DRAFT

An operational framework for seeing and simulating feedbacks in land change science

Burak Güneralp[1,*], Michael Reilly[2], and Karen C. Seto[1]

[1] School of Forestry and Environmental Studies, Yale University, 205 Prospect Street, New Haven CT 06511, USA.
[2] Department of Earth System Science, Stanford University, 397 Panama Mall, Stanford CA 94305, USA.
* Corresponding author. Tel.: +1 203 432 9784; fax: +1 203 432 5556. E-mail address: burak.guneralp@yale.edu.

Abstract
Progress towards sustainability demands recognizing nonlinear, time delayed interactions that are at the heart of dynamic integrated socio-economic and biophysical systems. Sustainability and land change science communities have recognized the need to go beyond static and vague depictions of nonlinear feedback processes in the study of these integrated systems. But to date, there have been few attempts to move beyond conceptualizations to develop operational frameworks that *i)* are spatially explicit and *ii)* incorporate feedbacks as endogenous structural sources of the observed behavior patterns *iii)* both within and across scales. Land use land cover change (LUCC) is a significant component of integrated socio-economic and biophysical systems. We present an operational framework that takes its strength from its clear emphasis on nonlinear feedback interactions as drivers of LUCC. The framework addresses both local- and regional-level processes by employing the complementary use of systems modeling and spatially-explicit discrete-choice modeling. We demonstrate the potential of the approach on a rapidly urbanizing region, Pearl River Delta (PRD) in South China. Urbanization as a significant land change process puts pressure on landscapes in both direct and indirect ways through conversion of land to urban uses and increased demands for various natural resources, respectively. To this end, we employ our systemic framework and identify the most influential feedbacks and linkages impacting the urban land conversion over the course of urban and economic growth as experienced in PRD. The integrated framework allows tracking both local and regional level dynamics simultaneously. We also discuss the potential of systems approaches and use of complementary methods in advancing land change science both in theory and in practice.

1. Introduction

Advance in sustainability science requires uncovering those processes of integrated socio-economic and biophysical systems that are relevant for the research questions at hand. These processes are a culmination of complex, and sometimes simply complicated interactions between the components of these systems and require the integration of knowledge from diverse natural and social science disciplines (Grimm, Morgan Grove et al. 2000; Alberti, Marzluff et al. 2003; Ostrom 2007). The challenge in dealing with integrated socio-economic and biophysical systems stems from the fact that typically, in such complex systems, the cause and effect are not only simultaneously distant and interlocking in both time and space (Forrester 1971; Forrester 1992; Costanza and Wainger 1993; Turner, Lambin et al. 2007) but may also be separated across different spatio-temporal scales (Turner, Dale et al. 1989; Gibson, Ostrom et al. 2000). Nonlinear feedback interactions and time delays are typical characteristics of these systems and measuring their impact on dynamics of interest is essential to bringing a deeper understanding to how these complex systems work and, more critically, how their functioning can be improved; integrative and quantitative approaches that take a systems-oriented stance have a crucial role to play in untangling these complex interactions (Newell, Crumley et al. 2005). As such, mathematical dynamic models can contribute immensely to the formation of an integrated perspective critical for sustainability science and in particular, land change science.

In land change science, there is indeed a proliferation of numerical simulation models (Agarwal, Green et al. 2002; Guhathakurta 2003; Gutman, Janetos et al. 2004; Lischke, Bolliger et al. 2007). This not only shows a growing level of interest in land change phenomenon but also demonstrates the challenges of dealing with the complex dynamics involved. In addition, it confirms that we have a broad range of tools with varying theoretical considerations and computational approaches (Verburg and Veldkamp 2005; Turner, Lambin et al. 2007). Nevertheless, most modeling studies on the subject still fall short of properly addressing the most pressing issues in land change science in particular and sustainability science in general: feedback structures across and among social, economic, and biophysical components (Verburg, Soepboer et al. 2002; Clarke, Gazulis et al. 2007), multiscale interactions (Evans, Ostrom et al. 2002; Lischke, Bolliger et al. 2007), and simultaneous employment of complementary modeling approaches (Castella and Verburg 2007).

We propose an operational integrative framework that dynamically incorporates nonlinear feedbacks and linkages between socio-economic and biophysical factors operating within and across scales using two well-established modeling paradigms. Thus, our framework addresses the three critical issues that have important relevance to land change science and sustainability science. We demonstrate the proposed framework by analyzing urban growth dynamics with a case study of Pearl River Delta (PRD), South China that has been undergoing unprecedented urbanization. Specifically we ask the question ‘What are some of the most critical local and regional processes at work in this part of the world that cause a parcel of land to *become* urban?’. We need to understand how urbanization as a land use change phenomenon *evolves* in concert with dominant socio-economic, political and biophysical factors so that appropriate high leverage policies can be identified. To this end, we bring together the explanatory power of a systems perspective in dealing with socio-economic processes and a spatially-explicit representation of the unfolding land use dynamics. Clear and dynamic representation of the changing influence of feedback processes between various components and scales of the land use system in a spatially-explicit context play a key role in this exercise.

2. Methodology

2.1. Theoretical base and operational framework

Theoretically, our conceptual framework falls under the umbrella of the hierarchy theory. The hierarchy theory emerged from the works of the general systems theorists and was influential in formulation of a general science of complexity (Simon 1962; O'Neill, Johnson et al. 1989). According to the hierarchy theory, the elements and their interactions at the lower level combine to give rise to elements and processes at the higher level in scale. In other words, the “whole” at the higher level is more than the sum of the constituent parts at the lower level. This type of hierarchical ordering is typical of most complex systems (Anderson 1972; Bar-Yam 1997) where the emergent higher level structure constrains the parts at the lower level as much as the parts shape the emergent structure. Therefore, the regional-level dynamics can be seen as a culmination of those dynamics that operate at levels that are below and above it (Gibson, Ostrom et al. 2000). However, it is worth noting that, in our study, we are not interested in how lower-level processes give rise to the emergent higher-level structure and vice versa; rather, we are interested in the interplays between and amongst the regional-level and the local-level factors that cause land use change. Hence, our focus requires two levels of scale which allows us to represent and simulate the interactions between regional and local level dynamics.

We present a hybrid spatially explicit framework of urban land-use change dynamics with foundations in economic and statistical discrete-choice models of land-use change (Geoghegan, Pritchard et al. 1998). It is a hybrid because it combines two different modeling paradigms in a single framework: a system dynamics module that represents socio-economic processes of urbanization at the regional level and a logistic regression module that predicts land use conversion for two categories (urban vs. non-urban) at the local level (Landis and Reilly 2003). The interactions of demographic, economic, and technological dynamics at the higher level create demand for land. The demand for land together with local level factors such as topography and proximity to major highways influence spatial patterning of urban growth and ultimately the amount of land remaining for development at a location (Figure 1). The two modules interact and, more importantly, constrain each other as land demand, population, and economic productivity are imposed over the local-level dynamics while land availability influences the regional-level socio-economic dynamics.

There are examples, in land change science literature, of multiscale land change models that use complementary modeling approaches (Engelen, White et al. 1995; White and Engelen 2000; Wang and Zhang 2001; Soares, Alencar et al. 2004; Overmars and Verburg 2006; Castella and Verburg 2007; Manson and Evans 2007; Verburg, Eickhout et al. 2008). However, our framework differs significantly from these studies in its theoretical foundations (e.g. non-equilibrium economic dynamics vs. input-output model, logistic regression grounded in urban economic theory vs. empirically derived rule-based CA), in its emphasis on nonlinearities and time delays, and lastly in its explicit focus on feedback structures as endogenous drivers of system dynamics. Considering that the purpose of the model is to understand the most influential regional- and local-level factors and mechanisms behind the rapid urban growth encompassing a considerably large area in the context of a developing country, our approach has modest data requirements compared to other approaches such as agent-based modeling.

2.2. Model building and validation

While the overall framework of our proposed methodology rests on hierarchy theory its various components draws upon different substantial theoretical foundations. Our effort aims to represent the drivers of urban land cover conversion at appropriate and interacting spatial scales: at the regional level we employ a socio-economic systems model relating truly regional phenomena such as GDP and demographics while at the site level we use a reduced-form profit-maximizing statistical approach to capture development level drivers such as highway access and topography.

2.2.1. System model. At the regional-level, a system dynamics model captures fundamental regional dynamics such as growth in population and economy. This model is comprised of six submodels each representing a particular county. Each submodel has three sectors each representing demographic, laborforce, and economic dynamics. We use an ecological economics framework to represent the economic structure at the regional level. This representation regards human, built, and natural capital as endogenous and accounts for the feedback processes among social and economic factors as well as the region’s land resource base (Figure 1; Table 2). The formulations of population dynamics are drawn from empirical findings and theoretical considerations on demographics and migration (Güneralp and Seto 2008). We also account for PRD’s relative economic position within the national and global economy through an exogenous ‘‘comparative advantage’’ variable that is assumed to decrease over time. Several decision-making processes are also explicitly represented in the model. The primary assumptions of the model, the structure of the submodels, the data used, and the validation of the model are described in detail in the supporting document and elsewhere (Güneralp and Seto 2008).

There are a number of ways to understand why a model behaves as it does all of which require modeler intuition in addition to formal procedures. In system dynamics models, there are traditional well-developed procedures such as trial-and-error simulations, involving changing parameter values or turning on and off certain links and feedback loops, and model reduction (Homer 1996; Saysel and Barlas 2006); there are also more sophisticated analyses of dominant loop structures (Güneralp 2006; Kampmann and Oliva 2008). The latter group of tests, while promising, is currently not mature enough and has limited applicability to models with a few state variables. Consequently, we relied on traditional procedures in our analysis of the most influential structures in our model.

2.2.2. Spatial logit model. The elaboration of local-level dynamics is based on statistical decision-theory and urban economics. We construct a discrete-choice model of land use conversion driven by factors likely to influence the spatial configuration of development at this scale. The logistic regression model used in this study is a descendant of the California Urban Futures modeling tradition at UC Berkeley's Institute of Urban and Regional Development (Landis and Zhang 1998). Consequently, the model predicts land use conversion using a binary urbanization dependent variable rooted in the maximization of a land developer's profit through the selection of locations with particular combination of accessibility, land purchase and development costs, and amenities (Landis and Reilly 2003). Fragkias and Seto (2007) demonstrate the usefulness of this type of approach in "data-sparse" locations in the developing world. While incorporating a range of drivers likely to influence local level site selection, this model also includes three variables from the upper level model in order to represent the strength and nature of the demand for land within a given county as driven by the macro-scale regional economy. This component is calibrated in SAS using a logistic regression model for the time period 1999–2005. The unit of analysis is an arbitrary hectare pixel on the landscape that captures the dependent variable and vector of independent variables. The dependent variable is an indicator variable representing the conversion of the dominant landcover of that pixel from any non-urban cover to urban cover. The urbanization variable is derived by upscaling classified Landsat imagery from the years 1999 and 2005 and marking urban conversion events as 1 and other sites as 0. The classifications have been performed by Alexandre Boucher and Karen Seto using an innovative method that incorporates both temporal and spatial context into the assignment of a given pixel to a class (Boucher, Seto et al. 2006).

Finally, we ensured that the linked model is a valid representation of the regional urban growth dynamics based on socio-economic data and spatial urban/non-urban maps. We pass numeric results from the systems model to the statistical model and back for each time step. This step in the future can be automatized by using Python script in ArcGIS (ESRI, 2008). The spatial logit model incorporates information on the growth of population, industrial capital, and service-sector capital by county. There we calculate probability of urbanization during that time step using the statistical equation generated in SAS. We assign the expected amount of growth for each county at a density determined by a simple linear trend model based on past urban intensity and the amount of land remaining in the vicinity. The amount of land remaining is then calculated and returned to the systems model where it influences that the rates of change of capital in each economic sector through investment as well as the density in the next time step. The interactions between neighboring counties also unfold at both regional- and local-levels. Local-level interaction is facilitated through the configuration of urban land and road network that influence where the next conversion to urban land will be together with the demand from economic activities and demographic changes within each county. On the other hand, regional-level interaction is through spillover effects of relative economic vitality in neighboring counties represented by the comparative GDP levels between them. It should be noted that these interactions mediate the influence of inter-level interactions within each county, with the influence of fraction of urban land acting as a proxy for the non-linear influence of land prices, ease of finding suitable land parcels, and related factors on investment flows to existing capital.

3. Urbanization as a land change process: A case study of Pearl River Delta, South China

The process of urbanization puts pressure on landscapes indirectly through increased demands for various natural resources and changing dietary preferences (Bohle 1994; Foley, DeFries et al. 2005; Grimm, Faeth et al. 2008). For example, by one account, urban areas are responsible for 76 % of wood used for industrial purposes and 60 % of residential water use although it is widely believed that they cover less than 3 % of Earth's land surface (Brown 2001). Nevertheless, direct conversion of land to urban uses poses its own particular challenges for the land change and sustainability science communities. The conversion of vegetated surfaces to urban areas results in loss of fertile agricultural land (Xie, Mei et al. 2005; Chen 2007) and modifies the exchange of heat, water, trace gases, aerosols, and momentum between the land surface and atmosphere (Arnold and Gibbons 1996; Crutzen 2004) leading to the ‘‘urban heat island effect’’, a situation characterized by elevated daytime and nighttime temperatures in and near urban areas (Oke 1974; Arnfield 2003) and reduced rainfall in some regions (Kaufmann, Seto et al. 2007).

The growing literature on land-use land cover models focuses almost exclusively on forested or arid landscapes (Gutman, Janetos et al. 2004); there are relatively few models that specifically focus on urban LUCC (Landis and Reilly 2003; Elvidge, Sutton et al. 2004; Clarke, Gazulis et al. 2007). More importantly, of the urban growth studies, even fewer focus on developing countries (Seto and Kaufmann 2003) in spite of the fact that the great majority of urban growth over the next fifty years will likely take place in the developing countries of Asia and Africa (UN 2006). These trends are likely to lead to phenomenal land use changes in those countries. From a sustainability standpoint, these anticipated changes will lead to loss of fertile agricultural lands, and will affect the local climate in urban areas potentially with adverse affects on the health of the billions of urban inhabitants. Ineffectively planned and regulated urban growth is doomed to be inefficient in terms of land use patterns with additional problems for the quality of life of urban residents. The same mechanisms leading to urban land conversion will also cause material demand originating from urban areas to grow putting more pressure on nonrenewable natural resources with destructive influences on places away from these demand centers. It is, therefore, crucial to understand the synergies involved in local-level land use changes and regional-level aggregate socio-economic transitions of newly emerging urban centers in developing countries.

Pearl River Delta (PRD), in China's Guangdong Province, is a particularly suitable region to demonstrate our approach to analyzing the dynamics of urban growth (Figure S1). PRD have experienced extraordinarily dramatic changes in terms of rapid population and economic growth since the initiation of economic reforms in late 1970s (Shen 2002). These changes have been accompanied by high rates and magnitudes of urbanization and increases in the material welfare of its residents as reflected by rising per capita income (Seto 2002; Güneralp and Seto 2008). As a functionally integrated urban agglomeration the core of the PRD is assumed to compose of six county groups surrounding the Pearl River Estuary (Table 1). These counties collectively represent virtually all the demographic and economic activity in the region. Each group, henceforth referred to as 'county' for brevity, is represented as a separate submodel. These six interacting submodels thus represent the regional-level dynamics. The timeframe of the study extends from year 1988 to 2015.

4. Results and Discussion

The urban expansion from 1999 to 2005 as determined from the processing of satellite imagery is given in Figure 4 (see Materials and Methods). During this period, the manufacturing sector's GDP share increases in all counties except Guangzhou and Foshan (historical urban agglomerations with already well-established manufacturing sectors) under the influence of a number of reinforcing (positive) feedback mechanisms (Figure 2). In these counties, economies of agglomeration continue to encourage further urban growth and industrial expansion (R1 in Figure 2). The economic growth and the increase in the population through migration stimulate each other through the reinforcing feedback loops (R2) and (R3) (Figure 2; Figure 3c). On the other hand, the increasing material welfare (already the highest in the region) keeps the tertiary sector strong through the feedback loop (R4) (Figure 3d). Consequently, although both sectors' contributions to GDP increase, the tertiary sector's GDP share decreases for most of our analysis period (Figure 3a-b). It is worth noting that, throughout the region, the counties see their secondary or tertiary sector shares rising at the expense of their primary sector (Figure 3a-b). The feedback loops (R2) and (R3) play a significant role in the economic and population growth of these counties (Figure 2).

For other parts of the region, their existing economic structure and population levels condition the influence of a different set of feedback mechanisms (Figure 2). The transitioning of the economy from one dominant sector to another characterizes the dynamics in these counties. For instance, the tertiary sector in Guangzhou and Foshan expand mostly at the expense of their already established secondary sectors (Figure 3a-b). In these counties, as well as in Shenzhen, a rising GDP per capita (as a proxy for residents' affluence) translates into increasing demand for tertiary sector goods and services (Figure 3d). As a result, there is additional investment in this sector and the feedback loop (R4) in time drives the GDP further up (Figure 2). Meanwhile, the tertiary sector becomes the main source of labor demand resulting in the shift of influence from the loop (R2) to another (R3).

Due to differences in relative locations and histories of the counties, the feedback mechanisms that are at work and their strength differ by county. In addition, interactions between neighboring counties also have an influence on dynamics. For instance, economic growth in Dongguan and Zhongshan is partly due to the spillover effects from Shenzhen and Foshan, respectively. Likewise the meager economic activity in Zengcheng is influenced by its neighbors, Dongguan and Guangzhou. Thus, although regulated by the decrease in relative competitiveness of the region, as the counties in the region are progressively integrated to the global economy more migrants and investment is drawn to and diffuse within the region, increasing the population and gross regional product (GRP) for the whole region. Our model also suggests that the agglomerative forces are largely strong in the region in driving urban and economic growth during the study period while the regulating influence of developable land scarcity is not experienced yet. The assumed decrease in the region's comparative advantage in China also influences the region's dynamics.

Because it is lacking many of theoretically-suggested variables in understanding urban expansion, the lower level logistic regression model demonstrates only a modest degree of statistical fit with the observed data. The representation of a broader array of drivers is desirable but often impractical in sparse data settings (Fragkias and Seto 2007). The relationships between the drivers and the probability of pixel conversion to urban land cover are mostly in the expected direction and are all statistically significant. Table 2 presents the coefficients as odds ratios meaning they represent the change in probability of an urbanization event with one interval of change in that independent variable (the intervals are indicated in parentheses and are one if not shown).

The first three variables in Table 2 represent the population, industrial capital, and service-sector capital in each county, respectively. These variables connect the lower level model to our representation of the regional economy. An additional 100 persons added per km^2 of a given county, increases the probability that any cell within that county will urbanize during the period by 3.7%, *ceteris paribus*. An additional million RMB of capital investmest in the second sector per km^2 of county area during the period meant that a given cell within that county was 1.2% more likely to develop. An additional million of capital investment in the less land intensive third sector resulted in a given pixel being 98.4% as likely to develop. Regional accessibility, which plays a significant role in the counties' socio-economic dynamics, also has a consistent influence on the spatial configuration of urban land conversion. An additional 10 kilometers of distance from Guangzhou (the region's most important historical Central Business District) sees a pixel only 97% as likely to undergo urban development. For each additional 10-kilometer distance from the closest major highway, the chance of urbanization is around ¾ as much. Access to existing urban land cover within one kilometer decreased the likelihood of development with an additional percentage of land within a kilometer being under urban cover translating into a slight drop in land conversion likelihood. Extensive testing also revealed the Zhongshan county consistently saw more land conversion than it ought to have based on the general characteristics of its landscape. This situation probably relates to the county's strong political interest in urban renewal and was controlled for a dummy variable that indicated that a Zhongshan pixel is 63.1% more likely to urbanize, all else equal.

The physical characteristics of a pixel in the start year also have a generally predictable impact on urbanization probability. If a location was in agricultural use its probability of conversion to urban land was 2.7 times more likely than if it was natural vegetation indicating that urban uses are offering much higher returns than agricultural ones. Surprisingly, water is almost 50% more likely to develop than land, all else equal. This reflects the intensity of the economic growth in the region, an abundance of water in highly desirable locations, and a lack of environmental regulation. Even with all the observed flattening of hills in PRD, an additional 5% of slope on the land makes that location only 97.3% as likely to see urbanization. Even more influential is topography, with an additional 5% of average slope within one-kilometer of a site leaving it is only 82.9% as likely to develop. Finally, for every ten kilometers further east a pixel is 1.1% more likely to develop and for every ten kilometers further north a pixel is only 91% as likely to see urbanization. These purely geographic variables aim to control for first order spatial autocorrelation.

Once calibrated, we ran the model in its most basic variant to construct a baseline prediction of urban expansion in 2-year steps until the year 2015. At the end of each prediction, the amount of land remaining in each county is calculated and passed back to the upper-level model. Figure 3 and Figure 5 show, respectively, the predicted regional-level dynamics and the spread of urbanization for the years 2005, 2007, 2009, 2011, 2013, and 2015. This simple extension into the future demonstrates the model's general usefulness and tractability; future work will explore multiple simulations generated by adjusting the nature of fundamental relationships within the systems model or by simulating policy such as the conservation of agricultural land within the lower-level model.

Our analysis is critical in interlinking the rate and pattern of urban growth on the landscape over a relatively broad spatial extent to both local-level factors such as accessibility and topography and to regional-level processes such as macroeconomic forces and population dynamics. Our understanding of the interaction of socio-economic processes and land use change will remain limited as long as we continue to rely on approaches that are poor in dealing with disequilibrium dynamics and that do not effectively address nonlinear, time-delayed feedback structures (Fiddaman 2002; Liu, Dietz et al. 2007). As in the study of land change dynamics in rural locales, studying socio-economic and biophysical interactions in urban settings requires the integration of theories and methods from both natural and social sciences (Gibson, Ostrom et al. 2000; Alberti, Marzluff et al. 2003; Grimm, Faeth et al. 2008). Contrary to the conventional thought, urban areas are integral parts of the Earth system by way of their interactions with the ecosystems within which they are embedded. As such, they should be viewed as complex, dynamic, and adaptive systems in which society and ecosystems coalesce at a continuum of scales (Folke and Rockström ; Grimm, Morgan Grove et al. 2000).

We note that the influence of both the magnitude and spatial configuration of relevant factors may need to be taken into consideration in land change studies (Verburg et al. 2002). For instance, as the focus of our study, urban land manifests itself both as a magnitude (i.e. total urban land in a county) in the higher-level with an influence on economic dynamics, but also as an indicator of location of change in the spatially-explicit representation of landcover change. Population and its spatially explicit counterpart population density play a similar role. Consequently, while the amount of land available for development matters for the further growth and changing sectoral composition of the economy in a county, the spatial configuration of existing urban land determines partly where the next set of urban land conversions will occur. All the while, there is organic link between the local and regional-level dynamics through urban land and population in the sense that the nature of interactions between the two levels includes the transformation of the same entity (e.g. in our study, urban land and population) in a higher and lower level of aggregation.

The proposed framework also has significant implications in terms of policy analysis because of its potential for experimenting with different policy options that would simultaneously affect both regional and landscape levels. Hence, one can experiment with different assumptions and policy formulations (such as giving priority to certain counties within the region over others) to understand the feedback processes and linkages through which these changes impact both the regional-level dynamics and the landscape in terms of most likely patterns of urban expansion. On the other hand, one could experiment with different land use policies (such as construction of additional roads) at landscape level and analyze their impacts not only spatially but also in terms of their reflection on regional-level socio-economic dynamics.

We question the persistent use of the term ‘driver’ to denote certain factors supposedly causing land-use change. The emphasis on certain factors as the drivers of land-use change breeds twin dangers of giving a false conceptual dichotomy between the so-called drivers and their resulting effects on the landscape and reflecting a static picture of the interactions between factors of interest that are actually dynamic and thus subject to continuous change. Hence, the term ‘driver’ potentially undermines establishing a more realistic appreciation of dynamic interactions between all factors of interest. The critical role of these interactions in understanding land change dynamics has been acknowledged repeatedly in the literature (Low, Costanza et al. 1999; Lambin 2005; Verburg 2006). Therefore, it may be more apt to speak of a temporarily surging influence of certain factors in relation to the others over the course of land change dynamics. For instance, though not yet experienced at any significant scale, our baseline simulation suggest that the reduced availability of suitable land (coupled with other factors) will eventually slow down the very high levels of growth in the so-called “driving forces” such as investment and migration which will be increasingly directed to other locations as witnessed in Shenzhen and Dongguan. Although investment, especially in the secondary sector, is primarily responsible for land use conversion in the initial decades of economic vitalization (Figure 2), later on land use availability becomes the determining factor in the further growth of the economy especially through its impact on the more land-intensive secondary sector (Figure 2). This not only results in a change in the composition of the economy in a particular county but may also be partly responsible of the kick-off of economy in the neighboring counties. In fact, it is because of the presence of dynamic feedback mechanisms, nonlinearities, and delays between various components of a system that abrupt or gradual shifts may occur over time: any component in such a system may become more influential over time on overall system behavior and thus on the behavior of other components making it difficult to sort out the impacts from the ‘driver’s (Mather, Needle et al. 1998; Bossel 1999; Verburg 2006; Liu, Dietz et al. 2007).

Sustainability science community has recognized that nonlinear feedbacks –both reinforcing and regulating– matter for most of the dynamic problems around us from epidemics to the persistence of poverty to urban sprawl. Thus, it is only natural that feedback interactions must be accounted for in models that claim to reflect relevant aspects of reality. Yet, it is sometimes claimed that incorporation of feedbacks lead to numerical instability in models (Turner, Lambin et al. 2007). This is, for the most part, due to the incapability of the particular modeling methods employed such as econometric tools which are known to be poor in handling feedback interactions and hence nonlinear disequilibrium dynamics (Costanza and Wainger 1993; Sterman 2000; Sterman 2002). For instance, while indispensable in teasing out some of the more important relationships between socio-economic and environmental factors in question statistical tools such as regression analysis inherently discounts the presence of fundamental interactions that are known to exist (Sterman 2000; Seto and Kaufmann 2003; Verburg 2006). The proper treatment of feedback mechanisms of real life requires an appreciation of the accumulation processes thus the presence of stock-flow dichotomy between variables of interest (Sterman 2000; Sterman 2002).

The fact that the dynamics of interest often play out at different scales of analysis poses particular challenges to understanding integrated land systems (Meentemeyer 1989; Turner, Lambin et al. 2007). In this respect, the specific research questions one tackles ideally determine the modeling approach that would prove most fruitful in generating insights into the dynamic nature of the problem at hand (Rindfuss, Walsh et al. 2004). Bottom-up approaches such as agent-based models tend to emphasize local entities (e.g. households, farmers etc.) and their interactions, which is feasible and most insightful when the focus is on understanding how the local-level interactions give rise to the ‘emergent’ structure at higher spatio-temporal levels over time and when applied on small spatial scales (Parker, Manson et al. 2003; Grimm, Revilla et al. 2005; Epstein 2007; Manson 2007). If the focus is on the role of higher-level socio-economic processes that interact with local land use dynamics an exclusively bottom-up approach might not be warranted (Rindfuss, Walsh et al. 2004; Moran and Ostrom 2005). In those cases, less disaggregated system-wide representation of the integrated socio-economic and biophysical interactions that adequately emphasizes the processes that matter for the research question at hand is a more economical and perhaps more insightful way to understand the underlying dynamics and develop strategic and effective policy options (Richardson 1999; Gibson, Ostrom et al. 2000; Fiddaman 2002; Waggoner and Ausubel 2002; Güneralp and Barlas 2003; Stave 2003; Newell, Crumley et al. 2005; Güneralp and Seto 2008; Levine, Hughes et al. 2008).

5. Conclusion

Our framework allows for an analysis of the unfolding of feedback dynamics and their combined impact on the landscape over time and complements more established approaches in land change science. The system model component of the framework proposed here can also be regarded as a regional model in and of itself; nevertheless, its coupling with a spatially-explicit statistical model allows to address changes in the landscape influenced by these higher-level processes. While there are examples of land use models where interscale interactions are involved (Engelen, White et al. 1995; White and Engelen 2000; Wang and Zhang 2001; Overmars and Verburg 2006; Castella, Kam et al. 2007; Lischke, Bolliger et al. 2007; Manson and Evans 2007) this is the first time such a dynamic coupling framework is realized with an explicit attention to nonlinearities and influential feedback dynamics in the system in a land change model.

Our analysis of a rapidly urbanizing region in China links the rate and pattern of urban growth on relatively large landscape to both local-level factors such as accessibility and topography and to regional-level processes including macroeconomic forces and population dynamics. Our approach allows for appreciating the heterogeneity of urban growth dynamics within the region at both regional and local levels. Such dynamic coupling between levels of analysis is a crucial aspect for reaching a better appreciation and understanding of scale relationships in complex socio-economic and biophysical systems.

Feedback structures are at heart of interactions between socio-economic and biophysical systems. Theoretically sound and comprehensible representation of these feedbacks is a prerequisite to formulation of a robust land use science theory. Such formulation will, in turn, open the way for the addressing of deeper level theoretical questions on the interactions of socio-economic and biophysical systems including LUCC dynamics. The framework we present is a significant step toward spatially explicit models that focus on multiscale nonlinear feedback-driven dynamics as well as decision-making processes across and within relevant levels of interest.

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Figures

Figure 1. Conceptual representation of the framework.

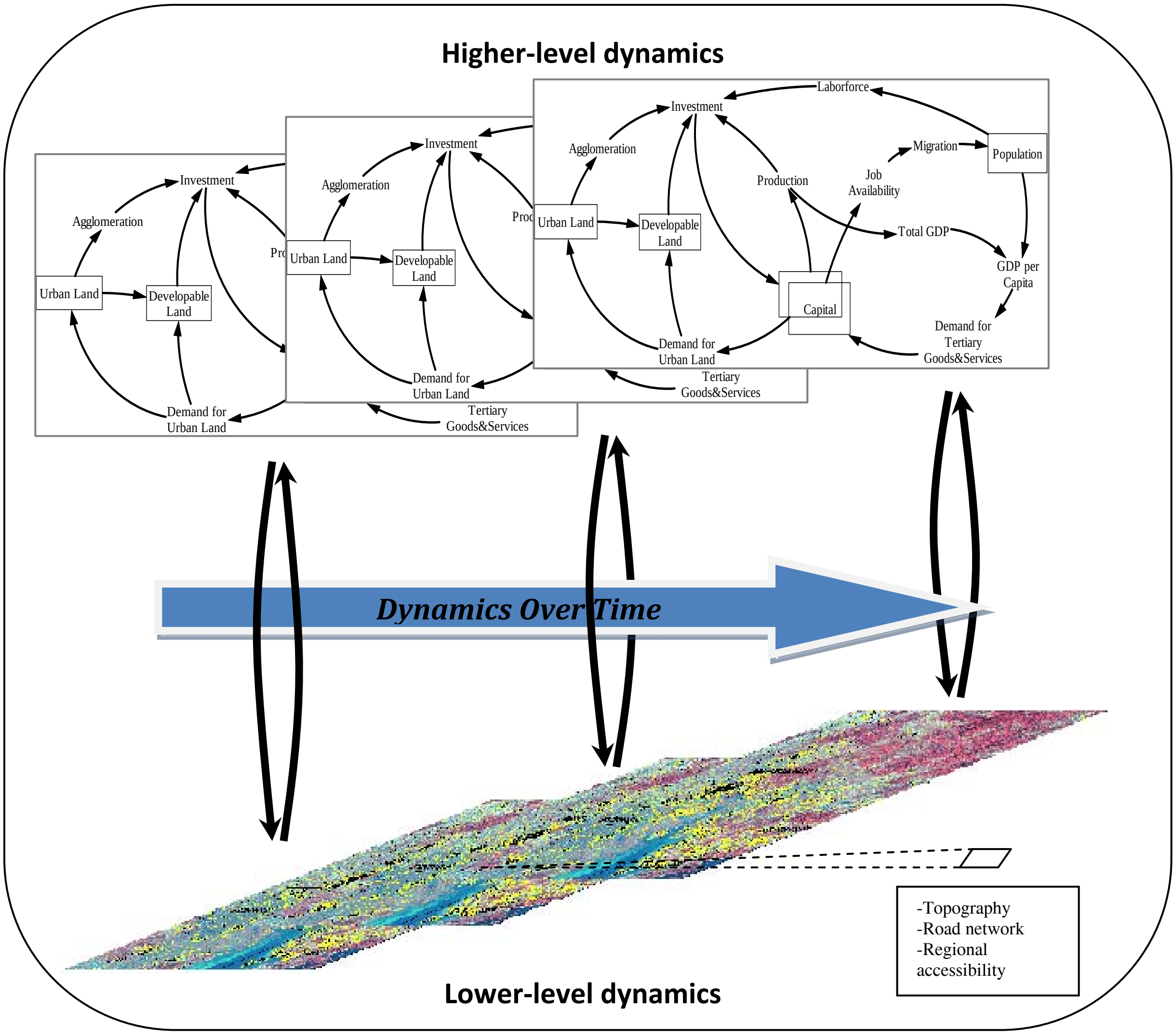
Figure 2. The most influential feedback loops creating the observed behavior patterns in the counties. Boxes represent main components (i.e., accumulations). The variables that are passed between the lower and higher level models are represented in italics. See text for explanation on the most influential feedback dynamics.

Figure 3. Patterns of growth in each modeled county for *(a-b)* GDP shares of secondary and tertiary sectors, respectively, *(c)* population, and *(d)* GDP per capita.

Figure 4. Historical urban expansion (1999-2005).

Figure 5. Predicted urban expansion (2005-2015).

Figures



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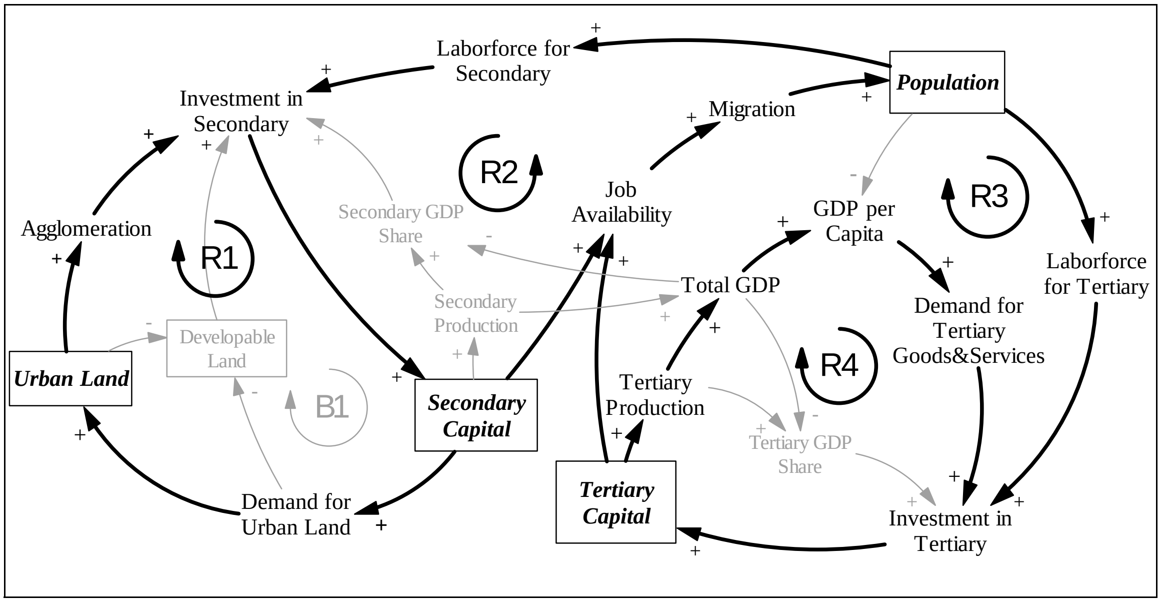

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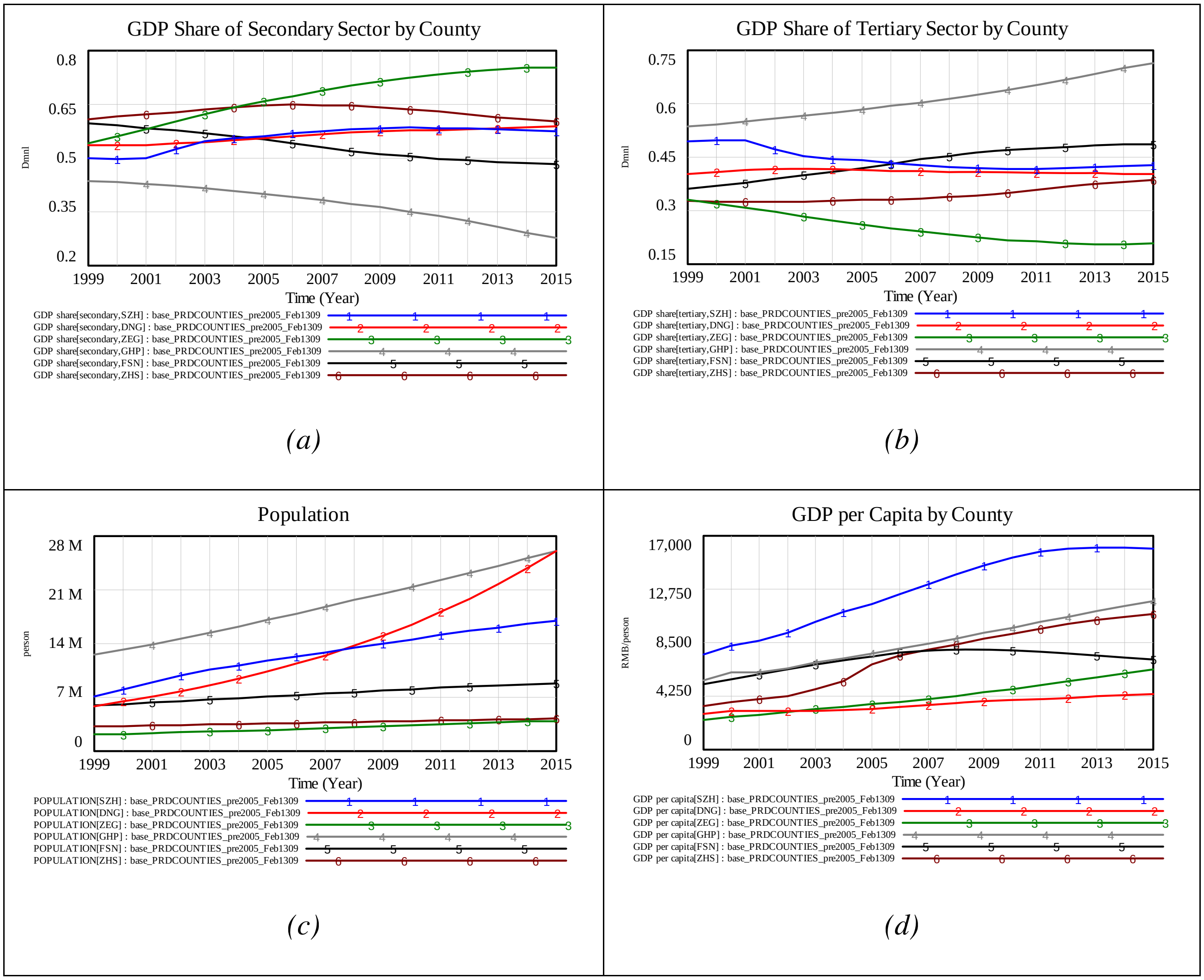

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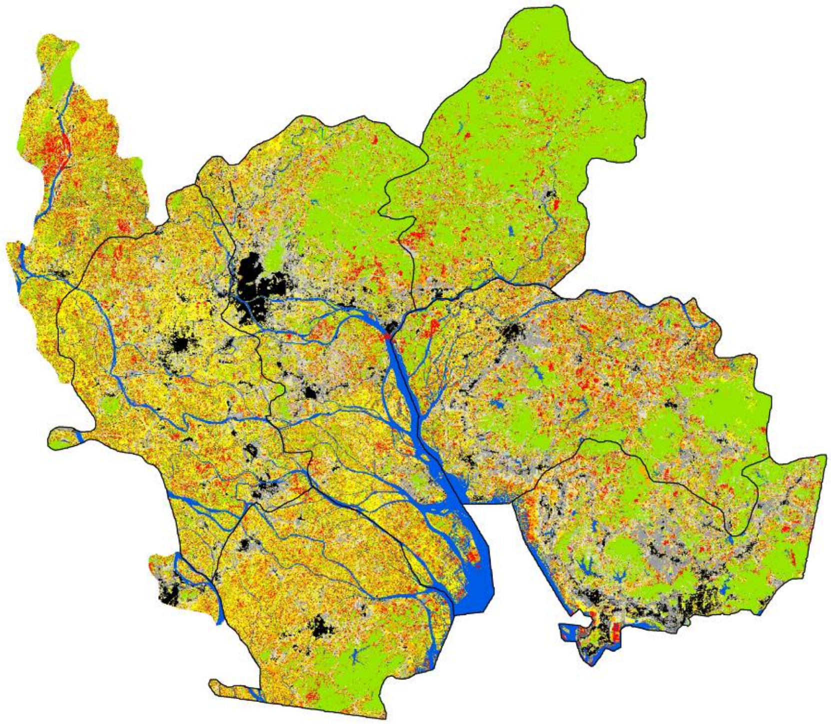

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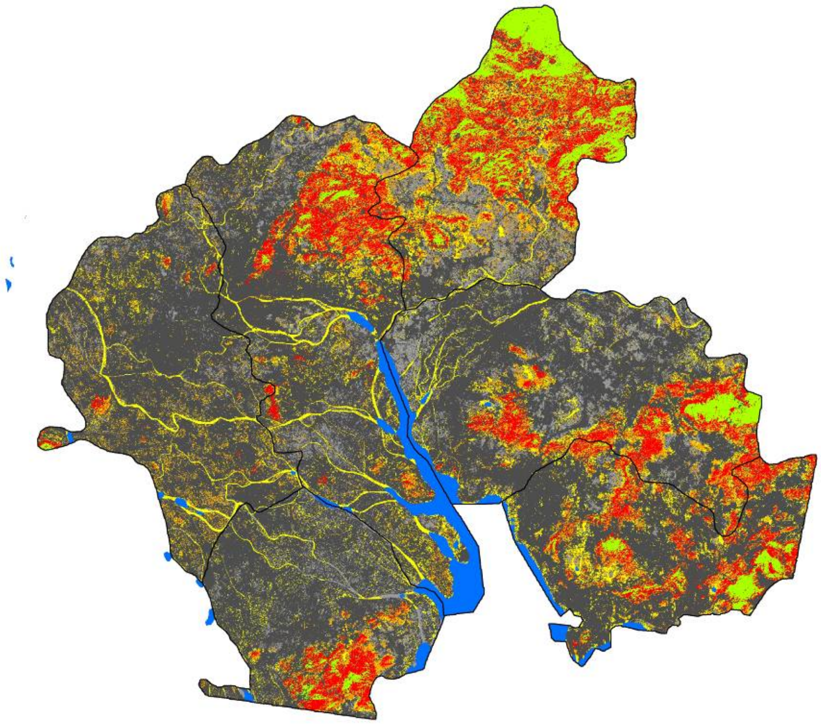

Figure 5. Predicted urban expansion (2005-2015).

Table 1. Groupings of administrative entities representing each subregion.

Grouping	Composed of
Shenzhen	Shenzhen
Dongguan	Dongguan
Zengcheng	Zengcheng
Guangzhou	Guangzhou, Huadu, Panyu –including recently formed Nansha
Foshan	Foshan, Shunde, Nanhai
Zhongshan	Zhongshan

Table 2. Odds ratios of local urbanization drivers, 1999–2005.

Variable (change interval)	**Odds Ratio**
	1999-2005
popch (100/km^2)	1.037
capsecch (million Yuan/km^2)	1.012
capterch (million Yuan/km^2)	0.984
gzdis (10 km)	0.97
majrddis (10 km)	0.782
urbneigh (25%)	0.878
water	1.480
ag	2.744
slope (5%)	0.973
topography (5%)	0.829
zsdum	1.631
x (10 km)	1.011
y (10 km)	0.905

Table 3. Sectors of the system dynamics model.

Sectoral Grouping	**Sector Name**	
Demographic Submodels	Population	
	Labor force	
Economic Submodels	Primary Sector	(Farming, forestry, animal husbandry, fishing)
	Secondary Sector	(Manufacturing, construction, mining and quarrying)
	Tertiary Sector	(Commerce, banking, tourism, entertainment, real estate trade)