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Simulating endogenous institutional behaviour and policy implementation pathways within the land system

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ABSTRACT

Policy interventions have substantial effects on land use change, providing key levers for multiple objectives, including mitigating climate change and biodiversity loss, and maintaining food security. Policy effects are often complicated, conflicting, and subject to regular change. Despite this, land system models typically treat policies as simple, exogenous modifications to models. To better represent the dynamic nature of policy-making, we develop an endogenous institutional model that can be embedded within land system models, here exemplified by an agent-based model. Numerical experiments are conducted to examine an institution with two policies targeting the production of ecosystem services. We find a clear scope for simulation-based exploration of policy-making, with emergent processes including the marginal diminishing effect of economic policy interventions, asymmetric spill-over effects for different ecosystem services, and trade-offs between policy goals. The endogenous institutional model demonstrates the potential to reveal various emergent patterns with important consequences for land systems.

1. Introduction

Policy interventions in the land system must address a wide range of interacting processes to achieve ambitious but essential goals including climate change mitigation and adaptation (Guo et al., 2024), food security (Bengochea Paz et al., 2020) and biodiversity recovery (Broussard et al., 2023). Progress towards these goals has been fitful at best, and absent at worst, with many policies being counterproductive, mutually confounding, or subject to frequent changes that undermine their efficacy (Brown et al., 2019a; Lee et al., 2019). The EU's Common Agricultural Policy alone provides a rich array of recent examples, with repeated attempts to balance food security and environmental protection largely failing, and the premature abandonment of controversial policies in the face of public opposition, such as farmer protests (Catalan News, 2024; European Court of Auditors, 2017).

Land system models often aim to support policy-making by analysing the impact of public policy interventions on land use change (Berchoux et al., 2023; Li et al., 2017; Lippe et al., 2022). However, these models apply policy interventions exogenously and usually singly, and so are unable to account for the feedbacks that exist between policies, land users and policy institutions themselves (Lambin and Meyfroidt, 2010; Long and Qu, 2018). These models are thus inherently unable to capture fundamental characteristics of policy development and implementation. In particular, models neglect the dynamics of policy interventions and the causal relationships with land users that could be represented by endogenizing the policy process, and so remove important facets of realism including interactivity (González, 2016; Ostrom, 2005), path dependency (Capoccia, 2015; Hegmon, 2017; Torfing, 2009), and complicatedness (Sun et al., 2016).

Endogenous institutions have been increasingly recognised in the literature, particularly in areas such as common-pool resource (CPR) management, where institutions are often treated as sets of rules, norms, or strategies (Crawford and Ostrom, 1995). Research has demonstrated that institutions can emerge organically from the interactions of individual actors (Ostrom, 1999). This perspective has been especially useful for understanding how institutions form around resources such as land, water, and energy (Ghorbani et al., 2021, 2020). Modelling efforts have further enriched this view. For instance, Ghorbani et al. (2017)

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developed the SONICOM model, an agent-based simulation that demonstrates how CPR users self-organise to develop sustainable rules through repeated interactions and adaptation, highlighting the importance of endogenous institutions.

These emergent institutions play important roles in social-ecological systems, and their simulation highlights the scope and value of institutional modelling—particularly in demonstrating the long-term, system-wide impacts of interactions between modelled entities. Meanwhile, policies are often understood as official rules imposed by governing authorities. These official rules may synergise with or conflict with those arising organically from individual interactions, leading to varied policy intervention outcomes (Grzymala-Busse, 2010; Helmke and Levitsky, 2004). Building on the understanding of endogenous institutions as dynamic and interaction-driven, this research views institutions as policymakers interacting with the land system or broader socio-ecological systems. This perspective extends the focus from localised, emergent rules to institutions functioning as adaptive decision-makers at a systems level. Such institutions are endogenous in that they dynamically adapt to the land systems they operate within. Their policy actions are also influenced by the actions of numerous individual agents and, potentially, by emergent norms or rules developed from individual-level interactions.

Nevertheless, examples of the modelling of institutions as decision-makers within land-use systems are still quite limited (e.g., see Holzhauer et al.(2019)), which might be attributed to challenges such as the complexity of institutional decision-making processes, the potential for institutional change over time, the availability and accuracy of data, and issues of institutional transparency and accountability. In addition, computational complexity increases as the number of institutions and their interactions increase. Despite these difficulties, the rewards in terms of a more holistic representation of system dynamics make the endeavour worthwhile because it can unveil previously unexplored emergent phenomena and insights into institutional behaviour and its impact on land use change. As Davidson et al. (2024) highlighted, considering endogenous institutional changes in modelling is significant for understanding the socio-behavioural processes relevant to sustainability transitions.

Several methodologies exist for simulating the decision-making behaviours of adaptive agents, among which machine learning and deep learning algorithms appear to be promising (Ramchandani et al., 2017). However, instead of using data-driven, black-box methods (Hu et al., 2023), we argue that modelling the complexities inherent in institutional decision-making should satisfy three guiding principles—parsimony, transparency, and extensibility (Loyola-González, 2019; Sun et al., 2016) while recognising the central roles of heuristics and incrementalism in institutional decision-making processes (Gigerenzer et al., 2022; Pal, 2011).

Heuristics is a vital component of both human and organisational decision-making processes (Gigerenzer et al., 2022, 2011). A significant feature of heuristic decision-making is its focus on limited information and the likely trade-off of optimality for speed (Gigerenzer and Gaissmaier, 2011; Gigerenzer and Goldstein, 1996; Kahneman, 2011; Russell and Norvig, 2010). Incrementalism is referred to as the science of "muddling through" (Lindblom, 1959), providing a model of policy-making through modest modifications rather than through comprehensive overhauls. Heuristics intrinsically resonates with incrementalism in political science on a theoretical basis (Dahl and Lindblom, 1965; Pal, 2011): both concepts illustrate the nature of bounded rationality in humans; moreover, incrementalism may represent a macroscopic manifestation of heuristic decision-making by policymakers.

The objective of this research is to therefore create a modelling framework that endogenises the institutional decision-making process while respecting the above principles and the central roles of heuristics and incrementalism. This framework enables multiple institutions with different policy instruments and targets to respond to changes in the land system as it evolves in response to policies implemented, providing new insights into the interplay of institutional dynamics and land use changes. The institutional model is applied to the CRAFTY agent-based land use model (Murray-Rust et al., 2014) to examine the potential emergent patterns the institutional model can produce alongside behavioural land user agents.

2. Methods

2.1. Model overview

Inspired by the work of Easton (1965) and Wlezien (1995), the role of endogenous institutions can be depicted as a sophisticated controller mechanism from a system perspective. Macroscopically, the outline structure of the endogenous institutional model coupled with a land use model (represented by the CRAFTY agent-based modelling framework) is a closed-loop control system, where an institution is populated with a sequence of components forming a decision entity. Within this system, institutions can observe and influence land use processes to achieve policy goals. Fig. 1 offers an overview of operational procedures within the loop. For illustrative clarity, these operational procedures are categorised into three parts, including the institutional model, the land use change model, and the part that solely represents the policy implementation procedure, the juncture where the two models tightly intersect.

Within the institutional model, we adopted two further methodological approaches from control theory: Proportional-Integral-Derivative (PID) and fuzzy control (Carvajal et al., 2000; Kaur and Singh, 2019; Misir et al., 1996). A PID controller continually adjusts the disparity between a set point (e.g., a policy target) and the system's existing state by factoring in three sources of error. In pursuit of policy goals, institutions can be modelled to adapt their decisions based on: 1) The current gap between the actual and desired policy outcomes (Proportional); 2) The accumulated impact of past policies and their resulting discrepancies (Integral); and 3) The changing speed with which these discrepancies are evolving (Derivative). Simulating policy adaptations based on these three types of gaps between the outcomes of interest and policy targets provides a simple yet systematic approach that mirrors the principle of heuristics and incrementalism in policymaking.

A Fuzzy Logic Controller (FLC) serves as a function approximator that maps the goal-output discrepancies onto policy measures. The merits of coupling the PID and fuzzy control are manifold. An FLC is driven by an inference engine using a set of IF-THEN logic rules (Kaur and Singh, 2019). This rule-based paradigm fosters intuitive comprehension amongst human stakeholders and facilitates the encapsulation of knowledge from model users and policymakers. Compared with a sole PID controller, the joining of an FLC endows the modelled institutions with the capability of coping with nonlinear systems (Brown and Harris, 1995; Carvajal et al., 2000). Here, the PID controller allows for an adaptive, feedback-orientated approach to evaluating the disparity between an imposed policy goal and the model output, whilst the FLC maps the goal-output discrepancies onto policy adjustments. These approaches not only resonate with our core principles of institutional modelling but also offer practical algorithms that facilitate the effective operationalisation of endogenous institutional behaviours upon a solid theoretical basis.

A policy implementation pathway comprises a series of time-dependent policy actions, which might differ from "ideal policy actions" because of monetary and non-monetary constraints. For instance, IF an institutional agent intends to rapidly increase meat production, THEN it might decide to offer substantial subsidies. The "substantial subsidies" can be understood as an ideal policy action. However, due to the limitations of budgets and pressure from other stakeholders (arising, for example, from environmental concerns), the eventual subsidies for meat production may be far lower than intended, essentially resulting in a compromise policy action. In this case, the three factors - "ideal policy

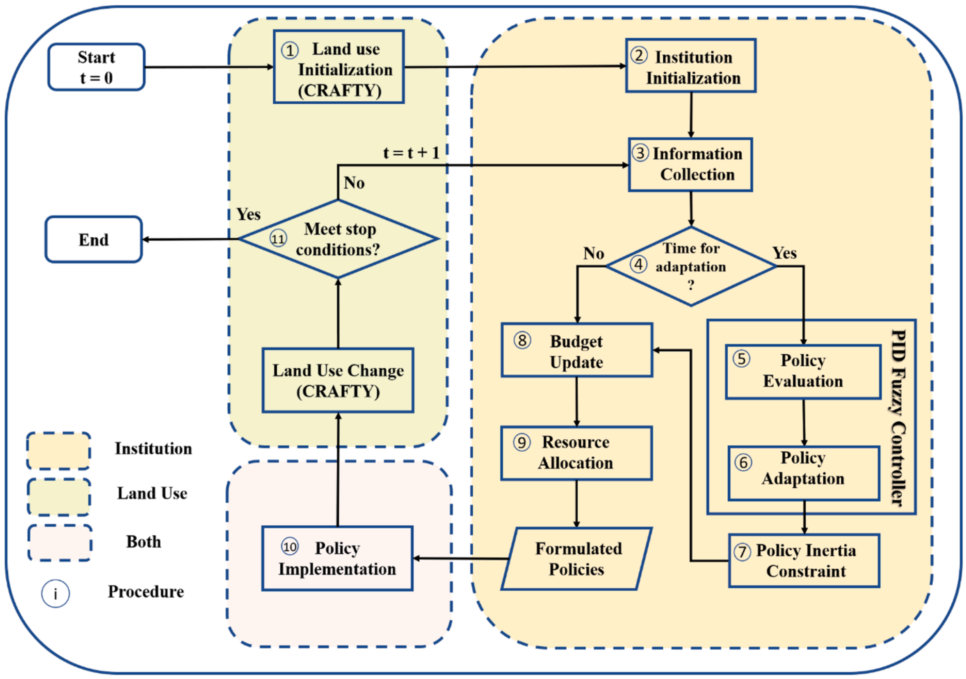

Fig. 1. The operational procedures of the institutional model when embedded in a land use modelling framework.

actions", budgetary constraints and stakeholder pressure – all contribute to the formation of policy actions and resultant policy implementation pathways, which tends to favour incremental policy adjustments. These mechanisms are detailed in Sections 2.3.2 and 2.3.3, where stakeholder pressure is generalised as policy inertia, which also reflects an institution's resistance to change.

2.2. Model process

The complete model process includes eleven operational steps as follows:

1. Initialise the land use model.
2. **Initialise the institutional agents**. This model can simulate many institutions simultaneously. Here, only one institution is shown for illustrative purposes. Within an institution, one crucial process is to initialise the policies, which includes defining the policy IDs, objectives, policy types, and any other policy characteristics to be included in the model.
3. **Information collection by the institutions** on whichever features of modelled land use are relevant (here, the demands and supplies of ecosystem services). Uncertainties might accompany the information collection.
4. **Determine if it is time to adapt the policies**. Policies remain unchanged within a set period of time that can represent, for example, election cycles. This step is considered here for three reasons. Firstly, institutions need time to allow the effects of the policies to become manifest and then to evaluate the outcomes. Secondly, institutions might have difficulties in responding to the changes with sufficient speed. Thirdly, policies might be designed in this way to gain more consistency.
5. **If it is time to adapt the policies, the institution evaluates the performance of existing policies based on the collected information**. The evaluation procedure uses the PID controller that considers the errors between the policy goals and actual outcomes. Optionally, the institution may also incorporate predicted errors into the evaluation.
6. **Using the evaluation results, the institution conceives policy adaptations**. A fuzzy logic module is applied to allow the integration of real-world policymakers' knowledge into decision-making. The fuzzy logic module serves as a function that maps the evaluation results to policy adaptation.
7. **A policy inertia constraint limits the magnitude of policy changes at each time step**, which reflects the non-monetary (e.g., public opinion, interested parties, legislation) resistance to policy changes.
8. **Subsequently, the institution deals with monetary constraints, i.e., budgets**. In reality, institutional budgets can come from multiple sources and vary over time. The incorporation of a dynamic budget update process adds another layer of realism to the institutional model.
9. **After updating the budget, the institution allocates the budget** among different policies and outputs the formulated policy interventions.
10. **The institution implements the policies** in the land use system to push land use changes in the desired direction.
11. **After the land use model processes the implemented policies, there is a check whether the end conditions are met**. If true, then the simulation is stopped; otherwise, the information collected by the institutions is updated for the next iteration of decision-making.

2.3. Sub-models

Further details about the various sub-models are provided here. To better present these details, the institutional model is segmented into four sub-models. The first sub-model focuses on the preliminary set-up and is limited to procedure 2: institution initialisation. The second sub-model, termed "information, evaluation, and adaptation", encompasses procedures 3 to 7 due to their intrinsic link. This sub-model deals with information collection, uncertainty injection, policy evaluation, and adaptation together with the policy inertia constraint. The third sub-model, termed "budget-allocation", deals with updating the budget and allocating resources. The final sub-model focuses on policy implementation.

2.3.1. Sub-model 1: initialisation

Each institution has a unique ID to distinguish itself from other institutions, a set that contains all policies available to this institution, a container to collect information, a list of variables to control the uncertainties, a set of variables and conditions defining its budget, and a set of decision rules (Fig. 2). A crucial task in this step is to initialise the policies and add them to the policy set. Each policy is essentially a group of attributes that can be adapted by the institution. The attributes/behaviours of institutions and policies as well as their relationships are shown in Fig. 2. The meanings of these behaviours and attributes are summarised in Tables A1 and A2 in Appendix A. The variables in the equations below are summarised in Table A3.

Of crucial significance is the setting of unambiguous policy goals, as these lead to institutional adaptation throughout the simulation. Real-world examples of clearly stated policy goals can be found in the Paris Agreement (2015) regarding carbon emission reductions. Some specific examples include that, the United States and European Union have set goals to reduce greenhouse gas emissions by 2030 by 50–52 % compared to 2005 levels and by at least 55 % compared to 1990 levels, respectively (European Council, 2020; Zhao et al., 2022).

These policies consistently specify a reference time, a deadline, and a targeted quantity. We use vector

$$\mathbf{G^{ij}} = \left[T_s^{ij}, T_e^{ij}, Q^{ij}\right] \tag{1}$$

to represent the goal of institution i's policy j, which contains three components: T_s^{ij} the time when the policy starts, T_e^{ij} the time when the policy ends, and Q^{ij} the quantity a policy is meant to change from T_s^{ij} to T_e^{ij}.

With the policy goals clearly defined, an appropriate initial policy intervention needs to be set up, which could be a real-world policy. For instance, if a simulation starts from the year 2020, the initial policy intervention could be the actual taxes and subsidies implemented in that year. The initial intervention can also be derived from model users' intuitive estimation or deliberate calculation.

2.3.2. Sub-model 2: information, evaluation, and adaptation

Institutions may have access to diverse sources of information to support decision-making processes, though the availability and quality of this information can vary depending on the context. While there are multiple sources of information available, gathering information can be resource-consuming, and the forms and extent of information can be limited as a result. Within the model, several categories of information are defined and represented as distinct data containers, labelled appropriately and filled with specific data points. Uncertainties can arise during information collection in reality, and so the collected data can be varied using defined value distributions, reflecting relevant forms of bias or error.

Based on the information, institutions evaluate the state of the land use system relative to their goals. In reality, policies normally do not change frequently; it takes time for existing policies to manifest their impact and for institutions to respond to recent changes (Hocherman et al., 2024). Hence, a time lag is added to periodically trigger the evaluation and adaptation procedures for each policy (e.g. see Brown et al. (2019a) for a discussion of time lags in the land system). Time lags can be fixed or changed over time to reflect different triggering mechanisms of policy adaptation. A common example of the time lags in policy adaptations is election cycles.

The evaluation of policy performance is a challenging task due to the complex nature of land use systems. It is difficult to attribute an outcome to a specific institutional action (González, 2016). We adopt a heuristic approach to mimic institutional behaviour using a PID controller that adjusts the input based on the evaluation of three types of output-goal errors: proportional, integral and derivative. In this model, the proportional, integral, derivative errors, and their weighted sum are calculated using Eqs. (2), (3), (4), and (5) respectively:

$$\varepsilon_{t_n}^{(P)} = \frac{Q^{ij} - o_{t_n}^{ij}}{\left|Q^{ij}\right|} \tag{2}$$

$$\varepsilon_{t_n}^{(I)} = \frac{1}{k}\sum_{m=n-k}^{n} \frac{Q^{ij} - o_{t_m}^{ij}}{\left|Q^{ij}\right|} \tag{3}$$

$$\varepsilon_{t_n}^{(D)} = \frac{\left(Q^{ij} - o_{t_n}^{ij}\right) - \left(Q^{ij} - o_{t_{n-k}}^{ij}\right)}{\left|kQ^{ij}\right|} \tag{4}$$

$$E = C^{(P)}\varepsilon_{t_n}^{(P)} + C^{(I)}\varepsilon_{t_n}^{(I)} + C^{(D)}\varepsilon_{t_n}^{(D)} \tag{5}$$

where t_n represents the specific time at which the institution evaluates the errors; $o_{t_n}^{ij}$ is the output intended to be adjusted by institution i's policy j at the time t_n; k is the time interval of interest; $\varepsilon_{t_n}^{(P)}$, $\varepsilon_{t_n}^{(I)}$,

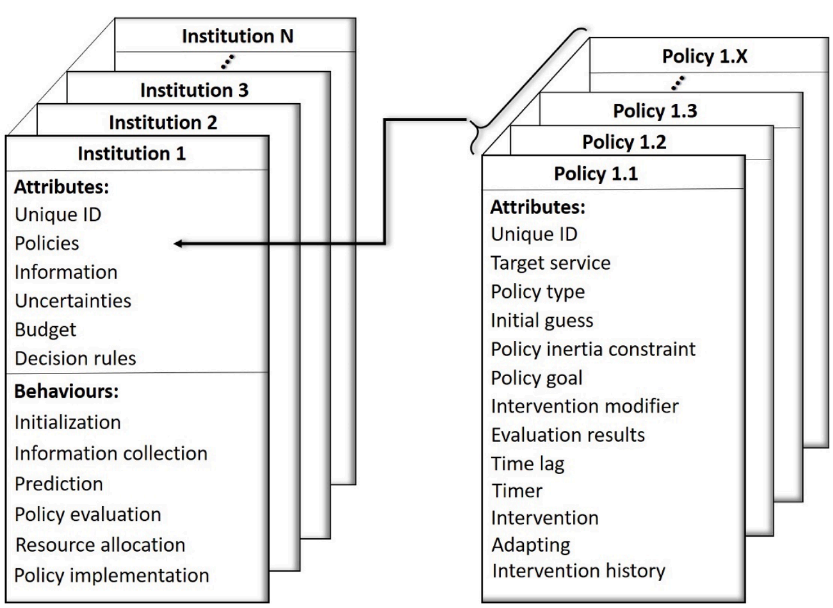

Fig. 2. Institution and policy structures.

$\varepsilon_{t_n}^{(D)}$ respectively denote the proportional, integral, and derivative errors of policy j regarding its outcome $o_{t_n}^{ij}$ at time t_n. The weight vector $[C^{(P)}, C^{(I)}, C^{(D)}]$, where $C^{(P)} + C^{(I)} + C^{(D)} = 1$ and $C^{(P)}, C^{(I)}, C^{(D)} \in [0,1]$, can be applied to depict the policymakers' sensitivity to these errors. The summation E of these errors, factoring in their respective weights compose the evaluation of the institution in terms of the performance of policy j. It is noteworthy that these errors can involve predicted outcomes, and thus, consider predicted errors in the calculation, depending on how institutions consider the reliability of the predictions.

The FLC uses the weighted sum of errors E as an input, representing the performance evaluation of implemented policies. This controller works by mapping output errors onto policy adaptations, a crucial feature since institutions typically cannot directly influence the output but do so through policy instruments. As the FLC receives the input E, it is processed through three modules: fuzzification, inference engine, and defuzzification (Dadios, 2012). Fuzzification is the process that converts the crisp value of E into a set of fuzzy variables based on predefined membership functions. These fuzzy variables are defined over a range of values, allowing for a degree of membership rather than discrete categorisation. For instance, if the error $E = 0.1$ representing the gap between the policy goal and actual crop production level is considered low here, this precise value might be classified under both the categories of 'low' and 'high' to extents determined by these membership functions. In this case, the fuzzification process might produce results such as "$E = 0.1$ belongs to 'low' with a membership degree of 0.9 and belongs to 'high' with a membership degree of 0.001", indicating $E = 0.1$ predominantly belongs to 'low'. Subsequently, fuzzy inference maps the fuzzified E onto fuzzy output based on user-defined decision rules that are formatted in the IF-THEN structure. These rules are linguistic representations of experts' knowledge, such as that of policymakers and researchers who have domain-specific interests. For example, a rule might be "IF E is low THEN the change of intervention of Policy j is small". The third process is defuzzification, which translates the fuzzy output back to crisp real numbers again to allow the computer to process. The flexibility in adjusting membership functions, decision rules, and defuzzification algorithms allows fuzzy controllers to effectively capture and manipulate the relationships between various inputs and outputs in decision-making processes.

Technically, the institutional agents' behaviour in approaching policy goals is analogous to iterative approaches such as Newton's method in solving ordinary differential equations (Cajori, 1911; Galántai, 2000; Ypma, 1995), but a critical difference is that the institutions do not know the precise mathematical representation of the target system and hence need to conduct a series of constrained trial and errors to approach the policy goals. Also, it should be noted that the FLC is used to map the errors onto the incremental quantity of policy adjustments rather than onto a direct value indicating the intensity of the policy adjustments, reflecting the approach of incrementalism.

Let F denote the function of FLC and F(E) indicate the incremental, quantitative adjustment to the existing policy, such as the changes in taxes, subsidies, geographical expansion of new protected areas. The policy adjustment is constrained by the policy inertia constraint N^{ij}, a variable whose value is prescribed to reflect the non-monetary resistance to policy adjustments. The constrained policy adjustment at $t+1$ is denoted as A_{t+1}^{ij} and calculated using Equation (6). The sign function outputs the sign of its input. A_{t+1}^{ij} is accumulated to form a policy modifier denoted as M_{t+1}^{ij}, as shown in Equation (7). It might be convenient to use normalised policy adjustment together with a fixed step size for iterative policy adaptation. In this way, the policy modifier is a coefficient of the step size. As shown in Equation (8), η^{ij} is the step size, and V_{t+1}^{ij} is the modified policy adjustment for the (t+1)-th iteration.

$$A_{t+1}^{ij} = sign(F(E)) \times \min(|F(\mathrm{E})|,\ N^{ij}) \tag{6}$$

$$M_{t+1}^{ij} = M_t^{ij} + A_{t+1}^{ij} \tag{7}$$

$$V_{t+1}^{ij} = \eta^{ij} \times M_{t+1}^{ij} \tag{8}$$

2.3.3. Sub-model 3: budget allocation

In modelling an institution with multiple policies, it is crucial to understand how much budget each has access to because the distribution of budget among institutions or policies is related to the power they can leverage to impact land use change or even other institutions. Hence, a process that updates the budget for an institution has been included in the model. The budget update process tracks the institution's income and expenditure whenever a policy is applied.

The institution can allocate the budget across multiple policies. It is assumed here that the intensity of a policy intervention is quantitively measurable, and that its absolute value is positively correlated to the budget the institution uses to implement the policy. As seen in Eq. (9), f is a monotone function that maps the absolute value of a policy intervention V_{t+1}^{ij} to the resource R_{t+1}^{ij} consumed. For simplicity, in the simulation section below, function f can be approximated as a linear function, and only subsidies are considered budget-consuming.

$$f\left(\left|V_{t+1}^{ij}\right|\right) = R_{t+1}^{ij}; \tag{9}$$

The allocation of the budget can be treated as an optimisation problem in quadratic form, which is a convex optimisation problem:

$$\min_{r \in (r_{\min},\ r_{\max})} \sum_j \xi_{ij} \left(r_{t+1}^{ij} - R_{t+1}^{ij}\right)^2 \tag{10}$$

$$s.t.\ 0 \le \sum_j r_{t+1}^{ij} \le B_t^i \tag{11}$$

$$\sum_j \xi_{ij} = 1 \tag{12}$$

where R_{t+1}^{ij} denotes the resource needed by institution i's to implement policy j; r_t^{ij} is the decision variable determining the resource allocated to implement policy j; ξ_{ij} is a weight reflecting the comparative importance of policy j perceived by institution i; B_t^i is the total budget of the institution i at t. The optimiser is intended to find a combination of r_t^{ij} that minimise the objective function. Alternatively, one might consider using IF-THEN rules instead of optimisation to determine the resource allocation, or modifying the weights to add more dynamics. While IF-THEN rules are a feasible approach to budget allocation here, framing the budget allocation as a convex optimisation problem offers several distinct advantages. First, it provides a unique optimal solution, ensuring manageability and clarity even with numerous policies involved. Second, this method standardises the allocation process, reducing the need for extensive parameterisation compared to IF-THEN rules. Third, it allows model users to focus on customizing the decision rules for policy adaptation. Additionally, this approach simplifies the interpretation of results, as the adaptability of institutional agents is primarily determined by the policy adjustment rules, rather than two sets of rules in different processes.

After finding the optimal resource allocation, it has to be transformed back to the policy intervention using the inverse function of f, as shown in Eq. (13):

$$V_{t+1}^{*ij} = \mathrm{sign}\left(V_{t+1}^{ij}\right) f^{-1}\left(r_{t+1}^{*ij}\right) \tag{13}$$

where r_{t+1}^{*ij} is the optimal resource for V_{t+1}^{ij}; the *sign* function returns the sign of V_{t+1}^{ij}; V_{t+1}^{*ij} is the resultant optimal policy intervention. Because the policies consume the budget, the budget B_t^i should be updated accordingly using Eq. (14):

$$B_t^i \leftarrow B_t^i - \sum_j r_{t+1}^{*ij} \tag{14}$$

2.3.4. Sub-model 4: policy implementation

The policy implementation sub-model is an intersection of the institutional model and the land use change model. This part is highly customisable and should be coupled with the specifics of the land use change model. Here we use the CRAFTY model (Murray-Rust et al., 2014) for this purpose. In CRAFTY, land managers of various Agent Functional Types (AFTs) manage unique combinations of productivity across multiple ecosystem services. These managers utilise the resources within their land to produce ecosystem services and compete to meet the societal demand for their respective services.

There is a diversity of policy instruments that can influence land use changes, among which economic measures play a crucial role. In this paper, we focus on the intervention of economic policies within the land use system represented by CRAFTY.

Typically, economic policies include taxes and subsidies. In real-world cases, when economic policies come into play, the equilibrium of demand and supply is determined by both the elasticities of the demand and supply, even if the policies are imposed on one side of the market. For instance, subsidies on the supply side may cause a price drop, which in turn induces more demand and causes friction on the price drop. Because the current land use change model is focused on the supply side of different land use types and uses prescribed demands for different ecosystem services, it is assumed that taxes and subsidies are only imposed on the land users rather than the ecosystem service consumers. That is, the demand is assumed to be completely inelastic. The economic policies are implemented as follows:

$$c_{xy} = \sum_S \left(p_S \left(\sum_i V_{t+1}^{iS} + m_S \right) \right) \tag{15}$$

where c_{xy} denotes the competitiveness of a land use agent at the land cell whose coordinates are (x, y); S is the ecosystem service the land user produces. p_S is the land user agent's production level of ecosystem service S within the land cell. V_{t+1}^{iS} is the institution i's economic policy that targets ecosystem service S; m_S is marginal utility brought by ecosystem service S. Transitions between land uses, and hence changes in the supply levels of different services, are constrained by parameters representing opportunity costs and other barriers, here set at a single low level to prevent unrealistically high rates of change.

2.4. Experimental settings

Although the institutional model allows for the incorporation of many institutions, it is not within this paper's scope to demonstrate the model's descriptive strength in modelling a variety of combinations of institutions and their policies. Instead, the experiments here serve as a proof of concept to explore what meaningful patterns can emerge at the system level and the interpretability of the model's micro mechanisms, given the significance of emergent patterns in socio-ecological system modelling (Grimm et al., 2005; Jakoby et al., 2014; Kramer-Schadt et al., 2007; Piou et al., 2009). Hence, the parameterisation of the institutional model is set to be parsimonious to facilitate the understanding, interpretation, and evaluation of the model.

Specifically, the numerical experiments here focus on the dynamics of one institution possessing two policies. Additional institutions and policies can be added in the same way. The experimental institution can be regarded as an agricultural policymaker responsible for direct interventions that address agricultural ecosystem services. The institution can affect two policies - Policy 1.1 and Policy 1.2 - that influence the production of meat and crops using taxes and subsidies. The simulated institution can use three types of decision rules labelled Economic, Tax, and Subsidy. In principle, decision rules can be arbitrarily complex. The current decision rules are designed to be a set of single-input-single-output functions that are straightforward enough for intuitive understanding. The detailed parametrisation of these decision rules and numerical settings are given in Tables B1–B3 in Appendix B using FLC language defined in the IEC 61131-7 (PLCopen, 2000). Moreover, the institution is assumed to evaluate only the integral errors to mitigate the influence of noise in the model.

The institutional model is applied to a newly developed CRAFTY emulator implemented in Java (Zeng, 2024c). The emulator utilises the MASON agent-based modelling framework (Luke et al., 2019) and enables rapid adaptation for exploratory research. The fuzzy logic controllers are implemented using the jFuzzyLogic library (Cingolani and Alcala-Fdez, 2012; Cingolani and Alcalá-Fdez, 2013). The emulator is built based on the CRAFTY-EU land use model (Brown et al., 2019b) and parametrised with data based on the climatic and socio-economic scenario (Brown et al., 2019b). These data define the change in demands over time for each of the ecosystem services. Each AFT has a matrix of sensitivities to 8 land capitals and represents a type of land manager that can provide a range of services: meat, crops, diversity, timber, carbon, urban development and recreation. AFTs also have a sequence of production levels corresponding to the ecosystem services, which function similarly to the total factor productivity in a Cobb-Douglas production function. The names of the AFTs are shown in Table C1 in Appendix C. The initial distribution of the AFTs and the AFT attributes are given in Figs. C1 and C2.

3. Results

3.1. Baseline simulation

To have a baseline understanding of how the land use model behaves, the model was run 100 times without institutional influence. Fig. 3 shows the model's output in terms of the supply of different ecosystem services over time. It can be seen that the model's output is stable across the simulations; except for timber production, the supply of all other ecosystem services shows a significant tendency to follow the demands, which means the model's macroscopic adaptive behaviours emerge from the competition between different AFTs. It should be noted that there are only 71 years (from the 0th to 70th step) of scenario-based data to update the annual demands and capitals, after which these are held static until 150 steps have been completed (i.e. in total covering the 0th to 149th) to manifest the model's equilibrium states. In the following experiments, the 70th and 149th years are respectively labelled as t_1 and t_2 for illustrative convenience. Timber production is an exception in this scenario because the timber yield capital decreases rapidly. That is, the deviation of timber production from the demand is caused by the limitation of relevant capital instead of by the model's inherent mechanism. In sum, the natural behaviour of the model is featured by the tendency to close the gap between supply and demand, which offers a clear-cut baseline scenario to understand the influence of institutions.

3.2. The individual impact of Policy 1.1 and Policy 1.2

We examine the influence of the institution's policies individually. The purpose of this experiment is to investigate the effectiveness of the institutional agents in functioning as actors that influence land use change as expected. To concentrate on this purpose, other influences are isolated: the budget constraints are temporarily deactivated and the fuzzy decision rules are set to "Economic". This means the policies are not restricted to subsidies or taxes but are purely negative rectifiers aimed at closing the gap between policy goals and actual supply. The parametrisation details of the institution, Policy 1.1, and Policy 1.2 are given in Table 1.

To probe the land use system's reaction to different policy goals, a sequence of policy goals for the supply of specific services ranging from

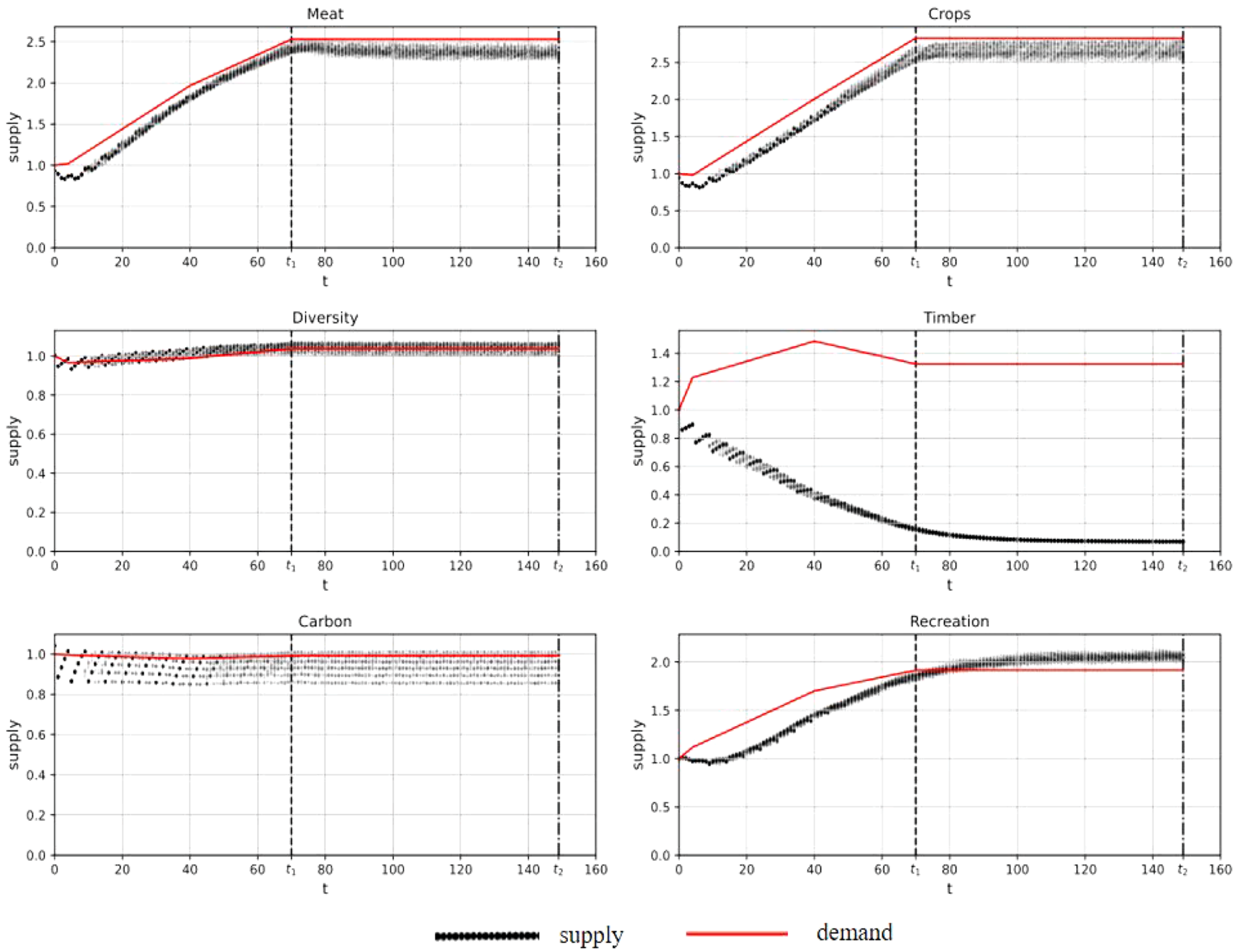

Fig. 3. Supply and demand of different ecosystem services without policy interventions. The 70th and 149th year are labelled as t_1 and t_2, respectively, marking the end of the scenario-based changes in input data and the subsequent period of static input data respectively.

0 to 6 with equal intervals of 0.1 are examined, resulting in 61 different policy goals. The results of applying a meat tax and subsidizing crop production are shown in Figs. 4 and 5, respectively. Combining the colours indicating different goals and the cluster of supply curves in each sub-figure, an evident trend can be observed: higher policy goals lead to higher production, and vice versa. This trend demonstrates that demand curves are no longer the only forces influencing the ecosystem service supply. In addition to this intuitive trend, there are three patterns worth noting: 1) different long-term and short-term impacts, 2) marginal diminishing effect, and 3) asymmetric spill-over effects.

Table 1
Parameterisation of the institution, Policy 1.1, and Policy 1.2. Experimental variables are highlighted in bold.

Institution parameter	Value	
Unique ID	1	
Policies	1.1, 1.2	
Information	Crop supply and demand, meat supply and demand.	
Uncertainties	Null	
Budget	Unlimited	
Decision rules	Economic	
Policy parameter	**First policy**	**Second policy**
Unique ID	1.1	1.2
Target service	Meat	Crops
Policy Type	Economic	Economic
Initial guess	1,000,000	1,000,000
Policy inertia constraint	0.2	0.2
Policy goal	**0.0 – 6.0**	**0.0 – 6.0**
Intervention	0.0	0.0
Intervention modifier	0.0	0.0
Evaluation result	0.0	0.0
Time lag	5	5
Timer	Equal to Time lag	Equal to Time lag
Adapting	False	False

The difference between long-term and short-term policy effects can be observed by comparing the vertical width of the cluster of supply curves at t_1 and t_2. At t_1, the lowest supply of meat reaches approximately 1.5 times the initial supply, and the highest point is around 3.5 times. Although the supply notably deviates from the original demand curve, gaps still exist between the supply and policy goals. At t_2, the lowest and highest supply reaches approximately 1 and 4.5 times the initial supply, respectively, signifying that the policy interventions are still in effect and leading the system closer to the policy goals. The same trend can also be observed in Fig. 5 for crop production. These patterns result from the fact that the institution applies an incremental adaptation strategy and that the land use system takes time to respond to policy interventions.

Fig. 6 presents the marginal diminishing effect more clearly. The actual supply achieved is concentrated around the demands. As the policy goals deviate from the demands along the horizontal axes, the discrepancies between the demands and actual supply become large, which signifies that the policy goals indeed influence ecosystem service

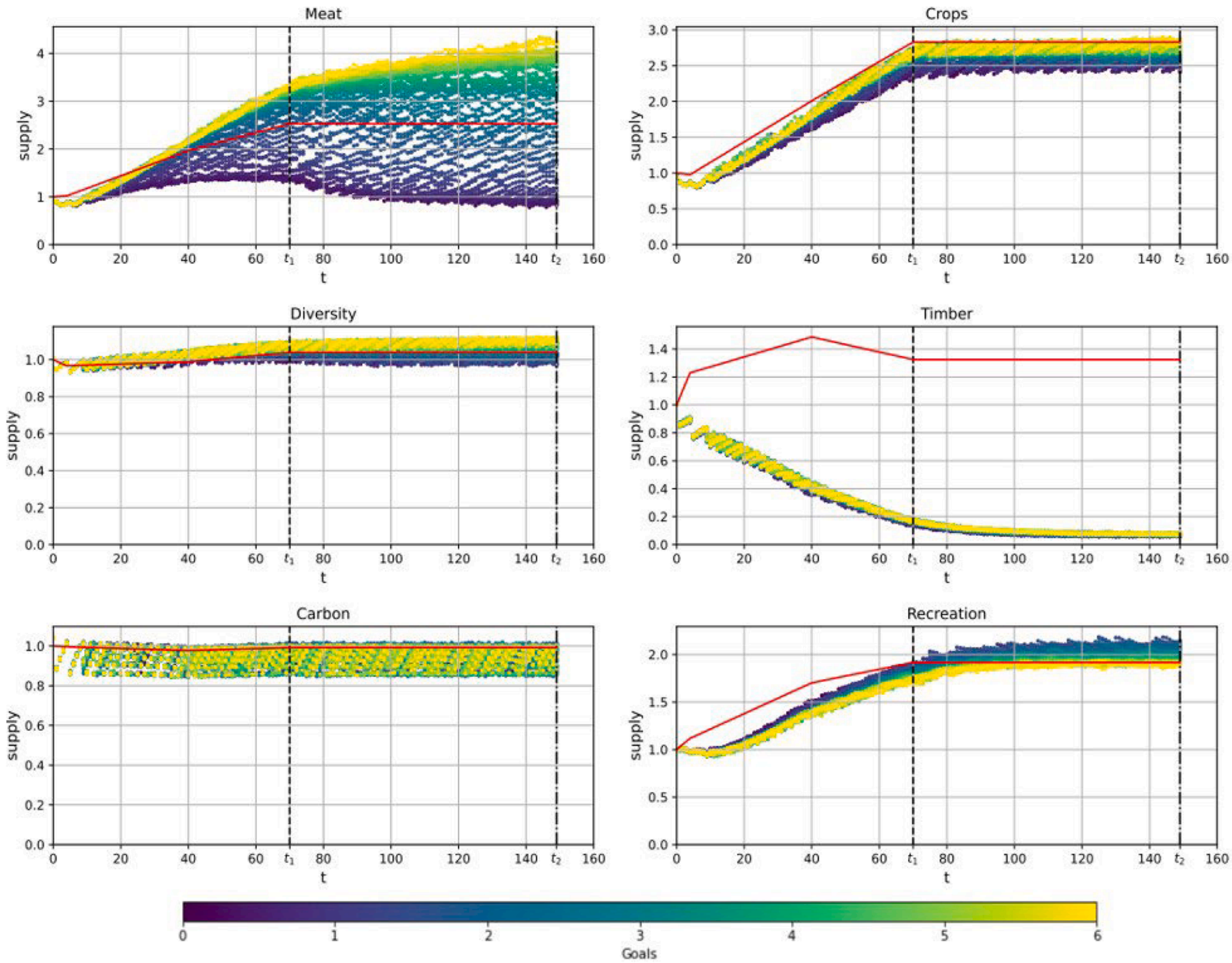

Fig. 4. The impact of Policy 1.1, in which the institution applies an economic policy to meat production with a policy goal ranging from 0 to 6 times the initial meat supply. The red line represents the demand. The 70th and 149th year are labelled as t_1 and t_2, respectively. Another pattern is the marginal diminishing effect of the policy interventions, which can be seen from two features of the cluster of supply curves. The first feature is that the lower and upper bounds of the supply curves exhibit a diminishing speed to approach the lowest and highest policy goals. The second feature is the uneven distribution of the supply curves. The supply curves tend to approach the lower and upper bounds, which leaves the space in between less dense.

production. However, as the policy goals move farther from the demands, the gap between the expected and actual supplies becomes larger, forming a flattened S shape that reflects the marginal diminishing effect of the institutional interventions. The results imply that the demand is a strong attraction for the supply to follow and can exert significant force against the policy interventions if the demand-goal discrepancies are significant.

From Figs. 4 and 5, a cross-service impact can be observed and labelled as an asymmetric spill-over effect. While the policies imposed on meat production have an insignificant spill-over effect on the other types of ecosystem services, the policies on crop production have a non-negligible impact on the meat supply. The asymmetric effect of policy interventions implies distinct AFT transitioning processes occurring “under the hood”. As most AFTs can produce multiple ecosystem services (at different levels), it is intriguing that the system can find a way to respond to the policy interventions on meat production while maintaining other ecosystem services including crop production almost at initial levels. Contrastingly, the system cannot react similarly to the crop policies, which causes a considerable spill-over effect on meat production. Comparing the gaps in the two sub-figures of Fig. 6, it can be seen that it is more challenging to achieve the policy targets of Policy 1.2 than Policy 1.1.

The asymmetric spill-over effect captured in the above experiments indicates differences in the underlying AFT dynamics. Fig. 7 displays six dominant AFTs across different policy goals. The numbers of different AFTs were recorded at the end of each simulation. It can be seen that the multifunctional (Multifun) AFT plays a major role in both Policy 1.1 and Policy 1.2 experiments, while its number does not show a substantial overall change. This is plausible because the multifunctional AFT is a major contributor to carbon sequestration (see Fig. C2), for which the demand is almost constant in the scenario. In Policy 1.1, the numbers of intensive arable (IA) and mixed farming (Mix_Fa) agents experience notable decreases as the policy goal rises. In contrast, the intensive farming (Int_Fa) AFT, as a productive meat supplier (see Fig. C2), starts from a low quantity but becomes the most dominant type when the policy goal for meat production is highest. In terms of Policy 1.2, as the goal of crop production increases, the numbers of intensive pastoral (IP) and extensive agro-forestry (Ext_AF) agents decrease, while the multifunctional, intensive arable, and intensive farming AFTs increase (Fig. 7). Nevertheless, intensive pastoral and extensive agro-forestry agents are not crop producers; the other three AFTs can produce considerable quantities of crops and meat, which makes the meat supply deviate from the demand.

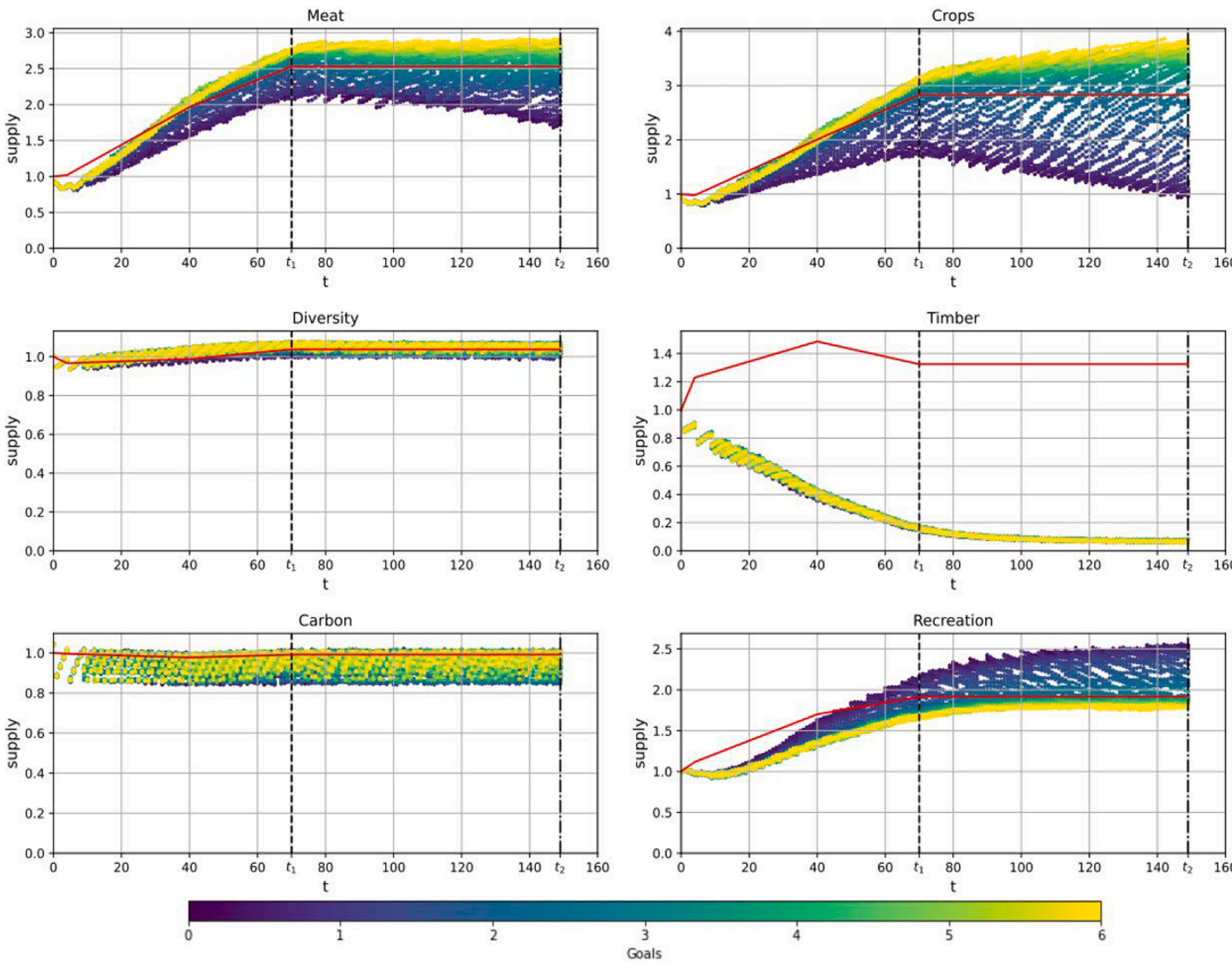

Fig. 5. The impact of Policy 1.2, in which the institution provides an economic incentive for crop production with a policy goal ranging from 0 to 6 times the initial crop supply. The red line represents the demand. The 70th and 149th year are labelled as t_1 and t_2, respectively.

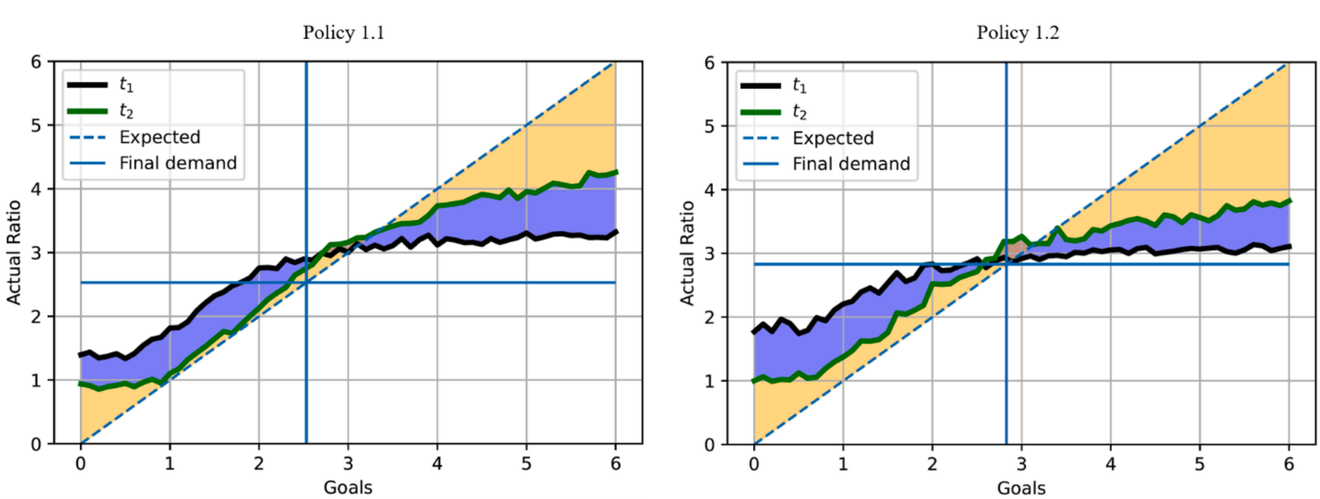

Fig. 6. Relative supply under different policy goals at t_1 and t_2. The horizontal axes represent the goals of Policy 1.1 adjusting meat production and Policy 1.2 adjusting crop production, while the vertical axes are the ratio of the actual supply to the initial supply. The black and green solid lines, respectively, indicate the supply of the corresponding ecosystem services at t_1 and t_2. The dashed straight lines show the expected supply ratio. The vertical solid lines indicate the final demands at t_1.

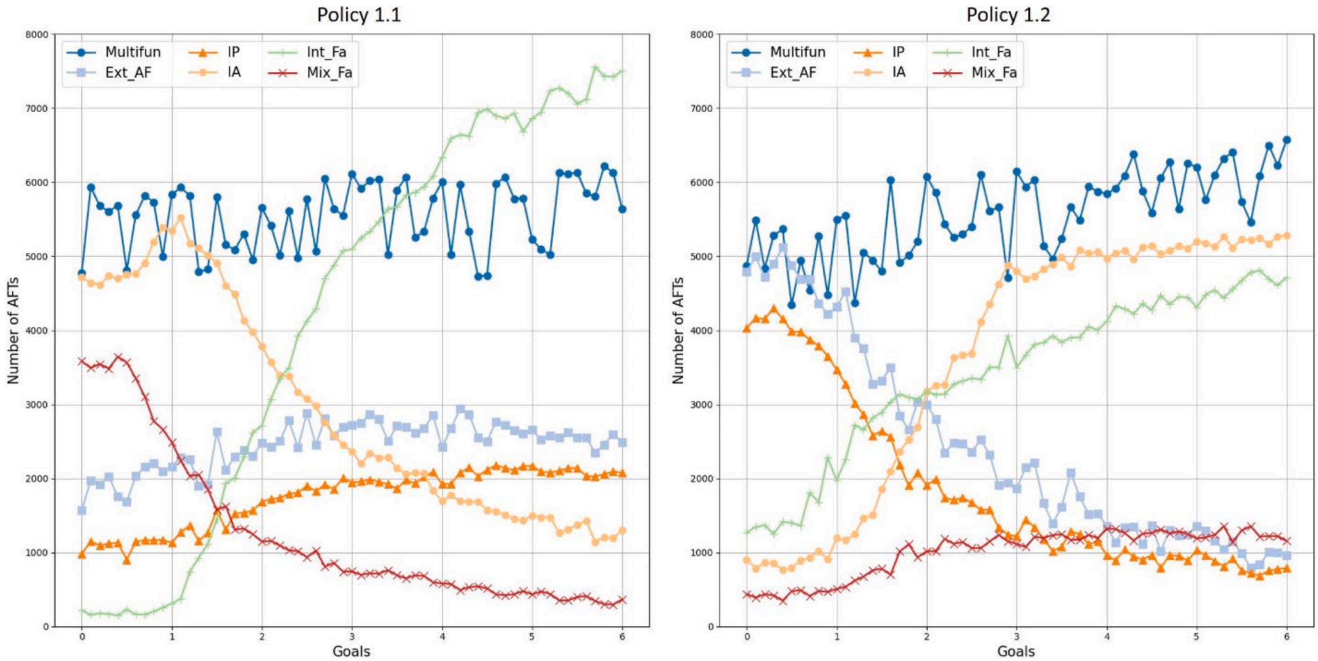

Fig. 7. Transitions of six dominant AFTs under different policy goals at the end of the model simulation at t_2. The full names of the AFTs are given in Table C1. The transitions of all AFTs are given in Fig. C3.

3.3. The joint impact of Policy 1.1 and Policy 1.2

In the real world, cross-subsidisation is a common policy instrument, which means institutions use the income from taxes to incentivise targeted production (Heald, 2002; Kratzke, 2009). Here, to maintain the meat production at the initial level and increase crop production fourfold, the agricultural institution taxes the former to attain the budget to subsidise the latter. Therefore, in this experiment, the subsidies are constrained dynamically by the taxes imposed on meat production. The parameterisation details are given in Table A4 in Appendix A.

With these settings, the simulation is run for 150 steps and the results are shown in Fig. 8. Within t_1, neither of the policies performs well enough to reach the goals. Meat production is driven to reach approximately twice its initial level at t_1, while crop production only hit three times its initial level within the same period. After t_1, the demands remain constant and the supplies of both services exhibit a more notable deviation from the demand curves and continue to head for the policy goals. It is natural to consider that the supplies of the services lack the sensitivity to policy interventions. There are two remedies to make the policy interventions more sensitive. One remedy is simply to use more intense policy interventions, such as higher levels of subsidies and taxes in each policy adaptation. The other measure is to make the policy adapt more frequently, that is, to gain more institutional swiftness. While both remedies should be effective, the latter might be of more interest. In the current settings, the institution adapts its policies every five iterations. If the policies can be adapted more frequently, the supplies of meat and crops might reach the policy goals more rapidly.

To better understand how the frequency of policy adaptation impacts the joint effect of meat and crop policies, we simulate various time lags ranging from 1 to 10 timesteps for both policies and obtain 100 combinations. The results are visualised in Fig. 9. The bars in the figure indicate the absolute difference between the policy goals and the supplies at t_1. The left sub-figure shows a consistent pattern that shorter adaptation lags on meat and longer on crops are favoured to meet the

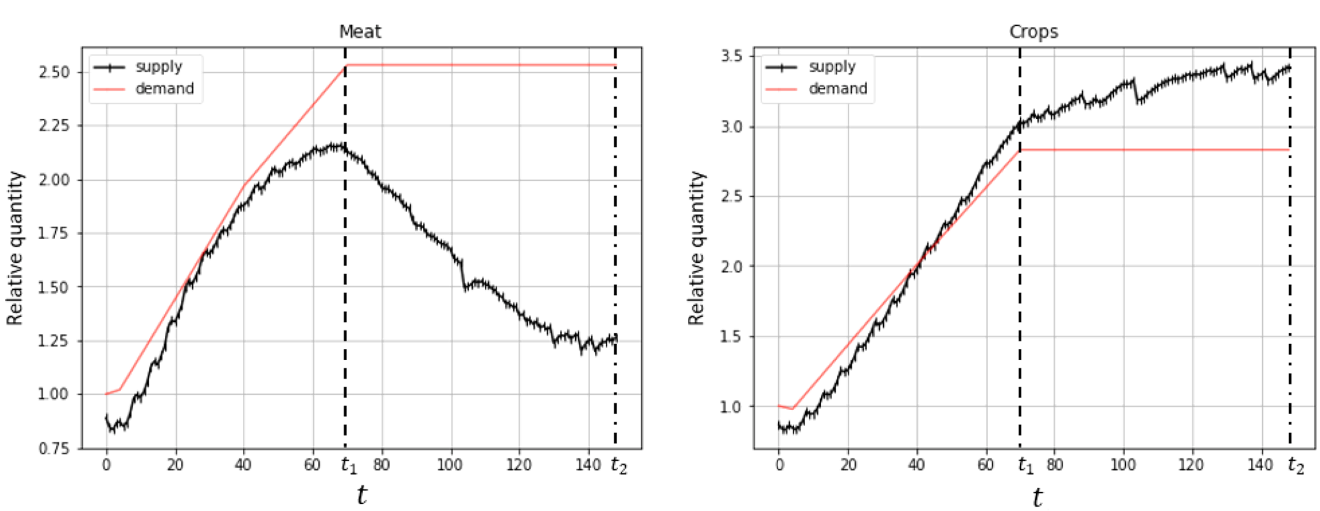

Fig. 8. Time series of meat and crop supply under the joint impact of Policy 1.1, meat taxation, and Policy 1.2, crop subsidisation. The 70th and 149th year are labelled as t_1 and t_2, respectively.

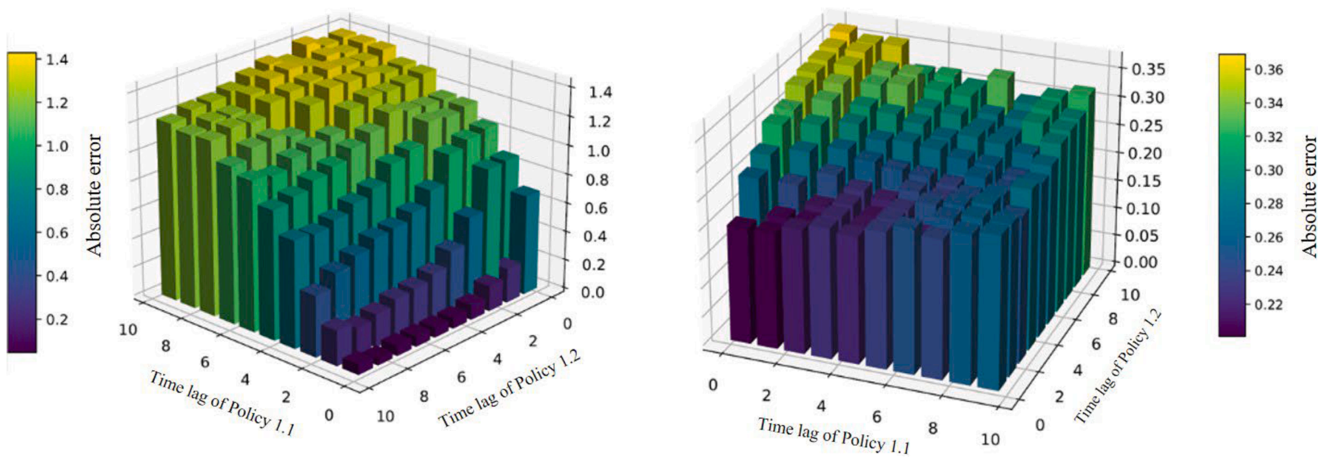

Fig. 9. Performance of joint impact of Policy 1.1 (meat taxation) and 1.2 (crop subsidisation) with different time lags in policy goal evaluation and intervention adaptation. The absolute error means the non-negative value of the gap between the policy target and the actual outcome.

policy goals of meat production. This is in line with the previous analysis of the policy spill-over effect. Intuitively, taxing meat production more frequently is more effective in reducing meat supply, while intervening with crop production less frequently reduces the spill-over effect on meat production. Additionally, meat production is relatively more sensitive to the adaptation lags of Policy 1.2 when Policy 1.1 is adapted at a moderate speed.

The right sub-figure displays the discrepancies between the crop supplies and the policy goal of Policy 1.2. The supply-goal gap of crop production reaches the minimum value when the adaptation lags of both Policy 1.1 and Policy 1.2 stay at their minimum. This is sensible because meat production does not have a significant spill-over effect on crop production, while the subsidies supporting frequent adaptation in Policy 1.2 are gained from the taxation of meat production. To sustain a frequent increase in crop subsidisation, the institution should evaluate the tax on meat production frequently.

The joint impacts of Policy 1.1 and Policy 1.2 highlight an intricate but intuitively understandable relationship between policy targets, policy adaptation frequencies, institutional budgets and cross-service spill-over effect. Policy 1.1 refuels the budget by taxing meat production based on the policy adaptation frequency; Policy 1.2 consumes the budget and provides subsidies to boost crop production; in turn, the boosted crop production stimulates meat production via cross-service spill-over effect, which then impairs the efficacy of Policy 1.1 in meat reduction. The interplay between multiple factors is a key attribute of complex systems, which poses a challenge to institutions facing trade-offs of different policy goals (Huang et al., 2022; Shrestha and Dhakal, 2019). If meat reduction is more important, the institution should apply Policy 1.1 more frequently and Policy 1.2 less frequently; if increasing crop production is more important, the institution should use both the two policies more frequently.

4. Discussion

4.1. Emergent dynamics

4.1.1. Marginal diminishing effect

The approach presented here has demonstrated the capacity to generate multiple meaningful emergent patterns when endogenizing institutional policy-making within a land system model. The emergence of these patterns is driven and explainable by the micro mechanisms of the coupled model, exhibiting systemic self-consistency. These patterns provide insights into a broader understanding of land system dynamics. A crucial finding is the marginal diminishing effect of policy interventions. Three factors might contribute to this effect. Firstly, the gains in policy interventions decrease as the supply-goal gaps become smaller, reflecting the adaptivity of the endogenous institutional agent. Secondly, the system itself has natural maximum and minimum production capacities. The maximum production capacity is constrained by the capitals and AFT productivities, which can be interpreted as resource capacity limitations. This is a common constraint that is similar to the carrying capacity in many social, economic and ecological systems (Arrow et al., 1995; Del Monte-Luna et al., 2004; Seidl and Tisdell, 1999). The third factor could be the trade-off between the derived benefits across different ecosystem services. For instance, if an AFT can produce crops and meat simultaneously (as some can, in small quantities), a policy intervention on one single ecosystem service can potentially impact the others, such as through enlarging the deviation of the untargeted service from its prescribed market or societal demand, which results in higher negative correction that counterbalances the policies' effectiveness. This mechanism can be understood as a cross-service effect and also applies in principle to disbenefits created in the production of desired services, as when intensive food production increases agricultural pollution (Czyżewski et al., 2021).

4.1.2. Asymmetric spill-over effect

The asymmetry of the spill-over effect can apply in the real world (e.g., when potentially valuable by-products saturate the market, driven by demand for the primary product), and is a reasonable result caused by the utility-seeking behaviour of AFTs in this model. The utility of crop production contributes more to the total utility of AFTs than meat production does. Thus, it is reasonable to prioritise crop production over meat production. An interesting point here is the adaptability exhibited by the heterogenous AFTs, which can drive some ecosystem service production at the system level to approach the policy targets while keeping the others almost unchanged. This illustrates the ability of many complex systems to absorb external disturbances (Miller and Page, 2009) and the adaptability of land users at a microscopic level within the land system (Bravo-Peña and Yoder, 2024; Funk et al., 2020; Makate et al., 2019).

The asymmetric spill-over effect implies that policies with stronger spill-over effects may face greater challenges in achieving their goals due to the added complexities they create. Spill-over effects can disrupt the balance between supply and demand in untargeted ecosystem services, leading to gaps between what is supplied and what is needed. These gaps act as significant market forces, prompting AFTs to address the imbalance. In contrast to Policy 1.1, Policy 1.2, which focuses on adjusting crop production, must tackle demand-supply imbalances not only in the crop market but also in the meat market due to these interconnected effects. Such effects may be stronger where specialised production systems are concerned, because changes in production levels have inevitable implications for other services, and weaker where a range of services can be produced in multifunctional settings.

In CRAFTY, a single land user agent can produce multiple ecosystem services and products. It is challenging for mixed service producers to achieve optimal flexibility to (often partially) switch swiftly between products in response to demand and policy changes. In reality, mixed service production is constrained by many factors, such as capacity and resource availability, production set-up time and cost, and supply chain agility (Clark, 2006; Stokes et al., 2023). When AFTs fail to fully adjust service mixes, demand-supply gaps start to form, and asymmetric spill-over effects emerge.

4.1.3. Policy adaptation frequency

The experiment combining the frequency of policy adaptation and cross-subsidisation reveals some significant challenges in institutional decision-making that involve multiple policy targets. These policy targets may not be explicitly conflicting but can impair policy efficacy through the cross-service effect. It is plausible that a portfolio of policy instruments requires different frequencies of policy adaptation. High policy adaptation frequencies do not necessarily lead to high effectiveness of policy intervention but might overshoot policy goals and bring unnecessary instability to the system (Batini and Nelson, 2001). In contrast, less frequent policy adaptation might be conducive to policy effectiveness because it gives a comparatively longer period of time to examine the policy performance (Watts et al., 2020). However, significant time lags can cause difficulties in decision-making by making it harder to discern the causal links between the system's response and the implemented policies (Bekaert et al., 2013).

4.2. Reflections on model design

4.2.1. Conceptual and technical choices

Modelling endogenous institutions within land systems is still an open challenge, whether representing emergent or pre-defined institutions (or even both) (Ghorbani et al., 2017, 2020, 2021). For example, an earlier study that incorporated institutional agents directly within the CRAFTY framework (Holzhauer et al., 2019) illustrates an analogous but distinct approach, which was less generalisable beyond CRAFTY itself, but commensurately more detailed in exploring the dynamics of that model. The work described here represents an extension to the Holzhauer et al. (2019) approach in that it is in principle applicable in different models, and incorporates more flexible representations of policy goals and interventions. The endogenous institutional modelling presented in this paper is also guided by the principles of parsimony, transparency, and extensibility. These principles are significant to the model's conceptual framework design and technical choices.

The model is parsimonious in the sense that its overall structure is a simple, intuitive closed-loop control system with the institutional agents working as controllers in response to land use changes under constraints. This idea is inspired by the thermostatic model in political science (Wlezien, 1995), although implemented slightly differently here. To achieve transparency in terms of institutional decision-making, we choose to avoid using machine learning or other data-driven approaches that may be challenging to interpret. Instead, PID-fuzzy logic control is used. Fuzzy logic controllers are particularly suitable for simulating decision-making with imprecise data, qualitative assessments, and complex input-output linkages, which are commonly seen in real-world policymaking processes (Guidara, 2020). The PID-fuzzy control approach provides an intuitive and systematic way to estimate the land use model's outcome against policy targets while allowing for the flexibility of integrating real-world policymakers' knowledge in an IF-THEN form (Dadios, 2012). In addition, fuzzy logic controllers can naturally preserve real-world policymakers' bounded rationality, which is more advantageous than data-driven approaches in realism and interpretability. Furthermore, the constrained behaviours of PID-fuzzy logic controllers resonate well with incrementalism in political science because of its heuristic, continually adaptive nature (Gigerenzer et al., 2022; Pal, 2011). The model's widely applicable closed-loop control framework and flexibly configurable fuzzy logic controller (Cingolani and Alcala-Fdez, 2012; Cingolani and Alcalá-Fdez, 2013) endow the model with extensibility to simulate many institutions and policies simultaneously.

4.2.2. Modelling assumptions

In addition to the primary assumptions of closed-loop control and heuristic decision-making that form the model's conceptual foundation, several key assumptions within each sub-model deserve attention.

First, policy goals should be explicitly expressed as vectors (see Eq. (1)). Similar to the target temperature of a thermostat, policy goals serve as set points that drive the system in the desired direction. Clearly defined policy goals provide the foundation for the second assumption: institutions evaluate policy performance based on goal-outcome discrepancies. While this assumption simplifies the complexity of real-world policy evaluation, it offers an intuitive and practical way to operationalise policy evaluation within the model. This approach aligns with the heuristic nature of human decision-making in complex environments, where simplified strategies are often favoured in practice (but may or may not be received better by citizens and more successful in achieving targets (e.g., D'Acunto et al. (2021) and Knickel et al. (2009)). Furthermore, it is rooted in the principles of closed-loop control systems and the thermostatic model in political science, both of which emphasise feedback mechanisms that guide adjustments in response to changes (Easton, 1965; Wlezien, 1995).

Third, the budgets required for policy interventions should be quantifiable. This is a natural assumption, as every policy intervention — whether taxation, subsidisation, or the establishment of protected areas — requires financial resources. Additionally, the model assumes that the budget needed to implement a policy is positively correlated with the policy adjustment intensity. This makes intuitive sense because the more aggressive a policy is made to influence a land-use system, the more resources it typically demands. This may not be the case where existing instruments are altered (e.g. Zahrnt (2009)), but a similar logic does apply to disincentive policies, such as taxes and fines, which require more funding for enforcement and monitoring compared to lighter regulations (Lans Bovenberg and Goulder, 2002; Mondal and Giri, 2023). The model does not, at present, consider issues of 'political capital' or other variable constraints that might affect policy implementation, although the design could be extended to incorporate these as explicit or generic factors.

4.2.3. Modelling non-incremental policy changes

As mentioned in Section 2.1, incrementalism is here modelled as constrained policy actions, representing an important facet of long-term policy change within relatively stable regimes. This aligns with Lindblom's (1959) observation that policymakers operate within the constraints of limited cognitive and resource capacities, as well as the boundaries of political feasibility inherent in democratic systems. Incrementalism in public policy has been widely identified and continues to be noted as a feature even of policy change involving transformative methods (e.g., digitalisation (Haug et al., 2024), goals (Kulovesi and Oberthür, 2020) or situations (Marsden and Docherty, 2021)). That said, many policy processes are clearly not incremental in nature. Non-democratic regimes may (in some cases) be characterised by rapid or drastic top-down policy-making, and theories such as punctuated equilibrium have been proposed to account for the operation of different modes of policy-making within diverse contexts (Benson and Russel, 2015; True, 2000).

However, incrementalism does not necessarily preclude radical policy changes, in the model or in reality (e.g. Buchan et al. (2019)). Here, institutional agents can be enabled to make drastic policy changes by setting the budget to be very large, giving policies a high priority, removing policy inertia constraints, using negligible policy time lags, or giving the fuzzy logic controller a very wide output range. For example, in Zeng et al. (2024a), an institutional agent with a large taxation change range for each policy adaptation and without budget or policy inertia constraints, demonstrates its powerful ability to diminish the goal-outcome errors in meat production in CRAFTY. Similar insights can also be gained from the Perceptual Control Theory (PCT) (Forssell and Powers, 2009), which can be mathematically analysed and indicates that if the closed-loop controller works as an infinitely powerful signal amplifier, it can maintain the system's immunity to very large disturbances. Such extreme settings diminish the institutional model's meaningful correspondence to real-world institutional systems, but less extreme settings may allow it to simulate institutions whose power and resources are highly centralised.

It is noteworthy that if many policies and institutions are considered simultaneously, the policies' net effect is determined by their synergistic or conflicting relationships and not their individual attributes alone. This may represent an informative target for a model of this kind, for instance, applied to climate change or other areas where multiple policies interact. Modelling in this context could explore the extent to which policy centralisation or fragmentation supports the achievement of (transformational) targets (Kowalewski and Birch, 2020; Pollak and Riekmann, 2008).

In addition to the capability of mimicking continual policy changes, this institutional model can also handle binary (0 and 1) variables, which might be useful in situations where structural, qualitative policy changes need to be modelled. For instance, a carbon trading sub-model could be constructed, with a PID-fuzzy logic controller to determine when carbon trading should be allowed or prevented in order to achieve a carbon reduction target. Such an approach could also be used to turn entire policy areas or actors 'on' or 'off', representing structural changes in governance.

4.3. Limitation and future research

4.3.1. Exogenous impact

"All models are wrong, but some are useful" (Box, 1976). Given the complexity of real-world policymaking, let alone its coupling with land use dynamics, this model does not attempt to be 'perfect'. Instead, it is intended to serve as a useful starting point for future studies. The current model's capability is limited in dealing with exogenous changes, such as unforeseeable disturbances out of the closed-loop system. The model might perform well if handling such changes does not require structural changes or measures beyond the existing policies. For example, if a sudden rise or drop occurs in meat supply, the institutional agent can still use existing economic policies to adjust meat supply accordingly. However, in cases where novel policies are needed, institutional agents may struggle to adapt effectively, such as coping with the consequences of unforeseen geopolitical conflicts, environmental disasters, or technological disruptions. Dealing with these circumstances might require drastically shifting policy goals, changing policy adaptation frequencies, or even creative policy portfolios (Ghorbani et al., 2023; Howlett et al., 2018). Future research could incorporate exogenous impact based on Punctuated Equilibrium Theory – a non-incrementalism policymaking paradigm that considers discontinuous but crucial policy changes (Givel, 2010; Princen, 2013; True et al., 2019), which is challenging but rewarding. A human-in-the-loop mechanism or tailoring the model for each individual case might be viable approaches, but it seems unlikely to be able to build a model that is generalisable enough for all exogenous disturbances given their unpredictable nature, without some role for human or artificial intelligence within the model.

4.3.2. Learning processes

When discussing the modelling of learning processes, reinforcement learning naturally comes to mind as a prominent approach. Designed to enable agents to make effective decisions without supervision (Wesselink et al., 2014), reinforcement learning has gained attention in policymaking research due to rapid advancements in artificial intelligence (e.g., Osoba et al. (2020), Wolf et al.(2023), and Zheng et al. (2022)). This method offers valuable insights into optimal or near-optimal solutions for policymaking problems, which can be used to guide real-world decision-making processes. Another approach leverages many-objective decision-making, typically employing evolutionary algorithms to determine sequences of time-dependent policy actions that strive for Pareto optimality (Kasprzyk et al., 2013; Quinn et al., 2017; Zeng et al., 2024d). However, real-world policymakers do not have the luxury of engaging in rapid, intensive trial-and-error learning processes. Instead, they learn through slower, more complex pathways, often facing overwhelming information (González, 2017).

Moreover, researchers in political science have long observed there exist gaps between policy learning and policy change (Moyson et al., 2017). Increasing governmental institutions' ability to gather and process more information does not necessarily give rise to greater governmental effectiveness (Etheredge and Short, 1983). In the context of evidence-based policymaking, political considerations often manifest indirectly through disputes over the credibility of evidence, rather than through direct discussions about the prioritisation of values (Wesselink et al., 2014). This highlights the multifaceted nature of learning in policymaking, where cognitive, procedural, and political factors interact in shaping outcomes.

In this model, learning processes are not currently incorporated. One significant challenge lies in establishing a causal link between policy learning and subsequent policy actions. Additionally, parameterizing these learning processes introduces the risk of increased model complexity, which could hinder interpretability. Nonetheless, the findings in this paper offer a baseline for future experiments that explore learning processes. These experiments could reduce reliance on data-intensive training by offering an alternative approach that uses expert input for parameterisation. The weighting and evaluation of policy outcome errors, the budget allocation weights, as well as the internal settings of fuzzy logic controllers, are key areas where institutional learning could be integrated. An extra layer of fuzzy logic controllers (Sharma et al., 2016) or interpretable decision trees (Balcan and Sharma, 2024) adjusting these parameters might be promising approaches. Another choice might be to use state-of-the-art large language models, which provide a novel method to simulate human-like experiential learning while generating examinable reasoning behind policy actions (Zeng et al., 2024a,b).

4.3.3. Empirical applications

Parameterizing decision-making models with empirically valid data is particularly challenging in policy-making due to the blend of objective and subjective elements involved. Objective aspects such as policy goals, budgets, and policy inertial constraints, though seemingly straightforward, are often complex. Some policy goals are clearly defined and can be conveniently integrated into a formal model, yet some are quite vague (Convention on Biological Diversity, 2020). Institutions' budgets are rarely fixed or definitive. Policy inertia constraints are abstract representations of non-monetary resistance to policy changes, which have no direct equivalent. Subjective parameters include the internal settings of fuzzy logic controllers, policy evaluation weights, and budget allocation weights. Given these complexities, it might be unrealistic to expect the model to be fully parameterised using accurate empirical data. Nevertheless, it is advisable to strategically prioritise data acquisition using multiple sources and approaches in further studies. To enable the application of the model to a more empirical case based on "real-world" data, the approaches listed in Table C2 may be useful, and the following steps could be taken in future studies:

Historical data: Historical data can be used to parameterise the behaviours and attributes required in the model (see Fig. 2). For example, historical policy information can be used to define the initial policy guess on expenditure on e.g. subsidies for crops, relative to other subsidies and taxes.

Integrate stakeholder feedback: Policymakers and other stakeholders involved in the decision-making process within the region of simulation can be involved in parameterizing the subjective parameters of the process. Stakeholder involvement can also help with objective parameters such as clarifying policy goals and estimating policy inertia to ensure the model runs under reasonable parameter settings.

Simulation design: Policies can be adapted and updated based on empirical evidence on the frequency of policy adaptation, tailored to the region or country and policy realm of interest. Simulations can be run based on current and emerging policies, such as the 30 % Protected Areas by 2030. Narrative-based simulation could be useful for handling vague or abstract parameters through meaningful narratives. Simulations can also utilise the data derived from other empirically valid models.

Sensitivity analysis: A systematic sensitivity analysis could be used to explore the impact of changing uncertain and subjective parameters, such as policy inertia, policy evaluation, and budget allocation on achieving the policy goal and the associated impacts on the land system.

Iterative Refinement: Model parameterisation can be continuously refined based on feedback from empirical applications and further stakeholder engagement. This iterative process is essential for generating new insights and adapting to evolving policy landscapes, thereby enhancing the model's utility and effectiveness in supporting policy assessment.

In addition, an example of parameterising the institutional model with potential application to organic farming in Germany is provided in Appendix D.

5. Conclusion

This research has focused on incorporating heuristics and incrementalism as interpretable endogenous institutional decision-making behaviours influencing land use change. This approach emphasises the provision of relevant information, irrespective of whether the institutions fail or succeed in achieving policy goals. The theories resonate with the algorithms and methods, including PID controller and fuzzy control theory, which have been long established in the field of control theory. Numerical experiments were carried out to investigate an institution that implements two policies influencing ecosystem service production. Our findings highlight the potential for using the endogenous institutional model in exploring policy formulation. This approach uncovers various processes including the marginal diminishing effect of economic policy interventions, asymmetric spill-over effects for different ecosystem services, and trade-offs between policy goals. The endogenous institutional model demonstrates the ability to uncover complex emerging patterns, which have substantial implications for land systems. However, challenges and further improvement have to be addressed, such as incorporating exogenous impact, institutional learning processes, and parameterising the model empirically.

CRediT authorship contribution statement

Yongchao Zeng: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Conceptualization. **Joanna Raymond:** Writing – review & editing, Validation, Methodology, Conceptualization. **Calum Brown:** Writing – review & editing, Writing – original draft, Validation, Project administration, Conceptualization. **Mohamed Byari:** Writing – review & editing, Validation. **Mark Rounsevell:** Writing – review & editing, Validation, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization.

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

Table A1
Attributes and behaviours of an institution agent.

	Name	Explanation
Attributes	Unique ID	A unique label that distinguishes an Institution from the others.
	Policies	A set that contains all policies.
	Information	A container where an institution saves necessary information supporting decision-making.
	Uncertainties	A list of variables determining the noise.
	Budget	A set of conditions that constrain the monetary sufficiency for implementing policies.
	Decision rules	A set of fuzzy rules reflecting how institutions make decisions.
Behaviours	Initialisation	Set the initial values of institutional attributes.
	Information collection	Collect information from the target land use system.
	Prediction	Make predictions based on the collected information.
	Policy evaluation	Evaluate the performance of existing policies using PID errors.
	Resource allocation	Allocate the budget among multiple policies based on budget constraints.
	Policy implementation	Apply the resultant policy interventions to the target land use system.

Table A2
Attributes of policy.

	Name	Explanation
Attributes	Unique ID	A unique label that distinguishes a policy from the others.
	Target service	In CRAFTY, the target service is the service an institution intends to influence with this policy. Technically, the target can be any modifiable variable in the model.
	Policy type	The type of policies can be taxes, subsidies, administrative orders, information, etc. Different types of policies can have very different ways to impact the target system.
	Initial guess	A value related to the initial policy intervention, which is generated based on the educated guess of model users. The initial guess is crucial for policymaking due to the path-dependency feature of complex systems.
	Policy inertia	Drastic policy changes are prone to encountering resistance from the public, interested parties, and physical limitations. Ideally, the inertia constraint serves as a comprehensive single indicator reflecting all non-monetary resistances to dramatic policy changes.
	Policy goal	The ultimate policy goal that the policy is intended to achieve.
	Intervention	The policy intervention implemented to influence the target land use system.
	Evaluation results	Measured by the PIDs errors that reflect the gaps between the policy goal and target service.
	Time lag	It takes time for policy interventions to become fully effective. Institutions also need time to respond to new challenges. The time lag depicts the duration between each two policy adaptations.
	Timer	The timer is updated and checked every iteration to judge if it is time for policy adaptation.
	Adapting	A Boolean variable signifying if it is the time for this policy to be adapted.
	Intervention modifier	A variable that modifies the policy intervention based on the evaluation results.
	Intervention history	A container to save the actual policy intervention in each iteration.

Table A3
Nomenclature.

Variables	Variable meaning
T_s^{ij}	The time when institution i's policy j starts.
T_e^{ij}	The time when institution i's policy j ends.
Q^{ij}	The quantity of policy goal that institution i's policy j is intended to change.
$\mathbf{G}^{\mathbf{ij}}$	A vector of $\left[T_s^{ij}, T_e^{ij}, Q^{ij}\right]$ defining the goal of institution i's policy j.
$\varepsilon_t^{(P)}$	Proportional error.
$\varepsilon_t^{(I)}$	Integral error.
$\varepsilon_t^{(D)}$	Derivative error.
o_t^{ij}	Model output under the influence of institution i's policy j.
$C^{(P)}$	The weight of proportional error.
$C^{(I)}$	The weight of integral error.
$C^{(D)}$	The weight of derivative error.
k	The time interval used to calculate integral and derivative errors.
E	Weighted sum of proportional, integral, and derivative errors.
F	A function representing a fuzzy logic controller that maps.
A_t^{ij}	The constrained policy variation of institution i's policy j at time t.
$sign$	A function output -1, 0 or 1 according to the sign of its input.
N^{ij}	The policy inertia constraint of institution i's policy j.
M_t^{ij}	A multiplier that modifies the institution i's policy j.
η^{ij}	The step size of intervention institution i's policy j.
f	A function that maps a policy intervention onto the resource needed for implementing this policy.
V_t^{ij}	Desired policy intervention without considering the budget constraints.
R_t^{ij}	The resource needed for implementing institution i's policy j.
ξ_j	A weight reflecting the comparative importance of policy j perceived by institution i.
r_t^{ij}	Resource allocated to implement institution i's policy j.
r_t^{*ij}	Optimal solution for r_t^{ij} under the budgetary constraints.
V_t^{*ij}	Policy intervention implemented using resource r_t^{*ij}.
B^i	Total budget of institution i.
c_{xy}	An AFT's competitiveness at land cell (x, y).
p_S	AFT production level of ecosystem service S.
V_t^{iS}	Institution i's economic policy that targets ecosystem service S.
m_S	Marginal utility of ecosystem service S.

Table A4
Parameterisation of the institution, Policy 1.1, and Policy 1.2. Experimental variables are highlighted in bold.

Institution parameter Value		
Unique ID	1	
Policies	1.1, 1.2	
Information	Crop supply and demand, meat supply and demand.	
Uncertainties	**Null**	
Budget	**Gain from taxation**	
Decision rules	**Tax or Subsidy**	
Policy parameter	**First policy**	**Second policy**
Unique ID	1.1	1.2
Target service	Meat	Crops
Policy Type	**Tax**	**Subsidy**
Initial guess	100,000	100,000
Policy inertia constraint	0.2	0.2
Policy goal	**1.0**	**4.0**
Intervention	0.0	0.0
Intervention modifier	0.0	0.0
Evaluation result	0.0	0.0
Time lag	**1 - 10**	**1 - 10**
Timer	Equal to Time lag	Equal to Time lag
Adapting	False	False

Appendix B

Table B1
Parameterisation of decision rule labelled as “Economic”.

```
FUNCTION_BLOCK economic
VAR_INPUT
gap: REAL;
  END_VAR
VAR_OUTPUT
Intervention: REAL;
END_VAR
FUZZIFY gap
TERM nhigh:= (−0.5,1) (−0.3,0);
TERM nmild:= (−0.5,0) (−0.3,1) (−0.1,0);
TERM nlight:= (−0.3,0) (−0.1,1) (0,0);
TERM neutral:= (−0.05,0) (0,1) (0.05,0);
TERM plight:= (0, 0) (0.1, 1) (0.3,0);
TERM pmild:= (0.1,0) (0.3,1) (0.5,0);
TERM phigh:= (0.3, 0) (0.5, 1);
END_FUZZIFY
DEFUZZIFY intervention
TERM nhigh:= (−0.2,1) (−0.1,0);
TERM nmild:= (−0.15,0) (−0.05,1) (0,0);
TERM neutral:= (−0.02,0) (0,1) (0.02,0);
TERM pmild:= (0,0) (0.05,1) (0.15,0);
TERM phigh:= (0.1,0) (0.2,1);
METHOD: COG;
DEFAULT:= 0;
END_DEFUZZIFY
RULEBLOCK No1
AND: MIN;
ACT: MIN;
ACCU: MAX;
RULE 1: IF gap IS nhigh THEN intervention IS nhigh;
RULE 2: IF gap IS nmild THEN intervention IS nmild;
RULE 3: IF gap IS nlight THEN intervention IS neutral;
RULE 4: IF gap IS neutral THEN intervention IS neutral;
RULE 5: IF gap IS plight THEN intervention IS neutral;
RULE 6: IF gap IS pmild THEN intervention IS pmild;
RULE 7: IF gap IS phigh THEN intervention IS phigh;
END_RULEBLOCK
END_FUNCTION_BLOCK
```

Table B2
Parameterisation of decision rule labelled as “Subsidy”.

```
FUNCTION_BLOCK Subsidy

VAR_INPUT
gap: REAL;
END_VAR
VAR_OUTPUT
intervention: REAL;
END_VAR
FUZZIFY gap
TERM plow:= (0,1) (0.15,0);
TERM plight:= (0.025, 0) (0.175, 1) (0.325,0);
TERM pmild:= (0.175,0) (0.325,1) (0.45,0);
TERM phigh:= (0.325, 0) (0.45, 1);
END_FUZZIFY
DEFUZZIFY intervention
TERM neutral:= (−0.015,1) (0.05,0);
TERM plight:= (0.025,0) (0.075,1) (0.125,0);
TERM pmild:= (0.075,0) (0.125,1) (0.175,0);
TERM phigh:= (0.125,0) (0.2,1);
METHOD: COG;
DEFAULT:= 0;
END_DEFUZZIFY
RULEBLOCK No1
AND: MIN;
ACT: MIN;
ACCU: MAX;
RULE 0: IF gap IS plow THEN intervention IS neutral;
RULE 1: IF gap IS plight THEN intervention IS plight;
RULE 2: IF gap IS pmild THEN intervention IS pmild;
RULE 3: IF gap IS phigh THEN intervention IS phigh;
END_RULEBLOCK
END_FUNCTION_BLOCK
```

Table B3
Parameterisation of decision rule labelled as “Tax”.

```
FUNCTION_BLOCK Tax

VAR_INPUT
gap: REAL;
END_VAR
VAR_OUTPUT
intervention: REAL;
END_VAR
FUZZIFY gap
TERM nhigh:= (−0.5,1) (−0.3,0);
TERM nmild:= (−0.4,0) (−0.3,1) (−0.2,0);
TERM nlight:= (−0.3,0) (−0.1,1) (0,0);
TERM nlow:= (−0.1,0) (0,1);
END_FUZZIFY
DEFUZZIFY intervention
TERM neutral:= (−0.05,0) (0,1) (0.025,1);
TERM light:= (−0.125,0) (−0.075,1) (−0.025,0);
TERM mild:= (−0.175,0)(−0.125,1) (−0.075,0);
TERM high:= (−0.2,1) (−0.125,0);
METHOD: COG;
DEFAULT:= 0;
END_DEFUZZIFY
RULEBLOCK No1
AND: MIN;
ACT: MIN;
ACCU: MAX;
RULE 1: IF gap IS nhigh THEN intervention IS high;
RULE 2: IF gap IS nmild THEN intervention IS mild;
RULE 3: IF gap IS nlight THEN intervention IS light;
RULE 4: IF gap IS nlow THEN intervention IS neutral;
END_RULEBLOCK
END_FUNCTION_BLOCK
```

Appendix C

Table C1
Names of the AFTs.

Abbreviation	Full Name
VEP	Very extensive pastoral
Int_AF	Intensive agro-forestry
Mix_P	Mixed pastoral
IP	Intensive pastoral
Min_man	Minimal management
EP	Extensive pastoral
Ext_AF	Extensive agro-forestry
UMF	Unmanaged forest
Multifun	Multifunctional
Mix_For	Mixed forest
UL	Unmanaged land
IA	Intensive arable
MF	Managed forest
Mix_Fa	Mixed farming
Int_Fa	Intensive farming
Ur	Urban
P-Ur	Peri-urban

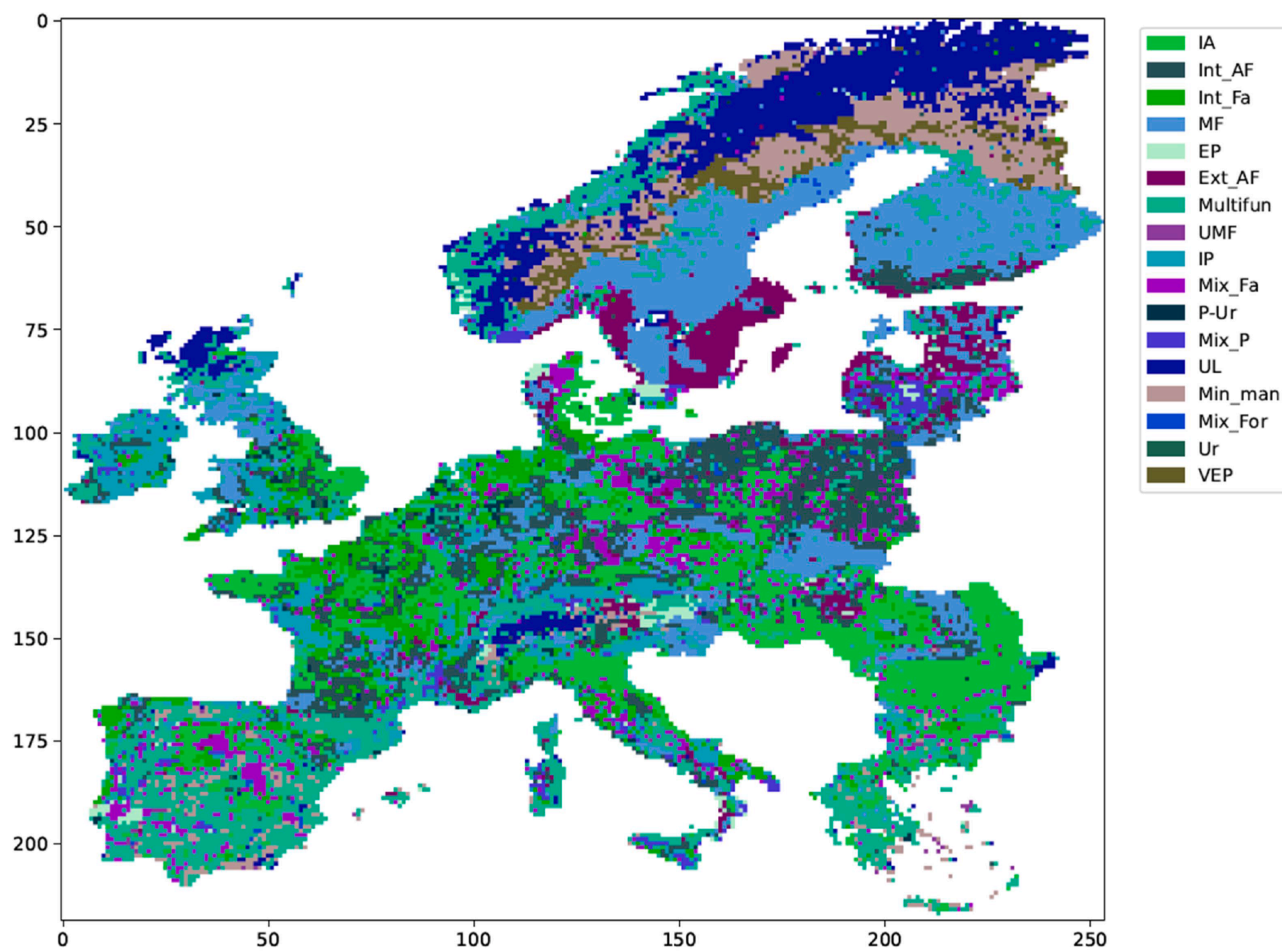

Fig. C1. Initial distribution of AFTs in CRAFTY-EU.

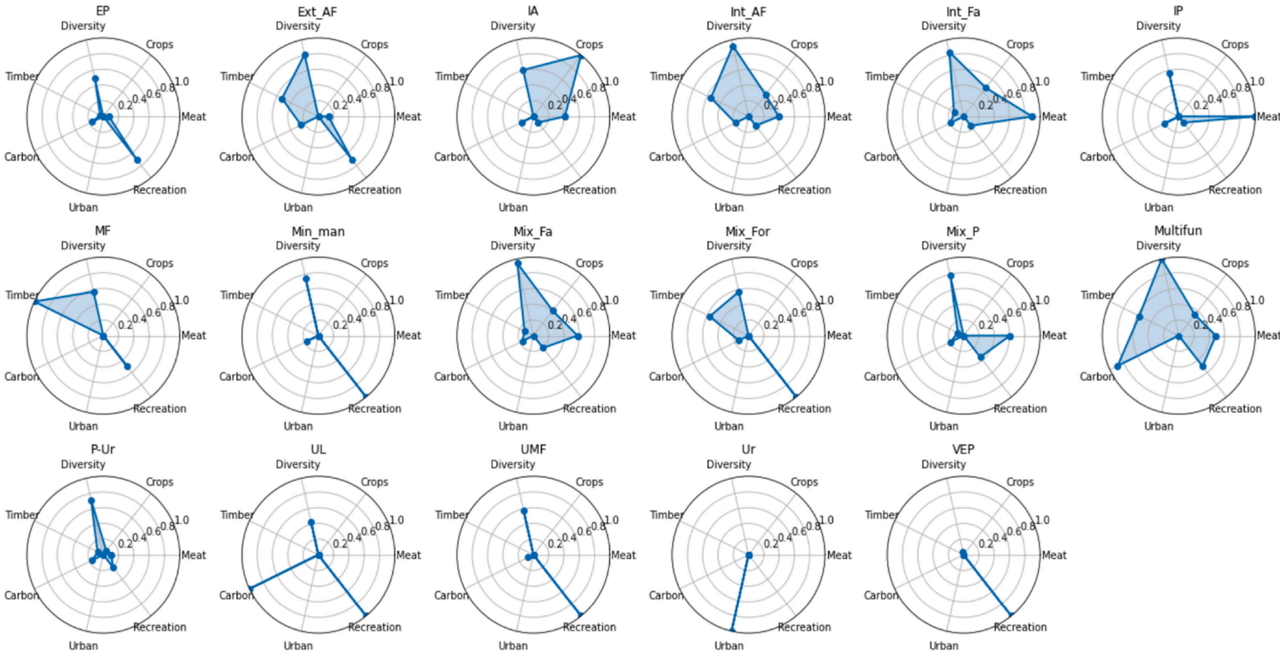

Fig. C2. Normalised ecosystem service production levels of the 17 AFTs in CRAFTY-EU.

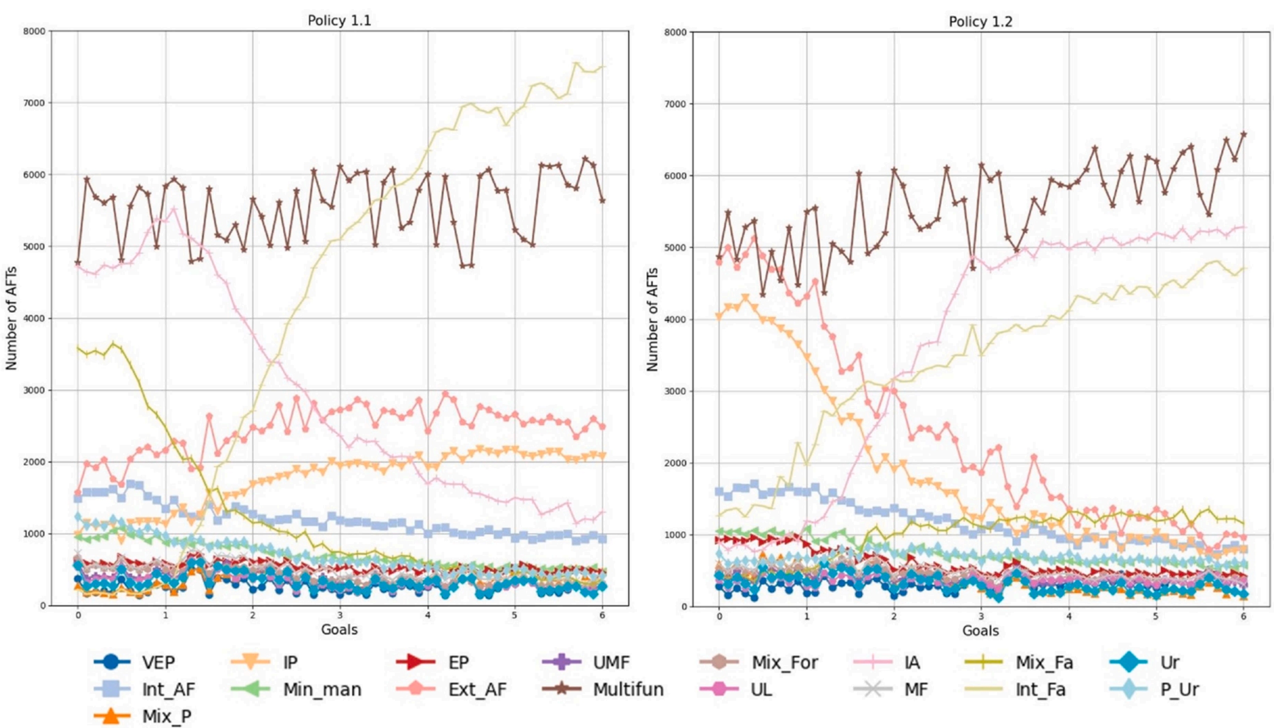

Fig. C3. Transitions of all AFTs under different policy goals at the end of the model simulation at t_2.

Table C2
Potential approaches to parameterizing the institutional model in future research.

	Parameter/ Potential data source	Stakeholder involvement	Historical data	Narrative-based simulation	Empirical modelling data	Sensitivity analysis
Institution	Policies	✔	✔	✔		
	Information	✔		✔	✔	
	Uncertainties	✔		✔		✔
	Budget	✔	✔	✔	✔	✔
	Decision rules	✔		✔		
	Policy evaluation	✔		✔		✔
	Budget allocation	✔		✔		✔
Policy	Target service	✔	✔	✔		
	Policy type	✔	✔	✔		
	Initial guess	✔	✔	✔		✔
	Policy inertia	✔		✔	✔	✔
	Policy goal	✔	✔	✔	✔	✔
	Time lag	✔	✔	✔	✔	✔

Appendix D

Example of Parameterizing the Institutional Model: Potential Application to Organic Farming in Germany

The example provided here is intended to enhance understanding of parameterisation and to illustrate guidance for the empirical application of this model. It might not be sufficiently detailed for a direct application, as this would require substantially more calibration and verification.

Policy Goal To parameterise the institutional model, policy goals can be taken directly from published policy documents. In this example, the Organic Action Plan targets 25 % of EU agricultural land to be under organic farming by 2030 (European Commission, 2024). For Germany, the national target is more ambitious, with organic farming expected to cover 30 % of the total agricultural area by 2030. (For unquantified policy goals, the framework proposed by Fetting (2020), involving stakeholder input, could be used to establish measurable targets.)

Information Historical data can be used to initialise key parameters. For example, the share of organically farmed land in Germany increased from 1.6 % in 1994 to 11.4 % by the end of 2023 (Kuhnert, 2024). This historical trend provides a basis for estimating the gap between the target (30 %) and the current share of organic farming. Spatial information on crop management (at least at state resolution) can be used to establish baseline distributions that affect subsequent uptake of organic farming (Kuhnert, 2024). Uncertainties may occur during real-world information collection, so the collected data can be adjusted and tested using predefined value distributions to account for relevant biases or errors.

Budget According to Becker et al. (2022) and Lampkin and Sanders (2022), in Germany, organic farming is supported under the *Second Pillar* of the CAP Strategic Plans (2023–2027), which allocates approximately 20 % of its funding to organic farming. The *second pillar* represents about 10 % of Germany's total CAP budget of over €30 billion for the period. Based on these figures, the approximate annual funding for organic farming in Germany can be inferred. This budget can be distributed evenly across the years or adjusted to follow an expected growth trajectory for organic farming areas.

Time Lag The institutional model should include time lags to account for the delayed effects of policy changes. Historical CAP funding periods, such as 2014–2020 (European Council, 2019) and 2023–2027 (European Council, 2024), suggest a time lag of 5–7 years for major adjustments. However, the EU Strategy on Adaptation to Climate Change (Climate ADAPT, 2024) advocates for faster responses, indicating that shorter time lags (e.g., 2–3 years) might also be meaningful.

Initial Guess When historical data is unavailable for a new policy, an initial parameter estimate can be inferred. For organic farming, conversion subsidies for arable land in Germany average €394/ha/year and maintenance subsidies are €264/ha/year (Kuhnert, 2023). These values can serve as initial subsidy levels for the model.

Policy Inertia Historical data on subsidies for organic farming can be analysed to determine the maximum and minimum annual changes. This range can be used to approximate policy inertia, which can help constrain the model to realistic variations and avoid erratic behaviour. Sensitivity analyses can further test the impact of different levels of policy inertia on model outputs.

Decision Rules, Policy Evaluation, and Budget Allocation These elements involve subjective judgment by policymakers. Hypothetical settings can be tested to align with intuitive decision-making. For instance, a straightforward decision rule could be: IF the gap between the policy goal and the current outcome is large, THEN adjust the policy significantly. For policy evaluation, historical trends in organic farming coverage, which show steady growth with minimal fluctuations, suggest that using the latest coverage of organic farming land might be enough to estimate the gap between the policy goal and actual coverage. Budget allocation can be estimated based on historical funding allocation within the CAP framework if multiple policies sharing the same budget account are considered. For greater accuracy, in-depth interviews with stakeholders—such as policymakers from the Federal Ministry of Food and Agriculture or experts from the Thünen Institute (Özdemir, 2022)—could further clarify strategies for policy adjustments and budget planning.

Data availability

I have shared the links to my data and code in the manuscript.

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