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Research

How spatial feedbacks between institutional and ecological patterns drive landscape dynamics in peri-urban commons

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ABSTRACT. Rapid urbanization is a critical landscape transition that impacts biodiversity, ecosystem goods and services, and social sustainability. Urbanizing locations may follow different ecological trajectories, with very different consequences for future inhabitants. Ostrom's design principles assert that effective land governance (that maintains biodiversity and ecosystem services) requires congruence between rules and local social-ecological conditions. However, little is known about how to achieve such congruence in peri-urban systems, partly because local landscape conditions are constantly changing. We used dynamic simulation models to address this gap, testing how spatially explicit feedbacks between ecological patterns and land governance might influence landscape dynamics. We captured the feedbacks by testing the outcomes of decisions made at two different spatial extents, regional (100 km²) and local (4 km²), for two different levels of landscape heterogeneity. Our approach extends and operationalizes Ostrom's design principle by explicitly defining the term "local" as relative rather than fixed; that is, as a spatial extent of decision-making based on an administrative hierarchy. We found that the rate of urbanization was higher for high heterogeneity landscapes than low heterogeneity landscapes. Further, the urbanization trend differed significantly between the regional and local scales for both high and low heterogeneity landscapes. The analysis shows how spatial mismatches between land governance and spatial processes can arise and explores their consequences for ecosystems in landscapes that are in transition from rural to urban.

Key Words: *Ostrom's design principles; SES Framework; spatial heterogeneity; urbanization; spatial mismatch*

INTRODUCTION

Urbanization is a global phenomenon. Regardless of their wealth and location, most nations face similar challenges in terms of climate change, sustainable urban growth, and loss of ecosystem goods and services (Morrison et al. 2022, Agboola et al. 2023, Li et al. 2023). Where urbanization is extremely rapid, it can lead to unplanned urban growth and informal urbanization, with cities struggling to meet increasing demands for basic infrastructure, such as in and around the cities of Global South (Dyachia et al. 2017, Randolph 2023). The loss and degradation of ecosystems in and near to cities has influenced ecological functioning in ways that directly influence human life and wellbeing, for example through changes in soil and water quantity, quality, and temporal ecological variability (e.g., floods, water scarcity, loss of fertile lands, forest fires, and spread of diseases). In many fast-growing cities, for example in India and sub-Saharan Africa, rising demand for urban land is still causing the destruction of wetlands and water bodies that were important for agriculture, recreation, and drinking water (Nagendra et al. 2013, Hettiarachchi et al. 2014, Mumuni et al. 2025).

Land governance includes institutional arrangements, decision-making processes, policy instruments, and underlying values. These factors influence how multiple actors - both state and non-state - pursue their interests in the use of land (Andersson 2021, FAO and UNCDD 2022, Salman and Mori 2023). Land governance is particularly important where human pressure on natural resources is high, such as in urbanizing landscapes. Its ultimate aim is to maintain the fine balance between economic production and ecosystem integrity for social and environmental sustainability (Morrison 2006, Kusters et al. 2020). Rules and policies for local land governance are often defined, developed and implemented by central authorities at higher (national or regional) levels (Zhang et al. 2019). For example, top-down zonation systems are often used to identify and regulate land use and conservation of green spaces (Evans et al. 2008). However, top-down approaches often have undesirable consequences, such as low community buy-in, leapfrog development, and urban sprawl, common in rapidly urbanizing areas and particularly in India (Evans et al. 2008, Salet and de Vries 2018, Zhang et al. 2019). Many of these problems are rooted in mismatches between the scale(s) of land governance and particularly between the spatial extents of land use policies and the extents and timing (duration, frequency) of environmental, ecological, and biophysical processes (Christophe and Tina 2015, Salet and de Vries 2018). For example, if administrative boundaries define smaller areas than those required to support critical ecological processes or cope with periodic environmental events such as flooding and fires (Robinson et al. 2017), local authorities may struggle to coordinate the management of key ecological resources across jurisdictions. These considerations suggest a need for inclusive, multi-scale approaches in land governance that acknowledge the complexities of urbanizing landscapes as integrated, common pool social-ecological systems (SESs; Vij and Narain 2016, Menatti 2017, Cerquetti et al. 2019).

Ostrom's design principles provide a widely accepted framework for thinking about commons governance in an SES context (Cox et al. 2010). The 8 design principles include (1) defining the system boundaries, (2) having congruence between rules and local conditions, (3) making collective choice arrangements to allow stakeholder participation, (4) effective monitoring, (5) graduated

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sanctions and punishments for the violation of rules, (6) having mechanisms for conflict resolution, (7) recognizing autonomy of institutions, and (8) having multi-layered organizations (Ostrom 1990). Ostrom's design principle 2 is particularly relevant to problems of scale mismatches in urbanizing locations because it emphasizes the need for congruence between rules and local conditions, both ecological and social, for effective resource management (Ostrom 1990, Agrawal 2001). For example, rules about harvesting resources should account for their spatial distribution and renewal rate (Ostrom 1990, Agrawal 2001, Cox 2010). Scientific understanding of "local resource conditions" was originally focused on single resources at relatively small spatial extents (for example, artisanal fisheries or local use of irrigation water) and/or the cost of extracting resources at relatively fine scales (Agrawal 2002). Over the last decade, however, researchers have sought to apply the design principles beyond their traditional small-scale, community based-focus to larger, more complex SESs that have multiple complex social-ecological elements, such as extensive resources, trans-boundary governance, or a high number and diversity of actors (Huntjens et al. 2012, Epstein et al. 2014, Fleischman et al. 2014, Villamayor-Tomas et al. 2014, Lacroix and Richards 2015). Despite expansion of the scope of design principle 2, the focus is often more on "local" social conditions, such as the lowest level of land use authority, than ecological conditions (Marshall 2008, Bell and Morrison 2014, Bluemling et al. 2021). In the case of complex SESs, there is a need to look beyond "local" social conditions and also focus on 'local' ecological conditions (Li et al. 2023).

A peri-urban landscape typically contains a complex mix of rural, urban, and natural characteristics and a mixture of governance regimes. The interactions and feedbacks among institutions, environment, and actors in many peri-urban areas are causing multiple and conflicting land uses, with old institutions corroding and new institutions evolving relatively slowly. In India, for example, this is leading in some cases to institutional mismatches, unplanned infrastructure development, over-exploitation and degradation of resources, and loss of various ecosystem goods and services (e.g., Mundoli et al. 2017, Patil et al. 2018, Singh and Narain 2019, Narain 2009, 2021). Factors that influence the evolution of institutions in a peri-urban SES are both internal and external (e.g., land use transformations, spatial heterogeneity, ecological diversity as well as actors' land use preferences) (Leslie et al. 2015, Gomes and Hermans 2016, Sharma et al. 2016, Gari et al. 2017, Cho et al. 2019).

Landscapes in a peri-urban area consist of a mosaic of diverse, interacting patches that range from natural terrestrial and aquatic land cover such as forests, grasslands, wetlands and human dominated land uses such as urban built-up, agricultural. Landscape heterogeneity in this context describes the degree to which such patches are similar or different from each other as well as the complexity of the spatial patterns that they create. Landscape pattern is driven by geomorphology (e.g., elevation, proximity to coasts) and a set of underlying processes such as water movement, seed dispersal, and agriculture (Zhou et al. 2014, Setturu and Ramachandra 2021) while also influencing land use policies, such as attempts to retain urban forestry or water quality (Cattarino et al. 2014). Landscape patterns exert a strong influence on the geography of institutions (Cumming and Epstein 2020). The feedbacks between spatial heterogeneity and land governance underpin outcomes in a peri-urban SES, but remain poorly understood, particularly in India (Srivathsa et al. 2023).

In this study we focus on the interplay between the spatial heterogeneity of the landscape and the spatial extent of decision-making, recognizing that decision-making is usually hierarchical with national and regional policies being complemented by local policies that facilitate more specific, locally-tailored responses to specific environmental and socioeconomic contexts. Frate et al. (2014) have shown that spatial extent of observation influences the information obtained about a landscape, and which in turn influences governance decisions. Descriptions of spatial heterogeneity are sensitive to the spatial scale (both grain and extent) of observation, suggesting that changes in the scale(s) of observation and regulation can lead to inconsistent policy decisions (and undesirable outcomes) across different spatial scales of governance (Cattarino et al. 2014, Görg 2007). We tested this hypothesis by exploring how the incorporation of a feedback between governance and the spatial extent of observation at different scales (keeping the grain of analysis consistent) might influence the impacts of urban expansion on green spaces in Indian cities. Specifically, we asked whether regional vs local implementation of the same rules led to notably different outcomes in terms of spatial heterogeneity and the conservation of urban green spaces. By framing the problem in this way, we operationalize design principle 2 in a simple simulation environment and use a controlled "experiment" in a modelling environment to explore its potential application to urbanizing landscapes in a peri-urban SES.

METHODS

We developed a dynamic simulation model to explore the importance of spatially explicit social-ecological feedbacks for the governance of dynamic landscapes. The model is loosely based on conditions and actors present in the periphery of major urban hubs such as Bengaluru, Pune, and Delhi. Cities in India have expanded both demographically and spatially beyond their traditional boundaries at an unprecedented rate since India's independence in 1947, followed by the IT boom in the 1980s and changes in economic policies in the 1990s. Their rapid expansion has led to various natural resource governance challenges (Ramachandra et al. 2012, 2014, Haase et al. 2014, Nagendra and Ostrom 2014). Indian cities and their peri-urban areas exemplify the challenges experienced in governing peri-urban SESs in fast-growing economies in the Global South (Ramachandra et al. 2012).

We first explain how we mapped the components of a peri-urban SES using Ostrom's SES framework. We then give a brief overview of the model before describing the *in silico* experiments and statistical analysis we performed to test and contrast the hypotheses. We use the standardized ODD+D (Overview, Design Concepts and Details + Decisions) protocol (Müller et al. 2013) to describe the model. The protocol was developed for researchers working in the SES community to describe the model design, sub-models, model parameters, and simulation experiments involved. We provide a detailed and comprehensive description of the model including all the parameters, attributes, and sum-modules in Appendix 1.

SES Framework

Ostrom's SES Framework is useful in identifying relevant variables and factors or components needed to address the research question through its multitiered structure. Each tier in the framework is a logical category of elements in an SES and represents the levels of nested systems (McGinnis and Ostrom 2014). For example, Tier-1 refers to the core subsystems - Resource Systems, Resource units, Governance Systems, and Actors (Fig. 1).

To map a typical peri-urban SES located in the periphery of the Indian cities we used tier-1 and tier-2 variables of the SES framework. We mapped the terrestrial resource system of a peri-urban SES into a lattice of 50 x 50 cells, where each cell represented a land parcel in the landscape and a Resource Unit (RU) in the SES framework (tier 1 variable). To distinguish each cell (RU6 - example of a tier-2 variable), we adapted the LULC classification of the Government of India and classified each cell into one of eight LULC classes: Agricultural land, Forest, Grassland, Rural Built up, Urban Built up, Water Body, Waste Land, and Wetland (NRSC 2012; Appendix 1: Figure_sup 1).

The Government of India's Department of Land Resources proposed a national level Land Utilization policy in 2013, categorizing the country into four major land use zones (Table 1) based on predominant land use, and ecological and historical importance of the land parcels (Government of India 2013). Ostrom's SES framework has a hierarchical structure that describes different variables of relevance for social-ecological systems. In Ostrom's SES framework, the high-level *governance system (GS)* includes institutional arrangements such as policies, rules and regulations (Ostrom 2007, 2009, McGinnis and Ostrom 2014) which describe land governance in a peri-urban landscape. For the *governance system* we simulated land use policy for each cell. Land use policy is a second-tier variable of the governance system, which means that it is defined in Ostrom's framework as one of the subcomponents that comprises the governance system. Land use policy regulates the type of land use in a region through a zoning system and guided the landscape management (Barredo et al. 2003). In the model, we assigned one of the four zones (henceforth called land use zones or LUZ) to each cell where a LUZ defined the type of land use allowed for the different land units in a landscape (GS6; Table 1). In the model, the land use zones were updated after every five years based on the current land use pattern using a land use policy sub-module (Appendix 1).

Because the Indian Government follows a federal system, the national level Land Utilization Policy is an overarching set of guidelines or recommendations to the state or regional governments (government agencies - GS5). The regional governments then formulate regionally and locally specific land use policies. The spatial scale of decision-making, in general, is usually within fixed administrative boundaries that define a "region" (Morrison and Lane 2014). In the SES Framework, the spatial scale of decision-making corresponds to the geographic scale of a governance system (which, as a subcomponent of the governance system, is another second-tier element of Ostrom's Framework). In the model, we varied the geographic scale of governance system and used two spatial levels of decision-making: a region level and a local level.

Fig. 1. Tier-1 variables of the SES framework, where components of an SES are broadly divided into four subsystems (rectangles with a wavy base): resource system (RS), resource unit (RU), governance (GS) and actors (A). The components are linked (solid arrows) and influence each other in a "Focal Action situation" that includes interactions and outcomes (middle rectangular box). The Focal Action situation influences components of SES via feedback (dotted arrows). The exogenous influences from other ecosystem and external social, ecological, and political settings are also included that can vary at multiple scale. The tier-1 components are further decomposed into tier-2 and tier-3 (Ostrom 2007, 2009, McGinnis and Ostrom 2014).

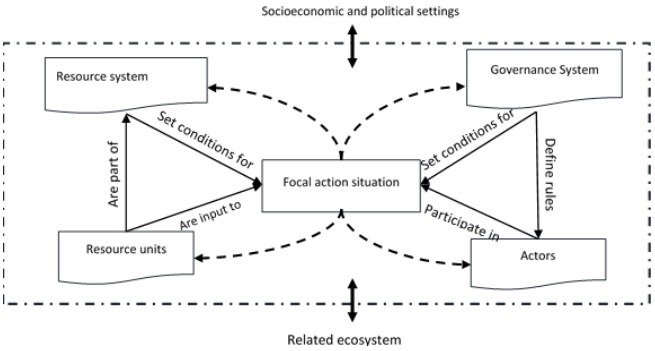


Table 1. The four land-use zones and their descriptions as per the national-level Land Utilisation Policy. Each zone has a level of restriction on land-use change based on criteria described in the table. The land-use zones are arranged in decreasing order of the level of restrictions on land-use change. For example, the Protected Areas are the zone with the highest restriction on land-use change, and the Guided Areas are the zone with the lowest restriction on land-use change.

Land-use zones	Description
Protected Areas	Strictly prohibited for land-use change.
Regulated Areas	Not legally restricted for land-use change yet have important functions associated with it.
Reserved Areas	Areas under pressure of development, usually due to significant land-use change in the neighboring areas.
Guided Areas	Areas having highest probability for land-use change.

In a peri-urban SES, the actors depend on resources for their livelihoods and/or a variety of additional ecosystem services and goods (Bian et al. 2018). We broadly classified *actors* into urban and rural actors based on tier two variables of the "Resource Users" component of the SES Framework. These subcomponents included socioeconomic attributes (A2), geographic location (A4) and importance of resources (A8; McGinnis and Ostrom 2014). Socioeconomic attributes and geographic location are commonly used indicators for identifying rural and urban actors (Vidyarthi et al. 2017).

In the model, broadly speaking, rural actors resided in the urban periphery before urbanization began; often have lower population density; and participate in an agrarian economy (Purushothaman

and Patil 2017). Urban actors, by contrast, live in urban areas and do not farm, although they depend on peri-urban areas for ecosystem goods and services such as drinking water and food. As urban areas expand beyond the original urban periphery, urban actors appropriate land in peri-urban areas for urban development such as housing, industries, and supporting infrastructures such as parks, roads, and highways (Bian et al. 2018). There are of course other variations and overlap in the behavior of rural and urban actors such as dependency on the food supply chain by urban actors on the rural areas, however, for sake of the model simplicity we have limited the characteristics of the actors as discussed.

The importance of the resource and relationships with the resource also vary among rural and urban actors (A8). The resource dependency of the actors includes the relationship of actors with their environment, their attempts to appreciate ecosystem services provided by the environment, and the understanding of the impact of their actions on the social and ecological outcomes (Tidball and Stedman 2013). In general, rural actors who were already residing in the urban periphery before the urbanization began may have a comparatively stronger association with a peri-urban SES. Rural actors often understand the rural complexities involved in the SES and the impact of their actions on the SES outcomes (Beilin et al. 2013). On the other hand, urban actors often are seen as those appropriating resources from peri-urban areas; they typically have a limited understanding of the complex interactions within a peri-urban SES and the impact of their actions on outcomes in the SES (Bian et al. 2018).

Simulation model

The model was designed to capture the most critical interactions among different components of a peri-urban SES described above to address the research question. We primarily focused on land use policies as the focal component of the governance system, recognizing that numerous additional complexities would arise through other governance elements in real-world situations; the urban and rural actor groups; and the LULC pattern of the landscape as the attributes of the model (see appendix). In the model, as urbanization progressed the urban actors moved out from urban areas into neighboring urban cells and appropriated land parcels for urban land use based on existing land use policy. In the process, various landscape patterns emerged depending on the different choices made by actor groups. The land use zones, on the other hand, were updated periodically based on the existing LULC patterns.

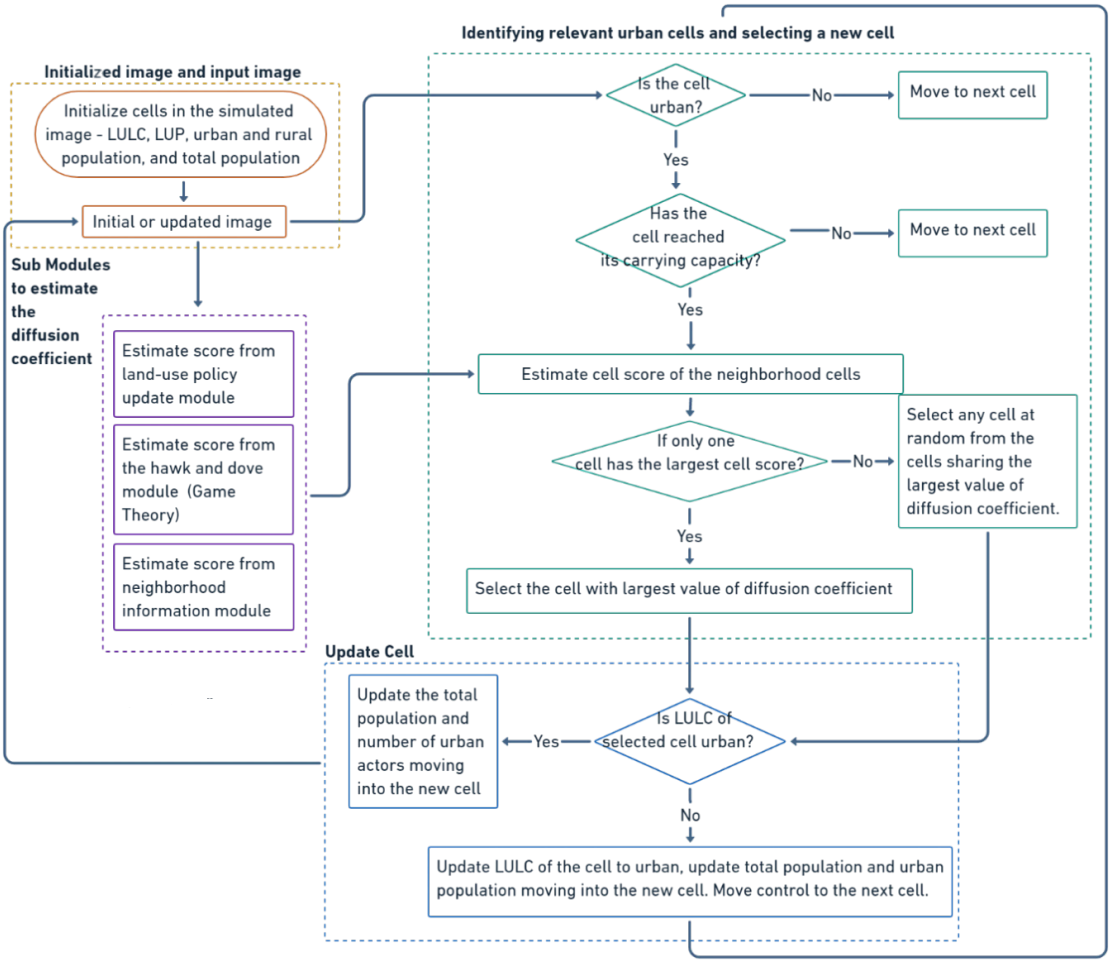
We explored the feedback between the resource system and the governance system by analyzing the resulting land use patterns as outcomes of SES action situations in the model. We particularly explored the environmental feedbacks between land use policy and landscape heterogeneity (Wu and Hobbs 2002) to address the question of spatial fit, thus contributing to a better understanding of the cross-scale dynamics of land use change (Seppelt et al. 2018). It is well recognized that actors' decisions at a local level can influence policies (Hersperger et al. 2013). In the model, the feedbacks between actors and land use policies are implicit. Actors make decisions at a local level about land use changes that create landscape level patterns, which in turn influence land use policies as these policies are updated based on the existing LULC patterns.

To capture the interactions among the components of the SES we used a modified reaction-diffusion equation coupled to a cellular automaton. Reaction-diffusion equations describe the spatial dynamics of a population that increases while spreading in geographic space (Fisher 1936, Tilman et al. 1997). A reaction-diffusion equation consists of two primary components, a reaction term (the population growth within a cell) and a diffusion term (movement of members of the population between cells). The diffusion term has an associated diffusion coefficient which determines the ease of movement across the cell's boundary (Cumming 2002). Recently, researchers have used reaction-diffusion equations in social sciences to model and understand various social processes such as spatial dynamics of protests (Petrovskii et al. 2020) and to study the propagation of a rumor in a social network (Zhu et al. 2023). We have adapted the reaction-diffusion equation to model the spread of an urban population into peri-urban areas in a simulated landscape under a given set of LULC conditions and land use policies.

Our choice of a reaction-diffusion based cellular automaton framework requires some additional justification. Various modelling approaches are available to capture the complex process of urbanization and land use transformations including the concepts of space, scale and social dimension to inform theory (Pratomoatmojo 2018). Popular land use modelling approaches are broadly classified into Agent-Based models (ABMs) and cellular automata-based models (CA; Ren 2019). While ABMs explicitly include choices and decisions made at the individual level, exploring micro-scale interactions among actors are inherently complex, require a large amount of ground data, and are frequently not generalizable. On the other hand, CA models are rule-based, and are widely used for spatiotemporal analysis and prediction in land use change studies. Standard CA models do not change their behavior over time and micro-scale interactions are implicit. These are desirable properties for an exercise in which we (1) repeatedly rerun the same model under slightly different assumptions about scale; and (2) seek to understand micro-scale outcomes rather than specify them individually. Integrated methods using Markov chain, GIS, and ABM can extend the capabilities of CA models, but these often contain the negatives of both approaches: i.e., being case study specific and hard to interpret.

A single model run included a series of steps (Fig. 2) over each simulated image. These steps were run iteratively for 200 times for all the images and cases involved (images and cases are described later in detail). Each simulated image consisted of 50 x 50 cells of 200 x 200 m each, where each cell corresponded to a land unit. Each cell had a list of attributes defined which include land use zones, total, urban and rural population, and LULC class previously described in the Ostrom Framework section. The total spatial extent of each image was 10 x 10 km^2 with a grain size of 200 m, which falls under the recommended range of the buffer zone to study peri-urban areas in India (Ramachandra et al. 2014). In addition, changing the grain size and spatial extent of the landscape will not affect the analysis in this paper, until they are kept the same for all the simulated images. Each cell in an image was first initialized with a LULC, land use zone, and total human population including rural and urban population, explicitly. As the population in an urban cell increased and reached the carrying

Fig. 2. A summary of the model as a flow diagram. After specifying the initial conditions (top left box), the model is left to estimate scores and sequentially update the landscape over a specified time period (Chawla et al. 2024).



capacity of the cell, a percentage of urban actors moved out of the cell into one of the cells in the immediate neighborhood. In the real world, urban actors can chose to move into any part of a landscape, however, to simulate the effect of local interactions we restricted the movement of the actors to only one of the eight immediate neighbors in the Moore's neighborhood window (Maria de Almeida et al. 2003). In the model, only a fixed number of urban actors could move into a neighboring cell at a given time. We assumed that in a cell where the urban population was dominant, the urban actors took a collective decision to move out of the cell and selected the cell with the highest cell score out of eight cells in the neighborhood window. The cell score, D, was calculated using equation 1 in the model. D was a combination of three variables associated with the target cell: land use zone associated with the cell (LUZ - Z), result of interaction with actors occupying the cell (GT), and the spatial neighborhood of the target cell (SI). All three variables were estimated using the three sub-modules respectively (Appendix 1). It is important to note that, if the urban actors moved into a cell, which belonged to a non-urban LULC class, the model updated the LULC of the cell into urban built-up.

$$D = LUZ[\lambda(SI) + (1 - \lambda)(GT)] \quad (1)$$

Their decisions were influenced by existing land use policies and LUZs of the cell among other factors. LUZs were updated periodically as the landscape evolved where model assigned a new LUZ to each cell after every 5 iterations or 5 years, where one iteration corresponds to one year, based on the existing landscape conditions. To design updated rules, the "land use policy update" sub-module used information about the amount and distribution of LULC classes in the landscape. The spatial extent of the landscape within which the LULC characteristics are considered for the decision-making is usually a fixed area based on administrative boundaries. However, local ecological conditions and LULC patterns vary across the landscape in a peri-urban SES.

Therefore, to apply design principle 2 and to establish congruence between local conditions and LUZ, we varied the spatial extent of decision-making in the landscape from regional to local at varying levels of spatial heterogeneity.

Experiments

Our objective was to test the sensitivity of spatial heterogeneity at different spatial scales of observation and regulation for policy and decision-making. Therefore, we created a 2x2-study design that contrasted high and low levels of spatial heterogeneity with LUZ updates based on the landscape conditions at the local and regional spatial extent of decision-making (referred to as "local" and "regional" from here on), respectively. We used two sets of simulated landscapes with two different levels of spatial heterogeneity. Each simulated image was one of the several possible realizations of dynamics involved in a peri-urban SES in the periphery of Indian cities, however, may not necessarily represent all possible realizations. Figure 3 (a, b) is an example of simulated images from each set of the two levels of landscape heterogeneity.

To keep the model simple, we used only two levels of spatial heterogeneity and prepared two simulated data sets of 100 landscapes each, using the *NLRM* package (Sciaini et al. 2018). The first set had 100 simulated images with low spatial heterogeneity (e.g., Fig. 3a) while the second had 100 simulated images with much higher spatial heterogeneity (e.g., Fig. 3b). Each simulated image consisted of 50 x 50 cells of 200 x 200 m each. We kept the degree of spatial heterogeneity constant for each set and changed the arrangement of patches for each image within a set; meaning the spatial configuration varied for each image within a set.

For the regional update, the model used the LULC characteristics of the whole landscape to update and assign LUZ to each cell. For the local-level update, we divided the landscape into 25 non-overlapping administrative windows of cells and identified the "local" extent by these windows (Figure 3c). To update the LUZ of cells for local update, the model considered the LULC characteristics only within the window that contained the cell. The model updated LUZ for each cell after every 5 iterations (or 5 years) for both the local and regional updates.

The cell-level interactions among the two actor groups and spatial neighborhood information of the target cells were also included in all the model runs using the sum-modules Game Theory and Spatial Information (Appendix 1).

We explored the outcome of the model by quantifying land use transformation to urban built-up over 200 iterations (200 years). In the model, LULC of a landscape is updated at every iteration and land use policies are updated every 5 iterations (5 years) where LUZ of each cell is updated (Table 1); to ensure that the governance system is adapted to ongoing changes in the landscape.

We used three quantities as indicators of the emergent outcomes of the peri-urban SES:

1. Total urban area in the landscape**:** Number of urban built-up cells in a landscape. This is the measure of area occupied by urban built-up.
2. Rate of urbanization: percentage change (gain) in urban area per year, which is an adaptation of the "intensity analysis" method for land transitions (Aldwaik and Pontius 2012).
3. Pattern of urbanization: area occupied by the rest of the seven classes (except urban built-up) at every iteration, estimated as the total number of cells per iteration. As urbanization progressed, the model converted cells belonging to other LULC classes into urban built-up. We wanted to test if there is any difference in the preference of classes selected to be replaced by urban built-up during urbanization which includes rural area.

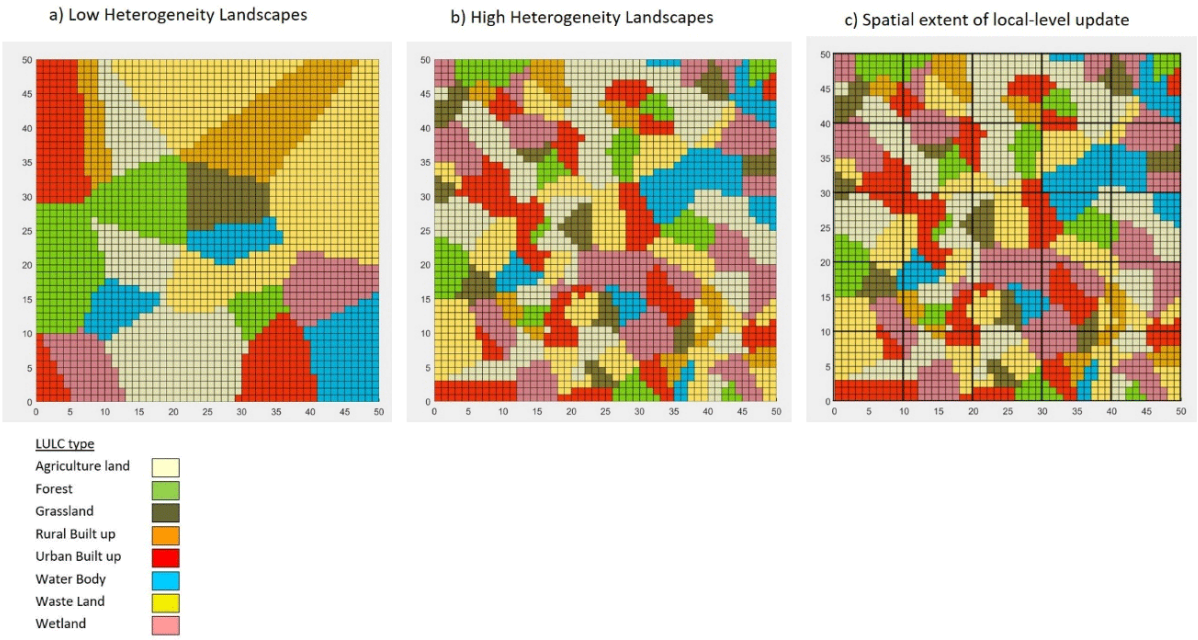
Each of the three indicators are related to the spatial sustainability of an urbanizing landscape. The amount of land converted together with the rate of urbanization influences the sustainability of the landscape (Zhang et al. 2019). Rapid land use change which is common in peri-urban areas, particularly in the Global South, adds to the complexity of the SES, for example, it influences soil properties and biodiversity loss (Rauws and de Roo 2011). In a peri-urban area, spatial expansion of urban land use often occurs at the expense of non-urban land use such as wasteland, forests, and wetlands (Deslatte et al. 2022). The impact of land use transformation for urbanization on the environment and ecological processes also depends on the pattern of urbanization. For example, developing a built-up area on a drained out wetland is more detrimental to the environment than using degraded agricultural land (Nuissl and Siedentop 2021). Therefore, the amount of urbanization together with the rate and the pattern of urbanization are useful indicators in assessing overall landscape sustainability.

Statistical analysis

We hypothesized that the results observed in the case of regional and local update would be influenced by the spatial heterogeneity of the landscape because of the interactions between landscape conditions and policies. To ensure that we genuinely tested this hypothesis we included a null model as a counterfactual that excludes the mechanism or process of interest (Gotelli and Graves 1996). At both region and local updates, existing landscape conditions were included to identify land use zones of a cell which influenced the outcomes in a landscape. In the null model, we assumed there was no interaction between the landscape conditions and decision-making to assign LUZ and, therefore, did not include the landscape conditions (which is the process of interest in this work) in identifying LUZ of the cells for both high and low heterogeneity landscapes. The LUZ were assigned randomly to the cells. We then compared the amount of urbanization as an outcome in the null model to the region and local-level results for both high and low heterogeneity.

In total we had 2x3 test cases, for two levels of spatial heterogeneity and three different levels of decision-making based on spatial extent including null model, local and regional. We performed 200 model runs for all six cases. We first performed initial assessment to test the above hypotheses on the data set with the null model for levels of spatial heterogeneity and then divided the experiments into two broad steps to test for the effects of heterogeneity and spatial extent.

Fig. 3. Examples of simulated landscapes with (a) low heterogeneity and (b) high heterogeneity, with the same areas of each of eight LULC classes in both. (c) The thick black lines show subsets of the non-overlapping windows (of 10 x 10 cells) demarcating spatial extent for the local and regional updates in a landscape. A similar subset was used for both low and high heterogeneity landscapes.



For the initial assessment, we tested whether the initial landscape composition and configuration had a significant influence on the model outcomes for both levels of decision-making and for the null model after a certain time period. We quantified spatial composition and configuration of a landscape which may influence the outcomes (Plexida et al. 2014). To quantify spatial composition and configuration and describe the landscape patterns before and after each model run, we utilized widely used patch-based landscape metrics: average size of the urban patches (Patch Area), the number of urban patches (No. of Patches), edge density of the urban patches (Edge Density), and the standard deviation of the urban patch size within each landscape (SD Patch; Turner et al. 2010). We estimated the landscape metrics using the *Landscapemetrics* package in R (Hesselbarth et al. 2019).

We performed multiple regression for the two data sets with the four landscape metrics as independent variables. Multiple regression assumes no collinearity between independent variables (Field et al. 2012). We thus used Principal Component Analysis to test and eliminate highly correlated variables (Field et al. 2012). We selected three out of four predictor variables (Patch Area, Edge Density, and Standard Deviation of the urban patch size; and dropped the number of urban patches because it was redundant) as the useful measures of landscape change. These three variables preserved the maximum information (60%) in the first component of the Principal Components Analysis. For both data sets, the predictor variables were Patch Area, Edge Density, and Standard Deviation of the urban patches at the beginning of the model. For the first data set, the response variable was the number of urban cells at the time when the slope of the curve first changed. We defined the saturation point as the time beyond which the urban area did not change significantly for the rest of the model's duration. We estimated the saturation point and the first point of change in the curve using the *findchangepts* function of MATLAB (MATLAB 2016).

For the second data set, the response variable was the gradient (or the rate of change of urban cells) at the first change point. We performed multiple regression for all six cases.

We performed the experiments in two steps, following initial assessment:

Step 1: We first measured the influence of spatial heterogeneity on the three outcomes by varying the spatial heterogeneity of LULC classes, keeping the spatial extent of land use policies constant to the regional updates. In step 1, we applied the model to the two sets of landscapes and reported the total urban area and the rate of urbanization.

Step 2: Having clarified expectations relating to path dependence in step 1, we tested the influence of spatial extent of decision-making for both high and low heterogeneity landscapes for both regional and local updates.

We then ran the model for 2x2 sets (high and low heterogeneity landscapes for region and local-level update). We reported total urban area, the rate of urbanization and the pattern of urbanization.

To compare the rate of urbanization between time series, we limited the duration of urbanization to year 120 because for almost all cases, the rate of urbanization tends to be zero beyond

year 120. We measured the dissimilarity between the rates of urbanization using the diss.AR.MAH function of the R-based package *TSclust* (Montero and Vilar 2014) to test if the time series are derived from the same auto-regression model, considering the autocorrelation of the time series.

RESULTS

Ostrom's design principle 2 asserts congruence between local conditions and rules. We focused on the interaction between spatial heterogeneity (as resource condition) and land use policy (as the governance system).

Initial Assessment

For both the high and low heterogeneity landscapes, urbanization happened faster for the null model (Fig. 4 and Table 2). The null model reached saturation point much earlier than for the regional and local updates, for both the high (at around the 25th year) and low heterogeneity landscapes (at around the 70th year). In addition, the total urban area was higher for the null model than regional and local updates, for both the low (68%) and high (84%) heterogeneity landscapes.

Multiple Regression

The result of multiple regression for all six cases (for all 100 images in each case) suggested that no significant linear relationship exists between the initial landscape conditions, the amount of urbanization and the rate of urbanization ($r^2<0.05$, $p<0.05$). We could, therefore ignore starting conditions as a potential confounding influence in the rest of the analysis. Refer to Appendix 1 for the detailed results of multiple regression.

From this point onwards, we only show the results of the regional and local updates for low and high heterogeneity landscapes and exclude the results of null model.

Results of step 1

For both low and high heterogeneity landscapes, the average urban area was the same at the beginning (Fig. 5). As the model proceeded, the amount of urban area increased at a much faster rate for the high heterogeneity landscapes than for the low heterogeneity landscapes. Consequently, the high heterogeneity landscapes reached saturation much earlier than the low heterogeneity landscapes (Fig. 5). Interestingly, at the saturation point, the total urban area for high heterogeneity landscapes was higher (~68%) than that of the low heterogeneity landscapes (~60%).

The rate of urbanization (Fig. 6) shows the process of urbanization in the two sets of landscapes. The time series curves include two components, a high-frequency component (small, irregular peaks), and a trend. The high-frequency component captured changes in the rate of urbanization occurring periodically corresponding to land use zone updates. Focusing on the more general trend, the rate of urbanization was higher for the landscapes with high heterogeneity than landscapes with low heterogeneity. This trend occurred for the first 5 years (Fig. 6), when similar cells were assigned similar land use zones for the two cases. After the model updated the LUZ for all cells, there was a steep decrease in the rate of urbanization for the high heterogeneity landscape with urbanization approaching zero by year 40. By contrast, the rate of urbanization decreased slowly for the low heterogeneity landscapes than the high heterogeneity landscapes. The two time series were tested for dissimilarity by checking if the time series were generated from same auto-regression models and were found to be dissimilar (with p-value ≈ 0.998 for 120 years' time).

Fig. 4. Comparison of the results of the null model, the regional update, and the local update for (a) low and (b) high heterogeneity landscapes. The thick lines show the average urban cells in all three cases; the dotted lines show the standard deviation in each case.

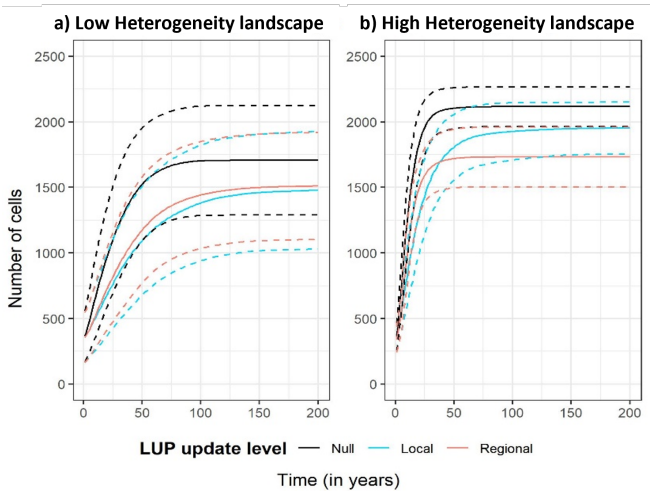


Table 2. Comparison of the time taken to reach the saturation point and the total area occupied at the saturation point for the two sets of landscapes for the regional, local, and null model.

Landscape heterogeneity	Level of update	Saturation point	% urban area at the saturation point
Low	Null model	At 70th year	68%
	Local	At 100th year	56%
	Regional	At 100th year	60%
High	Null model	Between year 23 and 25	84%
	Local	Between year 55 and 60	72%
	Regional	Between year 33 and 37	68%

Results of step 2

In step 2, we tested the influence of varying the spatial extent of the land use zone update for both high and low heterogeneity landscapes. We compared the total urban area, the rate of urbanization and the pattern of urbanization for all four cases.

In both high and low heterogeneity landscapes, the average urban area was same for all four cases in the beginning of the model runs. We compared the results of the regional and local update for each data set (Fig. 7) and across the two sets of landscapes (Table 2). The time taken to reach the saturation point was same for the regional and local update in the low heterogeneity landscapes. In the case of the high heterogeneity landscapes, time taken to reach the saturation point was higher for the local update than for the regional update. For the low heterogeneity landscapes, total urban area occupied (at saturation point) was slightly higher in the case of the regional update than in the local update when

Fig. 5. Total urban area after every iteration. The solid lines are the average urban cells per iteration for each set. Orange and blue dashed lines show the variation for the low and the high heterogeneity landscapes, respectively.

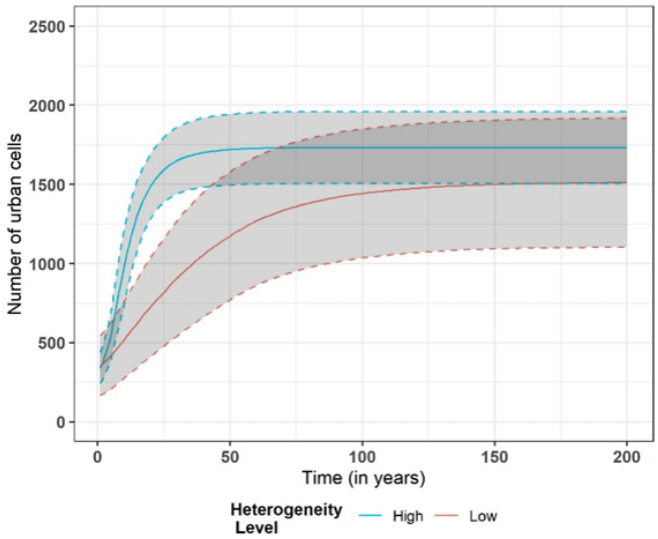
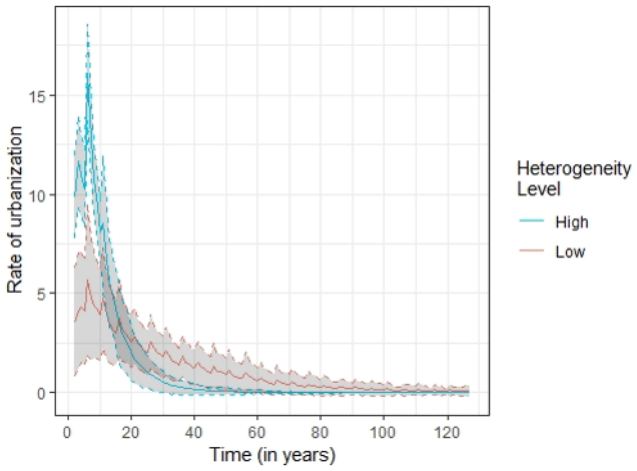


Fig. 6. Rate of urbanization for the high (blue) and the low heterogeneity landscapes (orange). The spikes represent high-frequency components which correspond to the land-use policies update cycle. The rate of urbanization was higher for the high heterogeneity landscapes but decreased drastically after year 10 compared to low heterogeneity landscapes.



compared to the high heterogeneity landscapes. In the high heterogeneity landscapes, the total area occupied at the saturation point was much higher for local update than for regional update (Table 2).

We further compared the rate of urbanization for all four cases (Fig. 8). The rate of urbanization was same for the regional and local update within each dataset. For low heterogeneity landscapes, the average rate of urbanization peaked at ~6.2% for the regional update, which was higher than the peak (average) rate of urbanization for the local update (~5%). For the high heterogeneity landscapes, the average rate of urbanization peaked at ~16% for the regional update, which was higher than the peak rate of urbanization for the local update (~11%). In the high heterogeneity landscapes, a cyclic trend was also prominent in the local update while it was absent in the regional update, except in first 15 years. The time series were tested for dissimilarity by checking if the time series were generated from same auto-regression models. The statistical dissimilarity existed between the regional and local update time series of the high (p-value = 0.999 for 120 years' time) and low heterogeneity landscapes (p-value = 0.999 for 120 years' time).

Pattern of urbanization

As the urban area increased, the area occupied by other classes decreased. While the saturation point was similar for both regional and local updates in the low heterogeneity landscapes, there was considerable variation in the pattern of urbanization for the regional and local update (Fig. 9). For instance, the average area of forest cover converted to urban was higher in the case of the region level update (25%) than the local-level update (14%), after 100 years (saturation point).

In the high heterogeneity landscapes, the difference in the saturation point is prominent for the regional and local update (Fig. 10). For the wasteland class, the "total area" curves overlapped. This result occurred due to the model design, which was to convert the wasteland class into urban before any other classes. For the agriculture, waterbody, grassland, wetland, and forest classes the "total area" curve corresponded to the results of the "total urban area occupied" (Fig. 7) and the rate of urbanization (Fig. 8). However, the rural built-up class did not follow the trend. For the local-level update, the area occupied by each of the classes was higher than the regional update until saturation point (year 40). The area occupied by the rural built-up class, by contrast, was lower for the local update than for the regional update.

DISCUSSION

Our analysis offers one of the first spatially explicit explorations of the application and relevance of Ostrom's design principles for peri-urban commons. Although differences in outcomes for ecosystems emerged from differences in the scale of governance, as envisaged by Ostrom, we also found an unexpectedly strong role for landscape heterogeneity. Highly heterogeneous landscapes appear to offer a different and more challenging context for governance than more homogeneous landscapes, and may require institutions that have a different spatial structure and scale.

Null model analysis and the saturation point

We first discuss the results of the null model analysis (Gotelli and Graves 1996). We used the null model to check that our results were not a trivial result of our assumptions. In the case of null model, where the feedbacks from land use dynamics were not included in updating land use zones, urbanization was rapid and the amount of urbanization was higher than the regional and local updates where environmental feedbacks were included (Fig. 4).

Further, our results confirm that the model includes various constraints outlined in the methodology. In all six cases, the

Fig. 7. Total urban area after every iteration for region and local update for (a) low heterogeneity landscapes, and (b) high heterogeneity landscapes for both regional and local update. The solid lines are the average urban cells per iteration for each set. Orange and blue lines show the standard deviation for the regional and local updates, respectively.

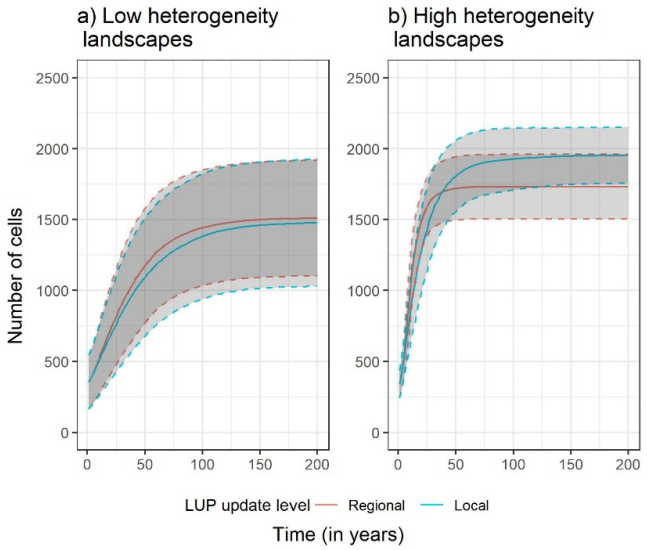
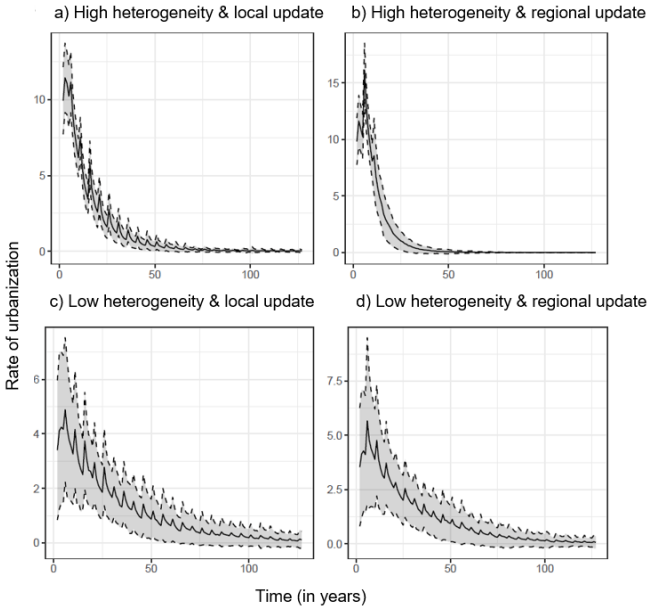


Fig. 8. Rate of urbanization for (a) local and (b) regional update for the high heterogeneity landscapes, and for (c) local and (d) regional update for low heterogeneity landscapes. The solid line is the average rate of change for each set.



amount of urbanization reached the saturation point, meaning that not all cells in a landscape were converted into urban class at the end of model runs (Fig. 4). This is because the area of interest across all landscapes was finite and the model could convert only a limited number of cells into urban built-up. The model reclassified the existing land use zone of some cells into Protected Area or Reserved Area which restricted land use transformation. In addition, the model did not allow land use transformation of the cells in the specific land use zones if the number of green spaces were reduced to a certain limit, in order to preserve the green spaces.

The results of multiple regression analysis (Appendix 1) show that landscape configuration and composition do not have a simple direct relationship to the outcomes, including the amount of urbanization and the rate of urbanization. This implies that our model captures at least some elements of the complex interplay among various components of the SES framework, including land use policies and actors' decisions (Meyfroidt 2012). There was, however, a difference in the rate of urbanization and the amount of urbanization for both the high and low heterogeneity landscapes at the saturation point (Fig. 8). The difference in the rate and amount of urbanization for the two landscapes occur because landscape conditions drive the land use policies and actors' decisions (Cumming and Epstein 2020, Izakovičová et al. 2021). Thus, the model captures some nuanced behaviors and scenarios which stem from the interplay of SES parameters and constraints included in the model.

Existing landscape conditions influence outcomes

The results from Step 1 clearly show that the outcomes of land-resource dynamics (the amount and rate of urbanization) vary for both the low and high heterogeneous landscapes when the LUZs were same for all the cells in the two landscape sets. The high heterogeneity landscapes had a higher rate of urbanization than the low heterogeneity landscapes even when the land use policies and LUZ were same for both the landscapes, particularly in the first 5 years (Fig. 6). In addition, in case of the null model, the amount of urbanization and time taken to reach the saturation point was different for both high and low heterogeneity landscapes (Table 2). The results confirm that the initial degree of spatial heterogeneity, and particularly the number and area of patches, influences the outcomes alongside land use policies (Zhou et al. 2014). Spatial heterogeneity is often an overlooked characteristic of the landscape governance and planning. However, spatial heterogeneity influences various abiotic and biotic processes in a landscape (Banerjee et al. 2013, Verburg et al. 2006). Our results show that for effective land governance it is important to align the spatial extent of decision-making with spatial heterogeneity (Görg 2007).

Spatial heterogeneity influences evolution of land use policies

We know that land governance is designed to critically affect land-resource management (Ostrom 1990, Morrison 2006), the spatial dynamics of landscapes (Pickard et al. 2016), and decisions made by individual actors (Fazal et al. 2015). In a peri-urban SES, however, the SES components and their interactions are continually evolving. Therefore, land use policies, which are a part of land governance, and resulting LUZs are not predetermined but emerge as urbanization progresses (Allen 2003, Anderies et al. 2004), as shown in our model. This is particularly problematic in the rapidly urbanizing cities of the Global South, where governments are often playing catch-up to control local land use change that is already occurring on the ground. Therefore, a fixed

Fig. 9. Area occupied by LULC classes for low heterogeneity landscapes at the regional and local update. Each plot in the figure corresponds to the seven LULC classes except for urban built-up. The plots follow the pattern of loss among the seven classes in the low heterogeneity landscapes

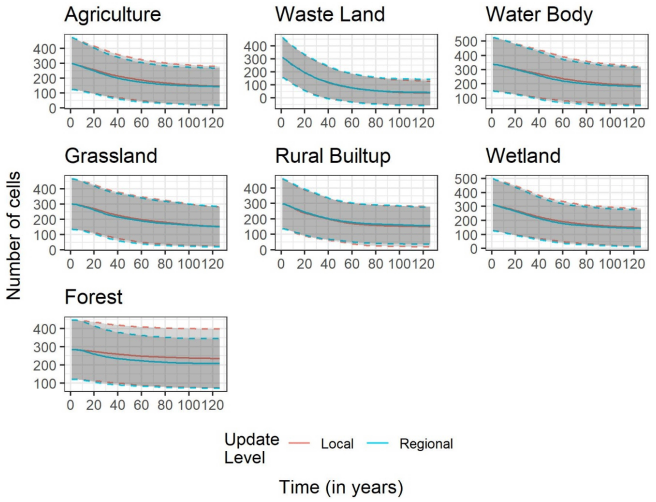
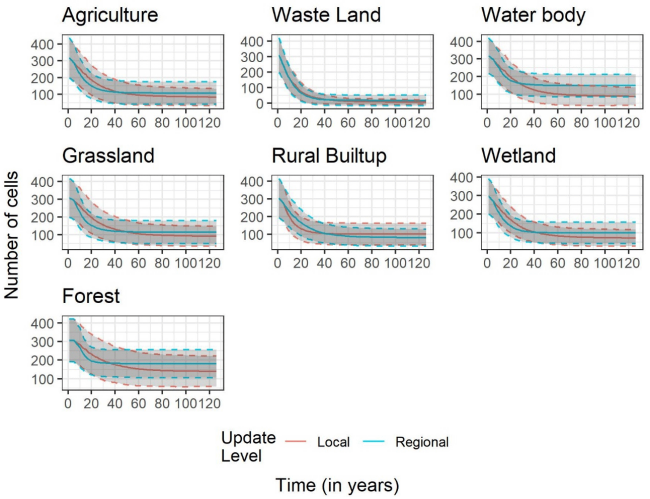


Fig. 10. Summary of simulated changes over time in different kinds of land cover classes. The plots follow the pattern of loss among the seven non-urban classes in the high heterogeneity landscapes at both the regional and local update. Each plot in the figure corresponds to one LULC class except for urban built-up.



or strictly planned approach such as having a fixed spatial extent of decision-making may be ineffective in a peri-urban SES, as often observed in the case of cities (Hedblom et al. 2017).

Interestingly, the results show that land use policies evolved differently for the two sets of landscapes. After year 5, when the LUZs were updated for the first time, the rate of urbanization drastically decreased for the high heterogeneity landscapes. For the low heterogeneity landscapes, the decrease in the rate of urbanization was comparatively gradual over the years (Fig. 6). This is because the spatial heterogeneity of the landscape also influenced the evolution of land use policies and the assignment of LUZs to the cells, which in turn guided and influenced actors' decisions about land use affecting the land use dynamics (Parsons 1995). These results suggest a need for decision-makers to better account for spatial heterogeneity in dynamic landscapes (Fazal et al. 2015, Hedblom et al. 2017).

Spatial scale of decision-making influences feedbacks between the land use policy and the spatial heterogeneity of the landscape

In the model, the aim was to explore institutional fit. Institutional fit is described as congruence between institutions and ecological, social, or social-ecological conditions to produce a desirable outcome (Epstein et al. 2015). Our analysis explored fit between land use policies and landscape level outcomes and explored the effectiveness of land use policies at two different spatial extents of update (local and regional). In the case of the high heterogeneity landscapes under regional governance, land use policy was not effective in controlling urbanization as the model reached the saturation point rapidly compared to the low heterogeneity landscape. There was a mismatch, or lack of institutional fit (Epstein et al. 2015), between the land use policy and the outcomes. When we varied the spatial extent of decision-making we observed that the model took more time to reach saturation point for the local updates than for the regional updates for high heterogeneity landscapes (Fig. 7).

The high-frequency components (small cyclic peaks) in (b) correspond to the times when the land use policies were updated in the landscape. The small peaks show the change in rate of urbanization due to the change in land use policies. The presence of high-frequency components for local level in the high heterogeneity landscapes confirmed that the land use policy could regulate the rate of urbanization (Fig. 8 a). However, for the regional updates and high heterogeneity landscapes, the peaks were not as prominent. This implies that there was a less significant influence of the land use policies on urbanization for the regional updates. Dividing the landscape into smaller units in high heterogeneity landscapes allowed regulation of local feedbacks on rules (Marshall 2008). The results, therefore, suggest that the spatial scale of decision-making influences feedbacks between the land use policy and the spatial heterogeneity of the landscape; accounting for spatial heterogeneity in a dynamic landscape can help address the problem of institutional fit.

Landscape dynamics were different for the low and high heterogeneity landscapes when we varied the spatial extent of decision-making. In the case of the low heterogeneity landscapes, the amount of urbanization followed a similar trend for both regional and local updates (unlike in the high heterogeneity landscape). For both regional and local updates, time taken to reach the saturation point was almost the same. The difference in total urban area occupied at the saturation point was more similar in the case of the local and regional update in the low heterogeneity landscapes compared to high heterogeneity landscapes (Fig. 7). The results, therefore, imply that a similar spatial extent may not result in similar landscape dynamics for landscapes with the different levels of heterogeneity. The patterns observed at a particular scale are very clearly influenced by spatial heterogeneity, which affects the decision-making process (Wu et al. 2000, Frate et al. 2014, Turner and Gardner 2015). For future

research we suggest adopting a mixed approach for the spatial extent of decision-making that varies with the ecological dynamics of the landscape.

The pattern of urbanization also varied for the two sets of landscapes. In the early periods of the model runs, land use policies did not allow any urbanization of forest cover for both levels of heterogeneity. As urbanization progressed, the forest class eventually converted into urban, implying that land use policies evolved to allow the conversion of the forest class. However, the land use policies evolved differently for the two spatial extent of decision-making, both in the high and low heterogeneity landscapes. The forest class decreased at different rates for the two sets of landscapes for both the regional and local updates (Fig. 9 and 10). Similarly, for the first five years, conversion of the grassland class was zero because of restrictions in the land use policy. However, the grassland was converted into urban-built up in later years.

Our approach was designed to provide a simple and transparent exploration of the relevance of scale and landscape heterogeneity for Ostrom's design principle 2. The "experimental" approach that we have adopted in the modelling environment has a number of obvious limitations, and ignores a range of real-world complexities; it would, for example, be unusual for a situation to arise in the real world in which policies were applied at different scales without there also being relevant differences in the political and socioeconomic context within which urbanization occurs. Feedbacks between the spatial heterogeneity and the spatial extent of decision-making should also shape other factors, such as the resultant heterogeneity of the urbanized landscape. The model could not capture this feedback due to a design limitation by which only cells in the immediate neighborhood could convert to urban built-up. In addition, it is important to note that both spatial and temporal variation influence the outcomes of urbanization (Epstein et al. 2015, Vogt et al. 2015). The temporal scale of decision-making should also take into account the temporal scale of ecological processes such as the lifespan of trees for forest landscape management and the return period of environmental disturbances (Fischer 2018). In the case of a peri-urban SES, in addition to the spatial extent of decision-making, the temporal scale of decision-making may also influence the urbanization process in the SES. This is an ongoing area of research (Morrison 2017).

Implications of the findings for urban land governance and conservation in the Global South

Our results suggest that starting conditions are important when understanding the impact of peri-urban expansion on biodiversity and ecosystem services. Analysis of patterns of land use transformation in urbanizing landscapes is important when making decisions for addressing resource management in a peri-urban SES. In some cases, findings from other locations may not be easily transferable to new contexts because of differences in pre-settlement landscape heterogeneity. Thus, planners and policy makers can expect surprises if they are working in landscapes with much higher or lower heterogeneity than previous case studies. The results suggest that the spatial extent of decision-making also influences the dominance of one LULC class over other for urbanization. In high heterogeneity landscapes, for example, the trend in the change of the area occupied by the rural built-up class was opposite to that of other classes in the region and the local-level update until the saturation point (Fig. 7). Thus, explicitly identifying the spatial extent of decision-making based on ecological heterogeneity can contribute to identifying specific patches for effective land use management and conservation measures, for example in maintaining ecological corridors during urbanization (Austin 2012, Vergnes et al. 2013, Frate et al. 2014). To address this, recommendations around policy design includes developing multi-level and flexible governance structures and decision-making processes (Azadi et al. 2023), developing monitoring and evaluation frameworks that can recognize and adapt to potentially conflicting regional and local levels of decision-making (Nuhu 2018); establishing policies that ensures participation of both state and non-state actors in decision-making at regional and local levels (Nuhu 2018); and investing in training and resources (such as models) for policymakers and managers to understand multi-scale and multi-level challenges (Wang et al. 2024).

Understanding ecological feedbacks to inform land governance

Our analysis suggests that Ostrom's design principle 2 is highly relevant for fast-changing landscapes, but requires some additional conditions to ensure that it is applied at a suitable scale. Land governance is challenging in peri-urban SESs, particularly in rapidly urbanizing areas of the Global South, which amplifies the challenges of effective land governance due to added emergent spatial and temporal complexity (Basawaraja et al. 2011, Hettiarachchi et al. 2013, Hettiarachchi et al. 2014). Compared to current top-down approaches, multi-scale and multi-level approaches have been advocated to support land governance (Bragagnolo et al. 2014) and management, but their implementation remains challenging. Researchers are increasingly emphasizing the need for a systems approach to support sustainable growth around cities in the Global South, and there have been calls to include ecosystems and ecological processes in and around cities in their master plans (e.g., in India) and to align administrative jurisdictions with environmental boundaries (Srivathsa et al. 2023). One way to support biodiversity and ecosystem service provision through land governance and management is to more directly consider environmental feedbacks between landscape characteristics and governance in the urban planning space (Meyfroidt 2012).

CONCLUSION

Our findings contribute to operationalizing the design principles and SES framework for multi-level landscape governance in peri-urban and urban settings. By showing how changing the spatial extent of decision-making and land governance can influence the relevant outcomes of urbanization, such as the amount and contiguity of green space, we emphasize that concepts of space and spatial dynamics can influence the interplay between components of a spatially dynamic SES. Thus, the spatial extent of decision-making and the institutions it requires should consider not only both regional and local ecological factors, but also the degree of landscape heterogeneity.

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Data Availability:

The data and code that support the findings of this study are openly available in PaperInstitutionalFitandDP2 at https://github.com/SiveeChawla/InstitionalFitanDP2_E-S.

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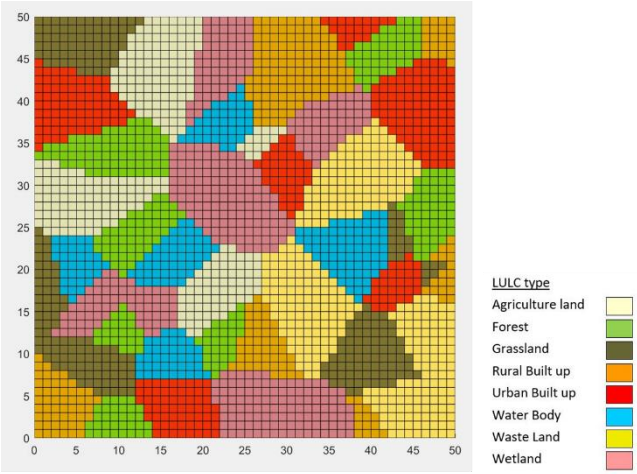
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APPENDIX 1

Ostrom's design principles

Table A_1: The design principles illustrated by common pool resources (Ostrom 1990); Refer to Ostrom (1990) for a detailed discussion on each design principle.

Ostrom's design principles
1) Clearly defined system boundaries
2) Congruence between appropriation and provision rules and local conditions
3) Collective choice arrangements by those affected by the rules
4) Effective monitoring practices
5) Graduated sanctions in place to check free riding
6) Mechanisms to resolve conflict
7) Minimal recognition of rights to organize
8) Supporting nested enterprises



Figure_sup 1: An example of a classified landscape with the eight LULC classes

Model description

We used ODD+D (Overview, Design concepts and Details + human Decision-making) protocol (Müller, Bohn et al. 2013) to describe the model.

Overview

Purpose: The model was developed to describe the interactions between different actor groups which is rural and urban actors in presence of other social and ecological variables in an urbanizing landscape.

Entities, state variables, and scales

Two entities were used in the model.

1. Land parcels or cells
The landscape was divided into spatial units of equal size called land parcels or cells. Each cell had associated attributes or variables that include carrying capacity of the cell, total population, urban and rural population, land-use land cover (LULC) and land-use zone score (Z).

2. Actors
We classified actors broadly classified into urban and rural actors based on the factors describe in the main paper. Urban cells had large population of urban actors and rural actors mostly dominated non-urban cells. The actors occupying cells took the decision collectively and were assumed to follow the principles of bounded rationality (Simon 1972).

The entire landscape or the spatial extent comprised of 50x50 such cells in the model with cell size of 100 m x100m. Each model run, which correspond to one simulated image, included 150 to 200 iterations, where 1 iterations corresponds to 1 year.

Design Concepts

Theoretical and empirical background

We developed the model based on Ostrom's SES framework. We have described the components of a peri-urban SES mapped to the SES Framework in the main document.

Individual Decision Making

In the model, urban actors decide to move into their immediate neighbourhood. In order to do so they select a cell from the eight immediate neighbours which has the highest cell score. These local update for land-use transformation made by urban actors influence patterns at landscape level. Further, the decision made at local level are also influenced by local spatial conditions such as LULC of the neighbouring cells (Verburg, Kok et al. 2006). We included the neighbourhood spatial conditions explicitly in the model.

In reality, in peri-urban SES the land parcels which urban actors seek for land-use transformation are usually already occupied by other actors. The cells are used by actors to support their livelihoods or for ecosystem goods and services. Therefore, the actors who are already using the cells may resist or comply with resulting land-use transformation by urban actors (Koch, Dorning et al. 2019). We captured the interactions (resistance and compliance) among actors using the Hawk and Dove model from game theory.

Adaptation

We included a sub-module in the model which adapted land-use zones to changes in the landscape. In the model, the sub-module updated land-use zone and related score for each cell after every 5 iterations (5 years). The sub-module included different landscape conditions such as the number of green spaces in the landscape and the distance from the urban patches as the criteria to update the land-use zones for each cell.

Emergence

In the model, new landscape patterns emerge as urban actors appropriated and transformed the non-urban cells into urban cells. These patterns varied because of other factors such as existing land-use policies, responses of rural actors and neighbourhood landscape conditions that influence the decision of urban actors.

Objectives

In the model, once the cell reached its carrying capacity the urban actors occupying the cell decide to move out of the cell. The urban actors were restricted to select only one cell to move into, from its immediate eight neighbours. The actors made the selection based on the cell score of the cells in the neighbourhood. The cell score was calculated based on the existing attributes of the cells including land-use zone, the spatial neighbourhood, and the response of the actors already occupying the cell.

Sensing

The aim of the model was to explore the influence of cell-level interactions on landscape level patterns. In the model, the interactions occur at cell level. First, urban actors could only move out of a cell by confirming if the cell reached its carrying capacity. Second, the urban actors selected a suitable cell from its immediate neighbourhood based on the attributes of the neighbouring cells including the land-use policies, the actors already dominating the neighbourhood cell and the neighbourhood LULC of the cells.

Interactions

In the model, the actors have conflicting land-use interest. As the urbanization progresses, the urban actors move out of the cell and interact with rural actors to appropriate non-urban cells dominated by rural actors such as rural built up and agricultural land. The rural actors may or may not allow land-use transformation into urban cells. The model captures the interaction among actors at different locations using Game Theory sub-module. In the model, we did not include any explicit communication among the interacting actors.

Stochasticity

We included stochasticity in multiple areas within the model. First, the model randomly assigned LULC classes to the patches in the simulated landscape. In addition, the score associated with Land-use Zones was randomly assigned from within a given range (**Error! Reference source not found.**). Third, the model assigned the strategy of Hawk or Dove randomly to the rural actors in the Game Theory Module. Finally, when rural Hawk and the urban Hawk fight both could win with an equal probability.

Collectives

Within each cell, the dominant actor group (either urban or rural actors) functioned as collective which took the decision to move out of a cell after reaching its carrying capacity. The collective also decided to adapt a Hawk strategy (to fight) to Dove strategy (to comply) in the Game Theory sub module.

Observation

For the outcome of the model we observed and analysed the resulting LULC pattern due to land-use transformation by urban actors. The model generated a new LULC map at the end of each iteration that showed the increase in number of urban cells, decrease in non-urban classes after urbanization, and change in landscape configuration and composition metrics.

Details

Input data and initialization

The input was a vector file of the simulated landscape/image where each cell had associated attributes and parameters given in Table B 1.

Table B 1: List of attributes and parameters, their definition and corresponding values used in the model.

	Attribute name	**Description**	**Range /Values**
1.	Land-use Land Cover class (LULC)	LULC class to each cell from the set of eight classes .	Forest, wetland, waterbody, grassland, rural built-up, agriculture land, wasteland and urban built-up.
2.	Land-Use Zone (LUZ)	Model assigned LUZ on the land-use policies using the sub-module – Land-Use Policy update.	See Table s2
3.	Land-Use Zone Score (Z)	The Z was based on LUZ	See Table s2
4.	Total Population (ToP)	All cells were assigned with the number of actors occupying the cell at a given time. This included both urban and rural actors. The initial value of ToP was set lower than the carrying capacity of the cell so as to allow the model to run for sufficient time before reaching saturation.	0 - 18
5.	Urban Population (Up)	Every cell had either or both urban and rural actors. *Up* was the number of urban actors occupying a cell.	0-18
6.	Rural Population (Rp)	Rp was the total number of rural actors occupying a cell.	0 - 18
7.	Strategy	Each cell was assigned the strategy of either Hawk (resist) or Dove (comply) based on dominant actor group.	H – Hawk D - Dove
8.	Carrying Capacity (k)	Every cell can support a certain amount of population based on the resources available. The carrying capacity was constant for all cells and for all the iterations.	18
9.	Weight Factor (wt)	wt determined the amount of spatial neighborhood information included in the decision making.	0 to 1

11.	Green cell threshold (G)	G was an input parameter in the Land-use Policy Update module. It was calculated as a ratio of green to grey cells in the landscape. The green cells were the sum of cells belonging to forest, grassland, and wetland class. The grey cells were the cells from Urban built-up, wasteland and rural built-up class added together. The threshold was used to identify if the next set of LUZ should be more strict or relaxed.	0.3,
12.	Neighbourhood window	The cells in the immediate neighbourhood.	3x3 cells , Moore's Neighbourhood window
13.	a, b, α	Parameters for the reaction module used for calculating rural population in the population growth model. The parameters were kept constant.	a = 0.02, b=0.01, α = 0.2044
14.	c, d, β	Parameters for the reaction module to calculate urban population in the population growth model. The parameters were kept constant.	c = 0.09, d = 0.05, β =0.8144

Sub models

Here we describe the reaction and diffusion modules and the sub-modules - Land-Use Policy, Game Theory and Neighbourhood interaction.

Reaction module

As the model run begins model first calls the preliminary module called the reaction module which calculates population growth within a cell. We used UN population growth models for urban and rural populations, adapted from Chen (2009). The reaction model uses the following equations for population growth:

$$\frac{dr(t)}{dt} = ar(t) + bu(t) - \alpha \frac{r(t)u(t)}{r(t)+u(t)}$$ ----- *Equation B1: equation for rural population growth*

$$\frac{du(t)}{dt} = cu(t) + dr(t) + \beta \frac{r(t)u(t)}{r(t)+u(t)}$$ ----- *Equation B2: equation for urban population growth*

In equation 1 and 2, a, b, c, d,α and β are the parameters described in Tab. We adjusted the parameters such that urban population growth was higher as compared to the growth of rural population. As the total population in a cell increased (due to either reproduction or

migration) and reached the carrying capacity (Table B 1) of the cell, a proportion of urban actors move into a cell in its neighbourhood.

Diffusion module

In the model, the diffusion module captures the movement of population outside the cell and therefore corresponds to the diffusion component of the reaction-diffusion equation.

In the model, urban actors selects the cell with the highest value of cell score. We used three factors or variables to calculate the cell score (equation B3): score estimated based on the land-use zone of the target cell (Z), the interaction between rural and urban actors (GT) and the LULC of the cells in the neighbourhood (SI).

$D = Z[\lambda(SI) + (1 - \lambda)(GT)]$ ----- *Equation B1*

To estimate each variable we developed sub-modules.

Submodules

1) Land-use policy (LUP) Module

In the model, we used the four land-use zones (LUZs) as described in the proposed national Land Utilization Policy by the Government of India . We assigned score to each LUZ where a higher value of LUZ implied a higher probability of change. For example, restrictions to change for the cell with LUZ as Guided Area (GA) was least and had the highest score (0.9). On the other hand, cells with LUZ as Protected Area (PA) was assigned a score of zero meaning no land-use transformation. All four land-use zones along with their description and corresponding score (Z) is given in table B2.

Land-use zone	**Land-use policy**	**Description**	**LUZ score for the model**
Protected Areas (PA)	Strict no change zone	Land-use change strictly prohibited. For example, Ecologically, socially or historically sensitive areas	0
Regulated Areas (RgA)	Restricted land use change	Land-use change not legally restricted but has important associated functions. For example, tourism, hazard prone zone, and prime agricultural land. Therefore, special permission may be required considering the legal conditions for land-use change and has comparatively less probability of land-use change.	0.1 to 0.4 (low probability of change)
Reserved Areas (RsA)	Land-use change permitted with conditions	Has the higher probability of land-use change. These are the cells that are under greater pressure of development mostly because they exist near the areas experiencing land-use change. For example, areas near already developed	0.5 to 0.8 (higher probability of change)

		urban area, areas next to an economic center, or close to road.	
Guided Areas (GA)	Land-use change permitted with no conditions	Areas with highest probability of land-use change which mostly exist in the urban periphery.	0.9 (highest probability of change)

Table B 2: LUZs along with level of restriction, their description, and associated score range used in the model (Z).

In the model, the land-use zone along with the corresponding score for each cell was updated every five iterations. To update the land-use zone of each cell, we used a rule-based approach. A set of rules were identified based on the spatial conditions in the landscape.

The rules are:

(i) Proximity to urban patches: The model assigned LUZ RsA or GA to a cell closer to urban patches.
(ii) LULC class to which the cell belong: For example, a cell belonging to a forest LULC class was assigned a more restricted LUZ such as RgA or PA, compared to a cell belonging to a wasteland class.
(iii) Ratio of green to grey cell in the entire landscape: A threshold was set to maintain a certain level of green cells in the landscape. If the ratio was below the threshold, the model restricted the land-use change by assigning the stricter land-use zones to the cells.

2) Game Theory (GT)

The rural urban interaction described in the manuscript was captured using the GT module. In the Hawk and Dove model, a player has two strategies to choose from. In the model, both urban and rural actors could choose to be a fight (Hawk strategy) or comply (Dove strategy). During the model run, at one iteration, only one strategy dominated a cell depending on dominant actor group.

3) Spatial neighbourhood Information (SI) sub-module

Decision for land-use transformation also depends on LULC of neighbouring cells (Verburg, de Nijs et al. 2004, van Schrojenstein Lantman, Verburg et al. 2011). In the SI module we estimated the 'enrichment factor' which was the score of similar land-use type in the neighbourhood of a target cell or the cell in the neighbourhood window of the urban actor (Verburg, de Nijs et al. 2004). Enrichment factor is the score of relative occurrence of individual LULC type in the neighbourhood of each cell given by Verburg, de Nijs et al. (2004) . It is estimated on a scale from 0 to 1 (equation S4).

$$SI_{i,k,d} = \frac{n_{k,d,i}/n_{d,i}}{N_k/N} \qquad \text{----- } \textit{Equation B2}$$

Where,

i - target cell,

k – LULC type

d - distance of the neighbourhood cells from the target cell

N - total number of cells in the landscape.

Additional Results

Summary Statistics of Multiple Regression

Table C 1: Result of multiple regression for all cases with the P-value (p) and R-square (r^2) value..

	Spatial level of update	**Response variable: First Change Point (p,r^2)**	**Response variable: Gradient at First change point (p, r^2)**
Low Heterogeneity	**Null Model**	0.3007 , 0.03955	0.565, 0.02627
	Local	0.3785, 0.03955	0.4728, 0.03233
	Region	0.317, 0.04509	0.452, 0.03382
High Heterogeneity	**Null**	0.6994, 0.01467	0.4478, 0.02715
	Local	0.508, 0.02379	0.5601 ,0.02112
	Region	0.4863, 0.02497	0.4478,0.02715

The summary statistics for multiple regression for low and high heterogeneity landscapes for local and region update of decision making.

Table C 2: Low heterogeneity landscape (y = Number of urban cells at the Change point 1(ChgPt1))

Independent variable	**Significance of the variable**	**Coefficient value**	**t-stat**	**Regression Model p-Value and R-square**	**Spatial extent for LUZ update (ChgPt1)**
Patch Area	0.0731	0.003380	1.818	P-value : 0.317	Regional (44)
Edge Density	0.8972	-92.644460	-0.130	R-Square : 0.04509	Regional
SDPatch	0.1880	-0.002148	-1.328		Regional
Patch Area	0.149	2.870e-03	1.459	P-value : 0.3785	Local (48)
Edge Density	0.338	-7.290e+02	-0.964	R-Square : 0.03955	Local
SDPatch	0.672	-7.273e-04	-0.425		Local
Patch Area	0.161	2.836e-03	1.415	P-value : 0.3007	Null (33)
Edge Density	0.622	-3.819e+02	-0.496	R-Square : 0.03955	Null
SDPatch	0.811	-4.176e-04	-0.240		Null

Table C 3: Low heterogeneity landscape (y = Gradient at the Change point 1(ChgPt1)

Independent variable	Significance of the variable	Coefficient value	t-stat	Regression Model p-Value and R-square	Spatial extent for LUZ update (ChgPt1)
Patch Area	0.863	-1.299e-03	-0.173	P-value : 0.4863 R-Square : 0.02497	Regional (44)
Edge Density	0.197	2.349e+02	1.299		Regional
SDPatch	0.851	8.970e-04	0.188		Regional
Patch Area	0.488	5.871e-03	0.696	P-value : 0.508 R-Square : 0.02379	Local (48)
Edge Density	0.258	2.310e+02	1.137		Local
SDPatch	0.451	-4.046e-03	-0.757		Local
Patch Area	0.824	1.378e-03	0.223	P-value : 0.6994 R-Square : 0.01467	Null (33)
Edge Density	0.277	5.513e-05 e+02	-1.194 1.093		Null
SDPatch	0.661	-1.719e-03	-0.440		Null

Table_Sup 1: High heterogeneity landscape (y = Number of urban cells at the Change point 1(ChgPt1))

Table_Sup 2: High heterogeneity landscape (y = Gradient at the Change point 1 (ChgPt1))

Independent variable	Significance of the variable	Coefficient value	t-stat	Regression Model p-Value and R-square	Spatial extent for LUZ update (ChgPt1)
Patch Area	0.517	-0.0001649	-0.650	P-value : 0.4478 R-Square : 0.02715	Regional (44)
Edge Density	0.299	6.3798112	1.044		Regional
SDPatch	0.406	0.0001342	0.834		Regional
Patch Area	0.837	3.002e-05	0.207	P-value : 0.5601 R-Square : 0.02112	Local (48)
Edge Density	0.281	3.793e+00	1.084		Local
SDPatch	0.926	-8.549e-06	-0.093		Local
Patch Area	0.615	-9.887e-05	-0.505	P-value : 0.6232 R-Square : 0.0181	Null (33)
Edge Density	0.322	4.698e+00	0.996		Null
SDPatch	0.586	*6.788e-05*	*0.547*		Null