An investigation of the spatial influences and governance implications of social-ecological heterogeneity, connectivity, and scale on landscape change

Sivee Chawla, M.Sc, B.Tech

November, 2021

A thesis submitted for the degree of Doctor of Philosophy

at the Australian Research Council

Centre of Excellence for Coral Reef Studies

James Cook University

ARC CENTRE OF EXCELLENCE

Coral Reef Studies

ॐ गुरुवे नमः ||

This thesis is dedicated to all my teachers, guardians and mentors

"The same stream of life that runs
through my veins night and day runs
through the world and dances in rhythmic measures.

It is the same life that shoots in joy
through the dust of the earth in numberless blades of grass and
breaks into tumultuous waves of leaves and flowers."

- Rabindranath Tagore, Gitanjali (The Stream of Life)

"The purpose of computing is insight, not numbers."

- R.W Hamming, Numerical methods for Scientists and Engineers

Acknowledgements

I believe that every PhD is a journey that brings with itself a unique set of challenges and experiences along the way. To have the right kind of support is what helps one to sustain through this arduous journey. I am lucky to have an amazing set of people who have supported me through all these years.

First thanks to my supervisory team, Professor Graeme S. Cumming and Professor Tiffany H. Morrison for their caring guidance, support and contribution. Coming from a predominantly technical background, I cannot imagine pursuing the PhD if it wasn't for their scientific inputs, trust and patience. I thank them for introducing me to the wonderful world of social-ecological research, helping me ground my ideas into theory and climbing the steep learning curve. I am fortunate to have a team of supervisors who have constantly emphasised the importance of mental wellbeing and healthy work-life balance, which have allowed me to complete the PhD and manage my family at the same time. It has been an honour and a pleasure to work with both Graeme and Tiffany.

I would like to thank the ARC Centre of Excellence for Coral Reef Studies and its incredible team including Janet Swanson, Vivian Doherty, Olga Bazaka, Jennifer Lappin and most importantly Associate Professor Alana Grech for running things smoothly even during the pandemic. Special thanks to the staff of Graduate Research School including Dr Liz Tynan for her academic writing courses and Jodie Wilson for seamless support throughout the PhD. It was impossible to get the PhD completed without the IT infrastructure and support provided by the team of Dr Wayne Mallett and not to forget Andrew Norton who was always a phone call away.

The Modelling Institutions Group from the SESYNC workshop, led by Graeme and Dr Graham Epstein of the University of Waterloo, deserves a special mention. I met some of the most wonderful researchers who were generous in sharing their knowledge and wisdom. Working closely with them provided me with the perspective and insights that helped me in addressing the knowledge gaps in this PhD. It helped me also to learn how to collaborate and write scientific papers. The multiple week-long brainstorming sessions helped me in refining my ideas and contributed immensely to my PhD. I thank Graeme for encouraging me in attending the workshop.

I thank the entire team for the DFG Research unit FOR2432/I for funding my research and providing the necessary support. Also, I thank the Indian partners at Azim Prem Ji University including Ms Sheetal Patil and Mr Rahguvendra for sharing their knowledge and the field visits to the peri-urban areas of Bangalore. Those have helped in conceptualizing peri-urban SES for the PhD.

I wouldn’t have applied for a PhD in the first place if it wasn’t for the motivation provided by my mentor Mr KNK Murthy and my M.Sc supervisors, Dr Anil Kumar and Dr Valentyn Tolpekin.

At the end of the day, it is the unconditional support and love from family and friends that keeps one going. Thanks to Nitin, my husband and a fellow researcher, who believed in me and stood by me in the best and worst of my times. Thanks for the endless brainstorming sessions, for bearing with my emotional ups and downs, for challenging me in pushing my limits and most importantly for cooking healthy and delicious meals. And thanks to our daughter Shivniti for patiently giving up on her playdates and outings for her mum who needed to work hard on her PhD.

I thank my parents and grandmother to nurture me with the value system that helped me sustain through the PhD. I am lucky to have a mother-in-law who trusted me with my unconventional ideas and supported me like a mother. The role of my childhood friends, Neha and Ashutosh, is indispensable for they have always believed in me more than myself. They have shown that true friendship knows no barriers, not even distance.

Finally, to the lovely bunch of friends at JCU including Mia, Marie, Severine, Jodie, Katie, Jennifer, Tiffany, Danielle and Vanessa. Special thanks to Jodie and Katie for supporting me even when I moved away to New Zealand during these challenging times of the pandemic.

Statement of the Contribution of Others

Thesis Committee

Graeme S. Cumming, Professor and Centre Director, Australian Research Council Centre of Excellence for Coral Reef Studies, James Cook University, Townsville, Queensland, Australia

Tiffany H. Morrison, Professor, Australian Research Council Centre of Excellence for Coral Reef Studies, James Cook University, Townsville, Queensland, Australia

Funding

Deutsche Forschungsgemeinschaft (DFG): Salary and field work

ARC Centre of Excellence for Coral Reef Studies: Travel costs to conferences

James Cook University: Tuition fee waiver

Research support

Theoretical and conceptual advice

Graeme Cumming and Tiffany Morrison

Methods design

Graeme Cumming and Tiffany Morrison

Statistical analyses

Graeme Cumming

Editorial support

Graeme Cumming and Tiffany Morrison

Technical support

Severine Choukron, Nitin Bhatia, and JCU IT (for providing infrastructure and supporting the transition to HPC)

Scientific contribution

Conference presentation

Oral presentation at ARC Centre of Excellence for Coral Reef Studies Symposium, July 2020.

The conservation relevance of spatially explicit social-ecological feedbacks in an urbanizing landscape Chawla,S, Morrison, T.H and Cumming G.S.

Oral presentation at 29th International Congress for Conservation Biology, July 2019.

Investigating the impact of individual responses to landscape change in dynamic social-ecological systems. Chawla,S, Morrison, T.H and Cumming G.S.

Other publications during candidature

GS Cumming, G Epstein, JM Anderies, CI Apetrei, J Baggio, Ö Bodin, **S Chawla,** HS Clements, M Cox, L Egli, GG Gurney, M Lubell, N Magliocca, TH Morrison, B Müller, R Seppelt, M Schlüter, H Unnikrishnan, S Villamayor-Tomas, CM Weible (2020) **Advancing understanding of natural resource governance: a post-Ostrom research agenda**, *Current Opinion in Environmental Sustainability*

Graham Epstein , Georgina Gurney, **Sivee Chawla**, Marty Anderies, Jacopo Baggio, Hita Unnikrishnan, Sergio Villamayor Tomas , Graeme S. Cumming (2021) **Drivers of compliance monitoring in forest commons,** *Nature Sustainability*

Abstract

For the sustainable management of natural resources, institutional arrangements and governance structures should acknowledge and address the complex, emergent, and non-linear dynamics of Social-Ecological Systems (SESs). Current best practices for the governance of small-scale Common Pool Resources, such as water and fisheries, are described by Ostrom's design principles. Researchers have explored the applicability of some of the design principles for larger, complex SESs. However, the interpretation and application of the design principles in a large SES are not straightforward due to such systems' inherent complexity and scale. Although the design principles include the concepts of self-organization, local knowledge and participation, and feedbacks, there are gaps in understanding and the relevance of the design principles for large SES with high spatial heterogeneity is unclear. The aim of the thesis is to extend SES theory by exploring the relevance of the design principles for urbanizing, spatially heterogeneous landscapes.

Peri-urban SESs are spatially dynamic landscapes experiencing degradation of natural resources and loss of related ecosystem goods and services. They are often characterised by multiple and conflicting resource use, overlap and gaps in policies, corroding institutions, actor heterogeneity, lack of social capital, and skewed power dynamics. Consequently, natural resource management is challenging in a peri-urban SES. Therefore, scholars have proposed commons-based approaches to manage resources in the SES.

I identified three research questions relating to the roles of space, scale, and connectivity in natural resource governance to explore the applicability of the design principles in a peri-urban SES. I addressed them using an exploratory dynamic simulation model based on Ostrom's SES framework. The model uses a modified reaction-diffusion equation and includes the concepts from game theory and land use change studies. I used a dataset of simulated landscapes (N=200), loosely based on urban peripheries of rapidly expanding tier -1 Indian cities.

First, I explored the applicability of design principle 2 for addressing the issue of institutional fit in dynamic landscapes. Design principle 2 asserts congruence between governance rules and local social-ecological conditions. However, little is known about how to achieve congruence in spatially dynamic SES, partly because the local conditions are constantly changing. Using the model, I explored social-ecological feedbacks between ecological patterns and landscape governance. I captured feedbacks by varying the spatial extent of decision making in the model from a regional to a local scale across landscapes for two different levels of spatial heterogeneity. I found that the rate of

urbanization and urbanization trend differed significantly at the regional scale as compared to the local scale for highly heterogeneous landscapes. For low heterogeneity landscapes, the trend was similar for both regional and local scales. I extended and operationalised the design principle by explicitly defining the term 'local' as relative rather than fixed, that is, as a spatial extent of decision-making based on landscape heterogeneity.

Second, I explored the influence of resistance among actors on effectiveness of design principle 3 for governing spatially dynamic landscapes. Design principle 3 emphasises the importance of collective participation by local actors in the rule making. In a peri-urban SES, urban actors appropriate land which often results in land fragmentation and affects the livelihood of rural inhabitants by reducing land availability for activities such as agriculture. Little is known about how rural actors resist or accept these impacts and whether the design principle is useful in this context. I simulated the consequences of individual rural and urban actor decisions on emerging land use patterns in the urban periphery. I used game theory to describe competition for land, and landscape metrics to quantify the impacts of increasing rural resistance on emerging landscape patterns. I found that landscape structure (number of patches, patch area, clumping of patches and edge density) had a non-linear response to resistance to urbanization. The responses of individual landscape structural elements varied for a given level of resistance. The non-linear response and presence of tipping points for ecological processes depending on connectivity or area can create significant challenges and opportunities for sustainable land use change in spatially dynamic SES. I conclude that efforts to use the design principles to manage complex landscapes must account for actor heterogeneity and the potential of actor resistance in achieving ecosystem sustainability.

Third, I explored the applicability of design principle 3 to situations where a group of actors have limited local knowledge. Design principle 3 stresses the importance of local knowledge and therefore, emphasizes including local actors in decision-making. In a peri-urban SES, however, urban actors have limited local knowledge of rural elements of the SES but wield strong influence over policymaking and landscape governance. In addition, it is known that local spatial conditions influence the decisions of actors. I hypothesized that urban actors can regulate the influence of existing landscape conditions on emerging landscape patterns by explicitly including local spatial information in decision-making. I explored the influence of varying levels of spatial neighbourhood information included in the decision-making on spatial composition and configuration of green spaces left after urbanization for high and low heterogeneity landscapes. I found that the change in patch area, which explained most of the variation in the outcomes, followed a sigmoidal curve in response to the varying level of neighbourhood information for both landscapes. For high heterogeneity landscapes, the change in patch area was higher than the low heterogeneity landscapes for the same level of neighbourhood information. As level of neighbourhood information increased in the decision making, the difference between the patch metrics for high and low heterogeneity reduced. The results show that urban actors can regulate the influence of existing landscape conditions on emerging landscape patterns by explicitly including local spatial information in the decision-making. Urban actors can compensate for lack of knowledge and contribute to integrated governance by making spatially conscious choices. My work sheds new light on cross-scale interactions in spatially dynamic landscapes.

In sum, I operationalised design principle 2 and 3 for spatially dynamic SES by exploring feedbacks and cross-scale interactions in the SES. The thesis provides new insights into the spatial interplay between governance and landscape change and extends SES theory for spatially explicit SES and landscape governance for dynamic landscapes with multiple land use.

Table of Contents

List of Tables

List of Figures

List of Acronyms

AIC	Akaike Information Criteria
ANCOVA	Analysis of Covariance
ANOVA	Analysis of Variance
CCA	Constrained Canonical Analysis
GS	Governance System
HPC	High Performance Computing
LULC	Land Use Land Cover
LUZ	Land Use Zone
ODD	Overview, Design concepts and Details
ODD+D	Overview, Design concepts and Details + human Decision -making
PCA	Principal Component Analysis
pCCA	partial Constrained Correspondence Analysis
RS	Resource System
RU	Resource Unit
SES	Social Ecological Systems

Chapter 1 : General Introduction

1.1 Background to SES theory

Human and natural systems are interdependent. Humans depend on natural systems to fulfil their need for ecosystem services and goods. In turn, human activities alter ecosystems by influencing biophysical processes (Millennium Ecosystem 2005). For example, the conversion of natural landscapes for human use (e.g., cultivation, expansion of urban centres) has resulted in the loss and degradation of forests (Foley et al. 2005, Seppelt et al. 2018). The intensity and scale of human activities have escalated (Gunderson and Holling 2003, Bennett et al. 2016), with impacts that are evident in changes in climate, biochemical flows, and freshwater use (Steffen et al. 2015). Such changes have resulted in an increase in the frequency and intensity of events such as drought, floods, forest fires, heatwaves and the emergence of new pathogens threatening the sustainability of natural resources and human-wellbeing (Millennium Ecosystem 2005, Biggs et al. 2021). As human dominance of the earth's system increases, it is important to address the association between natural and human systems for the effective management of natural resources (Vitousek et al. 1997, Gunderson and Holling 2003, Folke et al. 2021).

Researchers have long acknowledged the interconnections between human and natural systems (Holling and Chambers 1973, Redman et al. 2004, Liu et al. 2007). However, there are gaps in scientific and management solutions for environmental challenges (Berkes et al. 2002). Many conventional approaches and familiar responses to current environmental issues are insufficient to provide sustainable solutions for the management of natural resources, because they overlook the intertwined relationship between social and ecological systems and the inherent complexities within each system (Berkes et al. 2002). Conventional approaches limited by disciplinary boundaries have addressed the issues of natural resource management by treating either social or ecological systems as external drivers to the problem (Gunderson and Holling 2003). For example, land use change studies often treat humans as drivers that disturb the functioning of the ecosystem, thereby overlooking the interactions within social systems (Wu and Hobbs 2002, Foley et al. 2005, Menatti 2017). Similarly, economists and social scientists often consider natural systems as resources, which are 'managed' by humans (Berkes et al. 2002). Both approaches often fail to address the interactions among the elements of a system that in turn influence the interactions between systems through feedbacks. In doing so, they generate actions based on partial perspectives (Berkes et al. 2002, Preiser et al. 2018). Further, approaches looking for a tractable solution and bounding the problem to a particular spatial and temporal scale often ignore the concept of adaptation and variability within system components and overlook interactions that occur across levels (Cash et al. 2006) and spatial and temporal scales (Preiser et al. 2018, Anderies et al. 2019).

For example, neoclassical economic theories concerned with fast-moving variables often find it difficult to incorporate slow-moving variables, as well as the interaction between the slow-moving and fast-moving variables and resulting emergent dynamics (Gunderson and Holling 2003). Therefore, for dealing with environmental challenges in the current era of human dominance, we need broader, integrative approaches that acknowledge and address the fundamental interdependence among system components, between systems, and their wider environment.

1.2 Introduction to SES theory

The social-ecological systems (SES) approach, which is embedded in complexity thinking and systems science, recognizes the inextricable linkages between coupled social and ecological systems (Cumming 2011, Preiser et al. 2018). Redman et al. (2004) defines an SES as, 'A coherent system of biophysical and social factors that regularly interact in a resilient, sustained manner'. As components of an SES, social and ecological components form a complex web of interactions that vary across spatial, temporal, and organisational scales (Redman et al. 2004, Cumming 2011). Understanding SESs through the lens of complex adaptive systems provides a non-reductionist approach to understand interactions occurring across scales by treating the interactions as the fundamental elements of the system (Spies and Alff 2020). The complex adaptive systems' lens provides a systematic approach to understanding the inherent complexity in SES characterised by non-linearity, feedbacks, self-organising ability, and emergent phenomena (Holling 2001, Gunderson and Holling 2003).

SES theory extends the theories and concepts of complex adaptive systems to address environmental issues (Cumming 2011, Spies and Alff 2020). In particular, SES theory embedded in complex adaptive systems recognizes the role of institutions in the complex environmental governance interface between social and ecological systems (Cumming et al. 2020). Institutions include formal and informal laws, rules, norms, and strategies that influence human interactions among themselves and with the environment (Ostrom 2005, Cumming et al. 2020, Epstein et al. 2020). Institutions thus play an important role in guiding, supporting, and constraining human actions and decision-making (Bennett and Satterfield 2018). For the sustainable management of resources in an SES, institutional arrangements should acknowledge and address the complex, emergent, and non-linear dynamics of an SES.

Scholars have increasingly recognized the effectiveness of the commons approach for the sustainable governance of natural resources from an SES perspective (Partelow 2018, Cumming et al. 2020). Ostrom's seminal work on Governing the Commons (Ostrom 1990), which was based on extensive research on common pool resources, extended beyond the traditional models of (purely) state or market based institutional arrangements for addressing common pool resource use (Agrawal 2001).

Management of common pool resources such as fisheries, irrigation, and forests is challenging primarily because it is difficult to exclude potential resource users and the resources are subtractable (Ostrom 1990, Ostrom and Gardner 1993). However, studies have found that the resource users can self-organise to devise institutional arrangements for the sustainable management of the resources (Ostrom 1990, Schlager 2004).

Ostrom and her colleagues identified 8 design principles that support institutional arrangements for the successful management of resources. The 8 design principles established as a set of guidelines include: specifying well-defined system boundaries, emphasising congruence of rules and local conditions, having collective choice arrangements by those affected by the rules, establishing effective monitoring practices, having graduated sanctions in place to check free riding, having mechanisms to resolve conflict, recognising the autonomy of institutions by external authorities, and supporting nested enterprises (Ostrom 1990). Concepts such as participation, social capital, local knowledge, self-organization, and feedbacks, are inherent in the design principles (Cox et al. 2010, Saunders 2014).

Table 1.1: 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

To be able to study and analyse SESs and integrate the knowledge into a conceptual understanding, a theoretical framework is required. A framework provides an abstract understanding of an SES and its components for the diagnosis of the phenomena under study (Epstein et al. 2013; Schlüter et al. 2014). For a systematic conceptualization of an SES, Ostrom proposed an SES framework which was based on research in common pool resources, collective choice theory and natural resource management (Ostrom 2009, Binder et al. 2013). The SES Framework is a multi-tiered structure where components of an SES are organised into logical categories (Ostrom 2007, 2009, McGinnis and Ostrom 2014). In the first tier, the components of an SES are organised into eight sub-systems which are resources system (RS), resource units (RU), governance system (G) and actors (A) that interact and the interactions (I) produce outcomes (O). Related ecosystems (ECO) and social, ecological, and political settings (S) further influence the interactions and outcomes in an SES. The focal action situation captures the interactions among the components and resulting outcomes (McGinnis and Ostrom 2014, Dancette and Sebastien 2019). The SES Framework provides a generalised platform to systematically evaluate, diagnose and address the challenges of governances in an SES, and test hypotheses (Schlüter et al. 2014, Partelow 2018).

The Design Principles for large SES

Large SESs are characterised by complex social–ecological elements such as a large resource area (Tyson 2017), multiple resource-use types, multiple actor groups (Evans et al. 2014, Fleischman et al. 2014a), transboundary governance (Epstein et al. 2014), and gaps in institutions (Villamayor-Tomas et al. 2014). In addition, researchers have recognised that the design principles and the SES Framework although rooted in collective action theory and common pool resources are embedded in broader SES contexts (Anderies et al. 2007, Partelow 2018). Therefore, researchers have explored the applicability of the design principles and the SES Framework for larger, complex SES, beyond traditional small-scale common pool resources, such as for evaluating and assessing the multi-actor resource system of Great Barrier Marine Park (Evans et al. 2014, Morrison 2017), transboundary governance in the watershed region of the Rhine river (Villamayor-Tomas et al. 2014), national-level management of forests in Indonesia (Fleischman et al. 2014b), environmental policy and governance effectiveness in the context of the carbon tax (Lacroix and Richards 2015), and co-management of terrestrial and marine wildlife resources (Tyson 2017). For the applicability of the design principles to large SESs, the studies found stronger support for 5 out of 8 design principles (Table 1.1): (1) boundary conditions, (2) congruence between rules and local conditions, (4) monitoring, (5) having graduated sanctions in place to check free riding, (6) having mechanisms to resolve conflict. There is enough evidence to support the applicability of the design principles in large SESs.

Studies testing applicability of the design principles in large SESs, discussed above, have also found that interpretation and application of the design principles in large systems are not straightforward due to the inherent complexity and scale of such systems (Evans et al., 2014; F. D. Fleischman et al., 2014). For example, some aspects of the design principles lack direct relevance such as clear resource boundaries, monitoring, and graduated sanctions and therefore, have to be adapted to be applicable in large SES (G. Epstein et al., 2014; Evans et al., 2014). Similarly, there are gaps in understanding and relevance of the design principles for large-scale dynamic SES in a spatially explicit context such as for terrestrial resource systems (Gari et al. 2017).

The applicability of the design principles for a terrestrial SES in urbanizing landscapes, in particular, is not yet sufficiently studied (Mundoli et al. 2017).There is a growing interest among land use scientists to address landscape management and governance through the lens of SES (Patterson 2017, Turner et al. 2020). Experts emphasise that land use transformations and emerging landscapes are a result of human interactions with their environment and recognize that actors who use, value and share landscape are central to the landscape management (Menatti 2017, Cerquetti et al. 2019). Land use transformations such as those observed in peri-urban areas involve multiple interconnected resource use linked across scale, weak and overlooked feedbacks, multiple and a diverse set of actors and governance processes, and interplay of dynamics and drivers are common in terrestrial SES (e.g. in urbanizing landscapes) (Jagers et al. 2020). In the thesis, I test and extend the applicability of the design principles and SES theory for large and dynamic SES.

Peri-urban SES

I focus on peri-urban SES as an example of a large and dynamic SES with heterogeneous actor groups and complex use of the terrestrial resource system. Peri-urban areas are located along the urban periphery and serve as functional spaces to support urban well-being and provide for rural livelihoods (Narain 2009, 2021). As a result, peri-urban areas experience rapid land use transformations resulting in a complex mix of urban, rural, and natural landscapes (Elmqvist et al. 2013). This often leads to complex and continually evolving interactions and feedbacks among institutions, environment, and actors across scales in a peri-urban area (Narain 2009, Ramachandra et al. 2012, Sarkar and Bandyopadhyay 2013). Peri-urban areas are highly vulnerable due to these dynamic changes, yet are often neglected in science and policymaking. Often this neglect is in terms of institutional development (Roy 2009). Institutions that can deal with the complexities of a peri-urban area may not evolve as rapidly as needed, especially in fast-developing countries such as India, China and Ethiopia (Roy 2009, Sarkar and Bandyopadhyay 2013, Zhang et al. 2019, Gashu Adam 2020). For example, several cities in India, including Delhi, Bengaluru, and Kolkata, have experienced rapid urbanization since India's independence followed by changes in national economic policy in 1991 (Nagendra et al. 2012, Hettiarachchi et al. 2013, Vij and Narain 2016). The SES perspective offers a systematic approach to analyse complex interactions and address the issue of sustainable management of natural resources (Narain 2009, Haase et al. 2014, Okpara et al. 2018, Zhang et al. 2019, Narain 2021).

Natural resource governance is also challenging and controversial in a peri-urban SES due to its transitional nature (Žlender 2020). Peri-urban SESs are often characterised by multiple and conflicting uses of land and water, overlaps and gaps in policies and institutions, lack of clarity on ownership rights, corroding institutions, social and economic heterogeneity among actors, and skewed power dynamics

(Allen 2003, Narain 2009, Mundoli et al. 2017, Patil et al. 2018, Narain 2021). Consequently, urban sprawl, lack of sufficient infrastructure, degradation of natural resources, loss of ecosystem goods and services, and disruption of ecological processes are common among peri-urban SES (Ramachandra et al. 2012). For example, there is an increase in flood-related events in Kolkata and Bangalore due to the uncontrolled urbanization of wetlands (Nagendra et al. 2012, Hettiarachchi et al. 2013), and cities like Florida and Mississippi are witnessing loss of resilience to hurricane and sea-level rise (Noss 2011). As top-down approaches are increasingly ineffective in peri-urban SES to manage natural resources, scholars have therefore proposed commons-based approaches to manage resources in peri-urban SESs (Menatti 2017, Cerquetti et al. 2019, Zhang et al. 2019). However, there has been limited testing of these approaches in peri-urban SESs.

1.3 Aim and Gaps

In peri-urban areas, resources such as ponds, pasture, forest and wasteland are managed as common property systems which are now gradually being converted into private property systems as urbanization progresses leading to social conflict and deterioration of natural resources (Vij and Narain 2016, Mundoli et al. 2017, Singh and Narain 2019). Researchers have proposed commons based approached for the effective management of natural resources in a peri-urban SESs. Further, there is an increasing focus to move beyond limited sectorial focus such as watershed management, pastures (Baur and Binder 2013) and forests (Fischer 2018) in the land-use management (Wandl and Magoni 2016, Wandl et al. 2016). The terrestrial resource system in a peri-urban SES is an interconnected set of spatial units where land use is multifunctional (e.g., for food production, housing, and recreation), and a variety of potentially conflicting ecosystem goods and services are in demand (Wandl et al. 2016). Ostrom's design principles and the SES framework, rooted in collective action theory, can provide effective support for analysing and developing governance strategies for the management of urbanizing landscapes (Foster and Iaione 2019). Researchers have used the design principles for the diagnosis and analysis of the management of resources in a landscape such as forests(Nagendra and Ostrom 2012), urban lakes(Nagendra and Ostrom 2014), and residential open spaces(Gabriel Ling Hoh Teck et al. 2014). However, there is only limited research on how Ostrom's design principles and SES framework can be adapted to include the characteristics of the peri-urban SES such as spatial scale, heterogeneity and connectivity in a multifunctional landscape. Therefore, I explore how Ostrom's design principles can be used to explicitly address questions of space, scale, and connectivity in a peri-urban SES.

Geography, including spatial properties of the components and spatial variation in the system elements in a peri-urban SES, has a significant influence on the SES dynamics (Cumming 2011). Spatial heterogeneity, including heterogeneity among LULC classes, is a characteristic feature of the terrestrial resource system in peri-urban SESs that influences underlying ecological processes and flows of ecosystem services and goods (Banerjee et al. 2013). Spatial heterogeneity and connectivity also influence social processes such as land use change decisions and institutions (Cumming and Epstein 2020). However, questions related to spatial dynamics are poorly understood in Ostrom's design principles (Gari et al. 2017). Particularly, it is not clear how the SES Framework and the design principles address differences in spatial heterogeneity and their impact on outcomes in an SES.

Peri-urban SESs are dynamic in nature and witness the continual transformation of their components including institutions. Indeed, overexploitation and degradation of resources and lack of sufficient infrastructure show that environment planning and management is inadequate in peri-urban SESs (Butsch and Heinkel 2020). An important cause of ineffective natural resource management in peri-urban SES is a spatial mismatch of emerging institutions and dynamic landscapes (Beilin et al. 2013). Often, old institutions are gradually corroding and new institutions emerging in peri-urban SES (Filatova et al. 2013, Mundoli et al. 2017, Singh and Narain 2019). The evolution of institutions is not straightforward; new institutions cannot always be extrapolated from existing institutions (Allen 2003, Anderies et al. 2004). This is because changes in institutions are not only due to their internal adjustments but are also influenced by other components of the SES, such as transformation in the landscape and changes in actors' preferences (Morrison 2017), potentially leading to institutional mismatches that affect SES outcomes. It therefore remains unclear how landscape dynamics and their scale-dependent spatial characteristics influence the emergence of institutions (Cumming and Epstein 2020). Research is required to explore the interactions between landscape and institutions to address the question of spatial mismatch in a peri-urban SES.

A peri-urban SES is a self-organizing system where local level interactions among actors influence the outcomes in the SES (Lei et al. 2021). The design principles recognize the importance of local actors and emphasise their involvement in rulemaking (Ostrom 1990). Further, social capital, trust, and reciprocity among actors contribute to effective rule-making and successful outcomes in an SES (Ernstson 2011, Baggio et al. 2016). However, in a peri-urban SES, there exists multiple actor groups with varying socio-economic attributes, cultural attributes, levels of local knowledge and conflicting land use interests (Mundoli et al. 2017, Gashu Adam 2020). For example, there are rural actors living in the area before urbanization who depend on the peri-urban SES for their livelihood and daily activities such as land for farming, firewood for fuel, and grasslands for pasture. On the other hand, there are urban actors who come from the city centres and appropriate land parcels for urban land use such as for setting up industries or residential buildings leading to conflicts among urban and rural actors (Vidyarthi et al. 2017). Conflicts among actors in a peri-urban SES and unexpected outcomes in an SES such as urban sprawl are interlinked (Unnikrishnan et al. 2016). Therefore, to apply the design principle in a peri-urban

SES it is important to understand how the interactions among the actors groups can influence the outcomes in the SES.

The design principles recognize the importance of actor interactions and therefore emphasise including the local actors in the rule-making (Ostrom 1990). Local actors have insights into the economic and societal rationale and social conflict, knowledge about resources and understanding of the implication of their actions on the SES (Nuhu 2018). However, in a peri-urban SES, while urban actors exert a strong influence on the policymaking; they often have limited local knowledge and complexities of the SES (Purushothaman et al. 2012). It is not clear how the actors with limited local knowledge can contribute to effective decision making in a peri-urban SES.

1.4 Research Questions

A peri-urban landscape is a complex mix of land use land cover types. In an urbanizing landscape, the aim of land-use policies is sustainable urbanization of a peri-urban SES which is to maintain natural resources (such as green spaces) while also addressing economic needs and urban development. In the thesis, I test the applicability of Ostrom's design principles for the management of terrestrial resource systems. I particularly focus on design principle 2 and 3 to test and reflect upon how the commons approach and the design principles can be adapted to accommodate the dynamics and complexity of a peri-urban SES such as spatial mismatch, multiple actor groups and landscape heterogeneity. I assess policy success by measuring the spatial sustainability of an urbanizing landscape. I have identified the following research questions that I go on to answer in chapters 3, 4, and 5 respectively using the model described in chapter 2.

Q1. *How can spatially explicit social-ecological feedbacks shape governance of dynamic landscapes?*

Continually evolving landscapes such as those in peri-urban SES often witness the issue of institutional misfit. Design Principle 2 emphasizes that congruence between local (social and ecological) conditions and rule-making can address the issue of institutional fit in large-SES (Ostrom 1990, Fleischman et al. 2014b). In a peri-urban SES, the spatial characteristics of the landscape such as spatial heterogeneity may influence the outcomes in the landscape. However, it is not clear how the interactions between landscape dynamics and spatial characteristics such as connectivity and heterogeneity can influence institutions in an SES (Cumming and Epstein 2020). In Chapter 3, I explore the spatially explicit feedbacks between landscape heterogeneity and institutions to operationalize the design principle for spatially dynamic landscapes.

Q2. *How does resistance among actors influence the effectiveness of Ostrom's design principles for governing spatially dynamic landscapes?*

Design Principle 3 stresses the importance of the participation of actors in rulemaking (Ostrom 1990). To facilitate the creation of effective rules it is important to have social cohesion, trust, and reciprocity among the actors (Baggio et al. 2016). In the case of large and complex SESs such as peri-urban SESs, heterogeneity among actor groups is a dominant group characteristic. Peri-urban SESs also witness conflicts and lack of social cohesion among the actor groups, which may result in unexpected outcomes in the commons situation (Poteete and Ostrom 2004). Little is known about how conflicts among actor groups in a complex and dynamic landscape can challenge the validity of the design principle. Therefore, in Chapter 4 I explore the influence of actors' resistance on emerging landscape patterns in a dynamic landscape.

Q3. *How can spatially informed decision-making and landscape heterogeneity influence integrated governance of spatially dynamic landscapes?*

For effective governance of SESs, design principle 3 stresses the importance of local knowledge and therefore, emphasizes including local actors in decision-making (Ostrom 1990). In peri-urban SES, however, not all actors have sufficient local knowledge and understanding of the complexities of the SES but wield strong influence over policymaking and landscape governance (Purushothaman and Patil 2017). In addition, it is known that local spatial conditions influence the decisions of actors (Barredo et al. 2003). In Chapter 5 I explore the applicability of the design principle when actors with limited local knowledge contribute to informed decision making by harnessing local spatial information.

1.5 Method and data used

Computational models are powerful research tools to investigate complex interactions in an SES, facilitating the systematic representation, exploration, and assessment of patterns and processes occurring across scales in an SES (Elsawah et al. 2020). Such models have contributed in multiple ways to SES research, enabling assessment of policies, development of strategies for management and extending conceptual understanding of the system (Schlüter et al. 2019). While models have the capacity to generate and test hypotheses and contribute to theory development in SES studies (Cumming et al. 2020), models that extend SES theory for land use change studies are limited (Verburg et al. 2019). To address the research gaps in the thesis, I therefore developed a minimalistic dynamic simulation model. Simulation using a transparent, low-parameter approach allows identification and exploration of local relationships, such as feedbacks, in a low-cost environment characterised by low data availability (Salecker et al. 2019).

I developed a data set of simulated land use land cover vector images simulating landscapes in a peri-urban SES. These simulated images are a generalised representation of the periphery of larger metropolitan cities in India, also known as tier-1 cities, such as Bengaluru, Delhi and Pune (India).

Following India's Independence in 1947, the Information Technology boom of 1980, and economic liberalization in 1990, the cities in India have witnessed an unprecedented urban expansion beyond their initial urban boundaries (Sudhira et al. 2007, Nagendra et al. 2012, Ramachandra et al. 2012). Cities like Bengaluru and Delhi have increased 10-fold as a result of which areas around the urban periphery have experienced a rapid transition from rural to urban landscapes, particularly, over last three decades (Sudhira et al. 2007). The rapid rate of landscape transformations makes the peri-urban areas of Indian cities an interesting example for understanding dynamic resource governance as well as a representative example of the peri-urban challenge for rapidly growing economies, especially in the Global South (Ramachandra et al. 2012). A time span of a few decades is sufficient for studying land use transformation in such peri-urban SES making them a scientifically tractable example of a large dynamic SES (Ramachandra et al. 2012).

1.6 Thesis outline

I have structured my thesis into six chapters.

I first give a detailed description of the dynamic simulation model that I developed to answer the three research questions in **Chapter 2**. I start with an overview of the state variables and entities of the model, the sequence of different processes involved, and a theoretical description on which the model is based. I also describe the operationalizing of the SES Framework to build the model and connect it to SES theory. Finally, I give a detailed description of the variables, parameters, and sub-modules that link the spatial movement of actors constrained by policies and LULC types. I have used this model to answer the three research questions. 0, 4 and 5 correspond to the three research questions respectively.

In **Chapter 3,** I discuss the first research question addressing spatial mismatch and institutional fit in a dynamic landscape. According to the second design principle, for effective natural resource management, there should be a congruence between local conditions and rulemaking. However, in a peri-urban SES, the ecological conditions of the landscape vary and are sensitive to the spatial extent of decision-making and therefore, rendering the concept of 'local' elusive. In addition, local ecological conditions also influence the institutions in a landscape; therefore, I explored the environmental feedbacks between institutions and landscape heterogeneity to inform interpretation of the concept of 'local'.

In **Chapter 4,** I addressed the second research question about how resistance among actors influences the effectiveness of the design principles. In a peri-urban SES, actor heterogeneity, lack of trust and reciprocity, and conflict among actors may influence the effectiveness of the design principles and lead to unexpected outcomes in the SES. I therefore explored the influence of interactions among heterogeneous actor groups with varying levels of conflicts on the emerging landscape patterns. To capture the interactions I used a game theory approach. The analysis showed that it is important to consider actor heterogeneity when involving local actors in decision-making, because differences between actors can significantly influence landscape pattern. In addition, explicitly addressing actor heterogeneity can create opportunities for sustainable landscape management in an SES.

In **Chapter 5,** I explored the influence of including local spatial information in decision-making at a fine spatial scale on emerging landscape patterns. In large SESs where there is a dominance of actors with limited local knowledge, local spatial information can play a significant role in addressing knowledge gaps and contributing to more informed decision making. I show that actors with limited local knowledge can contribute to integrated governance of large-scale dynamic SESs, especially by bridging the gap between urban centres and peri-urban areas by enabling spatially informed decisions.

Finally, in **Chapter 6**, I summarize my main findings from each chapter and how the work contributes to SES theory and land use change studies more broadly. I discuss limitations and future recommendations, then provide by a general conclusion.

Chapter 2 : Description of the Model

2.1 Introduction

Social-ecological systems are complex adaptive systems that are characterised by nonlinearity, feedbacks, self-organisation and emergent phenomena (Levin et al. 2012). In SES studies, models are often used to systematically support theoretical and empirical investigations in order to understand SES dynamics (Cumming 2011, Cumming et al. 2012, Schlüter et al. 2014). An SES spans social and ecological domains, at multiple scales and levels (Schlüter et al. 2014). Therefore, models should ideally allow evaluation and investigation of the complex, non-linear interactions among relevant variables (Ostrom 2007, Cumming 2011, Schlüter et al. 2014, Arkema et al. 2015, Martin and Schlüter 2015). In addition, missing data or insufficient knowledge, inadequate theories and unresolvable uncertainties (also known as deep uncertainties) are common in SES studies; these make it virtually impossible to develop a model that can both simplify and predict real-world outcomes (Moallemi et al. 2020). Instead, models in SES studies are used as conceptual tools to understand a system's potential responses under various assumptions and to generate and/or test hypotheses with limited variables and parameters relevant to the research objective under investigation (Bankes 1993, Moallemi et al. 2020).

A dynamic model supports investigation of a dynamic SES by providing a simplified mechanistic representation of changes through time in the system under study and the related processes (Schlüter et al. 2014). For example, the landscape of a peri-urban SES may gradually shift from a dominantly rural-natural landscape to a mix of urban, rural and natural landscape and eventually become fully urbanised. As the landscape transforms and human demography changes, interactions and feedbacks among the components of the SES change, resulting in emergent outcomes. To explore the implications of Ostrom's design principles at the landscape level I used simulated data to support greater generality and facilitate the use of appropriate controls, such as the creation of gradients of landscape pattern and the use of null models as a frame of reference (Gotelli and Graves 1996, Salecker et al. 2019).

Ostrom's SES Framework (Ostrom 2007, 2009) drew heavily on collective action theory in developing diagnostic for the systematic evaluation of governance of small common pool resources. Its purpose was to support empirical studies by describing the interlinkages and causal relationships between the social and ecological components involved in an SES (Binder et al. 2013, Partelow 2015, Tyson 2017). However, scholars are gradually starting to use Ostrom's Framework as a tool to assess sustainability in larger, more complex SESs (Partelow 2018). The Framework supports the conceptualization and development of a model by allowing for abstraction from the target system. It provides a common taxonomy of variables across disciplines, identification of key processes, model conceptualization, and integration of theories allowing model development in a systematic, integrative and transparent manner (Cumming 2014, Schlüter et al. 2014, Williams and Tai 2016). I used the SES Framework to develop a model for spatially explicit analysis of Ostroms' design principles in a peri-urban SES context.

To model the spatial interactions among the components of a peri-urban SES and understand their influence on the emerging land use patterns, I used reaction-diffusion equations. Researchers have used the reaction-diffusion equation in spatial ecology to model and understand patterns resulting from spatial dynamics of populations in an ecosystem (Fisher 1936, Tilman et al. 1997, Flather and Bevers 2002). The reaction-diffusion equation is originally based on the idea of passive diffusion, where objects of interest (such as insects) move into a region of low concentration from a region of high concentration (Fisher 1936, Tilman et al. 1997, Wilson et al. 2007). Movement between cells is further regulated by the diffusion coefficient, 'D', which dictates the permeability of a cell boundary (Cumming 2011). Studies in spatial ecology have used discrete reaction-diffusion equations to model population growth and dispersal across discrete units of space and time (Flather and Bevers 2002). Petrovskii et al. (2020) used reaction-diffusion equation to model the spatial aspect of dynamics in social protests. The reaction-diffusion framework was well suited to my goals of capturing the spread and impacts of a growing urban population across a simulated landscape.

A GIS based Hybrid-CA model

Over the past few decades, researchers have developed various land use change models to simulate, explore and predict urbanization patterns and processes (Koch et al. 2019). However, there is an increasing emphasis on modelling land use change to inform theory and explicitly include the concepts of space and scale, and social dimension such as actors' behaviour (Agarwal et al. 2002, Turner et al. 2020). With the availability of better geo-visualization techniques and high-speed computing, developing and running spatially explicit land use change models have become easier (Pratomoatmojo 2018). Various modelling approaches are used for modelling land use change and urban expansion. Agent-Based Models (ABM) and Cellular automata (CA) models are two popular approaches for modelling urban expansion (Ren et al. 2019). ABMs explicitly model the social aspects by modelling choices and decisions made by individual actors (Gotts et al. 2019) and micro-scale interaction of the actors (Ren et al. 2019). However, ABMs are limited to case studies with conditions specific to the study area and are therefore not easily transferable from one study area to another (Mustafa et al. 2017). In addition, they are inherently complex and require a large amount of ground data limiting their use (Ren et al. 2019). On the other hand, CA-based models are rule-based models used for prediction and spatio-temporal analysis of land use change. CA-based models are based on simple rules and can generate complex behaviour including self-organization and therefore, are increasingly used in land use change models (Samat et al. 2011). The models use discrete spatial cells, land units or pixels as the smallest unit of simulation with a fixed set of rules. CA-based models also allow the modelling of spatial interactions among the cells. Therefore, CA-based models are widely used for mapping urban expansion and land use changes. However, in a purely CA-based model, the decision making by actors is implicit and their behaviour over time doesn't change (Mustafa et al. 2017, Jin et al. 2021). Lately, to overcome the limitations of CA-based models, researchers have integrated CA with various other approaches such as Markov Chain (Nath et al. 2020, Jafarpour Ghalehteimouri et al. 2022), GIS (Pratomoatmojo 2018) and ABM (Mustafa et al. 2017). For example, the HEUM model by Mustafa et al. (2017) models urban expansion by explicitly integrating choices made by three different type of actors into a CA model. However, most of the land use change models are used for prediction and are limited to a specific study area which makes it hard to generalise (Ren et al. 2019). In addition, to model land use change in a peri-urban area as an SES requires linking of human and environment systems as interactions and feedbacks between policies, actors and land-use changes (Ren et al. 2019). My objective was to test hypothesis and extend Ostrom's design principles in a spatially explicit context. To answer my research questions, I needed to simulate a generic landscape in a controlled environment meaning the number of variables influencing the landscape change were limited while exploring interactions among various components of a peri-urban SES. Therefore, I developed a GIS-based hybrid-CA model centred on reaction-diffusion equation using a simulated dataset. The model allows testing of Ostrom's design principles by varying the conditions such as policies, landscape characteristics and actors' interactions, and exploring the influence of the interactions and feedback on outcomes at the landscape level.

To describe the model, I have followed the ODD + D (Overview, Design concepts and Details + human Decision-making) protocol (Müller et al. 2013) which is an extension of ODD+ protocol by Grimm et al. (2010). Its purpose is to foster standard descriptions of Agent-Based Models (ABM) (Grimm et al. 2010) and it has a history of use in the SES community (e.g., Koch et al. 2019). ODD + D is an extension of ODD+ protocol that explicitly includes human decision-making into model description (Müller et al. 2013). I included the compulsory and relevant components of ODD + D protocol to describe the model.

2.2 Model Description

Overview

Purpose: The purpose of the model was to test hypotheses and extend SES theory for spatially dynamic SES. The focus was to understand the spatially explicit, cross-scale interactions and feedbacks between rural and urban actors, landscape heterogeneity, and land-use policies in a peri-urban SES.

Entities, state variables, and scales

I developed a dataset of simulated images based on peri-urban areas of tier-1 cities in India, using the NLMR package in R (Sciaini et al. 2018). Each simulated image represented the terrestrial resource system of a peri-urban SES comprising of land units and actor as entities. Each entity had its corresponding attributes. Limited number of variables and parameters are included in the model to allow the results to be tractable. Therefore, it is important to note that the simulated data used in the model is only one of several possible realizations of dynamics involved in peri-urban SESs and do not necessarily represent all possible realizations of peri-urban SES dynamics.

I mapped the land surface to a lattice of 50 x 50 cells of size 200 x 200 m each. The cells corresponded to land units, which was an entity in the model. The grain size was 200 m with a spatial extent of 10x10 sq. km. The spatial extent falls in the recommended range of the buffer zone to study peri-urban areas in India (Ramachandra et al. 2014). Due to the computational limitations the cell size of 200 m was used to limit the number of cells. In addition, changing the extent and grain will not affect the analysis of the results specific to the research questions in the thesis. Each cell corresponds to a spatial unit in the model. Cell attributes were a carrying capacity of the cell, a LULC class, and a land-use zone. The carrying capacity of the cell was the total population it could support at a given time. In the model, I used land-use policies as a proxy for the governance system that influences actors' decisions to transform a land parcel into urban land use. Each cell had an associated land-use zone and a score, estimated based on the land use policy. The land-use policies and land-use zones are described in detail in section 0.

The actors were the second entity in the model who collectively took a decision at cell level and followed principles of bounded rationality (Simon 1972). I broadly classified actors into urban and rural actors based on the type of land use they occupied or were associated with. In the model, urban and rural actors occupied different cells and may use neighbouring cells for their livelihood. For example, most of the actors in cells with urban built-up were urban actors and those occupying areas surrounding the agriculture cells or occupied rural built-up cells were rural actors. The actor population changed within each cell after every iteration according to a growth function described later in the reaction module. The actor groups interacted with actor groups from other cells to appropriate and transform a cell. The actors included neighbourhood spatial conditions when taking decisions for appropriating a cell and could vary their preference to include neighbourhood spatial conditions in the decisions. The decisions of actors were influenced by land-use policies, discussed later in the chapter.

The model used discrete units of both space and time. The cells identify the space and spatial extent. The time corresponds to the iterations in a model run. Each model run, which correspond to one simulated image, included 150 to 200 iterations. To demonstrate and correctly document that a model has reached saturation point I ran the model for about 150 to 200 iterations. In the model, I have set 1 iteration equal to 1 year. However, to answer the research questions, the relative frequency or rate such as the frequency of change in institutions relative to the rate of landscape changes is relevant, instead of the actual time. Therefore, ‘the model time’ need not correspond to the actual time which means instead of years it can be read as months or weeks.

Processing overview and scheduling

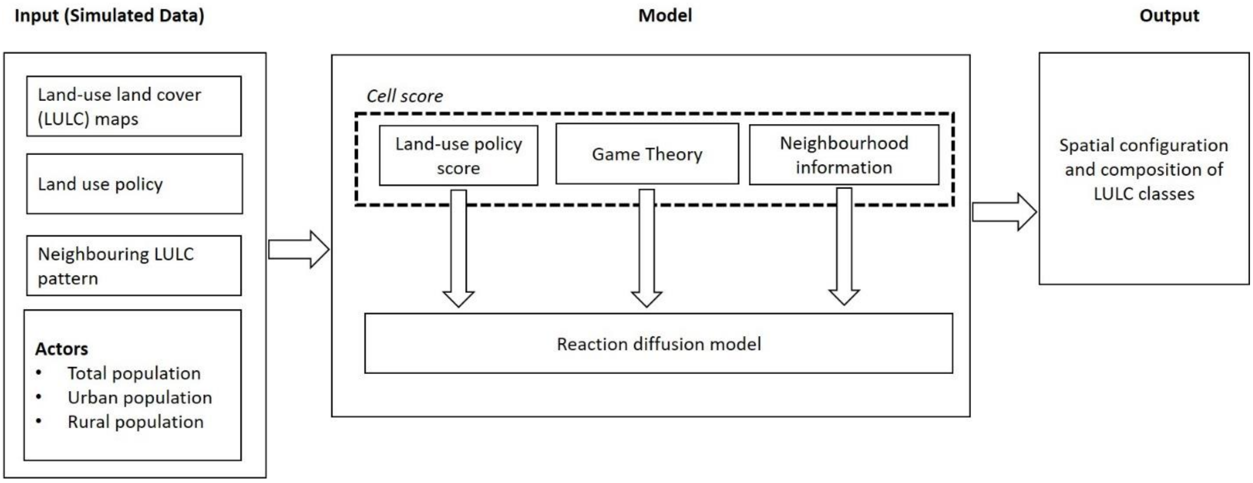

Figure 2-1: Conceptual diagram of the model with input data including the LULC maps, land-use policy score, neighbourhood information and actors' count. This data is used to estimate the cell score using three sub modules which is then used in reaction –diffusion model. The decisions taken by actors at cell-level influence the landscape level LULC patterns as the urbanization progressed. The landscape level patterns including spatial configuration and composition of classes were used to estimate the output.

The aim of the model was to capture the land use transformation decisions made by urban actors at a finer spatial scale and their influence on emerging landscape level patterns in a peri-urban SES. I used a data set of simulated images consisting of at least 100 images for each research question. Figure 2-1 shows the conceptual diagram of the model.

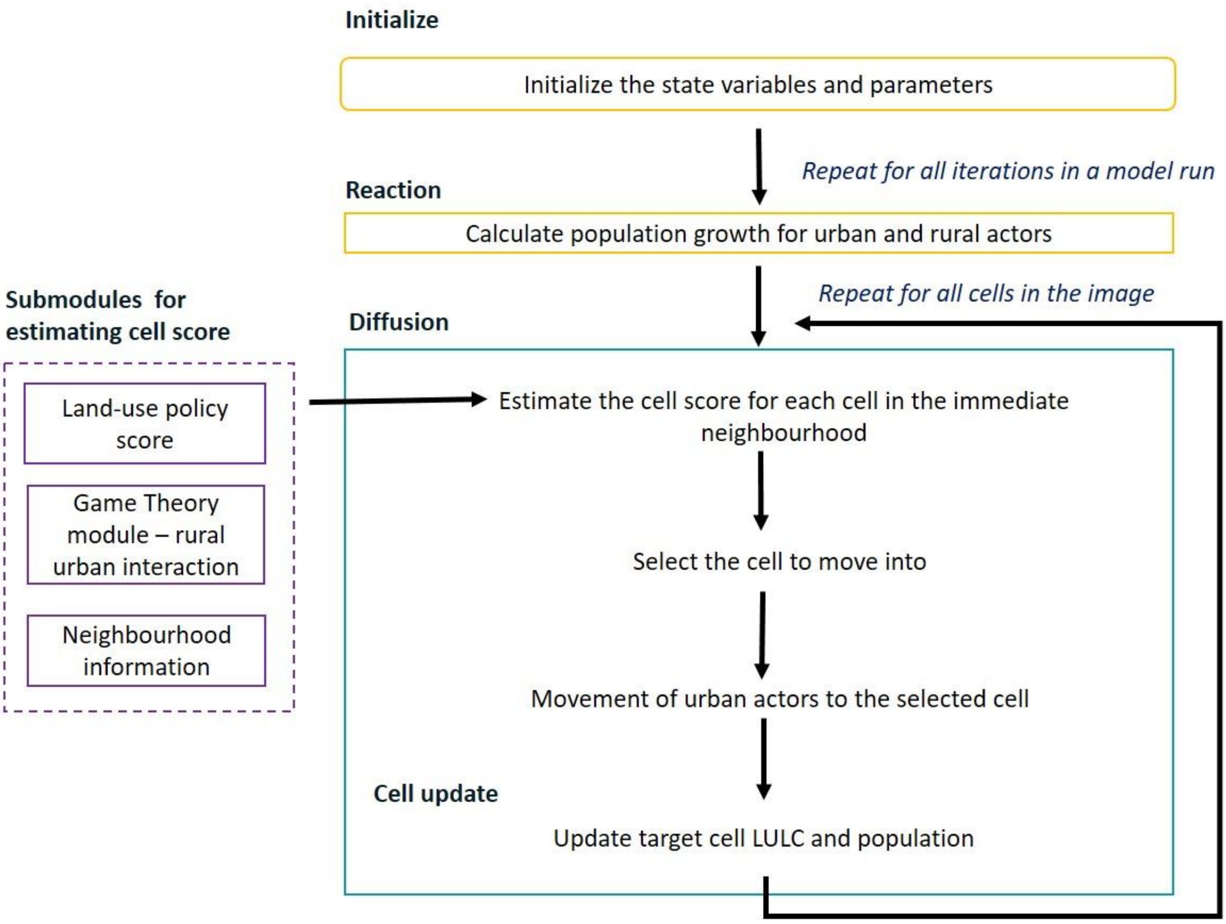

Figure 2-2: Block flow diagram showing the flow of model process and sequence of different modules and sub-modules. The reaction and diffusion model and sub-modules are described in detail in section 0.

The flow of the model process is explained in Figure 2-2. I modelled the reaction and diffusion terms separately. The reaction term was the preliminary module after initializing the state variables and attributes in an image. The reaction module approximated the population growth of actors within each cell. Once the cell reached its carrying capacity (see Table 2.2), a proportion of actors moved out of the cell and sought other cells in the peri-urban landscape (Cumming 2002). To estimate population growth of urban and rural actors, I used the UN population growth model described in (Chen 2009). The model was applied in each cell. The population growth model had different growth curves for the rural and urban populations. To converge the model, the parameters of the model were set such that urban population had higher population growth compared to the rural population. Each cell reached carrying capacity at different times during a model run, depending on the total population and the type of actors (rural or urban) occupying the cell. For simplicity, the carrying capacity for all the cells was same and was constant for all the model runs.

The diffusion module simulated the movement of urban actors into other cells based on the decisions made by the group of actors at the cell level. Once the population in a cell reached its carrying capacity, a proportion of actors in a cell move out of the cell. In general, only a proportion of population diffused into other cells (Cumming 2002). Therefore, in the model a fixed proportion of 50% of the total actors moved out of a cell. Urban actors in a cell sought other cells to move into and used the cell for urban land use. In reality, actors can chose to move in any direction in the landscape and select a land parcel in any location in the landscape. However, in the model, for simplicity I have restricted the movement of actors to the eight immediate neighbours that share the same boundary with the cell (cells in N, E, W, S, N-E, N-W, S-E, and S-W). The directions correspond to the cells that lie in their immediate neighbourhood also known as Moore's neighbourhood window (Maria de Almeida et al. 2003). In the model, if a cell happened to be on the boundary of a landscape, then neighbourhood window included only those cells that shared the immediate boundary with the cell. The urban actors from each cell were restricted to select only one target cell to move into at every iteration.

A classic reaction-diffusion equation is a deterministic equation with a constant diffusion coefficient that regulates the movement of population between cells (Cumming 2011). In addition to the diffusion coefficient, I included a factor (called cell score) that determines the direction of diffusion of urban actors. The decisions made by urban actors for the appropriation of cells is numerically calculated as the cell score in the model. When selecting a cell for urban land use in reality, urban actors consider various socio-economic and environmental factors such as the price of the land parcel, availability of infrastructure, biophysical factors in the area, policies, and rules (Benson et al. 1993). In the model, urban actors used three criteria to select the new land parcel from the neighbourhood: land-use policies of the target cell, the result of interaction with the actor group already occupying the cells in the neighbourhood window or the target cells, and the spatial neighbourhood of the target cells. I explicitly quantified these criteria using three sub modules: the Land-Use Policy module, Game theory module and Neighbourhood Information module respectively (described later under section 2.2.4 Details). The combined score from the three sub modules was used as the cell score by the urban actors to decide which cell to move into. Half of the total number of actors moved into the cell with the highest cell score. If the target cell into which urban actors moved belonged to a non-urban class, the model reclassified the cell into urban built-up. The model followed the process for all cells in the landscape for every iteration, to simulate the gradual build-up and expansion of urban actors into the peri-urban areas of a developing city (Figure 2-3).

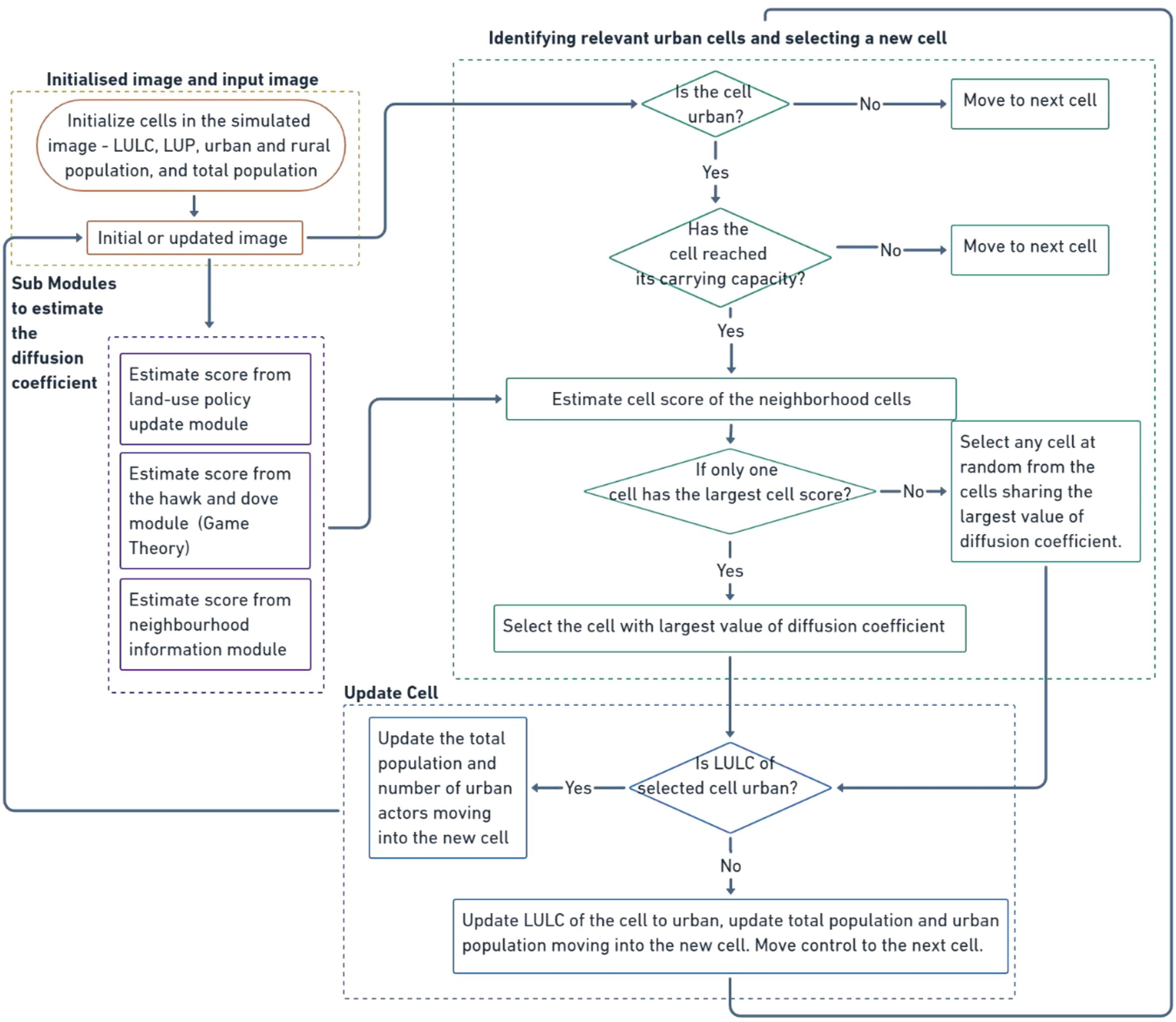

Figure 2-3: Detailed flow diagram of the model describing decisions made at cell level at every iteration. Each box represent the sub-modules and modules corresponding to figure 2.1.

The output of the model was a time-series of maps in which the attributes of land units and actors were sequentially updated at every iteration (Figure 2-4). For each map, I calculated the total number of urban cells, number of non-urban cells left for each class, landscape configuration, and composition metrics including patch area, a number of patches, edge density, clumpy index, aggregation index, and fractal dimension. The estimated output varied for every research question as described in detail in Chapters 3, 4, and 5.

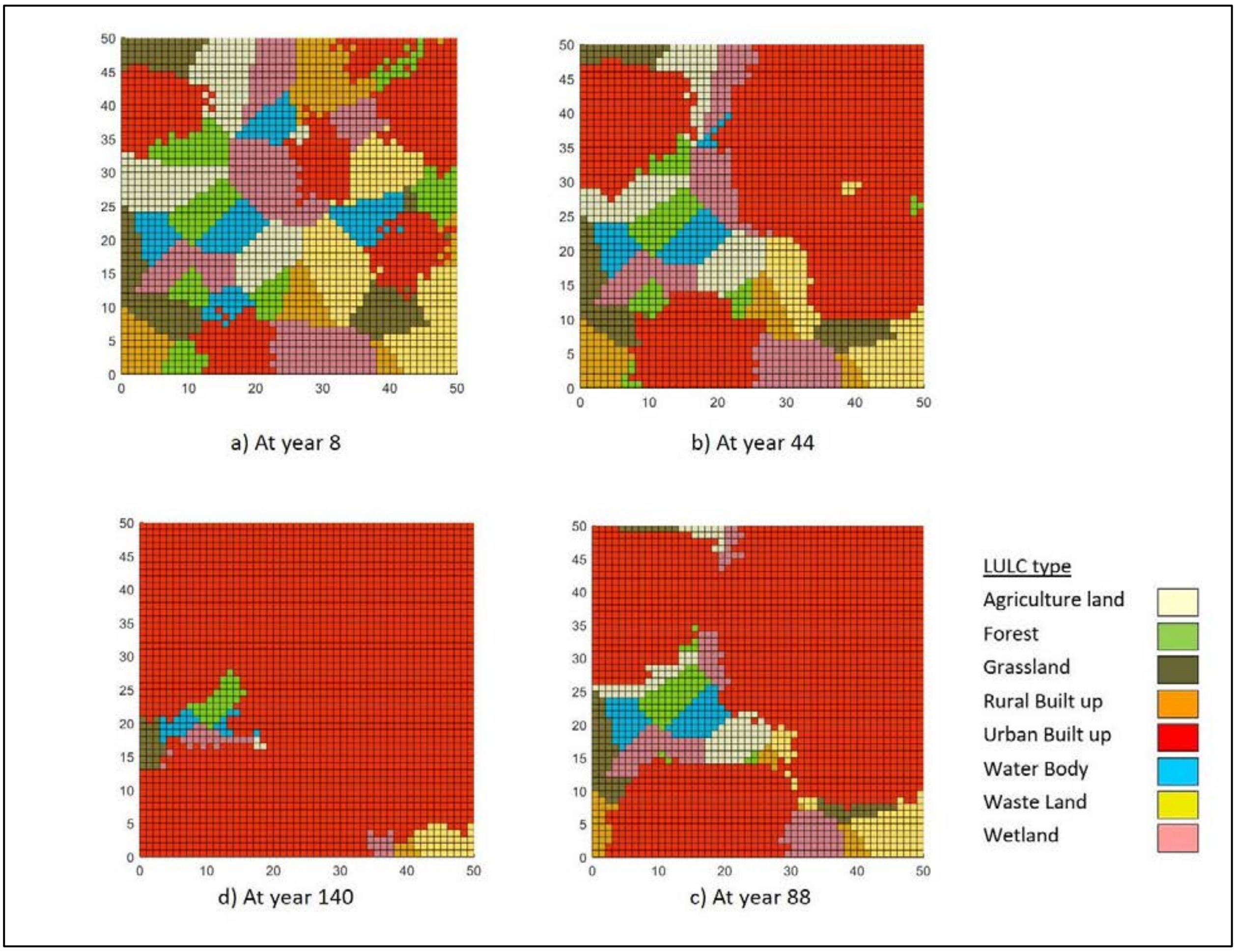

Figure 2-4: Example of time series of map generated at different iteration for a model run for four different years. The color in the image shows the LULC of the cells at the given year described in the legend.

Design Concepts

Theoretical and empirical background

I used the SES Framework to identify the components of a peri-urban SES. The SES Framework is a multi-tiered framework with a nested hierarchy of variables (Figure 2-5). The purpose of the Framework is to identify relevant variables that broadly identify factors or components needed to address in a research question (McGinnis and Ostrom 2014).

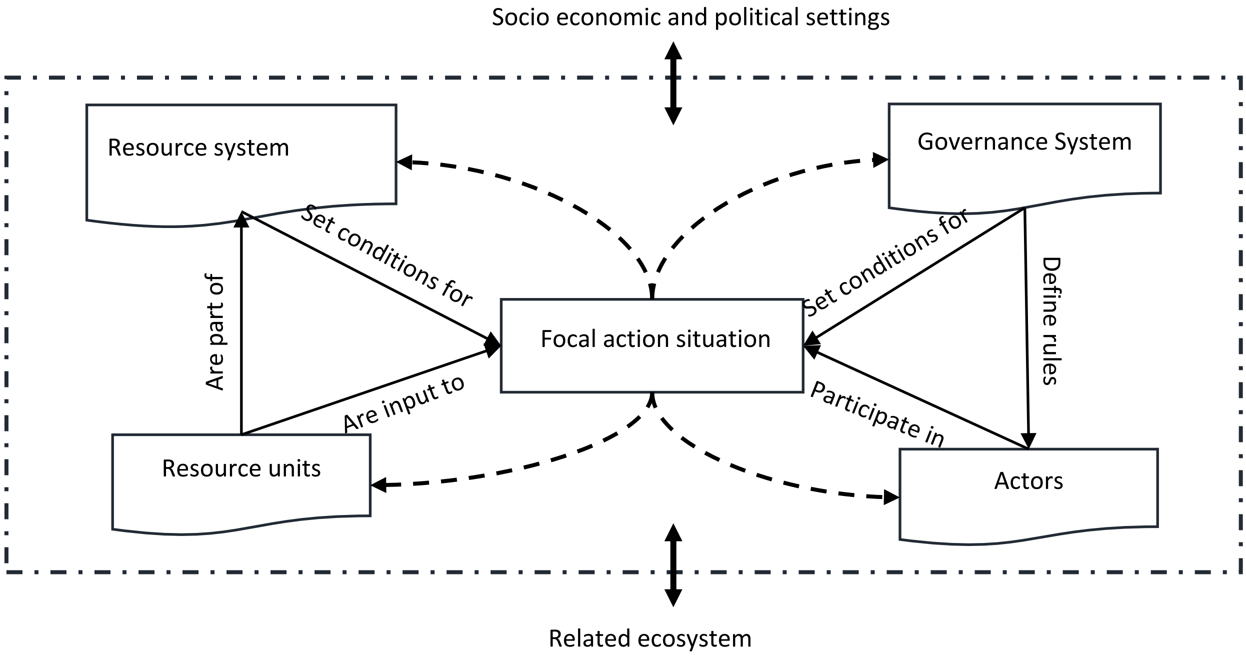

Figure 2-5: This diagram shows the first tier of SES framework, where components of the SES are broadly divided into four subsystems (solid boxes with multiples instances): resource system (RS), resource unit (RU), governance (GS) and actors (A). These components are further unraveled as second tier and third tier variables. The components are linked (connection represented by solid arrows) to and influence each other via 'Focal Action situation' that includes interactions and outcomes. The Focal Action situation influences components of SES via feedback represented by dotted arrows. The exogenous influences from other ecosystem and external social, ecological and political settings are also included that can vary at multiple scale (Ostrom 2007, 2009, McGinnis and Ostrom 2014).

Peri-urban SES consisted of cells as resource units (RU) identified as an entity in the model. I used second tier variables of the SES Framework to describe the cells. Resource unit mobility (RU1) was zero. To distinguish the cells (RU6) I classified the cells into eight LULC classes. I used the level-i and level-ii LULC classification system by the Government of India to identify LULC classes (NRSC 2012) (see Figure 2-6).

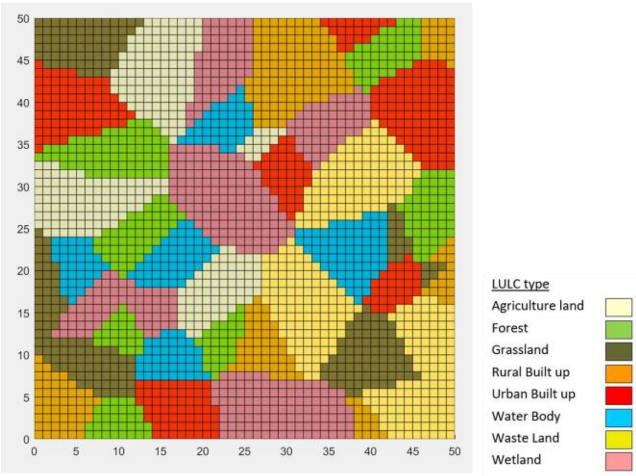

Figure 2-6: An example of input simulated image with LULC classification. I defined eight LULC classes – forest, wet land, water body, grassland, rural built-up, agricultural land, wasteland, and urban built-up.

In 2014, McGinnis and Ostrom (2014) suggested an alternative list of second-tier variables for governance system. The alternative list provides a more clear and logical understanding of the governance system in a large SES. I used this list to characterize the governance system in the model. The land-use policy corresponds to the governance system in the SES Framework. The land-use policy regulates (GS1) the type of land use in a region through a zoning system and guidance of management in a landscape (Barredo et al. 2003). The Government of India's Department of Land Resources, proposed a national level Land Utilization policy in 2013 , categorising the country into land-use zones based on criteria such as predominant land use, ecological and historical importance (India 2013). Because India is characterised by a federal system of Government, the national level Land Utilization Policy is an overarching set of guidelines or recommendations to the state or regional governments (government agencies - GS5) that must then formulate regionally and locally specific land-use policy.

The Land Utilization Policy identifies four major land-use zones based on the land-use policy proposed. I used the same four zones in the model. Each zone had a level of restriction on land use change based on criteria described in Table 2.1. The land-use policy and corresponding land-use zones provided clarification on land use type allowed for the different land units in a landscape (GS6).

Table 2.1: The four land-use zones and their description as per the national level Land Utilization Policy, Government of India. The land-use zones are arranged in decreasing order of level of restrictions to land use change. For example, Protected Area is the zone with highest restriction to land use change and the Guided Area is the zone with lowest restriction to 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 neighbouring areas.
Guided Areas	Areas having highest probability for land-use change.

In the model, land-use zone was set as an attribute of the cells in the landscape. The 'Land-Use Policy' submodule was used to assign and update land-use zone to each cell (Table 2.3). The land-use zones described in the table are in order from highest restrictions (Protected Area) to lowest level restrictions (Guided Area) for land use change. The land-use zones were updated after every 5 years (or 5 iterations) based on the current land use pattern. For example, as urbanization progressed, the distance of non-urban cells from urban cells decreased and the model reclassified the land-use zone of the non-urban cells that were in proximity of urban cells into reserved areas, thereby relaxing the restrictions for land use transformations. I also calculated the number of green spaces left in the region after every five years and used another criterion to decide if land-use zones should be more restricted (such as preserved area or regulated area) or restrictions could be lifted. 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 geographic scale of governance system, which is a tier-2 variable of the SES Framework (GS2). In the model, specifically for chapter 3, I varied the geographic scale of governance system and used two spatial scales of decision making, one at a regional level and one at a local level.

In a peri-urban SES, diverse actors exist who depend on peri-urban resources for their livelihoods and/or ecosystem services and goods (Bian et al. 2018). I classified actors into rural and urban actors based on second tier variables (McGinnis and Ostrom 2014) of the SES Framework. The variables are socioeconomic attributes (A2), geographic location (A4) and importance of resource (A8). Socio-economic attributes and geographic location correspond to indicators commonly used in India for identifying rural and urban actors (Vidyarthi et al. 2017). Broadly speaking, rural actors reside in peri-urban/rural areas before urbanization, have low population density, and have an agrarian-based economy (Purushothaman and Patil 2017). Urban actors, by contrast, live in densely populated urban areas and depend on peri-urban areas for various ecosystem goods and services such as extracting minerals, drinking water, and dumping waste. As the urban areas expand beyond their 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). In addition, the importance of the resource and relationships with the resource varies 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 action on the social and ecological outcomes in the SES (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; have limited understanding of the complex interactions involved in a peri-urban SES and the impact of their actions on the outcomes in the SES (Bian et al. 2018).

Decision Making

My aim was to unfold the action situation and understand how the interactions among the components of the SES Framework shape emerging landscape patterns. In an urbanizing landscape, the decisions by the actors are made at the local spatial level such as land units which are heavily regulated by governments and markets (Foster and Iaione 2019). In the model, urban actors make decisions at cell level within an eight neighbourhood window. The urban actors took bounded rational decisions to select a cell to move into within their immediate neighbourhood. For simplicity, I assumed that the actors within each cell had already made a unanimous decision to move out of the cell. Land use transformations decisions made by urban actors at the local level or cell level were a collective or group decision. The actors then interact with other actors occupying the target cells. In reality, the land parcels that urban actors want to appropriate are usually already in use by other actors for supporting their livelihoods or for ecosystem goods and services. Actors already occupying/using the cells in the neighbourhood window may resist or comply with land use transformation desired by urban actors coming from urban cells (Koch et al. 2019). I included the interactions among actors occupying the different cells using the Hawk and Dove model from game theory. The module captures the outcomes of different combinations of interactions (resistance and compliance) among actor groups. In addition, the LULC of the neighbouring cells affects decisions made by the actors at the local level (Verburg et al. 2006). For example, for urban residential built up , urban actors may prefer cells which are in the neighbourhood of other similar cells or may want to stay away from the cells which are set up as wastelands being used for industrial waste or dumping. The decisions made by actors based on neighbourhood LULC conditions were explicitly modelled using the sub-model 'Spatial neighbourhood Information'. The decisions made by the actors at local level influenced landscape level patterns.

Adaptation

To understand the potential influence of landscape conditions on institutions, I incorporated a routine that made land-use zones adaptive to changes in the landscape. The model updated land-use zones for the cells after every five years based on the landscape conditions at the time of update, such as the number of green spaces left and the distance from the urban patches.

Emergence

In the model, the transformation of non-urban cells into urban cells by the urban actors resulted in an increase in the number of urban cells and decrease in non-urban cells, which led to the emergence of new landscape patterns. However, the land-use policies, responses of rural actors and landscape conditions prevented urban actors from converting the entire landscape into urban built-up. Therefore, after a point in time, the total number of urban cells did not change significantly.

Objectives

In the model, the urban actors made an implicit decision to move out of cells they occupied once the cell was about to reach its carrying capacity. The urban actors could move into one cell from its immediate neighbourhood window. The actors selected a target cell where land-use policies allowed the land-use transformation. Urban actors selected cells with highest cell score. In the model, the cell score was the combined score of the cell's land-use zone score estimated from land-use policies, spatial neighbourhood, and the result of interactions between urban actors wanted to occupy a cell and actors already occupying the cell.

Sensing

The aim was to explore the influence of interactions across scale on the outcomes. Therefore, the interactions in the model occur at cell-level where urban actors consider the state of the cell they are occupying and that of the cells in its immediate neighbourhood window. The urban actors first confirmed if the total population of the cell they were occupying reached a threshold, identified as the carrying capacity of the cell. To select a suitable cell to move into, the urban actors used information about the attributes of the neighbouring cells such as their land-use zone, the response of the actors occupying or dominating the cells, and the spatial neighbourhood of the cells.

Interactions

The model captured the lateral interactions among the actors in different locations with conflicting resource use interests. During the process of urbanization, urban actors moved out of the urban cells into peri-urban areas and appropriate non-urban cells. The urban actors then had to interact with rural actors dominating the non-urban cells, such as built-up rural and agricultural land. The rural actors could 'choose' whether or not to allow the transformation of non-urban cells for urban land use. The interactions were captured using the Game Theory sub-module. There was no specific or explicit communication involved during interactions.

Stochasticity

I included stochasticity in multiple areas. First, I randomly assigned LULC classes to different patches. Second, the Z score associated with Land-use Zones were assigned randomly from within a given range (Table 2.3). Third, in the Game Theory module, rural actors could adapt either a Hawk or Dove strategy. The models assigned Hawk and Dove strategy to the rural cells randomly across the landscape (Chapter 4). Finally, both the rural Hawk and the urban Hawk had an equal probability of winning the fight (Chapter 4).

Collectives

The urban actors and rural actors functioned as collectives with in each cell. The dominant group of actors (rural or urban) was the collective that took the decision to move out of a cell after reaching its carrying capacity and the decision to adapt a strategy to fight (Hawk strategy) or comply (Dove strategy) in the Game Theory sub module.

Observation

The model output was the LULC pattern at the end of the iteration generated as LULC map at each time step. The resultant maps then provided the change in the number of urban cells, the change in landscape patterns (configuration and composition metrics), and the change observed in non-urban classes after urbanization.

Details

Platform used

I used Matlab R2016a to develop the model. In addition, I used R language, R-studio and several R based packages to develop the input data set and to estimate, analyse, and visualise the results.

I used the High Performance Computing system (HPC) at James Cook University to run the models. To run the simulations on spatially explicit data sets such as those used in the model needs resources with higher processing speed and large storage size than over a laptop/desktop. HPC provides a network of computers and related resources (such as storage) clustered together.

The model is available on GitHub for open access:
https://github.com/SiveeChawla/RD_4_Institutions.git

Input data and initialization

The input was a vector file of the image where each cell had the associated attributes and parameters given in Table 2.2

Table 2.2: List of attributes and parameters, their definition and corresponding values used in the model.

	Name and id	Description	Range /Values
1.	Land-use Land Cover class (LULC)	LULC class to each cell from the set of eight classes (Figure 2-6).	Forest, wetland, waterbody, grassland, rural built-up, agriculture land, wasteland and urban built-up.
2.	Land-Use Zone (LUZ)	LUZ was assigned based on the land-use policies. LUZ and LUZ-S was assigned based on a set of criteria described in the sub-module – Land-Use Policy update.	See Table 2.3
3.	Land-Use Zone Score (Z)	The Z was based on LUZ	See Table 2.3
4.	Total Population (ToP)	Cells classified as urban, rural built-up, agriculture and cells in the vicinity were assigned a population of actors. Total population was a sum total of urban and rural population described below. I initialized cells with ToP lower than the carrying capacity of the cell to allow the model to run for sufficient time before reaching saturation.	0 - 18
5.	Urban Population (Up)	Total number of urban actors occupying a cell. In the beginning of the model, the urban actors only occupied the cells classified as urban.	0-18
6.	Rural Population (Rp)	Total number of rural actors occupying a cell. Rural actors occupied the cells that belong to rural built-up class, agriculture class, and cells near rural built-up and agriculture class. Population of rural actors dominated these cells and urban actors occupying the rural dominated cells were limited from 0 to 2. No rural population occupied the cells in the urban centres. However, the urban cells on the outer edge of urban patches had a mix of rural and urban population with urban population still dominating the total population size.	0 - 18
7.	Strategy	The actors collectively within a cell adopted the strategy of either Hawk (resist) or Dove (comply).	H – Hawk D - Dove
8.	Carrying Capacity (k)	Carrying capacity is the total population a cell can support. In the model, the actors used the carrying capacity as the threshold to determine when to move out of a cell at a given iteration. The carrying capacity was the same for all cells in the landscape and across all model runs.	18

9.	Weight Factor (λ)	Weight factor determined the preference given to spatial neighbourhood information of the target cell in the decision-making by the urban actors.	0 to 1
10.	Window Size (Sz)	The window size for regional and local scale update of land-use zones. In the model, it was a square window defined by the number of cells in each window. This parameter is specific to Chapter 53.	10x10 cells
11.	Green cell threshold (G)	A threshold green to grey cell ratio was set to maintain a certain number of green cells in the landscape. The green cells were calculated as the sum of cells belonging to three classes which include forest, grassland, and wetland. The grey cells were the sum total of cells belonging to the Urban built-up, wasteland and rural built-up class. G was an input parameter for LUZ update.	0.3, LUZ were more strict if the G<0.3. For example, if a cell was assigned land-use zone as registered area it was not classified into a less restricted zone (reserved area) if G < 0.3 during the update.
12.	Neighbourhood window	The number of cells in the immediate neighbourhood of urban cells.	3x3 cells , Moore's Neighbourhood window
13.	a, b, α	Parameters for rural population growth model in equation 2.1 below. The parameters were kept fixed.	a = 0.02, b=0.01, α = 0.2044
14.	c, d, β	Parameters for urban population growth model in equation 2.2 below. The parameters were kept fixed.	c = 0.09, d = 0.05, β =0.8144

Sub models

This section describes the sub-modules (identified as sub models in the ODD + D protocol) for reaction and diffusion. Sub-modules Land-Use Policy, Game Theory and Neighbourhood interaction are part of the diffusion module. I programmed each of the modules and sub-modules such that each module was independent of each other to ensure scalability. For example, the population growth model used at present can be replaced by any other population growth model if needed.

Reaction module

The model calls the reaction module to calculate population growth within a cell. I used different growth models for urban and rural populations, adapted from Chen (2009), who used the UN population growth model. The UN 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 2.1 : equation for rural population growth*

$$\frac{du(t)}{dt} = cu(t) + dr(t) + \beta\frac{r(t)u(t)}{r(t)+u(t)}$$ ----- *Equation 2.2: equation for urban population growth*

In equation 1 and 2, a, b, c, d,α and β are the parameters and r and u are the rural and urban population in a cell (Table 2.2). I adjusted the parameters to ensure higher urban population growth compared to rural population growth. It was a preliminary module used to estimate the point in time when the urban actors from an urban cell will decide to move out into other cells. The total population in a cell increased (due to either reproduction or migration) and reached a threshold, understood as the carrying capacity (Table 2.2) of the cell in the model. Once the population reaches the carrying capacity, a proportion of urban actors decide to move into neighbouring cells in the landscape.

Diffusion module

In the model, the diffusion module corresponds to the diffusion term of the reaction-diffusion equations that captures the movement of population outside the cell.

In the model, the urban actors selected the cell to move into based on three criteria. The criteria were: the land-use zone of the target cell (Z), the interaction with the actor group already occupying the target cell (GT) and the spatial neighbourhood of the target cell (SI). I developed three sub-modules to calculate each term separately (see section 2.2.4). The output from the three sub-modules was then used to calculate the cell score (equation 2.3). The cell score was a combined score of the values estimated from three criteria and was used in the model by the urban actors to select a target cell. The urban actors selected the cell with the highest score.

Cell Score = $Z[\lambda(SI) + (1 - \lambda)(GT)]$ ----- *Equation 2.3*

Where, Z is the land-use zone score associated with each cell and estimated from the Land-use policy Module. GT is the score estimated from the interactions between the actor groups estimated using the Game Theory sub module, λ is the weight parameter and SI is the neighbourhood information calculated from the spatial neighbourhood Information sub-module

Submodules

1) Land-use policy (LUP)

In the model, I identified four land-use zones (LUZs) adapted from the national Land Utilization Policy proposed by the Government of India in 2013 (Table 2.3). A higher score implied a higher probability of change. For example, there were no restrictions to change in the land use of a cell if the cell falls under the land-use zone identified as a Guided Area (GA). The GA land-use zone had the highest score (0.9). On the other hand, policies did not allow land use change of the cells categorized as a Protected Area (PA) land-use zone, hence, the score assigned was zero. Table 2.3 describes all land-use zones, corresponding policies and restriction, and Z. The model assigned scores from within a range of probability values given in the table.

Table 2.3: LUZs and their details, identified based on the National Land Utilization Policy set by the government of India. Based on the description, each land-use zone was associated with a probability of LULC change. The model assigns the score from the score from the range of values in the column Z.

Land-use zone	**Land-use policy**	**Description**	**LUZ score for the model**
Protected Areas (PA)	Strict no change zone	Areas strictly prohibited for land-use change. For example, Ecologically, socially or historically sensitive areas	0
Regulated Areas (RgA)	Restricted land use change	Not legally restricted for land use change yet have important functions associated with it. For example, tourism, hazard prone zone, and prime agricultural land. Often may need permit based on the legal conditions for land use change. Hence, has less probability of land-use change.	0.1 to 0.4 (low probability of change)
Reserved Areas (RsA)	Land-use change permitted with conditions	Areas under pressure of development, usually due to significant land-use change in the neighboring areas. For example, areas near human habitat, newly planned development/economic centre, proximity to road.	0.5 to 0.8 (higher probability of change)
Guided Areas (GA)	Land-use change permitted with no conditions	These were the areas mostly in the urban periphery and have highest probability of land-use change.	0.9 (highest probability of change)

In the model, the land-use zone (and Z) of each cell was updated after a fixed period of every five iterations (or five years). I used a cellular automaton based approach that followed a set of rules to update the land-use zone of each cell based on the spatial conditions in the landscape. The rules themselves did not change over time. They were:

i) Distance of the cell from the urban patches: The module assigned LUZ RsA or GA to a cell that was close to urban patches.
ii) LULC class of the cell: For example, the module assigns LUZ RgA or PA to a cell located near urban patches and belonging to either water body class or forest class.
iii) Green to grey cell ratio in the landscape: The cells with forest, grassland or wetland classes were categorised as green cells. 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 changes by assigning

the stricter land-use zones to the cells. For example, the cells mostly fall under RgA category over RsA category.

I used rules 1 and 2 for initialisation and rule 3 together with rule 1 and 2 for updating the land-use zones for the rest of the model runs. For Research Questions 2 and 3 (Chapters 4 and 5, respectively) the updates were based on the properties of the entire landscape (called regional level update in the model). In Chapter 3, a comparison was made between regional and local level updates of land-use policies to address Research Question 1.

2) Game Theory (GT)

The GT module captured the interaction between urban and rural actors at cell level, using the Hawk and Dove model derived from game theory (Weibull 1995). In the Hawk and Dove model, a player has two strategies to choose from. The strategies are (1) to compete (Hawk) or (2) to co-operate (Dove) (Kohli and Haslam 2017). In the model, as urbanization progressed, the urban actors appropriated cells in the landscape for urban land use. In the process, the urban actors from one cell interacted with rural actors occupying or dominating the target cell, as a group, to appropriate a non-urban cell. Both the group of actors, urban actors who want to move into a cell and groups of rural actors who dominate the target which urban actors want to appropriate, could choose to either compete for the cell or co-operate. The strategy was selected by the actors at cell level. Urban Hawks were the urban actors who compete against rural actors for a cell and urban Doves were those urban actors who did not wish to appropriate the non-urban cells and therefore, did not compete against the rural actors. Rural Hawks were the rural actors who already dominated a cell that urban actors wanted to appropriate and resisted urban Hawks from appropriating and transforming the cell for urban land use. Rural Doves were the rural actors dominating a cell however ready to comply with urban Hawks and allow land use transformation. During the model run, at one iteration, only one strategy dominated a cell. In the model, the focus was on the interaction between the group of rural and urban actors representing a cell, therefore, urban actors never competed with other urban actors in the model.

3) Spatial neighbourhood Information (SI)

In addition to actors' interactions between cells, availability of infrastructure, and land-use policy, spatial interactions in a landscape play an important role in defining LULC patterns. Land use change decisions made by urban actors depend heavily on already existing nearby land use (Verburg et al. 2004, van Schrojenstein Lantman et al. 2011). To include neighbourhood preferences of urban actors in their decision making for appropriation of calls and land use transformation, I estimated the number of similar land use cells in the neighbourhood of a target cell, as an 'enrichment factor' of the cell (Verburg et al. 2004). I calculate the enrichment factor by measuring the relative occurrence of each land-use type in the neighbouring cells, on a scale from 0 to 1. The factor is the ratio of similar land use cells in the neighbourhood of a cell estimated for all the classes in the landscape (equation 2.4). In the model, for simplicity, I limited the preference of urban actors to urban neighbourhoods which means urban actors preferred to move into a cell which had more numbers of urban cells in its spatial vicinity. To quantify the preference of urban actors, I estimated the enrichment factor of the urban land use as SI which was included in the cell score (Cell Score = $Z\,\lambda(SI) + (1-\lambda)(GT)$ ----- Equation 2.3). The enrichment factor by Verburg et al. (2004) is given in the following equation.

$$SI_{i,k,d} = \frac{n_{k,d,i}/n_{d,i}}{N_k/N} \qquad \text{----- } \textit{Equation 2.4}$$

Where, i is the target cell, k is the land use type and d is the distance from the neighbourhood of the target cell. N is the total number of cells in the landscape.

2.3 Verification

Verification is an important step that is done to test and ensure a computational model is free from bugs and matches the underlying conceptual model. Verification of a model is done when the model is implemented from its conceptual form into computational (programming) model (Graebner 2018). Graebner (2018) emphasis that verification of the model is to assess the 'internal consistency' of the model. I performed a series of tests to verify the model. Most of the checks for bugs were performed as the model was being programmed. I used three different sets of data to verify the model. First was a subset of an image (e.g. 10x10 cells) with a limited number of LULC classes (ranging from 2 to 4), second was a single image and third, was the entire dataset of the images but for a limited number of iterations. I verified the results by printing the results of key intermediate steps and variables using *print* statements during the model run. In addition, the intermediate results were saved as shapefiles (vector images) with respective attributes of each cell. This was to check if the model proceeded as expected. For example, in the model, the urban cells should increase and the count of cells with other LULC classes should decrease. Record with a count of all cells with different LULC classes was saved after every iteration into Excel sheets. Further, it was important to make sure that only immediate neighbours were selected, particularly at the landscape boundary.

I also embedded a set of checks at various points in the model to ensure that model is running correctly and smoothly throughout the actual model runs. A check was maintained at the start of the model to ensure that there weren't any unknown classes in the image. In the Land-use policy update Module, the criteria used to initialize LUZ (at first iteration) and corresponding score (Z) was slightly different from criteria used to update respective LUZ and corresponding Z (later iterations) (discussed in Section 2.2.4). Therefore, a check was maintained during the model runs to confirm if it was the first iteration of the model run or was the periodic update. In the Spatial Neighbourhood information (SI) Module for estimating enrichment factors in the neighbourhood window, it was ensured that all LULC classes were included in estimating the neighbourhood values. For all the cells, at different steps, it was checked if the cell belonged to the image boundary or was in the middle of the landscape to ensure only available neighbours were included in the neighbourhood window.

2.4 Sensitivity Analysis

Sensitivity analysis of computational models is performed to determine the influence of parameters on the output. Not all parameters exert the same influence on the output, some parameters may be insignificant and therefore, can be eliminated from the model to reduce the model complexity. In addition, parameters also influence the output uncertainty. Sensitivity analysis is also performed to identify the parameters that may need more knowledge in order to reduce the output uncertainty (Hamby 1994, Pianosi et al. 2016).

I first selected the level of neighbourhood information or weight factor (λ) and heterogeneity of input landscapes as the parameters that (Table 2.2) have a strong influence on the outputs based on experience and knowledge of the model (Hamby 1994). For addressing the research questions I have used two levels of landscape heterogeneity (high and low). The landscape heterogeneity in the model corresponds to the spatial arrangement of different patches in the landscape (Chapter 3 and Chapter 5). There are various approaches for sensitivity analysis broadly classified into local and global approaches(Pianosi et al. 2016). I have used the one-at-a-time (OAT) approach to perform sensitivity analysis on the two parameters. OAT is a localized approach where one parameter is changed at a time and the rest are kept constant for model runs to estimate the influence of the parameter on the output (Hamby 1994). In the model, I first changed the value of the level of neighbourhood information and kept the landscape heterogeneity constant and estimated the resulting variability in the number of urban cells as the output. I then performed the sensitivity analysis for different levels of heterogeneity, where I changed the landscape heterogeneity from low, medium, and high while the level of neighbourhood information was constant. The results showed variability in the neighbourhood information which implies there was stochasticity in the model due to the two parameters. See box plots in the appendix A. In addition, because the model was theoretical in scope therefore, calibration and verification was not performed.

2.5 Conclusion

I have described the dynamic simulation model developed to address three research questions in subsequent chapter. The components of peri-urban SES used in the model are mapped to the tier-1 and 2 of the SES Framework. The equation (2.3) to estimate cell score described here are used in Chapter 3, 4 and 5. In the method section of each chapter I have described how I have used the model to answer the related research question.

The next three chapters use the model to explore spatially explicit feedbacks and their relevance for Ostrom's design principles.

Chapter 3 : Spatially explicit social-ecological feedbacks shape governance of dynamic landscapes

3.1 Abstract

Rapid urbanization is critical landscape transition that threatens biodiversity, ecosystem goods and services, and social sustainability. Interactions between social-ecological processes and landscape governance drive such landscape transitions and are critical to controlling urbanization. Ostrom's design principles assert that effective landscape governance requires congruence between governance rules and local social-ecological conditions. However, little is known about how to achieve congruence in large-scale, complex, dynamic SESs such as peri-urban systems, partly because the local conditions are constantly changing. Using dynamic simulation models, I tested how spatially explicit feedbacks between ecological patterns and landscape governance influence landscape dynamics. I captured the feedbacks by varying the spatial extent of decision making from regional to local scale across landscapes for two different levels of LULC heterogeneity. I found that the rate of urbanization was higher for high heterogeneity landscapes than low heterogeneity landscapes. Further, the urbanization trend differed significantly at the regional-scale as compared to the local-scale for highly heterogeneous landscapes. For low heterogeneity landscapes, the trend was similar for both regional and local scales. I extended and operationalised Ostrom's design principle for large-scale SES by explicitly defining the term 'local' as relative rather than fixed, that is, as a spatial extent of decision-making based on landscape heterogeneity. The analysis extends our understanding of fit between landscape governance and spatial processes.

3.2 Introduction

Across the globe, natural resources are under tremendous pressure from increasing human population and the demands for economic growth. This has led to the decline and loss of important ecological landscape elements. Degradation of natural resources and loss of ecosystem and services and goods is particularly prominent in urbanizing landscapes. For example, in some cities of the Global South, rising demand for urban land has led authorities to reclaim wetlands and water bodies for urbanization (Nagendra et al. 2013, Hettiarachchi et al. 2014). The loss of these ecosystems has not only influenced the ecological functioning of the area but has affected humans, for example through changes in water quantity, quality, and variability (e.g., floods, water scarcity). Where human pressure on resources is high, effective landscape governance is critical to achieving the balance between economic growth and ecosystem integrity that is essential for social and environmental sustainability (Morrison 2006).

Landscape governance has both formal (e.g. land administration, land-use rights and land-use planning) and informal (e.g. norms, structures, and processes) elements(Kusters et al. 2020). It structures actors' decisions (Fazal et al. 2015) and influences the spatial and ecological dynamics of land use (Pickard et al. 2016). In urbanizing landscapes, often the governance structure follows a linear, top-down approach which means rules and policies related to environmental management are largely defined, developed and implemented by central authorities at higher (national or regional) levels (Zhang et al. 2019). For example, top-down zoning systems are often used to create rules for identifying and regulating land use and conservation of green spaces in urbanizing areas (Evans et al. 2008). However, predominantly top-down approaches are not always sufficient in managing urbanizing landscapes, and may lead to undesirable results such as low community buy-in, leapfrog development and urban sprawl which is common in the urban peripheries of the countries witnessing rapid urban development such as China and India (Evans et al. 2008, Salet and de Vries 2018, Zhang et al. 2019). This often occurs due the mismatch between the scale of governance and the scale of environmental, ecological, and biophysical processes (Christophe and Tina 2015, Salet and de Vries 2018). For example, there is often a spatial mismatch between administrative boundaries and underlying ecological processes when managing landscapes (Robinson et al. 2017). This is due to limited understanding of the interactions and feedbacks between the governance units and social and ecological components of the urbanizing landscapes occurring across multiple scales and levels (Borgström et al. 2006, Cash et al. 2006, Gomes and Hermans 2016). Researchers are therefore increasingly advocating for more inclusive governance approaches that acknowledge the complexities of urbanizing landscapes as integrated social-ecological systems (Vij and Narain 2016, Menatti 2017, Cerquetti et al. 2019).

Commons approaches acknowledge the complex interface between ecological and social systems (Görg 2007, Cerquetti et al. 2019). Ostrom's design principles (summarised in Table 1.1), for example, propose generalized governance rules for Social-Ecological Systems (Ostrom 1990), based on the characteristics of both social and ecological components of the underlying SES and their interactions (Cox et al. 2010). Design principle 2, in particular, emphasises congruence between rules and local conditions for effective management of resources (Ostrom 1990). Initially, scientific understanding of 'local resource conditions' revolved around the availability of resources (e.g. artisanal fisheries and irrigation water) at relatively fine scale as well as the cost of extracting the resources (Agrawal 2002). However, over the last decade, researchers have sought to apply the design principles beyond the traditional small-scale, community based-focus to large SESs that have multiple complex social-ecological elements, such as extensive resources, trans-boundary governance, or a large number and diversity of actors (Huntjens et al. 2012, Epstein et al. 2014, Fleischman et al. 2014a, Villamayor-Tomas et al. 2014, Lacroix and Richards 2015). Studies based on large SESs and resource systems such as air pollution and open ocean fisheries have emphasised the importance of design principle 2 for the management of complex SESs (Epstein et al. 2014, Fleischman et al. 2014a). With further research and expansion of Ostrom's design principles to large and complex SESs, the list of resource characteristics considered relevant to governance has expanded to include spatial and temporal heterogeneity (Cox et al. 2010, Cox 2014, Vogt et al. 2015). However, operationalising the design principles to address the issue of mismatch and landscape governance in dynamic terrestrial resource systems remains limited (Robinson et al. 2017, Foster and Iaione 2019, Myers 2020). I address this gap by operationalising design principle 2 for urbanizing landscapes in peri-urban SESs.

Peri-urban SESs are transient in nature. The landscape is continually transforming from natural-rural landscapes to urban landscapes leading to a mix of rural, urban, and natural landscapes and this is often accompanied by a shift in the governance structure, whereby existing institutions including rules, norms, and strategies in the peri-urban SES corrode and new institutions emerge (Mundoli et al. 2017, Singh and Narain 2019). For example, to address the demands of a growing city, formal institutions led by urban authorities often replace the existing commons in a peri-urban SES (Singh and Narain 2019). Both internal adjustments and external components such as land use transformations and actors' preferences influence the evolution of institutions in a peri-urban SES (Gomes and Hermans 2016). Spatial attributes of the terrestrial resource system such as geographical context, topography, ecological diversity, and the total area also influence the governance structure in dynamic landscapes (Leslie et al. 2015, Sharma et al. 2016, Gari et al. 2017, Cho et al. 2019). Therefore, for effective landscape governance, it is important to consider local resource conditions and the spatial characteristics of the terrestrial resource system.

Design principle 2 emphasises congruence between local conditions and appropriation rules with two elements, one of which focuses on the relationship between the level of restriction (rules) and local conditions in an SES (Agrawal 2001). The local conditions include both social and ecological conditions such as resource characteristics. However, in the literature related to operationalizing the design principles, there is less focus on local ecological conditions as compared to local social conditions in an SES (Bluemling et al. 2021). A close reading of the literature suggests that local is assumed to mean the lowest level of land use authority (Marshall 2008, Bell and Morrison 2014). However, the ecological processes and their spatial characteristics are sensitive to the spatial scale. Often, the spatial extent of social, economic, and ecological processes do not always match the spatial extent of land-use policies (Epstein et al. 2015). Frate et al. (2014) have shown that spatial extent of observation influences the information inferred from the landscape, which in turn influences the decision-making. Further, the term 'local' is not clearly defined in the context of spatial extent of the ecological conditions in a terrestrial resource system in the design principle 2 (Agrawal 2002, Marshall 2008). To address this gap, I explore the interactions between local ecological conditions and landscape governance to understand the influence of varying spatial extent on the emerging outcomes in a peri-urban SES.

Ecological conditions can influence landscape governance through various pathways. Spatial heterogeneity including LULC patterns are one of many influences on landscape governance (Leslie et al. 2015, Sharma et al. 2016, Charnley et al. 2017). Spatial heterogeneity of LULC classes is a characteristic feature of a peri-urban SES and is often used in geovisualization approaches as input to both understand dynamics in an urbanizing landscape and inform policy making (Setturu and Ramachandra 2021). The spatial heterogeneity of the LULC classes is associated with the underlying ecological processes and influences flow of ecosystem services and goods (Zhou et al. 2014, Turner and Gardner 2015). For example, fragmentation of forest patches influences the connectivity and habitat in a region (Turner et al. 2012). Spatial heterogeneity across a landscape provides information about the underlying processes that generate landscape patterns (Zhou et al. 2014, Setturu and Ramachandra 2021). The spatial characteristics including spatial heterogeneity are sensitive to the spatial extent and may produce different results as the spatial scale of governance varies (Cattarino et al. 2014). I tested the hypothesis that the impact of spatial heterogeneity on outcomes of a peri-urban SES varies as the spatial extent of decision making varies via emergent feedbacks. The feedback, therefore, can help reveal underlying mechanisms (Zhou et al. 2014) that can inform the term 'local' to operationalise design principle 2 for peri-urban SES. To test this hypothesis, I used a dynamic simulation model to explore the influence of varying spatial extent on the response of feedback between landscape conditions and governance and tested the results with a counterfactual whereby the landscape conditions were not included in the decision making.

3.3 Methods

I used the components of a peri-urban SES as mapped to the SES Framework, discussed in Chapter 2. In the following section, I first give a brief overview of the model followed by a description of how I used the model to test the hypothesis.

The model was designed to capture the interactions among different components of a peri-urban SES which include interactions among urban and rural actors, the land-use policies as a governance system, and the LULC pattern of the landscape. In the model, the focus was on the movement of urban actors into peri-urban areas and resulting land use transformations of the cells into urban built-up. As the population in a cell increased and reached the carrying capacity of the cell, a percentage of urban actors moved out of the cell into one of the cells in their immediate neighbourhood. The urban actors selected the cell with highest cell score out of all the cells in the neighbourhood window (equation 2.3). The cell score was a combination of three variables which include LUZ of the target cell (Z), interaction with actors occupying the target cell (GT), and the spatial neighbourhood of the target cells (SI). Each of the three variables were estimated using the three sub-modules respectively (see section 04 for the details). If the urban actors moved into a cell, which belonged to a LULC class other than urban built-up, the model updated the LULC of the cell into urban built-up.

I explore the feedbacks between the resource system and governance system which I captured using the sub-module 'Land-use policy update'. In the model, urban actors made decisions for land use transformation at a cell level, at which existing land-use policies and corresponding LUZs of the cell influenced the decisions of urban actors among other factors. In a dynamic landscape such as a peri-urban area, the LUZ to which a cell belongs is updated as the landscape evolves. Therefore, the model also updated the LUZ of each cell periodically and assigned new LUZ to each cell based on the existing landscape conditions.

To design update 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, I varied the spatial extent of decision making in the landscape. To test the hypothesis, I varied the spatial extent of decision making from regional to local scale and explored the implications of decision-making at different scales for landscapes with different levels of spatial heterogeneity.

I created a 2x2-study design that contrasted high and low levels of spatial heterogeneity with land-use zone updates based on the landscape conditions at the local scale and the regional-scale, respectively. I used two sets of landscapes with different levels of landscape heterogeneity based on the urbanization patterns of the Indian cities (Vidyarthi et al. 2017). The landscape conditions around peripheries of the cities, e.g. in Pune and Bengaluru, are not similar in all directions. For example, the LULC pattern such as spatial heterogeneity is higher in one direction as compared to another. The spatial heterogeneity varies because of various social and ecological reasons including existing topographic features, previous policies, and existing LULC type. The different landscape conditions influence the pattern of urban expansion beyond the initial boundary of the cities. In Pune, for example, the spatial expansion tends to dominate in the North-West direction (Ramachandra et al. 2014). To keep the model simple, I used only two levels of landscape heterogeneity. I prepared two simulated data sets comprising of 100 landscapes in each set, using the *NLRM* package (Sciaini et al. 2018). The first set had 100 simulated images of landscapes with low spatial heterogeneity (e.g. Figure 3-1 a) while the second had

100 simulated images with much higher spatial heterogeneity (e.g. Figure 3-1 b). I maintained the degree of spatial heterogeneity constant for each set and changed the arrangement of patches for each landscape within the set.

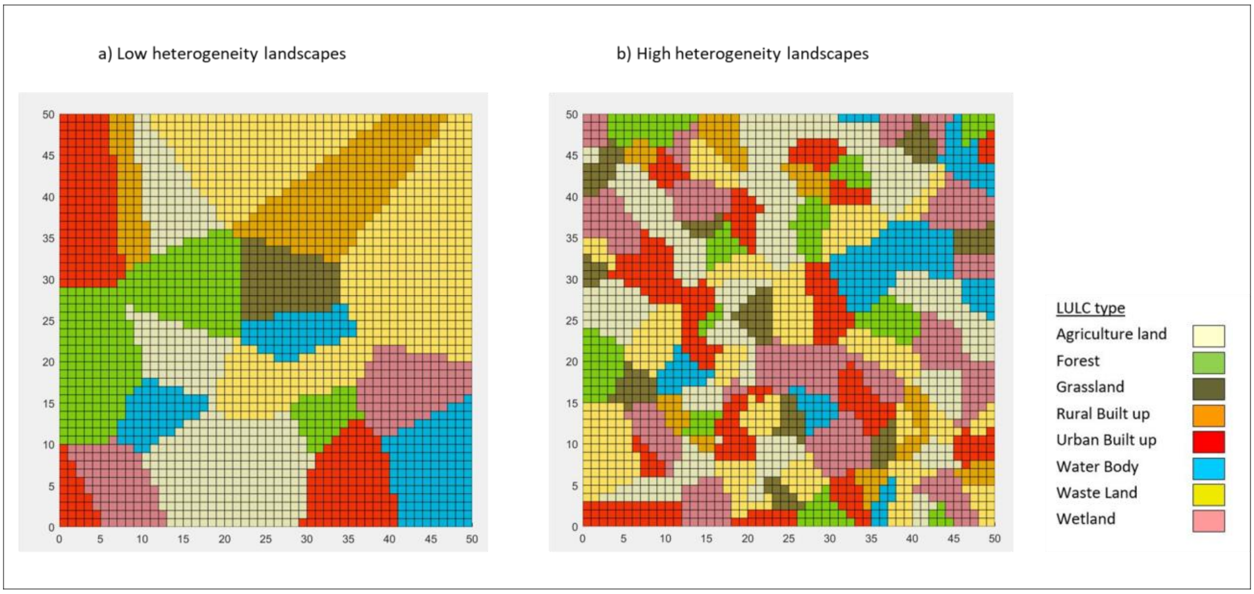

Figure 3-1: an example of simulated landscapes, (a) low heterogeneity landscape and (b) high heterogeneity landscape. Both landscapes consist of eight LULC classes listed in the legend. 100 images of each landscape was used in each dataset, where spatial arrangement of patches varied in each image within one dataset.

For the regional-scale update, the model considered the LULC characteristics of the whole landscape to update and assign LUZ to each cell. For the local-scale update, I divided the landscape into 25 non-overlapping administrative windows of 10×10 cells and identified 'local' extent by the windows (Figure 3-2). To update the LUZ of cells at local-scale, 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 scales.

The GT sub-module and the SI sub-module, the other two sub modules, were also run simultaneously to capture the cell-level interactions among rural and urban actors and spatial neighbourhood information about LULC in the neighbourhood of the target cells, respectively.

Spatial extent of local-scale update

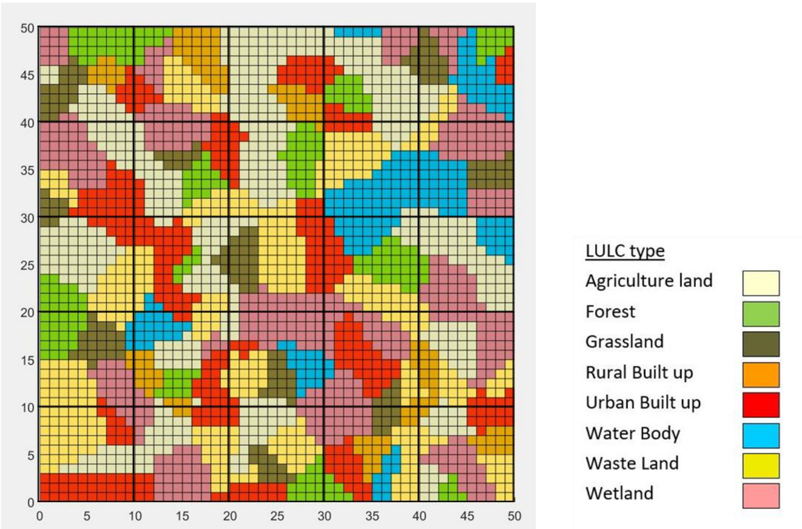

Figure 3-2: Thick black lines forming a grid and dividing the images into 10x10 subsets is an example of the non-overlapping windows demarcating spatial extent for the local- scale updates in a landscape. Each window is represented is of size 10 x 10 cells.

I explored the outcome of the model by quantifying land use transformation to urban built-up over 200 iterations (which is 200 model years). In the model, LULC of a landscape is updated every year (per iteration), while land-use policies are updated every 5 years (every 5 iterations) by re-categorizing each cell into a new LUZ (Table 2.1) to ensure that the governance system is adapted to ongoing changes in the landscape.

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

1. **Total urban area in the landscape:** Number of urban cells in a landscape. This is the measure of area occupied by urban land cover.
2. **Rate of urbanization**: percentage change (gain) in urban area per year. This measure 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. I wanted to test if there is any difference in the preference of change in LULC classes to urban built-up for different cases.

Each of the three indicators including the total urban area, rate of urbanization and pattern of urbanization are related to the spatial sustainability of an urbanizing landscape. Researchers have associated the increase in urban land use with detrimental effects on the environment resulting in the degradation of ecosystem goods and services. For example, an increase in indiscriminate transformation of land for urban land use such as urban sprawl causes an increase in heat island effects, an increase in greenhouse emissions, loss of groundwater and an increase in flood-related events (Izakovičová et al. 2021, Nuissl and Siedentop 2021). The amount of land converted together with the rate at which the land is converted for urban land use (or the rate of urbanization) influences the sustainability of the landscape (Zhang et al. 2020). For example, Zhang et al. (2020) have shown that the rapid land-use change has influenced the soil properties in Lanzhou New Area in China. Rapid land-use change which is common in peri-urban areas, particularly in the Global South, adds to the complexity of peri-urban SES (Rauws and de Roo 2011). In a peri-urban area, often spatial expansion of urban land use occurs at the expense of non-urban land use such as wasteland, forests, and wetlands. The impact of land use transformation for urbanization on the environment and ecological processes also depends on the pattern of urbanization which means the type of LULC class transformed for urban land use. For example, developing a built-up area on a drained out wetland is more detrimental to the environment as compared to using formerly agricultural land which was already degraded or was used as a wasteland (Nuissl and Siedentop 2021). Therefore, the amount of urbanization together with the rate of urbanization and the pattern of urbanization are useful indicators to assess the sustainability of a landscape.

Statistical analysis

I hypothesized that the results observed in the case of the regional and local scale update were influenced by spatial heterogeneity of the landscape because of the interactions between landscape conditions and the policies. To test the hypothesis I used a null model. A null model acts as a counterfactual by excluding the mechanism or process of interest (Gotelli and Graves 1996). At both regional and local level 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, I assumed there is no interaction between the landscape conditions and decision making to assign land-use zones. Therefore, I didn't include the landscape conditions in identifying land-use zones of the cells for both high and low heterogeneity landscapes, as was done in the case of regional level and local level updates. The land-use zones were assigned randomly to the cells. I then compared the amount of urbanization as an outcome in the null model to the cases when the landscape conditions were included in updating land-use zones.

I then performed preliminary analysis on the data set and then divided the experiments into two broad steps to test for the effects of heterogeneity and scale.

For the preliminary analysis, I tested whether the initial landscape composition and configuration had a significant influence on the model outcomes for both scales of decision making and for the null model after a certain time period. I used patch-based landscape metrics (Turner et al. 2010) to describe landscape pattern before and after each model run. I estimated the 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) for all input landscapes using the *Landscapemetrics* package in R (Hesselbarth et al. 2019). Patch Area, number of patches, Edge density and SD patch are some of the commonly used metrics used to quantify spatial composition and configuration of a landscape which may influence the outcomes (Plexida et al. 2014).

I performed multiple regression for the two data sets where landscape metrics were the independent variables. One of the assumptions for multiple regression is no multi-collinearity which means that independent variables are not highly correlated with each other (Field et al. 2012). I used Principal Component Analysis to test and eliminate highly correlated variables (Field et al. 2012). I selected three out of four predictor variables (Patch Area, Edge Density and Standard Deviation of the urban patch size; dropping the fourth because it was redundant) as 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 when the slope of the curve first changed. I defined the saturation point as the time beyond which the urban area did not change significantly for the rest of the model's duration. I estimated the saturation point and the first point of change in the curve using the *findchangepts* function of MATLAB (Figure 3-3).

For the second data set, the response variable was the gradient (or the rate of change of urban cells) at the first change point. I performed multiple regression for all six cases (Table 3.1).

Table 3.1: Experimental design used to test the effects of landscape heterogeneity and the scale of governance on the amount of urbanization. Numbers indicate number of model runs under each pair of conditions.

Landscape heterogeneity / Scale of governance	Low heterogeneity	High heterogeneity
[none: the null model]	200	200
Local	200	200
Regional	200	200

After the preliminary analysis, I performed the experiments in two steps:

Step 1: I first measured the influence of spatial heterogeneity on the three outcomes. I varied the spatial heterogeneity of LULC classes, keeping the spatial extent of land-use policies constant to the regional-scale update. In step 1, I applied the model to the two sets of landscapes. I reported the total urban area and the rate of urbanization.

Step 2: Having clarified expectations relating to path dependence in step 1, I tested the influence of scale of decision-making for both high and low heterogeneity landscapes. I used two scales of decision-making (regional and local) for both landscapes of heterogeneity. I ran the model for 2x2 sets (high and low heterogeneity landscapes for regional and local scale update). I reported total urban area, the rate of urbanization and the pattern of urbanization.

To compare the rate of urbanization between time series, I limited the duration of urbanization to year 120 because for almost all cases, the rate of urbanization tends to be zero beyond year 120. I measured the dissimilarity between the rates of urbanization using the diss.AR.MAH function of the R-based package *TSclust* (Montero and Vilar 2014). The metric tests if the time series are derived from the same auto-regression model, considering the autocorrelation of the time series.

3.4 Results

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

Preliminary Analysis

For both the high and low heterogeneity landscapes, urbanization happened more rapidly for the null (Figure 3-3 and Table 3.2). The null model reached saturation point much earlier than for the regional-scale and the local-scale update, for both the high heterogeneity (at around 25th year) and low heterogeneity landscapes (at around 70th year). In addition, the total urban area was higher for the null model than the regional-scale and the local-scale update, for both the low (68%) and high (84%) heterogeneity landscapes.

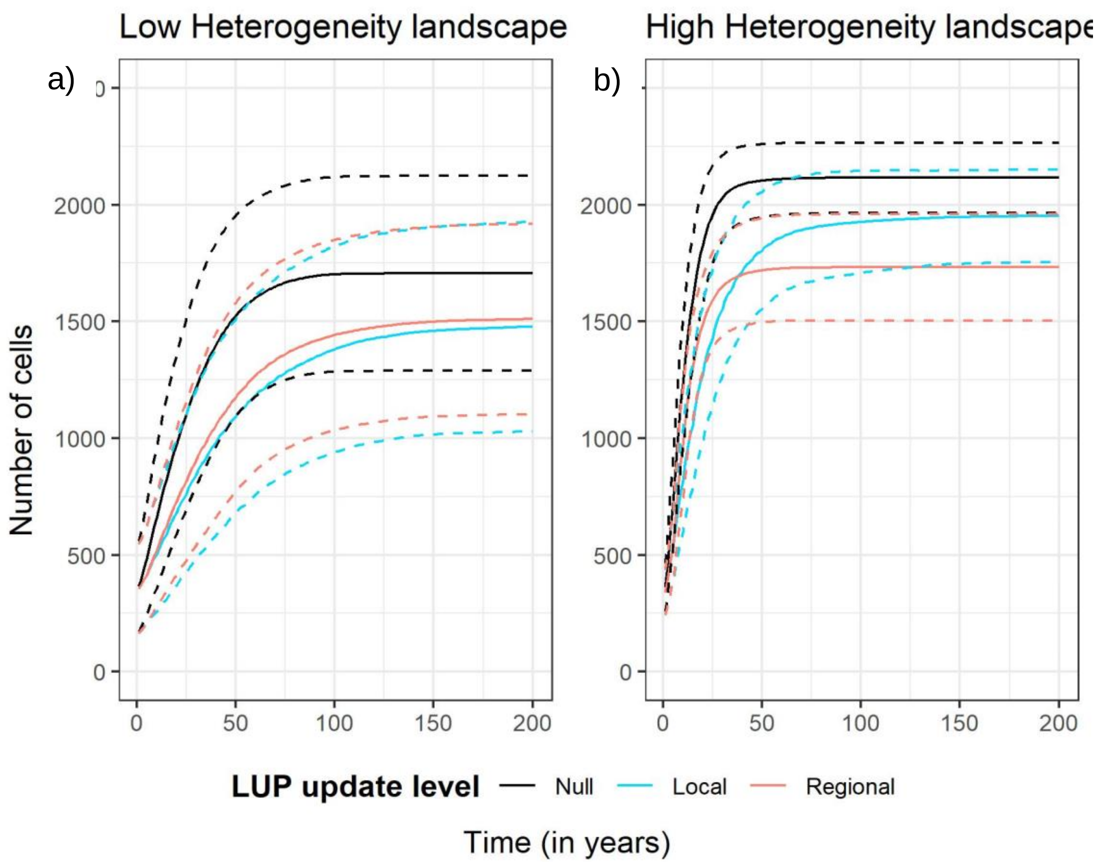

Figure 3-3: Comparison of the results of the null model, the regional scale update, and the local scale update for (a) low and (b) high heterogeneity starting landscapes. The thick lines show the average urban cells in all three cases; the dotted lines show the standard deviation in each case.

Table 3.2: Comparison of the time taken to reach the saturation point and the total area occupied at the saturation for the two sets of landscapes when the model updated the LUZ at regional-scale and local-scale respectively and for the null model.

	Scale of update	Saturation point (at year)	% urban area at the saturation point
Low Heterogeneity landscape	**Null Model**	70	68%
	Local-scale update	100	56%
	Regional-scale update	100	60%
High Heterogeneity landscape	**Null Model**	23 to 25	84%
	Local-scale update	55 to 60	72%
	Region-scale update	33 to 37	68%

Multiple Regression

The result (Table 3.3) of multiple regression for all six cases had P>0.05 (for all 100 images in each case) and R-square value <0.05, which suggested no significant linear relationship of the amount of urbanization and the rate of urbanization with the initial landscape conditions.

Table 3.3 : Result of multiple regression for the six cases. The numbers show the P-value and R-square value. The summary statistics for multiple regression is in Appendix B.

	Scale of update	Response variable: First Change Point	Response variable: Gradient at First change point
Low Heterogeneity	**Null Model**	P-value: 0.3007 R-Square: 0.03955	P-value: 0.565 R-Square: 0.02627
	Local	P-value: 0.3785 R-Square: 0.03955	P-value: 0.4728 R-Square: 0.03233
	Regional	P-value: 0.317 R-Square: 0.04509	P-value: 0.452 R-Square: 0.03382
High Heterogeneity	**Null**	P-value: 0.6994 R-Square: 0.01467	P-value: 0.4478 R-Square: 0.02715
	Local	P-value: 0.508 R-Square: 0.02379	P-value: 0.5601 R-Square: 0.02112
	Regional	P-value: 0.4863 R-Square: 0.02497	P-value: 0.4478 R-Square: 0.02715

From this point onwards, I only show the results of the regional and local level updates for the low and high and high heterogeneity landscapes and didn't include the results of the null model.

Results of step 1

For both low and high heterogeneity landscapes, the average urban area was the same at the beginning (Figure 3-4). As the model proceeded, the amount of urban area occupied 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 (*Table 3.3*). Interestingly, at the saturation point, the total area occupied by urban cells for high heterogeneity landscapes was higher (~68%) than that of the low heterogeneity landscapes (~60%).

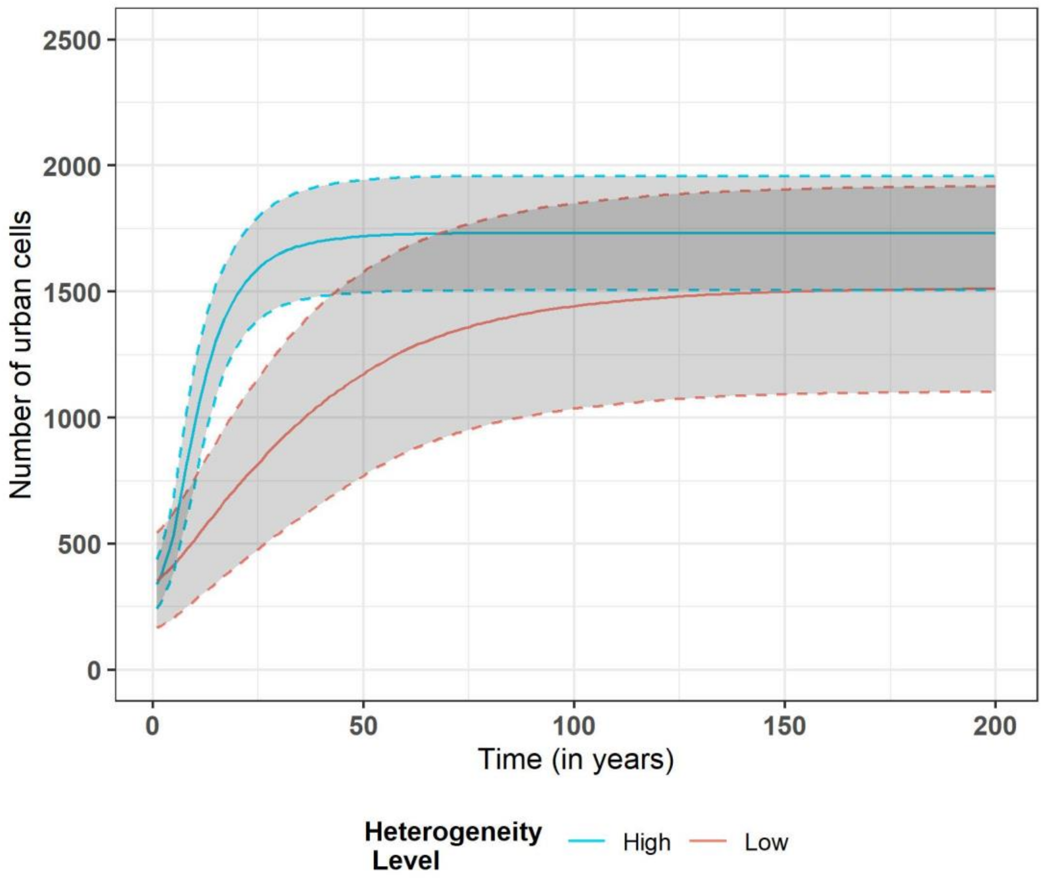

Figure 3-4: Total urban area after every iteration. The solid lines are the average urban cells per iteration for each set. Orange and blue dashed lines show the variation for the low heterogeneity and the high heterogeneity landscapes, respectively.

The rate of urbanization (Figure 3-5) 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. As indicated in Fig. 3.5, this trend occurred for the first 5 years, 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 around 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. The two time series were found to be dissimilar (with p-value ≈ 0.998 for 120 years' time assessed auto-regression model analysis).

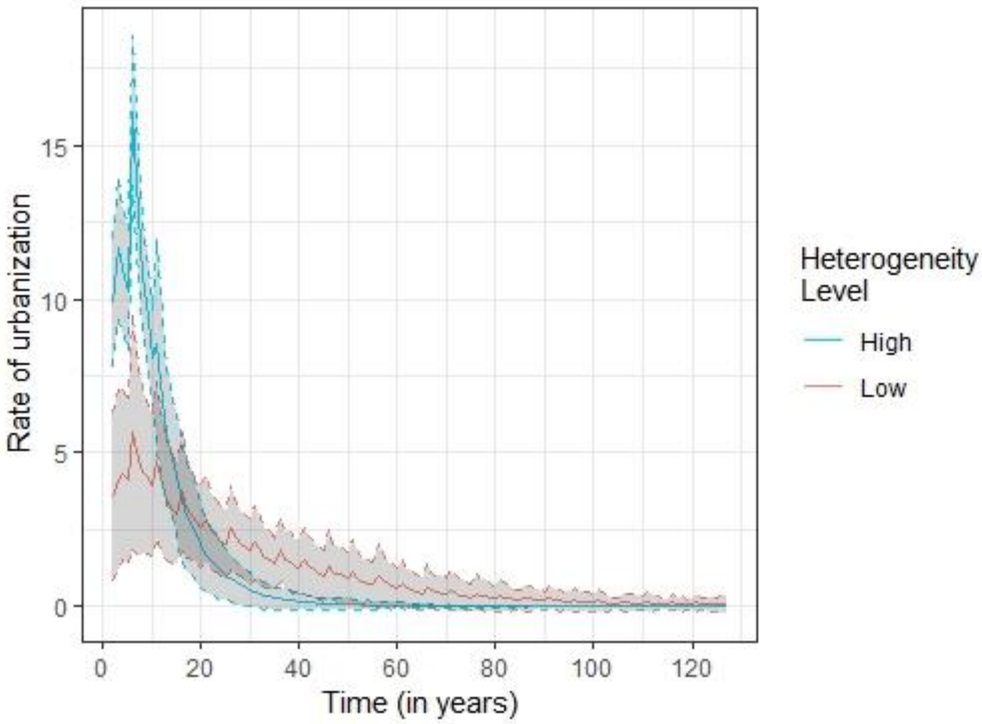

Figure 3-5: Rate of urbanization for the high heterogeneity (in blue) and the low heterogeneity landscapes (in orange). The spikes represent high frequency components which correspond to the time when land-use policies were updated. The rate of urbanization was higher for the high heterogeneity landscapes but decreased drastically after year 10 when compared to low heterogeneity landscapes.

Results of step 2

In step 2, we tested the influence of varying the spatial extent of the land-use zone update for both the 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 of the total urban area was same for all four cases in the beginning of the model runs. We compared the results of the regional-scale and local-scale update for each set of landscapes (Figure 3-6) and across the two sets of landscapes (Table 3.2). The time taken to reach the saturation point was same for the local-scale and the regional-scale 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-scale update than for the regional-scale update. For the low heterogeneity landscapes, total urban area occupied (at saturation point) was slightly higher in the case of the regional-scale update than in the local-scale update when compared to the high heterogeneity landscapes. In the high-heterogeneity landscapes, the total area occupied at the saturation point was much higher for local-scale update than for regional-scale update (Table 3.2).

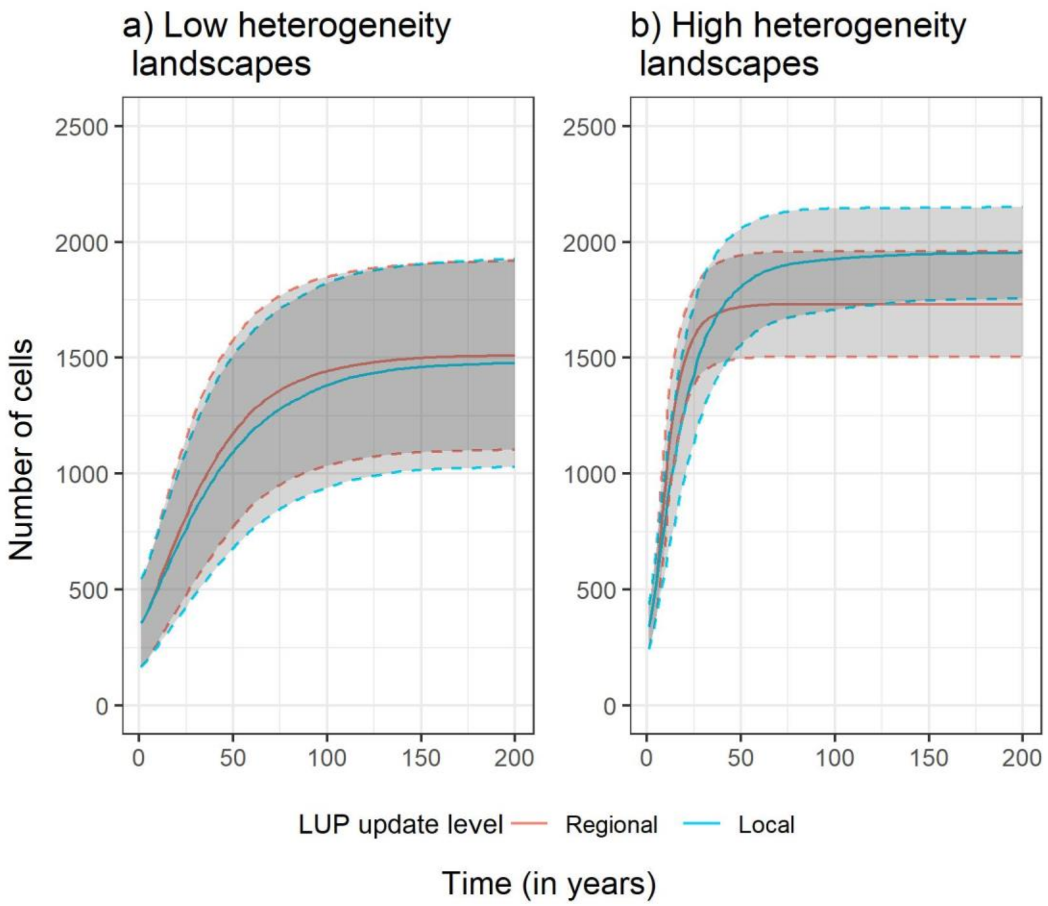

Figure 3-6: Total urban area after every iteration. (a) Corresponds to the results of regional and local scale update for the low heterogeneity landscapes, while (b) corresponds to the result of high heterogeneity landscapes for both regional and local scale update. The solid lines are the average urban cells per iteration for each set. Orange and blue lines show the standard deviation for local and region scale update, respectively.

I further compared the rate of urbanization for all four cases (Figure 3-7). The rate of urbanization was same for the regional-scale and local-scale update within each set. For low heterogeneity landscapes, the average rate of urbanization peaked at ~6.2% for the regional-scale update, which was higher than the peak (average) rate of urbanization for the local-scale update (~5%). For the high heterogeneity landscapes, the average rate of urbanization peaked at ~16% for the regional-scale update, which was higher than the peak rate of urbanization for the local-scale update (~11%). In the high heterogeneity landscapes, a cyclic trend was also prominent in the local-scale update while it was absent in the regional-scale update. The time series were tested for dissimilarity by checking if the time series were generated from same auto-regression models. The statistical dissimilarity (with p-value = 0.999 for 120 years' time) existed between the regional-scale update and local-scale update time series of the high heterogeneity landscapes. Similarly, the regional-scale update and local-scale update time series were statistically different (p-value = 0.999 for 120 years' time) for the low heterogeneity landscape.

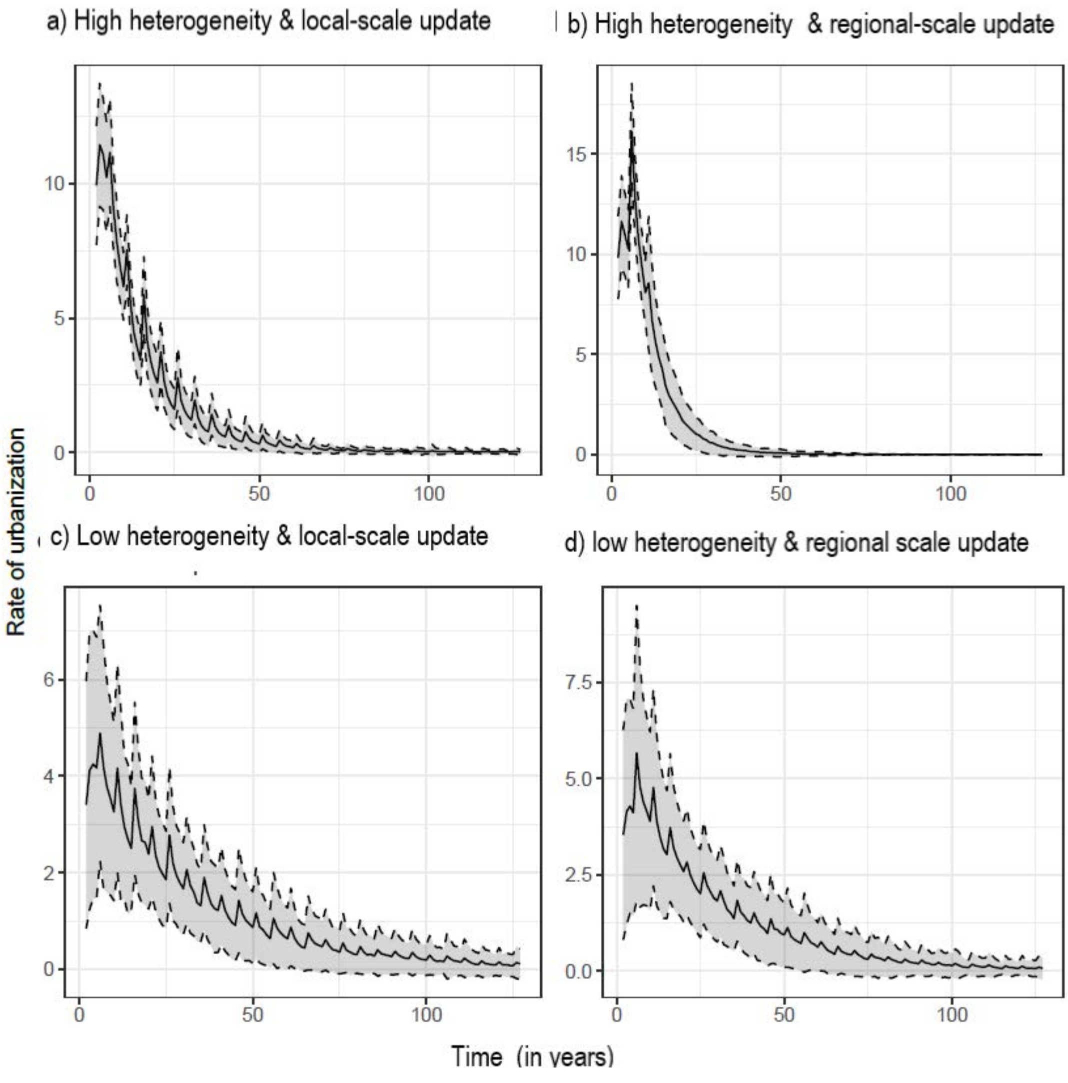

Figure 3-7: Rate of urbanization for (a) local and (b) regional scale update for the high heterogeneity landscapes and for (c) local and (d) regional scale update for low heterogeneity landscapes. The solid lines is the average rate of change for each set.

Pattern of urbanization

As the urban area increased, the area occupied by other classes decreased. While the saturation point was similar for both scales of update in the low heterogeneity landscapes, there was considerable variation in the pattern of urbanization for the two scales of update (Figure 3-8). For instance, the average area of forest cover converted to urban was higher in the case of the region-scale update (25%) than the local-scale update (14%), after 100 years (saturation point).

In the high heterogeneity landscapes, the difference in the saturation point is prominent for the local-scale and the regional-scale update (Figure 3-9). 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' (Figure 3-6) and the rate of urbanization (Figure 3.-5). However, the rural built-up class did not follow the trend. For the local-scale update, the area occupied by each of the classes was higher than the regional-scale update until saturation point (year 40). The area occupied by the rural built-up area, by contrast was lower in the local-scale update than in the regional-scale update.

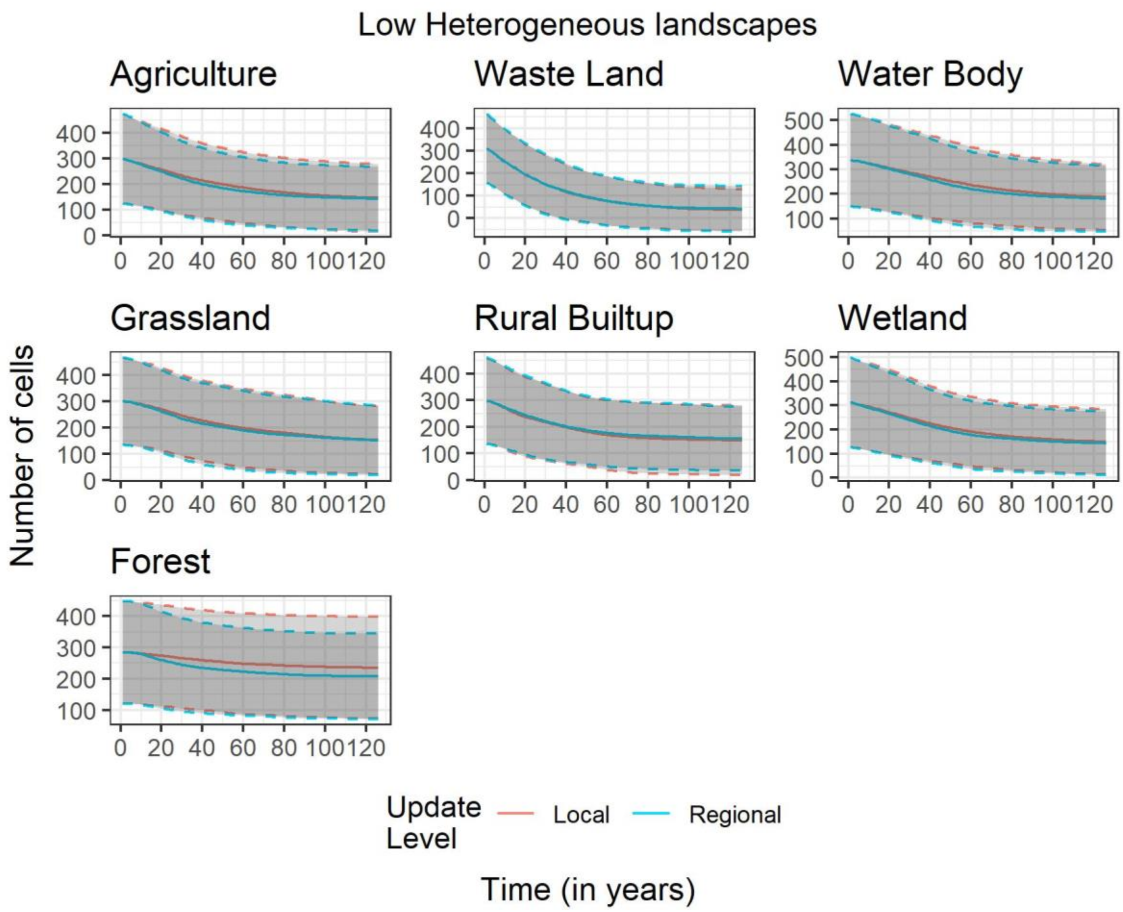

Figure 3-8: Area occupied by a LULC class at every time interval for low heterogeneity landscapes at the regional-scale and the local-scale update. Each plot in the figure corresponds to the seven LULC classes

except urban built-up (see legend in Figure 2-6 for the LULC classes). The plots follow the pattern of loss among the seven classes in the low heterogeneity landscapes.

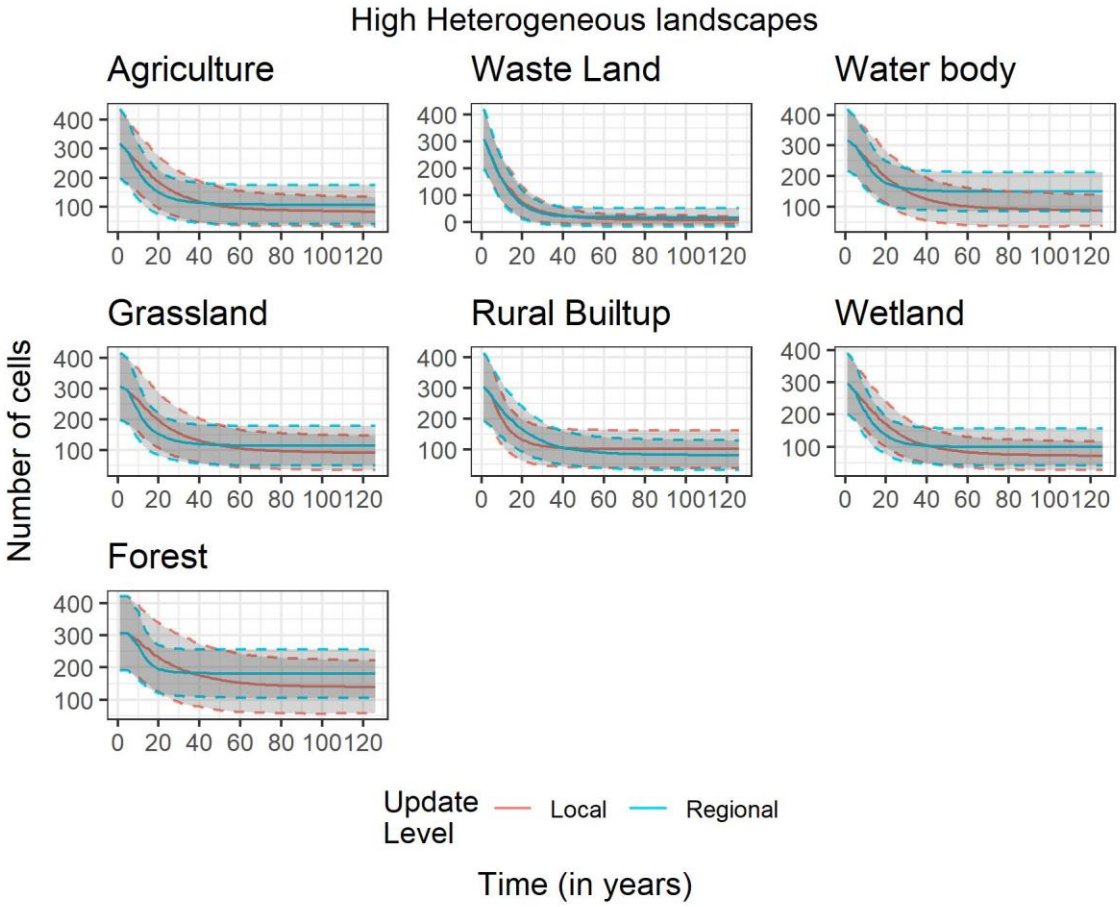

Figure 3-9: The plots follow the pattern of loss among the seven non-urban classes in the high heterogeneity landscapes at both local and regional scale. Each plot in the figure corresponds to one LULC classes except urban built-up (see legend in Figure 2-6 for the list of LULC classes). The plots follow the pattern of loss among the seven classes in the high heterogeneity landscapes.

3.5 Discussion

Null model analysis and the saturation point

For both high and low heterogeneity landscapes, in the case of the null model where the model did not include land use dynamics for updating LUZ of each cell, urbanization was more rapid than in the case of regional-scale and local-scale updates. The landscape reached saturation point much earlier for the null model and the amount of urbanization was higher when compared to the regional-scale and local-scale updates. This implies that patterns observed in the case of the regional-scale and local-scale were non-trivial and not a simple result of a random process (Gotelli and Graves 1996).

In all six cases, the amount of urbanization reached a saturation point which means not all cells in a landscape were converted into urban land use at the end of model runs. 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. In addition, the model classified the land-use zone of some cells into Protected Area and Reserved Area which further restricted the land use transformation. The model didn't allow land use transformation of the cells in the specific land-use zones if the number of green spaces in a landscape reached below a set threshold.

In addition, the results of multiple regression analysis show that the landscape configuration and composition do not have a direct relationship to the outcomes including the amount of urbanization and the rate of urbanization. In the model, other factors such as land-use policies and actors' decisions, together with landscape conditions, influenced the outcomes. There was a difference in the rate of urbanization and the amount of urbanization for both the high and low heterogeneity landscapes at the saturation point (Table 3.1) because the landscape conditions drive the land-use policies and actors' decisions which in turn influence the outcomes in a landscape (Cumming and Epstein 2020, Izakovičová et al. 2021).

Existing landscape conditions influence the outcomes

The results from Step 1 clearly show that the outcome of land-resource dynamics (the amount of urbanization and rate of urbanization) vary for the two 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 (Figure 3-5). In addition, in the case of null models, the amount of urbanization and time taken to reach the saturation point was different for both high and low heterogeneity landscapes (Table 3.3). 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 influences evolution of land-use policies

We know that governance critically affects 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 peri-urban SES, however, the SES components and their interactions are continually evolving. Therefore, land-use policies and resulting LUZs are not predetermined but evolve or emerge as urbanization progresses (Allen 2003, Anderies et al. 2004), as shown in our model. This is particularly problematic in the rapidly urbanising 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, having a fixed or strictly planned approach such as having a fixed spatial scale 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 the land-use policies evolved differently for the two sets of landscapes. After year 5 when the LUZ were updated, 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 (Figure 3-5). This is because the spatial heterogeneity of the landscape also influenced the evolution of land-use policies and the assignment of land-use zones to the cells, which in turn guided and influenced actors' decisions about land use affecting the land use dynamics (Parsons 1995). Therefore, we need governance approaches that 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 the institutions and the conditions to produce a desirable outcome (Cox 2012). The conditions can be ecological, social or social-ecological (Epstein et al. 2015). I have explored fit between land-use policies and landscape level outcomes by setting up balance between the rate of urbanization and the area of green space in an urbanizing landscape. I focus on the spatial fit (Epstein et al. 2015) between land-use policies and existing landscape conditions and explored the effectiveness of land-use policies at two different spatial scales. In the case of the high heterogeneity landscapes at regional-scale update, the 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. However, when I varied the spatial extent of decision-making I observed that the model took more time to reach the saturation point at the local-scale update than at the regional-scale update for high heterogeneity landscapes (Figure 3-6(b)).

The high frequency components (small cyclic peaks) in Figure 3-7(b) correspond to the time when the land-use policies were updated in the landscape. The small peaks show the change in the rate of urbanization due to change in land-use policies. The presence of high-frequency components at the local-scale in high heterogeneity landscapes confirmed that the land-use policy could regulate the rate of urbanization (Figure 3-7 (a)). However, at the region-scale update for the high heterogeneity landscapes, the peaks were not as prominent which implies there wasn't a significant influence of land-use policies on urbanization at region-scale update. This is because dividing the landscape into smaller units in high heterogeneity landscapes allowed regulation of local feedbacks on rules (Marshall 2008).

The results therefore show that the spatial scale of decision-making influences feedbacks between the land-use policy and the spatial heterogeneity of the landscape.

Landscape dynamics were different for the low heterogeneity landscapes and high heterogeneity landscapes when the model varied the spatial scale of decision-making for the low- heterogeneity landscapes. In the case of the low heterogeneity landscapes, the amount of urbanization followed a similar trend unlike in the case of the high heterogeneity landscape. For both the region-scale and the local-scale update, time taken to reach the saturation point was almost the same. The difference in total urban area occupied at the saturation point was similar in case of the local-scale update than the region-scale update in the low heterogeneity landscapes (Figure 3-6).The results therefore imply that a similar spatial scale will not result in similar landscape dynamics for landscapes with different levels of heterogeneity. The patterns observed at a particular scale are influenced by the spatial heterogeneity due to LULC classes in a landscape which in turn affect the decision making process (Wu et al. 2000, Frate et al. 2014, Turner and Gardner 2015).

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 and land became limited, 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 scales 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-scale and local-scale update (Figure 3-8 and Figure 3-9). 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.

The influence of 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. However, the model could not capture this due to design limitations where only cells in the immediate neighbourhood could convert into the 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 scale 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).

The feedbacks can be used to inform design principle 2

Landscape governance is challenging in peri-urban SES due its transient nature resulting in gaps and misfits between institutions and outcomes (Hedblom et al. 2017, Mundoli et al. 2017). In addition, cities in developing countries (e.g. India and Sri Lanka) are witnessing rapid urbanization which increases the challenges of effective landscape governance due to added spatial and temporal complexity (Basawaraja et al. 2011, Hettiarachchi et al. 2013, Hettiarachchi et al. 2014). The lack of efficient landscape governance and management is evident from the lack of sufficient infrastructure such as roads, urban sprawl and loss of green spaces in peri-urban areas (Sudhira and Nagendra 2013). Scholars, therefore, have advocated multi-scale and multi-level approach to support landscape governance (Bragagnolo et al. 2014) and management particularly when using Ostrom's Design Principles (Robinson et al. 2017). The scale includes both social and ecological scale, which influences the processes in an urbanizing landscape (Robinson et al. 2017). My findings here contribute to operationalizing the design principles for multi-scale governance approaches in dynamic landscapes such as those in peri-urban SES by showing that feedbacks between spatial heterogeneity of the LULC classes and governance can be used to inform the term 'local' in the design principle.

In the model, I have given an example of landscapes with two different levels of heterogeneity against two different spatial extent of decision-making. In the results, the set of responses at the regional-scale and local-scale were not same for the two landscape types. This corresponds to previous studies that show that there may exist multiple spatial scales along which specific landscape characteristics may be more evident (Frate et al. 2014). Therefore, my findings suggest that for operationalizing Design Principle 2 in large-scale dynamic landscapes the term 'local' cannot be fixed but will vary depending on the landscape conditions.

Implications of the findings for landscape governance and conservation

Considering patterns of land use transformations in urbanizing landscapes, along with the amount and rate of urbanization, are important when making decisions for addressing natural management issues in the peri-urban SES. The variation in LULC types, their composition, and configuration can influence the flow of ecosystem goods and services (Rodriguez-Loinaz et al. 2015). For example, the particulate matter in the air varies with different LULC types and land use changes(Yang and Jiang 2021). The results show that the spatial scale of decision-making also influences the dominance of one LULC class over the other for urbanization. For example, in the high heterogeneity landscapes, 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-scale update and the local-scale update until the saturation point (Figure 3-9). Thus, explicitly identifying the spatial extent of decision-making 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).

3.6 Conclusion

I have extended and operationalized Ostrom's design principle 2 by applying it to a dynamic large-scale SES. I showed that in governing large-scale and dynamic SESs such as peri-urban SES, policymakers should take spatial heterogeneity of the LULC into account when designing land-use policies. More importantly, I have shown that the term 'local' is a relative rather than a fixed concept; that is, it should be specified as the spatial extent of decision-making identified based on local ecological factors including landscape heterogeneity, rather than merely fixing it to the lowest level of authority.

In the next chapter, I will address the second research question that explores the effectiveness of design principle 3 for a peri-urban SES when there is conflict among actors.

Chapter 4 : Actor resistance influences effectiveness of Ostrom's Design Principles for governing spatially dynamic landscapes

4.1 Abstract

Ostrom's principles for the effective management of common pool resources emphasize the importance of local participation by actors in the design of rules. Design Principle 3, in particular, assumes that including local knowledge will facilitate the creation of effective rules that fit local social and ecological settings. However, the validity of the design principles is challenged in situations of high actor heterogeneity, especially in complex and dynamic social-ecological systems. I used a dynamic, spatially explicit simulation model to test design principle 3 in a highly heterogeneous simulated study representing the peri-urban area of a fast-growing city. During rapid urbanization, urban actors appropriate land in peri-urban social-ecological systems. Appropriation fragments peri-urban ecosystems while affecting the livelihoods of rural inhabitants by reducing land availability for activities such as agriculture. Little is known about how rural actors resist or accept these impacts and whether Ostrom's design principles are useful in this context. I thus simulated the consequences of rural and urban actors' decisions on emerging patterns of land use types in the urban periphery. I used game theory to describe competition for land and landscape composition, and configuration metrics to quantify the impacts of increasing rural resistance on landscape pattern. Landscape metrics (such as urban patch area, number of urban patches, clumping of urban patches, and edge density of urban patches) had a non-linear response to resistance to urbanisation. The results suggest that a small percentage of resisting rural actors can influence emerging landscape patterns. For example, resistance as low as 10% of the rural population to urbanisation was sufficient to influence the degree of clumping of urban areas. The responses of individual landscape properties varied for a given level of resistance. The non-linear and varying response of emerging landscape patterns to conflict among actors, and the presence of tipping points for ecological processes that depend on connectivity or area, can create significant opportunities and challenges for sustainable land use change in a spatially dynamic SES. I conclude that efforts to use Ostrom's design principles to manage complex and dynamic landscapes such as peri-urban SESs must account for actor heterogeneity and the potential of actor resistance in achieving ecosystem sustainability.

4.2 Introduction

The global sustainability of natural resource use depends on effective governance of human impacts on ecosystems. Ostrom's design principles (Ostrom 1990) are often invoked as best practices for the governance of common pool resources, such as water, pastures, and fisheries. Ostrom identified eight design principles (summarised in Chapter 1, Table 1.1) and linked them to social-ecological sustainability through her SES Framework (Ostrom 2007, 2009). The SES Framework provides a structured approach for a systematic evaluation of the governance of common pool resources, and supports additional empirical studies by describing the interlinkages and causal relationships between social and ecological components involved in common pool resource management (Binder et al. 2013, Partelow 2015, Tyson 2017). Many scholars have proposed a commons based approach to manage natural resources in a peri-urban SES (Vij and Narain 2016, Menatti 2017, Cerquetti et al. 2019).

One of the main findings of Ostrom's research was that groups can self-organise to devise effective institutional arrangements for the governance of the commons (Ostrom 1990, Schlager 2004). Design principle 3 emphasises participation of actors in collective decision making for effective governance of such resources. However, the validity of the design principle is challenging in situations of heterogeneity among actors, especially in complex and dynamic social-ecological systems (Fleischman et al. 2014a). Heterogeneity among actors such as conflicting resource-use interests, variable political influences and dominance, and variability in social, cultural, and economic status can lead to lack of cohesion, trust and give rise to situations of conflict among actors - leading to unexpected outcomes in an SES (Vij and Narain 2016, Murunga et al. 2021, Narain 2021). In addition, researchers have flagged the urgent need to move beyond the saturated focus on collaborative governance to understand other important processes, such as appropriation and resistance (Morrison et al. 2020b).

In a peri-urban SES, heterogeneity among actors is recognized as one of the dominant actor group characteristics that influences outcomes, such as urban sprawl (Chirisa 2010, Magliocca et al. 2015). Actors also often have conflicting land use interests, varying socio-economic attributes, and cultural heterogeneity (Gashu Adam 2020). Local rural actors engaged in farm-related activities, for example, compete against urban actors seeking land use transformation for housing or industry. Additionally, governmental policies often support the urbanization of land in peri-urban areas, overruling traditional institutions and marginalising the responses of rural actors to the land use transformation (Patil et al. 2018, Gashu Adam 2020). The actors in a peri-urban SES frequently lack the social cohesion, trust, and reciprocity that are important in developing norms and rules for natural resource governance (Baggio et al. 2016, Vij and Narain 2016). However, little is known about how these characteristics could generate unexpected outcomes in commons situations (Vedeld 2000, Poteete and Ostrom 2004).

To understand the applicability of SES theory and design principle 3 to interactions among heterogeneous actors in spatially dynamic environments, it is important to understand the influence of cross-scale interactions (such as conflict) among heterogeneous actors at multiple social and spatial scales (Cox 2008, Ratner et al. 2013, Robinson et al. 2017). Based on previous observations of emerging land use patterns and conflicts among actors (Poteete and Ostrom 2004, Rauws and de Roo 2011, Magliocca et al. 2015), I hypothesized that responses of rural actors would affect decisions made by urban actors and that the nature of these responses could provide a mechanism that determines emerging land use patterns. To test this hypothesis, I used dynamic simulation models to explore the influence of rural-urban interactions on land use transformations, contrasting the results with a counterfactual in which there was no simulated conflict among urban and rural actors. Due to the anticipated relevance of cross-scale influences, I expected to find both non-random and non-linear relationships between emergent land use patterns and the degree of conflict between rural and urban actors.

4.3 Methods

In **Chapter 2**, I described the different components of the peri-urban SES and mapped them to the SES Framework. Chapter 2 also includes the detailed description of the model used here. To avoid redundancy, I now describe how I have used the model to test the hypothesis including experimental design, data description, and statistical methods used for the analysis.

The Simulation Model

For this analysis I focussed on capturing the lateral interactions among the actors and their influence on emerging landscape patterns as SES outcomes in the presence of other interacting social and ecological components.

As discussed earlier in chapter 2, the urban cells were dominated by urban actors and the non-urban cells were mostly dominated by rural actors. In the model, ideally, as the population increased the urban actors within a cell collectively decide to move out of the cell and occupy a neighbouring cell called the target cell. The urban actors transformed the non-urban cell they move into, into urban land use. Actor groups dominating the target cell and urban actors who wanted to occupy the cell collectively decide to perform land-use transformation if the land-use policy allowed the transformation. However, in the model, the rural actors dominating the target cell can resist the rule to transform land-use or they can give up their position as rural actors and allow land-use transformation for the target cell.

I have modelled the interactions (resist and comply) between urban actor groups and the actor group already occupying the target cell using the Hawk and Dove model of game theory. A player in a Hawk and Dove game adopts a strategy to either compete (Hawk) or cooperate (Dove) (Kohli and Haslam 2017). The game of cooperation and conflict was played between the actors at the cell level which means in the model, each cell could have either a hawk or dove strategy. I adapted Hawk and Dove strategies for both urban and rural actors in the peri-urban SES. In the model, an urban Hawk represented the cell with urban actors who wanted to compete or fight to acquire land parcels in the peri-urban SES for urban land use. An Urban Dove meanwhile was the cell where urban actors avoided conflict (or cooperate) with rural actors and mutually decide with rural actors not to appropriate a cell for urban land use. In the model, this implies that urban Doves were not interested in appropriating a land parcel. In peri-urban areas of the Global South, there are various reasons (such as value systems, lack of sufficient alternative jobs and skills, and a sense of security) as to why rural actors may not be ready to give up their land and allow land use transformation. I categorised those rural actors who resisted land-use transformations (e.g., by refusing to sell their land or staging protests to save agricultural land (Tyson 2017, Vidyarthi et al. 2017)) and fight against urban actors as rural Hawks. In the model, the cell in which dominant rural population adapted Hawk strategy was the rural Hawk. Rural Doves were the cells which were occupied by rural actors who were ready to give up land and comply with urban Hawk to allow land-use change for urban land-use.

I modelled the spread of the urban population beyond the urban boundary into peri-urban areas and the emergence of different landscape patterns based on choices made by dominant actor group in each cell. At the start of the model (see Figure 2-3), I initialised each cell with LULC classes, LUZ, Z and population (including total population, urban population and rural population). As the urban population increased (due to migration or reproduction) and reached the carrying capacity, not all but a percentage of urban actors moved out of urban cells to seek more land for urban land uses. The urban actors could move into only one of their cell's eight immediate neighbours (as in Moore's neighbourhood window (Maria de Almeida et al. 2003)) at a given time. The urban actors used cell score (Equation 2.3, Chapter 2) as the decision criterion and selected the cell with highest value of cell score. If the cell into which urban actor moved was not an urban cell, then the cell was reclassified as an 'urban' class .

The focus of the study was to understand the interactions between rural and urban actors in presence of other interactions including the change in land-use policies and the spatial neighbourhood interaction. The urban actors, therefore, could transform a cell only if land-use policies allowed the transformation. Land-use policies were included using the score Z. The land-use policy sub-module estimated Z for each cell and updated the same periodically after every five years as described in Chapter 2. I kept the spatial scale (or governance scale) constant at landscape level for this chapter. Additionally, urban actors included the spatial neighbourhood information (SI, calculated using Neighbourhood Information sub-module) of the target cells in their decisions.

Experimental Design

4.3.1.1 Simulated Data

For this chapter, I used a data set with 100 simulated images. I maintained the number of classes and the level of heterogeneity constant for all the images and randomly assigned the patch sizes and distributions to all 100 images to add variability (see Figure 2-6 in chapter 2).

In order to observe the impact of the response of the rural actors on resulting land-use patterns, I fixed the urban strategy to urban Hawk in the model and changed the strategy of rural actors in discrete steps by adjusting their level of resistance to urbanisation. I defined the level of resistance as the percentage of rural population resisting the change, which correspond to the percentage of rural Hawks in the landscape. I assigned a strategy to all the non-urban cells irrespective of their spatial location. The level of resistance ranged from one to 10 with a step size of 1. Each level represented the percentage of rural actors who adopted the strategy of Hawks (rural Hawks). For example, at level 1 meant that there were 10% rural Hawks, at level 2 represented 20% rural Hawks, and level 10 meant 100% rural Hawks or maximum resistance. I also included level zero, with no rural Hawks.

Hawks pay a cost for fighting against other Hawks in a Hawk and Dove model (Nowak & May 1992). In the model, the pay –off values was normalised between 0 and 1. Urban actors (urban Hawk) received a lower payoff when urban Hawks fought against rural Hawks and a higher payoff when they fought against rural Doves. The model used the pay-off urban actors received as input GT to estimate the cell score (Equation 2.3, Chapter 2).

I ran the model on each of the 100 simulated images for 150 iterations for all 11 levels of resistance of rural actors (from 0 to 10). In the model, urban actors converted non-urban cells into urban class. As the area of interest had a finite space with 2500 cells, the landscape reached a saturation point, which I defined as the year beyond which the total urban area did not change significantly. I estimated the saturation point from the plot number of urban cells per iteration using the *findchangepts* function of Matlab (MATLAB 2016). I determined the iteration or the year when the slope of the curve depicting the number of urban cells first changed. I calculated the landscape configuration and composition metrics (discussed below) of the urbanizing landscape at the saturation point.

4.3.1.2 Landscape configuration and composition metrics

The aim of land-use policies is to have a sustainable landscape in a peri-urban SES which means to have an optimal distribution of land uses in the limited space (Botequilha Leitão and Ahern 2002). The land-use transformation should serve economic needs but also maintain natural resources and provide social benefits. The LULC of land parcels are spatially interdependent and the resulting spatial patterns such as patch area and connectivity influence both social and ecological processes and resulting ecosystem goods and services (Cumming et al. 2012, Banerjee et al. 2013). In conservation biology, conventional species-area relationship and island biogeography theory support the statistical relationship between various ecological processes such as species richness and various spatial characteristics of a landscape including habitat size, distance from the mainland, and patch complexity including edge effects and clumping of patches (Campos et al. 2013, Turner and Gardner 2015). Therefore, to test the policy's success, I used standard landscape ecology metrics that measure the areas of different land uses (composition) and their shapes and relative positions to one another (configuration) (Turner and Gardner 2015). The metrics are used in quantifying the spatial dimension of landscape sustainability and contribute to landscape planning and management to address the sustainability goal (Botequilha Leitão and Ahern 2002).

Table 4.1: List of spatial configuration and composition metrics used to estimate the change in urbanization pattern as the level of resistance varied. Number of urban cells, total urban patch area, number of urban patches, edge density and clumpy index were estimated at class level for urban patches. Aggregation index and Mean Fractal dimension index was estimated at landscape level.

Name of landscape metric	Spatial Level	Description
Number of urban cells	Class	Total number of the urban cells in the landscape
Total Urban Patch Area (PA)	Class	Sum of area occupied by the urban built-up
Number of urban patches (NP)	Class	Total number of urban patches
Edge Density (ED)	Class	Measure of edges associated with shape complexity of the resulting urban patches
Clumpy Index (CLUMPY)	Class	Aggregation measure independent of landscape composition
Aggregation Index (AI)	landscape	Aggregation measure
Mean Fractal Dimension index (FRAC_MN)	landscape	Shape complexity measure based on perimeter area relationship

4.3.1.3 *Statistical Analysis of landscape metrics*

I first tested whether differences in the landscape patterns resulting from various levels of rural resistance were a result of a random process or not. I used null models to test the hypothesis. Null models exclude a mechanism or process of interest, acting as a counterfactual (Gotelli and Graves 1996). For the null model, I tested the case when there was no resistance at all from the rural actors against land use transformations by urban actors which was at level 1 when the number of rural hawks were zero. I used t-tests and estimated p-values to compare the result of landscape metrics for the null model to those from different levels of resistance.

I then tested for the effect of confounding variables that may influence both the emerging landscape patterns and the level of resistance. If not accounted for, the confounding variables may lead to a distortion of the true relationship between the response variable (landscape metrics) and the predictor variable (the level of resistance) (Skelly et al. 2012). In general, urbanization and changes in landscape metrics are interconnected (Yi et al. 2021) and the rate of urbanization may influence the results in the model. I checked for an influence of rate of urbanization on the relationship between landscape metrics and levels of resistance using linear regression (Pourhoseingholi et al. 2012).

I first estimated the rate of urbanization by calculating the slope of the line representing the number of urban cells from zero iteration to the iteration at the saturation point for all levels of resistance. I then checked for the confounding variable which was the rate of urbanization and estimated the change in variance both before and after including the confounding variables. See 1.1.1.1.1.1Appendix C (section C.2), for the details.

Fitting a curve to discrete data allows statistical inference of the relationship between the predictor and response variable and of the underlying mechanisms that relate the two variables (Johnson 1991, Frazier and Wang 2013, Turner and Gardner 2015). To perform curve fitting, I first calculated the mean value of landscape metrics estimated from the data set of 100 images. I then established that the mean value plots of landscape metrics are non-linear using effective degrees of freedom (edf). The edf reflects the degree of non-linearity between the driver and the response variable (Hunsicker et al. 2016). If edf = 1 suggests that the relationship is linear; 1< edf <2 suggests a weak non-linear relationship and edf > 2 suggests that the non-linearity in the relationship is high (Hunsicker et al. 2016). I fitted standard curves (power, log, logistic and exponential) on the mean values of the resistance level 1 to 10 using nls (Nonlinear Least Squares) function in R (RCoreTeam 2019). To find the best-fit curve I used three measures: AIC (Akaike Information Criteria) and log-likelihood. Lower AIC values indicate better fit whereas for log-likelihood the opposite applies. I estimated the inflection point for each curve using the function bese (library: inflection) of R (Christopoulos 2019). An inflection point indicates the location on a curve where the curve changes sign. In other words, it is the point where the dependent variable is most sensitive to the change in independent variable and is calculated from the double derivative of the equation of the curve (Frazier and Wang 2013). It is a point where a change in the direction of the curve occurs in a continuous function.

4.4 Results

Number of urban cells and the saturation point

The results in Figure 4-1 highlight the effect of resistance of rural actors to the decisions made by urban actors as a function of degree of resistance. The urbanization happened rapidly for the low resistance level as compared to the higher resistance level. For instance, in 25 years more than 60% of the total area was urbanized when resistance level was 1 whereas for the same period only 18% of the total area was covered by urban cells at resistance level 10. Urbanization was most rapid when there was no resistance from the rural actors—a condition for the null model. Under these conditions, about 70% of cells were urban in 25 years.

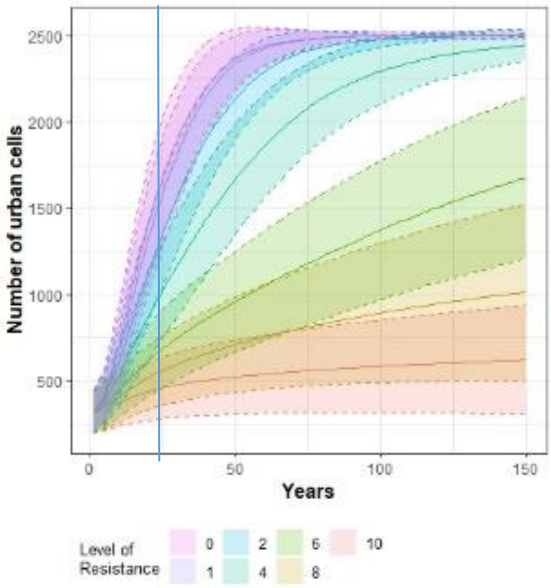

Figure 4-1: Number of urban cells occupied at every iteration. For the purpose of clarity, I only include every alternate level of resistance. Blue line at year 24 marks the saturation points for level 1. I take the saturation point of level 1 as the point of reference for the landscape metrics. . In the figure, thick line represents the average value of amount of urban cells for each level of resistance and dotted line represent the variation (calculated as standard deviation) for all 100 images.

Landscape metrics

The response of the landscape metrics to varying level of resistance suggests that rural-urban negotiations have a strong and statistically significant effect on the emerging land use patterns (Figure 4-2 and Table 4.2). For all six-landscape metrics the relationship was significant ($p<0.05$ after t-tests for 100 images) with R^2 > 0.9 for the least square fit of regression curves across the mean values for different level of resistance (Table 4.2).

I found that the response of all six landscape metrics was not random ($p<0.05$) by conducting a two-sample t-test to compare the result of null-model (resistance level 0) and resistance level 1 to 10. Interestingly, the resistance level after which the result of the t-test was significant varied for each landscape metrics (Table 4.2). For example, the number of urban patches and total urban patch was not random once the percentage of resisting rural actors reached 40%. For spatial configuration metrics which includes clumpy index, edge density, mean fractal dimension index, and aggregation index the emerging patterns were significant even when the percentage of rural actors was low (<20%).

Value of edf was greater than 1 for all landscape metrics, which confirmed a non-linear response to the varying level of resistance for all the metrics (Table 4.2). Total urban patch area and degree of clumping among urban patches followed a reverse logistic curve with a sharp curving sigmoid and a clear inflection point between level 4.5 and 3, respectively. As the total urban patch area increased, the urban patched coalesced and the number of urban patches decreased. The number of patches were lower at lower resistance level and increased with increase in level of resistance following a logistic curve. The quadratic curve of edge density indicates that a small change in the resistance level lead to significant changes in the shape complexity of the urban patches. The landscape level metrics also followed a non-linear trend. The aggregation index followed a reverse logistic curve and mean fractal dimension (which represents the shape complexity) of all the patches in a landscape followed a quadratic curve.

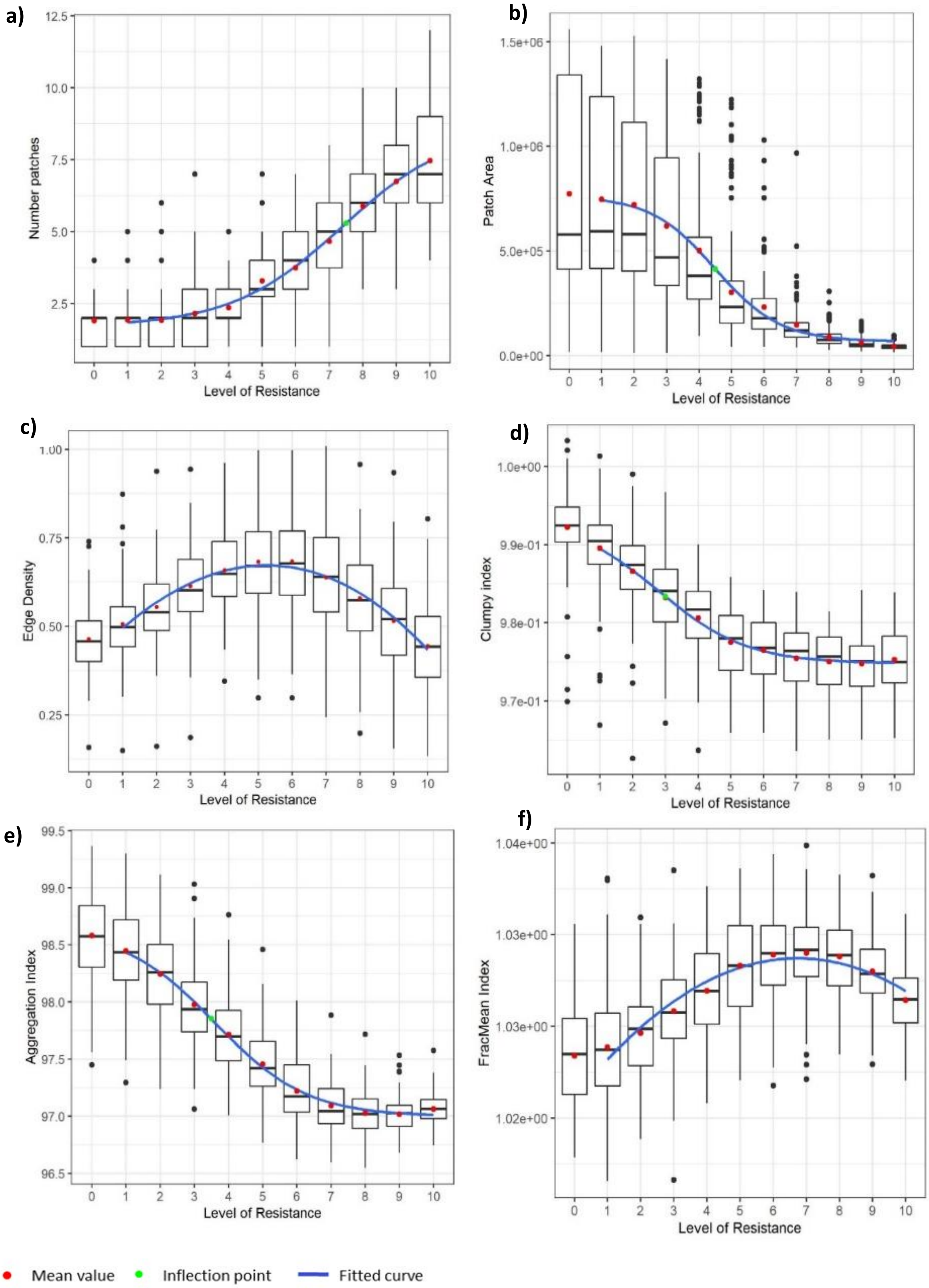

Figure 4-2: Response of six landscape metrics to the varying level of resistance. (a) to (d) are class level metrics including (a) number of urban patches, (b) patch area, (c) edge density and (d) clumpy index showing the pattern in the urban built-up. Figure (e) aggregation index and (f) frac_mean index are landscape level metrics showing patterns at the landscape level.

Table 4.2: Curve fitted to the mean value of all six landscape metrics and the corresponding statistics. AIC and likelihood signify goodness of fit for each landscape metrics is available in the (Appendix C, table C.1 to C.6).

Landscape metrics	**Equations and R^2 value (x is the resistance level)**	***Resistance level corresponding to the inflection point***	***Resistance level at which t-test was significant***
Number of urban patches	$\frac{26.7127}{1+20.42e^{(-0.2106x)}}$, $R^2 = 0.9864$	7.5	4
Total area of urban patches	$(\frac{6.961\times10^5}{1+e^{x-4.493}}) + 67230,\ R^2 = 0.9$	4.5	4
Edge Density	$-0.0067x^2 + 0.09453x + 0.40862$, $R^2 = 0.9802$	Inflection point doesn't exist for quadratic curve	2
Clumpy index	$\left(\frac{0.0186}{1+0.13e^{0.735x}}\right) + 0.975, R^2 = 0.9846$	3	1
Aggregation Index	$\left(\frac{1.63}{1+0.068e^{0.746x}}\right) + 96.99, R^2 = 0.9977$	3.5	2
Mean Fractal Dimension index	$-0.00017x^2 + 0.002261x + 1.026$, $R^2 = 0.9442$	Inflection point does not exist for quadratic curve	2

I also checked for the cofounding variables for all the curves. I found that effect of rate of urbanization was mildly confounding as the change in R-square before and after addressing for confounders was not significant (<0.04). In addition, the significance of x and its power variants were still significant (p value <0.05, result of t-tests for 100 images), after addressing for the confounding variable. I therefore did not include the confounding variable in the curve fitting.

4.5 Discussion

My analysis confirms that rural-urban interactions influence the emerging land use pattern. The influence of rural-urban interactions on spatial composition and configuration metrics is non-random and non-linear. Koch et al. (2019) have shown that individual decisions in an urbanizing landscape affect emerging landscape level patterns. The results confirm that the landscape metrics follow a non-linear response curve to the varying resistance level of the actors. The non-linearity exists because the impact of interaction among rural and urban actors on the landscape level patterns is not a process of simple aggregation; other contextual components of the peri-urban SES also influence the dynamics of the system (Rauws and de Roo 2011). However, the response of each landscape metrics varies for the same level of resistance.

For individual landscape metrics, I found that the response of each landscape metrics was different for a given level of resistance. For example, both clumpy and total urban patch area decreased with increase in resistance level, however, the inflection point for the clumpy index was at resistance level 3, whereas for urban patch area it was at resistance level 4.5. Further for the clumpy index, the outcome was significant at all levels of resistance when compared to the null model for all 100 images using t-test ($p<0.05$). For the urban patch area, the resistance from the rural actors was significant only after resistance level 3. The different inflection points and varying response curves of each landscape metrics showed that at each stage of conflict may influence landscape patterns and related ecological processes differently.

In the model, the increase in the level of resistance from rural actors implies that urban actors are not left with many non-urban cells to appropriate and transform for urban land use. This is evident from the amount of urbanization. An increase in resistance from rural actors affected the number of cells that urban actors could transform for urban land use. Urban actors could transform some cells even when all rural actors resisted (level 10) because both urban hawks and rural hawks had an equal probability of winning the game. A decrease in urban patch area for higher level of resistance further confirmed the influence of resistance among actors on urbanization. However, the number of patches increased as the resistance level increased which means connectivity among urban patches was reduced (Elmi et al. 2022). A decrease in patch area and an increase in the number of patches together show that urbanization was patchier as the level of resistance increased (Ramachandra et al. 2012). Patchy urban areas implies mixed urban land-use which may contribute to lower levels of air pollution (Huang et al. 2021). For example, researchers have found that mixed urban land use with high green spaces influence the particulate matter concentration in the atmosphere. Specifically, particulate matter concentration ($PM_{2.5}$) is influenced by the complexity and aggregation of urban patches. In the model, the shape complexity of urban patches was highest when the level of resistance was between levels 5 and 6, however, the aggregation among urban patches (clumpy index) was comparatively less when the resistance level was lower than 5. Therefore, when half of the total rural actors resisted the land-use transformation, the spatial patterns of the landscape may contribute to less particulate matter concentration(Huang et al. 2021). The results show that the landscape patterns resulting from varying levels of resistance may have different implications for processes in a landscape.

For understanding how a pattern influences the process, inflection points offer a critical reference point which signals a transition from one state to another (Frazier and Wang 2013). The inflection point showed the point where the change in landscape metrics was most sensitive to the level of reflectance.

For example, the inflection point for the total number of urban patches was at resistance level 7.5 and for the urban clumpy index, the inflection point was at level 3. Identifying inflection points for the landscape metrics gives additional information about resulting landscape patterns due to conflict among actors(Frazier and Wang 2013). For example, the Clumpy Index, which is the measure of aggregation of urban patches (low inflection point), is more sensitive to conflict among actors as compared to the number of patches (high inflection point).

Modelling constraints and additional recommendation

Models play an important role in theoretical investigations and extending SES theory (Ostrom 2007, Cumming 2011) by allowing analysis of interactions between one or more subsystems in a simplified yet systematic manner (Ostrom 2005). To explore mechanisms a model should be suitably interpretable, with a limited number of variables and parameters (Gotelli and Graves 1996, Cumming et al. 2012). The model developed here, like other simulation models, had its limitations. In the model, I focussed on the response of the rural actors irrespective of their spatial context. Spatial context such as the location of rural actors and their distance from urban areas or markets can influence the response of rural actors (Koch et al. 2019). While I have included the influence of LULC information of neighbouring cells in decision-making by the urban actors, further investigation is needed to include the influence of various spatial contextual factors in response of the rural actors such as the spatial location of peers, distance from the urban areas, marketplaces, and presence of other institutions/rules. In addition, biophysical characteristics and underlying ecological processes are also important drivers of outcomes in an SES (Epstein et al. 2013, Leslie et al. 2015, Vogt et al. 2015, Sharma et al. 2016). The presence (or absence) of biophysical factors and change in certain environmental conditions influence the decisions of rural actors to allow land-use transformations.

Implication of actors' conflict on the SES outcomes

The latest wave of privatisation of rural and agricultural land en masse, particularly in the cities of the Global South such as Kolkata and Colombo, has gained global attention under the new critique of 'land grabbing' (Hettiarachchi et al. 2019). However, detailed study of appropriation and resistance in peri-urban SESs remains comparatively sparse (Morrison et al. 2020a). An SES perspective and Ostrom's design principles can provide a systematic way to govern the use of resources in a peri-urban SES, especially when top-down approaches for natural resource governance are ineffective in controlling ecological degradation (Haase et al. 2014, Vij and Narain 2016, Okpara et al. 2018, Zhang et al. 2019). Individual actors who share common goals, sentiments and demands across space-time and using similar methods can act autonomously over various points in time and enforce transformative changes for natural resource management (Ernstson 2011). For instance, in the urban areas of Stockholm, social actors came together to enforce the establishment of the National Urban Park in the city (Ernstson 2011). However, conflicts (such as socio-economic and cultural differences) among actor groups can hamper collective action efforts for sustainable resource management (Murunga et al. 2021). For example, in urbanizing landscape of Bengaluru, the previously used commons such as lakes are increasingly becoming unavailable to rural actors who depend on them for their livelihood and day to day activities resulting in conflicts, encroachment and urban sprawl (Unnikrishnan et al. 2016, Mundoli et al. 2017). I show that these interactions at the group level between rural and urban actors with conflicting land use interest are inherently complex. The interactions at the individual level have a non-linear influence on landscape level patterns. Non-linearity and presence of inflection point imply that the extrapolation of the interactions across scale is not straightforward and can produce significant challenges for sustainable land use changes (Turner and Gardner 2015, Milkoreit et al. 2018).

Challenges for sustainable land use transformations in a peri-urban SES are further aggravated by varying levels of conflict. The results show that the heterogeneity among actors influences different landscape metrics at different stages of conflicts. Each landscape metric is associated with different aspects of a spatial pattern (Turner and Gardner 2015) and may affect a different ecological process. The characteristics of spatial patterns identified by the landscape metrics are in turn associated with different ecological processes such as the movement of organisms (connectivity), spread of natural disasters, and nutrient distribution (Turner and Gardner 2015) that underpin different ecosystem services and flows (Banerjee et al. 2013). As the level of resistance increases, the diverse array of ecological processes (and eventually associated ecosystem services and flows) are affected at different levels. The link between marginal change in the level of resistance and its influence on different ecological processes can contribute to understanding and developing better policies.

In addition, for managing sustainable land use transformations and developing related policies, requires the handling of multiple objectives in an urbanizing landscape. For example, the objective to maintain contiguous agricultural land goes hand-in-hand with developing infrastructures such as roads and highways for urban development. I show that models can guide policy decisions linking local stakeholders to broader institutional context by evaluating the outcomes of conflict across scale (Ratner et al. 2013). Identifying inflection points, which are widely used in management literature as switching points(Arin et al. 2021), can help in identifying the points of rapid change in social-ecological systems that may contribute to explore transition pathways that can contribute to the development of strategies in spatially dynamic landscape (Milkoreit et al. 2018, Mathias et al. 2020).

4.6 Conclusion

Management of resources in a peri-urban SES is often challenging and complex. Degradation of traditional institutions around the commons, overlap and/or gaps in policy, and the influx of actors (formal and informal) with little or no connection with existing social-ecological interdependencies require explicitly recognizing cross-scale interactions (Cox 2008, Unnikrishnan et al. 2016, Mundoli et al. 2017). The non-linear and varying response of emerging landscape patterns to conflict among actors, and the presence of tipping points for ecological processes that depend on connectivity or area, can create significant challenges for sustainable land use change in a spatially dynamic SES. I show that to operationalize Ostrom's Design Principle for a commons-based approach for governing resources in a spatially dynamic SES requires including actors and recognizing conflict among actors involved in the decision-making process. Lastly, achieving the desired set of landscape level outcomes calls for the heterogeneity among actors to be compensated for the potential impact of resistance.

In the next chapter, I address the third research question where I once again focus on design principle 3 and explore how actors with limited local knowledge can contribute to informed decision making by harnessing local spatial information.

Chapter 5 : Spatially informed decisions and landscape heterogeneity influence collective governance for sustainable peri-urban landscapes

5.1 Abstract

Peri-urban SESs are spatially dynamic landscapes experiencing degradation of natural resources and loss of related ecosystem goods and services. Best practice (specifically, Ostrom's design principles) emphasises a collective approach to governing resources in all SES, whereby all actors should participate in decisions that affect them. However, for rulemaking to be effective, actors should have enough local knowledge and capacity to contribute usefully to decision-making. In peri-urban SES, urban actors often have limited knowledge of rural elements of a peri-urban SES but still wield stronger influence in landscape governance than rural actors wield. I explored the applicability of Ostrom's design principles to such situations, whereby a group of actors have limited local knowledge and instead, harness local spatial information such as neighbouring land-use land cover to inform decision-making. I hypothesized that urban actors can regulate the influence of existing landscape conditions on emerging landscape patterns by explicitly including neighbourhood information in decision-making. I used dynamic simulation models to explore the influence of spatially explicit decisions on patterns of green spaces left after urbanization. I calculated the percentage change in spatial composition and configuration of the green spaces before and after urbanization for high and low heterogeneity landscapes. Multivariate analysis showed that patch area metrics could explain most of the variation in the results. The change in patch area metrics followed a sigmoidal curve in response to the varying level of neighbourhood information for both landscapes. For high heterogeneity landscapes, the percentage change in patch area was higher than the low heterogeneity landscapes for the same level of neighbourhood information. As preference for the neighbourhood information increased, the difference between the patch metrics for high and low heterogeneity reduced. My results show that urban actors can regulate the influence of existing landscape conditions on emerging landscape patterns by explicitly including local spatial information in the decision-making. Urban actors can therefore bridge the gap between peri-urban areas and policymaking by harnessing local land use information for making spatially conscious choices. My analysis sheds new light on cross-scale interactions in spatially dynamic landscapes.

5.2 Introduction

Urban populations have increased across the globe from 30% of the global total in the 1950s to 55% in 2018, with urban spaces expanding even faster (Elmqvist et al. 2013, United Nations 2019). As cities continue to physically expand beyond their traditional boundaries against a backdrop of increasing urban populations and rising demand for ecosystem goods and services, the urban periphery in many locations is experiencing rapid land use transformation, resulting in a complex mix of urban, rural and natural landscape elements (Elmqvist et al. 2013). Peri-urban areas serve as important functional spaces for the wellbeing of urban centres while also supporting livelihoods of local rural dwellers (Narain 2009, Vij and Narain 2016). Their complex, transitional nature makes natural resource governance extremely challenging and often controversial (Žlender 2020). Diverse and conflicting resource use, rapidly changing demography, a lack of clarity on ownership, and gaps or overlap in institutions and policies are common (Shaw 2005, Mundoli et al. 2017, Žlender 2020). Without effective governance, peri-urban SESs will continue to experience degradation of natural resources and loss of related ecosystem goods and services (Ravetz et al. 2013, Hedblom et al. 2017). Unintended consequences of decades of economic reforms and intensification of private investment in India, for example, have led cities like Delhi and Bengaluru to continually expand beyond their initial boundaries, resulting in the loss of important cultivable land, forest area and green spaces (Das 2017).

Governance in peri-urban SESs is typically centralised and top-down, with local government actors often playing a dominant role. In such cases, local institutions located in urban centres, distant from the urban periphery, are unable to resolve resource degradation in an urbanizing landscape (Zhang et al. 2019, Lei et al. 2021). For instance, many cities in India and China are unable to control urban sprawl and informal settlements, regardless of having zoning systems and urban master plans in place (Zhang et al. 2019). The breakdown of zoning plans occurs partly because top-down approaches ignore the self-organizing capabilities of the informal actors in an urbanizing landscape (Scott 1998). Both formal (including government agencies) and informal actors (e.g. landowners and farmers) influence natural resource governance in peri-urban SESs and can therefore play a central role (Boonstra and Boelens 2011, Cerquetti et al. 2019). Vij and Narain (2016) have shown that actors at a local level can successfully adapt to changes and evolve norms and rules accordingly in a peri-urban SES. Scholars, therefore, have proposed a commons-based approach for the governance of natural resources in a peri-urban SES (Vij and Narain 2016, Menatti 2017, Cerquetti et al. 2019).

Commons scholars acknowledge the existence of complex relationships between social and ecological components that together influence the sustainability of natural resource use. They recommend Ostrom's design principles as best practice for designing institutional arrangements related to common pool resources such as fisheries, irrigation, and pasture. Researchers are increasingly recognizing that collective action theory and common pool resources are embedded within a larger SES context (Anderies et al. 2007, Partelow 2018). This recognition has led to the use of Ostrom's design principles and the SES Framework in a broader social-ecological systems discourse that moves beyond traditional small-scale common pool resources. The SES Framework provides a theory-neutral list of exhaustive and generalizable variables that researchers have utilised to diagnose the environmental issues in a large-scale complex SES (Partelow 2018). However, there are gaps in understanding how and whether Ostrom's design principles and the SES Framework are applicable in complex and dynamic social-ecological systems such as in a peri-urban SES.

Ostrom's design principles emphasise the participation of those affected by the rules in modifying the rules for the effective management of resources (Ostrom 1990). Local actors, who often have long standing associations with ecosystems and depend on the SES for their livelihood, in turn, have low-cost, fine spatial scale information that can contribute to the development of effective management strategies (Cox et al. 2010, Herse et al. 2020, Sen and Nagendra 2020). In a peri-urban SES, the actor groups can be broadly categorised in to rural and urban actors based on their varying relationship and understanding of the SES complexity and land use interest (Gashu Adam 2020). Rural actors in a peri-urban SES typically have a long-standing association with peri-urban SES and depend on the resources for their livelihood. As local conditions change, local actors can perceive changes faster and can contribute to adapting the rules for natural resource governance appropriately (Cox et al. 2010, Herse et al. 2020, Owusu Ansah and Chigbu 2020). Inner-city dwellers or urban actors, on the other hand, come from urban centres to appropriate resources such as land to develop it for residential, recreational, and industrial purposes (Žlender 2020). Urban actors appear to be the ones appropriating resources from peri-urban SES such as land and water with limited understanding of the complexity in the peri-urban SES and impact of their decision on the social-ecological outcomes (Tidball and Stedman 2013, Mundoli et al. 2017). Urban actors and their choices therefore largely influence land use transformations in peri-urban SES. Because, rising demands and needs of urban dwellers influence land-use policies, and therefore, the policies are often skewed in favour of urban growth (Purushothaman and Patil 2017, Owusu Ansah and Chigbu 2020, Žlender 2020). However, it is not clear as to how urban actors with limited local knowledge and dominant influence on policymaking can contribute to more informed and responsible decision making in a peri-urban SES.

I explored the applicability of Ostrom's design principles to situations in which a group of actors have limited local knowledge and instead, harness local spatial information such as LULC in the local neighbourhood to inform decision-making. Various factors drive the choices of urban actors that influence land use transformations at fine spatial scales, such as local environmental characteristics, policies, social and economic factors (Barredo et al. 2003). Surrounding land uses also influence the local decision making process (Verburg et al. 2004, Braimoh and Onishi 2007). For example, urban actors often prefer to develop new residential areas next to existing residential neighbourhoods (Braimoh and

Onishi 2007). Land use patterns often exhibit spatial autocorrelation (Verburg et al. 2006). Since urban actors appear to take spatially conscious decisions, they have the potential to drive landscape level outcomes in a peri-urban SES. I hypothesized that urban actors regulate the influence of existing landscape conditions on emerging landscape patterns by explicitly including neighbourhood information in decision-making. I tested my hypothesis using dynamic simulation models to explore the impact of localised knowledge, expressed through policy, on landscape pattern, and contrasting the results with a counterfactual when no neighbourhood information is included in decision-making. In the model, I varied the weight given to neighbourhood information by the urban actors in the decision-making. Based on previous studies (Koch et al. 2019) I expect to find a non-random relationship between emerging land-use patterns and spatially explicit decisions made by urban actors.

5.3 Methods

I explored influence of micro-level interactions on emerging landscape patterns by varying the preference for neighbourhood information in decisions related to land use transformation. I first mapped the components of the peri-urban SES to the SES Framework to define the building blocks of the model and then simulated the emergence of landscape pattern as already discussed in Chapter 2.

I now discuss how I used the model described in Chapter 2 and set up relevant experiments to test my core hypothesis.

Model description

I simulated the movement of urban actors and the resulting urban expansion into rural areas using a modified version of the reaction-diffusion equation (Chapter 2). A classic reaction-diffusion equation is a deterministic equation with a constant diffusion coefficient that regulates the movement of actors. In addition to the diffusion coefficient, I have included a factor (called cell score) that determines the direction of diffusion of urban actors based on the decisions made by the urban actors. I estimated the cell score numerically in the model (see equation 5.1 below).

At the start of a model run, the model initialised all cells in the landscape with a LULC class, LUZ, Z, and population including total population, urban population and rural population (see Chapter 2). Urban actors dominate the urban cells and rural actors dominated the non-urban cells. At every iteration, the urban actors collectively decided to move out of the cell, once the cell reached its carrying capacity, into one of the cells within the immediate neighbourhood window. The neighbourhood window consists of eight cells in the eight directions (N, E, W, S, N-E, N-W, S-E, and S-W). Dispersal of actors through space and resulting land-use change involves multiple interactions including the interaction of actors with the existing institutions such as land-use policies, other actors occupying the cell of interest and current

LULC conditions (Basse et al. 2016). In the model, the urban actors selected only those cells from the eight neighbourhood window where the land-use policies allowed land use transformation. Out of the selected cells, the urban actor group in the cell interacted with actors groups occupying the selected target cells to appropriate a cell for urban land use. These interactions were captured using game theory in the model (Chapter 2 and Chapter 4). In reality, urban actors have specific spatial neighbourhood preferences when selecting an area to develop (Aburas et al. 2016). In the model, I explicitly included local spatial factors that influence decision-making and land use transformation by urban actors (Barredo et al. 2003, Verburg et al. 2004, Verburg et al. 2006). The urban actors considered the LULC information of the cells in the vicinity of the potential target cells ((Verburg et al. 2006), henceforth, 'neighbourhood information') and had a choice to include the neighbourhood information when making decisions (Verburg et al. 2006, Aburas et al. 2016). The neighbourhood information was calculated as SI in the model using the submodule - Spatial neighbourhood Information (Chapter 2). All decisions were taken at the cell level by the actors. I captured the interactions of actors using the cell score. Once a cell with the highest score was selected, a fraction of the total urban actors in the cell moved into the selected cell. If the cell into which urban actors moved belonged to a non-urban class, the model reclassified the cell into urban built-up.

The model followed the process iteratively for all cells in the landscape for every iteration, to simulate the gradual build-up and expansion of urban actors into the peri-urban areas of a developing city.

The urban actors use the cell score calculated in the model using equation 5.1, to identify a suitable cell to move into:

$$\mathrm{CellScore} = \mathrm{Z}[\lambda\ \mathrm{SI} + (1-\lambda)\ \mathrm{GT}] \qquad \text{Equation 5.1}$$

The three variables were neighbourhood information (SI) interaction with rural actors (GT), and land-use zone (Z). For each iteration the model estimated the neighbourhood information (SI) using the enrichment factor given by Verburg et al. (2004). GT captured the interaction between the urban actors and the actors occupying the target cell. GT is the pay-off that urban actors receive on interacting with actors in the target cell. The pay-off indicates the benefits of moving into a target cell. Urban actors prefer to move into cells with higher pay-off. Parameter λ controlled the preference urban actors gave to the neighbourhood information against the preference they gave to the pay-off received as a result of interaction with actors in the target cell, when selecting a cell. Z is the score based on the LUZ of the target cell (Table 2.3). The description of sub-modules used to calculate SI, GT and LUZ-S is given in Chapter 2 (section 2.2.4).

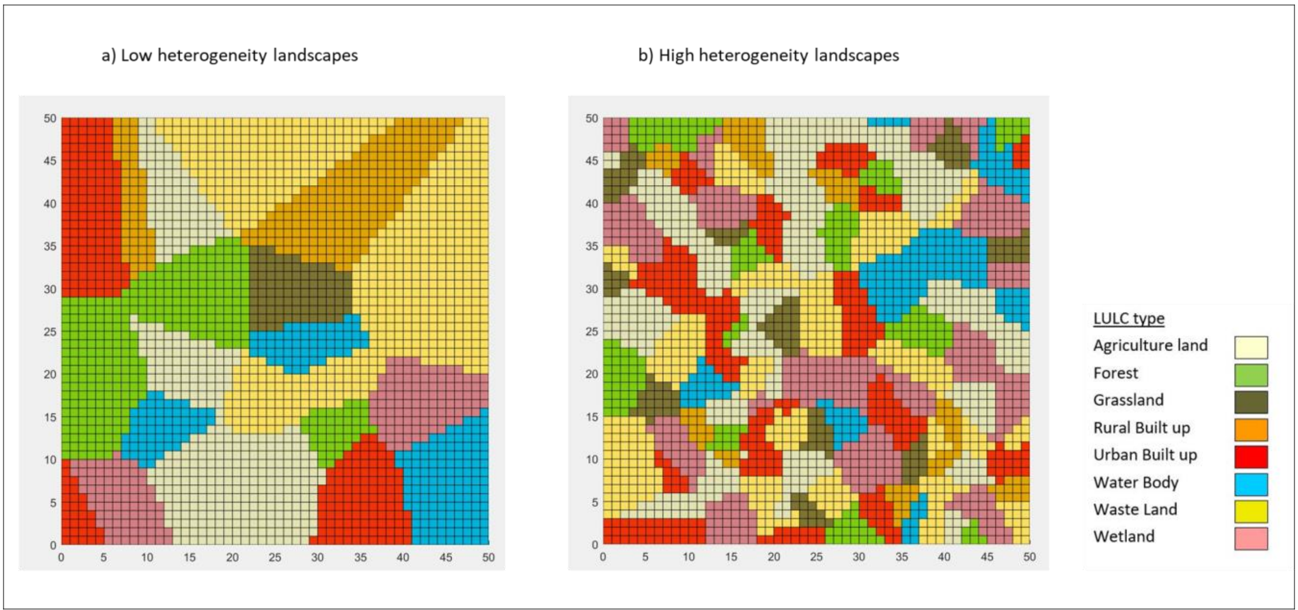

Figure 5-1: Example of (a) low and (b) high heterogeneity images developed for the model. Both datasets consisted of 50 images. The level of LULC heterogeneity was constant in each data set, however, the arrangement of patches varied within a data set.

Experimental design

The aim of the experiment was to capture the influence of existing landscape conditions and actors' decisions to include the neighbourhood information on the emerging landscape patterns. To capture the impact of varying landscape conditions I developed two sets of 50 simulated images using the NLMR package in R (Sciaini et al. 2018). The land units and actors had the same attributes as discussed in Chapter 2. However, the spatial heterogeneity of LULC classes varied for the two sets of images. The first set had (Figure 5-1 (a)) landscapes with low spatial heterogeneity and the second set (Figure 5-1(b)) had landscapes with higher spatial heterogeneity. Within each set, I maintained the degree of spatial heterogeneity as constant and changed the arrangement of patches among images of each set to induce variability in the dataset. I performed 150 iterations for both low and high heterogeneity landscapes. Each iteration corresponds to one year.

I varied the amount of neighbourhood information included in the decision-making by varying the weight parameter (λ, equation 5.1), from zero to 1 with a step size of 0.05 between each model run, for both high and low heterogeneity landscapes. A higher value of λ meant urban actors gave higher preference for the neighbourhood information as compared to the pay-off from the target cell. For example, λ = 0.5 means urban actors gave equal preference for both neighbourhood information and the target cell value in the decision making, and λ=0 means no neighbourhood information was included in the decision-making. In the model, the urban actors gave preference to the cells that had higher amount of urban neighbourhood (estimated as SI) and avoid converting cells closer to green spaces such as forests, wetlands and grasslands.

I compared the results for low and high heterogeneity landscapes across different level of neighbourhood information represented by value of λ . Each level corresponds to the weight given to the neighbourhood information in the land use transformation decisions made by the urban actors. There were in total 21 levels of neighbourhood information. Levels 1 to 21 correspond to λ, which varied from 0 to 1 with a step size of 0.05. Level 1 corresponds to $\lambda = 0$, which was the case when no neighbourhood information was included in the decision making and level 21 corresponds to $\lambda = 1$ when only neighbourhood information of the cell was included in the decision making.

Estimating outcomes and statistical analysis

I calculated the number of cells corresponding to green spaces left after urbanization and the number of urban cells in the landscape for each iteration.

Optimal distribution of land uses in the limited space along with preservation of green spaces is important for landscape sustainability in an urbanizing landscape and is also one of the aims of the land-use policies (Botequilha Leitão and Ahern 2002, Santo-Tomás Muro et al. 2020). The spatial pattern of a landscape influences social and ecological processes and in turn influences ecosystem goods and services (Banerjee et al. 2013). For example, spatial composition and configuration affects the species richness and interactions, and ecosystem processes such as nutrient retention and surface water run-off (Turner et al. 2012). Therefore, to test the success of policies in the peri-urban SES, I calculated the number of green spaces left after urbanization and also, estimated landscape metrics of the green spaces. Landscape metrics are standard measures used in ecology to quantify area of different patches (composition) and their shapes and relative positions (configuration) (Turner and Gardner 2015), that allow us to measure the spatial sustainability of a landscape and inform landscape planning and management (Botequilha Leitão and Ahern 2002).

Table 5.1 : Summary of spatial configuration and composition metrics. The change in landscape metrics of green spaces were estimated as outcomes in the peri-urban SES

Name of landscape metrics	Landscape Property	Description
Number of urban cells	composition	Total number of urban cells in the landscape
Number of green cells	composition	The number of green cells left in the landscape after urbanization. The model counted the cells belonging to forest, grassland, and wetland LULC together as green cells.
Total Patch Area of urban patches (PA)	composition	Sum of area occupied by green patches

Number of urban patches (NP)	composition	Total number of green patches
Edge Density (ED)	configuration	Measure of edges associated with shape complexity of the resulting green patches
Clumpy Index (CLUMPY)	configuration	Aggregation measure independent of landscape composition

In the model, urban actors converted the non-urban cells they appropriated in the landscape into urban cells at each iteration. Since the total land area was finite, the total number of urban cells reached a saturation point after a certain number of iterations. The saturation point was the point in time after which the number of cells per iteration did not change significantly. I used the *findchangepts* function of Matlab to detect the saturation point at which the slope of the curve first shifted (MATLAB 2016).

I calculated landscape metrics for green cells for each level of neighbourhood information at the start and end of urbanization and estimated the percentage change in the landscape metrics. The end of urbanization was set as the time when the slope reached the saturation point.

I checked for a confounding effect of initial landscape conditions (patch area, edge density, number of patches and clumpy index) on the percentage change in four landscape metrics for both high and low heterogeneity landscape using an Analysis of Covariance (ANCOVA) (Pourhoseingholi et al. 2012). I first performed ANOVA on the percentage change of each landscape metrics to assess if there was a statistically significant difference among group means across different level of neighbourhood information. I used the *aov* function in R to assess the significance of the outcome using p-value estimates (RCoreTeam 2019).

The null model provides a counterfactual by excluding the mechanism of interest (Gotelli and Graves 1996). I compared the percentage difference of each landscape metric across varying level of neighbourhood information against the null model to confirm whether the observed land use patterns were a result of a random process. The model run in which urban actors did not include any neighbourhood information in decision-making (λ = 0) was as used as the null model. I performed a two-sample t-test and estimated p-value to compare the result of null model against the resultant change in landscape metrics across different level of neighbourhood information.

In a landscape, patch area influences other landscape metrics (clumpy index, edge density, and number of patches) which may mask the actual relationship between varying level of neighbourhood information and the landscape metrics. I used partial constrained correspondence analysis (pCCA) to estimate the relative importance of neighbourhood information in explaining the variability in the clumpy index, edge density and number of urban patches. pCCA is an extension of constrained canonical analysis (CCA) which is used to perform the analysis by controlling the effects of covariates (Beasley and Kneale 2002). For the analysis, I used *CCA* in the *vegan* package of R (Oksanen et al. 2020). Percentage change of patch area metrics was set as covariate in the analysis. Implementation of pCCA report the inertia (or variability) that was explained by the level of neighbourhood information (independent variable) after accounting for the inertia explained by percentage change in patch area. I used permutation test to assess the significance of resultant pCCA models.

To compare the response of varying level of neighbourhood information in high and low heterogeneity landscapes I fitted curves to percentage change in patch area using the *nls* function in R and estimated the inflection point using the *inflection* package in R (Christopoulos 2019, RCoreTeam 2019). The inflection point gives the location on the curve where the percentage change in patch metrics was most sensitive to the level of neighbourhood information (Frazier and Wang 2013). In mathematics, statistics and economics, inflection points are used to identify statistical thresholds (Arin et al. 2021). It is a point where a change in the direction of curve occurs in a continuous function. To assess dissimilarity between two response curves I performed a two-sample Kolmogorov-Smirnov test (*ks.test* in R; RCoreTeam (2019). The results give a dissimilarity index D and p-value <0.05 implies that the two curves belong to different distribution.

5.4 Results

Number of urban cells, number of green cells, and saturation point

For both high and low heterogeneity landscapes the amount of urbanization decreased, and the number of green cells left after urbanization increased, with an increase in the level of neighbourhood information from 1 to 21 which is the change in λ .

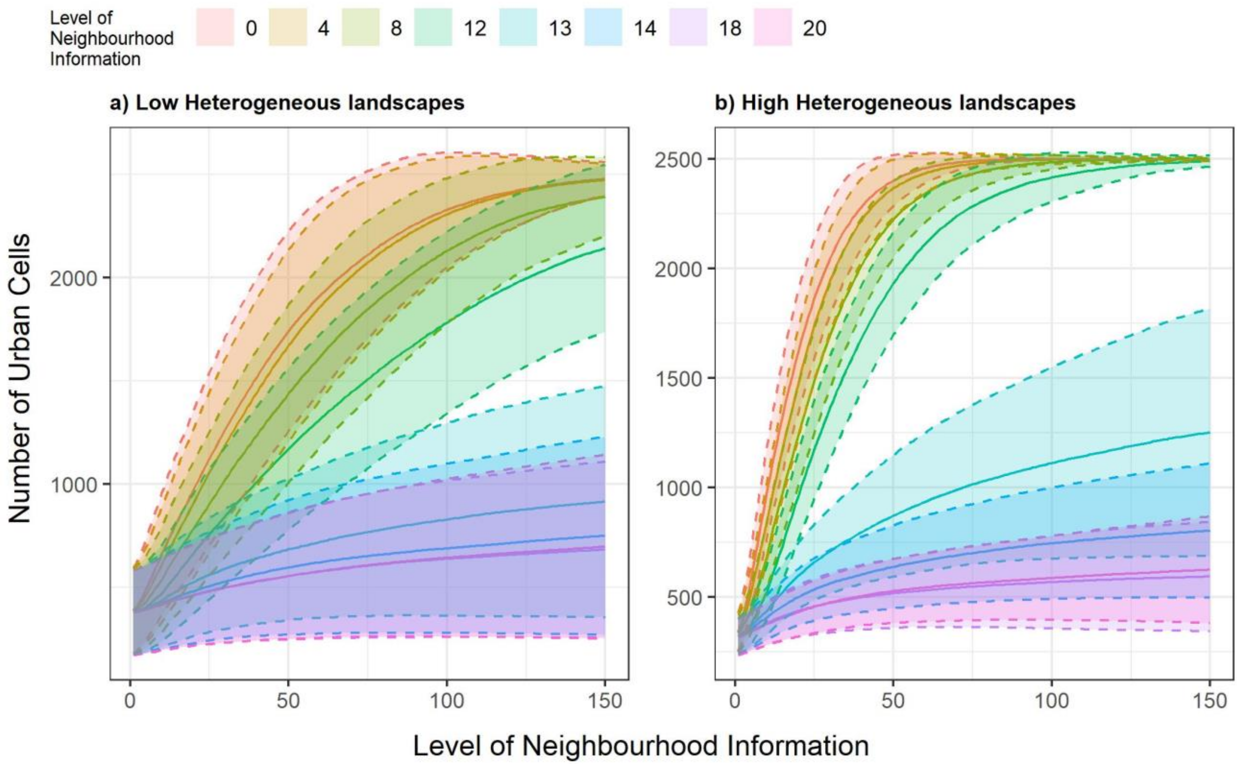

Figure 5-2: Number of urban cells per iteration for (a) low and (b) high heterogeneity landscapes from year 0 to 150. The vertical red lines shows the saturation point which is at year 44 for the low heterogeneity landscape and at year 28 for the heterogeneity landscapes. The solid lines represent the mean value of urban cells for all 50 images and area between dotted lines shows the standard deviation (variation) in the data. For neighbourhood level 16 and 20, there is complete overlap of the variation and mean values.

For both the high and low heterogeneity landscapes, the amount of urbanization decreased as the level of neighbourhood information increased in the decision making (Figure 5-2). At year 50 and level 4 (λ = 0.2), when preference for the neighbourhood information was low, the number of urban cells was high (~1750 for low heterogeneity landscapes and for ~2250 high heterogeneity landscapes, respectively). By contrast, for the same year, at level 12 (λ = 0.6) when the preference for neighbourhood information was high, the number of urban cells was low (~ 1300 for low heterogeneity landscapes and ~2150 for high heterogeneity landscapes, respectively). The results of the t-test suggest that the value of group means was different between the null model (level 0) and different levels of the neighbourhood for both high and low heterogeneity landscapes (p-value <0.05 for 50 images). For low heterogeneity landscapes, p-value was significant (p-value <0.05) from level 8 onwards (λ = 0.4) and for high heterogeneity landscapes, p-value significant (p-value< 0.05) from level 10.

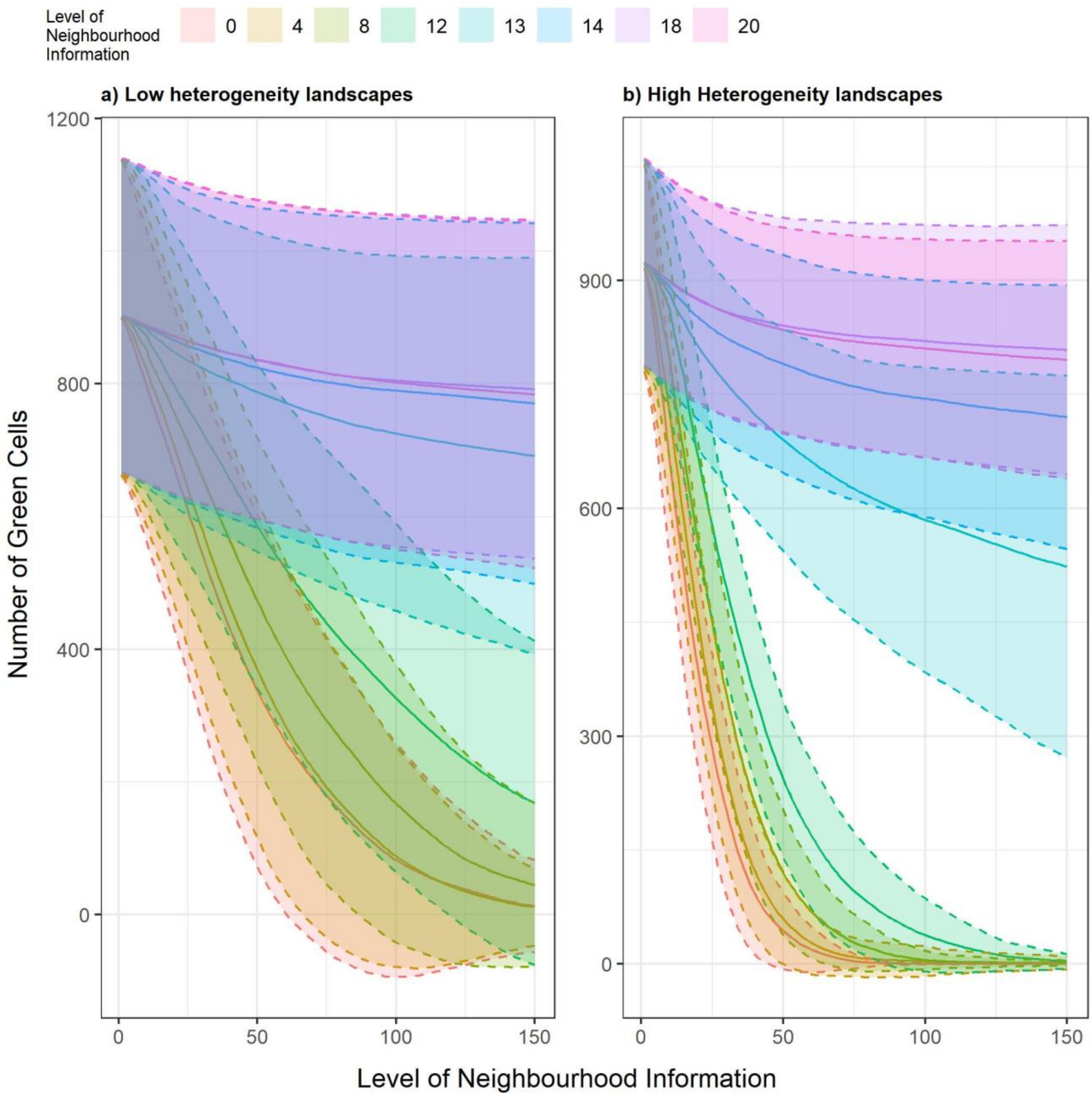

Figure 5-3: Number of green cells left after urbanization at every iteration for different levels of neighbourhood information for all the years for both (a) the low heterogeneity and (b) high heterogeneity landscapes. The solid line is the mean value of number of green cells at each level of neighbourhood information, averaged for all 50 images. The area under dotted line shows the variation in the data set. The number of green cells decrease as the urbanization progresses for low and high heterogeneity landscapes.

For both high and low heterogeneity landscapes, as the level of neighbourhood information increased the number of green spaces left after urbanization was higher (Figure 5-3). At year 50 and level 4, when the preference for the neighbourhood information was low, an average of 300 green cells were left after urbanization in the low heterogeneity landscapes and an average of 150 green cells were left in the high heterogeneity landscapes. By contrast, at level 12 (λ= 0.6) when preference for the neighbourhood information was higher, an average of 450 green cells were left in the low heterogeneity landscapes and an average of 200 green cells were left in the high heterogeneity landscape. The results of the null model for the number of green cells left after urbanization were found to be the same as in the case of number of urban cells. In addition, for both high and low heterogeneity landscapes, there was a significant change in outcome at level 13 in number of urban cells and number of green spaces.

The response of urbanization was different for both the high and low heterogeneity landscapes. At level 1 (λ = 0.05), for the high heterogeneity landscapes the urban cells reached saturation point at year 28 whereas for the low heterogeneity landscapes time taken to reach the saturation point was 44 years (Figure 5-2). In addition, the total number of green cells left at the saturation point across all levels of neighbourhood information varied between low and high heterogeneity landscape. For example, at level 1, the amount of green space left after urbanization was high for the low heterogeneity landscapes (~290 cells) compared to the high heterogeneity landscapes (~183 cells).

Landscape metrics of green spaces

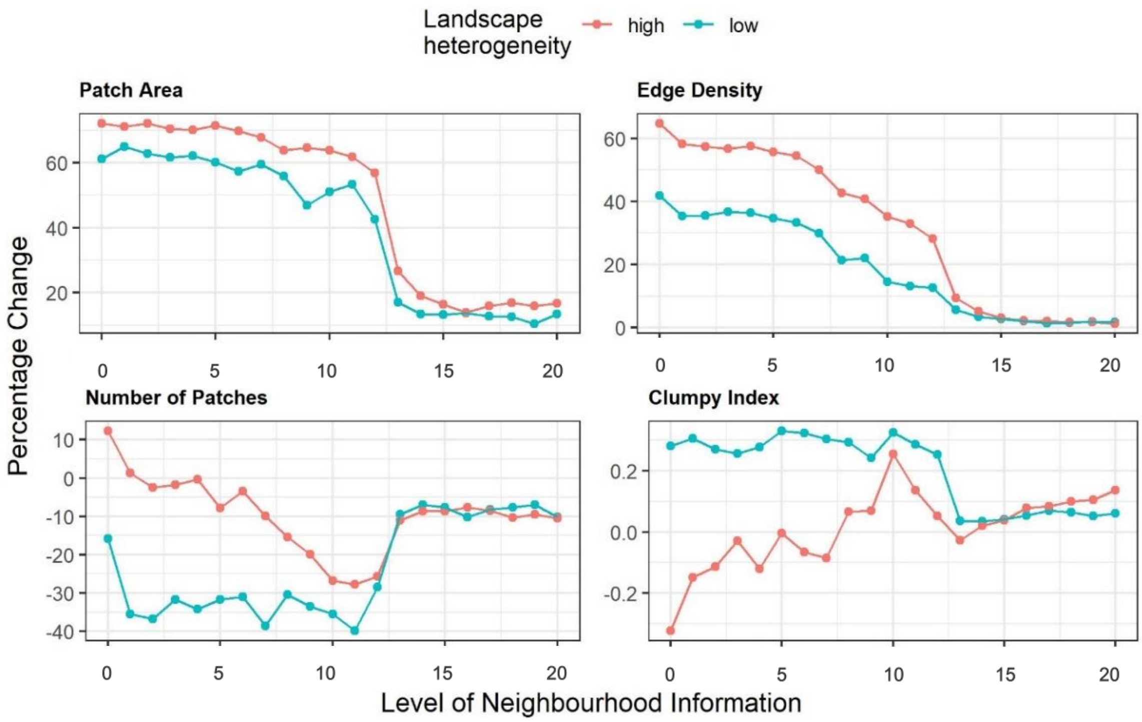

Figure 5-4: Percentage change in landscape metrics of green spaces for both the high and low heterogeneity landscapes

The percentage change in the landscape metrics, for both the high and low heterogeneity landscapes at their respective saturation point, varied across the level of neighbourhood information. However, once the level of neighbourhood information reached beyond 0.62, the change in the landscape metrics almost coincided for both the landscapes across all four landscape metrics.

The result of the one-way ANOVA test showed no confounding effect of values of the initial landscape metrics on the percentage change estimated for the landscape metrics after urbanization for the dataset of 50 images (p-value <0.05).

The results of the t-test suggest that value of group means was different between the null model and different level of neighbourhood for both patch area and edge density, for both the high and low heterogeneity landscapes (p-value <0.05 for 50 images). However, the null model analysis was different for the high and low heterogeneity landscape for clumpy index and number of patches. For clumpy index and number of patches, the difference between group means of the null model and different level of neighbourhood was significant (p-value <0.05) in the high heterogeneity landscapes but not significant in the low heterogeneity landscape.

Multivariable Analysis using partial constrained correspondence analysis

Multivariate analysis using pCCA of the percentage change in the three landscape metrics (NP, Clumpy index and ED) with level of neighbourhood information as the explanatory variable and percentage change in patch area as the covariate showed that most of the variability in the three metrics was explained by conditional variable which was the percentage change in patch area. This was true for both the low and high heterogeneity landscapes. For the low heterogeneity landscapes, 80.6% of variation was explained by percentage change in in patch area, whereas 2% of variation was explained by neighbourhood information. For the high heterogeneity landscapes, 83.7% of variation was explained by percentage change in patch area and 5.9% of variation was explained by neighbourhood information. The permutation test showed that pCCA models was significant for both low (F = 6.359, p = 0.01) and high (F = 29.621, p = 0.01) heterogeneity landscapes (See appendix D, Figure C.5)

Curve fitting and patch area metrics

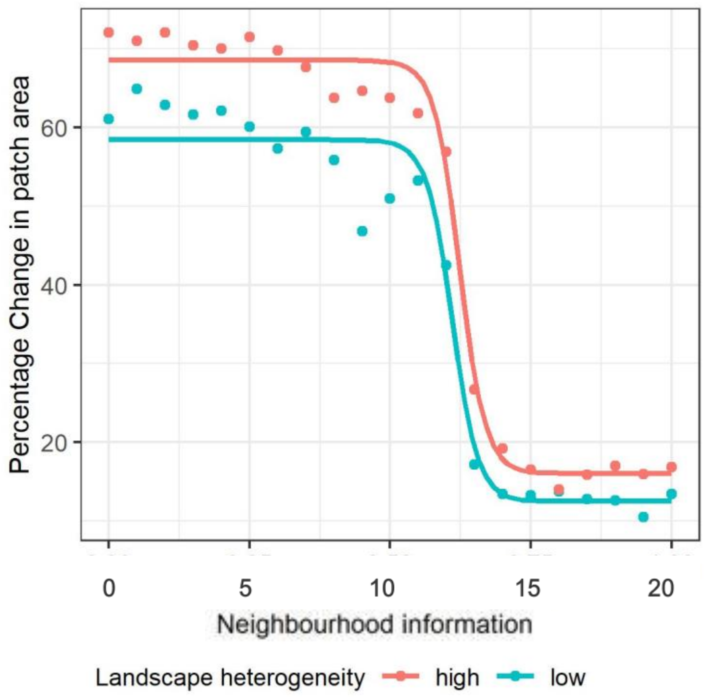

Figure 5-5: Normalized and transformed values of percentage change in patch area of green spaces for both high (orange) and low heterogeneity (blue) landscapes with corresponding fitted curves.

The response of change in the patch area was non-linear to the varying level of neighbourhood information (Figure *5*-*5*). For both the high and low heterogeneity landscapes, change in the patch area followed a sigmoid curve with r-square >0.95 for both the curves. The Kolmogorov-Smirnov test showed that the two curves were significantly dissimilar from each other (D = 0.45, p <0.05). The curves follow a similar pattern and with the inflection point at λ = 0.625 which lies between level 13 and 14 of the neighbourhood information, for both the curves. However, the magnitude of percentage change for the high heterogeneity landscapes was higher as compared to the low heterogeneity landscapes. For example, at the inflection point, the percentage change in patch area was 41.31% for the high heterogeneity landscapes and for the low heterogeneity landscapes; it was comparatively lower (28.43%).

5.5 Discussion

My results demonstrate that, under the assumptions and conditions of the model, urban actors can effectively regulate emerging landscape patterns and conserve green spaces during urbanization by explicitly including spatial neighbourhood information of the land units in their decision making. Hersperger et al. (2013) have shown that actors influenced the process of urbanization, particularly land use densities in different Swiss cities depending on choices and decisions actors made at the local level. In the model, actors selected a target cell based on the benefits the actors received from transforming a target cell and the LULC in the neighbourhood of the target cell. If the actors emphasised more on the benefits from the target cell as their decision criteria for land use transformation, the amount of urbanization increased and the number of green spaces left after urbanization decreased. However, when the actors preferred the land units within the urban neighbourhoods the number of suitable land units was limited which influenced the amount of urbanization and therefore, the number of urban cells decreased as the preference for neighbourhood information increased. In addition, number of green spaces preserved increased. The results confirmed that decisions made at the local level by urban actors influenced the resulting landscape level patterns of green spaces for both the high and low heterogeneity landscapes.

The results of the null model analysis show a significant difference between group means for the amount of urbanization and the number of green spaces between level zero and the rest of the levels, for both high and low heterogeneity landscapes. Similarly, the null model analysis for landscape metrics shows a significant difference between group means of patch area at level zero vs rest of the levels of neighbourhood information for both high and low heterogeneity landscapes. It is clear that the results were not random and neighbourhood information, when included in the decision making at local level, had a significant influence on the emerging landscape patterns (Koch et al. 2019).

One of the several measures of spatial sustainability in urbanizing landscapes is the number of green spaces preserved (Santo-Tomás Muro et al. 2020). In the model, the urban actors made spatially conscious decisions and preferred to transform the cells which had a higher amount of urban neighbourhood. In the process, the actors avoided the cells which had more green spaces in their neighbourhood. The local level decisions also influenced the land-use policies that update the land use zones of the cells periodically based on the existing LULC of the landscape. Therefore, local level decisions together with land-use policies preserved more green spaces as the amount of spatial information increased in the decision making. However, the number of green spaces alone is not a sufficient measure of landscape sustainability. The pattern of green patches also influences underlying ecological processes and ecosystem services in a landscape (Botequilha Leitão and Ahern 2002, Turner and Gardner 2015).

For the patterns observed in the case of a clumpy index, edge density, and the number of patches, I found that the patch area metrics heavily confounded the variation observed in each of the three landscape metrics. Flather and Bevers (2002) have shown that the patch area is enough to explain landscape-level changes than the spatial patterns themselves. In the model, patch area metrics explained most of the variation in emerging landscape patterns across varying levels of neighbourhood information. Therefore, for further analysis, I focussed on the results of patch area metrics.

The results of the null model analysis show that the change in patch area metrics followed a non-random response for both low and high heterogeneity landscapes, which allowed the response to be readily modelled. The changes in patch area for low and high heterogeneity landscapes followed a non-linear, sigmoid, curve as the weight of the neighbourhood information changed. Existing spatial conditions influenced decisions made across social levels and the outcomes in an SES as observed in the case of forests (Sharma et al. 2016) and fisheries (Leslie et al. 2015). Zasada et al. (2017) have also acknowledged the influence of existing spatial heterogeneity on decision-making and landscape policies. There was a difference in the resultant patterns for the low and high heterogeneity landscapes. I observed that magnitude of change was different for the high and low heterogeneity landscapes even though the response curve followed a similar trend for the two sets of landscapes. The inflection point or the statistical threshold at which a significant change in the patch area of green spaces was observed, was the same for both high and low heterogeneity landscapes (at around $\lambda = 0.62$). However, the percentage change in patch area was higher for the high heterogeneity landscapes as compared to the low heterogeneity landscapes. It was further confirmed by the results of the number of urban cells and the number of green spaces, where a significant difference was observed between levels 12 and 13 (at around level 0.62) for both high and low heterogeneity landscapes. However, the number of green spaces left after urbanization was higher for low heterogeneity landscapes compared to high heterogeneity landscapes.

The landscape conditions such as LULC heterogeneity influences the decisions at the local spatial level, which in turn affects the resulting landscape patterns. In addition, the distance between the two curves reduced after the inflection point (at neighbourhood level = 0.625). This further indicates that by giving higher preference for the neighbourhood conditions at local levels, local actors can mask the influence of existing landscape heterogeneity on the emerging landscape patterns to some extent. However, the resulting patterns may vary depending on the initial landscape conditions.

To allow simplified and systematic analysis of mechanisms in complex systems I limited the number of variables and parameters in the model, as recommended for such analysis (Gotelli and Graves 1996, Ostrom 2005, Cumming et al. 2012). I have limited the neighbourhood effect to the cells among the immediate neighbours. However, spatial correlation can exist beyond this immediate neighbourhood and decays with distance (Barredo et al. 2003, Verburg et al. 2006). Therefore, a more realistic understanding of the neighbourhood effect would include cells beyond those that are directly adjacent. In addition, in a transforming landscape the preferences of urban actors for certain neighbourhoods includes various factors that may both attract and repel (Barredo et al. 2003, Verburg et al. 2006). For example, repulsion might occur when actors seeking residential land choose to stay away from an industrial neighbourhood. In the model, the urban actors only consider the 'attraction' factor; further research is needed on the influence of negative spatial externalities that cause 'repulsion' among land use parcels.

Harnessing local spatial information

In a landscape, information about the classes is the interface between existing landscape conditions including biophysical and ecological features and the local social interactions and decision-making process (Hersperger et al. 2018). The LULC in the spatial neighbourhood is one of the factors that influence decisions of land use transformation at local level and is an integral part of various land dynamic studies (Barredo et al. 2003, Verburg et al. 2004). It is based on Tobler's first law of geography, "everything is related to everything else, but near things are more related than distant things" (Tobler 1970). I show that urban actors can contribute to informed decision-making in an urbanizing landscape by harnessing local spatial information such as LULC information to make spatially conscious decisions.

Motivation to include urban actors in landscape governance

Peri-urban areas typically suffer from weak landscape governance resulting in various socio-economic-environmental issues such as urban sprawl, poor infrastructure, insecure land tenure, social conflicts, and loss of ecosystem goods and services (Nuhu 2018). Plans and policies for natural resource management in peri-urban areas also suffer from the problem of scale and ecological misfit (Epstein et al. 2015, Cheok et al. 2020). Urban planners and policymakers often initiate broad-scale decisions such as declaring an area as a conservation zone or transforming land use for building highways or industries, yet urban sprawl remains common in peri-urban areas (Zhang et al. 2019). It is difficult for actors from urban centres to understand the intrinsic and dynamic geographic relationships that exist in a peri-urban SES, due to peri-urban SESs being spatially remote and disconnected from the more stable urban political centres (Shaw 2005).

Ostrom has suggested including local actors in the decision making for effective natural resource management (Ostrom 1990) . To strengthen landscape governance in areas going through transitions, local actors must be involved in landscape governance (Nuhu 2018). Local rural actors, such as farmers and landowners, have local knowledge, specific needs and requirements, and insights into economic and societal rationales including knowledge of social conflict. Urban actors, on the other hand, often have limited local knowledge and understanding of the complexities involved in a peri-urban SES. However, urban actors have unique characteristics that emphasise the involvement of urban actors in decision-making and planning for the effective management of resources in peri-urban SES. Urban actors are spatially 'extra-regional'; they typically come from beyond the urban periphery and interact with peri-urban areas at a fine spatial scale (Morrison 2007). The governmental policies around urbanization are influenced by the needs and demands of urban actors (Patil et al. 2018). Urban actors are capable of ‘jumping scale’ as they are politically more connected to the planners and policymakers in the urban centres than rural actors (Morrison 2007). By engaging both urban and rural actors more actively in peri-urban policy making and setting up collaborations, planners can harness social networks to achieve sustainable outcomes in human-dominated social-ecological systems (Ernstson et al. 2010).

Motivations for urban actors to participate in landscape governance in peri-urban areas

Urban actors are often known to appropriate resources and influence land use transformations in peri-urban areas with limited understanding of the social-ecological implications of their actions (Tidball and Stedman 2013). In addition, traditional environmental studies about stewardship patterns for conservation of natural spaces emphasize upon indigenous knowledge and long-standing association of rural communities with place (Gurney et al. 2017). However, non-native dwellers such as urban actors can be custodians of natural spaces and contribute to conserving them (Sarker 2020, Sen and Nagendra 2020). Complex SESs with a diversity of actors, such as peri-urban areas, call for approaches that involve new settlers, non-native dwellers, and non-local actors. Involving urban actors as an integral part of the SES along with opportunities to engage can encourage and reinforce their involvement and stewardship for ecological sustainability such as conservation of green spaces that will allow urban actors to nurture a positive dependency on the resource (Tidball and Stedman 2013, Murphy et al. 2019).

5.6 Conclusion

The actor groups in a peri-urban SES are diverse and each has unique characteristics and roles to play in contributing to the better management of resources in a peri-urban SES. Non-native actors such as urban actors can contribute to addressing social and ecological mismatch in policies related to peri-urban areas by making spatially conscious decisions at the local level and therefore, can regulate the cross-scale feedback between landscape and landscape governance. To implement Ostrom’s design principle 3 in a peri-urban area requires adapting the design principle by including diverse actor groups in the decision making based on their unique characteristics.

In the following chapter I summarize my findings and give a broad picture of how my thesis contributes to extend SES theory.

Chapter 6 : General discussion

SES theory embedded in complex adaptive systems gives an opportunity to understand land use change systems as a coupled SES. I have explored the applicability of Ostrom's design principle 2 and 3 for large scale spatially dynamic SES, such as peri-urban SESs. I have sought to test and reflect upon how Ostrom's design principles and commons approach can be used and extended to accommodate dynamic concepts of space and scale relevant to peri-urban SESs.

6.1 Key findings

Chapter 2: The model

There has been a shift from using models for prediction to using models to understand and explain the complexities in a system by focussing on a subset of variables and processes (Moallemi et al. 2020). Treating models as 'boundary objects' with a unifying platform to bring multiple disciplines and perspectives together in SES studies (Parker et al. 2008). In Chapter 2, I explain how I developed an exploratory modelling approach to systematically test hypotheses and investigate the relevance of the design principles for a spatially dynamic SES.

Specifically, I used the SES Framework to guide model development for a peri-urban SES. The SES Framework has primarily been used as a diagnostic tool for small-scale common pool resources, with characteristics such as single-resource use, homogenous actors, and defined system boundaries. However, the focus has now shifted to using the SES Framework for large and complex SESs (Partelow 2018). I operationalised the SES Framework by developing a model to facilitate spatially explicit analysis of the interactions in a peri-urban SES. In the model, I explored feedback and cross-scale interactions between spatial and institutional scales to answer multiple questions of space and scale relevant to peri-urban governance. The influence of interactions and feedback between actors' decisions at the cell level, land-use policies defined at regional spatial scales and the existing spatial conditions of the landscape on the emerging landscape level spatial patterns were explored.

I used a modified reaction-diffusion approach to develop a GIS-based hybrid-CA model which is simple and scalable. The model captures the movement of urban population into peri-urban areas and emerging land-use patterns as outcomes using the reaction-diffusion equation. The model captures decisions taken by actors at the cell level. The urban actors collectively take a decision at the cell level to move into non-urban cells and transform the cells into urban land use. The urban actors select locations for urban land use based on the social and ecological characteristics of the cells in the neighbourhood. In the model, the urban actors take decisions to select a cell based on a set of criteria including land-use policies of the target cell (governance system), the response of rural actors already occupying the target cell (lateral interactions), and the LULC in the immediate neighbourhood of the target cell (spatial contextual information). The urban actors first select the cells for which the land-use policies allowed land use transformation. Rural and urban actor groups then interact at the cell level, where rural actor groups may resist the decision to transform cells dominated by the rural actors. Further, urban actors may decide only to transform cells based on the LULC of other cells in the neighbourhood of the target cell. I developed sub modules to calculate the three factors and integrate concepts of game theory and spatial context with the reaction-diffusion equation.

Chapter 3: Institutional misfit

I explored the question of institutional fit between the governance system and the spatial characteristics of a landscape in a spatially dynamic SES. As per design principle 2, there should be congruence between the rules and local ecological conditions (Ostrom 1990, Cox et al. 2010). However, in a peri-urban SES the ecological conditions of the landscape vary and are subjective to the spatial extent considered. Therefore, the term local is elusive in the case of peri-urban SES. To inform the term local for design principle 2, I explored the environmental feedbacks between institutions and landscape heterogeneity.

The spatial heterogeneity of the landscape underpins the ecological patterns and the ecological conditions that influence the land-use policy in urbanizing landscapes. I explored the influence of landscapes for two different levels of spatial heterogeneity on land-use policies and resulting land-use zones. In a landscape, spatial heterogeneity in a landscape is sensitive to spatial extent. I tested the influence of varying spatial scales of decision-making on the emerging landscape patterns for high and low heterogeneity landscapes. I found that for the design principle to be effective in a spatially dynamic landscape, the spatial extent of decision-making should not be limited to administrative boundaries but should also consider the existing landscape conditions such as the spatial heterogeneity of LULC classes.

Institutional misfit is a common problem in the management of natural resources (Epstein et al. 2015). The spatial fit of institutions is further complicated when the landscapes are dynamic. The results of chapter 3 suggest that the spatial extent of decision making shouldn't be fixed as usually is the case in small-scale common pool resources but should be flexible to include the spatial dynamics of the landscape (Dressel et al. 2018).

Chapter 4: Rural Urban interactions

Ostrom's design principle 3 emphasises on the participation in the design of local rules and decision making (Ostrom 1990). Involving actors in the decision-making improve the outcomes for natural resource management. However, actors can collectively make decisions resulting in successful outcomes if they exhibit trust, social cohesion, and reciprocity among themselves (Baggio et al. 2016). In a peri-urban SES, the actors are heterogeneous and often have conflicting resource use interests.

Heterogeneity among actors is a common characteristic of a large complex SES, which contributes to a lack of successful outcomes in an SES (Fleischman et al. 2014a). Conflict among actors can lead to unexpected outcomes in an SES (Murunga et al. 2021). It is often hard to understand the relationship between actor heterogeneity and outcomes due to various interacting factors (Fleischman et al. 2014a). Using the model, I have explored the influence of conflict among rural and urban actors on the emerging landscape patterns by limiting the number of influencing factors in the model.

In Chapter 4, I explored the influence of conflict among urban and rural actors on landscape level patterns in an urbanizing landscape using a combination of game theory and reaction-diffusion model (Hadzikadic et al. 2010). I used the Hawk and Dove model from game theory to capture the interactions among the urban and rural actors at the cell level. The response of rural actor group varied from cell to cell in a landscape at every iteration, which influenced the decision of urban actors to transform cells for urban land use and therefore, influenced the resulting land use patterns. I found that the emerging landscape patterns were non-linear, and the response of each landscape metrics varied for the same level of resistance among the rural actors. This shows that the impact of the interactions among actors is a complex aggregation process at the landscape level. Further, the non-random patterns suggest that conflicts among actors can be modelled which provides an opportunity for informing policies. For example, the inflection points estimated in the case of patch area metrics, number of patches, and clumpy index can contribute to identifying social-ecological tipping points.

The chapter emphasises on involving actors in decision making and recognizing conflict among actors for governing resources in a spatially dynamic SES. The chapter is an attempt to go beyond the usual discussion of collaborative governance rules and explore the influence of actor appropriation and resistance on the ecological outcomes in a large SES (Morrison et al. 2020b).

Chapter 5 : Spatial Neighbourhood Information

As landscapes are continually transforming, there is a need for a revised definition of actors and their involvement in the decision-making process (Sarker 2020). Design principle 3 emphasises the participation of local actors in decision making because they have local knowledge and have an understanding of the complexities involved in an SES (Ostrom 1990). However, a peri-urban SES is unique in terms of the actors involved. Non-local urban actors who come from within the city centres to appropriate resources from a peri-urban SES lack sufficient knowledge and understanding of the implication of their actions on the SES outcomes (Tidball and Stedman 2013). However, they have a strong influence on the process of urbanization and the policies that influence the peri-urban SES (Purushothaman and Patil 2017).

In Chapter 5, I explored how actors with limited local knowledge can contribute to informed decision-making. In the model, urban actors influenced the landscape level patterns by explicitly including the local spatial information in their decision making at the cell level. The results of this chapter show that existing landscape conditions, such as landscape heterogeneity, can influence outcomes in an SES. By explicitly including the spatial information in their decision making urban actors can regulate the influence of existing landscape conditions on emerging landscape patterns. I combined ideas from land system studies and the commons approach by harnessing local spatial information actors with limited knowledge can contribute to informed decision-making.

Chapter 5 shows that to implement Ostrom's design principle 3 in a peri-urban SES, it is important to recognize diversity among actor groups and their unique characteristics and accordingly adapt the design principle for the effective governance of resources in the SES.

6.2 Contribution to SES Research

In summary, my research has contributed to SES theory in two broad ways. First, I have extended the commons approach for natural resource governance by exploring the relevance of the design principles for a spatially explicit dynamic SES. Second, I have also contributed to a more holistic understanding of land-use change as a set of complex interactions between social and ecological systems. I explain each of these contributions in turn below.

Contribution to the commons approach

I have operationalised the SES Framework for a spatially dynamic system and explored the applicability of design principles in a peri-urban SES.

In the SES Framework and related studies, ecological components and theories are often overlooked or are not explicitly included in understanding their influence on outcomes (Vogt et al. 2015, Partelow 2018). I have explicitly included the ecological dimension of the peri-urban SES represented by spatial heterogeneity of the LULC classes as landscape conditions. I explored the influence of landscape conditions on the interactions and the outcomes in the SES. For example, I interrogated the influence of spatial heterogeneity on spatial scale of decision-making in Chapter 3 and showed how the spatial heterogeneity and decisions at finer spatial scale together influence the landscape level patterns in an urbanizing landscape in Chapter 5.

In an SES involving a terrestrial resource system such as a peri-urban SES, the associated spatial properties of the components significantly influence the dynamics of the SES and therefore should be included in the analysis. However, the implications of spatial properties in the context of design principles remain elusive. I focussed on spatial extent and spatial context as two spatial properties (other than landscape heterogeneity). In Chapter 3, I demonstrated the influence of varying spatial extent on the social-ecological feedbacks and outcomes in the SES. Decision-making at the local spatial level was also influenced by the local spatial conditions such as the presence or absence of certain LULC classes in the neighbourhood (Verburg et al. 2006). In Chapter 5, I explored the potential of using spatial neighbourhood information or spatial contextual information explicitly for informed decision making by the urban actors at local level.

In addition, each chapter explores the applicability of the design principles in a peri-urban SES.

The results of Chapter 3, for example, show that design principle 2 could guide the issue of spatial fit between institutions and landscape by aligning the spatial extent of local decision making with spatially sensitive local ecological processes.

A peri-urban SES consists of heterogeneous actors that have multiple and contested land use interests, varying influence on the policy-making and different levels of local knowledge. The results of Chapter 4 show that to apply design principle 3 which suggests involving those affected by rules in the decision-making, it is important to account for the heterogeneity among actors (Patterson 2017). The heterogeneity among actors and resultant conflict lead to the emergence of non-linear responses, which provides both challenges and opportunity to address sustainable management of resources.

The dominant actors in a large-scale complex SES may not be the ones with sufficient local knowledge and understanding of the complexities (Patterson 2017). In Chapter 5, I have shown that by explicitly including local neighbourhood information in their decision making, social actors can compensate for lack of knowledge and contribute to informed decision-making.

Contribution to land-use change studies and land-use change models

In the last few decades, researchers have developed various models to predict LULC change and urbanization (Mustafa et al. 2017). However, there is an increasing need to develop theories and models for land use change analysis through the lens of social-ecological systems (Verburg et al. 2019). The models are expected to capture the complexity of social-ecological systems including actors, institutions and spatially explicit interactions. On one hand, CA-based models are simple and rule-based, which are useful in exploring self-organizing systems. On the other hand, ABM models can explicitly include actors' behaviour unlike CA-based models (Gotts et al. 2019, Ren et al. 2019). However, ABM based models are specific to case studies and require a large amount of ground data (Ren et al. 2019). With the availability of high processing computing systems and visualization methods, researchers are now developing hybrid models which explicitly include actors' behaviour and spatially explicit interactions (Mustafa et al. 2017, Pratomoatmojo 2018). My model falls in the category of the hybrid models which combines a rule-based approach (for land-use policies updated), and explicitly includes actors' behaviour at the cell level (game theory) and spatial interactions among cells (spatial neighbourhood) using the cell score in a reaction-diffusion equation. The model explores the interactions and feedback among various components of a peri-urban SES including actors' decisions, landscape conditions, and land-use policies and their influence on the landscape-level patterns using simulated data. The aim of the model is to explore and test hypotheses instead of predicting land-use patterns by operationalizing the SES framework. The model, therefore, contributes to recent studies (Foster and Iaione 2019, Myers 2020) that are exploring the design principles and the SES framework for urban and peri-urban settings. Further, from a modelling perspective, the model includes a limited number of variables which makes it simple and tractable. It is also scalable and can be expanded to include more variables for future use.

The Land-Use Policy sub-module captures the changes in the LUZs for each cell influenced by emerging landscape patterns, using a rule-based approach. In Chapter 3, I used the submodule to explore environmental feedbacks (Wu and Hobbs 2002) between institutions and landscape heterogeneity to address the question of spatial fit, thus, contributing to a better understanding of the cross-scale dynamics in land use change (Seppelt et al. 2018). Researchers have shown that actors' decision at local level influence the policies (Hersperger et al. 2013). In the model, I have included implicit feedbacks between actors and land-use policies. Actors make decision at local level that influence the landscape level patterns which in turn influence the land-use policies as land-use policies are updated based on the existing landscape patterns at the time t.

Verburg et al. (2015) and Verburg et al. (2019) have emphasised on the need to account for variation in interactions among decision-makers at local level and resulting cross-scale dynamics in land use change. I have used game theory based Hawk and Dove model together with the reaction-diffusion equation to explore the varying social interactions at a fine spatial scale and resulting cross-scale dynamics in Chapter 4. The results of Chapter 4 show that understanding and modelling the dynamics of interactions among the actors and emerging landscape patterns can contribute to identifying SES tipping points and exploring new transition pathways in dynamic landscapes (Milkoreit et al. 2018, Mathias et al. 2020, Morrison et al. 2020b).

Researchers in land use studies have recognized the importance of spatial autocorrelation and resulting structural spatial dependencies and interactions in emerging land use patterns (Verburg et al. 2006). In Chapter 5, I have shown how the dynamics between neighbourhood spatial patterns and local level decisions can be harnessed to understand self-organization and emergent land use patterns in a landscape.

6.3 Limitations

There are three main limitations to this study. First, I have used simulated images to represent the terrestrial resources system. I have focused on two dimensional (2-D) features such as water bodies, grasslands and forest patches, however, in a landscape; there are also linear or one-dimensional features (1-D) such as roads that may affect the dynamics of the landscape and preferences of the actors (Roques & Bonnefon 2016). For example, the presence of a road network may increase the connectivity and proximity to the market for the rural actors, which may influence their decisions to comply or resist land use transformations (in Chapter 4) and eventually may affect the emergence of land use patterns. Further, combining single urban land use is not sufficient to capture heterogeneous preferences among actors, as there are different kinds of urban built-up with different needs and preferences such as industrial areas vs residential areas.

Second, the actors form a complex mosaic in a peri-urban SES. It is hard to have a clear distinction between actors' choices in a peri-urban SES (Nagendra et al. 2013). I have focused on a broad category of urban and rural actors where urban actors are the ones appropriating land specifically for urban land use and have a comparatively higher influence on policymaking. I have included the diversity among actors' responses in Chapter 4 in form of change in the percentage of actors resisting the land use transformation. Further, in Chapter 5 I have included changes in preferences among urban actors with change in LULC classes in the spatial neighbourhood. However, the diversity among actors is much more complex and dynamic in a peri-urban SES. For example, rural-urban migration influences the preferences of actors to land use transformations. The choices of actors and their attributes vary along the rural-urban continuum, which does not necessarily follow a fixed gradient (Vidyarthi et al. 2017, Murali et al. 2019). For example, the changes in biophysical factors such as depletion of sufficient water quantity in a local neighbourhood and spatial dynamics such as the development of a road network influence actors' preferences for different land uses as the landscape urbanizes. The socio-spatial patterns also influence actors' preferences for land use transformations such as peer-influence to sell land in urban fringes influences landscape heterogeneity and emerging land use patterns (Koch et al. 2019, Narain 2021). In addition, there is a need to include the economic variables that influence actors' decision and resulting spatial patterns (Magliocca et al. 2015) .

Finally, the multi-tiered structure of the SES Framework provides a rich set of variables to organize and support model building and hypothesis testing for larger SESs (Binder et al. 2013). However, I found that the original SES Framework has limitations and lacks sufficient support for exploring dynamics including feedbacks (Partelow and Winkler 2016, Anderies et al. 2019). This can be because the structure of feedback and interactions among components of the system beyond tier-one of the SES Framework are not explicitly identified (Anderies et al. 2019). For example, resource users and governance system components of the first tier identify the user groups and social components. However, it is difficult to structure the interactions explicitly among heterogeneous actors, say rural and urban actors, in an SES using the SES Framework.

6.4 Recommendations

Methodological challenges

To keep the model simple and tractable, I have made some assumptions and included limited variables in the model that may limit the outcomes. However, there are various spatial, social and economic that influence actors' decisions that need to be integrated in the model for a better understanding of human-decision making. Linear spatial features such as the presence of a road network or a river stream influence the decisions for land use transformation. The linear features can be included as an additional spatial layer in the model. However, there are dynamics associated with the features such as the development of a new road network as the urbanization progresses and it may influence actors' decisions at later stages of urbanization. Models such as EFFortS-LGraf by Salecker et al. (2019) can generate simulated scenarios for agricultural landscapes. The output of the EEForts-LGraf model can be used as input to my model to include the effect of linear features. In addition to spatial variables, there is a need to explore the influence of economic variables on actors' decisions and behaviour. One way to do this is to explore economic agent based-models (Magliocca et al. 2015). Another assumption in the model was that only urban actors migrated and moved away from the city centre. However, migration is a two-way process which may influence the outcomes. The next challenge is to include migration as a factor in the model.

Ways to extend the Ostrom's SES Framework

I have shown that the SES Framework with its multi-tiered structure allows mapping of complexities involved in a peri-urban SES. However, the interactions within a peri-urban SES are spatially dynamic and continually evolving. Scholars favor a gradient approach over a rural-urban dichotomy to address the complexities in a peri-urban SES (Nagendra et al. 2013). For example, actors' choices are dynamic and transformative along the continuum. Therefore, it would be interesting to analyze actors' preferences in a larger spatial and social context. One way to do so would be to connect the SES Framework with the Ecosystem Services concept (Partelow and Winkler 2016). Ecosystem service choices often vary among actors in peri-urban areas depending on their socio-economic and spatial attributes such as level of income, gender, education and access to natural resources and markets (Murali et al. 2019). Using Ecosystem Services choices as indicators can help in addressing the dynamics in actors' choices based on their spatial locations and social preferences.

In a landscape, the spatial units are interlinked and change in a particular land use influences the LULC in the neighbourhood and related ecological functions in the landscape (Verburg et al. 2006, Banerjee et al. 2013). This in turn influences the ecosystem services and flows (Banerjee et al. 2013), actors' preferences (Chapter 5) and rules (Chapter 3). To understand the interactions in a dynamic landscape it is important to include the interlinkages among resource units within a resource system explicitly. The concept of Ecosystem Services can help in extending the SES Framework to include the interlinkages in a landscape. However, the concept of Ecosystem Services includes an understanding of Ecosystem Services flows, trade-offs and Ecosystem Services bundles. The next challenges is to look for suitable methods to include the concept of Ecosystem Services with the SES framework.

Further, I suggest using the SES Framework with a combination of other frameworks that include different components of an SES and feedbacks more explicitly such as the robustness framework for answering the questions of dynamics, trade,-offs and resilience in an SES (Anderies et al. 2019). One such framework is the Coupled Infrastructure Systems (Anderies et al. 2004, Anderies et al. 2016, Anderies et al. 2019) framework, where the interactions among SES components are explicit, including a typology to describe the process that further helps in addressing the dynamics and feedbacks involved in an SES.

Urban planning and civic engagement for peri-urban areas

To have higher civic engagement between the policy makers, planners, and the different stakeholders it is important to recognize the potential of actors to self–organise. For example, actors with limited local knowledge (Chapter 5) or with limited influence on policy-making (Chapter 4) can influence the emerging landscape patterns. Therefore, I recommend that planners and policy managers consider the sufficient representation of different group of actors in planning exercises. Planning across different spatial scales should also take into account baseline landscape heterogeneity (Chapter 5). However, in my thesis I have only explored two design principles. The next challenge is to explore the suitability of other design principles in the context of landscape studies.

Linking the design principles to land system science

Operationalizing Ostrom's design principles particularly for larger SESs such as terrestrial SESs requires understanding the concept of space and spatial dynamics as potential factors that influence the interplay between the components of the SES including institutions (Cumming 2011). The application of design principles and analysis of institutions in a spatially explicit context can benefit from the integration of theories related to land system change such as theories of land-use spill overs and displacement, land-sparing, intensification and rebound effects (Meyfroidt et al. 2018). For example, the theory of leakage and indirect land use change explains the effect of land use change at local and distant places, resulting from policy interventions at the national or regional level (Meyfroidt et al. 2018, Turner et al. 2020) and therefore, in turn, can facilitate the exploration of the causal relations or mechanisms of interactions and their outcomes at broader spatial scale (Cumming et al. 2020).

There is a gap in theoretical understanding of the causal interplay between ecological dynamics and institutions (Cumming and Epstein 2020, Cumming et al. 2020). On the other hand, there is an increased emphasis on addressing land use changes as integrated social-ecological systems with explicit attention to institutions (Turner et al. 2012, Meyfroidt et al. 2018, Turner et al. 2020). Linking design principles to the developments in land use change studies through theories and frameworks can further contribute to addressing this gap. For example, Turner et al. (2020) has proposed a framework that aims at explaining the causal variables related to land use change by including the most of the variables and interlinkages existing in a land system. They have explicitly included links to biophysical subsystems and the institutions in the framework. Similarly, using Ecosystem Services concept can be useful as it connects the ecosystem function and structures to the human well-being (Millennium Ecosystem 2005, Meyfroidt et al. 2018). Such frameworks and concepts can contribute to addressing the gaps in contextual understanding of the interlinkages between institutions and biophysical processes across scales (Turner et al. 2020).

6.5 Conclusion

In conclusion, I have used a model based approach to explore and provide new insights into the spatial interplay between governance and landscape change and extend SES theory for spatially explicit SES. I have used an explanatory model approach to test Ostrom's Design Principles for large-scale dynamic SES. The model is scalable and can be easily extended to include additional variables and theories.

The thesis contributes to ongoing research in the area of large, complex, and dynamic SES using Ostrom's design principles (Cox 2014, Tyson 2017). I have particularly focussed on design principle 2 and 3. I have shown that for the design principles to be effective researchers have to adapt the design principles to include the unique characteristics of a peri-urban SES including evolving institutions, actor heterogeneity, and spatial characteristics of the terrestrial resource system.

The institutions in a dynamic SES such as peri-urban SES are continually evolving and spatial characteristics including LULC patterns of the resource system influence the evolution of institutions. I have shown that to operationalize design principle 2 for a spatially dynamic SES, one has to explicitly define the term 'local' as relative rather than fixed that is, as a spatial extent of decision-making based on landscape heterogeneity. The analysis thus extends the understanding of the fit between landscape governance and spatial processes for large SESs.

The complex and dynamic landscapes such as peri-urban SES have diverse groups of actors each with unique characteristics, such as limited local knowledge, conflicting resource-use, and varying levels of influence on institutions and policies. The actors' interactions at the fine spatial scale in the SES vary, which influences the response of emerging landscape level patterns. Therefore, to include the local actors in the decision making as emphasised in design principle 3, one must account for actor heterogeneity and the potential of actor resistance in achieving ecosystem sustainability.

I also conclude that actors with limited local knowledge can contribute to informed decision making in urbanizing landscapes by explicitly considering the neighbourhood LULC to inform their choices for land use transformation. In a peri-urban SES where often the policymakers are spatially distant from the urban periphery, the urban actors can bridge the gap between policymakers at urban centres and peri-urban areas by making spatially conscious decisions at local level and therefore, can regulate the cross-scale feedback between landscape and landscape governance.

In sum, by operationalizing design principles for a terrestrial resource system with multiple land use, I have shown how SES theory offers the opportunity to address questions and inform solutions for landscape governance from the systems thinking perspective. The thesis contributes to extending existing SES theory to better understand feedbacks and cross-scale interactions in dynamic SESs, thus contributing to a more general, quantitative theory for social-ecological systems.

References

Aburas, M. M., Y. M. Ho, M. F. Ramli, and Z. H. Ash'aari. 2016. The simulation and prediction of spatio-temporal urban growth trends using cellular automata models: A review. International Journal of Applied Earth Observation and Geoinformation **52**:380-389.

Agarwal , C., G. M. Green, J. M. Grove, T. P. Evans, and C. M. Schweik. 2002. A Review and Assessment of Land-Use Change Models: Dynamics of Space, Time, and Human Choice.

Agrawal. 2001. Common property institutions and sustainable governance of resources. World Development **29**:1649-1672.

Agrawal. 2002. Common resources and institutional sustainability.*in* E. Ostrom, T. Dietz, N. Dolšak, P. C. Stern, S. Stovich, and E. U. Weber, editors. The Drama of the Commons. National Academic Press, Washington DC.

Aldwaik, S. Z., and R. G. Pontius. 2012. Intensity analysis to unify measurements of size and stationarity of land changes by interval, category, and transition. Landscape and Urban Planning **106**:103-114.

Allen, A. 2003. Environmental planning and management of the peri-urban interface: perspectives on an emerging field. Environment and Urbanization **15**:135-147.

Anderies, J. M., O. Barreteau, and U. Brady. 2019. Refining the Robustness of Social-Ecological Systems Framework for comparative analysis of coastal system adaptation to global change. Regional Environmental Change **19**:1891-1908.

Anderies, J. M., M. A. Janssen, and E. Ostrom. 2004. A framework to analyze the robustness of social-ecological systems from an institutional perspective. Ecology and Society **9**:18.

Anderies, J. M., M. A. Janssen, and E. Schlager. 2016. Institutions and the performance of coupled infrastructure systems. International Journal of the Commons **10**.

Anderies, J. M., A. A. Rodriguez, M. A. Janssen, and O. Cifdaloz. 2007. Panaceas, uncertainty, and the robust control framework in sustainability science. Proc Natl Acad Sci U S A **104**:15194-15199.

Arin, P., M. Minniti, S. Murtinu, and N. Spagnolo. 2021. Inflection Points, Kinks, and Jumps: A Statistical Approach to Detecting Nonlinearities. Organizational Research Methods.

Arkema, K. K., G. M. Verutes, S. A. Wood, C. Clarke-Samuels, S. Rosado, M. Canto, A. Rosenthal, M. Ruckelshaus, G. Guannel, J. Toft, J. Faries, J. M. Silver, R. Griffin, and A. D. Guerry. 2015. Embedding ecosystem services in coastal planning leads to better outcomes for people and nature. Proc Natl Acad Sci U S A **112**:7390-7395.

Austin, G. D. 2012. Multi-Functional Ecological Corridors in Urban Development. International Journal of Urban and ExtraUrban Studies **2**.

Baggio, J. A., A. J. Barnett, I. Perez-Ibarra, U. Brady, E. Ratajczyk, N. Rollins, C. Rubiños, H. C. Shin, D. J. Yu, R. Aggarwal, J. M. Anderies, and M. A. Janssen. 2016. Explaining success and failure in the commons: the configural nature of Ostrom's institutional design principles. International Journal of the Commons **10**.

Banerjee, O., N. D. Crossman, and R. S. de Groot. 2013. Ecological Processes, Functions and Ecosystem Services. Ecosystem Services in Agricultural and Urban Landscapes.

Bankes, S. 1993. Exploratory Modeling for Policy Analysis. Operations Research **41**:435-449.

Barredo, J. I., M. Kasanko, N. McCormick, and C. Lavalle. 2003. Modelling dynamic spatial processes: simulation of urban future scenarios through cellular automata. Landscape and Urban Planning **64**:145-160.

Basawaraja, R., K. B. Chari, S. R. Mise, and S. B. Chetti. 2011. Analysis of the impact of urban sprawl in altering the land-use, land-cover pattern of Raichur city, India using geospatial technologies. Journal of Geography and Regional Planning **4**:455-462.

Basse, R. M., O. Charif, and K. Bódis. 2016. Spatial and temporal dimensions of land use change in cross border region of Luxembourg. Development of a hybrid approach integrating GIS, cellular automata and decision learning tree models. Applied Geography **67**:94-108.

Baur, I., and C. R. Binder. 2013. Adapting to Socioeconomic Developments by Changing Rules in the Governance of Common Property Pastures in the Swiss Alps. Ecology and Society **18**.

Beasley, G., and P. E. Kneale. 2002. Contamination risk and in-stream ecological stress: metals, PAHs and macroinvertebrates.*in* British Hydrological Society's 8th National Hydrology Symposium. Hydrology and Earth System Science, Birmhingam.

Beilin, R., N. Reichelt, and T. Sysak. 2013. Resilience in the Transition Landscapes of the Peri-urban: From 'Where' with 'Whom' to 'What'. Urban Studies **52**:1304-1320.

Bell, J., and T. Morrison. 2014. A Comparative Analysis of the Transformation of Governance Systems: Land-Use Planning for Flood Risk. Journal of Environmental Policy & Planning **17**:516-534.

Bennett, E. M., M. Solan, R. Biggs, T. McPhearson, A. V. Norström, P. Olsson, L. Pereira, G. D. Peterson, C. Raudsepp-Hearne, F. Biermann, S. R. Carpenter, E. C. Ellis, T. Hichert, V. Galaz, M. Lahsen, M. Milkoreit, B. Martin López, K. A. Nicholas, R. Preiser, G. Vince, J. M. Vervoort, and J. Xu. 2016. Bright spots: seeds of a good Anthropocene. Frontiers in Ecology and the Environment **14**:441-448.

Bennett, N. J., and T. Satterfield. 2018. Environmental governance: A practical framework to guide design, evaluation, and analysis. Conservation Letters **11**.

Benson, D. l., J. a. Sherratt, and P. k. Main. 1993. Diffusion driven instability in an inhomogeneous domain. Bulletin of Mathematical Biology **55**.

Berkes, F., J. Colding, and C. Folke. 2002. Navigating Social–Ecological Systems.

Bian, Z. X., S. Wang, Q. B. Wang, M. Yu, and F. K. Qian. 2018. Effects of urban sprawl on arthropod communities in peri-urban farmed landscape in Shenbei New District, Shenyang, Liaoning Province, China. Sci Rep **8**:101.

Biggs, R., A. d. Vos, R. Preiser, H. Clements, K. Maciejewski, and M. Schlüter. 2021. The Routledge Handbook of Research Methods for Social-Ecological Systems.

Binder, C. R., J. Hinkel, P. W. G. Bots, and C. Pahl-Wostl. 2013. Comparison of Frameworks for Analyzing Social-ecological Systems. Ecology and Society **18**.

Bluemling, B., H. S. Tai, and H. Choe. 2021. Boundaries, limits, landscapes and flows: An analytical framework for boundaries in natural resource management. J Environ Manage **285**:112129.

Boonstra, B., and L. Boelens. 2011. Self-organization in urban development: towards a new perspective on spatial planning. Urban Research & Practice **4**:99-122.

Borgström, S. T., T. Elmqvist, P. Angelstam, and C. AlfsenNorodo. 2006. Scale Mismatches in Management of Urban Landscapes. Ecology and Society **11**.

Botequilha Leitão, A., and J. Ahern. 2002. Applying landscape ecological concepts and metrics in sustainable landscape planning. Landscape and Urban Planning **59**:65-93.

Bragagnolo, C., C. Rizzi, and S. Staniscia. 2014. A Multi-scale Approach to Support Integrated Landscape Management in Rural Mountainside Areas (RMAs) of Alps. Pages 61-88 *in* C. Rega, editor. Landscape Planning and Rural Development.

Braimoh, A. K., and T. Onishi. 2007. Spatial determinants of urban land use change in Lagos, Nigeria. Land Use Policy **24**:502-515.

Burdett, R., and P. Rode. 2018. Shaping cities in an Urban Age. Phaidon.

Butsch, C., and S.-B. Heinkel. 2020. Periurban Transformations in the Global South and Their Impact on Water-Based Livelihoods. Water **12**.

Campos, P. R., A. Rosas, V. M. de Oliveira, and M. A. Gomes. 2013. Effect of Landscape Structure on Species Diversity. PLoS One **8**:e66495.

Cash, D. W., W. N. Adger, F. Berkes, P. Garden, L. Lebel, P. Olsson, L. Pritchard, and O. Young. 2006. Scale and cross-scale dynamics: Governance and information in a multilevel world. Ecology and Society **11**.

Cattarino, L., C. A. McAlpine, and J. R. Rhodes. 2014. Land-use drivers of forest fragmentation vary with spatial scale. Global Ecology and Biogeography **23**:1215-1224.

Cerquetti, M., C. Nanni, and C. Vitale. 2019. Managing the landscape as a common good? Evidence from the case of "Mutonia" (Italy). Land Use Policy **87**.

Charnley, S., T. A. Spies, A. M. G. Barros, E. M. White, and K. A. Olsen. 2017. Diversity in forest management to reduce wildfire losses: implications for resilience. Ecology and Society **22**.
Chen, Y. 2009. Spatial interaction creates period-doubling bifurcation and chaos of urbanization. Chaos, Solitons & Fractals **42**:1316-1325.
Cheok, J., R. Weeks, T. H. Morrison, and R. L. Pressey. 2020. Scalar capital as ingredient of success in conservation governance: evidence from Melanesia. Global Environmental Change **62**.
Chirisa, I. 2010. An Analysis of the Environmental Stewardship Concept and Its Applicability in Peri-Urban Towns: Lessons from Epworth In Zimbabwe. Journal of Sustainable Development in Africa **12**.
Cho, S. H., K. Thiel, P. R. Armsworth, and B. P. Sharma. 2019. Effects of Protected Area Size on Conservation Return on Investment. Environ Manage **63**:777-788.
Christophe, B., and R. Tina. 2015. Integrating water resource management and land-use planning at the rural–urban interface: Insights from a political economy approach. Water Resources and Economics **9**:45-59.
Christopoulos, D. T. 2019. inflection: Finds the Inflection Point of a Curve.
Cox, M. 2008. Balancing accuracy and meaning in common-pool resource theory. Ecology and Society.
Cox, M. 2012. Diagnosing Institutional Fit: a Formal Perspective. Ecology and Society **17**.
Cox, M. 2014. Understanding large social-ecological systems: introducing the SESMAD project. International Journal of the Commons **8**:265-276.
Cox, M., G. Arnold, and S. V. Tomas. 2010. A Review of Design Principles for Community-based Natural Resource Management. Ecology and Society **15**.
Cumming, G. 2002. Habitat shape, species invasions, and reserve design: Insights from simple models. Conservation Ecology **6**.
Cumming, G. 2011. Spatial Resilience in Social-Ecological Systems. Springer.
Cumming, G., J. Southworth, X. J. Rondon, and M. Marsik. 2012. Spatial complexity in fragmenting Amazonian rainforests: Do feedbacks from edge effects push forests towards an ecological threshold? Ecological Complexity **11**:67-74.
Cumming, G. S. 2014. Theoretical Frameworks for the Analysis of Social–Ecological Systems. Pages 3-24 Social-Ecological Systems in Transition.
Cumming, G. S., and G. Epstein. 2020. Landscape sustainability and the landscape ecology of institutions. Landscape Ecology.
Cumming, G. S., G. Epstein, J. M. Anderies, C. I. Apetrei, J. Baggio, Ö. Bodin, S. Chawla, H. S. Clements, M. Cox, L. Egli, G. G. Gurney, M. Lubell, N. Magliocca, T. H. Morrison, B. Müller, R. Seppelt, M. Schlüter, H. Unnikrishnan, S. Villamayor-Tomas, and C. M. Weible. 2020. Advancing understanding of natural resource governance: a post-Ostrom research agenda. Current Opinion in Environmental Sustainability **44**:26-34.
Dancette, R., and L. Sebastien. 2019. The Actor in 4 dimensions: A relevant methodology to analyze local environmental governance and inform Ostrom's social-ecological systems framework. MethodsX **6**:1798-1811.
Das, N. D. 2017. Land-Use Dynamics of Peri-Urban Areas of Metropolitan Cities with Special Focus on Delhi. Pages 21-41 Marginalization in Globalizing Delhi: Issues of Land, Livelihoods and Health.
Dressel, S., G. Ericsson, and C. Sandström. 2018. Mapping social-ecological systems to understand the challenges underlying wildlife management. Environmental Science & Policy **84**:105-112.
Elmi, M., A. Rouhani, and E. Keshavarz. 2022. Landscape Metrics for Urbanization and Urban Land-Use Change Monitoring from Remote Sensing Images : A case of Shiraz Metropolis, Iran. International Journal of Earth Sciences Knowledge and Applications **4**.
Elmqvist, T., M. Fragkias, J. Goodness, B. Güneralp, P. J. Marcotullio, R. I. McDonald, S. Parnell, M. Schewenius, M. Sendstad, K. C. Seto, and C. Wilkinson. 2013. Urbanization, Biodiversity and Ecosystem Services: Challenges and Opportunities.
Elsawah, S., T. Filatova, A. J. Jakeman, A. J. Kettner, M. L. Zellner, I. N. Athanasiadis, S. H. Hamilton, R. L. Axtell, D. G. Brown, J. M. Gilligan, M. A. Janssen, D. T. Robinson, J. Rozenberg, I. I. T. Ullah, and S.

J. Lade. 2020. Eight grand challenges in socio-environmental systems modeling. Socio-Environmental Systems Modelling **2**.
Epstein, G., T. H. Morrison, A. Lien, G. G. Gurney, D. H. Cole, M. Delaroche, S. Villamayor Tomas, N. Ban, and M. Cox. 2020. Advances in understanding the evolution of institutions in complex social-ecological systems. Current Opinion in Environmental Sustainability **44**:58-66.
Epstein, G., I. Pérez, M. Schoon, and C. L. Meek. 2014. Governing the invisible commons: Ozone regulation and the Montreal Protocol. International Journal of the Commons **8**.
Epstein, G., J. Pittman, S. M. Alexander, S. Berdej, T. Dyck, U. Kreitmair, K. J. Rathwell, S. Villamayor-Tomas, J. Vogt, and D. Armitage. 2015. Institutional fit and the sustainability of social–ecological systems. Current Opinion in Environmental Sustainability **14**:34-40.
Epstein, G., J. M. Vogt, S. K. Mincey, M. Cox, and B. Fischer. 2013. Missing ecology- integrating ecological perspectives with the ses framework. International Journal of the Commons **3**.
Ernstson, H. 2011. Transformative collective action: a network approach to transformative change in ecosystem-based management.*in* Ö. Bodin and H. C. Prell, editors. Social Networks and Natural Resource Management: Uncovering the Social Fabric of Environmental Governance. Cambridge University Press.
Ernstson, H., S. E. van der Leeuw, C. L. Redman, D. J. Meffert, G. Davis, C. Alfsen, and T. Elmqvist. 2010. Urban transitions: on urban resilience and human-dominated ecosystems. Ambio **39**:531-545.
Evans, L. S., N. C. Ban, M. Schoon, and M. Nenadovic. 2014. Keeping the 'Great' in the Great Barrier Reef: large-scale governance of the Great Barrier Reef Marine Park. International Journal of the Commons **8**.
Evans, T. P., A. M. York, and E. Ostrom. 2008. Institutional Dynamics, Spatial Organization, and Landscape Change.*in* J. L. J. Wescoat; and D. M. Johnston, editors. Political Economies of landscape change.
Fazal, S., N. Banu, and S. Sultana. 2015. Expanding Cities, Contested Land: Role of Actors in the Context of Peri-Urban Interface. Current Urban Studies **03**:187-198.
Field, A., J. Miles, and Z. Field. 2012. Discovering Statistics Using R. SAGE.
Filatova, T., P. H. Verburg, D. C. Parker, and C. A. Stannard. 2013. Spatial agent-based models for socio-ecological systems: Challenges and prospects. Environmental Modelling & Software **45**:1-7.
Fischer, A. P. 2018. Forest landscapes as social-ecological systems and implications for management. Landscape and Urban Planning **177**:138-147.
Fisher, R. A. 1936. The wave of advance of advantageouse genes. Annals of Human Genetics:15.
Flather, C. H., and M. Bevers. 2002. Patchy reaction-diffusion and population abundance: the relative importance of habitat amount and arrangement. Am Nat **159**:40-56.
Fleischman, F. D., N. C. Ban, L. S. Evans, G. Epstein, G. Garcia-Lopez, and S. Villamayor-Tomas. 2014a. Governing large-scale social-ecological systems: Lessons from five cases. International Journal of the Commons **8**:428-456.
Fleischman, F. D., B. Loken, G. A. Garcia-Lopez, and S. Villamayor-Tomas. 2014b. Evaluating the utility of common-pool resource theory for understanding forest governance and outcomes in Indonesia between 1965 and 2012. International Journal of the Commons **8**.
Foley, J. A., R. Defries, G. P. Asner, C. Barford, G. Bonan, S. R. Carpenter, F. S. Chapin, M. T. Coe, G. C. Daily, H. K. Gibbs, J. H. Helkowski, T. Holloway, E. A. Howard, C. J. Kucharik, C. Monfreda, J. A. Patz, I. C. Prentice, N. Ramankutty, and P. K. Snyder. 2005. Global consequences of land use. Science **309**:570-574.
Folke, C., S. Carpenter, T. Elmqvist, L. Gunderson, and B. Walker. 2021. Resilience: Now more than ever : This article belongs to Ambio's 50th Anniversary Collection. Theme: Anthropocene. Ambio **50**:1774-1777.
Foster, S. R., and C. Iaione. 2019. Ostrom in the City: Design Principles and Practices for the Urban Commons.*in* B. Hudson, J. Rosenbloom, and D. Cole, editors. Routledge Handbook of the Study of the Commons.

Frate, L., S. Saura, M. Minotti, P. Di Martino, C. Giancola, and M. Carranza. 2014. Quantifying Forest Spatial Pattern Trends at Multiple Extents: An Approach to Detect Significant Changes at Different Scales. Remote Sensing **6**:9298-9315.

Frazier, A. E., and L. Wang. 2013. Modeling landscape structure response across a gradient of land cover intensity. Landscape Ecology **28**:233-246.

Gabriel Ling Hoh Teck, Nor Eeda Haji Ali , Ho Chin Siong, and H. M. Ali. 2014. Ostrom's Design Principles in Residential Public Open Space Governance : Conceptual Framework and Literature Review. INTERNATIONAL JOURNAL OF BUILT ENVIRONMENT AND SUSTAINABILITY **1**.

Gari, S., A. Newton, J. Icely, and M. M. Delgado-Serrano. 2017. An Analysis of the Global Applicability of Ostrom's Design Principles to Diagnose the Functionality of Common-Pool Resource Institutions. Sustainability **9**.

Gashu Adam, A. 2020. Urban Built-Up Property Formation Process in the Peri-Urban Areas of Ethiopia. Land Use Change and Sustainability.

Gomes, S. L., and L. M. Hermans. 2016. Institutions in transitioning peri-urban communities: spatial differences in groundwater access. Proceedings of the International Association of Hydrological Sciences **373**:125-129.

Görg, C. 2007. Landscape governance. Geoforum **38**:954-966.

Gotelli, N. J., and G. R. Graves. 1996. Null Models in Ecology. Simthsonian Institution Press.

Gotts, N. M., G. A. K. van Voorn, J. G. Polhill, E. d. Jong, B. Edmonds, G. J. Hofstede, and R. Meyer. 2019. Agent-based modelling of socio-ecological systems: Models, projects and ontologies. Ecological Complexity **40**.

Grimm, V., U. Berger, D. L. DeAngelis, J. G. Polhill, J. Giske, and S. F. Railsback. 2010. The ODD protocol: A review and first update. Ecological Modelling **221**:2760-2768.

Gunderson, L. H., and C. S. Holling. 2003. Panarchy: Understanding Transformations In Human And Natural Systems.

Gurney, G. G., J. Blythe, H. Adams, W. N. Adger, M. Curnock, L. Faulkner, T. James, and N. A. Marshall. 2017. Redefining community based on place attachment in a connected world. Proc Natl Acad Sci U S A **114**:10077-10082.

Haase, D., N. Frantzeskaki, and T. Elmqvist. 2014. Ecosystem services in urban landscapes: practical applications and governance implications. Ambio **43**:407-412.

Hadzikadic, M., T. Carmichael, and C. Curtin. 2010. Complex Adaptive Systems and Game Theory: An Unlikely Union. Complexity **16**:34-42.

Hamby, D. M. 1994. A review of techniques for parameter sensitivity analysis of environmental models. Environ Monit Assess **32**:135-154.

Hedblom, M., E. Andersson, and S. Borgström. 2017. Flexible land-use and undefined governance: From threats to potentials in peri-urban landscape planning. Land Use Policy **63**:523-527.

Herse, M. R., P. O. B. Lyver, N. Scott, A. R. McIntosh, S. C. Coats, A. M. Gormley, and J. M. Tylianakis. 2020. Engaging Indigenous Peoples and Local Communities in Environmental Management Could Alleviate Scale Mismatches in Social–Ecological Systems. BioScience **70**:699-707.

Hersperger, A. M., M.-P. Gennaio Franscini, and D. Kübler. 2013. Actors, Decisions and Policy Changes in Local Urbanization. European Planning Studies **22**:1301-1319.

Hersperger, A. M., E. Oliveira, S. Pagliarin, G. Palka, P. Verburg, J. Bolliger, and S. Grădinaru. 2018. Urban land-use change: The role of strategic spatial planning. Global Environmental Change **51**:32-42.

Hesselbarth, M. H. K., M. Sciaini, K. A. With, K. Wiegand, and J. Nowosad. 2019. landscapemetrics : an open-source R tool to calculate landscape metrics. Ecography **42**:1648-1657.

Hettiarachchi, M., C. McAlpine, and T. H. Morrison. 2013. Governing the urban wetlands: a multiple case-study of policy, institutions and reference points. Environmental Conservation **41**:276-289.

Hettiarachchi, M., T. H. Morrison, and C. McAlpine. 2019. Power, politics and policy in the appropriation of urban wetlands: the critical case of Sri Lanka. The Journal of Peasant Studies **46**.

Hettiarachchi, M., T. H. Morrison, D. Wickramsinghe, R. Mapa, A. De Alwis, and C. A. McAlpine. 2014. The eco-social transformation of urban wetlands: A case study of Colombo, Sri Lanka. Landscape and Urban Planning **132**:55-68.

Holling, C. S. 2001. Understanding the complexity of Economic, Ecological and Social Systems. Ecosystems **4**:15.
Holling, C. S., and A. D. Chambers. 1973. Resource Science: The Nurture of an Infant. BioScience **23**:13-20.
Huang, Q., C. Xu, W. Jiang, W. Yue, Q. Rong, Z. Gu, and M. Su. 2021. Urban compactness and patch complexity influence PM2.5 concentrations in contrasting ways: Evidence from the Guangdong-Hong Kong-Macao Greater Bay Area of China. Ecological Indicators **133**.
Hunsicker, M. E., C. V. Kappel, K. A. Selkoe, B. S. Halpern, C. Scarborough, L. Mease, and A. Amrhein. 2016. Characterizing driver-response relationships in marine pelagic ecosystems for improved ocean management. Ecol Appl **26**:651-663.
Huntjens, P., L. Lebel, C. Pahl-Wostl, J. Camkin, R. Schulze, and N. Kranz. 2012. Institutional design propositions for the governance of adaptation to climate change in the water sector. Global Environmental Change **22**:67-81.
India, C. o. https://www.censusindia.gov.in/DigitalLibrary/MFTableSeries.aspx.
India, G. o. 2013. National Land Utilization Policy (Draft).*in* G. o. I. Department of Land Resources, editor.
Izakovičová, Z., F. Petrovič, and E. Pauditšová. 2021. The Impacts of Urbanisation on Landscape and Environment: The Case of Slovakia. Sustainability **14**.
Jafarpour Ghalehteimouri, K., A. Shamsoddini, M. N. Mousavi, F. Binti Che Ros, and A. Khedmatzadeh. 2022. Predicting spatial and decadal of land use and land cover change using integrated cellular automata Markov chain model based scenarios (2019–2049) Zarriné-Rūd River Basin in Iran. Environmental Challenges **6**.
Jagers, S. C., N. Harring, A. Lofgren, M. Sjostedt, F. Alpizar, B. Brulde, D. Langlet, A. Nilsson, B. C. Almroth, S. Dupont, and W. Steffen. 2020. On the preconditions for large-scale collective action. Ambio **49**:1282-1296.
Jin, M., R. Feng, L. Wang, and J. Yan. 2021. A Study of Diffusion Equation-Based Land-Use/Land-Cover Change Simulation. ISPRS International Journal of Geo-Information **10**.
Johnson, A. T. 1991. Curvefitting. Pages 309-335 *in* R. Weitkunat, editor. Digital Biosignal Processing. lsevier, Amsterdam E.
Koch, J., M. A. Dorning, D. B. Van Berkel, S. M. Beck, G. M. Sanchez, A. Shashidharan, L. S. Smart, Q. Zhang, J. W. Smith, and R. K. Meentemeyer. 2019. Modeling landowner interactions and development patterns at the urban fringe. Landscape and Urban Planning **182**:101-113.
Kohli, I. S., and M. C. Haslam. 2017. An Analysis of the Replicator Dynamics for an Asymmetric Hawk-Dove Game. International Journal of Differential Equations **2017**:1-7.
Kusters, K., M. De Graaf, L. Buck, K. Galido, A. Maindo, H. Mendoza, T. Nghi, E. Purwanto, and R. Zagt. 2020. Inclusive Landscape Governance for Sustainable Development: Assessment Methodology and Lessons for Civil Society Organizations. Land **9**.
Lacroix, K., and G. Richards. 2015. An alternative policy evaluation of the British Columbia carbon tax: broadening the application of Elinor Ostrom's design principles for managing common-pool resources. Ecology and Society **20**.
Lei, Y., J. Flacke, and N. Schwarz. 2021. Does Urban planning affect urban growth pattern? A case study of Shenzhen, China. Land Use Policy **101**.
Leslie, H. M., X. Basurto, M. Nenadovic, L. Sievanen, K. C. Cavanaugh, J. J. Cota-Nieto, B. E. Erisman, E. Finkbeiner, G. Hinojosa-Arango, M. Moreno-Baez, S. Nagavarapu, S. M. Reddy, A. Sanchez-Rodriguez, K. Siegel, J. J. Ulibarria-Valenzuela, A. H. Weaver, and O. Aburto-Oropeza. 2015. Operationalizing the social-ecological systems framework to assess sustainability. Proc Natl Acad Sci U S A **112**:5979-5984.
Levin, S., T. Xepapadeas, A.-S. Crépin, J. Norberg, A. de Zeeuw, C. Folke, T. Hughes, K. Arrow, S. Barrett, G. Daily, P. Ehrlich, N. Kautsky, K.-G. Mäler, S. Polasky, M. Troell, J. R. Vincent, and B. Walker. 2012. Social-ecological systems as complex adaptive systems: modeling and policy implications. Environment and Development Economics **18**:111-132.

Liu, J., T. Dietz, S. R. Carpenter, M. Alberti, C. Folke, E. Moran, A. N. Pell, P. Deadman, T. Kratz, J. Lubchenco, E. Ostrom, Z. Ouyang, W. Provencher, C. L. Redman, S. H. Schneider, and W. W. Taylor. 2007. Complexity of coupled human and natural systems. Science **317**:1513-1516.

Magliocca, N., V. McConnell, and M. Walls. 2015. Exploring sprawl: Results from an economic agent-based model of land and housing markets. Ecological Economics **113**:114-125.

Maria de Almeida, C., M. Batty, A. M. Vieira Monteiro, G. Câmara, B. S. Soares-Filho, G. C. Cerqueira, and C. L. Pennachin. 2003. Stochastic cellular automata modeling of urban land use dynamics: empirical development and estimation. Computers, Environment and Urban Systems **27**.

Marshall, G. R. 2008. Nesting, subsidiarity, and community-based environmental governance beyond the local level. International Journal of the Commons **2**:75-97.

Martin, R., and M. Schlüter. 2015. Combining system dynamics and agent-based modeling to analyze social-ecological interactions—an example from modeling restoration of a shallow lake. Frontiers in Environmental Science **3**.

Mathias, J. D., J. M. Anderies, J. Baggio, J. Hodbod, S. Huet, M. A. Janssen, M. Milkoreit, and M. Schoon. 2020. Exploring non-linear transition pathways in social-ecological systems. Sci Rep **10**:4136.

MATLAB. 2016. version 9.0.0.3 (R2016a). The MathWorks, Inc, Natick, Massachusetts.

McGinnis, M. D., and E. Ostrom. 2014. Social-ecological system framework: initial changes and continuing challenges. Ecology and Society **19**.

Menatti, L. 2017. Landscape: from common good to human right. International Journal of the Commons **11**.

Meyfroidt, P., R. Roy Chowdhury, A. de Bremond, E. C. Ellis, K. H. Erb, T. Filatova, R. D. Garrett, J. M. Grove, A. Heinimann, T. Kuemmerle, C. A. Kull, E. F. Lambin, Y. Landon, Y. le Polain de Waroux, P. Messerli, D. Müller, J. Ø. Nielsen, G. D. Peterson, V. Rodriguez García, M. Schlüter, B. L. Turner, and P. H. Verburg. 2018. Middle-range theories of land system change. Global Environmental Change **53**:52-67.

Milkoreit, M., J. Hodbod, J. Baggio, K. Benessaiah, R. Calderón-Contreras, J. F. Donges, J.-D. Mathias, J. C. Rocha, M. Schoon, and S. E. Werners. 2018. Defining tipping points for social-ecological systems scholarship—an interdisciplinary literature review. Environmental Research Letters **13**.

Millennium Ecosystem, A. 2005. Ecosystems and Human Well-being: Synthesis : a Report for the Millennium Ecosystem Assessment. Island Press.

Moallemi, E. A., J. Kwakkel, F. J. de Haan, and B. A. Bryan. 2020. Exploratory modeling for analyzing coupled human-natural systems under uncertainty. Global Environmental Change **65**.

Montero, P., and J. e. A. Vilar. 2014. TSclust: An R Package for Time Series Clustering. Journal of Statistical Software **62**.

Morrison, T., and M. Lane. 2014. The convergence of regional governance discourses in rural Australia: Enduring challenges and constructive suggestions. Rural Society **16**:341-357.

Morrison, T. H. 2006. Pursuing Rural Sustainability at the Regional Level: Key Lessons from the Literature on Institutions, Integration, and the Environment. Journal of Planning Literature **21**:143-152.

Morrison, T. H. 2007. Multiscalar Governance and Regional Environmental Management in Australia. Space and Polity **11**:227-241.

Morrison, T. H. 2017. Evolving polycentric governance of the Great Barrier Reef. Proc Natl Acad Sci U S A **114**:E3013-E3021.

Morrison, T. H., N. Adger, J. Barnett, K. Brown, H. Possingham, and T. Hughes. 2020a. Advancing Coral Reef Governance into the Anthropocene. One Earth **2**:64-74.

Morrison, T. H., W. N. Adger, K. Brown, M. Hettiarachchi, C. Huchery, M. C. Lemos, and T. P. Hughes. 2020b. Political dynamics and governance of World Heritage ecosystems. Nature Sustainability **3**:947-955.

Müller, B., F. Bohn, G. Dreßler, J. Groeneveld, C. Klassert, R. Martin, M. Schlüter, J. Schulze, H. Weise, and N. Schwarz. 2013. Describing human decisions in agent-based models – ODD + D, an extension of the ODD protocol. Environmental Modelling & Software **48**:37-48.

Mundoli, S., B. Manjunatha, and H. Nagendra. 2017. Commons that provide: the importance of Bengaluru's wooded groves for urban resilience. International Journal of Urban Sustainable Development **9**:184-206.
Murali, R., K. Suryawanshi, S. Redpath, H. Nagendra, and C. Mishra. 2019. Changing use of ecosystem services along a rural-urban continuum in the Indian Trans-Himalayas. Ecosystem Services **40**.
Murphy, A., J. P. Enqvist, and M. Tengö. 2019. Place-making to transform urban social–ecological systems: insights from the stewardship of urban lakes in Bangalore, India. Sustainability Science **14**:607-623.
Murunga , M., S. Partelow, and A. Breckwoldt. 2021. Drivers of collective action and role of conflict in Kenyan fisheries co-management. World Development **141**.
Mustafa, A., M. Cools, I. Saadi, and J. Teller. 2017. Coupling agent-based, cellular automata and logistic regression into a hybrid urban expansion model (HUEM). Land Use Policy **69**:529-540.
Myers, J. 2020. Fixing Urban Planning with Ostrom: Strategies for existing Cities to Adopt Polycenric, Bottom-up Regulation of Land Use. Mercatus Research Paper.
Nagendra, H., and E. Ostrom. 2012. Polycentric governance of multifunctional forested landscapes. International Journal of the Commons **6**.
Nagendra, H., and E. Ostrom. 2014. Applying the social-ecological system framework to the diagnosis of urban lake commons in Bangalore, India. Ecology and Society **19**.
Nagendra, H., H. S. Sudhira , K. Madhusudan, M. Tengö, and M. Schewenius. 2012. Urbanization, ecosystem and biodiversity : Assessments of India and Bangalore.
Nagendra, H., H. Unnikrishnan, and S. Sen. 2013. Villages in the City: Spatial and Temporal Heterogeneity in Rurality and Urbanity in Bangalore, India. Land **3**:1-18.
Narain, V. 2009. Growing city, shrinking hinterland: land acquisition, transition and conflict in peri-urban Gurgaon, India. Environment and Urbanization **21**:501-512.
Narain, V. 2021. Social capital and disaster risk reduction in a periurban context. Pages 651-665 Disaster Resilience and Sustainability.
Nath, B., Z. Wang, Y. Ge, K. Islam, R. P. Singh, and Z. Niu. 2020. Land Use and Land Cover Change Modeling and Future Potential Landscape Risk Assessment Using Markov-CA Model and Analytical Hierarchy Process. ISPRS International Journal of Geo-Information **9**.
Noss, R. F. 2011. Between the devil and the deep blue sea: Florida's unenviable position with respect to sea level rise. Climatic Change **107**:1-16.
Nuhu, S. 2018. Peri-Urban Land Governance in Developing Countries: Understanding the Role, Interaction and Power Relation Among Actors in Tanzania. Urban Forum **30**:1-16.
Okpara, U. T., L. C. Stringer, M. Akhtar-Schuster, G. I. Metternicht, M. Dallimer, and M. Requier-Desjardins. 2018. A social-ecological systems approach is necessary to achieve land degradation neutrality. Environmental Science & Policy **89**.
Oksanen, J., F. G. Blanchet, M. Friendly, R. Kindt, P. R. Minchin, L. Dan, R. B. O'Hara, G. L. Simpson, P. Solymos, M. Henry, H. Stevens, E. Szoecs, and H. Wagner. 2020. vegan: Community Ecology Package.
Ostrom, E. 1990. Governing the commons : The Evolution of Institutions for Collective Action. Cambridge University Press.
Ostrom, E. 2005. Understanding Institutional Diversity. Princeton University Press.
Ostrom, E. 2007. A diagnostic approach for going beyond panaceas. Proc Natl Acad Sci U S A **104**:15181-15187.
Ostrom, E. 2009. A General Framwork for Analyzing Sustainability of Socio-Ecological Systems.pdf. Science:422.
Ostrom, E., and R. Gardner. 1993. Coping with Asymmetries in the Commons: Self-governing irrigation systems can work. The Journal of Econonmic Perspectives **7**.
Owusu Ansah, B., and U. E. Chigbu. 2020. The Nexus between Peri-Urban Transformation and Customary Land Rights Disputes: Effects on Peri-Urban Development in Trede, Ghana. Land **9**.

Parker, D. C., S. M. Manson, M. A. Janssen, M. J. Hoffmann, and P. Deadman. 2008. Multi-Agent Systems for the Simulation of Land-Use and Land-Cover Change: A Review. Annals of the Association of American Geographers **93**:314-337.
Parsons, W. 1995. Public Policy : an introduction to the theory and practice of policy analysis. Edward Elgar, Aldershot, UK ; Brookfield, Vt., US.
Partelow, S. 2015. Coevolving Ostrom's social–ecological systems (SES) framework and sustainability science: four key co-benefits. Sustainability Science **11**:399-410.
Partelow, S. 2018. A review of the social-ecological systems framework: applications, methods, modifications, and challenges. Ecology and Society **23**.
Partelow, S., and K. J. Winkler. 2016. Interlinking ecosystem services and Ostrom’s framework through orientation in sustainability research. Ecology and Society **21**.
Patil, S., B. Dhanya, R. S. Vanjari, and S. Purushothaman. 2018. Urbanisation and New Agroecologies. Eoconomic & Poliltical Weekly **LIII**.
Patterson, J. 2017. Purposeful collective action in ambiguous and contested situations: exploring 'enabling capacities' and cross-level interplay. International Journal of the Commons **11**.
Petrovskii, S., W. Alharbi, A. Alhomairi, and A. Morozov. 2020. Modelling Population Dynamics of Social Protests in Time and Space: The Reaction-Diffusion Approach. Mathematics **8**.
Pianosi, F., K. Beven, J. Freer, J. W. Hall, J. Rougier, D. B. Stephenson, and T. Wagener. 2016. Sensitivity analysis of environmental models: A systematic review with practical workflow. Environmental Modelling & Software **79**:214-232.
Pickard, B. R., D. Van Berkel, A. Petrasova, and R. K. Meentemeyer. 2016. Forecasts of urbanization scenarios reveal trade-offs between landscape change and ecosystem services. Landscape Ecology **32**:617-634.
Plexida, S. G., A. I. Sfougaris, I. P. Ispikoudis, and V. P. Papanastasis. 2014. Selecting landscape metrics as indicators of spatial heterogeneity—A comparison among Greek landscapes. International Journal of Applied Earth Observation and Geoinformation **26**:26-35.
Poteete, A. R., and E. Ostrom. 2004. Heterogeneity, Group Size and Collective Action: The Role of Institutions in Forest Management. Development and Change **35**.
Pourhoseingholi, M. A., A. R. Baghestani, and M. Vahedi. 2012. How to control confounding effects by statistical analysis. Gastroenterology and Hepatology From Bed to Bench **5**.
Pratomoatmojo, N. A. 2018. LanduseSim Algorithm: Land use change modelling by means of Cellular Automata and Geographic Information System. IOP Conference Series: Earth and Environmental Science **202**.
Preiser, R., R. Biggs, A. De Vos, and C. Folke. 2018. Social-ecological systems as complex adaptive systems: organizing principles for advancing research methods and approaches. Ecology and Society **23**.
Purushothaman, S., and S. Patil. 2017. Regional Economies and Small Farmers in Karnataka. Economic and Political Weekly **46**.
Purushothaman, S., S. Patil, and I. Francis. 2012. Assessing the impact of policy-driven agricultural practices in Karnataka, India. Sustainability Science **8**:173-185.
Ramachandra, T., B. H. Aithal, and D. D. Sanna. 2012. Insights to urban dynamics through landscape spatial pattern analysis. International Journal of Applied Earth Observation and Geoinformation **18**:329-343.
Ramachandra, T. V., B. H. Aithal, and B. Barik. 2014. Urbanization pattern of incipient mega region in india. Journal of Land use, mobility and environment.
Ratner, B. D., R. Meinzen-Dick, C. May, and E. Haglund. 2013. Resource conflict, collective action, and resilience: an analytical framework. International Journal of the Commons **7**.
Rauws, W. S., and G. de Roo. 2011. Exploring Transitions in the Peri-Urban Area. Planning Theory & Practice **12**:269-284.
Ravetz, J., C. Fertner, and T. S. Nielsen. 2013. The Dynamics of Peri-Urbanization. Peri-urban futures: Scenarios and models for land use change in Europe.

RCoreTeam. 2019. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienn, Austrai.
Redman, C. L., J. M. Grove, and L. H. Kuby. 2004. Integrating Social Science into the Long-Term Ecological Research (LTER) Network: Social Dimensions of Ecological Change and Ecological Dimensions of Social Change. Ecosystems **7**.
Ren, Y., Y. Lü, A. Comber, B. Fu, P. Harris, and L. Wu. 2019. Spatially explicit simulation of land use/land cover changes: Current coverage and future prospects. Earth-Science Reviews **190**:398-415.
Robinson, L. W., E. Ontiri, T. Alemu, and S. S. Moiko. 2017. Transcending Landscapes: Working Across Scales and Levels in Pastoralist Rangeland Governance. Environ Manage **60**:185-199.
Rodriguez-Loinaz, G., J. G. Alday, and M. Onaindia. 2015. Multiple ecosystem services landscape index: a tool for multifunctional landscapes conservation. J Environ Manage **147**:152-163.
Roy, A. 2009. Why India Cannot Plan Its Cities: Informality, Insurgence and the Idiom of Urbanization. Planning Theory **8**:76-87.
Salecker, J., C. Dislich, K. Wiegand, K. M. Meyer, and G. Pe Er. 2019. EFForTS-LGraf: A landscape generator for creating smallholder-driven land-use mosaics. PLoS One **14**:e0222949.
Salet, W., and J. de Vries. 2018. Contextualisation of policy and law in sustainable urban development. Journal of Environmental Planning and Management **62**:189-204.
Samat, N., R. Hasni, and Y. A. E. Elhadary. 2011. Modelling Land Use Changes at the Peri-Urban Areas using Geographic Information Systems and Cellular Automata Model. Journal of Sustainable Development **4**.
Santo-Tomás Muro, R., C. Sáenz de Tejada Granados, and E. J. Rodríguez Romero. 2020. Green Infrastructures in the Peri-Urban Landscape: Exploring Local Perception of Well-Being through 'Go-Alongs' and 'Semi-Structured Interviews'. Sustainability **12**.
Sarkar , S., and S. Bandyopadhyay. 2013. Dynamics of the Peri-Urban Interface: Issues and Perspectives of Management. Transactions of the Institute of Indian Geographers **50**.
Sarker, A. 2020. Economics of underproduction: A polycentric approach for a depopulated commons in Japan. Ecological Economics **171**.
Saunders, F. P. 2014. The promise of common pool resource theory and the reality of commons projects. International Journal of the Commons **8**.
Schlager, E. 2004. Common-pool Resource Theory. Pages 145-175 Environmental Governance Reconsidered: Challenges, Choices, and Opportunities. MIT Press, Cambridge, MA.
Schlüter, M., J. Hinkel, P. W. G. Bots, and R. Arlinghaus. 2014. Application of the SES Framework for Model-based Analysis of the Dynamics of Social-Ecological Systems. Ecology and Society **19**.
Schlüter, M., B. Müller, and K. Frank. 2019. The potential of models and modeling for social-ecological systems research: the reference frame ModSES. Ecology and Society **24**.
Sciaini, M., M. Fritsch, C. Scherer, C. E. Simpkins, and N. Golding. 2018. NLMR and landscapetools : An integrated environment for simulating and modifying neutral landscape models in R. Methods in Ecology and Evolution **9**:2240-2248.
Scott, J. S. 1998. Seeing Like a State. Yale University Press.
Sen, A., and H. Nagendra. 2020. Local community engagement, environmental placemaking and stewardship by migrants: A case study of lake conservation in Bengaluru, India. Landscape and Urban Planning **204**.
Seppelt, R., P. H. Verburg, A. Norström, W. Cramer, and T. Václavík. 2018. Focus on cross-scale feedbacks in global sustainable land management. Environmental Research Letters **13**.
Setturu, B., and T. V. Ramachandra. 2021. Modeling Landscape Dynamics of Policy Interventions in Karnataka State, India. Journal of Geovisualization and Spatial Analysis **5**.
Sharma, D., I. Holmes, G. Vergara-Asenjo, W. N. Miller, M. Cunampio, R. B. Cunampio, M. B. Cunampio, and C. Potvin. 2016. A comparison of influences on the landscape of two social-ecological systems. Land Use Policy **57**:499-513.
Shaw, A. 2005. Peri-Urban Interface of Indian Cities. Economic and Political Weekly **40**:8.
Simon, H. 1972. Theories of Bounded Rationality.*in* C. B. M. ; and R. Radner, editors. Decision and Organization.

Singh, A. K., and V. Narain. 2019. Fluid Institutions: Commons in Transition in the Periurban Interface. Society & Natural Resources:1-10.
Skelly, A. C., J. R. Dettori, and E. D. Brodt. 2012. Assessing bias: the importance of considering confounding. Evid Based Spine Care J **3**:9-12.
Spies, M., and H. Alff. 2020. Assemblages and complex adaptive systems: A conceptual crossroads for integrative research? Geography Compass **14**.
Steffen, W., K. Richardson, J. Rockstrom, S. E. Cornell, I. Fetzer, E. M. Bennett, R. Biggs, S. R. Carpenter, W. de Vries, C. A. de Wit, C. Folke, D. Gerten, J. Heinke, G. M. Mace, L. M. Persson, V. Ramanathan, B. Reyers, and S. Sorlin. 2015. Sustainability. Planetary boundaries: guiding human development on a changing planet. Science **347**:1259855.
Sudhira, H. S., and H. Nagendra. 2013. Local Assessment of Bangalore: Graying and Greening in Bangalore – Impacts of Urbanization on Ecosystems, Ecosystem Services and Biodiversity.*in* M. F. Thomas Elmqvist , Julie Goodness , Burak Güneralp,, R. I. M. Peter J. Marcotullio , M. S. Susan Parnell , K. C. S. Marte Sendstad , and C. Wilkinson, editors. Urbanization, Biodiversity and Ecosystem Services: Challenges and Opportunities. Springer.
Sudhira, H. S., T. V. Ramachandra, and M. H. B. Subrahmanya. 2007. Bangalore. Cities **24**:379-390.
Tidball, K., and R. Stedman. 2013. Positive dependency and virtuous cycles: From resource dependence to resilience in urban social-ecological systems. Ecological Economics **86**.
Tilman, D., C. L. Lehman, and P. Kareiva. 1997. Population Dynamics in Spatial Habitats.*in* D. TILMAN and P. KAREIVA, editors. Spatial Ecology. Princeton University Press.
Tobler, W. R. 1970. A Computer Movie Simulating Urban Growth in the Detroit Region. Economic Geography **46**:234-240.
Turner, B. L., P. Meyfroidt, T. Kuemmerle, D. Müller, and R. Roy Chowdhury. 2020. Framing the search for a theory of land use. Journal of Land Use Science **15**:489-508.
Turner, M. G., D. C. Donato, and W. H. Romme. 2012. Consequences of spatial heterogeneity for ecosystem services in changing forest landscapes: priorities for future research. Landscape Ecology **28**:1081-1097.
Turner, M. G., and R. H. Gardner. 2015. Landscape Ecology in Theory and Practice. second edition.
Turner, M. G., R. H. Gardner, and R. V. O'Neill. 2010. Landscape Ecology in Theory and Practice: Pattern and Process. Springer.
Tyson, W. 2017. Using social-ecological systems theory to evaluate large-scale comanagement efforts: a case study of the Inuvialuit Settlement Region. Ecology and Society **22**.
United Nations, D. o. E. a. S. A., Population Division. 2019. World Urbanization Prospects 2018: Highlights (ST/ESA/SER.A/421).
Unnikrishnan, H., S. Mundoli, B. Manjunatha, and H. Nagendra. 2016. Down the drain: the tragedy of the disappearing urban commons of Bengaluru. South Asian Water Studies **5**.
van Schrojenstein Lantman, J., P. H. Verburg, A. Bregt, and S. Geertman. 2011. Core Principles and Concepts in Land-Use Modelling: A Literature Review. Pages 35-57 Land-Use Modelling in Planning Practice.
Vedeld, T. 2000. Village politics: Heterogeneity, leadership and collective action. Journal of Development Studies **36**.
Verburg, P. H., P. Alexander, T. Evans, N. R. Magliocca, Z. Malek, M. D. A. Rounsevell, and J. van Vliet. 2019. Beyond land cover change: towards a new generation of land use models. Current Opinion in Environmental Sustainability **38**:77-85.
Verburg, P. H., N. Crossman, E. C. Ellis, A. Heinimann, P. Hostert, O. Mertz, H. Nagendra, T. Sikor, K.-H. Erb, N. Golubiewski, R. Grau, M. Grove, S. Konaté, P. Meyfroidt, D. C. Parker, R. R. Chowdhury, H. Shibata, A. Thomson, and L. Zhen. 2015. Land system science and sustainable development of the earth system: A global land project perspective. Anthropocene **12**:29-41.
Verburg, P. H., T. C. M. de Nijs, J. Ritsema van Eck, H. Visser, and K. de Jong. 2004. A method to analyse neighbourhood characteristics of land use patterns. Computers, Environment and Urban Systems **28**:667-690.

Verburg, P. H., K. Kok, R. G. Pontius, and A. Veldkamp. 2006. Modeling Land-Use and Land-Cover Change. Pages 117-135 Land-Use and Land-Cover Change.

Vergnes, A., C. Kerbiriou, and P. Clergeau. 2013. Ecological corridors also operate in an urban matrix: A test case with garden shrews. Urban Ecosystems **16**:511-525.

Vidyarthi, S., S. Mathur, and S. K. Agarwal. 2017. Understanding India's New Approach to Spatial Planning and Development: A Salient Shift? Oxford University Press.

Vij, S., and V. Narain. 2016. Land, water & power: The demise of common property resources in periurban Gurgaon, India. Land Use Policy **50**.

Villamayor-Tomas, S., F. D. Fleischman, I. P. Ibarra, A. Thiel, and F. van Laerhoven. 2014. From Sandoz to Salmon: Conceptualizing resource and institutional dynamics in the Rhine watershed through the SES framework. International Journal of the Commons **8**.

Vitousek, P. M., H. A. Mooney, J. Lubchenco, and J. M. Melillo. 1997. Human Domination of Earth’s Ecosystems. Science **277**.

Vogt, J. M., G. B. Epstein, S. K. Mincey, B. C. Fischer, and P. McCord. 2015. Putting the "E" in SES: unpacking the ecology in the Ostrom social-ecological system framework. Ecology and Society **20**.

Wandl, A., and M. Magoni. 2016. Sustainable Planning of Peri-Urban Areas: Introduction to the Special Issue. Planning Practice & Research **32**:1-3.

Wandl, A., R. Rooij, and R. Rocco. 2016. Towards Sustainable Territories-in-Between: A Multidimensional Typology of Open Spaces in Europe. Planning Practice & Research **32**:55-84.

Weibull, J. W. 1995. Evolutionary Game Theory. MIT Press, Cambridge, Massachusetts.

Williams, K., and H.-S. Tai. 2016. A Multi-Tier Social-Ecological System Analysis of Protected Areas Co-Management in Belize. Sustainability **8**.

Wilson, J., L. Yan, and C. Wilson. 2007. The precursors of governance in the Maine lobster fishery. Proc Natl Acad Sci U S A **104**:15212-15217.

Wu, J., and R. Hobbs. 2002. Key issues and research priorities in landscape ecology: An idiosyncratic synthesis. Landscape Ecology **17**:355-365.

Wu, J., D. E. Jelinski, M. Luck, and P. T. Tueller. 2000. Multiscale Analysis of Landscape Heterogeneity: Scale Variance and Pattern Metrics. Geographic Information Sciences **6**:6-19.

Yang, W., and X. Jiang. 2021. Evaluating the influence of land use and land cover change on fine particulate matter. Sci Rep **11**:17612.

Yi, Y., C. Zhang, G. Zhang, L. Xing, Q. Zhong, J. Liu, Y. Lin, X. Zheng, N. Yang, H. Sun, M. Shi, and H. Kang. 2021. Effects of Urbanization on Landscape Patterns in the Middle Reaches of the Yangtze River Region. Land **10**.

Zasada, I., K. Häfner, L. Schaller, B. T. van Zanten, M. Lefebvre, A. Malak-Rawlikowska, D. Nikolov, M. Rodríguez-Entrena, R. Manrique, F. Ungaro, M. Zavalloni, L. Delattre, A. Piorr, J. Kantelhardt, P. H. Verburg, and D. Viaggi. 2017. A conceptual model to integrate the regional context in landscape policy, management and contribution to rural development: Literature review and European case study evidence. Geoforum **82**:1-12.

Zhang, S., G. de Roo, and W. Rauws. 2019. Understanding self-organization and formal institutions in peri-urban transformations: A case study from Beijing. Environment and Planning B: Urban Analytics and City Science **47**.

Zhou, W., M. Cadenasso, K. Schwarz, and S. Pickett. 2014. Quantifying Spatial Heterogeneity in Urban Landscapes: Integrating Visual Interpretation and Object-Based Classification. Remote Sensing **6**:3369-3386.

Žlender, V. 2020. Characterisation of peri-urban landscape based on the views and attitudes of different actors. Land Use Policy.

Appendix A : Supplementary materials for Chapter 2

Results of Sensitivity Analysis

a) Low Heterogeneity landscape *b) High Heterogeneity landscape*

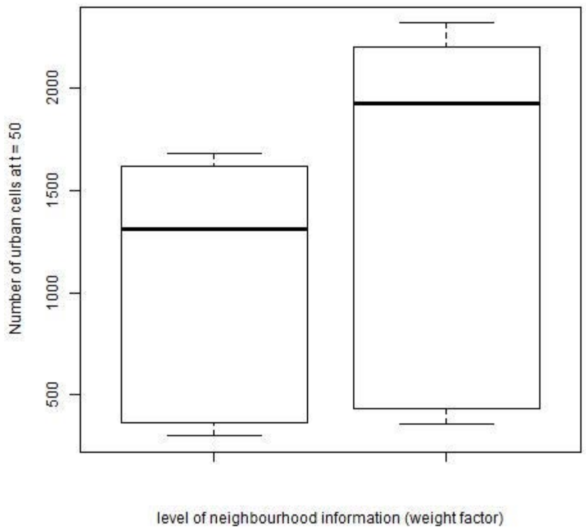

Figure A.1 : The two box plots show the variability in the number of urban cells at time = 50 year for different value of level of neighbourhood information when input landscape heterogenenity was (a) low and (b) high.

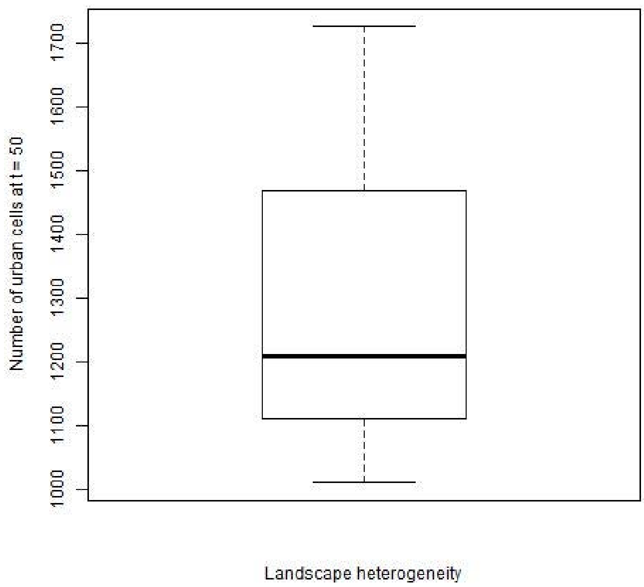

Figure A.2: The box plot shows the variability in number of urban cells at t= 50 when input landscape heterogeneity was varied from low to high when the level of neighbourhood information was constant.

Appendix B : Supplementary materials for Chapter 3

Summary Statistics of Multiple Regression

Table B.1: 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 B.2: 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	0.155	5.355e-05	1.435	P-value : 0.452	Regional (44)
Edge Density	0.774	-4.124e+00	-0.288	R-Square : 0.03382	Regional
SDPatch	0.119	-5.117e-05	-1.577		Regional
Patch Area	0.243	3.800e-05	1.176	P-value : 0.4728	Local (48)
Edge Density	0.168	-1.730e+01	-1.393	R-Square : 0.03233	Local
SDPatch	0.558	-1.656e-05	-0.589		Local
Patch Area	0.236	5.513e-05	1.194	P-value : 0.565	Null (33)
Edge Density	0.408	-1.476e+01	-0.832	R-Square : 0.02627	Null
SDPatch	0.708	-1.512e-05	-0.377		Null

Table B.3: High 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	0.863	-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	e+02	1.093		Null
SDPatch	0.661	-1.719e-03	-0.440		Null

Table B.4: 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

Appendix C : Supplementary material for Chapter 4

C.1 Amount of urbanization across different levels of resistance

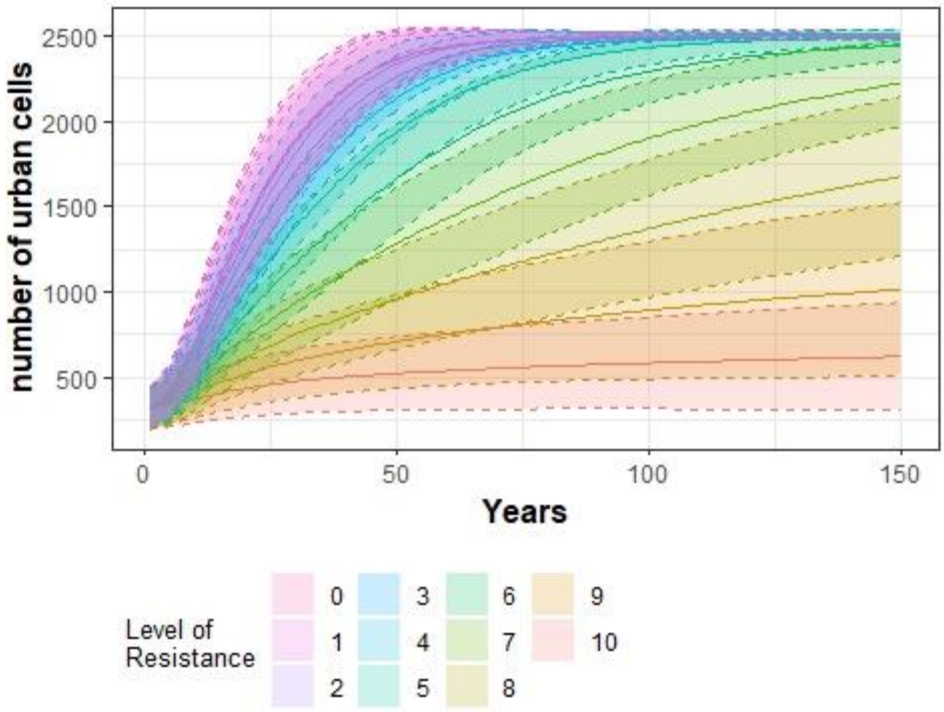

Figure B.1: Number of urban cells at all levels of resistance (0 to 10). As the level of resistance among rural actors increase the amount of urbanization decreases. For example, when the level of resistance was 1 (10% of rural Hawks) the amount of urbanization was about 2250 cells (violet line) at 50th year whereas for the same year the amount of urbanization was 510 cells (orange line) when level of urbanization was 100% i.e. all rural actors were rural Hawks. In the figure, thick line represents the average value of amount of urban cells for each level of resistance and dotted line represent the variation (calculated as standard deviation) for all 100 images.

C.2 Checking for the confounders

To address confounding variables statistically logistic regression, linear regression, and ANCOVA are three common methods (Pourhoseingholi et al. 2012). For chapter 4, the independent variable (level of resistance) was a categorical variable and the confounding variable (rate of urbanization) was a continuous variable, hence, I used ANCOVA. However, the initial assumptions of linearity and homogeneity were violated (Field et al. 2012). Therefore, I performed linear regression on interaction between intendent variable and the confounding variable and estimated regression coefficient with and without confounders. For all landscape metrics, the change in regression coefficient was greater than

10%. However, when I addressed the coefficient in the resulting curves we found that the change in R-square value was <0.01. In addition, the coefficient of level of resistance and its power terms were significant (with p-value <0.05) for before and after addressing for confounding variables. Hence, the confounding was mild and it did not add much information (Field et al. 2012), therefore, I dropped the confounding variable from the analysis.

C.3 Result of Curve fitting

The following tables show the goodness of fit test of the standard curves to the mean value of respective landscape metrics.

Table C.1: Goodness of fit measures for mean values of number of patches across resistance levels (from 1 to 10). The logistic curve was the best fitting cure for Patch Area

Standard Curves	**AIC**	**Log likelihood**
Exponential	8.375051	-1.187525
Power	22.6095	-8.304751
Log	36.08806	-15.04403
Logistic (sigmoidal)	22.8592	-8.4296

Table C.2: Goodness of fit measures for mean values of Patch Area across resistance levels (from 1 to 10). The logistic curve was the best fitting cure for Patch Area.

Standard Curves	**AIC**	**Log likelihood**
Exponential	270.554	-120.703
Power	249.406	-132.277
Log	260.2597	-127.1298
Logistic (sigmoidal)	**244.846**	**-119.4232**

Table C.3: Goodness of fit measures for mean value of Edge Density across resistance levels (from 0 to 1). The power curve fits best for the Edge density function.

Standard Curves	**AIC**	**Log likelihood**
Exponential	-17.38417	11.69208
Power	-33.93269	19.96635
Log	-16.86541	11.4327
Logistic (sigmoidal)	208.369	-102.1845

Table C.4: Goodness of fit measures for mean value of Clumpy index of urban patches across resistance levels (1 to 10). Log was best fitting curve.

Standard Curves	**AIC**	**Log likelihood**
Exponential	-92.11443	48.3836
Power	-107.4907	55.72903
Log	-105.4547	55.72735
Logistic (sigmoidal)	-128.0799	69.03997

Table C.5: Goodness of fit measures for mean value of Aggregation Index (landscape level metrics) across the resistance level (1 to 10). Log was the best fitting curve.

Standard Curves	**AIC**	**Log likelihood**
Exponential	-2.514411	4.257205
Power	10.5754	-2.287698
Log	-9.536308	7.768154
Logistic (sigmoidal)	18.26796	-6.133978

Table C.6: Goodness of fit measures for mean value of Fractal Mean Index (landscape level metrics) across the resistance level (1 to 10). Log was the best fitting curve.

Standard Curves	**AIC**	**Log likelihood**
Exponential	-98.70242	52.35121
Power	-119.399	63.69951
Log	-103.5536	54.77682
Logistic (sigmoidal)	208.3688	-102.1844

Appendix D : Supplementary material for Chapter 5

Patch Area

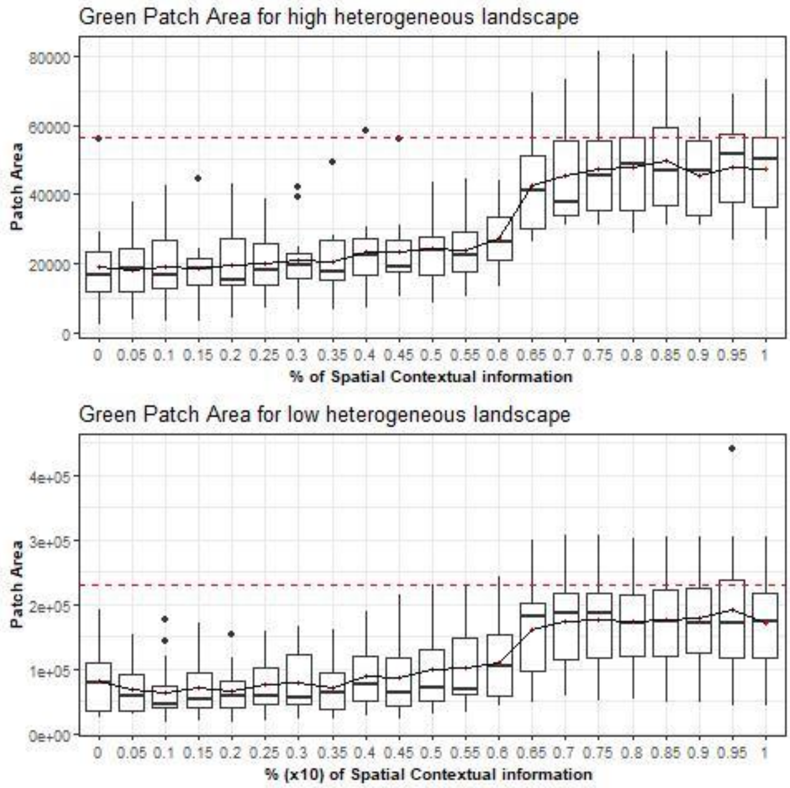

Figure D.1: Patch Area at initial value and at saturation point for different values of neighbourhood information. Red dotted line shoes mean patch area for the initial landscape.

Number of patches (NP)

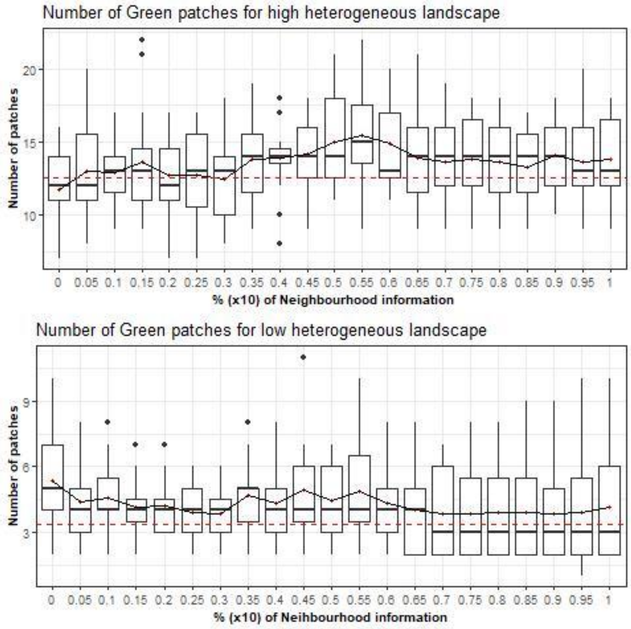

Figure D.2: Number of patches at initial value and at saturation point for different values of neighbourhood information. Red dotted line shows mean patch area for the initial landscape.

Edge Density

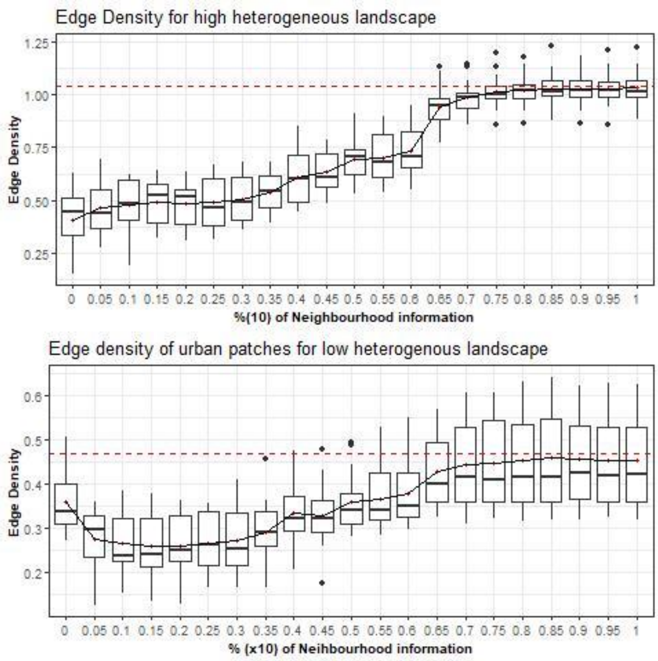

Figure D.3: Edge Density at initial value and at saturation point for different values of neighbourhood information. Red dotted line shows mean patch area for the initial landscape.

Clumpy index

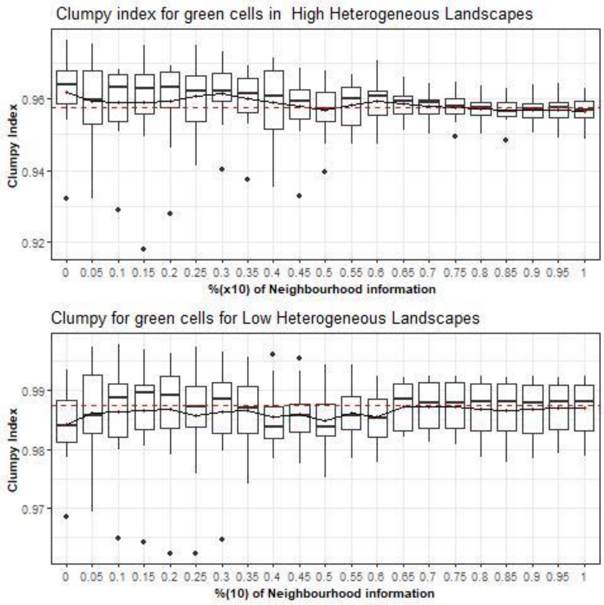

Figure D.4: Clumpy Index at initial value and at saturation point for different values of neighbourhood information. Red dotted line shows mean patch area for the initial landscape.

Multivariate analysis using pCCA

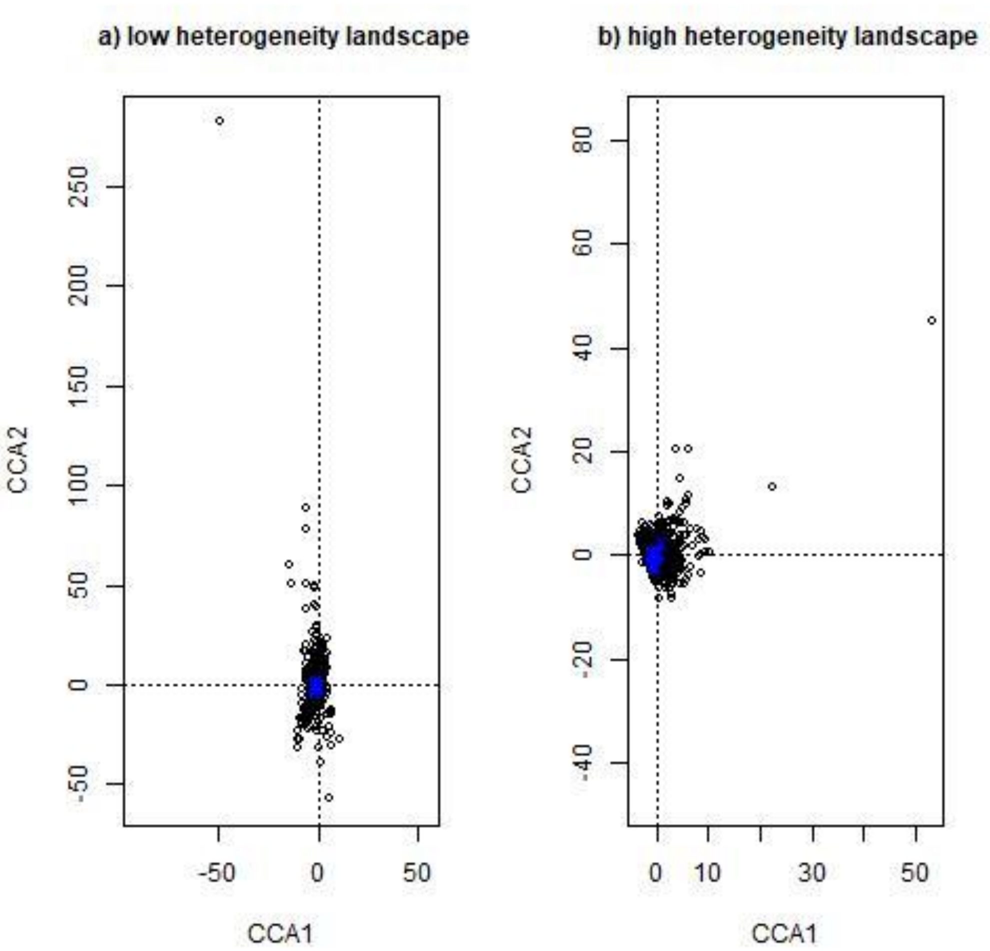

Figure D.5: Ordination diagram for low and high heterogeneity landscape for percentage change in NP, Clumpy Index and ED as response variable, level of neighbourhood information as explanatory variable and PA as covariate. It is clear from the ordination diagram where the response variables represented by points are clustered around the center. Arrows (blue clusters in the ordination diagram) represent the explanatory variable and the length of the arrows represent the correlation with ordination axes ([Beasley and Kneale 2002](#)). As the lengths of arrow are much smaller, the cluster shows that the explanatory variables are not very closely related to pattern observed among the response variables.