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Recent Advances in Remote Sensing of Urban Heat Islands

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Remote Sensing of Urban Heat Islands

- Remotely sensed imagery has been increasingly used to study UHIs by computing land surface temperatures from satellite images.
- Remote sensing has the advantage of providing a time-synchronized dense grid of temperature data over a whole city.
- A key issue in the application of remote sensing technology is how to use surface temperature measurements at the micro-scale to characterize and quantify heat islands observed at the meso-scale.

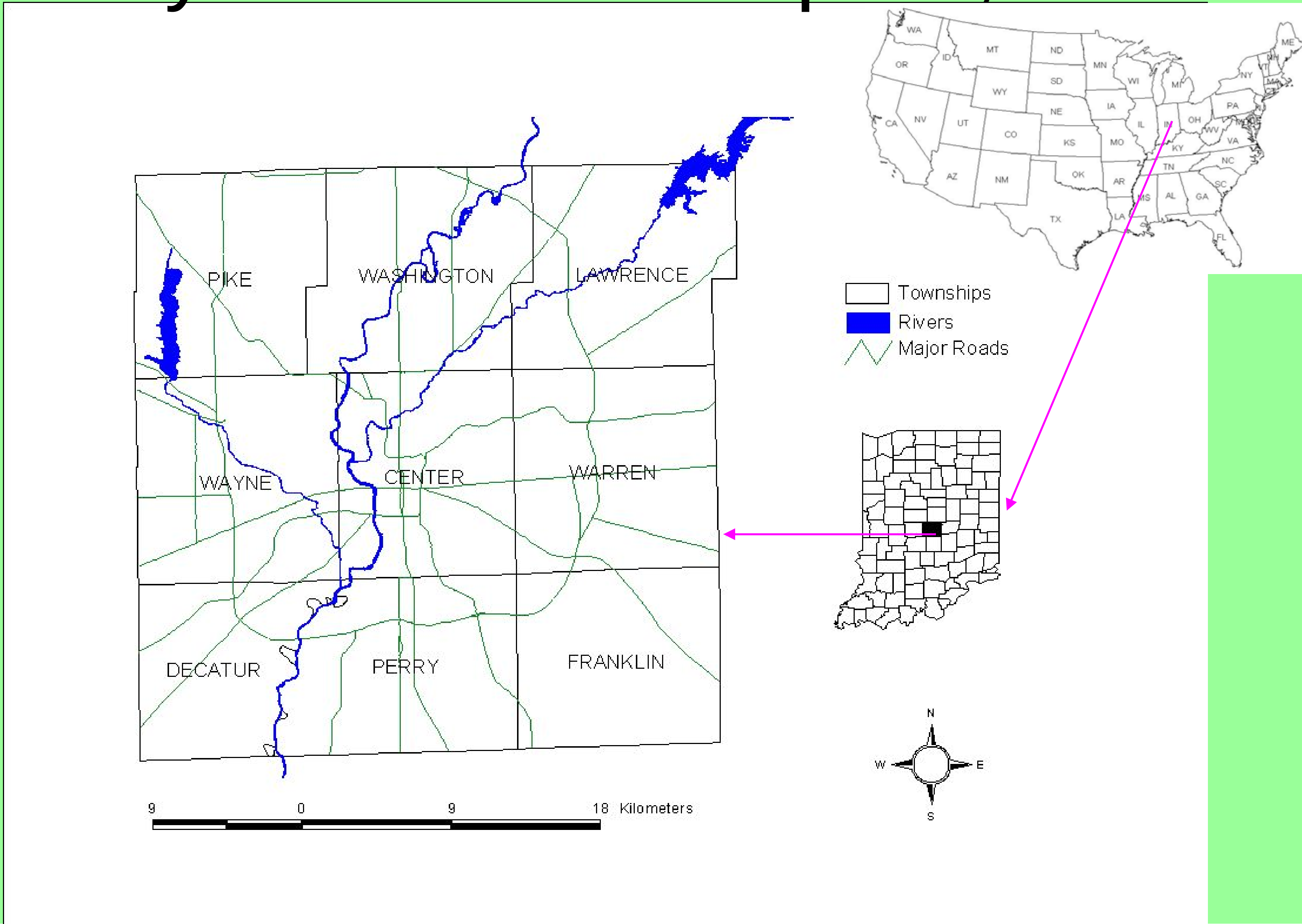
Remote Sensing of Urban Heat Islands

- Another issue: How to deepen the understanding of the correspondence between the reception/loss of radiation of urban surfaces and the distribution of land use and land cover (LULC) characteristics.
- Third issue: How to develop and use quantitative surface descriptors, not LULC thematic data, to describe urban thermal landscapes (Voogt and Oke, 2003).

Research Objectives

- To investigate the relationship between land surface temperature (LST) and vegetation fraction;
- Determine the optimal scale to study the relationships between the patterns of landscape and LST; and
- To characterize and quantify urban heat islands by using LSTs.

Study Area – Indianapolis, USA



Data Used

- ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) images
  - ✓ Oct. 3, 2000 (time: 17:00:51) - Fall;
  - ✓ June 16, 2001 (time: 16:55:29) - Summer;
  - ✓ Jan. 26, 2002 (time: 16:49:17) - Winter;
  - ✓ April 5, 2004 (time:16:46:39) - Spring.
- Landsat TM image of June 6, 1991, July 3, 1995, ETM+ image of June 22, 2000.
- MODIS images of 2006 (300 day and night images)
- High resolution aerial photographs: 1997 and 2002 digital orthophotographs.

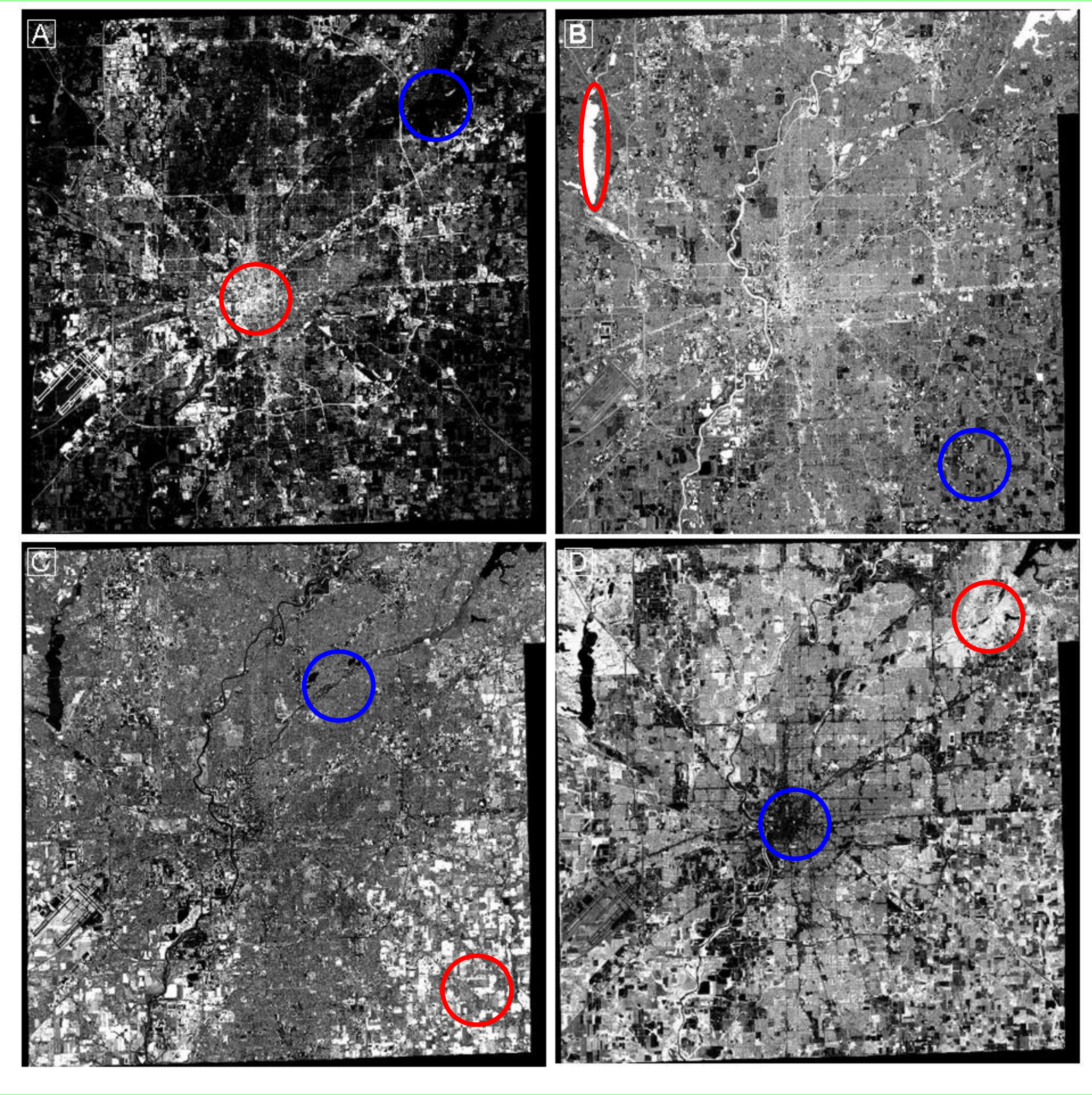
(I)

Relationship between LST and Green Vegetation Fraction

(Weng et al. 2004, *Remote Sensing of Environment*)

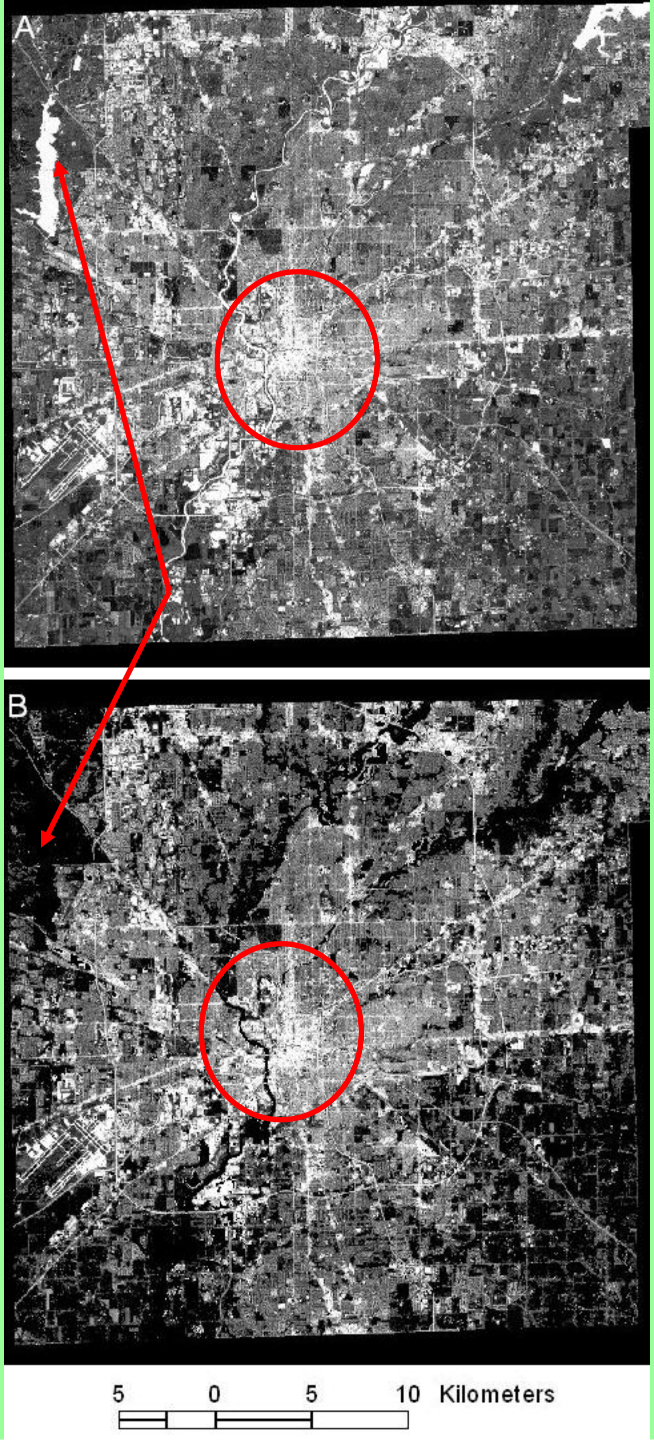
Spectral Mixture Analysis:

Fraction images computed from ETM+ reflective bands using LSMA (A: high albedo; B: low albedo, C: soil; and D: green vegetation)



A: Impervious surface estimation based on combination of high-albedo and low-albedo fractions

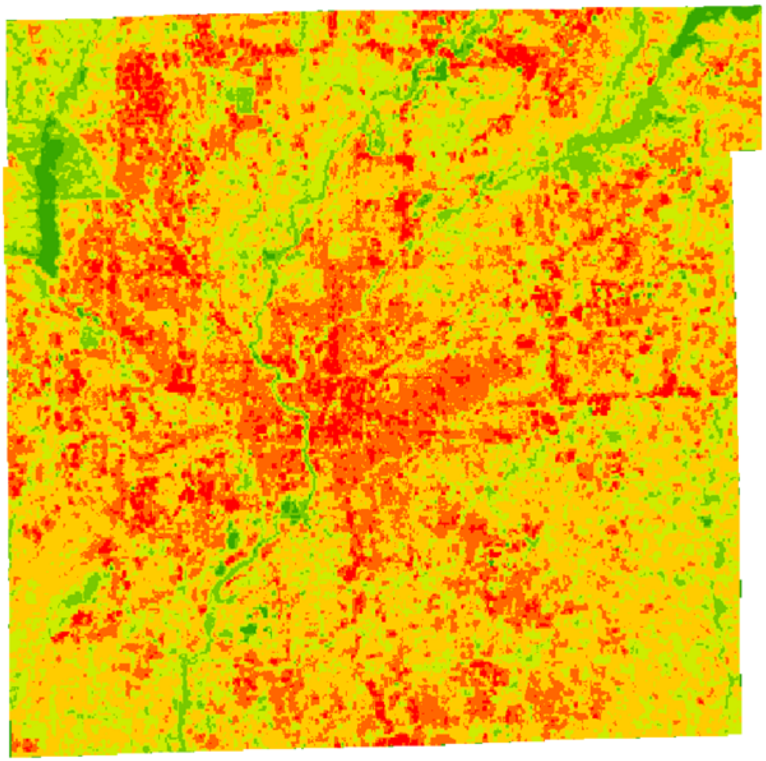
B: Improvement of estimation by combined use of land surface temperature and the fraction images.



(Lu and Weng, 2006, *Remote Sensing of Environment*)

RMSE = 9.22%

76 plots sampled (300m*300m)

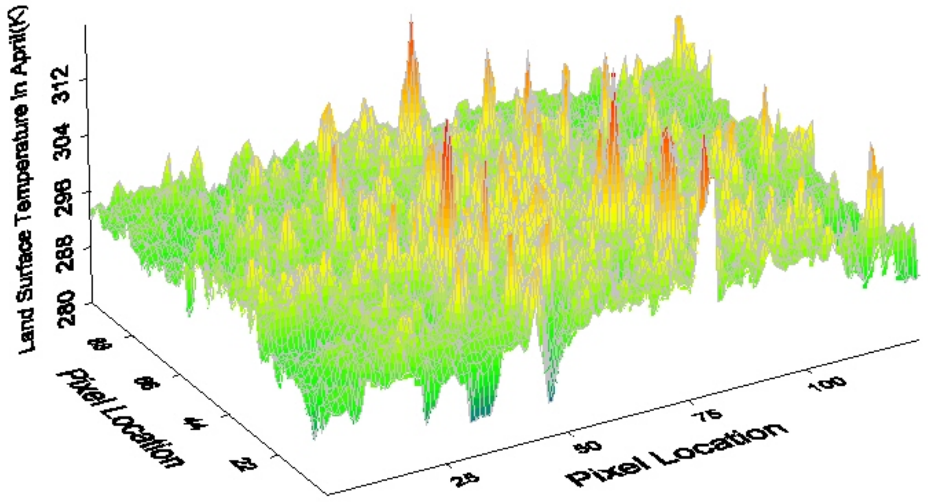


marion_ts_04.img

<VALUE>

- 267.4018375 - 284.031733
- 284.0317331 - 287.3007106
- 287.3007107 - 290.5696882
- 290.5696883 - 293.8386658
- 293.8386659 - 297.1076435
- 297.1076436 - 317.1866625

Mean: 292.30K,
Standard Dev. 3.27K



Land Surface Temperature (**LST**) of Indianapolis, April 5, 2004

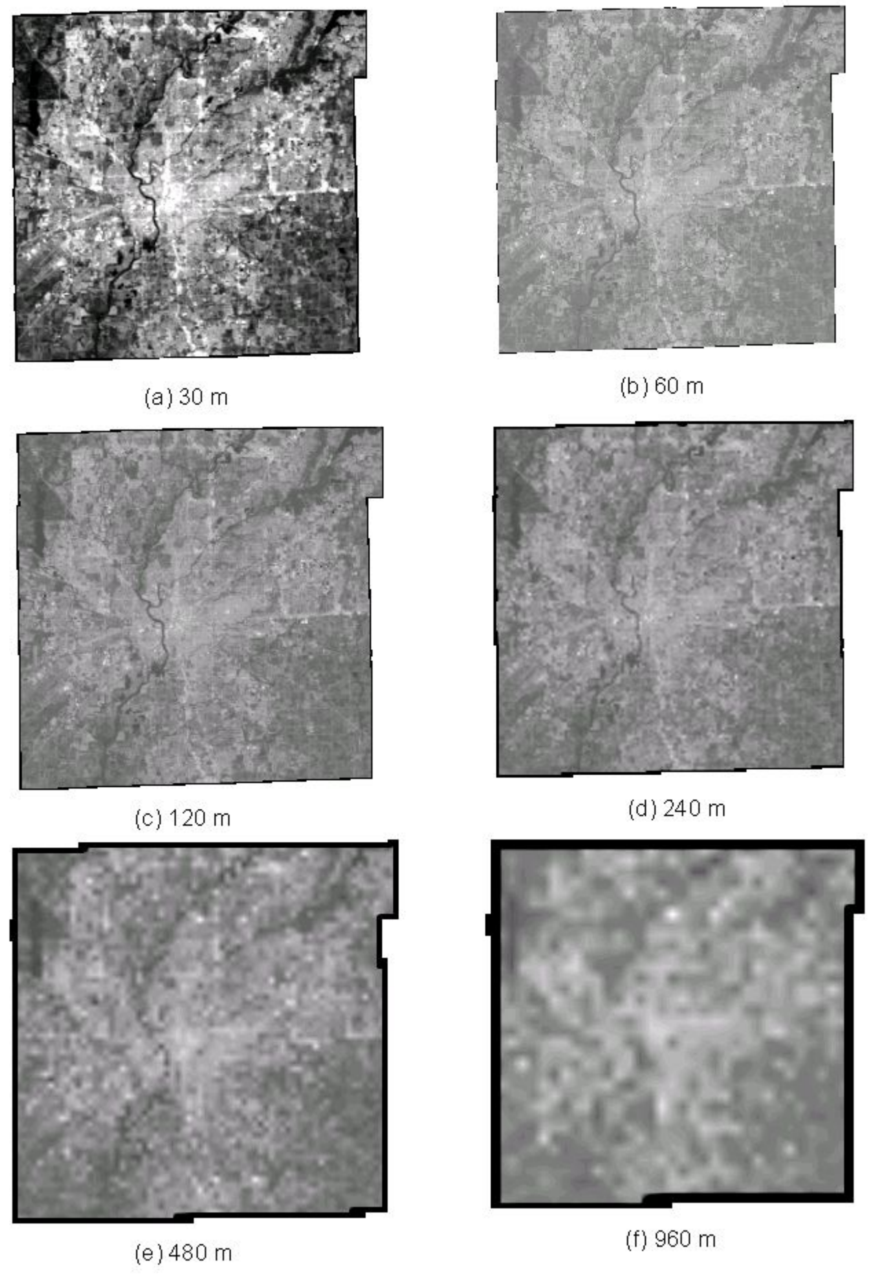
Methods

- Pixel measurements of spectral radiance and image texture for LST, GV, and NDVI (a widely used vegetation index) images.

- Pixel-by-pixel correlation analysis: between LST and NDVI *vs*. between LST and GV fraction.

- Calculate Fractal Dimension (a texture index) of LST, GV, and NDVI images, and examine how their textures are related.

Pixel Aggregation, 30 m to 960 m



Correlation Coefficients between LST and GV fraction, and between LST and NDVI

Resolution	30 meters		60 meters		120 meters		240 meters		480 meters		960 meters	
	S_t/GV	S_t/NDVI	S_t/GV	S_t/NDVI	S_t/GV	S_t/NDVI	S_t/GV	S_t/NDVI	S_t/GV	S_t/NDVI	S_t/GV	S_t/NDVI
Com. and Ind.	-0.6559	-0.6125	-0.6630	-0.6244	-0.6729	-0.6360	-0.6694	-0.6107	-0.5863	-0.5594	-0.5430	-0.5217
Residential	-0.6763	-0.6663	-0.6897	-0.6812	-0.6909	-0.6845	-0.6875	-0.6365	-0.6003	-0.5619	-0.5862	-0.5449
Cropland	-0.7538	-0.7265	-0.7982	-0.7915	-0.8613	-0.8041	-0.8316	-0.7641	-0.7901	-0.7304	-0.7751	-0.6192
Grassland	-0.3760	-0.3573	-0.4431	-0.4056	-0.4856	-0.4149	-0.4546	-0.3934	-0.4097	-0.3382	-0.3656	-0.2911
Pasture	-0.4105	-0.3363	-0.4589	-0.4422	-0.4920	-0.4563	-0.4795	-0.4288	-0.4176	-0.3539	-0.3952	-0.3144
Forest	-0.7343	-0.7156	-0.7919	-0.7330	-0.8333	-0.7751	-0.7509	-0.7137	-0.7087	-0.6468	-0.6556	-0.5772
Water	-0.2416	-0.1972	-0.2601	-0.2587	-0.2719	-0.2707	-0.2219	-0.2178	-0.1935	-0.1887	-0.1130	-0.1027

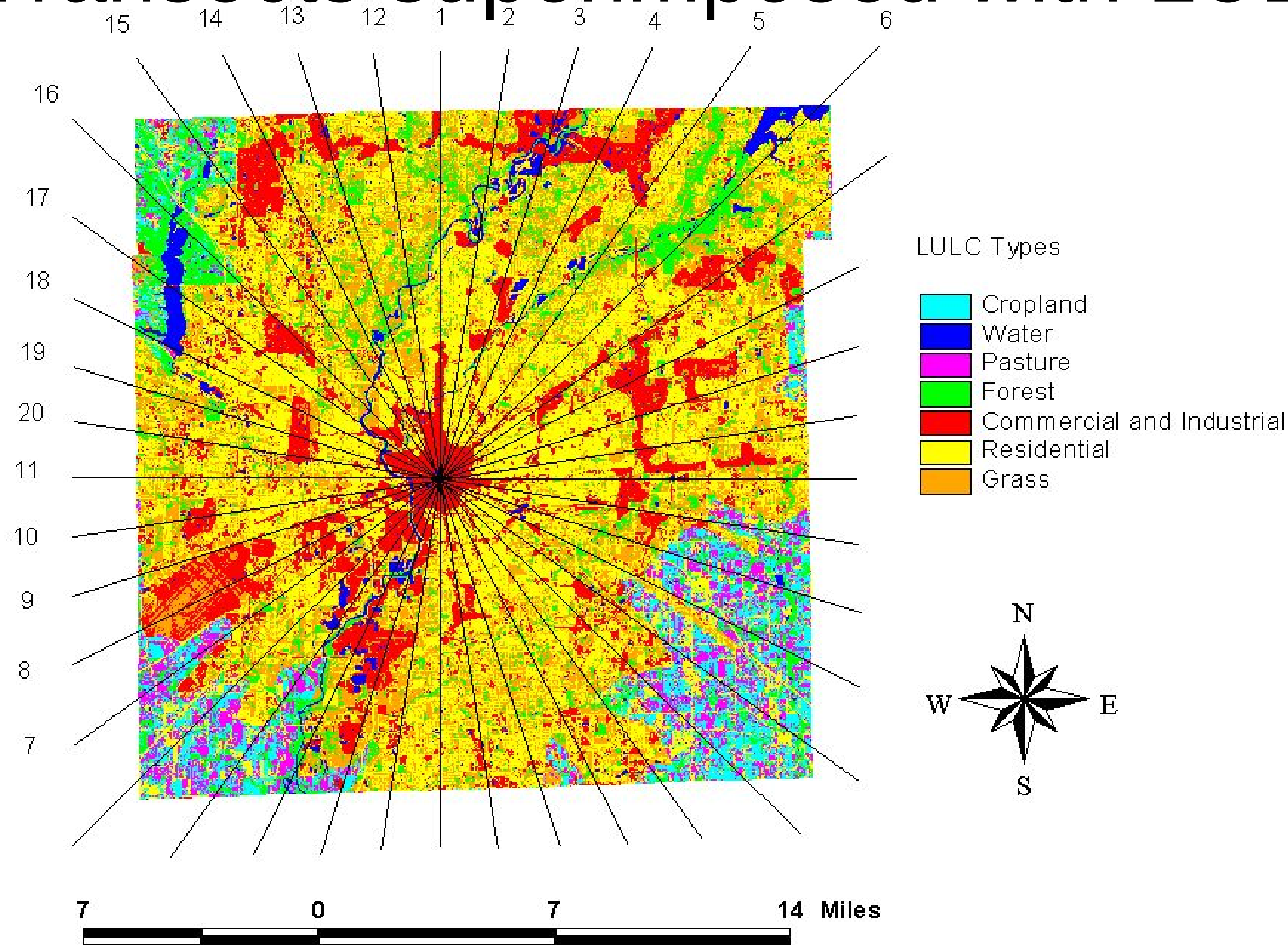
Relationship of LST with NDVI and GV Fraction

- ***Negative*** correlations between LST and NDVI, and between LST and vegetation fraction, varying by LULC type.

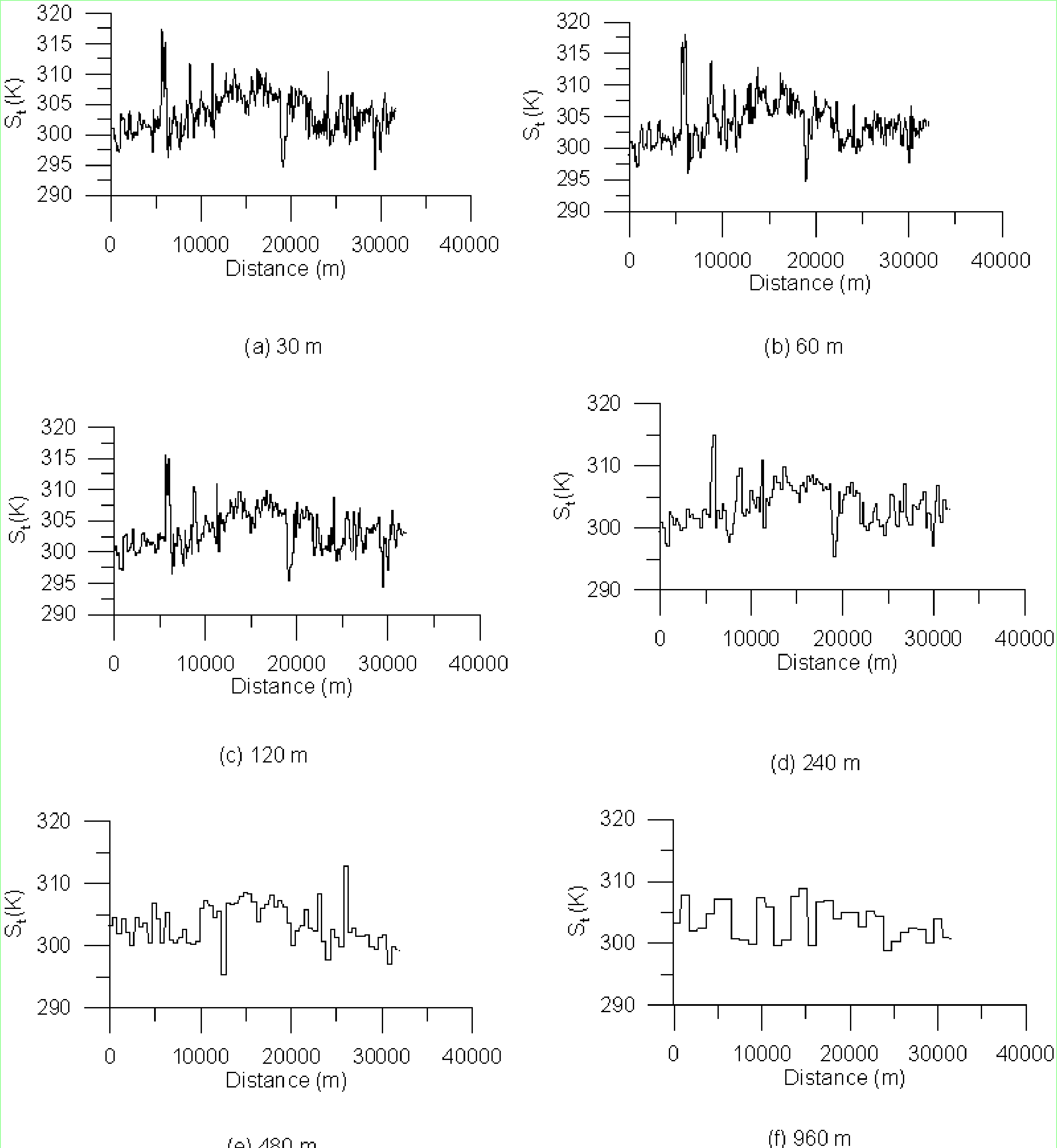
- Correlation varies across the spatial scales: Increases as pixel size increases up to a resolution of **120 m**, and then decreases with increasing pixel size.

- **Vegetation fraction** provides a slightly stronger correlation for all LULCs at all resolutions.

Transects superimposed with LULC map



Transect Fractal Dimension (D) of LST, GV, and NDVI images at different resolutions were computed.



Variation of *LST* along the Transect #11 (W to E) is displayed for different resolutions.

Fractal Analysis

- The complexity of LST, NDVI, and GV fraction images increases initially with pixel aggregation and peaks around **120 meters**, but decreases with further aggregation.

- The spatial variability of texture in LST is ***positively*** correlated with those in NDVI and GV fraction.

- Strongest correlation in texture occurs at the resolution of 120 meters - **the operational scale**.

Summary

- The areal measure of GV abundance provides a more direct correspondence with LST than NDVI.
- NDVI measurements dependent upon the spectral width of visible and near infrared band in a particular sensor.

(II)

Optimal scale for examining the relationship between LULC and LST patterns

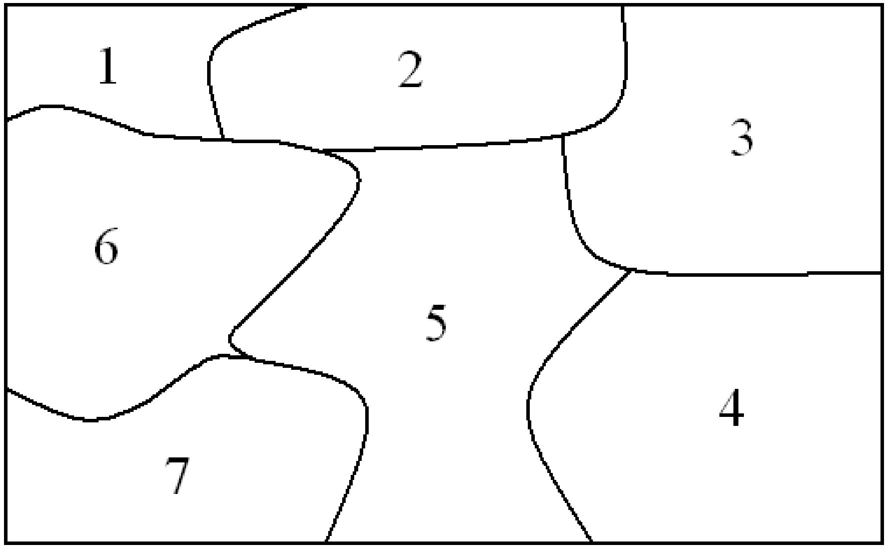
Weng, Q. et al. 2007, *Urban Ecosystems*.

Liu, H. and Weng, Q. 2008 (forthcoming), *Environmental Monitoring and Assessment*.

Liu, H. and Weng, Q. 2009 (forthcoming), *Photogrammetric Engineering & Remote Sensing.*

Definition of Patch

- The basic elements or units that make up a landscape.
- Landscape metrics:
  - Mathematically characterize the spatial patterns of landscapes, and
  - Compare ecological quality across the landscapes.
  - Examples:
    - Patch Percentage (PP)
    - Shape Index (SI)



Patches 1, 2, & 4: Urban
Patches 3 & 7: Grass
Patches 5 & 6: Forest

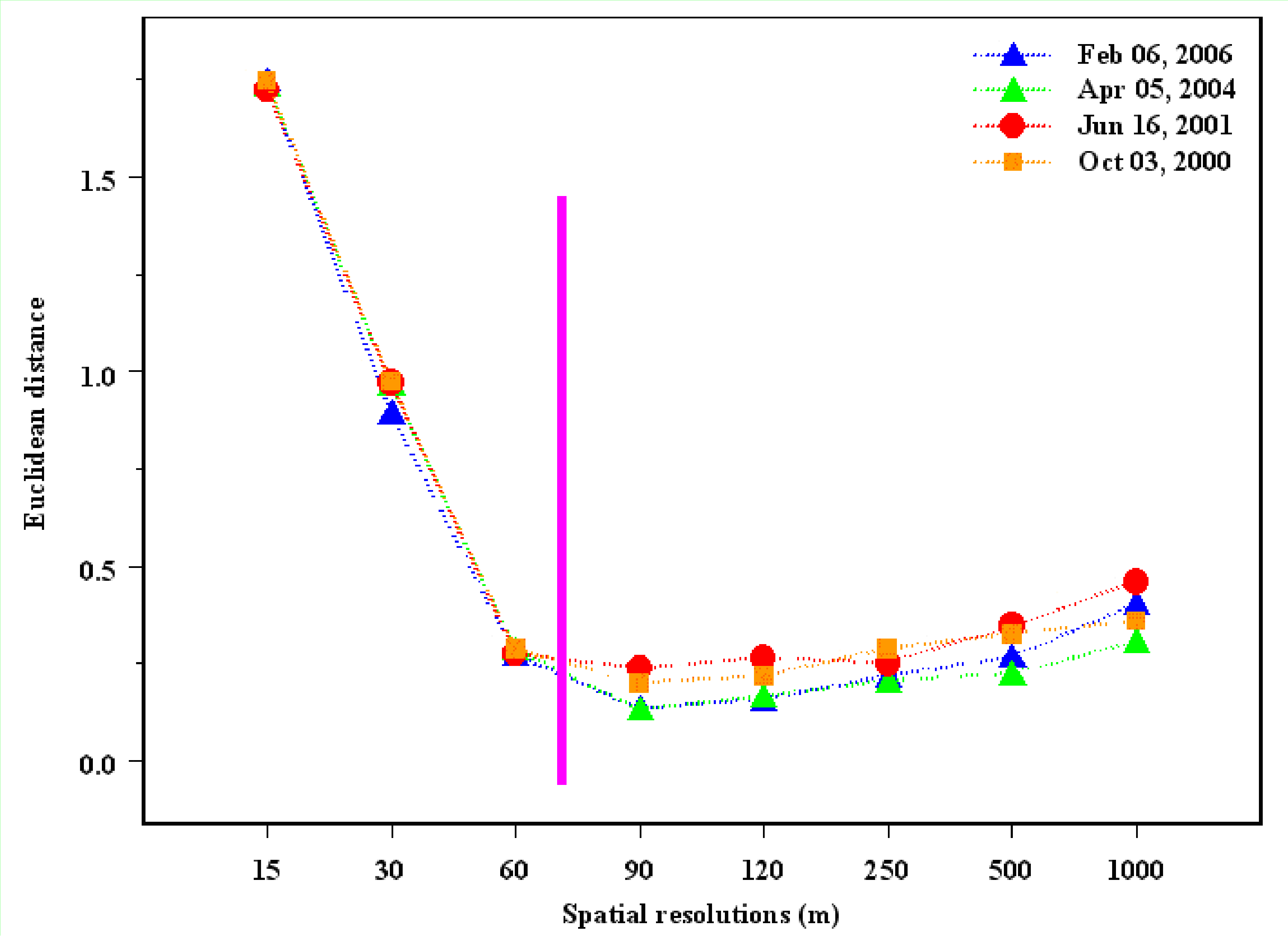
Methods

- Each data layer was re-sampled to the resolutions of 15, 30, 60, 90, 120, 250, 500, and 1000 meters.
- Landscape metrics were derived from each LULC and LST map in each season.
- Derivation of landscape metrics: including Patch Density (PD), Landscape Shape Index (LSI), Perimeter- area Fractal Dimension (PFD), Mean Perimeter-area Ratio (MPR), Proximity Index (PI), and Contagion Index (CI).

Determination of Optimal Scale

- Each metric represented one dimension in the space.
- Optimal scale related to the operational scale of a phenomenon.
- Optimal scale was determined based on the minimum distance in the landscape metric spaces. All indices were standardized to the values from 0 to 1 before calculation of Euclidean distances.
- At the optimal scale, the patterns of LULC and LST were most closely related:
  - If the pixel size were too small, the effect of LULC pattern on LST could not be fully identified.
  - If the pixel size were too large, the effect of various LULC types on LST would not be differentiated.

Normalized Euclidean Distances between the LULC and LST maps across the spatial resolutions



Summary

- Ninety meter was found to be the optimal spatial scale for assessing the landscape-level relationship between LULC and LST.
- The landscape and LST patterns in the winter were unique, while the rest of three seasons had more agreeable landscape and LST patterns.
- Limitations: Subject to the quality of remote sensing data, acquisition time, processing methods, the sensitivity of individual landscape metric, and the study area.

(III)

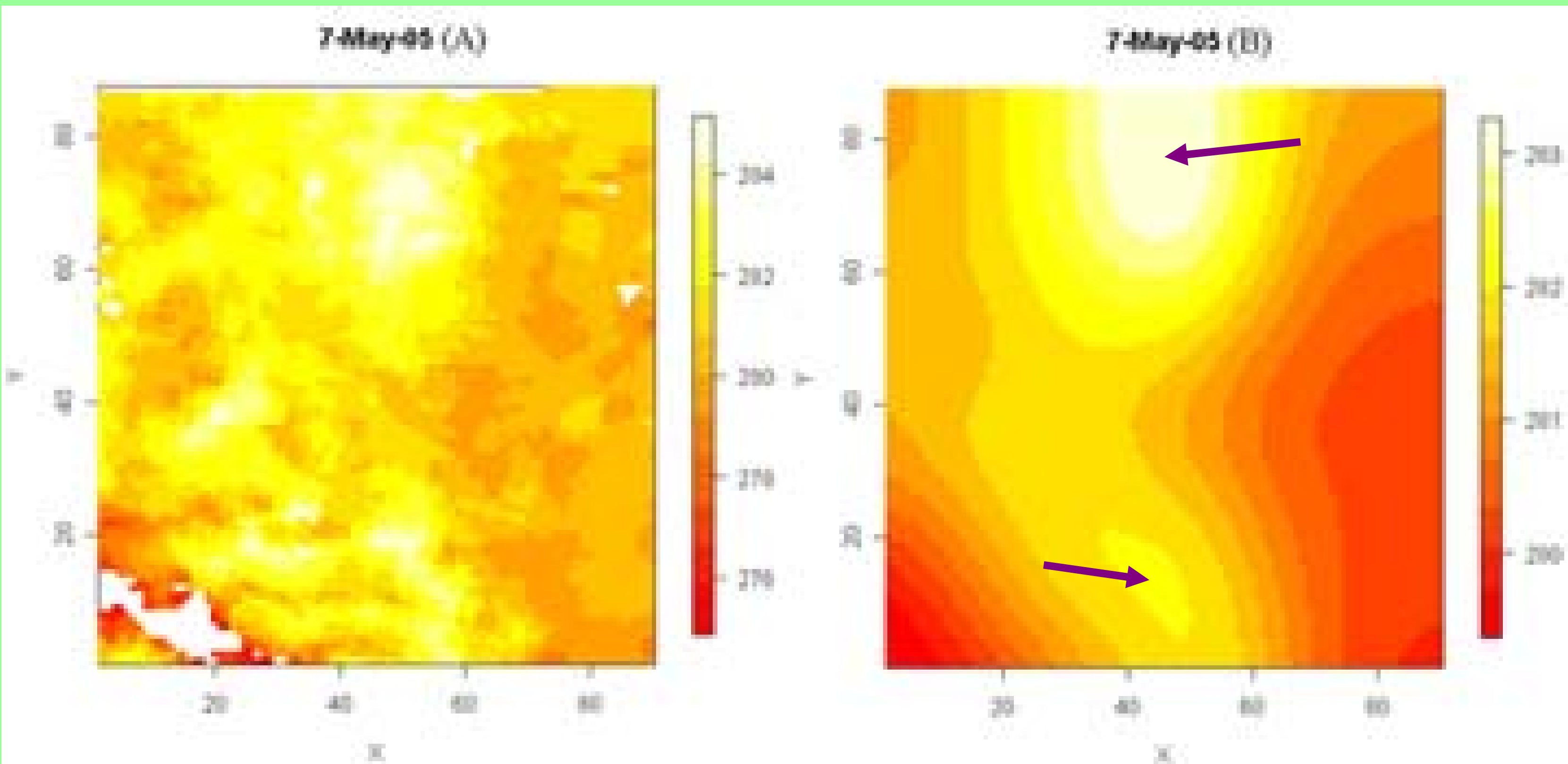
Modeling Urban Heat Islands by Using LSTs

Rajasekar, U. and Weng, Q. 2009 (expected). *ISPRS Journal of Photogrammetry and Remote Sensing*.

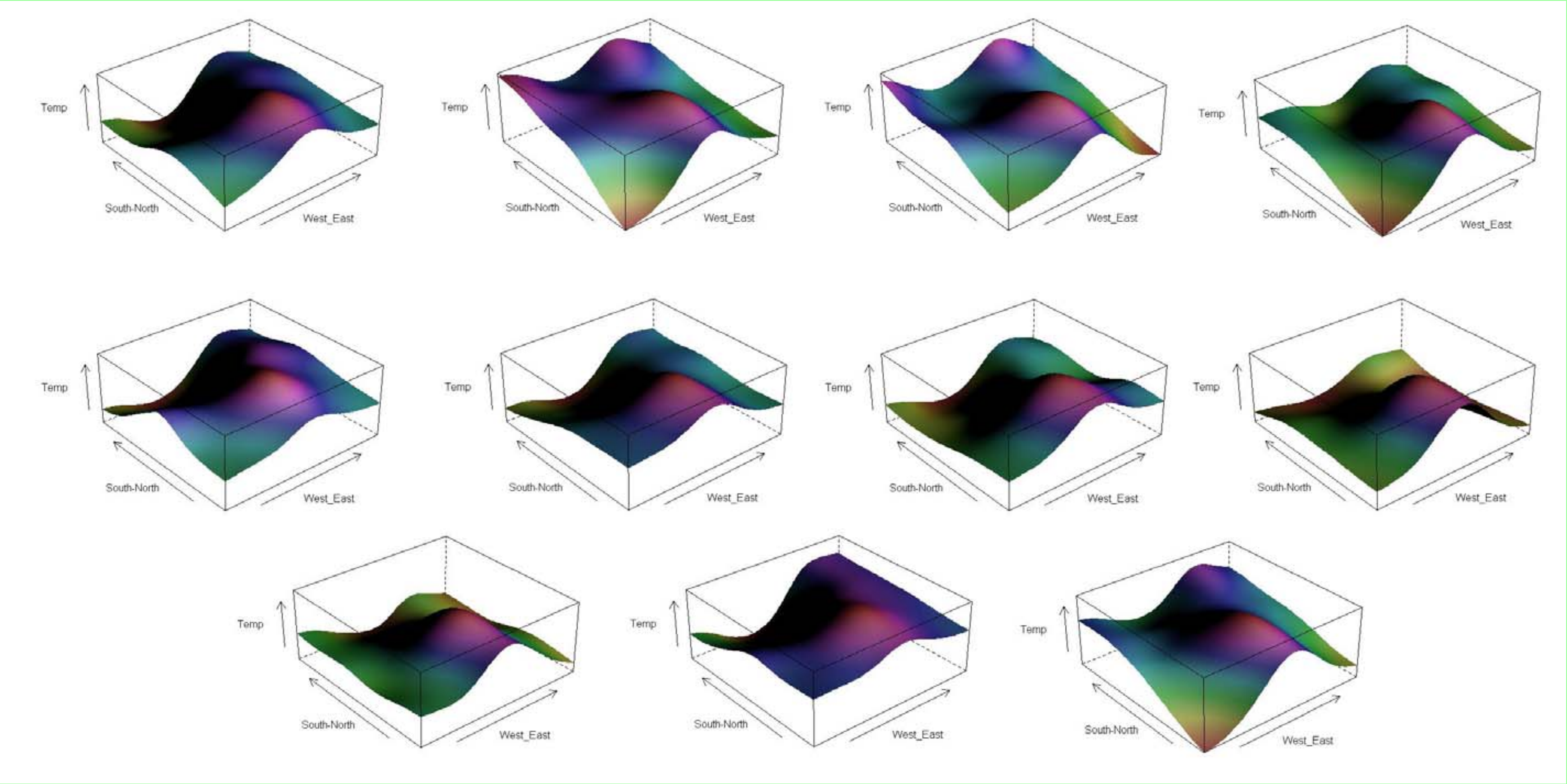
Objective

- To utilize micro-scale (pixel) measurements of LST to derive meso-scale UHI parameters of the entire city (including: magnitude, the spatial extent, the orientation, and the central location).

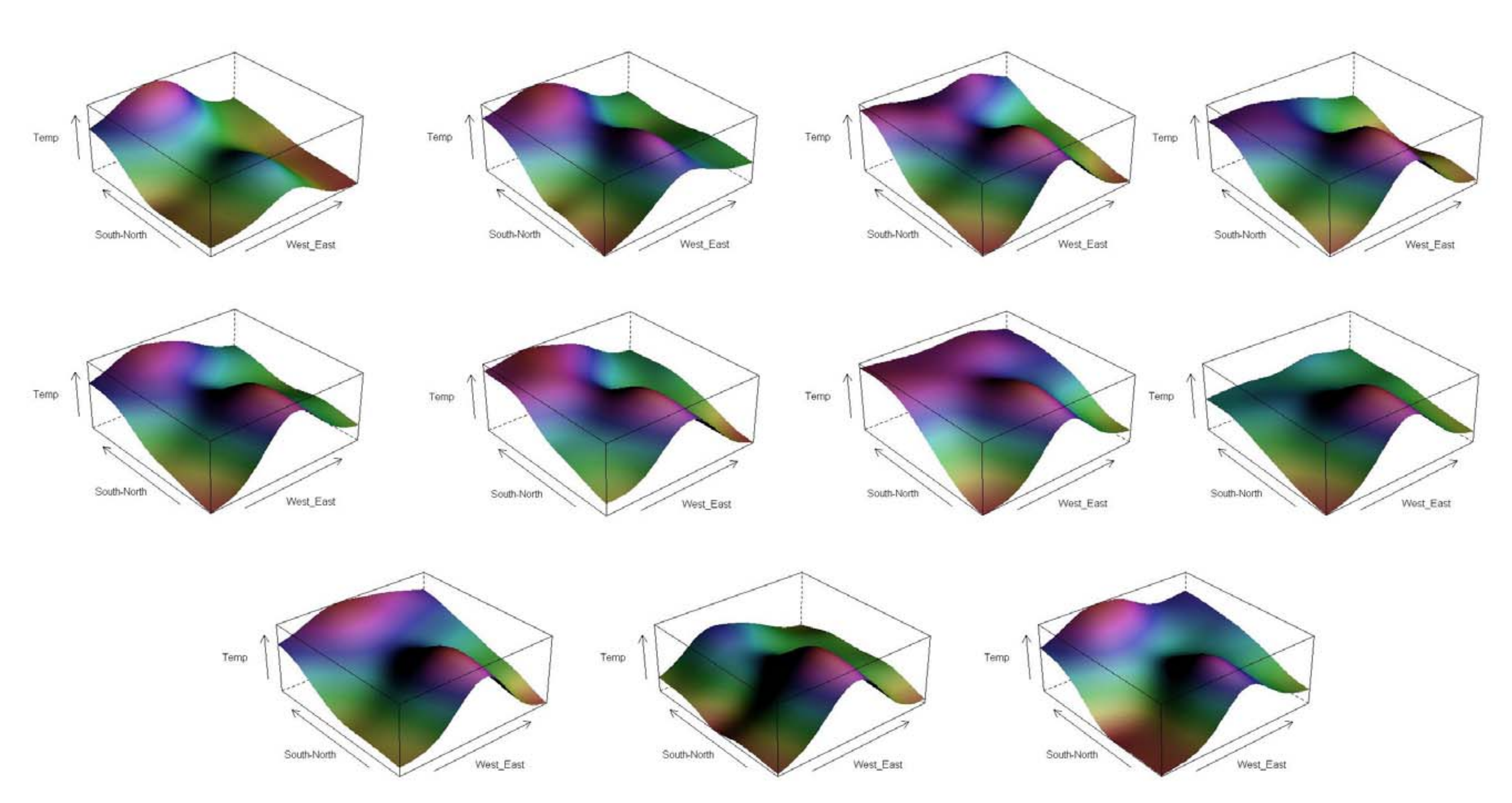
A Gaussian model fitted to LSTs to derive UHI parameters (including magnitude, spatial extent, orientation, and the central location). Figure below illustrates the data fit in two-dimension.

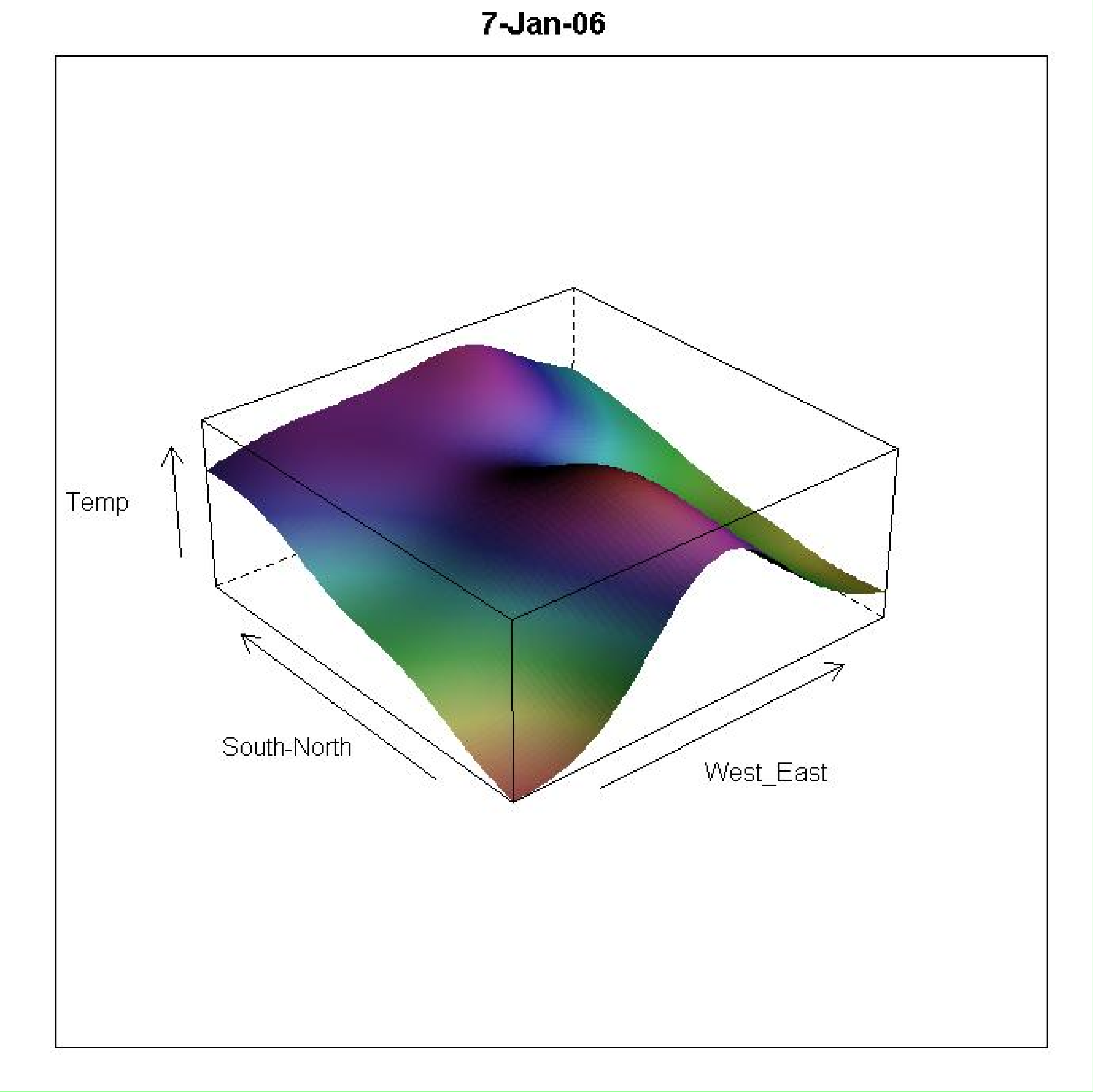


3-D Models of Daytime UHIs

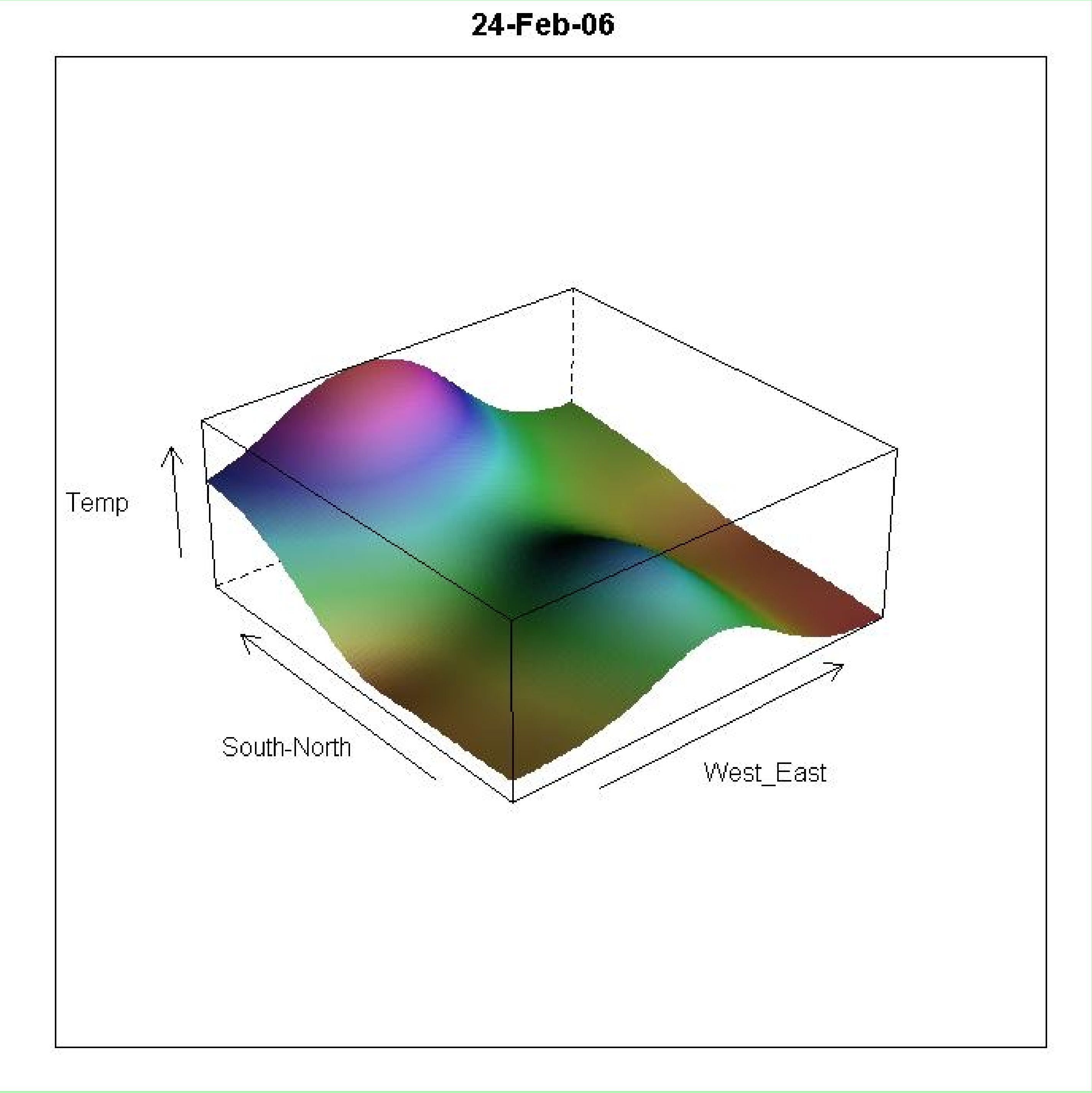


3-D Models of Nighttime UHIs



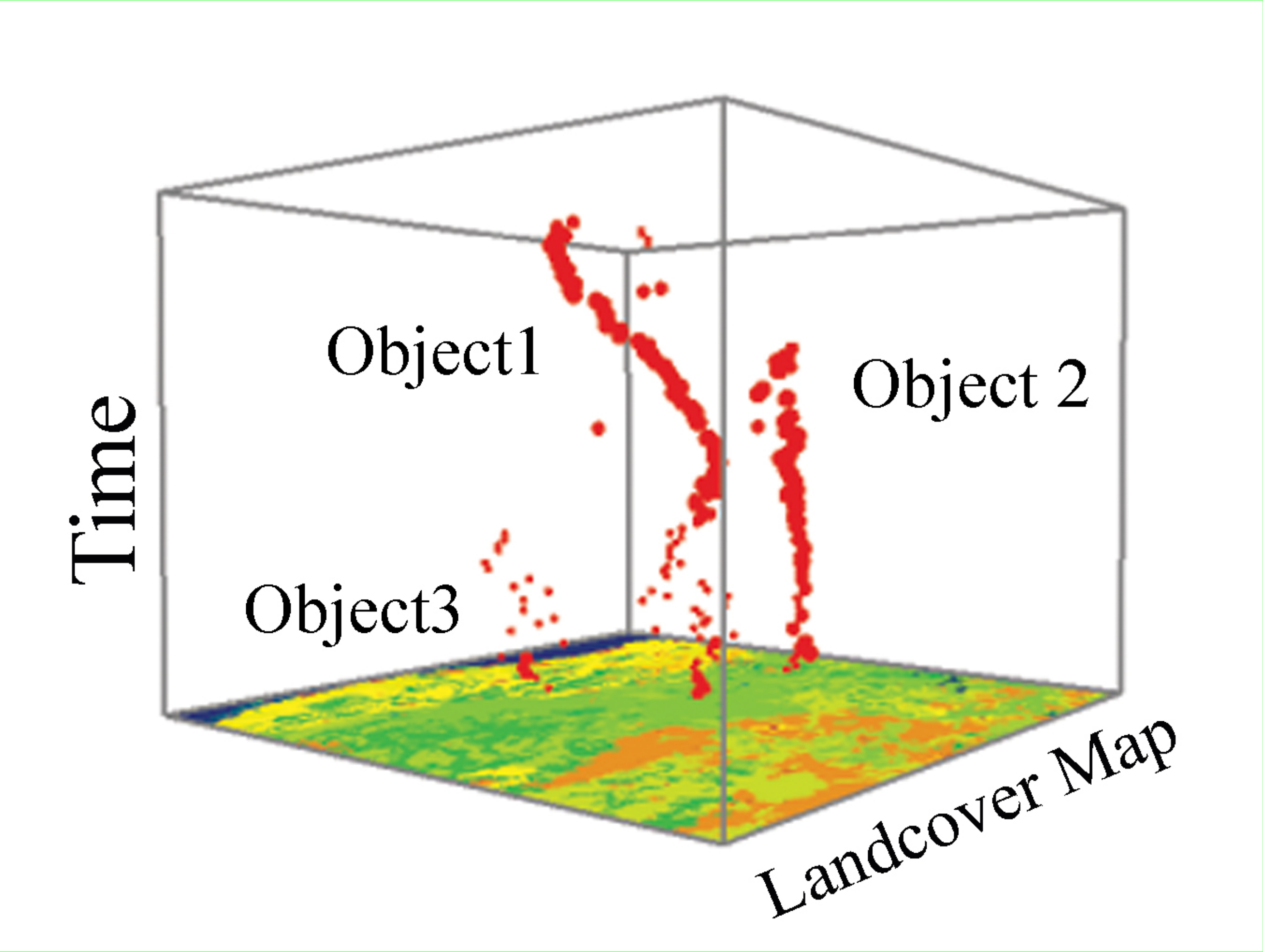


MODIS
2006 Day
Images

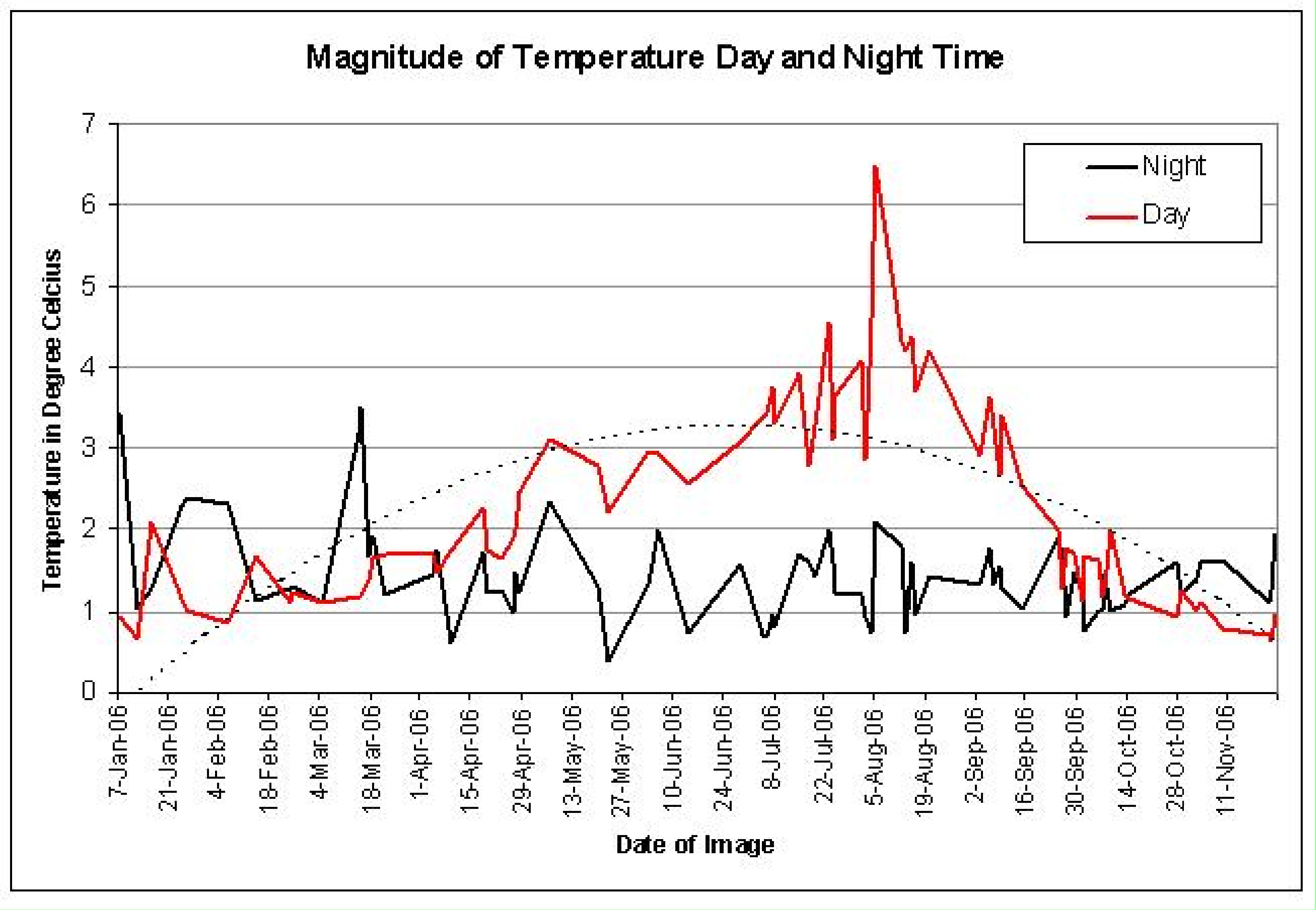


MODIS 2006 Night Images

UHI as an Moving Object over the Space and Time



UHI Magnitude Measurements Derived from MODIS Images



Day Mean: 2.28C (Std Dev: 1.22); Night Mean: 1.47C (Std Dev: 0.59)

Summary

- The Gaussian model for characterizing UHIs with LSTs are effective.

- The relationship between LST and UHI may be further examined by using texture measurements.