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Simulating Emergent Urban Form: Desakota in China

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Abstract

We propose that the emergent phenomenon know as "desakota", the rapid urbanization of densely populated rural populations in the newly developed world, particularly China, can be simulated using agent-based models which combine both local and global features. We argue that deskota represents a surprising and unusual form of urbanization well-matched to processes of land development that are driven from the bottom up but moderated by the higher-level macro economy. We develop a simple logic which links local household reform to global urban reform, translating these ideas into a model structure which reflects these two scales. Our model first determines the rate of growth of different spatial aggregates using linear statistical analysis. It then allocates this growth to the local level using developer agents who determine the transformation or mutation of rural households to urban pursuits based on local land costs, accessibilities, and growth management practices. The model is applied to desakota development in the Suzhou region between 1990 and 2000. We show how the global rates of change predicted at the township level in the Wuxian City region surrounding Suzhou are tempered by local transformations of rural to urban land uses which we predict using cellular automata rules. The model, which is implemented in the *RePast 3* software, is validated using a blend of data taken from remote sensing and government statistical sources. It represents an example of generative social science that fuses plausible behavior with formalized logics matched against empirical evidence, essential in showing how novel patterns of urbanization such as desakota emerge.

Keywords: emergence, desakota, rural-urbanization, agent-based modeling, lower Yangtze River Delta

Emergence and Desakota

Rapid urban change often leads to patterns of morphology which are surprising in that they are unanticipated, often counter to what is expected. Recent regeneration and redistribution taking place in the industrial city has led to increasing specialization manifesting itself in phenomena such as the "edge city" while patterns of segregation, particularly with respect to the concentration of ethnic groups appear under regimes where different populations are quite content to live side by side, notwithstanding a mild preference towards their own kind (Ormerod 2005). These patterns are often described as "emergent", reflecting processes which act from the bottom up, producing growth and change which is organic and unplanned in its genesis. A particularly clear example of these phenomena is associated with urbanization in some newly developed countries, particularly in East Asia. There, rural landscapes usually within the hinterlands of large cities, are rapidly urbanizing, not through rural depopulation to the cities with their subsequent outward growth, but through a process of spontaneous change in which a majority of the rural population are transforming their lifestyles and activities into urban pursuits *in situ*. In these situations, the longstanding migration of the population to large cities which has historically marked third world urbanization is less significant than the transformations that are taking place as the rural population becomes urban without substantial movement to the cities. This phenomenon is called "desakota".

Desakota is a pattern of settlement characterized by an intensive mixture of agricultural and non-agricultural activities which reveals itself as a close "interlocking" of villages and small towns (Lin 2001). These patterns are neither urban nor rural, but demonstrate features of both. The term desakota was first used by McGee (1989, 1991) who identified these morphologies with the Bahasa Indonesian word "desakota" from the words for village "desa" and town "kota". In one sense, it is easy to see why this pattern of growth characterizes rapid urbanization in places like China. Rural life has formed the bed rock of Chinese society for many thousands of years revealing itself in a dense polynucleated quilt of villages and small towns with close economic links to the larger cities. Unlike the wholesale movement from the countryside to the towns in places like Britain in the 19^{th} century, modern technologies now make it possible to urbanize *in situ*, so to speak, with the network of social and economic connections associated with an urban society already largely in place. Some argue that understanding this rural-urban nexus and its new landscape is a key to understanding China's tremendous social and economic transformation (Tang and Chung 2000). Somehow the patterns are representative of China's extraordinary economic vitality and provide clues to its continuing social and political stability in the face of great economic upheavals (Lieberthal 1995). Indeed, the phenomena is by no means confined to China; an equivalent of desakota has existed in parts of urban Europe for the last half century as urban growth has put flesh on the polycentric network of towns and cities established over 500 years ago (Kloosterman and Musterd 2001).

Emergence is a much more difficult concept to explain than to illustrate but one way of proceeding is to build models of such phenomena whose fundamental entities or objects, sometimes called "agents", interact with one another from the bottom up (Parker et al. 2003). The key to understanding emergent phenomena which results from such interactions is to fully understand the way the model's agents influence one another, usually over multiple time periods and across extended spaces, where surprising patterns often emerge as a consequence of nonlinear interactions between agent behavior, the results of positive feedback. This is the conventional wisdom underlying the rationale for complex systems modeling. Once a satisfactory understanding of such emergence has been gleaned, then it is an open question as to whether or not the phenomenon is still to be called emergent. In terms of urban growth and form, purely bottom-up explanations are unlikely to reflect the range of processes and agents that generate such spatial organization (Urry 2003). In the case of desakota for example, efforts to explain such phenomenon are reflected in at least two schools of thought.

The first emphasizes the role of rural areas as the locations for development and gives priority to rural urbanization. Since Deng Xiaoping's "reform and opening-up", central government control of rural areas has been relaxed and local cadres have assumed responsibility for many resources and institutions in the countryside. Townships and village officials have sought to replace declining state revenues with taxes and fees on local industries and have promoted and subsidized collective and commercial enterprises, an approach that has been widely adopted since the 1980s. This school argues that, while large metropolitan cities may provide markets and new technologies, much of the energy and drive for production is not demand-driven but comes from rural peasants and local cadres seeking to improve their lives. This is truly a bottom-up process reflecting local action (Tang and Chung 2000).

In contrast, the top-down approach highlights the contributions of China's largest cities and coastal trade zones which appear to have reinvigorated and internationalized China's economy, culminating in its recent entry into the World Trade Organization (Li and Yeh 1998). This school argues that it is only the metropolitan regions that have supported the conditions for China's social and economic transformation to a modern economy consistent with relaxed labor markets, high worker mobility, and free trade (Yeung and Zhou 1991; Yao 1992). In fact, McGee's (1991, 1998) model of desakota is a hybrid, drawing on elements from both approaches where he implies that the resultant landscapes are based on industrialization in rural areas but consistent with a "friction of space" that privileges certain locations up to 200 kilometers beyond the largest cities or between adjacent metropolitan areas (Oi 1999).

Desakota has been quite widely studied in a qualitative sense but to date, the phenomenon has been mainly identified and analyzed in descriptive terms, focusing on how the transformation of China in terms of the global economy and its internal restructuring has forced the pace of this variety of urbanization. There have been attempts to simulate incremental urban change in rural areas using mainly physical models such as those based on cellular automata and developed by Li and Yeh (2000) for the Pearl River Delta. There have been attempts at measuring the resultant morphologies which show particular patterns of fragmentation (see Sui and Zeng 2000) and there are approaches to detecting differences between rural and urban in urbanizing regions using ideas from fuzzy sets (Heikkala, et al. 2003). Xie, Yu, Bai, and Xing (2005) and Xie, Mei, Guangjin, and Xuerong (2005) have explored how these processes have resulted in the loss of agricultural land and changes to the ecological balance. However to date, there have been no attempts to simulate the way in which developers and entrepreneurs engage in the process of land development which is central to the way rural activities are transformed to urban. We will redress this here through explaining the evolution of desakota using an agent-based model which is embedded within a land development process that is driven both from the top down and bottom up. We will argue that desakota regions emerge from a combination of behaviors towards the land and housing markets that reflect State and City policies which are instituted from the top down, and developer, entrepreneur, and consumer behavior which responds to local conditions from the bottom up. Indeed like Li et al. (2005), agent-based modeling should not be restricted to processes simulating growth and change from the bottom up.

In the next section, we will describe how the processes which lead to desakota can be simulated by a spatial logic that meets both local and global conditions and constraints in the particular area of China we develop the application for: the City of Wuxian which surrounds Suzhou City in the lower Yangtze Delta about 100 kilometers north west of Shanghai. We will then outline the formal structure of the model used to transform the landscape surrounding big cities into desakota, emphasizing the way top-down processes of social and economic development interact with developer-agent behavior which operates from the bottom up, initiating various feedback effects that determine the spontaneous transformation of land uses. We then describe the data we have for 5 year periods from 1990 to 2000, showing how this data can be used to estimate rates of urban change for 27 townships that comprise the region and which determine the controls on overall growth that take place over the observed period. We outline the way the model works at a fine spatial scale, in the cells that agents occupy in making the transformation from rural to urban. We show how well this model simulates the observed trajectories of urban change from 1990 to 2000 and then indicate how we can use the model to make forecasts for the middle range until 2010 and thence beyond. Our emphasis on using the model in prediction is to show how agents operating spontaneously at the fine spatial scale are influenced by and influence policy at the global level which is governed by the actions of policy makers in the townships. We then conclude with ideas for further research and a brief commentary on the suitability of this approach for explaining unusual spatial patterns such as desakota.

A Logic for Modeling Spontaneous Urban Change in China

Urban development everywhere is influenced by decision-making at multiple levels and scales. But for desakota in China in general, and development in the Suzhou City region in particular over the period from 1990 to 2000, we simplify the chain of development decisions to two levels which we call 'local' and 'global'. The global level is reflected in aggregate social and economic factors which pertain to districts or townships within the region, and which are used to define instruments that steer development to favorable locations consistent with regional and national economic policy. The local level involves the decisions which households in rural villages and small towns make to realize local scale economies through the transformation of their activities from rural to urban pursuits or to a mix of these. We call this "two-front growth" which combines two different policy-making levels which both contribute to the simultaneous development of urban and rural areas by fusing "city-leading-county" initiatives in the cities with the "household responsibility system" that has been introduced in the countryside. City-leading-county initiatives are geared to transforming decaying state-owned enterprises into private but often State sponsored investments that reflect China's growing international trade and investment through the gateway cities. These new developments are initiated by local enterprises adjacent to large cities with foreign investment, often appearing in what was once farming land like "flying intruders" (Wei 2002).

In contrast at the more local level, since the early 1980s, the introduction of a "household responsibility system" (HRS) has dramatically changed rural areas through the decollectivization of agriculture and a return to family-centered crop production. HRS has provided strong incentives for rural towns and villages to diversify and grow their economies by developing non-agricultural enterprises. In general, this kind of rural urbanization often involves small-scale, individual, private-owned non-agricultural land use, which is termed "rural construction" in official Chinese statistical yearbooks (Wuxian City Statistical Bureau 2001) with most construction registered as housing. But the functional uses of such rural construction are diverse; many individual houses are in mixed use, based on small factories, craft and other retail shops, restaurants, and related privately-owned and operated businesses. It has been argued that this bottom-up impetus is core to China's economic vitality and is a primary factor sustaining China's continued economic miracle (Marton 2000). Agent-based modeling is an ideal way of encapsulating this kind of institutional policy-making with local physical responses in terms of land development and we will fashion our model around this logic.

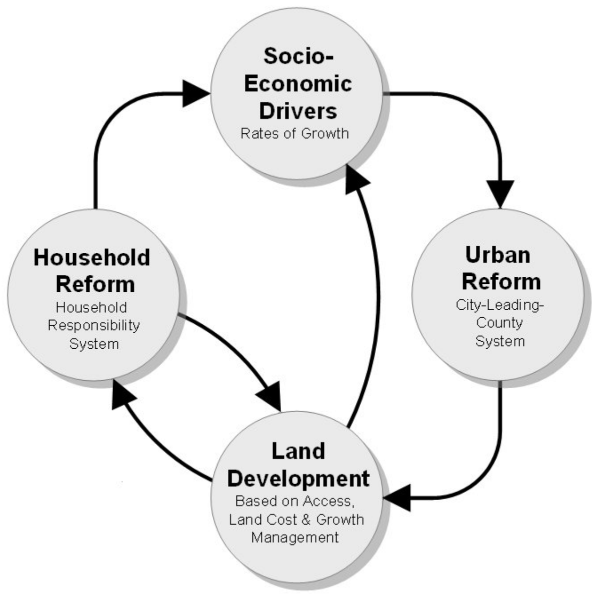


Figure 1: The Logic of Deskota

We have abstracted this process in Figure 1 where we show the key feedbacks that appear to be plausible drivers of the processes that determine the transformation of the rural landscape into desakota in the Lower Yangtze Delta. At this point, we must digress to justify our approach to understanding desakota using agent-based models. As Page (2003) so cogently argues: "… our models become better, more accurate, if they make assumptions that more closely match the behavior of real people…" and to this end, we consider the processes embodied in Figure 1 to be close to those we observe, albeit in a somewhat aggregate manner. We will further translate this by approximating the outputs of these processes by data when we come to validate the model in a later section but in terms of verifying the model structure, we consider this to be consistent with the wide literature on desakota that has appeared so far. Before we specify the model formally, we need to describe its structure in somewhat more detail.

In abstracting in this manner, we assume that distinct objects of interest can be defined as agents whether literally such as individuals and/or households, or somewhat more metaphorically as townships, districts, policy instruments and the like. We also assume that the canvas or landscape on which and about which agents make their decisions is geographical in the traditional sense of the map. Agent-based models essentially simulate processes in which agents interact with each other but also with the landscape, where the assumption is that all possible feedbacks between landscape and agent can, in principle, take place (Batty 2005a). In this context, we have already define two levels – the local and the global and we can thus define two types of agent and two types of landscapes associated with each of these levels. In terms of agents, we define developer agents who might be households, foreign investors or even the State at the local level, while at the global level, we assume that the agents are townships. The associated landscapes are both geographical with the global being the area of each of 27, in this case, townships that exhaust the space of the Suzhou region while at the local level, the landscape is a regular grid of cells which is the most neutral way of defining a geography where each individual location has no *a priori* advantage over any other.

These definitions map onto Figure 1 in the following manner. In general, the socio-economic drivers of change are determined at the global township level where various policy instruments are exercised in terms of urban reform. At the township level, regional and national policies are determined and in general this fixes the rate of growth, at least in the medium term. At the local level, household reform enables individuals and families to transform their lives by adopting urban pursuits, both to attract development and to initiate it themselves. In this sense, households are developer agents and respond to more local conditions such as the costs and benefits of various types of accessibility as well as the cost of land and top-down policies for growth management. The interactions between these levels are of course critical and Figure 1 implies a degree of asymmetry in the processes just explained. Essentially the outer loop in Figure 1 represents a process in which socio-economic conditions slowly determine urban policy which in turn provides the conditions for development that households in the rural areas respond to. In turn, these households initiate urban development on a much shorter cycle than the outer loop implies. This means that at the local level, development takes place in a stable context of wider global policy and economic conditions but can be much more volatile due to feedbacks posed by local conditions. The development that occurs then changes the socio-economic conditions which policy will respond to in the longer term. Flow charts such as Figure 1 could imply that everything is connected to everything else but in this context, it stresses that the global level responds more slowly than the local. We will incorporate this feature somewhat bluntly in our model by computing rates of change at the global level over longer time periods than are those used to initiate urban development at the local cellular level.

A Formal Statement of the Model

There are two kinds of agents in the model: the set of townships Z_k which are indexed spatially by location as $k = 1, 2, ..., K$ and the set of developer agents which we index as $j = 1, 2, ..., J$. The developer agents move on a landscape of cells which we index as $i = 1, 2, ..., I$ while the township agents are immobile and are directly associated with their equivalent geographical space: that is each township k occupies an equivalent space k where the number of townships is much less than the number of cells, that is $K << I$. There is also a strict nesting of cells within townships, that is $\sum_k \sum_{i \in Z_k} \# i = I$ where the hash symbol simply indicates that we count *i* as 1 if it is part of the township *k*. Just as cells are nested in townships, the micro-time periods over which development takes place from t to $t+1$ …., are nested within more macro-time periods denoted from time *T*, to $T+1$, … such that $\Delta T = [T+1] - [T] = \tau$. τ is a number of micro-time instants which are associated with the change between *t* and $t + \tau$ used to simulate local land development.

The model is specified at two levels. The key driver at the global level is a function that determine the rates of change in each of the townships measured by changes in households which can be converted into developable units. The rate of change in k , $R_k(\Delta T)$ is defined from the function $f(\bullet)$ which is specified as

$$R_k(\Delta T) = f\left\{X_k^1(T),\ X_k^2(T), \ldots\right\} \tag{1}$$

where $X_k^{\ell}(T), \ell = 1, 2, ..., L$ are socio-economic drivers associated with economic development and regional policy appropriate to the township level. This need not delay us here but equation (1) is the basis for the estimation of the importance of exogenous variables to the rates of change which are fitted using linear regression in a later section. These rates in fact determine the amount of growth over the macro-time period ΔT. To generate a total for the end of such a time period, they are applied straightforwardly to the total households (as developable units) in k, $P_k(T)$, as

$$P_k(T+1) = \left[1 + R_k(\Delta T)\right] P_k(T) \qquad . \tag{2}$$

To anticipate the lower-level local allocation, then the total households allocated at time $T+1$ will always sum to those at the lower level, that is $P_k(T+1) = \sum_{i \in Z_k} p_i(T)$ where the households have already been aggregated over the number of time periods τ at this lower level.

From equations (1) and (2), total households can be counted at any scale and over any time period but in the model, the rates of change are in fact applied at the local level where all allocation takes place. If we define the cumulative rate from equation (2) as

$$1 + R_k(T) = \frac{P_k(T+1)}{P_k(T)} \qquad , \tag{3}$$

then we can factor this rate into a rate per unit time period $\Delta t = [t+1] - [t]$ by discounting the cumulative rate as

$$\tilde{r}_k(t) = \left\{\frac{P_k(T+1)}{P_k(T)}\right\}^{\frac{1}{\tau}} = 1 + r_k(t) \qquad . \tag{4}$$

When applied cumulatively to the population $P_k(t) = P_k(T)$, equation (4) updates the totals at each time period t to meet the constraint that $P_k(t+\tau) = P_k(T+1)$.

In each macro-time period ΔT, the total change $\Delta P_k = P_k(T+1) - P_k(T)$ is broken into its finer temporal parts using equation (4) and each subtotal $\Delta P_k(t)$, $\Delta P_k(t+1)$, …, $\Delta P_k(t+\tau)$ forms the control for the detailed urban development process at the cellular level. At this level, the variables that determine location are quite different from the global level in that it is accessibilities, land cost reflected through suitability, and growth management policies that determine the allocations. At this stage, we will define land suitability in the fine cell i as $C_{ik}(t)$, accessibility to economic centers as $E_{ik}(t)$, and accessibility to transportation facilities as $T_{ik}(t)$. We also define a policy index $S_k(t)$ which is related to the rate of change in k, $R_k(T), \forall_{i,t}$. This tempers the effects of accessibility and suitability with respect to the growth management and economic policies set at the township level. This index is set in proportion to the rate of growth of each township (see Xie, Mei, Guangjin, and Xuerong 2005). We will specify these variables in more detail when we validate the model but in general, these factors are used to determine a probability for development $\rho_{ik}(t)$ which is a form of utility given as

$$\rho_{ik}(t) = g\{T_{ik}(t), E_{ik}(t), S_k(t)\} \quad . \tag{5}$$

In general, land is converted to urban uses by the developer agent j who for each cell i in township k evaluates the probability of development, subject to the suitability of the land in question as reflected in the measure $C_{ik}(t)$. In principle, what each agent is doing is converting the land in question to an urban use, to $p_{ik}(t)$ by maximizing $\rho_{ik}(t)$ subject to the constraint posed by the land suitability $C_{ik}(t)$.

Because this process is implemented algorithmically in sequential form, the details differ from a pure optimization. As we will explain below, at the start of each macro-time period T in the first micro-time period t, we set up a series of master agents which effectively seed the development process in the periphery of existing urban development. We define $P_k(t)$ such agents and we locate these so that they occupy $P_k(t)$ cells i which have the highest probability for development $\rho_{ik}(t)$ using the standard random (Monte Carlo) mechanism used in such modeling (see Batty 2005a). In fact, during this process because land suitability is taken into account, developers will not develop a cell if the land suitability is less than a certain threshold $\Xi_k(T)$, that is, if $C_{ik}(t) < \Xi_k(T)$. The reasons for this initial allocation step which is different from the subsequent steps within the macro-time period, rests on the fact that there was a strong shift in policy between 1995 and 2000 in this region and this needs to be reflected in the initial placement as we will recount in the discussion below. We call this first process *random allocation* but in subsequent time periods, the master developer agents are used to "spawn" additional agents which add to up to the total required in subsequent micro-time periods. These agents begin by considering development in the cellular neighborhood of each master agent activating a process we call *neighborhood allocation*. It is at this point that the probabilities define in equation (5) are considered in neighborhood order: that is, the developer begins by considering cells in the immediate band of eight cells around the master agent – in the Moore neighborhood – and if no suitable cell is found, then the agent considers the next band of cells, and so on until a suitable cell is located. The reason for this somewhat convoluted process is to ensure that development remains "close" to existing development which reflects the need for connectivity in the urbanizing system.

Once the process is concluded at the end of each micro-time period, new development changes the accessibility to transport infrastructure and economic centers as well as land suitability. In short, there are positive feedbacks initiated at this lower level from each time period to time period as reflected in the direct feedback loop between developers and households in Figure 1. Formally, then

$$\left.\begin{aligned} T_{ik}(t+1) &= z\{T_{ik}(t),\ p_{ik}(t+1)\} \\ E_{ik}(t+1) &= q\{E_{ik}(t),\ p_{ik}(t+1)\} \\ C_{ik}(t+1) &= h\{C_{ik}(t),\ p_{ik}(t+1)\} \end{aligned}\right\} \qquad (6)$$

Feedbacks at the higher level of course exist although we have not implemented any so far due to the nature of the estimation that we will describe in the next section. Moreover there are many extensions that we might make to this model with respect to increasing the connectivity between the various elements. Nevertheless we consider that this captures enough of the desakota process to mirror the process of spontaneous development. In Figure 2, we illustrate the crucial steps in this simulation from which it will be clear to the reader how we might make additional connections and extensions to the model structure.

Estimating Global Rates of Urban Change

The data for this model was derived from diverse sources. As population, household and related socio-economic data was not available at a scale equivalent to land parcels or even census blocks, data on urban and rural construction (which we assume proportional to household change) was generated from remote sensed imagery using Landsat Thematic Mapper (TM) images for 1990, 1995 and 2000. These images were classified into a dozen or so land use categories which were then used to derive the transition matrices indicating the amount of each land use which was converted to any other during the two periods in question: 1990 to 1995 and 1995 to 2000: $T \rightarrow T+1$ and $T+1 \rightarrow T+2$. These images were used to extract land parcel data which was then converted to vector data sets, complemented by data associated with topography, geomorphology, vegetation, precipitation and temperature used as the ancillary data in the interpretation process. Further details are given in (Liu et al. 2002). There are many methods for detecting land cover changes available based on image differencing through various transforms (Almeida, et al. 2005). The method adopted here to extract dynamic changes in the vector land use datasets was based on post-classification image comparison complemented by field sampling to ensure quality control in the resulting classifications. Control was executed by checking the identities and the boundaries of sample land use patches with manual adjustment to decrease the incidence of major errors. In fact over both time periods comparing 1990 with 2000 data, the percentage accuracy of measured areas is about 97% (Liu et al. 2002) which gives us a high level of confidence in the extracted change data and its allocation into land use categories.

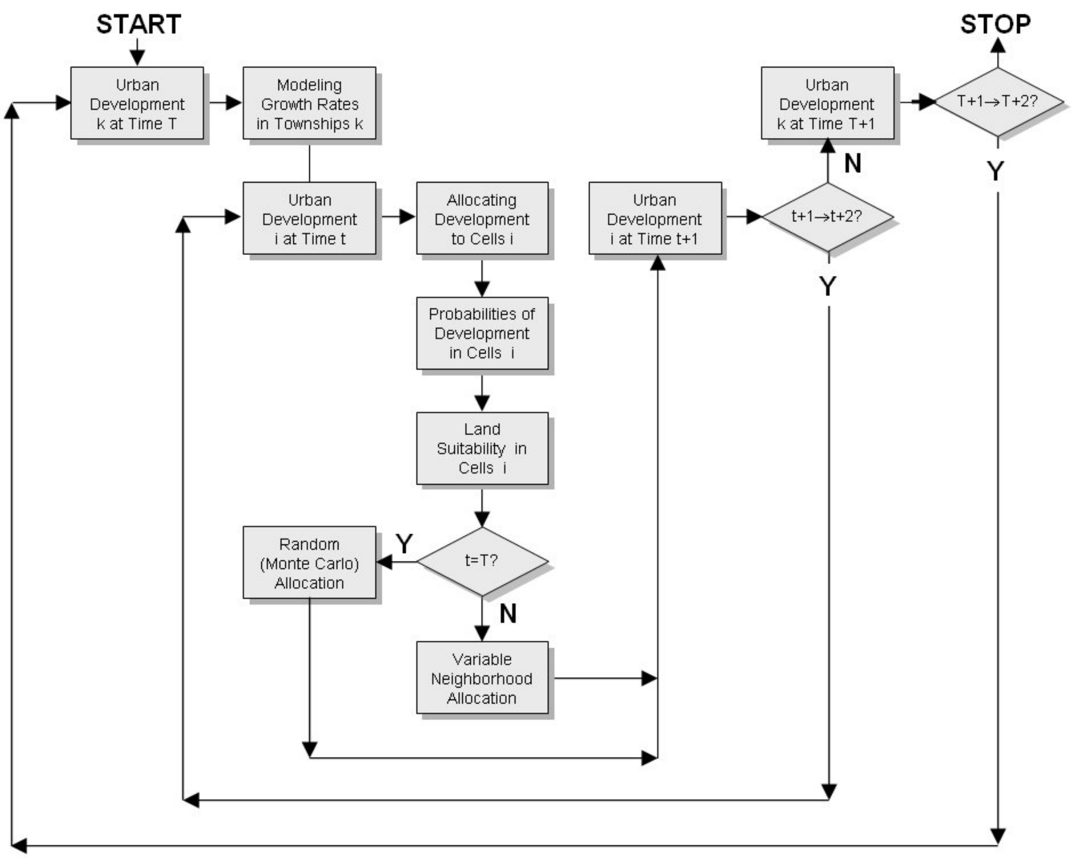


Figure 2: Sequence of Operations in the Model

We will not show the complete transition matrix between each of the 13 categories of land use that we have extracted at these three dates for our focus is not on how particular land uses are transformed into one another *per se* but on the impact of urban development on the range of land cover types. In Table 1, we have extracted the changes from an aggregated set of classes to urban and rural construction (which we take to be urban/household unit development in this context). Although there is a sharp increase in land use being converted from paddy fields and a consequent drop in conversions from drylands between the first and second time periods, these two land use categories completely dominate the process forming some 98 percent of the entire land use change in the first period and some 88 percent in the second period. As conversion from paddy fields is the largest category in both periods, we can also examine the extent to which paddy fields are converted to other land uses which we show in Table 2. Urban and rural construction still dominate taking some 77 percent and 74 percent of paddy field land in the two respective time periods with factory and transportation uses taking 4 percent and 7 percent. The only other substantial transition is from paddy field to reservoirs and ponds which simply indicate traditional changes in this kind of wetland agriculture with no real significance for urbanization.

Table 1: Percent Conversion of Land Use to Urban and Rural Construction over the Two Macro-Time Periods

Land Use Cover Type	**1990-1995**	**1995-2000**
Dense Forest	1.01	3.42
Shrub and Loose Forest	0.09	2.08
Other Forest including Orchards	0.2	3.37
Highly-Covered Grassland	0	1.24
Lake, Reservoir and Pond	1.17	1.88
Shoal	0	0.03
Hill and Plain Paddy Field	50.84	77.13
Hill and Plain Drylands	46.69	10.85

It is not very meaningful in such a large region to examine absolute volumes of change. Suffice it to say that Shuzhou City's population in 1990 was some 0.84m (million) and this grew 1.11m in 2000 with Wuxian City, the surrounding region falling from 1.12m to 0.96m people during this time. In fact in 1995, due to boundary changes Suzhou incorporated three townships from Wuxian but the key point is that the entire region grew only slowly from 1.97m in 1990 to 2.03m in 1995 to 2.07m in 2000. Nevertheless, there has been dramatic urbanization of Wuxian during this period which is quite evident from analysis of the imagery. In terms of land area, however, some 60 percent of Wuxian is permanent lake but paddy field is the next largest use at around 25 percent of the area in 1990. Paddy fields have reduced by 5 percent in each of the five year periods (roughly dropping by 1 percent per year) and now constitute some 22 percent of the region. This loss has been taken up by rural construction which was 3 percent of the region's area in 1990 and 4 percent in 2000, growing by some 25 percent in the first period and 46 percent in the second. Urban construction (within Wuxian) grew even more dramatically by some 18 percent in the first period and a staggering 240 percent in the second. The scale of this growth is quite characteristic of desakota with the boundary between what is defined as rural and urban entirely blurred (Heikkala et al. 2003). In Figure 3, we show the location of the region centered on Suzhou City with the 27 townships within Wuxian. In Figure 4, we show the distribution of land uses taken from the remote imagery for 1990, 1995 and 2000, the differences between each of these dates, and the difference from 1990 to 2000 which indicates the degree of overall change. It is from these difference maps that we compute the urban change used to drive the model from the township level.

Table 2: Percent Conversion of Paddy Fields to Other Land Uses over the Two Macro-Time Periods

Land Use Cover Type	**1990-1995**	**1995-2000**
Dense Forest	0.12	0.00
Shrub Forest	0.03	0.00
Sparse Forest	0.19	0.00
Orchard	0.14	0.48
Dense Grassland	0.05	0.83
River	0.12	0.00
Lake	2.66	0.00
Reservoir and Pond	14.02	17.73
Shoal	0.01	0.00
Urban Construction	39.33	32.96
Rural Construction	38.10	40.91
Large Factory and Transportation	3.51	6.93
Plain Dry Land	1.72	0.16

The rates of change at the township level which are applied to the total land use change extracted from the remote imagery at 1990 and 1995 are generated from a linear statistical model whose independent variables are based on socio-economic data reflecting economic conditions and policy imperatives. Two rather different models resulted from the estimations in each macro-time period, the first being based on simple demographic variables, the second on new data reflecting income and tax. This is simply due to the stepwise procedure used to identify significant independent variables in the model rather any differences in data. The fact that the models from the two periods are different in structure reflects quite distinct differences between the political and economic regimes dominating development in the Suzhou region over the last decade. During this period, there was a strong shift to economic issues associated with income and taxation in contrast to the earlier period when demographic factors appeared stronger. In making forecasts, we will use the rate model from the second period for this has variables that can be more directly associated with policy.

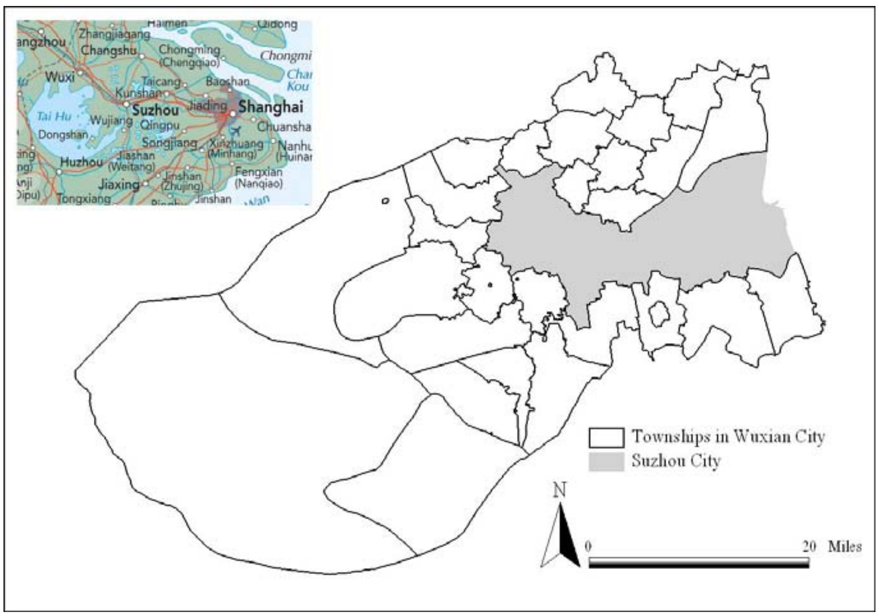


Figure 3: Suzhou, Wuxian, and the Township Level

In general the rate of urban change in township k, $R_k(\Delta T)$, defined above in equation (1), can be estimated from the following linear form

$$R_k(\Delta T) = \alpha(T) + \sum_{\ell} \beta_{\ell} X_k^{\ell}(T) + \varepsilon_k^{\ell}(T) \qquad , \qquad (7)$$

where β_k^{ℓ} are weights on $X_k^{\ell}(T)$, $\ell = 1, 2, ..., L$, the L independent socio-economic

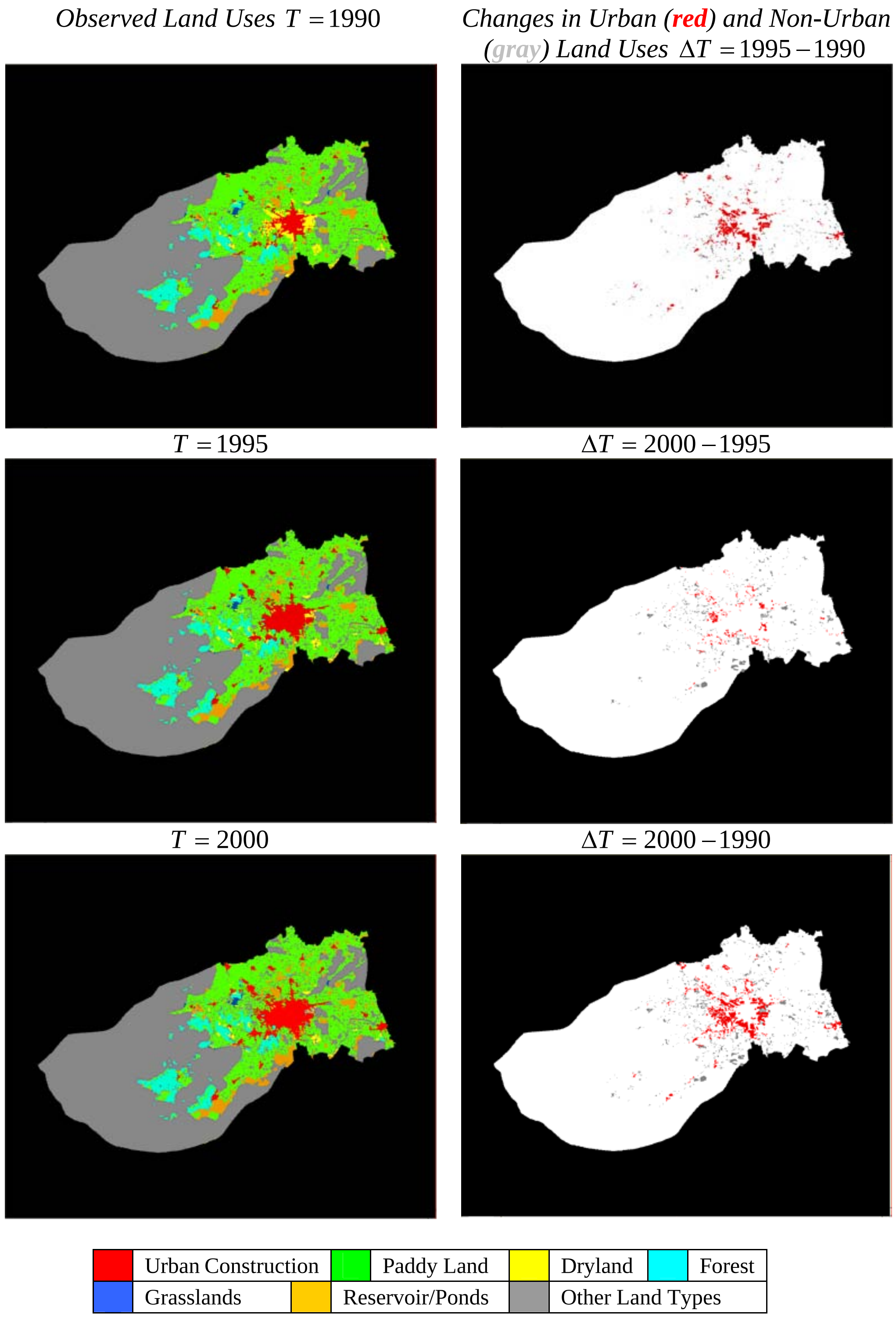


Figure 4: Land Use Types at 1990, 1995 and 2000 and First Differences Associated with Modeling Urban Change

variables defined at the township level k, $\alpha(T)$ is a constant, and $\varepsilon_{zk}(T)$ are the associated error terms. In the period 1990 to 1995, a stepwise regression using the large data set described below which includes a series of population and employment-labor force variables, resulted in the following equation being judged to be the most parsimonious with the best fit:

$$\left.\begin{array}{l} R_k(1990 \rightarrow 1995) = \underset{(\mathbf{0.89})}{15.68} + \underset{(\mathbf{2.48})}{0.627}\, RP_k(1990) + \underset{(\mathbf{4.54})}{7.69}\, P_k(1990) \\ \qquad\qquad\qquad\qquad - \underset{(\mathbf{-3.49})}{5.02}\, E_k(1990) \end{array}\right\} . \tag{8}$$

$RP_k(1990)$ is the rural (non-urban population), $P_k(1990)$ the urban population, and $E_k(1990)$ the employment (labor force) total, all at 1990. The *t* statistics (**bold**) under each weight and variable make clear that the parameters β_k^ℓ are all significantly different from zero at the 5 percent level. The amount of variance explained by this equation is 72 percent which is acceptable for driving the simulation from its start point.

In the second period from 1995 to 2000, other variables from the data base based on the same 20 key economic and demographic variables used in the 1990 to 1995 calibration, appeared. The data set included output by employment sector, fixed asset values, incomes in different sectors, revenue, and taxable receipts. As in the first time period, we cycled through a stepwise regression procedure which ultimately converged on an equation with a larger and very different set of independent variables, more related to policy instruments such as taxation. The form of this equation is

$$\left.\begin{array}{l} R_k(1995 \rightarrow 2000) = \underset{(\mathbf{-0.17})}{0.99} + \underset{(\mathbf{8.58})}{0.24}\, TAX_k(1995) - \underset{(\mathbf{-4.65})}{0.28}\, INA_k(1995) \\ \qquad\qquad\qquad\qquad + \underset{(\mathbf{4.35})}{0.17}\, GDP_k(1995) - \underset{(\mathbf{-4.04})}{0.14}\, FA_k(1995) + \underset{(\mathbf{2.37})}{0.25}\, RE_k \end{array}\right\} \tag{9}$$

$TAX_k(1995)$ is the total tax levied in the township, $INA_k(1995)$ income in the non-agricultural sectors, and $GDP_k(1995)$ gross domestic product in the township, $FA_k(1995)$ the net value of fixed total assets, and $RE_k(1995)$ the expenditure in the rural economy, all at 1995. The *t* statistics (**bold**) under each variable imply that the β_k^ℓ parameters are all significantly different from zero at the 5 percent level. The variance explained by this equation is 88 percent which is particularly high, given the aggregation and uncertainties posed by the quality of the data.

Equations (8) and (9) are those used in the global model which in terms of the simulation provide the parameters determining the overall rates of change from 1990 to 1995 and 1995 to 2000 in the 27 townships. These are used to compute the rates which are input to equation (2) which in turn is used to factor the total urban change into its constituent components which are allocated to the cells by the lower-level agent model. Note that the calibration of the global model is accomplished outside the overall model framework as represented in Figure 2.

Agents in a Cellular Landscape: Simulating Growth and Change in Wuxian City

The cellular level used to allocate urban change generated at the global level is based on defining probabilities of transition from whatever use the cell has at the start of the simulation at time t to urban use at time $t+1$. These probabilities were defined generically in equation (5) above where it was argued that they depend on accessibility to economic activity in town centers $E_{ik}(t)$, and accessibility to transport infrastructure $T_{ik}(t)$. There is another factor which we call a policy index $S_k(t)$ that is related to the rate of growth at the township level, thus cementing the local and global levels together not only through controlling the amount of growth but inputting the influence of the township on the local level. We will now detail how these factors are used to define the probabilities of urban change.

Economic accessibility is based on distance to town centers. It is determined through a GIS operation, buffering the town centers at 5 successive distances 0.5km, 1.0km, 1.5km, …, from their physical centroids and then recoding the distances as 1 (< 0.5km), 2 (0.5–1.0km), 3 (1.0–1.5km), and so on. We refer to the zones that are created as economic opportunity zones. In the same way, transportation accessibility to the main roads is computed by buffering at the same ranges of distance and then scoring the successive buffers in the same way. These simplifications are required so that the hundreds of thousands of interactions between cells in the model can be computed efficiently. The way this works in the model is as follows. When an agent considers accessibility to transport or to town centers, in the absence of any detailed information at the cellular level, it assumes that with increasing distance to the town center, more and more economic opportunities are accumulated, and this is then weighted against the index score so that an opportunity surface is established. This is similar to gravitational notions in terms of intervening opportunities weighted against distance and it enables an accessibility score to be computed for each of the accessibilities in question. The policy index is also computed by transforming township attributes into scores. Townships are sorted from high to low according to how many urban agents are associated with the urban change predicted for the township in question. We simply order the towns in terms of the growth rates from largest to smallest and assign priority orders of 1 to the townships ranked from 1 to 5, 2 from 6 to 10, 3, from 11 to 15, 4 from 16 to 20 and 5 above 20. The elements then used to compute the probabilities are dimensionless. The probability equation is then set up in linear form as

$$\rho_{ik}(t) = \mu T_{ik}(t) + \lambda E_{ik}(t) + \psi S_{ik}(t) \quad , \tag{10}$$

where each variable ranges from 1 to 5 with the entire range being between 1 and 15. The parameters $\mu, \lambda,$ and ψ are those which enable the model to be calibrated at the local level, a process that we will describe below. One last feature of the local allocation needs to be established before we briefly describe how we calibrate the model and then consider it for use in forecasting. This involves land suitability which we earlier formalized as a constraint on the optimization of the probability of urban development. In fact, we use a strict priority ordering for the transition of land to urban use. The urban agents will try to occupy dryland first, then paddy fields, forest, reservoirs and ponds, and finally grassland.

The land suitability process is initiated in the first micro-time period when the random allocation of master agents to locations is made. We outlined this process earlier but at this point we need to be crystal clear about how the whole micro-simulation is implemented. This is at the heart of the process of generating spontaneous urban growth in the countryside which is the essence of the way desakota emerges. Each cell is 100 meters x 100 meters and there are roughly 687,000 cells in total allocated to the 27 townships. In each macro-time period of the simulation from $T \to T+1$, there are about 50,000 to 60,000 urban developer agents $\{j\}$ that roam the cellular landscape $\{i\}$ looking for cells to transform from rural to urban. These of course are discounted back to around 9,000 to 12,000 for each micro-time period $t \to t+1$. The transformation process that they initiate is different from the usual cellular automata model structure in which cells change state from rural to urban dependent on land suitability and accessibility rules for the urban developer agents are essentially mobile. Strictly speaking for a model to be agent-based, it must contain agents that can move, for if the agents are passive and simply in one-one correspondence with cells, then the agent layer is redundant (Batty 2005a). In this case at the micro-cellular level, the agents act as "probes" searching the landscape for cells which are suitable for transformation from rural to urban and their movement on the landscape reflects the process of searching for suitable sites (cells).

As noted earlier, the process of allocation consists in first randomly allocating the first round of agents to cells which have the highest probability of development based on equation (10) subject to the land suitability ordering, when $t = T$ or $t + \tau + 1 = T + 1$, i.e. in the time period from 1990 to 1991 or from 1995 to 1996. These agents are the master agents which then seed all subsequent allocation of agents using the neighborhood allocation rules in the remaining time periods of the micro simulation, from 1992 to 1993, from 1993 to 1994 and so on, up until the end of the second macro-time period in 2000. In the second micro-time period, an appropriate number of new urban agents associated with the master agents in each township area but at the cellular level, are generated and then allocated using the neighborhood allocation rules. This involves these new agents assessing the suitability and probability of land for urban development in the neighborhood of the master agents. If these agents are unable to find suitable land for conversion in these immediate neighborhoods (which will always be the case because the number of agents being generated is likely to far exceed the available cells in these restricted Moore neighborhoods, the search is widened and the agents move to the next band of cells, continuing in this way until all the agents associated with township in that micro-time period are allocated. At this point, these new agents become master agents seeding the next round of conversions in the next micro-time period until all the urban agents associated with that macro-time period have been allocated. This process is akin to a process of continual mutation of land uses until enough urban development has been generated to meet the control totals consistent with the rates of change which are simulated at the township level using the linear model.

The local level model which is essentially the structure pictured in Figure 2 is implemented in the open source modeling language *RePast 3* (Collier, Howe, and North 2003; and http://repast.sourceforge.net/). Our implementation is unusual in that we have a very large cellular landscape and thousands of agents and is one of the first "realistic" implementations of *RePast* for spatial agent-based simulation as the results below will show. The details of the simulation process need not concern us, other that noting that there is another layer of time within the operation of the simulation, which is referenced as ticks. These ticks do not match the real times t and T for they are essentially used to track the movement of agents across the space as they search for suitable cells to transform and as such, reflect the various iterations that are used to achieve the control totals from the global level. It is also important to note that the search process for an urban agent is not confined to the cells associated with a particular township but agents are free to search over the entire space and one major measure of fit that we will use is to compute how many units of development are generated in each township.

We have run the model in two ways: first calibrating the model from 1990 to 2000 in terms of the local parameters $\mu, \lambda,$ and ψ associated with the probability of development in equation (10); and second having chosen these best parameter values, running the model from 2000 to 2010 using the global parameters from the regression model in equation (9). What we should do in terms of calibrating the local level model is to choose a range of values for each parameter and run the model over all significant combinations of values in these ranges. For each combination, we compute the goodness of fit of the model in terms of the number and location of cell conversions from rural to urban land, and then choose that combination of values which is closest to what we observe in the overall period from 1990 to 2000. The values of the three parameters μ, λ, and ψ are arbitrary as the scoring used in forming their variables makes them comparable and thus it is their relative values that are important. This is a very standard method of searching for best fit parameters in intrinsically nonlinear models which goes back many years (see Batty 1976) although what we have actually done is to sample the phase space in a systematic way rather than sweeping the entire space in comprehensive fashion. In extensions to this model, we will selectively sample and search the space hierarchically as we have done in other agent-based models we have been working with (Batty 2005a, 2005b).

The goodness of fit criterion that we are currently using is based on the difference between the urban cells that have been converted from rural predicted by the model with respect to those observed from the remote imagery maps shown earlier in Figure 4. This is for the entire period from 1990 to 2000 but aggregated to the 27 townships. Although the townships act as the control on total growth at the global level, urban development at the local, cellular level is not restricted to particular townships as we noted earlier: that is agents are free to search the entire space. Formally this criterion is

$$\Phi(\mu, \lambda, \psi) = \sum_{k=1}^{27} \left[P_k (T \to T+2) - \sum_{\tau=1}^{10} \sum_{i \in Z_k} p_i(\tau) \right]^2 \Big/ 27 \qquad (11)$$

where the temporal summations are over the period from 1990 to 2000 and the spatial summations over the number of cells in each township.

To get the best parameter values, we first developed a very crude sweep of the phase space choosing 4 values of each parameter and focusing in on the area of the space that seemed to yield the lowest goodness of fit. This was the area around

$25 \le \mu \le 35, 1 \le \lambda \le 10,$ and $1 \le \psi \le 10$. We searched one dimensionally across each of these parameters, that is computing the goodness of fit $\Phi(\mu,\lambda,\psi)$ varying $\mu,$, then λ, then ψ with the respective other two parameters held constant in each case. We show variations in the goodness of fit in Figure 5, which represent transects through the three-dimensional phase space. The best values ultimately identified were $\mu \sim 30, \lambda \sim 5,$ and $\psi \sim 5$ and Figure 5 shows that these give a point of minimum difference between predictions and observations with respect to this local area of the phase space. Short of sweeping the entire phase space at this level of detail which would involve running the model thousands of times, we consider this to be as good as we are likely to get at this initial stage. This is may not be the optimum optimorum but we are also certain that these are no such global optima within phase spaces associated with models of this kind. Nevertheless we are confident that the parameters values identified produce good simulations for these reveal patterns of growth close to those that we observe over the calibration period 1990 to 2000.

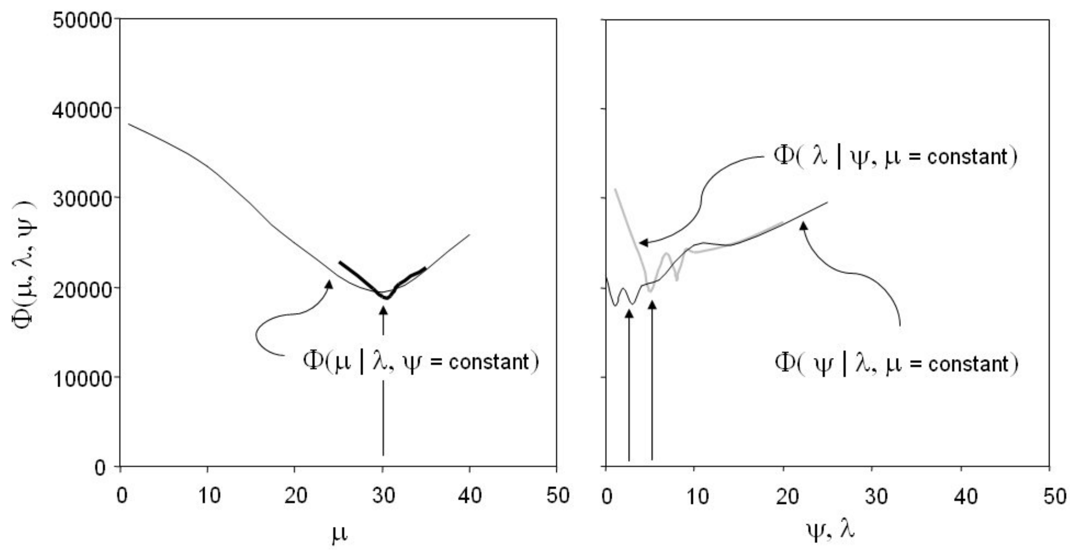
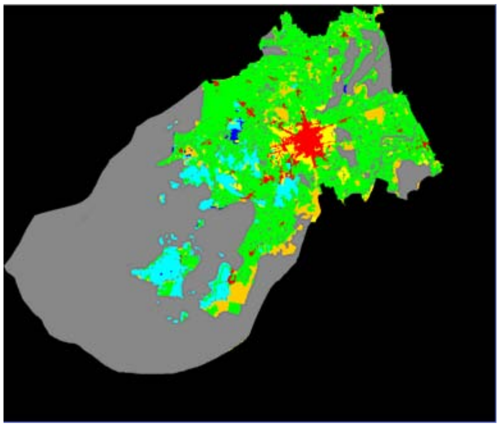


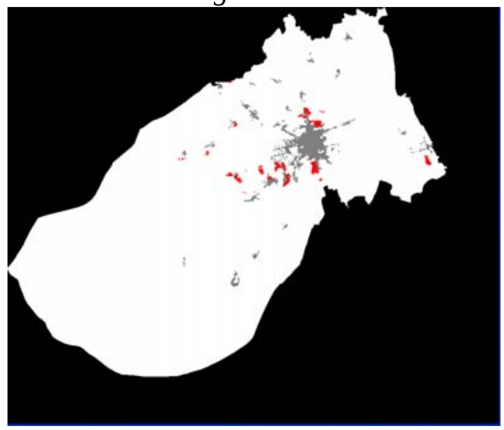
Figure 5: Optimizing the Goodness of Fit within the Search Space defined by Local Parameter Values

It is important to examine these spatial results directly as statistics such as those in equation (11) are not spatially weighted in any way. When we look at the predictions from 1990 to 1995 and 1995 to 2000 as we do in Figure 6, we see that the model produces rather plausible patterns of desakota, quite consistent with what we have

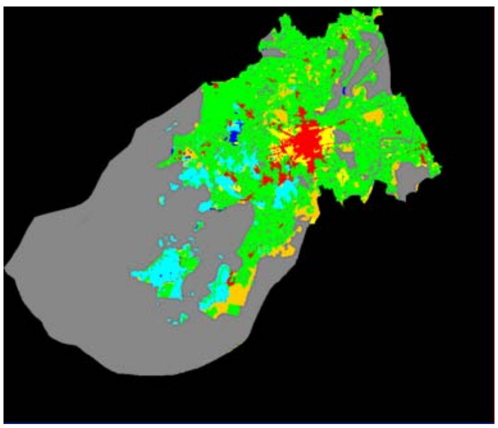
Observed Land Uses $T = 1990$



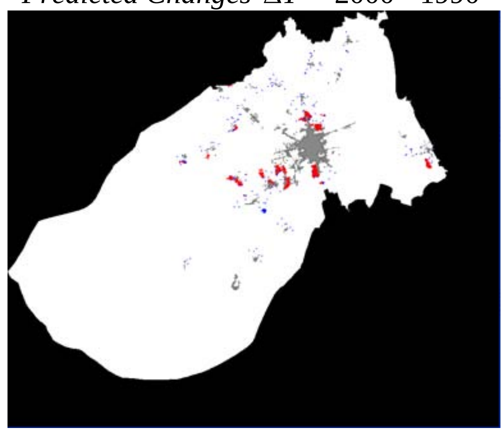
Predicted Changes $\Delta T = 1995 - 1990$



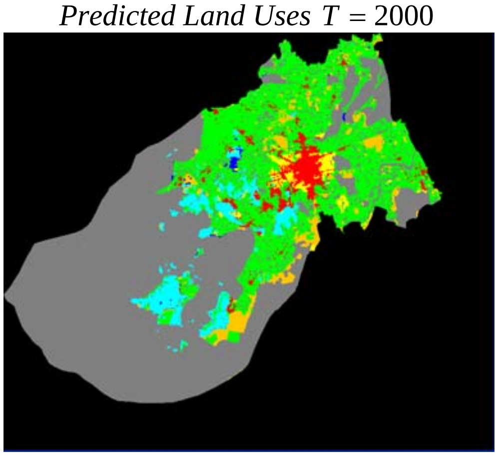
Predicted Land Uses $T = 1995$



Predicted Changes $\Delta T = 2000 - 1990$



Predicted Land Uses $T = 2000$



Change Legend (above figures)

1990 Development	
1990- 1995 Development	
1990-2000 Development	

Land Use Legend (left figures)

	Urban Construction		Paddy Land
	Dryland		Forest
	Grasslands		Reservoir
	Other		

Figure 6: Predicted Land Use and Changes in Land Use 1990 – 2000

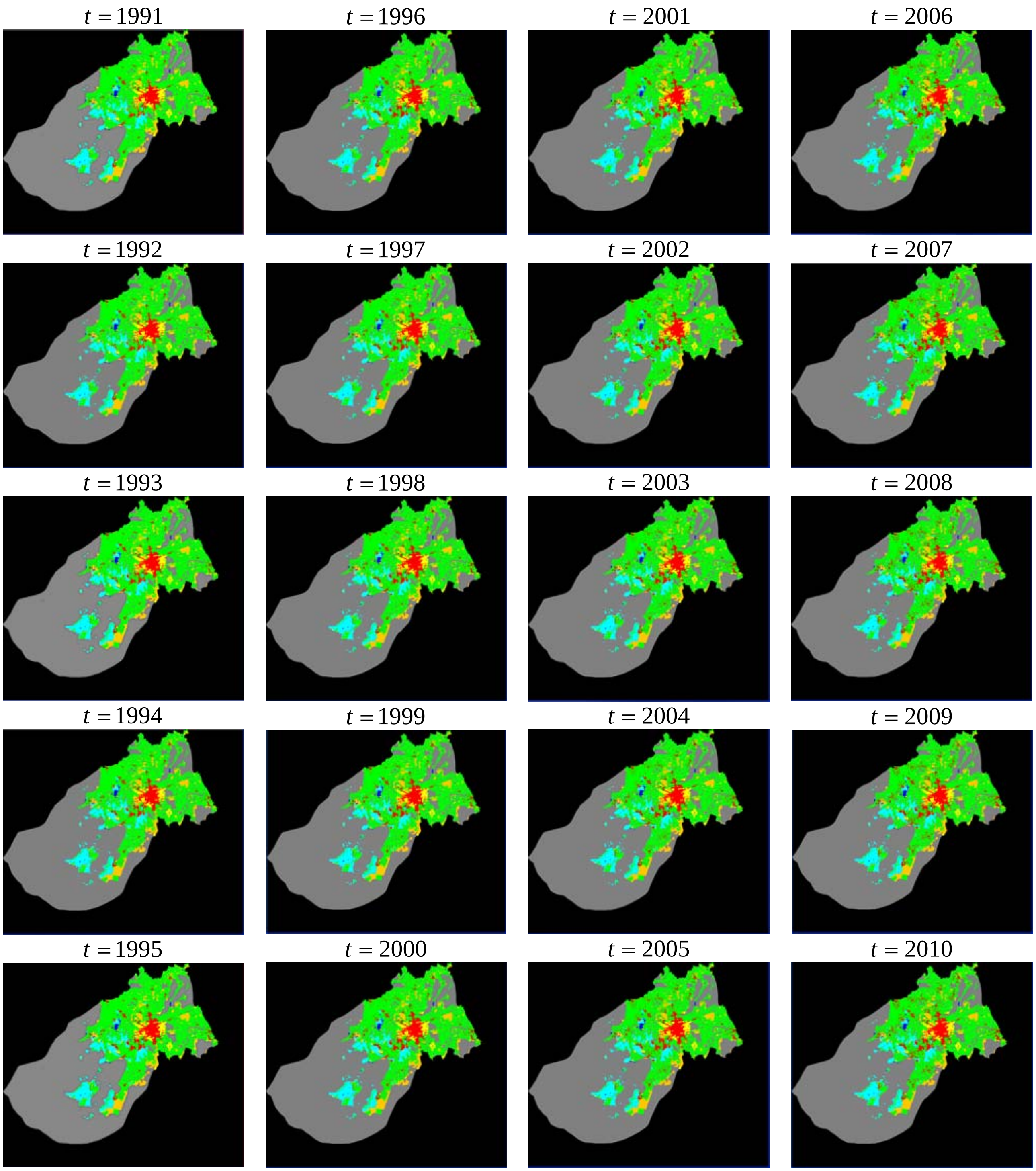


Figure 7: An Animation of Urban Development Through the Micro-Time Periods 1991 to 2010

extracted as observed urban development from the remote imagery. The patterns show that there is spontaneous growth into the hinterland of Suzhou in all townships as land is converted to urban. In fact, a much clearer picture of what is happening and the ability of the model to generate *in situ* growth and change is given in the animation that is shown in Figure 7 where we plot the actual change in urban development from 1990 to 2000. This is then extended as a forecast to 2010 using the 1995 to 2000 global parameters in fixing the amount of urban change over this future 10 year period. These figures speak for themselves in illustrating how urban development pops up all over the region, notwithstanding the modest population growth in the area which was very close to only 1 percent per annum through the decade from 1990 to 2000. If you log onto http://www.casa.ucl.ac.uk/desakota/ you can load an animation of this process from which these snapshots are taken.

Conclusions: Next Steps

We have illustrated a number of features about both agent-based models and desakota in China in this article. First we have designed a relatively large scale model of urban growth and change which is agent-based in terms of its local simulation, with the agents being used a probes to convert land use from rural to urban development. Agents are used as devices to search the space and in future versions, we will give these objects a more realistic form by dividing them into urban entrepreneurs/developers and farmers, elaborating the search process as one of profit maximizing where the various accessibility and land suitability attributes are considered as relevant to the market process (Xie and Batty 2005). Second, our use of agents in this fashion is rather innovative as they are designed to be "change agents" rather than literal households or individuals, thus enabling the dynamics of the agent-based software we have used to be configured not only for temporal change but for change which is associated with search and optimization within the model structure. Third, to our knowledge this is one of the first applications of agent-based modeling which uses large data sets fusing remotely sensed imagery with socio-economic data. Fourth, we are firm in our belief that agent-based models do not simply apply to disaggregate system but can be used to integrate different levels and scales essential to simulating what at first sight appears to be bottom-up phenomenon such as desakota.

There are many features of our simulations which are rough around the edges and require considerable refinement. Moreover we are also aware that in calibrating such models to match real data, we are hardly testing the model in its widest sense. But this is little different from the movement in science and social science to embed plausible behavioral assumptions into our models which we consider to be important to explanation but are often, indeed usually, absent from more parsimonious model structures. The new quest for generative modeling in the social sciences is illustrated rather well in the model developed here (Epstein 1999). The idea that we need to demonstrate how our assumptions can generate plausible outputs is encapsulated in the idea of growing our systems through various forms of dynamics, temporal and otherwise. As Page (2003) notes: " … the generative claim that 'if you didn't grow it, you didn't show it' should be ignored at our peril …". The example of desakota is rather a good test bed on which to illustrate this argument.

We are planning a number of extensions of this model. We need to develop a much stronger link from the global to the local and vice versa is based on strengthening the feedback loop between development and socio-economic drivers which we illustrated in Figure 1. We need to generate different types of agents for the rural and urban regimes in our model and we need to consider transitions other than those between rural and urban. In this way, we plan to extend our model to examine the impacts on the environment and the extent to which the kind of desakota appearing in China is sustainable. We intend to calibrate the model at the fine cellular scale and to develop strategies for multi-level calibration which is a relatively new feature of agent-based modeling occasioned by our use of more than one scale of agent. And last but not least, we intend to improve the detailed measurement and simulation of accessibilities in the model relating the allocation process to capacities on land as well as its suitability. These are all extensions which will be reported in future articles.

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