

PROGRESS REPORT

MULTI-SCALE AND MULTI-SENSOR ANALYSIS OF URBAN CLUSTER DEVELOPMENT AND AGRICULTURAL LAND LOSS IN CHINA AND INDIA

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PI: Karen C. Seto

Yale School of Forestry and Environmental Studies

195 Prospect Street

New Haven, CT 06511

karen.seto@yale.edu

tel: 203-432-9784

fax: 203-432-5556

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1. Introduction

The objective of this project is to use multi-sensor imagery to identify the growth of urban clusters and the loss of agricultural land in China and India. The project has 3 primary components. First, we will use MODIS and DMSP OLS data to develop remote sensing methods that can rapidly identify urban clusters that are experiencing rapid expansion. Second, we will identify the types of land cover changes in these urban cluster hot spots and when they occurred, with an emphasis on the loss of agricultural land. Third, we will explain the drivers of urban cluster expansion by developing multi-level econometric and agent-based models of land change.

During the 11-month period covered in this report, we have made considerable progress on all aspects of the project. Specifically, our principle activities during this period include:

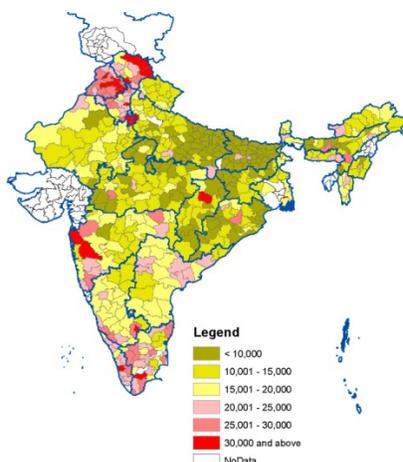
- 1) Constructing land use, public policy, and socioeconomic databases for China and India;
- 2) Developing methods to identify urban cluster growth using DMSP and MODIS data;
- 3) Developing new methods to detect urban boundaries;
- 4) Developing a multi-level model of urban cluster growth and loss of agricultural land in China;
- 5) Conducting a moderate resolution land change analysis for Chandigarh;
- 6) Developing an exploratory agent-based model of land change in the New Delhi-Chandigarh region;
- 7) Field work in India including high level meetings with national Ministers of Urban Development, Rural Development, and Home Affairs;
- 8) Estimating econometric models of urban expansion in India.

Each of these efforts are summarized briefly below.

2. Research Activities

2.1. Constructing land use, public policy, and socioeconomic databases for China and India

Figure 1. Example of information in the India Geodatabase: Per Capita Income by District



We have been constructing urbanization databases for India and China which include various spatially detailed public policy, economic, socio-demographic, and geophysical variables. Our India geo-referenced database currently includes state government capital expenditure by item, including investment in education and construction (1991-2010), district-level GDP by industrial sector (1999-2008), state-level Per Capita Income (1993-2009), slope and elevation, district-level population by total and urban/rural (2001), district-level literacy rate by urban/rural and by

gender (2001), and coastal eco-zones. We are continuously improving on this database and will combine it with the results from urban cluster hotspot analysis in model the drivers of urban land conversion and explicitly evaluate the role of public policies (e.g., fiscal transfer, government capital).

In China, we used the fiscal transfer data from the Central Government to develop a geodatabase. We analyzed the fiscal transfer data, including its geographic structure and spatial patterns of distribution. Our analysis shows that for the period 1999-2004, the province with the maximum overall revenue and internal revenue has 43.7 times and 207.2 times of the smallest one, respectively! We further show that the province with the highest amount of “free money” from the central government is only 14.1 times of the smallest one. We are now exploring the role of the fiscal transfers in driving urban growth. This is the first time these fiscal transfer data have been used for such an analysis.

Our hypotheses with regard to the fiscal transfers are that: (1) The counties with bigger financial difficulties have the stronger motivation to lease land for development, and therefore experience more urban land expansion, and (2) The counties with high levels of economic development receive money from the central government than lower productivity counties. Because of the higher levels of fiscal transfers, these countries then experience more urban land expansion than the poorer ones. We are in the process of developing an econometric to test these relationships.

2.2. Developing methods to identify urban cluster growth using DMSP and MODIS data

Using data on time series MODIS and DMSP/OLS nighttime light (NTL) and spatial analysis, we have developed new methods to detect urban cluster growth. Our first analysis used only DMSP data and we found that it was possible to identify urbanization dynamics using a time series of these data and utilizing standard unsupervised classification algorithms in an iterative fashion. We tested the methodology at the national scale for several countries, including the US, where we compared the urban land change results with urban population and economic activity statistics. This DMSP-only analysis has been published in *Remote Sensing of Environment* (Zhang and Seto, 2011).

We further conducted a spatial correlation analysis at the county level with only DMSP data. Moving from a comparison of luminosity and vegetation dynamics across counties to a grid-based analysis allowed us to deal with any bias associated with

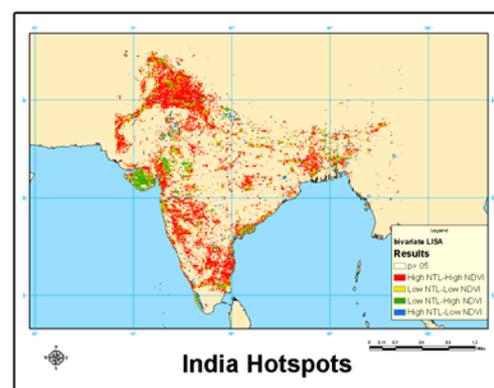


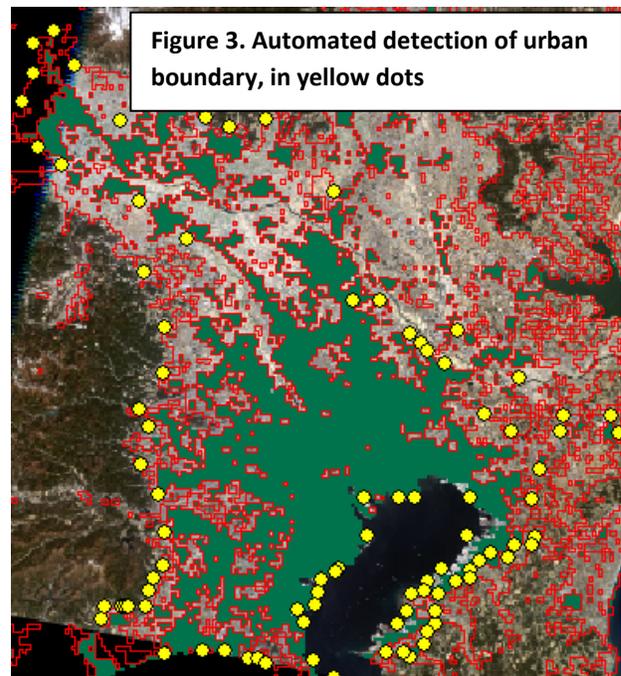
Figure 2. LISA results of urban hotspots in India at 1km resolution for 2001-2008

the mean areal unit problem in a LISA analysis. In addition, this allowed us to test the results of applying this method at multiple spatial scales. Using a 10X10 km cell size, results from India indicate that a LISA analysis does not accurately capture variation in NDVI that are associated with urban change (Figure 2).

Though extensive experimentation with our proposed LISA approach and the identification of two additional methodological approaches to rapid urban change detection, our team is focused on discovering the most implementable and accurate method for analysis of rapid urban expansion at regional, national, and global scales. We are currently refining these methods and organizing the results from all experimental trials into a series of methods papers that will make an important contribution to the literature on urban change detection and monitoring. Historically, change detection methods have focused on two-period, per pixel analysis using supervised and unsupervised classification. The critical methodological challenge that we address in this work is how to move beyond per pixel detection to identify inter-temporal urbanization patterns occurring in particular spatial configurations.

2.3. Developing methods to detect urban boundaries

In the process of examining our data for China and India, our team took a step back from the LISA method to look at patterns emerging in the raw data from DMSP OLS and NDVI data. Two additional methodological approaches for urban change detection have emerged from that analysis. One method, tacitly referred to as the “X-edge method,” identifies the changing urban periphery as the boundary where the increasing magnitude of the luminosity signal from an urban area intersects the decreasing magnitude of the NDVI signal. While the physical basis of the method is not entirely obvious, this method provides an extremely rapid assessment technique and with high accuracy. A preliminary accuracy assessment was conducted using a comparison to a sample of 30 urban boundaries in our study region (determined visually using Google Earth imagery). The X-edge method came within 1km of an urban edge for more than 70% of the sample (Figure 3).



An alternative operational definition of an urban edge is the location where luminosity magnitudes increase rapidly across a short distance and NDVI magnitudes decline rapidly across a short distance. When measuring this across an urban-nonurban gradient, this takes the form of a large positive NTL slope and a large negative NDVI slope. Using this definition, we have designed an algorithm to identify these overlapping slopes called the “slope method.” The slope parameters have also been demonstrated very effective at defining an urban boundary and their physical basis is clearer. However, the identification of proper thresholds for the slope of an urban boundary has proven challenging as the slopes of NTL and NDVI signals tend to vary across urban regions. We are currently writing up these results to submit to *Remote Sensing of Environment*.

2.4. Developing a multi-level model of urban cluster growth and loss of agricultural land in China

3.

China has undergone large-scale urban expansion and rapid loss of agricultural land for more than two decades. Despite the magnitude and pace of urban expansion across the country, there is little understanding about the patterns and the underlying processes of urban land use change at the national scale. A majority of the research on urban expansion in China have been devoted to studying the growth of individual cities or regions. Among the few studies at the national scale, fewer explain the process of urban expansion and none examine the urban conversion of agricultural land. Furthermore, to our knowledge, no study simultaneously takes into consider the legalization of the land leasing market, urban planning policies, and the increasingly decentralized and unstructured nature of China’s urban development. We have conducted a study that examines the relative importance of socioeconomic and policy factors across different administrative levels on urban expansion and associated agricultural land conversion.

We carried out the analysis for urban hotspot counties across the entire country. We used multilevel modeling techniques to examine how socioeconomic and policy factors at different administrative levels affect agricultural land conversion across three time periods, 1989-1995, 1995-2000, and 2000-2005. Our results show that at the county level, both urban land rent and urban wages contribute to total agricultural land conversion. Contrary to expectations, agricultural investment drives farmland conversion, suggesting a policy failure with contrary effects. At the provincial level, urban wages and foreign direct investment both positively contribute to agricultural land conversion. We also find that higher GDP correlates with more urban expansion but the relationship is nonlinear. Finally, the Granger causality test identifies an interrelationship between the land rent ratio of agriculture and urban uses and agricultural

land conversion. A manuscript describing the methodology and results has been reviewed at *Landscape and Urban Planning* and is currently undergoing revision.

2.5. Conducting a moderate resolution land change analysis for the New Delhi-Chandigarh region

We conducted a decision tree change detection analysis with single band subtraction and NDVI differences between previous and subsequent year for the city of Chandigarh. Chandigarh is the capital of the States of Punjab and Haryana, and is often listed as the best planned city in India. Its modern day design and development was largely inspired by Western Architects, especially Le Corbusier and its grid patterned urban structure is noticeable in satellite images (Figure 4—right).



Our decision tree analysis shows that during 1972-1980 and 1980-1989 periods., urban growth was faster within the city boundary than outside of it. After this period, both the rate and magnitude of urban expansion declined considerably, both within and outside of the city boundary. The satellite analysis further shows that the peripheral areas became priority locations to for urban

development since there is no more space inside of the city (Figure 5—left). The results of this analysis will be used in the urban cluster model for the New Delhi-Chandigarh region.

2.6. Developing an exploratory agent-based model of land change in the New Delhi-Chandigarh region

We are developing an agent-based model of urbanization in the New Delhi-Chandigarh cluster. This model will be used to assess the principle drivers and feedbacks driving rapid growth in India, using this region as a case study. We have synthesized descriptions of drivers and feedbacks from current peer-reviewed literature with interviews with local experts to produce

a conceptual model of the system. This conceptualization serves as the basis from which the numerical agent-based model is being developed. The model will represent the behavior of actors across scales including decisions made by households, corporations, and local and central government on a spatially explicit grid. The dynamics included in the model (i.e., the types of decisions made and the ways in which they are made) will be confirmed through interviews with Indian stakeholders this summer during fieldwork. We will use the model to project urban development over long-time-scales and rigorously examine the potential

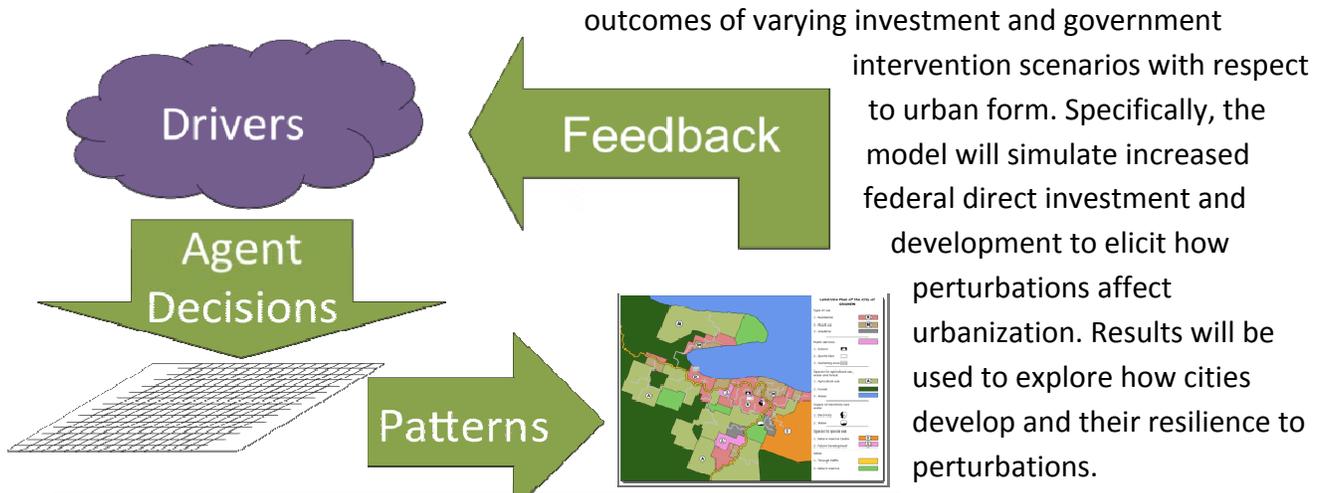


Figure 6. Patterns in urban form will be modeled as emergent behavior from agents responding to feedbacks.

2.7. Field work in India including high level meetings with national Ministers of Urban Development, Rural Development, and Home Affairs

In November, 2011, three members of our team (PI Karen Seto, and graduate students Chris Shughrue and Peter Christensen), were invited to India to take part in a high level conference and meetings with Indian stakeholders and decision-makers. The meeting comprised of two separate components: the first taking place in Mysore in South India, and the second taking place in New Delhi, including discussions with senior Ministers on the issues of urbanization and environment in India (Figure 7--right). One of the key outputs from these meetings is gaining access to and networking with senior officials and decision-makers. These connections



will be important during summer fieldwork when we return to India to collect additional information on drivers of urban growth. In addition to meeting with decision-makers, we also conducted 3 days of fieldwork in the greater New Delhi area with a graduate student of co-PI PK Joshi. These days in the field were important to collect ground truth data for our remote sensing analysis.

2.8. Estimating econometric models of urban expansion in India

Our strategy to land change modeling in India is to (1) link the newly constructed geo-referenced data into the urban land-use change data from urban cluster hotspot analysis, and (2) do multilevel regression analysis to test the effect of public policy and other socio-economic variables –which are measured at various levels -- on land change.

The multilevel modeling procedure will be as follows: Consider an idealized country with the three-level nested hierarchical structure: county, cluster, and state. Let $y_{i,j,k}$ represent the rate or magnitude of change in urban extent of county i in cluster j in state k for a given sample time period, which comes from the urban cluster hotspot analysis. The dependent variable, $y_{i,j,k}$, will be explained by (1) a set of observable explanatory variables and (2) unobservable random disturbances ($\varepsilon_{i,j,k}$). As explanatory variables, we would include a set of public policy variables ($P_{i,j,k}$), and other control variables including economic, socio-demographic and geophysical variables ($X_{i,j,k}$).

In mathematical terms, our land-use change model can be written as $y_{i,j,k} = \beta_0 + P'_{i,j,k}\beta_1 + X'_{i,j,k}\beta_2 + \varepsilon_{i,j,k}$ where β_1 and β_2 are vectors of corresponding coefficients which measure the size of the effect of explanatory variables. The model also can include urban cluster level variables –which are county-invariant -- and state level variables – which are both county- and urban cluster-invariant -- as explanatory variable. In the three-level modeling, the error term can be specified as the three error components, $\varepsilon_{i,j,k} = \nu_{j,k} + \xi_k + \eta_{i,j,k}$. In the equation, ξ_k captures state-specific effects which come from political, economic, and geographic context where the county is situated. To estimate the effects, we use both classical and Bayesian methods. We anticipate having a preliminary model and model results by early summer 2012.

3. Moving Forward into Year 2

We have made considerable progress in Year 1. Our effort has focused on collecting data and developing a database for India and China, and we are well positioned to develop models of land change at the urban cluster scale.

Papers submitted or published

Zhang, Q., & Seto, K. C. 2011. Mapping urbanization dynamics at regional and global scales using multi-temporal DMSP/OLS nighttime light data. *Remote Sensing of Environment*, 115(9): 2320-2329.

Jiang, L., Deng, X., and Seto, K. C. Multilevel modeling of urban expansion and agricultural land conversion for hot spot counties in China, *Landscape and Urban Planning* (reviewed, in revision).

Papers in preparation (to be submitted by June 2012)

Fragkias, M., Seto, K. C., and Kim, D. W. A multi-level model of urban cluster growth in India, to be submitted to *Land Economics*.

Jiang, L., Seto, K. C., and Deng, X. Urban cluster growth and impacts on agricultural land use intensity in China, to be submitted to *Agriculture, Ecosystems, and Environment*.

Pandey, B., Joshi, P.K., and Seto, K. C. Monitoring urban dynamics in India using DMSP/OLS night time lights and SPOT-VGT data, to be submitted to *International Journal of Remote Sensing*.

Seto, K. C. and Zhang, Q. Global urbanization hotspots and threats to biodiversity and agricultural land, to be submitted to *Nature*.

Zhang, Q. and Seto, K. C. Mapping urban areas by combining NDVI with DMSP/OLS nighttime light: indices and assessment, to be submitted to *Remote Sensing of Environment*.

Zhang, Q., Seto, K. C., Wallace, J. The role of fiscal transfers in driving urbanization in China: evidence from remote sensing and government statistics, to be submitted to *Land Policy*.