West meets East:
Monitoring and modeling urbanization in China

Land Cover-Land Use Change Program Science Team Meeting
April 3, 2012
Annemarie Schneider
Center for Sustainability and the Global Environment, University of Wisconsin-Madison
Introduction

How do urban processes contribute to global environmental change?

- How are humans changing the Earth?
- What are the drivers and implications of this change?
- How does the built environment affect energy use, carbon emissions, and climate?

New attention to urban areas in land use/land cover research

- Can urban development strategies be aligned with climate change adaptation?
- How can urban planning tools be used to develop more resilient cities?
Introduction

Understanding urbanization in China and the Monsoon Asia region

- Monitoring urban systems and land patterns regionally-globally using satellite data
- Local case-study analysis of geographically comprehensive sample of cities
- Predictive modeling, forecasting of dynamic socio-economic forces and land-based outcomes
Introduction

Tremendous opportunity to shape the built environment

Majority of urban development on the ground by 2050 in China will be built between now and then

Single-family home and ‘villa’ development – new trends in China
Urbanization in China

Policy reforms

- 1978 economic, land reforms: decentralization, land use rights, liberalization of household registration system (*hukou*) and work unit (*danwei*)
- 1990s great western development program
- 2001 new emphasis on villages

Impacts?

- Rapid rural-urban migration
- Rapid land use change
- Agricultural expansion, intensification
- GDP 1978-2008: 8-14%
- Increase in income - vehicles, housing, diet
Urban expansion in China

Sample of 15 urbanizing regions...

Case study methods

- Remote sensing - multi-date change detection
- Work closely with collaborators, contacts
- Assess trajectory of multiple time points
- Monitor peri-urban, village development
- Spatial analysis
- Compare east vs. west
Remote sensing methods

Numerous change detection methods, 30 year history

Common problems
- Complexity of landscape in SE Asia
- Confusion between new urban and bare agriculture plots
- Agricultural, vegetation variability

Choice of method:
- Supervised multi-date classification
- Multi-temporal, multi-seasonal approach
- Dense time stacks of Landsat data
- Training examples: stable and changed classes
- Accuracy assessment
Dense time stacks of Landsat data

Sample Landsat dense time series for Kunming, 50 images 1988-2009
Enhanced vegetation index (EVI)

Phenology of urban areas

- **Urban land 100%**
- **Urban land 80-99%**
- **Urban land 60-89%**
- **Agriculture**
- **Forest types**
- **Shrubland**
- **Grassland**
Seasonal trajectories of land cover types

Multi-year NDVI trajectories derived from atmospherically-corrected Landsat data (LEDAPS, Masek, 2007).
Remote sensing methods

1. Which supervised classification algorithm performs the best given complex, dense temporal stacks?
   - Traditional maximum likelihood classifier
   - Boosted decision trees (C4.5) - recursive partitioning of training data into successively more homogeneous subsets based on entropy
   - Support vector machines (libSVM) - optimal boundaries between classes are defined in feature space using optimization algorithms

2. Can feature selection lead to greater map accuracy?
   - 40-55 scenes, uncorrected Landsat data
   - Additional inputs: NDVI, min, max, mean of each band

3. How well do multi-temporal approaches work in peri-urban environments given the small size of settlements?
Characterizing urban expansion

How do we map changes in urban areas with satellite data?

- Extremely difficult with medium resolution data
- Training site collection revolutionized by Google Earth, availability of time series VHR imagery
- Development of cross-platform methods
# Results

## Accuracy assessment – algorithm performance

- Cross-validation approach using tenfold 80/20 splits
- Decision trees and SVM outperform traditional max likelihood
- Decision trees and SVM perform equally well (statistically speaking)
- Additional data inputs caused small increase in accuracy

### Overall accuracy results

<table>
<thead>
<tr>
<th></th>
<th>Chengdu</th>
<th>Xi’An</th>
<th>Kunming</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>a. Maximum likelihood</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>all landsat bands</td>
<td>56.3 (1.6)</td>
<td>76.1 (0.6)</td>
<td>68.6 (1.1)</td>
</tr>
<tr>
<td>all landsat, all ndvi</td>
<td>53.4 (1.5)</td>
<td>74.9 (1.0)</td>
<td>68.2 (1.7)</td>
</tr>
<tr>
<td>all landsat, all metrics</td>
<td>48.9 (2.1)</td>
<td>73.4 (1.5)</td>
<td>67.7 (1.2)</td>
</tr>
<tr>
<td>all landsat, ndvi, metrics</td>
<td>51.4 (1.5)</td>
<td>74.5 (0.9)</td>
<td>68.7 (0.9)</td>
</tr>
<tr>
<td>all landsat, no slc-off</td>
<td>67.9 (1.4)</td>
<td><strong>89.4</strong> (0.6)</td>
<td>63.6 (24.2)</td>
</tr>
<tr>
<td>all ndvi</td>
<td>71.8 (1.3)</td>
<td>84.1 (0.7)</td>
<td><strong>76.8</strong> (0.7)</td>
</tr>
<tr>
<td>all ndvi, all metrics</td>
<td><strong>74.6</strong> (1.8)</td>
<td>86.6 (1.2)</td>
<td>71.3 (17.7)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Chengdu</th>
<th>Xi’An</th>
<th>Kunming</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>b. Decision trees</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>all landsat bands</td>
<td>85.5 (0.7)</td>
<td>93.0 (0.6)</td>
<td>91.1 (0.9)</td>
</tr>
<tr>
<td>all landsat, all ndvi</td>
<td>88.1 (0.9)</td>
<td>93.6 (0.7)</td>
<td>91.7 (1.0)</td>
</tr>
<tr>
<td>all landsat, all metrics</td>
<td>88.0 (0.6)</td>
<td>93.7 (0.7)</td>
<td>91.9 (0.8)</td>
</tr>
<tr>
<td>all landsat, ndvi, metrics</td>
<td><strong>89.8</strong> (0.8)</td>
<td><strong>93.8</strong> (0.6)</td>
<td><strong>92.9</strong> (0.4)</td>
</tr>
<tr>
<td>all landsat, no slc-off</td>
<td>75.6 (1.4)</td>
<td>91.8 (0.3)</td>
<td>86.7 (0.7)</td>
</tr>
<tr>
<td>all ndvi</td>
<td>77.5 (1.1)</td>
<td>91.0 (0.9)</td>
<td>86.7 (0.7)</td>
</tr>
<tr>
<td>all ndvi, all metrics</td>
<td>82.6 (0.8)</td>
<td>93.2 (0.5)</td>
<td>91.2 (0.7)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Chengdu</th>
<th>Xi’An</th>
<th>Kunming</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>c. Support vector machines</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>all landsat bands</td>
<td>90.0 (1.3)</td>
<td>93.9 (0.8)</td>
<td>92.5 (0.6)</td>
</tr>
<tr>
<td>all landsat, all ndvi</td>
<td>89.3 (0.7)</td>
<td><strong>94.1</strong> (0.5)</td>
<td>92.8 (0.8)</td>
</tr>
<tr>
<td>all landsat, all metrics</td>
<td><strong>91.0</strong> (0.7)</td>
<td>93.8 (0.6)</td>
<td>92.9 (0.7)</td>
</tr>
<tr>
<td>all landsat, ndvi, metrics</td>
<td><strong>90.9</strong> (0.8)</td>
<td><strong>94.1</strong> (0.7)</td>
<td><strong>93.0</strong> (0.8)</td>
</tr>
<tr>
<td>all landsat, no slc-off</td>
<td>79.5 (1.0)</td>
<td>91.5 (0.5)</td>
<td>87.8 (0.4)</td>
</tr>
<tr>
<td>all ndvi</td>
<td>76.1 (1.1)</td>
<td>90.2 (0.9)</td>
<td>84.4 (1.2)</td>
</tr>
<tr>
<td>all ndvi, all metrics</td>
<td>84.0 (0.9)</td>
<td>93.4 (0.7)</td>
<td>90.9 (0.5)</td>
</tr>
</tbody>
</table>
Monitoring peri-urban development

Assessing classifier performance in peri-urban areas

- Sample of 60-100 9 km² sites in each study area, capturing 700-2600 settlements
- Simple presence/absence of settlement determined from Google Earth
- Results show omission and commission errors < 2%
Results – waves of urban expansion

Amount of urban land (standardized), 1970s-2010

- Guangzhou: 11.3% (1990-2000) and 4.4% (2000-2009)
- Tianjin: 0.3% (1990-2000) and 7.0% (2000-2009)
- Hangzhou: 4.9% (1990-2000) and 4.0% (2000-2009)
- Ningbo: 4.9% (1990-2000) and 12.7% (2000-2009)
- Fuzhou: 4.8% (1990-2000) and 4.0% (2000-2009)
- Chengdu: 3.9% (1990-2000) and 8.9% (2000-2009)
- Xian: 2.9% (1990-2000) and 6.0% (2000-2009)
- Kunming: 7.5% (1990-2000) and 5.6% (2000-2009)
- Urumqi: 1.9% (1990-2000) and 2.4% (2000-2009)

Average annual rates of change, 1990-2000 and 2000-2009

(amount of land, km² (30 km radius))
Results - rapid rates of expansion

Amounts, rates of land use change in western cities are approaching levels witnessed in coastal cities, although role of planning and FDI differ.

Registered investment by foreign enterprises by province or region in 2006 (100 million US dollars)

Guangdong, Shanghai, Zhejiang, Fujian, Tianjin

Perlstein et al., in review
Results - rapid expansion, loss of arable land
Results - planned nuclei growth

Urban expansion has been directed out of the central core to nearby towns, leading to poly-nucleated urban form.
Results - planned nuclei growth

Urban expansion has been directed out of the central core to nearby towns, leading to *poly-nucleated urban form*.

Simple measurement:
amount of urban land within core, nuclei at each time point.

[Bar charts showing urban land change in Chengdu, Xi’An, and Kunming]
Results - planned expansion far from city

Urban expansion has been directed out of the central core to nearby towns, leading to poly-nucleated urban form.

For each period, is development proximate to or far from existing urban land?

Chengdu 1988

Chengdu 2000

Chengdu 2009
Results - planned expansion far from city

In later periods (2003-2006, 2006-2009),
urban expansion occurs farther from the city’s edge (5-10 km)
Results – population change vs. expansion of urban land

Change in urban land vs. population change - core city

1970s-2010

[Graph showing change in urban land (km²) vs. change in population (millions) for different cities.]
Conclusions

How are urban areas changing across China? How can we monitor rapid expansion across multiple time periods?

New era of remote sensing - increasing availability of VHR and multi-temporal datasets

Results show that urban expansion can be mapped successfully with dense time stacks of Landsat data

- Overall accuracy across cities - 90-94%
- DTs and SVMs perform equally well in terms of accuracy, but DTs perform better with respect to **noisy, missing data**
- Feature selection produced mixed results, yet including NDVI and metrics showed modest accuracy increases (1-4%)
- High quality training data
Conclusions

How are urban areas changing across China?
What are the drivers and implications of these changes?

Mapping urban land characteristics is possible using medium resolution satellite data

Understanding urban spatial patterns is critical, but keep it simple!

Factors that affect urbanization are multi-faceted, vary over space and time

- multi-scale planning
- preferential policy, zones
- foreign direct investment
- fiscal transfers
- road development
- economic transition
- migration
Acknowledgments

Special thanks to…

Collaborators:
Kurt Paulsen (Wisconsin)
Jennifer Alix-Garcia (Wisconsin)
A-Xing Zhu (Wisconsin)
Jianfa Shen (Chinese Univ. of Hong Kong)
Karen Seto (Yale)

Local contacts:
Alishir Kurban (Xinjiang University)
Wenze Yue (Zhejiang University)
Rong Tan (Zhejiang University)
Hangqiu Xu (Fuzhou University)
Yimin Li (Yunnan University)
Liyan Ren (Ningbo University)

Graduate students:
Carly Mertes, Chaoyi Chang,
Zhiwei Ye, and Na Zhao (Wisconsin)