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Modelling dynamic effects of multi-scale institutions on land use change

Sascha Holzhauer[1,2] · Calum Brown[1,3] · Mark Rounsevell[1,3]

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Abstract

Formal institutions impact on the dynamics of land use change through their objectives, actions and decision-making processes in response to socio-economic or environmental changes such as climate change. The effects and interplay of these actions are not fully understood, and hence, institutional processes are rarely integrated in modelling analyses of land use change. The complex effects of institutional interactions within land systems can be better understood through modelling approaches that address the heterogeneity of the institutional actors involved and how their decisions affect temporal and spatial dynamics. In this paper, we present an agent-based model of autonomous land managers interacting with institutional agents at two spatial scales. We explore different parameters of institutional intervention (subsidy rate, triggers for action, delay in monitoring, scale-based precedence) under socio-economic drivers and analyse key metrics such as the maximum over- and undersupply of ecosystem services, connectivity of land uses, and degree of change in land use patterns. Levels of subsidy and action triggers have the greatest impact on the magnitude of land use change and the maximum oversupply of ecosystem services. In terms of achieving institutional objectives, subsidy rate is the most important single parameter in the model. Furthermore, we find non-linearity with variations in parameters that have important implications for current land use change modelling and requirements for empirical studies of land use planning institutions. Finally, the effects of high-end climate change may require entirely novel institutional behaviours.

Keywords Land use change · Governance · Formal institutions · Decision-making · Complex socio-ecological systems · Agent-based modelling

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✉ Mark Rounsevell
mark.rounsevell@kit.edu

Sascha Holzhauer
sascha.holzhauer@uni-kassel.de

Calum Brown
calum.brown@kit.edu

1 School of GeoSciences, University of Edinburgh, Edinburgh EH8 9XP, UK

2 Integrated Energy Systems Group, Department of Electrical Engineering and Computer Science, University of Kassel, Wilhelmshöher Allee 73, 34121 Kassel, Germany

3 Karlsruhe Institute of Technology, Institute of Meteorology and Climate Research, Atmospheric Environmental Research (IMK-IFU), Kreuzeckbahnstr 19, 82467 Garmisch-Partenkirchen, Germany

Introduction

Understanding the land use system and its possible future development is crucial for the design of effective environmental policies. This is especially important as the dynamic nature of climate (Porter et al. 2014), demography (e.g. through migration and ageing) and consumption patterns (Mulligan et al. 2014) increasingly have substantial impacts on the land use system. More rapid socio-economic disturbances such as economic crises or policy changes, e.g. following the collapse of the Soviet Union (Hostert et al. 2011; Prishchepov et al. 2012) can also have dramatic effects on land use. Effects on land use are likely to be particularly large under high-end climate change, not only due to changes in the productivity of land but also due to changes in demand for ecosystem services arising from population dynamics (Mulligan et al. 2014; Stürck et al. 2015). In turn, changes in land use affect the provision of ecosystem services such as carbon storage (Robinson et al. 2013), habitats (Butler et al. 2007) and the non-material benefits of landscapes.

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Land use dynamics are tightly interlinked with the activities of formal institutions such as governmental agencies or non-governmental organisations at different spatial levels (Lambin et al. 2001). While local conditions and land manager decisions are responsible for the actual distribution of land use change, regional and (supra-)national institutional and market processes inform these local decision processes (Verburg 2006; Willemen et al. 2012). The extension of intergovernmental regimes in global governance of the environment by civil society organisations (CSOs), expert networks, and multinational corporations during recent decades has increased interaction amongst these actors and policy levels. The complexity of interactions has also increased because of overlap in regulatory content and the dissolution of the principle of territoriality (Pattberg and Widerberg 2015). For instance, the spread of organic farming is supported by a mix of policy instruments such as subsidies, product labels and advice, implemented by governmental bodies and non-governmental organisations (Stolze and Lampkin 2009; Jaime et al. 2016). Furthermore, institutions play a key role in adaptation to climate change, with objectives including securing ecosystem service provision, the dissemination of effective adaptation strategies, and smoothing out shocks. Multilevel coordination and the interplay between governmental, administrative agencies and the private sector are important aspects in determining the adaptive capacity of individual land managers (Mimura et al. 2014; Nay et al. 2014).

Imperfect knowledge arising from delayed or inaccurate monitoring, susceptibility to lobbying, imperfect rules for triggering actions, and expectations about intervention timescales affect the ways in which institutions intervene. For example, hierarchical governance structures can lead to mismatches between the objectives of policy makers and bureaucrats at a local level (York et al. 2006). Additionally, the design of interventions is hampered by uncertainty of climate change and population dynamics, untested strategies, and time lags in implementation (Lyle 2015; Koontz et al. 2015). At the same time, institutional action may have severe unintended effects on the provision of ecosystem services through path dependencies (Pierson 2000), e.g. when legacies of a previous policy supporting a certain land use prevent future more holistic interventions (Howlett et al. 2009). Furthermore, institutions change over time, interact with one another and operate at the regional, national or international levels in linked, but distinctive ways (van Zanten et al. 2013) (see section 3.4 in Rounsevell et al. (2014) for a discussion of institutions in land systems).

Understanding the interplay of institutional actions at different spatial levels within the land system is therefore challenging (Paloniemi et al. 2012), and projecting their impacts more difficult still. Moreover, high-end climate change requires transformative solutions and, accordingly, tools that address multiple feedbacks, irreversibility, non-linearity and tipping points (Tàbara et al. 2018). The necessary simultaneous assessment of policy processes, applied practices, drivers, impacts and uncertainties can be supported by dynamic modelling, which also allows for the exploration of various socio-economic and environmental scenarios (Balint et al. 2017). Crucially, such an approach enables the representation of institutional actions, the omission of which may lead to biased or misleading simulation results (Parker et al. 2003; Manson 2005).

Dynamic models have a number of important requirements. Investigating direct or indirect interactions between multiple institutions at different levels or with different preferences requires their explicit inclusion within models. In terms of adaptation to global change, explicit consideration of triggers that motivate action, and time lags that limit their effectiveness, is necessary (Holman et al. 2018). There is also a need to incorporate constraints related to imperfect knowledge or limitations of power that operate in the real world.

Agent-based models (ABMs) are able to satisfy many of these requirements. They can represent the heterogeneity of system entities such as land managers and formal institutions in terms of attitudes, objectives, strategies and actions, amongst other characteristics (Wilson and Hart 2000; Arneth et al. 2014; Morgan et al. 2015; Mercure et al. 2016). Moreover, agent-based modelling allows the isolation of particular mechanisms and therefore the identification of efficient ways to improve institutional decision-making. Such models have been used, for example, to explain inefficiency in policy uptake arising from decision-based time lags (Alexander et al. 2013; Brown et al. 2016).

However, in spite of the importance of institutions in affecting land use systems, they have not yet been represented as autonomous, responsive entities in large-scale land use change models. Instead, institutional actions are usually represented as external drivers, with simulations conducted under fixed assumptions about policy interventions in distinct runs that are compared afterwards (Rounsevell et al. 2014). Only a few models have attempted to represent institutions as explicit entities that are able to interact with the land use system (Schulze et al. 2017; Brown et al. 2017). For example, Schouten et al. (2013) compared the impacts of agri-environment scheme (AES) payments on habitat networks in the context of volatile milk market conditions, but did not allow institutions to react to network configuration. Caillault et al. (2013) found various effects of isolated and combined incentives on land use patterns at global, intermediate, and local levels, but again did not model responses to system dynamics. Polhill et al. (2013) explored the performance of four government agents' strategies in providing incentives to support biodiversity in a small, abstract model region. While their modelled subsidies varied according to land manager activity and species' occurrence, the strategies themselves were static over time.

Here, we present a mid-level ABM (O'Sullivan et al. 2015) that integrates formal institutions as autonomous entities at 'global' and regional-scale levels ('global' is used here to refer to the full geographic extent of the modelled area). Institutions are designed in the model to perform actions according to their preferences and knowledge of current conditions, therefore allowing for crucial feedbacks in the land use system. The purpose of this paper is to explore how institutional action can be better represented in models of land system change and to investigate the institutional dynamics that arise from this improved representation especially in interactions across spatial-scale levels. Identification of the most important parameters in terms of the interventions' effectiveness towards institutional objectives is ultimately intended to highlight sensitivities and effective adjustments in real-world institutional action.

Methods

We apply CRAFTY SIRIOS,[1] an instance of the CRAFTY-CoBRA[2] modelling framework, to undertake experiments in institutional processes (see Online Resource 2 for an ODD+D (Müller et al. 2013) description and Fig. 1: for a schematic overview). CRAFTY-CoBRA is a derivative of the CRAFTY framework (Murray-Rust et al. 2014; Blanco et al. 2017a, b) that is able to represent decision-making for a wide range of institutional actions. The model takes initial land use and capital levels (human, social, financial and manufactured capital) as well as the societal demand for ecosystem services over time and simulates outputs of land use change and the supply of ecosystem services. Subsequent sections describe the model region, the way land managers are represented as agents, institutional agents' decision-making and their preferences, and experimental design.

Model region

Land use change was simulated annually over 30 years (because input data is limited to that period) in three adjacent administrative regions (NUTS-2[3]) with a total area of 26,296 (8628, 8316 and 9352) cells of 1 km^2 each (see Fig. 1 in Online Resource 1). This spatial domain is large enough to apply institutions meaningfully at regional and global levels, and spans a range of land covers and uses, with similar areas of intensive and extensive cropland and grazing as well as forest. The initial land use is that of 2010, based on the CLUE (Stürck et al. 2015) land cover data (Institute for Environmental Studies 2016a) and agricultural land use intensity (Institute for Environmental Studies 2016b).

Representing land managers

Different kinds of land managers are represented by agent functional types (AFT), comprising a behavioural component (BC) that describes decision-making and a functional role (FR) that describes land use, i.e. the set of provided services and associated productivities. This is based on the concept of human functional types (Rounsevell et al. 2012; Arneth et al. 2014) that identifies different types from distinct functional roles, decision-making strategies and preference sets. We define extensive and intensive cereal and livestock farmers as well as forest managers as broad AFTs (Brown et al. 2016), all with simple rule-based decision-making (these AFTs are listed with their parameter values in Online Resource 1, Table 1). In this semi-abstract setting, the heterogeneity of land managers within AFTs is captured by drawing parameter values from AFT-specific, random distributions.

We consider the provision of the ecosystem services cereals, meat, and timber. Production of each service λ^c is modelled by a Cobb-Douglas-style function (Douglas (1976); see Eq. (1)), taking into account capital sensitivities λ_s^c and optimal production o_s (see Online Resource 1 Tables 2 to 6). Six capitals (crop productivity, livestock productivity, forest productivity, infrastructure, economic capital, natural capital) are used to model the productive potential of land (see Online Resource 1, Fig. 2 and Table 7 for initial values and data sources). Extensively managing functional roles have lower sensitivities to capitals, but also lower optimal production levels compared to intensively managing functional roles. Thus, compared to intensive farmers, extensive farmers are more successful on less productive cells, but less successful at more productive locations.

$$p_s = o_s \prod_{i \in C} c_i^{\lambda_s^c} \tag{1}$$

The benefit functions (Online Resource 1, Table 8) determine the value of the production of an additional unit of a particular service, given the service's residual demand (the difference between defined demand and the previous year's supply). Demands for each region were set to match service supply of the initial land use map (based on given production functions and capitals data) and then varied over time in response to a set of scenario assumptions (see Online Resource 1, Tables 9 to 11). This approach was used to drive the model dynamics and was not intended as a comparative scenario exercise. Land manager agents compete for cells according to their production of services and their preferences for abandoning (giving up) their land management and allowing a change in management (giving in). The giving-up threshold specifies the benefit value below which land managers leave

[1] Competition for Resources between Agent Functional TYpes in SImulation of Responsive Institutions On multiple Scales

[2] Competition for Resources between Agent Functional TYpes with COmponent-Based Role Agents

[3] NUTS (Nomenclature of territorial units for statistics) is a hierarchical classification of the economic territory of the European Union. NUTS-2 designates basic regions for the application of regional policies (eurostat 2016).

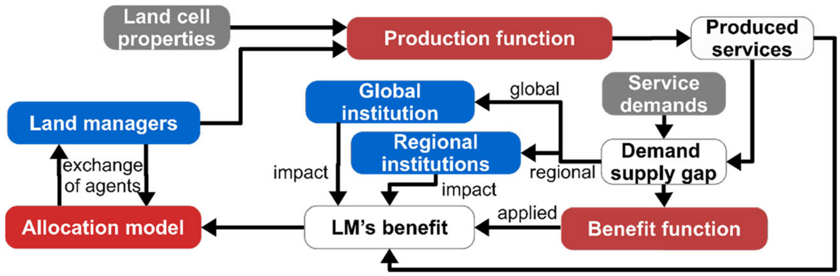


Fig. 1 A schematic description of the structure of CRAFTY SIRIOS. Blue boxes are agents, red boxes are other CRAFTY components, white boxes denote variables and grey boxes are externally defined parameters. Arrows represent data flows, if not labelled otherwise. Land managers produce services according to their production function based on the properties of the cell they manage. Together with regional demand for services the productions determine the demand-supply gap which enters into the benefit function and is considered by regional and global institutions for their decision about which functional roles to subsidise. The allocation of new land managers is based on benefit values

the system. Where the incumbent agent's benefit is lower than the benefit of a competing agent minus the giving in value, the competing agent takes over the cell. Probabilities for giving up and the allocation of unmanaged cells introduce time lags, reflecting delayed reactions to market conditions partly motivated by the costs of land use change.

Institutional agents' preferences and behaviour

A 'global' and three regional institutions were defined, with the objectives of service supply meeting demand 'globally' and regionally, respectively. These institutional agents were able to monitor supply and demand, and intervene by subsidising certain AFTs. Once the supply-demand gap of an observed service (cereal, meat, timber) exceeds a defined threshold, an institution triggers a decision-making process to choose an action that is designed to close the gap according to the institution's preferences (see Table 1 for an overview of represented institutions, their preferences, and their potential actions, and section "Individual Decision-Making" in Online Resource 2). Institutions select a single functional role of land managers whose most-supplied service is subsidised in order to increase the land managers' benefits and enable them to take over from other land managers (see Fig. 2). Therefore, institutions interact with land mangers indirectly when they control the benefit from particular services, and land managers respond when they abandon production of certain services and establish production of others.

Four preferences guide institutional decision-making: a preference for less expensive actions (denoted as 'LOW_COST'), a preference for supply matching demand at global level (denoted as 'GLOBAL_DEMAND_MATCHING'), a preference for supply matching demand at regional level (denoted as 'REGIONAL_DEMAND_MATCHING') and a preference for actions assumed to have greater public support (denoted as 'SOCIAL_APPROVAL'). The 'LOW_COST' preference is expressed as a willingness to subsidise extensive, rather than intensive, land managers on the basis that each produces less service and therefore receives less subsidy. To measure a potential action's usefulness for demand matching of each service, institutional agents consider the proportion of cells that potentially can be taken over by subsidised land managers (i.e. where their benefit exceeds that of the incumbent land manager by its giving-in parameter), and assume that they would not be able to take over without subsidies. Furthermore, the relative optimal production of subsidised farmers (o_s in Eq. (1)) and forest managers is taken into account, multiplied by the subsidy rate and the supply-demand gap of the particular service: it is preferable to support those agents that produce relatively more of a service that is needed. Under SOCIAL_APPROVAL, actions are modelled to enhance public support when they benefit larger numbers of land managers and when they benefit extensive, rather than intensive, land managers. The parameter values for the four preferences (see Table 1) have been determined to be representative of different institutional priorities at different scales and, are determined according to plausibility assumptions (see Table 12 in Online Resource 1) and not varied during the experiments presented here. These preference values are important as they characterise differences between potential actions and therefore influence their selection (see Table 13 in Online Resource 1 for an overview of potential actions and details of the calculation of each action's utility values).

The selection of interventions is done deliberatively, with all available actions evaluated: their current utility towards each of the preferences is multiplied by the institution's preference weight and summed to result in an intervention's score (see Table 14 in Online Resource 1 for the evaluation of two potential actions). The highest scoring intervention is selected. This process is modelled by the LARA (Lightweight Architecture for boundedly Rational Agents) framework (Briegel et al. 2012). The decision is boundedly rational in the sense that the evaluation of actions is based on heuristics rather than perfect knowledge of their effects.

Experimental design

We investigated four parameters that influence the institutional decision-making process: coordination between hierarchical

Table 1 Global and regional institutions, their objectives, their preferences which are relevant to evaluate actions, the variables they monitor, their condition for triggering action decision-making and the potential actions they are able to perform

Institution	Objective	Preferences	Preference settings	Monitors	Triggering	Potential actions
Global subsidising institution	Match demand globally	Minimising cost of interventions (‘LOW_COST’); satisfying regional demand (‘GLOBAL_DEMAND_MATCHING’); social acceptability of interventions (‘SOCIAL_APPROVAL’)	LOW_COST = 0.8; GLOBAL_DEMAND_MATCHING = 1.0; SOCIAL_APPROVAL = 0.7	Demand and supply per service	global demand-supply gap > 5% of demand	Subsidise one of the services globally (GlobalSubsidyPa)
Regional provision institution	Match demand regionally	Minimising cost of interventions (‘LOW_COST’); satisfying regional demand (‘REGIONAL_DEMAND_MATCHING’); social acceptability of interventions (‘SOCIAL_APPROVAL’)	LOW_COST = 0.7; REGIONAL_DEMAND_MATCHING = 1.0; SOCIAL_APPROVAL = 0.8	Demand and supply service	regional demand-supply gap >5% of demand	Subsidise one of the services regionally (RegionalSubsidyPa)

levels, the sensitivity of reaction, the degree of revision and the strength of interventions (see Table 2). Coordination between hierarchical levels is simulated assuming that the ‘global’ institution monitors and intervenes during odd time steps (and is therefore the first to act) while the regional institutions act during even time steps (parameter Precedence switched on). Alternatively, institutions at the regional and ‘global’ level act independently at the same time (set of simulations when parameter Precedence is switched off). The sensitivity of reaction is simulated by the Triggering threshold above which a supply-demand gap triggers action and is varied between low and high values, representing fast and slow reactions. The degree of revision refers to the Action lifetime of an implemented action, which takes values of 1 and 4 years. The duration also defines the waiting time for subsequent measures, as institutions are assumed not to be able to perform multiple actions at the same time. Finally, the strength of interventions is simulated in terms of the Subsidy rate, which has a major impact on land use dynamics as it determines the competitiveness of subsidised land managers. Subsidy rate is added to the constant term of the benefit functions (see Table 8 in Online Resource 1).

To evaluate the impact of parameters of institutional action, a set of land use metrics are calculated (see Table 16 in Online Resource 1 for exact definitions and detailed descriptions). These measure the variability of land use (‘Number of land use changes’), the degree of service supply (‘Maximum oversupply’, ‘Mean oversupply’, ‘Mean undersupply’ and ‘Mean regional undersupply’, all relative to the demand of a particular service), impacts on conservation (‘Proportion of extensively managed cells’) as well as efficiency of institutional action (‘Number of performed actions’ and ‘Number of performed extensive land use-targeted actions’). The metrics were recorded for each time step of the simulation and then aggregated as mean or maximum values.

To explore the impact of specific parameters of institutional behaviour, we conducted a Design of Experiment (DoE) analysis (Law 2007; Lorscheid et al. 2011). The DoE approach provides an overview of the effects of particular parameters. It compares response variables across all model runs with the ‘low factor’ values against all model runs with the ‘high factor’ values (see Table 2). Thus, a parameter’s impact is determined under different settings of the other parameters. We simulated every combination of parameter values, resulting in 2^4 = 16 experiments. Since the model involves stochastic elements (see ODD+D protocol in Online Resource 2) we analysed the variation of all recorded metrics and decided to perform 20 repetitions with distinct random seeds. This means a relative experimental error (half length of the 95% confidence interval divided by the mean) of below 0.10 for all response variables except ‘Number of land use changes’, for which the experimental error is 0.16 (see Fig. 3 in Online Resource 1). To explore effects apart from the low and high parameter factors, we performed sensitivity analysis

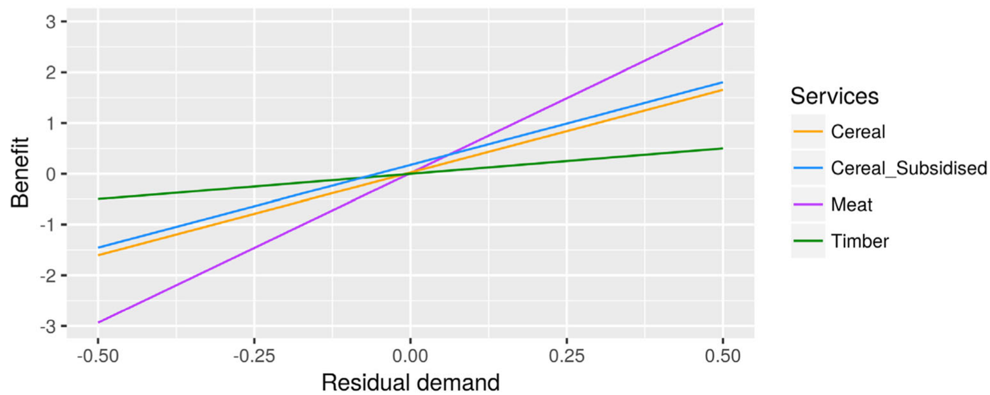


Fig. 2 Depending on residual demand for a specific service, land managers have a benefit from producing that service. Subsidies raise the original benefit function (orange for cereal) by the subsidy rate (blue)

for the triggering threshold and the subsidy rate as these have the highest effects on recorded metrics. Applying default values for all other parameters, subsidy rate was varied between 0.0 and 0.3 and added to the benefit, which on average across all land managers and over the entire simulation time span is about 0.07 in the absence of subsidies, and triggering threshold from 1 to 30% of service demand.

Results

We start by presenting results of the Design of Experiments analysis to provide an overview of parameter effects on land use metrics. We then focus on the sensitivity analysis of triggering threshold and subsidy rate, before we give insights into the effectiveness of parameters when it comes to desired developments of particular metrics.

Design of Experiments

The effects of each of the analysed parameters were recorded as the difference between low and high factors from the DoE analysis, as shown in Fig. 3. An increase in the triggering threshold (i.e., institutions are more reluctant to take action) decreased the number of performed actions, the maximum global oversupply across all services, and also the mean global over- and undersupply. Consequently, more reactive institutions are prone to cause undesired outcomes when they intervene too strongly in situations where the system would otherwise correct spontaneously.

The subsidy rate had significant impacts on most of the response variables except mean undersupply. As subsidies increased, the number of actions, especially those targeting extensive land uses, decreased. While the number of land use changes, maximum and mean oversupply increased for higher subsidies, the mean regional undersupply of cereals decreased. Therefore, fewer actions come at the cost of more fluctuations and higher oversupply, with a larger number of less costly actions allowing institutions to implement more successful strategies.

However, the picture is different when subsidy rate is considered jointly with the triggering sensitivity. Figure 4 shows performed actions, number of land use changes and maximum oversupply as well as supply-demand gaps over time for two runs with contrary parameter settings. Together with high triggering thresholds, high subsidy rates led to relatively few fluctuations and smoother transitions to optimal supply, even

Table 2 Parameter variations of Design of Experiments. To explore a parameter's impact simulations have been conducted with a low factor value and a high factor value. See text for details

Parameter	Factor low	Factor high	Dimension	Rational for inclusion
Precedence	On	Off	Boolean	Represents the level of coordination between institutions on different hierarchical levels
Triggering threshold	3	20	% demand	Addresses the tendency to intervene. Institutions can be either pro-active or reluctant
Subsidies rate	0.15	0.4	Benefit	Representing the extent of intervention; the average benefit without subsidising across all land managers and ticks is about 0.7; can be set by institutions subject to their resources
Action lifetime	1	4	Ticks	Addresses the frequency of revision of interventions and can be set by organisations liberally

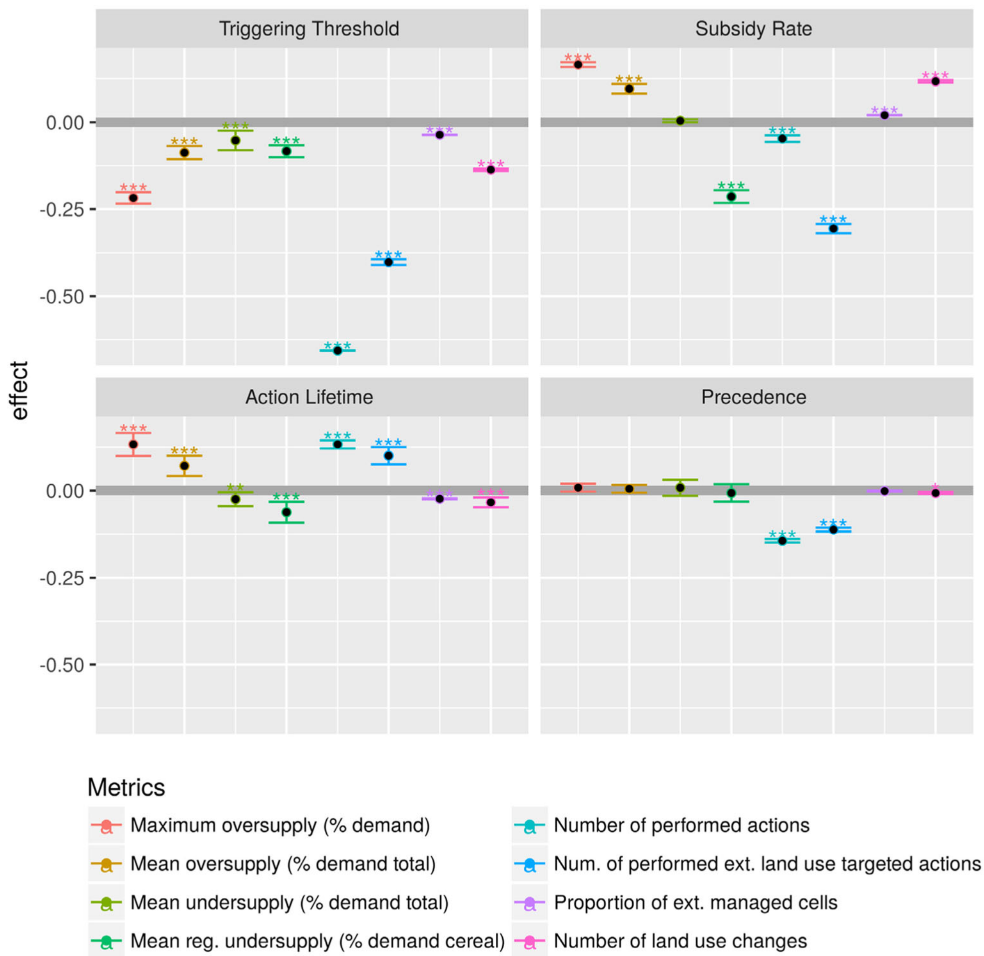


Fig. 3 Effects of four parameters (triggering threshold determines when institutions act, the subsidies rate represents the magnitude of subsidies, action lifetime is how long actions are in place, when precedence is on global institutions act first, followed by regional institutions the next time step) on a set of land use metrics from Design of Experiments runs: compares response variables across all model runs with the 'low factor' values against all model runs with the 'high factor' values (see Table 2). For example, a shift in the triggering threshold from 3 to 20% of demand results in a reduction of maximum oversupply of about 20%. Error bars show the 90% confidence interval. Stars above error bars denote levels of significance: ***⇨ 0.001; **⇨ 0.01; *⇨ 0.05

though it took longer to mitigate undersupply (left part of figure). By contrast, higher reactivity combined with lower subsidy rates still caused perturbations leading to more land use change (right part of figure). An important reason is the inactivity of the 'global' institution in the first scenario, preventing undesired interactions with the regional institutions. In other words, substantial (costly) actions that were only prompted by substantial deviations from the desired outcome proved to be a relatively efficient form of intervention.

The precedence of the 'global' institution had minor effects apart from reducing the number of performed actions, whereas the number of land use changes decreased only slightly. However, a commitment to specific actions for longer periods prohibited short-term reactions and thus caused higher maximum and mean oversupply, but less mean 'global' and regional undersupply. Interestingly, the number of land use changes was also slightly reduced: the longer lifetime of actions helped different institutions to focus on a specific service and to raise the production of under-supplied services in an enduring way without fluctuations due to coordination problems. In general, adverse impacts of longer lifetimes were limited, but these caused around 15% more actions to be performed, increasing overall expense. There was therefore a trade-off between short-term, responsive actions that limited fluctuations in supply, and longer-term, less responsive actions that improved mean supply levels.

Sensitivity analyses

The sensitivity analyses allow conclusions to be drawn about the interplay between the parameters and metrics. Less reactive subsidising agencies (expressed by higher triggering thresholds) reduced the number of interventions, the number of land use changes, and also the proportion of extensively managed cells (see Fig. 5). The analyses of over- and undersupply metrics all show non-linear effects with changes in the triggering threshold. There is a (local) maximum in deviations from the demand for institutional action that is triggered at supply-demand gaps of about 12% of demand. Lower and higher triggering thresholds caused less over- and undersupply. Furthermore, the volatility in many metrics (e.g. maximum and mean oversupply, number of land use changes) for small triggering thresholds, which is due to changes in parameter values rather than stochasticity, indicates the system's

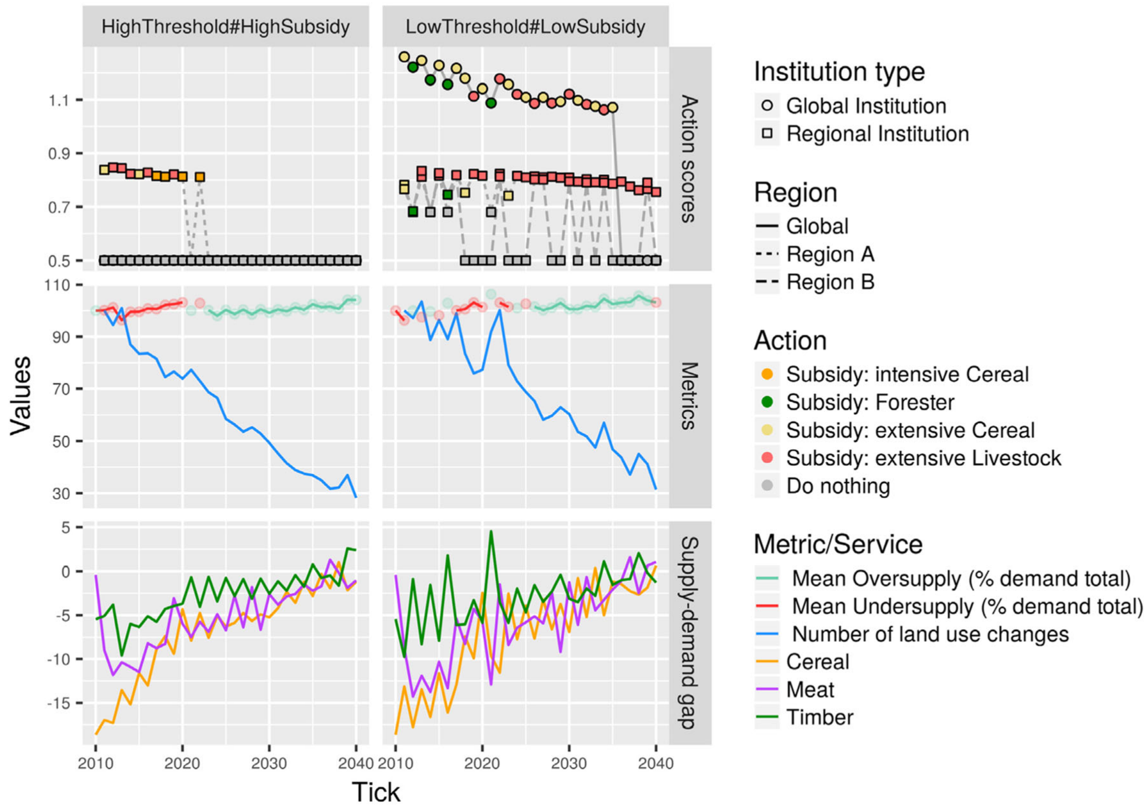


Fig. 4 Performed actions and their score, representing the institution's belief about the efficacy of that action (top panels), percentaged change in mean oversupply, mean undersupply and number of land uses that change (middle panels), as well as global supply-demand gaps for cereal, meat and timber (in percentage of their demand levels; bottom panels) for a single run with high triggering threshold and high subsidies rate (LHS) compared to a run with low triggering threshold and low subsidies rate (RHS). Actions lifetime is 1, and there is no precedence between institutions. For reasons of clarity only two of three regions are presented (top panels). Metrics are divided by their initial value (middle panels)

sensitivity and the difficulty in predicting effects in the case of very reactive institutions.

With the subsidy rate, it is important to find the right balance, as high subsidies tended to have adverse effects on meeting demand levels, the number of performed actions and the number of land use actions (see Fig. 6). In terms of maximum oversupply as well as mean under- and oversupply subsidy rates of about 50% were optimal. For higher subsidy rates, even the mean undersupply across all services was higher when certain services are over-subsidised. The number of land use changes increased moderately with an increasing subsidy rate up to 150% and more rapidly after that. We observed a stronger increase in extensively managed cells when the proportion of actions that target extensive land use was higher, which demonstrates effective subsidising taking place in the model.

Effectiveness of parameters

The most effective parameters were identified with respect to their weighted effect on the four metrics: Proportion of extensively managed cells, Number of performed actions, Mean undersupply and Mean regional undersupply of cereals. To this end, each parameter's effects on metrics, which were obtained in the DoE analysis, were weighted between 1 and 100 and summed across the four metrics for all combinations of weights. Figure 7 gives the most effective parameter for each combination of importance weight for the four considered metrics. As the figure shows, when reducing the number of performed actions was more important (higher weights), increases in the triggering threshold became the most efficient measure. In other words, institutions that allowed outcomes to deviate more widely from their target implemented fewer actions in total. Increasing subsidy rate was the best option when weights for mean undersupply and proportion of extensively managed cells became relevant, demonstrating the effectiveness of more costly and substantial interventions in improving overall performance and ensuring more consistency in favoured forms of land management. When mean regional undersupply of cereal had priority, a combination of higher triggering thresholds and higher subsidy rates was beneficial, suggesting that institutions that were less willing to act, but

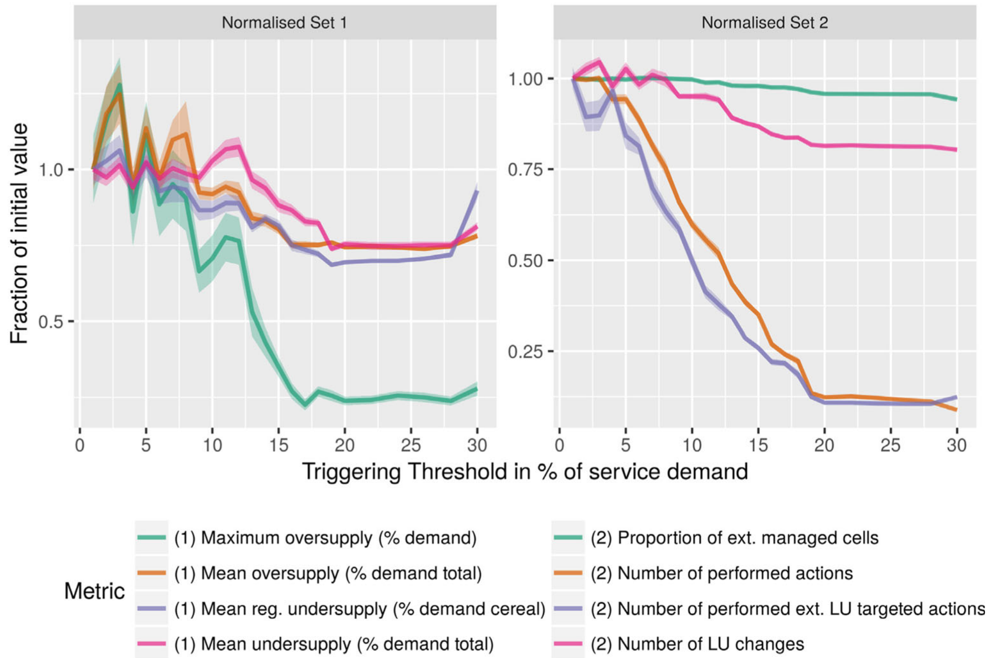


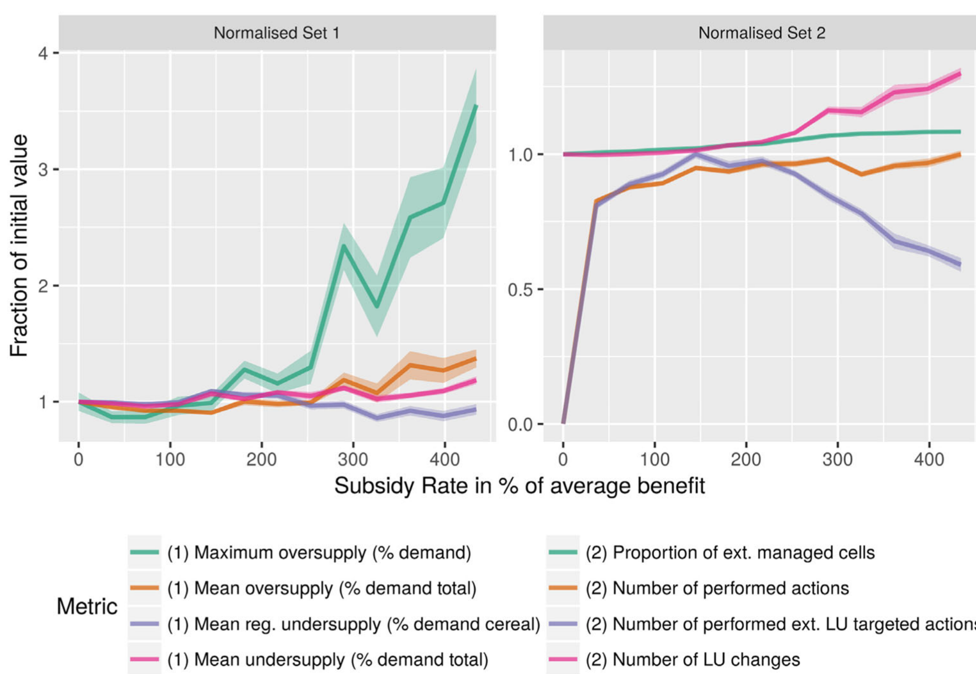
Fig. 5 Sensitivity analysis for the triggering threshold, which is varied between 0 and 20% of service demand in steps of 1% and between 20 and 30% in steps of 2%, towards metrics of land use. Data is based on 20 replications with distinct random seeds, and lines show mean values whereas ribbons indicate standard deviation. Subsidy rate is 434% on average, action lifetime is 2, and there is a delay of one time step for regional institutions and no delay for the global institution in monitoring, and no precedence between institutions. Metrics were divided by their initial value (except when it was 0 as for number of performed actions, and metrics were divided by their maximum mean in this case). To account for different value ranges metrics are separately shown in set 1 (left) and set 2 (right)

committed themselves to more substantial interventions when they did, improved overall regional performance (although sometimes with the trade-off of allowing short-term fluctuations in supply levels).

Discussion

The exploration of dynamic institutional interventions in a stylised land system reveals important dynamics that would

Fig. 6 Sensitivity analysis for subsidy rate, which is varied from 0 to 434% subsidies of average benefit, towards metrics of land use. Data is based on 20 replications with distinct random seeds, and lines show mean values whereas ribbons indicate standard deviation. Triggering threshold is 5%, action lifetime is 2, and there is a delay of one time step for regional institutions and no delay for the global institution in monitoring, and no precedence between institutions. Metrics were divided by their initial value (except when it was 0 as for number of performed actions, and metrics were divided by their maximum mean in this case). To account for different value ranges metrics are separately shown in set 1 (left) and set 2 (right)



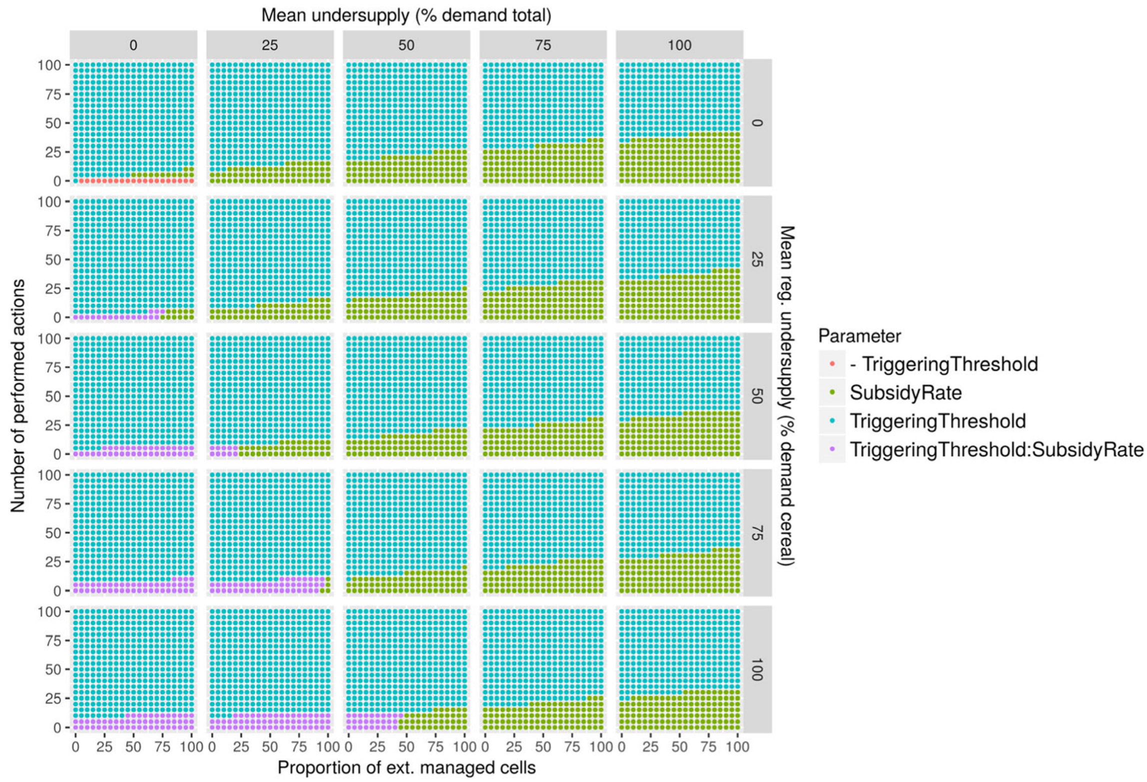


Fig. 7 Parameter with strongest effects weighted according to importance of metrics Number of ext. managed patches (horizontal facets), Maximum oversupply in percentage demand (vertical facets), Number of performed actions (*y* axis inside facets), and Number of land use changes (*x* axis within facets). When lower metric values are preferable (all but Number of extensively managed patches), effects were negated before summed while TriggeringThreshold represents a decrease in the triggering threshold, TriggeringThreshold represents an increase

be missed even by far more complex models that treat institutional behaviour exogenously. We find that even simplified interplay between institutions at different levels and the land managers they affect results in highly divergent and non-linear system dynamics that have strong implications for rates of land use change, ecosystem service provision, and achievement of institutional objectives. The strength and significance of these effects suggest that they justify far more attention in theoretical and applied land system research than they have so far received.

Non-linear effects

This study only explored a few key aspects of institutional behaviour: coordination of action between hierarchical levels, sensitivity to changing conditions, the extent to which institutions revise their actions, and the strength of interventions. The observed non-linearity of effects of important parameters, such as those controlling the timing and strength of institutional actions, highlights the need to account for realistic system dynamics in policy design. For instance, the intuitive effect of higher subsidy rates leading to more stability in land use did not hold across the modelled experiments, with lower rates actually producing less change and smaller supply-demand gaps in some circumstances. Similarly, the expected relationship between the threshold values that trigger actions and supply-demand gaps was reversed in all but a small range of triggering thresholds (between 8 and 12% of demand), meaning that higher sensitivity to ecosystem service supply levels usually increased these gaps. Notably, thresholds below 6% of service demand showed strong variations, indicating unpredictable system behaviour. Crucially, these non-linear effects are subject to change as the land use system changes, suggesting that the effects of high-end climate change may require novel, responsive institutional action.

Accuracy of monitoring vs. design of interventions

Another important characteristic of institutional behaviour that was revealed here is path-dependency. This has previously been demonstrated in an empirically grounded model of institutional land acquisition for conservation (Bakker et al. 2015), and we find that its strength varies with the lifetime of institutional actions. Where institutions cannot adjust interventions promptly, changes in ecosystem service supply level endure, but often stronger than desired and costly. Nevertheless, the strongest effects we find relate to thresholds for triggering action (representing sensitivity of reaction to current economic and environmental conditions) and the subsidy rate (representing strength of intervention). These particularly affect supply-demand gaps, number of land use changes and the number of institutional actions. We also explored the impact of noise in monitoring (adding normally distributed values with mean = 0 and sd = 0.2 to the demand-supply gap), but we could not detect meaningful effects on response variables. This suggests that imperfect knowledge may be less detrimental to the achievement of institutional objectives than imperfect design of interventions – provided that knowledge imperfections are random, as simulated here, and not systematically biased. To the extent that this finding is applicable to the real world, it implies that the application of well-understood interventions in poorly-understood circumstances is preferable to the application of poorly-understood interventions, again provided that circumstances are not consistently misjudged in any one way. Similarly, allowing coordination of institutional actions through precedence of the 'global' institution had little impact beyond reducing the total number of interventions made.

Integrated development needed to acquire necessary data

The strength, range and variability of these effects underline the complexity of policy making under global change. Clearly, this complexity also represents a challenge for decision-support models that seek to represent institutional action. Not only are the processes involved manifold, but also the empirical basis for how, when, and why institutions intervene in the land use system is still weak. Current models often focus on regional scales and/or specific policies such as payments for ecosystem services (Matzdorf et al. 2013) or support for organic farming (Stolze and Lampkin 2009), but rarely consider multiple scales or the interplay of a wider range of institutional interventions (Uthes and Matzdorf 2012; Daugbjerg and Sønderskov 2012). Here, meta-studies and further empirical analyses of institutional decision-making are urgently needed to complete the picture.

In this case study, institutional preferences and parameters were chosen to be as plausible as possible. Whilst this is appropriate for an abstract setting, better-supported parameterisations would be needed for a more realistic, applied exploration of institutional behaviour. These could be achieved, for example, through techniques for eliciting parameter values in complex contexts from stakeholders (Gramberger et al. 2015). We also propose an integrated development in which abstract computer simulations of institutional action are used to identify relevant types of institutions and kinds of interventions for empirical research and also to specify required data to enrich computer simulations of land system dynamics. Data requirements are likely to extend well beyond the parameters explored here, most obviously in terms of the accuracy of institutional monitoring, the range and ranking of preferences and inter-institutional power relations. Moreover, simulation research about the dependence of institutional effects on the regional land use context is needed. Investigated interventions can also include additional forms of subsidy (Merckx and Pereira 2015), as well as regulation, promoting innovation, improving infrastructure or facilitating access to financial capital, all for a range of objectives including conservation, food security, climate mitigation or adaptation. The interplay of these is of great relevance to policy making and a key target for future model applications.

Conclusion

Effective governance of the Earth system requires adaptive, anticipatory top-down processes of policy design, and bottom-up actions to reconfigure incentives and support behavioural change. These in turn require integrated analysis of multiple policies in order to understand different options, risks, stresses, and outcomes (Nilsson and Persson 2012). To enable such an analysis, models need to integrate institutions as responsive, internal entities, which has not been done previously in land use models used to inform applied policy decisions (Verburg and Overmars 2009; Britz and Witzke 2011).

The ABM presented here simulates land managers and institutional agents at a 'global' scale and regional scale with distinct preferences when reacting to supply-demand gaps of ecosystem services. The model is therefore capable of analysing institutional impact on the complex temporal and spatial dynamics of the land use system, which is important in light of increasing uncertainty due to climate change and population dynamics. Simulations showed substantial, non-linear impacts of institutions' tendency to react (triggering threshold), extent of intervention (subsidy rate), coordination between levels of spatial scale (precedence of the global institution) and revision of action (action lifetime). Design of Experiment analysis showed that subsidy rate and the threshold for triggering actions are more important than action lifetime and precedence between institutions at the different levels in order to decrease supply-demand gaps and the number of land use changes. Sensitivity analysis demonstrated non-linearity in subsidy rate and triggering threshold, which suggests that both an increase and a decrease in the parameter value could improve outcomes for certain metrics, depending on the current parameter values and the magnitude of change. Together, these findings indicate the relevance of responsive institutional action in the exploration of land use change, and reveal significantly different dynamics depending on when and how institutions react compared with a model without institutional action.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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