved, and ran the series of trade and climate scenarios plus improved drivers (Fig. 3). For instance, we did not run simulations on improved "dollar value" because the exchange rate is less likely to be controlled by individual farmers and stakeholders. We assumed these drivers as potential "leverage points" to improve the land-use systems towards conservation and agricultural intensification, given their importance from the models and literature (Hampf et al., 2020; Santiago et al., 2018; Weaver et al., 2013). Specifically, the conditions in Table 3 are improved by fixing the values throughout the iterations. The end values of land-use change-related concepts in these scenarios were compared with values from the trade and climate change scenarios without improvement (i.e., no change to the drivers' value). We compared two aspects of land-use change: 1) area of land cover and land-use change (e.g., agricultural area expansion, planted area) as indicators for expansion; and 2) land-use intensity (e.g., cattle, maize following soybean production in the same year) as indicators for agricultural intensification.

In summary, three groups of comparison were made:

(1) to show how local farmers perceive global changes and envision future risks: (a) baseline scenario vs more demand change scenarios; (b) baseline scenarios vs more extreme climatic events scenarios;.

(2) to show how trade could affect land-use change (i.e., expansion and intensification) with and without the improved drivers: more demand scenarios with current conditions vs improved conditions;.

(3) to show how climate change could affect land use change (i.e., expansion and intensification) with and without improved social-ecological conditions: scenarios of more extreme climate events under current conditions vs improved conditions.

The intention of these three sets of scenarios comparison is not to predict or depict a plausible future. When setting the value of extreme climatic events as 1.0 we were assuming more climatic events compared to current conditions. Similarly, for the trade scenario, the value of international demand setting to be 1.0 assumes larger trade demand compared to the current. Scenario analysis yields trends of changes, relative to the impact change from other scenarios using the same model. We aimed to use the comparison of these scenarios to evaluate the relative changes in land-cover and land-use intensity that are most significantly affected by the global forces and local conditions that policy-makers can use as leverage points.

Table 3
Descriptive on changed model properties in different scenario runs.

Scenarios	Trade	Climate	MT	GA	TO
Baseline	current	current	current	current	current
Expanded soybean trade without improvement	international commodity = 1.0; commodity demand = 1.0	current	current	current	current
Expanded soybean trade with improvement	international commodity = 1.0; commodity demand = 1.0	current	chemical/tech packages = 1.0, soy cycle duration = 0.1; climate information = 1.0, collecting window precision = 1.0, market information = 1.0; insurance = 1.0, rural credit = 1.0	chemical/tech packages = 1.0, soy cycle duration= 0.1; climate information = 1.0, planting timing = 1.0, promptness to start planting season = 1.0; access to credit = 1.0, agricultural insurance = 1.0;	chemical/tech packages = 1.0, seed technology/ varieties = 1.0; climate information = 1.0, not clear information on climatic event = 0.1; access to credit = 1.0, agricultural insurance = 1.0
More extreme climatic events without improvement	current	extreme climatic events = 1.0	current	current	current
More extreme climatic events with improvement	current	extreme climatic events = 1.0	chemical/tech packages = 1.0, soy cycle duration = 0.1; climate information = 1.0, collecting window precision = 1.0, market information = 1.0; insurance = 1.0, rural credit = 1.0	chemical/tech packages = 1.0, soy cycle duration= 0.1; climate information = 1.0, planting timing = 1.0, promptness to start planting season = 1.0; access to credit = 1.0, agricultural insurance = 1.0;	chemical/tech packages = 1.0, seed technology/ varieties = 1.0; climate information = 1.0, not clear information on climatic event = 0.1; access to credit = 1.0, agricultural insurance = 1.0

3. Results

3.1. Individual and regional heterogeneity across states

3.1.1. Heterogeneity in model structure and complexity of individual models

We collected five FCMs from Goiás, five models from Tocantins, and 17 models from Mato Grosso, a much larger state. The five metrics of these models are reported in Table S1. When asked to discuss their agricultural production, producers mentioned a variety of concepts and relationships that are important to their land-use decisions and land management, resulting in models with a range of structure and complexity.

The structure and complexity of the individual models differ across the three states (Fig. 4, Table S2). Producers in Mato Grosso discussed more outcomes than producers in the other two states (Fig. 4, evident from the ANOVA test on the number of receivers). On average, producers in Mato Grosso discussed 11 outcomes while producers in Goiás and Tocantins mentioned about nine and seven outcomes, respectively. The differences among the number of receivers reflect that producers in MT actively evaluate diversified outcomes from agricultural production in their decision-making. These outcomes extend beyond the sole production and economic outcomes, and also include the socio-ecological development (e.g., investment in local education), which are not mentioned by producers in Goiás and Tocantins. However, the similar number of drivers suggests that producers in different states may view the driving forces in a more or less similar way.

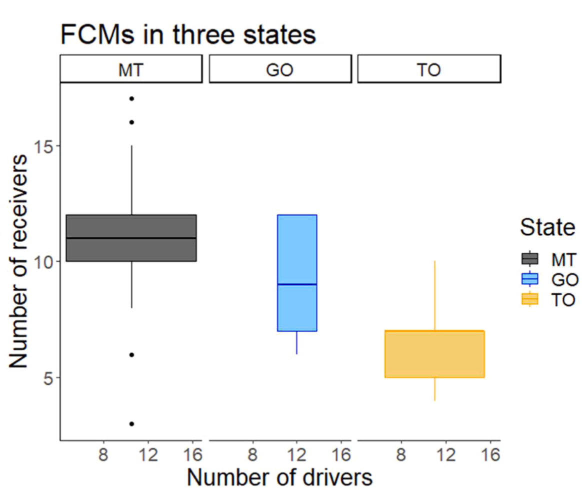

Fig. 4. Heterogeneity of model structure and heterogeneity of individual models across the three states. MT: Mato Grosso, GO: Goiás, TO: Tocantins.

3.1.2. Content heterogeneity of aggregated state models

The aggregated state models vary in the most important transmitters (Table 4), receivers (Table 5), and ordinary factors (Table 6). Among the top five drivers (transmitters, Table 4), there are more climate and technology-oriented factors in Goiás and Tocantins than in Mato Grosso, such as the length of the soybean cycle (the period from planting to harvesting) and the chemical/tech packages (a bulk of agro-chemicals including pesticides, herbicides, fungicides sold by agri-business companies). The most forceful drivers in Goiás and Tocantins are extreme climatic events, while in Mato Grosso it is soil conservation. Market drivers also rank high but appear as different concepts. For example, producers in Goiás mentioned the “commodity demand” directly, while in Tocantins, producers valued “price stability” more than demand. In Mato Grosso, the important market drivers are the exchange rate (dollar value) and production quality, rather than the demand and the price. Factors in transportation and infrastructure are also important but producers in Mato Grosso referred more to the development of the local industry while producers in Tocantins believed that better infrastructure contributes more to agricultural production.

The top-ranked concepts representing outcomes share some

Table 4
Top drivers (transmitters with the highest centrality) in the aggregated FCMs.

Transmitter Rank	MATO GROSSO	GOIÁS	TOCANTINS
1	soil conservation/ management	extreme climatic events	extreme climatic events
2	production quality	commodity demand	chemical/tech packages
3	dollar price	soybean cycle duration	price stability
4	arrival of industries	chemical/tech packages	seed technology/ varieties
5	soybean cycle duration	land price	infrastructure

Table 5
Top outcome (receivers with the highest centrality) in the aggregated FCMs.

Receiver Rank	MATO GROSSO	GOIÁS	TOCANTINS
1	risk	risk	social development
2	grain quality	planted area	international demand
3	soybean premium	maize production	sorgo production
4	maize productivity	plagues/diseases	transportation logistic
5	millet	productivity	pressure on pastures

Table 6
Top ordinary factors (ordinary factors with the highest centrality) in the aggregated FCMs.

Ordinary Factor Rank	MATO GROSSO	GOIÁS	TOCANTINS
1	soybean production	soybean production	soybean production
2	profitability	profitability	risk
3	cost of production	access to credit	maize production
4	extreme climatic events	agricultural area expansion	cost of production
5	second crop	cost of production	economic stability

similarities but also vary among the three states. Risk ranks number one in both Goiás and Mato Grosso, suggesting that producers in these two states consider (reducing) risk as one of the end goals in their perception. In Tocantins, the most valued and connected outcome is social development, along with the improvement of transportation logistics as one of the other top ranked outcomes. Production of other crops is also an important outcome, such as the maize production in Goiás, maize and millet in Mato Grosso, and sorgo production in Tocantins. In Mato Grosso, products with high quality and premium prices are one of the outcomes considered by producers. Environmental factors appear less frequent as outcomes than being considered as driving forces, but the planted areas, the plagues and diseases, and the pressure on pastures are among the perceived results in the complex agricultural systems. International demand, as an important outcome in the aggregated Tocantins FCM, is connected to commodity demand, government incentives, and soybean production, indicating that producers also have a relatively complex recognition of international trade relations.

Not surprisingly, soybean production has the highest centrality among all ordinary factors (and the highest centrality among all concepts). Perhaps the most interesting results are the self-looped relationship of soybean production. In Tocantins, soybean production is in a positive loop with productivity, planted area, economic stability, and workforce qualification. More production will likely expand the agricultural areas. In Goiás, a similar loop relationship appears between profitability and agricultural area expansion. A positive relationship between soybean production and productivity also appears in Goiás and Mato Grosso. However, there is a negative loop between soybean production and soybean price, resembling the classic demand-supply dynamics in economics. Profitability has the second highest centrality in both Mato Grosso and Goiás. The second highest-ranked ordinary factor in Tocantins is risk. Factors, including more extreme climatic events, lower soybean production, fewer cattle, less stable soybean price, and less access to irrigation, all contribute to higher risk, while higher risk contributes to a less secure economic stability. More key concepts across different states can be found in Table S2, where we summarized concepts that appeared more than twice in the states, to provide better descriptions across the states.

3.2. How climate and trade scenarios affect local land-use changes

3.2.1. Most affected concepts and relationships by demand changes

The heterogeneity among producers' perceptions of trade and climate results in various impacts on land use and production systems (Fig. 5 and Figs. S3, S4). The most noticeable pattern is that not many relations are significantly affected (bigger than 1%) in the trade scenario of Mato Grosso, only tax and supply would change more than 1%. However, the impacts of demand are affecting vast concepts and relationships in Goiás and Tocantins. More international demand will not only have a positive impact on agricultural expansion and export, but also improve other factors including self/third party storage facilities, and access to credit and future contracts, in Goiás. In Tocantins, relations between land-use change variables and trade are also pronounced (e.g., maize production, and agricultural area expansion), compared to Mato Grosso. Another interesting pattern is that international demand is perceived as the opposite of the national demand by producers in Tocantins.

3.2.2. Most affected concepts and relationships by climate change

The most distinct pattern in climate scenarios is the perception of risk, which is shown in two out of three states. More extreme climatic events will increase the appearance of plagues/fungus significantly and therefore require higher agricultural insurance in Goiás and Mato Grosso and higher cost of production in Tocantins. This scenario also shows a negative impact on second-crop maize (or sorgo) production and productivity by almost 10%, and reduced total agricultural production by more than 10% because it decreases the suitability for the second harvest and requires less promptness of the planting and harvesting timing. This negative impact on soybean and maize production is also linked with more agricultural plagues and diseases, and more uncertainty of information needed to ensure a good harvest.

3.3. Which driving factors appear most influential for land-use change under trade and climate change

We conducted a series of expanded trade and extreme climatic events scenarios, which included improved drivers across three states. We compared to what extent these improvements would affect land-use intensification and agricultural expansion, in both baseline scenarios and under global changing scenarios. To simplify the results, we reported the percentage changes from both global drivers and local drivers in the supplementary material (Figs. S3 and S4); here we only show the impact of improving local drivers under global change scenarios, to highlight the mitigation effects to future risks.

3.3.1. Leverage points for land use changes under demand uncertainty

We ran expanded trade scenarios with improved top drivers, while we set the demand to be more in three states (Figs. 6 and S3). Technology drivers, such as improved seed varieties, would have more significant impacts on land-use change compared to other drivers. These technological advancements can lead to a notable increase in agricultural production and productivity, thereby expanding the planted area [e.g., land use efficiency increase by double cropping] and reducing the need for further agricultural expansion. For instance, in Tocantins, such improvements would increase productivity by 5% and limit agricultural expansion by 4%.

On the other hand, we observed that improved information communication has varying impacts across the three states. It has no impact on land-use changes in Mato Grosso, a neutral impact in Tocantins, and may contribute to agricultural area expansion in Goiás. Interestingly, we found that increased access to credit and insurance (middle panel, social) may result in more pasture degradation than crop intensification in Mato Grosso. In Tocantins, it was surprising to note that better insurance and credit also contribute to less maize production under a more soybean demand scenario.

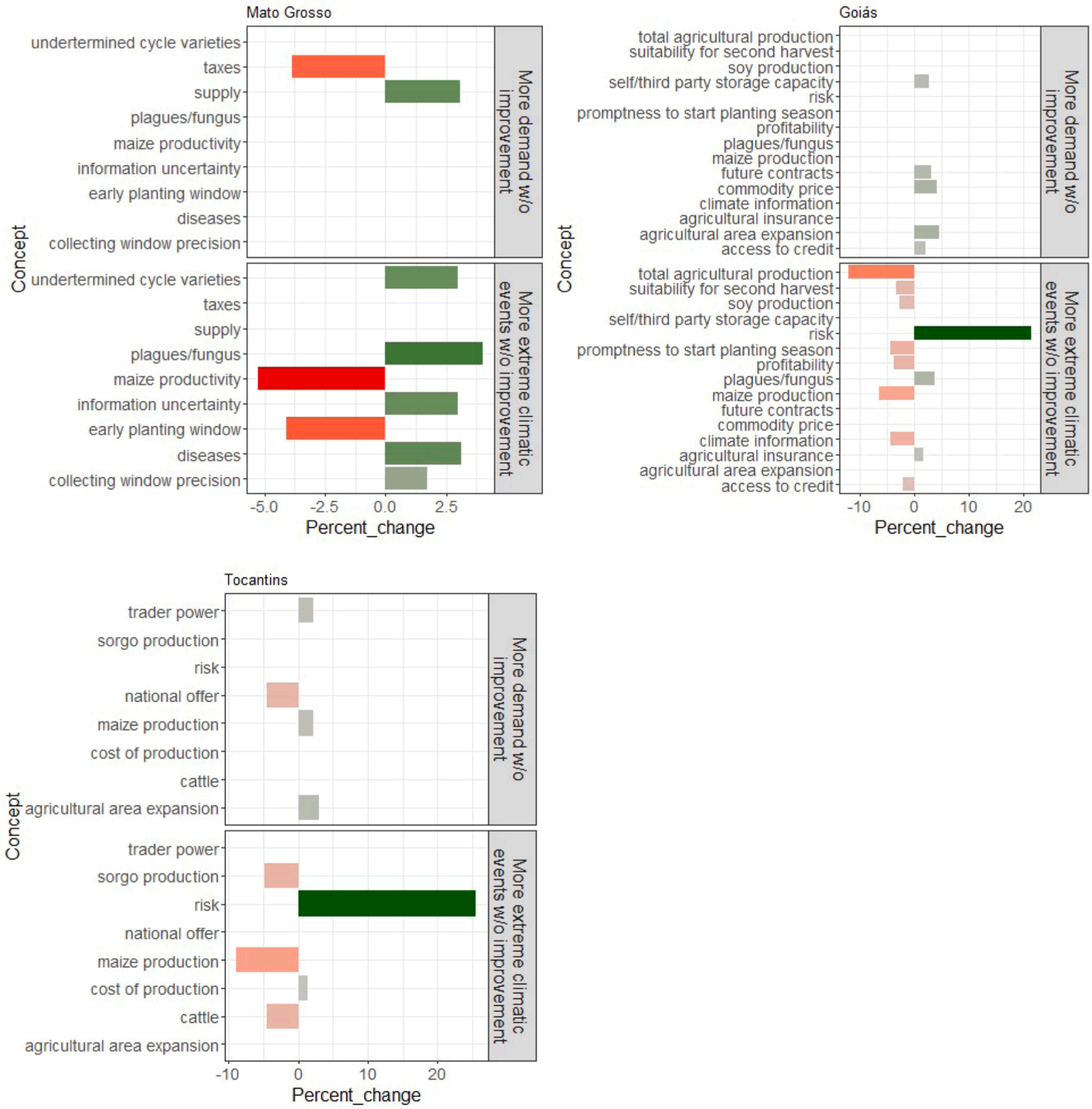

Fig. 5. Differences between climate and trade scenarios and baseline (current condition) scenarios for the three states. The y-axis indicates the concepts that are being affected by commodity demand and extreme climatic events. The x-axis indicates the direction and magnitude of change, relative to the baseline scenarios that all concepts are in current states. We only reported changes that are larger than 1%.

3.3.2. Leverage points for land use changes under climate change

Under climate change scenarios, our analysis suggests that most improvements may lead to more agricultural expansion rather than intensification (Fig. 7). The exception to this is the improvement of technology drivers, which was also the most significant driver in the demand scenarios. Our results indicate that the technology driver improvement can reduce agricultural expansion by 0.5% in Goiás and 3% in Tocantins.

However, we also found that some improved drivers will cause more agricultural expansion than their contribution to productivity. For instance, in Goiás, information sharing and access to credit can lead to an almost 5% increase in agricultural expansion. Improved social drivers, in general, show positive impacts on pasture in both Mato Grosso and Goiás.

4. Discussion

4.1. The importance of climate change and trade in local producers' perception of land-use change and agricultural production

Both the analyses of model content and the scenario simulations suggest that climate change, particularly in the form of extreme climatic events, is becoming a more forceful driver shaping agricultural production in Brazil. Climate change is the most important contributor to their risk perception. The concept of "extreme climatic events" is the single most influential driver in Goiás and Tocantins, as well as among the top five ordinary factors in Mato Grosso (Tables 4 and 6). Interviewees mentioned climate variables many times. For example, in Tocantins, one respondent stated that "*In recent years the lack of rain has become the most important factor for the loss of production*". Farmers may have experienced more frequent and more severe droughts and other climatic events than before (Silva et al., 2017; Marengo et al., 2022). This is also in line with the climate data, showing consistently increasing patterns of warm extremes and consecutive dry days (Avila-Diaz et al.,

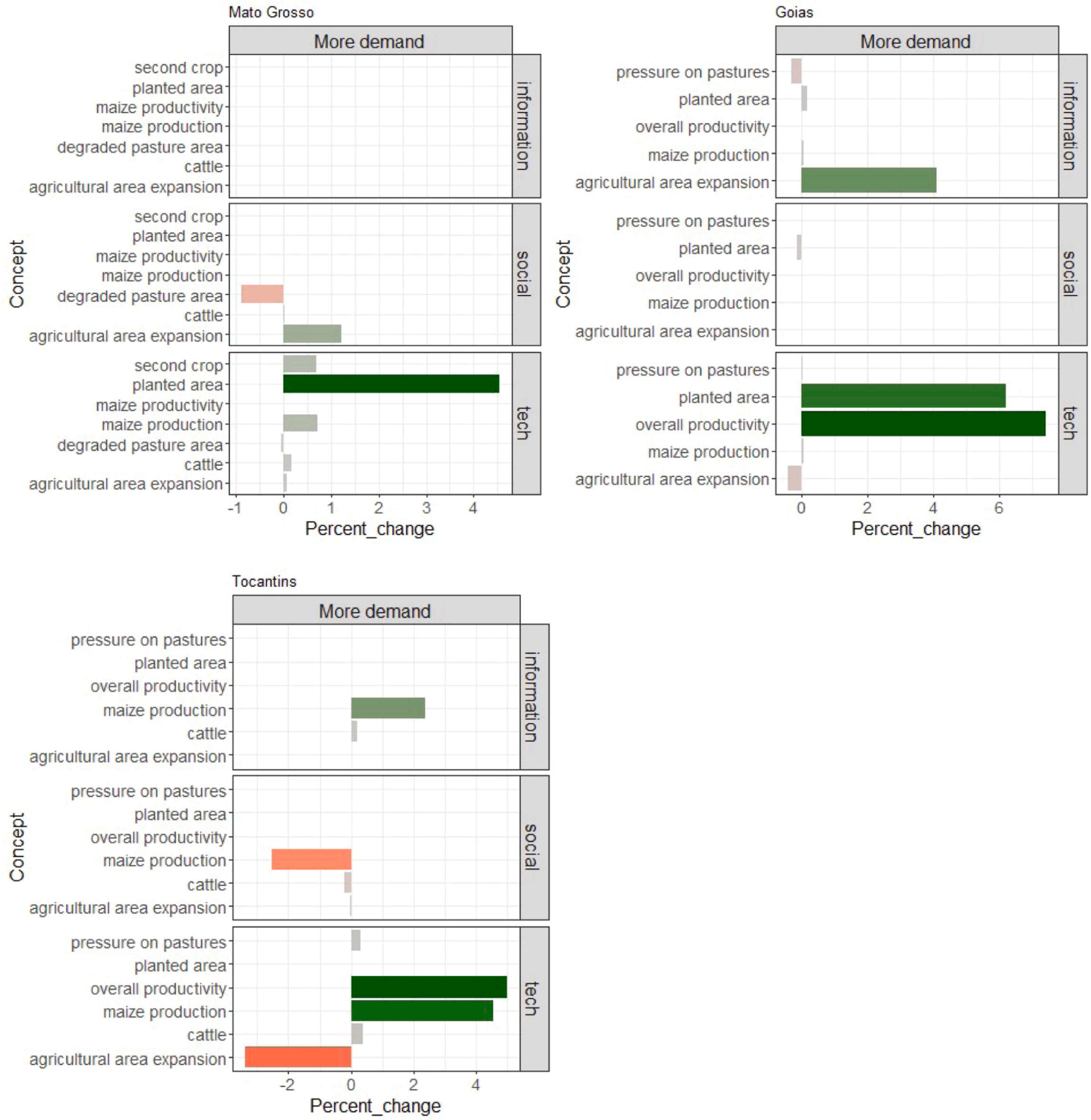

Fig. 6. Impacts of drivers under more trade scenarios. Within each panel, the percent change (x-axis) shows the change magnitude that the improved drivers would have on land-use change and intensification under the more demand scenario.

2020). Results from the scenario analysis clearly indicate that farmers are aware of the strong impact of "extreme climatic events" on many aspects of their farms (Figs. 5, 7). These impacts include the spread of plagues and diseases among their crops, and the productivity of the crops in the second growing season (more so than soybean production in the first growing season). A stronger negative impact on maize yield than soybean yield is captured by our model [e.g., Fig. 5 shows that in Mato Grosso and Goiás, maize productivity and production are negative but changes to soybean productivity are insignificant], which is in line with climate change simulations (Spera et al., 2020). The climate extremes also affect cattle production (e.g., Tocantins) and access to credit (e.g., in Goiás). These indirect impacts may not be discovered if not for using FCMs. From the FCMs, it is also clear that farmers appreciate climate predictions, require more prompt and accurate information, and they are willing to try new technologies to cope with the negative climate change impacts.

The process and functionality of trade in producers' perception are different from climate change. First, most trade-related concepts are in the ordinary factors (Table 6), unlike those in climate change which are often drivers. Soybean production is shown as the ordinary factor with the highest centrality in all three states (Table 6). This means that soybean production is central to all the concepts and relationships. Profitability and stability are also among the important ordinary factors. Producers acknowledge the importance of trade to local socio-economic development, including the reinforcement of local infrastructure and schools (Table 5, Tocantins, and Table S2). The importance of soybeans for socio-economic development has been noted in previous studies (Garrett and Rausch, 2016; Martinelli et al., 2017; Richards et al., 2015).

Another important perspective is the joint impact of climate events and trade. Sometimes producers are unable to adjust their planting behaviors or respond to a forecast of an El Niño weather pattern a year in advance, for instance, because they are beholden to traders to sell their products. Producers are often strongly tied to other supply chain actors (e.g., banks that provide financial credit, or traders whom they signed future contracts with), therefore reducing their maneuver capacity to decide when and which amounts to produce — the so-called soybean trap (Silva et al., 2020). This is more relevant to some producers in Tocantins and Goiás than in Mato Grosso since they have suffered more

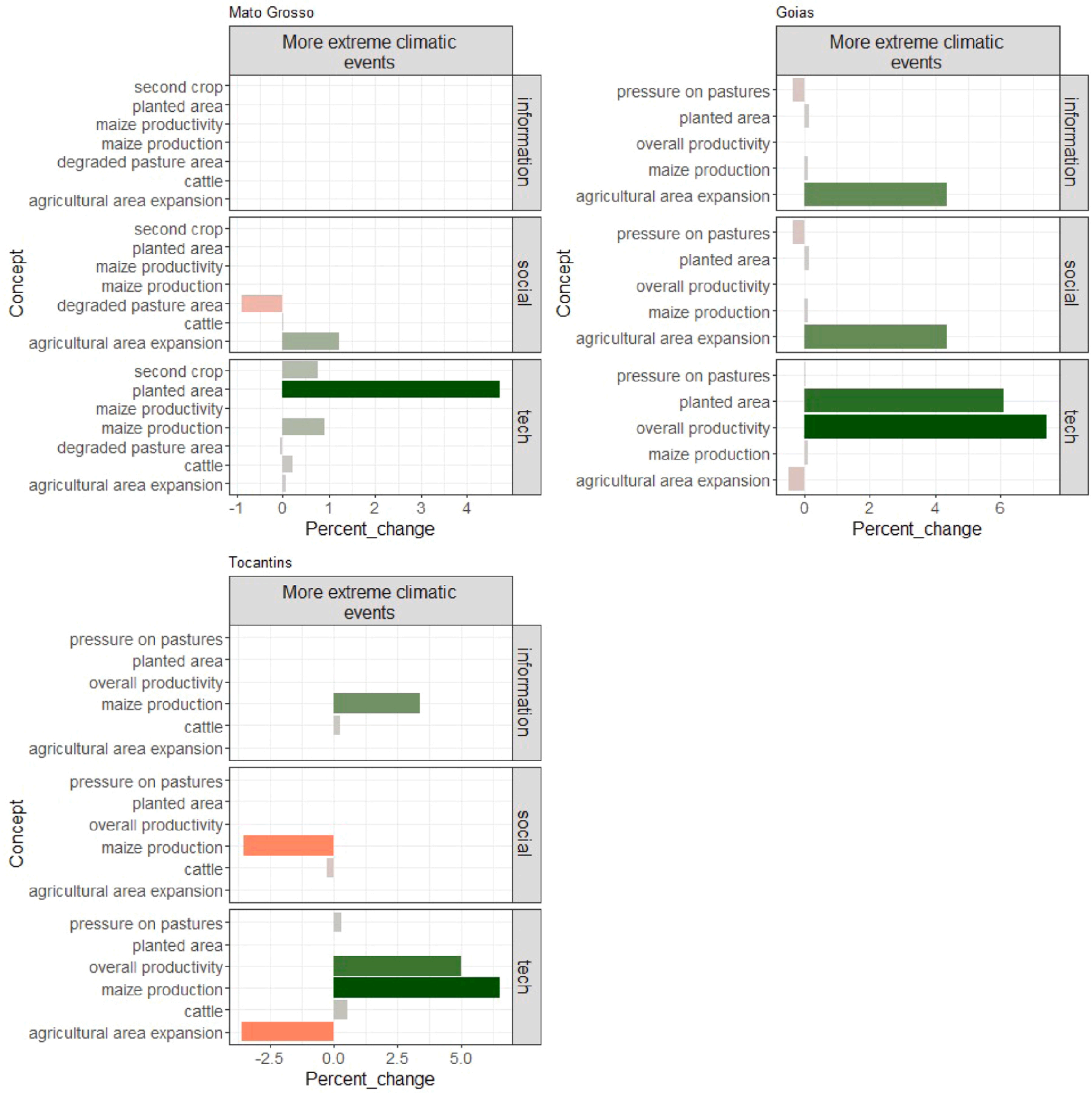

Fig. 7. Impacts of drivers under more climate change scenarios. Within each panel, the percent change (x-axis) shows the magnitude of changes the improved drivers would have on land-use change and intensification under the increased extreme climatic events scenarios.

severe droughts. However, climate extremes will affect all regions to some extent in the future. How to facilitate producers dealing with climate change may take a plural-perspective, for example, on the provision of an alternative trade format and on agricultural divesification.

Trade affects local land-use change through multiple channels and mechanisms. Trade not only increases soybean production, but also positively spillovers to other crop productions through the intensification via the double-cropping practice (e.g., increased maize production), or the self/third storage capacities. Climate change, on the other hand, leads to more negative impacts overall.

4.2. Leverage points that may play an important role in climate change and trade uncertainty

By using FCM's structural indexes and the model simulations, we systematically compared several local and regional factors that are important in farmers' decision-making in the agricultural frontier. Among transmitters with the highest centrality, variables related with technology such as soybean cycle duration and seed/tech packages can affect the land-use change more than the socio-economic variables such as rural credit. For instance, if better soybean seed varieties can be developed, we will see an increase in soybean planted areas (almost 10% impact) in Goiás. All the improvements have larger impacts under climate change scenarios than in trade scenarios. It is essential to note that compared to the baseline, all three states are likely to suffer severe productivity reduction scenarios (see Fig. S4). The improvement of drivers can reduce the loss. This knowledge could be useful in several ways: ecological variables are more powerful than socio-economic variables to leverage the whole system, particularly the land-use changes; improvement in certain variables can increase farmers' capacity to cope with both trade and climate change uncertainties, more so when the global force is on the negative side.

In addition, we highlight the social-economic improvements, including "access to credit" and sharing climate information (**top and middle panels of** Figs. 6 and 7). Literature have widely discussed efforts from the supply-chain side (e.g., supply-chain configuration and voluntary agreements) on affecting land-use changes in the Amazon and Cerrado regions (Garrett et al., 2013; Gibbs et al., 2015), yet other potential assistance from other actors (e.g., credit from government and sharing information more accurately and timely) that can be relatively easily provided to producers with great leverage potentials for environmental sustainability have not received attention. The Brazilian federal government provides highly subsidized credit to rural producers through the National Rural Credit systems. The importance of this credit has been shown in the FCMs as an important ordinary factor (Table 5) that is strongly affected by trade (Fig. 5) and climate change (Table S4: aggregated state model of Goiás), positively affecting the second harvest and total production, and reducing the risk perception of producers (Fig. S2).

Despite the importance of credit, it is not always the most sustainable option under climate change futures. Having better access to credits, although could mitigate climate risks, may lead to more agricultural expansion. Therefore, improving the accessibility of credit with environmental strings may benefit producers in achieving stable agricultural production and environmental conservation under the climate and market risks. Moreover, more environmental strings can be attached to the provision of credit, including the adoption of green cover crops to improve soil conditions, water retention, and crop productivity (Andrade et al., 2021). This can be complementary to the legal reserve and voluntary supply-chain agreement. Many producers also commented on the storage capacity as the main constraint for their expansion of production, which is identified in previous studies (da Silva et al., 2020). This calls for better infrastructure development.

4.3. Heterogeneity among the producers from different states

Just as no two snowflakes are the same, no producers' perceptions of the land use and agricultural production are the same. This is shown by the structure and complexity of the individual FCMs (Table S1). Some models have a relatively low connection and complexity (e.g. No. 17 has only 11 concepts and nine relationships mentioned). On the other hand, some models show a complex relationship, resulting in more than 30 concepts and relationships being discussed during the interview. Interesting enough is the difference shown among producers from the three states. Producers from different states, although sharing some similarities, show more differences across the states in both model complexity and important concepts and relationships. This is particularly true that producers from Mato Grosso have a higher number of receivers than the average of the other two states (Fig. 4). This indicates that when making decisions, producers from Mato Grosso may have more goals to meet or criteria to consider. It is also worth noting that trade in Mato Grosso, compared to the other two states, has a less important role in the overall perceptions. Drivers related to trade, such as profit, price stability, and demand are more often mentioned and with a relatively higher value in the other two states than in Mato Grosso (Table 3). This may be explained because Mato Grosso is among the earliest developed state and has more established trade relationships with soybean buyers. Producers in Mato Grosso are transitioning to a more management- and development-oriented typology, rather than the early explorers in Tocantins. The heterogeneity is further emphasized by the scenario simulations with different trade, climate change, and improvements. For example, the improvement of soybean cycle duration may not change agricultural expansion in Mato Grosso, but may be more effective to decrease the expansion in Goiás under more extreme climate events scenario. This may be explained by the special land use in Goiás (direct quote from the interview):

> "Producers in the state, in general, already adopted several practices to intensify production (and increase productivity) in areas under production (with soybean and maize), but due to the international demand for grains, there is now a tendency to expand new areas to meet this demand.
>
> Land in the State of Goiás has a better opportunity cost for opening compared to Tocantins, as there (in Tocantins) the requirement of Legal Reserve (i.e., a percentage of the rural property to be spared for conservation of natural vegetation according to the Brazilian Forest Code) is 35% of the property, while in Goiás it is only 20%. It is a 15% advantage in relation to the potential production area."

4.4. Using FCM in land-use changes

FCMs have been increasingly used in studies of land-use changes and sustainability in recent years, particularly in interdisciplinary research projects that involve stakeholders and experts from multiple fields. The main purpose of this study is to use FCM to map the mechanisms through which telecoupled processes affect local producers' perceptions and land-use changes. The FCM approach allowed us to identify a wide range of concepts and aspects that global forces shape local land-use changes, which may not be visible using other approaches that lack the stakeholders' engagement. The results are reinforced by literature on agricultural intensification asserting that the soybean trade promoted the wide adoption of the second growing season of other crops, which shows its importance in the overall agricultural production and conservation potential. During the interviews, we avoided using scientific terms such as "coupled human-natural system" or "socio-ecological system," yet FCM results indicate that producers are well aware that their agricultural profit and production are affected by both bio-physical factors and socio-economic conditions, and that their actions will impact both. For example, a producer in Mato Grosso stated: "*Soybean monoculture brought many problems, especially due to damages to the soil.*"; "*When you improve the organic matter in the soil composition (through good management practices including diversification), it functions in the soil as a sponge (to store water) and this reduces the risk of climate events (such as short-term droughts)*".

Although our research provides insights into producers' perceptions about the complex land-use changes in a dynamic Brazilian agricultural region, there are several limitations that we hope to address in the future. First, we are not able to link the FCMs with real landscape changes due to confidentiality issues, hence we cannot interpret the FCMs through the farm-level change trajectory. In our study, we also did not include any representatives from corporations and supply-chain actors. Although all farmers were interviewed by the same team of scientists, the interviews among the 27 producers were carried out in two different years (i.e., Goiás and Tocantins in 2016 and Mato Grosso in 2017) when climate conditions may have introduced biases to the producers' answer. The FCM method and the models constructed later are influenced by the temporal bias as pointed out by the literature (Reckien, 2014). This could have introduced biases caused by the recent drought events some producers experienced. Although we went through validation with producers during the interviews, it is best to have a time lag between these events and the interviews. We assumed trade and climate extreme events as shocks in the scenario simulation. However, FCM cannot assume the shocks a system may not yet know. Therefore, the models may not capture certain impacts that a real extreme shock could have caused. Moreover, the FCM method is not able to capture how the shocks propagate through the non-linear relationships between nodes or the time delays between the status changes of these nodes. All these can be useful information to design adaptation and mitigation strategies when a shock hits the land-use change system. All these caveats may contribute to the uncertainty in our results. However, the patterns observed in the individual and collective models are valid to demonstrate the complexity and heterogeneity of how producers perceive global drivers on local land-use changes.

The way we analyzed these models contributes to the FCMs in bridging stakeholders and researchers. Often FCMs are constructed in a workshop with a group of stakeholders (Gray et al., 2015; van der Sluis et al., 2019). The FCMs are already models of collective thoughts and perceptions that blur heterogeneity among individual stakeholders. One of the less-utilized advantages of the FCM is its ability to incorporate multiple stakeholders' views and perceptions. Through its semi-quantitative form, it can encode multiple actors' different perspectives and ideas into a standardized format. We collected our FCMs with each individual producer, aiming to capture the individual perceptions and identify differences between individuals and across regions. This enables the integration of communities and stakeholders from different fields and disciplines into one model and thus is more inclusive of different types of knowledge and representations of stakeholders.

4.5. Policy implications and recommendation

The soybean producers' perspective on the process of land-use change and risk in a Brazilian important agricultural powerhouse bring insights into understanding how global forces affect local landscapes. Through the interactions with producers and stakeholders for the construction of the FCMs, factors involved in agricultural production and cognitive processes are revealed.

The results of the FCMs demonstrate the complex interactions through which global forces, such as international trade and climate change, affect local and regional land-use change. Concurrently, differences shown in individual and collective FCMs call attention to varied perceptions among producers across the selected neighboring states in Brazil.

These findings imply that, although national policies are needed to regulate land use and environmental conservation (e.g., the Brazilian Forest Code), they fail to capture the myriad of perceptions and priorities of local farmers. Our relatively small sample size in terms of interviews, but huge in terms of the area managed by the interviewed farmers and stakeholders, is already enough to show the need for place-based policies.

Therefore, our recommendation for policy-makers is to co-design a multitiered policy system for Brazil taking these local and regional differences into consideration. For example, the Forest Code uses the limits of the Brazilian biomes to set a certain percentage of the farm area to be kept with native land cover (i.e., the so-called "legal reserve"). But other instruments, focusing on information sharing and insurance, for example, could be regulated at the state or the municipality level, on top and in compliance with the federal regulation. These other policy instruments can also be grouped with environmental strings, to promote producers' capacity to mitigate climate change as well as conserve the environment.

It is of national interest to be the main global exporter of agricultural commodities, but it is of individual producers the risk of dealing with the expected growing demand for agricultural commodities and the previously unexpected extreme climatic events. For that reason, a decentralized bottom-up policy-making and governance approach that has been called for (Lundquist et al., 2021; Meynard et al., 2012; Pereira et al., 2020) should arise from the integration of qualitative and quantitative methods, as used in this research.

5. Conclusion

Land-use changes are affected by global and local driving forces. The Brazilian agricultural region addressed here is highly dynamic, where food security, livelihood, land degradation, conservation, and ecosystem services are all at play. Our results are among the first attempt to understand the complex decision-making directly from local actors. This contributes directly to current land system research trends calling for a more nuanced investigation into human agency and spatial heterogeneity in land-use modeling. Stakeholder insights gained from the FCMs can be used to guide policies and governance towards leverage points for both agricultural intensification and environmental conservation, taken into consideration through the intertwined global and local forces. Producers acknowledged climate change via a range of concepts and relationships, showing interest in climate adaptation and mitigation actions. International trade was considered the most important driving force of deforestation in the region. Yet the FCM results suggest the impacts of climate change are way beyond the impacts of trade, in both magnitude and breadth. There are potential aspects in the complex land-use process that policy-makers and other stakeholders can work on as leverage incentives for environmental conservation and agricultural intensification to address these global challenges. Our results show that improvement in socio-economic and technological domains can work as adaptation and mitigation for future uncertainties, particularly under climate change risks. However, the magnitude of these impacts may vary.

This study shows that understanding how farmers think and perceive these drivers shed light to other approaches without the participation of stakeholders. The insights on the complexity and heterogeneity of land actors' perceptions, revealed by FCMs, bring crucial perspectives and solutions when searching for leverage points towards balancing environmental conservation and agricultural development. Our contribution offers stakeholder-centered perspectives regarding trade and climate change and provides bottom-up examples of how coupled forces affect local and regional land-use changes, thus requiring multiscale innovation in land-use policy-making.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used ChatGPT in order to improve the abstract. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Declaration of Competing Interest

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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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.landusepol.2023.106862.

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