Multi-Sensor Analysis of Global Daytime and Nighttime Urban Heat Islands

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**Outline:**
2. Landsat spectral mixture analysis (SMA) and Boston urban heat island.
3. Testing of project central hypothesis.
1. Mapping urban expansion globally: Methods/results for North America and East Asia, 2000-10

Methods
Step 1:
Delineate study area extent

- Merge 2001 MODIS map of urban extent with all point datasets on cities (GRUMP, UN, etc.)
- Buffer by urban patch size
Methods
Step 2:

Characterize urban extent, c. 2010

- Synthesize new global urban maps (Landsat scale) – Globeland30, Global Human Settlement Layer, DLR urban extent map – to create urban probability surface at 500m resolution.

- Merge with MODIS 500m decision tree classification of urban land, using Bayes Rule (Mertz et al., 2015).
Methods

Step 3:

Change detection

- Work backwards – were 2010 urban areas built-up in 2000, or did they become urban between 2000 and 2010?

- 10 years growing season max EVI data from MODIS (2001-2011).

- Supervised boosted decision tree algorithm

- Training data:
  
  (1) stable urban areas
  (2) areas that became urbanized, 2000-2010

- Output probabilities iteratively thresholded, compared to c2010 Google Earth imagery.
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Step 4: Accuracy assessment

Beijing, China

Bangkok, Thailand

Phoenix, USA

Boston, USA

Houston, USA

Urban land 2000

Urban expansion, 2000-2010

20 km

A. Schneider et al., UW
Mapping urban expansion

Progress and next steps

- Mapping c. 2010 global urban land extent to be completed in 2016.
- Change detection work ongoing; maps released as completed.
- Robust, two-tier accuracy assessment using stratified random sample of sites labeled by multiple analysts, double-blind procedure.

City-level results for top 30 urban agglomerations in East Asia.

A. Schneider et al., UW
2. Boston MA – Urban Heat Island Landsat Spectral Mixture Analysis

August, 2010

R: Substrate  G: Green Vegetation  B: Urban

L. Cheek & M. Friedl, BU

4th end-member (not included): Shade
Defining Urban Heat Island: daytime $\Delta T$

Land Surface Temperature Clusters

Urban Heat Island, August 2010

L. Cheek & M. Friedl, BU
Relative fractions of four endmembers vary across scene and through year.

1. **green vegetation**, 
2. **urban** (built), 
3. **substrate** (e.g., dirt, dead grass & leaves, leafless trees), 
4. **shade** (dark).

L. Cheek & M. Friedl, BU
Urban Heat Island ~ Spectral Mixture Analysis

$\Delta T$ increases in summer and with urban fraction; $\Delta T$ decreases with green vegetation fraction.
ΔT high in downtown Boston, but there are cooler spaces.
Urban Cool Islands

Low $\Delta T$

L. Cheek & M. Friedl, BU
Urban Cool Islands – Vegetation

**Green/Red**: Low ΔT with high green vegetation.  
**White**: Low ΔT with 0% vegetation.

L. Cheek & M. Friedl, BU
Urban Cool Islands – Shade

**Red/Orange**: low ΔT that has abundant shade.

**White**: low ΔT with <20% shade.

Shade fraction

L. Cheek & M. Friedl, BU
Urban Cool Islands – Shade

Red/Orange: low ΔT that has abundant shade.
White: low ΔT with <20% shade.

Urban cool islands: Boston’s urban core includes cooler areas arising not only from vegetation, but also from shading.
3. Hypothesis – Urban core development impacts urban heat island

Big cities have strong backscatter.
1999-2009 change in night time lights and microwave backscatter

DMSP/OLS night time lights (NL; max. = 63)

- 11 x 11 grid (0.05°) centered on each city.
- Summer mean backscatter; annual mean night time lights.
- Arrows point from NL and PR in 1999 to NL and PR in 2009.
- Urban fraction (arrow color) from MODIS land cover product.
- Water grid cells masked out.

Frolking et al. 2013 ERL
A central hypothesis of the project: rapid growth in the urban core built environment (as quantified by Quikscat) will have an observable impact on the urban core temperature relative to surrounding rural areas that are not experiencing rapid building growth, and thus on the urban heat island.

Method:

1. Target large cities – 30 in East Asia (rapid growth) and North America (slower growth).
2. Dissaggregate into urban core, urban non-core, near rural (10-40 km), far rural (40-70 km).
3. Assemble data, including:
   - MODIS AQUA & TERRA LST (day & night);
   - MODIS EVI
   - Quikscat;
   - DMSP/OLS stable lights.
4. Evaluate UHI and trends across samples.
Hypothesis (trend in Quikscat $\rightarrow$ trend in LST) not supported.
30 large cities in East/SouthEast Asia and North America

Mean urban core backscatter vs mean TERRA UHI $\Delta T$
urban core minus rural 10-40 km

Seasonal mean, 2000-09, urban core diurnal LST range (day minus night)

summer (JJA)  winter (DJF)

TERRA UHI $\Delta T$ (°C)

TERRA

AQUA UHI $\Delta T$ (°C)

AQUA

Hypothesis (trend in Quikscat $\rightarrow$ trend in LST) not supported.
30 large cities in East/SouthEast Asia and North America

Mean urban core backscatter vs mean TERRA UHI ΔT
urban core minus rural 10-40 km

Rate of backscatter increase, 2000-09, vs rate of increase in AQUA LST UHI ΔT,
urban core minus rural 10-40 km

Hypothesis (trend in Quikscat → trend in LST) not supported.
Strong contributions of local background climate to urban heat islands

CLM dominant terms in simulated UHI:
- *evaporation* – daytime > nighttime.
- *thermal storage* – nighttime > daytime.
- *convection* – mixed geographic results.

NATURE, 2014
“Managing the convection efficiency or heat storage of urban land does not seem viable, even though these are large contributors to $\Delta T$ [UHI], because it would require fundamental changes to the urban morphology, such as a city-wide increase in building height.” [p. 219]

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We will work with Dan Li, urban climate modeler at BU, on sensitivity of urban climate to building boom in Beijing.

What is impact on modeled urban temperatures (air and radiative; day and night) of building height changes in central Beijing during 2000-2010?
Conclusions

• Ongoing mapping of global urban expansion 2000-2010.

• Daytime cooler areas in urban core can occur not only with high vegetation cover, but also with structure-derived shading.

• Rapid building development in urban core of large cities does not lead to changes in MODIS LST (day or night, TERRA or AQUA).
Extra slides
Hovmöller diagrams of time series of monthly mean (x-axis) of the 30° binned (y-axis) QuikSCAT Level 1B σ^0 HH data (in dB).

**Beijing, China**

- strong increase over time.
- strong azimuthal asymmetry.

**São Paulo, Brazil**

- weaker increase over time.
- weak azimuthal asymmetry.
Azimuthal dependence of individual backscatter returns vary by city (high to none).

Seems to be strongly correlated with orientation of major urban road networks.

Averaging over one or more months fully samples azimuthal range.

Paget et al. 2015 IJRS
Although urban backscatter magnitude changed over 1999-2009, there was no trend in azimuthal dependence for several large cities we sampled.
Urban Heat Island ~ Spectral Mixture Analysis

Seasonality of ΔT increases as pixel fraction of green vegetation decreases.

L. Cheek & M. Friedl, BU
Night lights & backscatter – different urban characteristics.

2009

Beijing

Night lights

Backscatter power

Delhi

Plan view: 21x21 grid cells (0.05°)

Frolking et al. 2013 ERL
Night lights & backscatter – different urban characteristics & modes of change.

**Beijing**
- Night lights
- Backscatter power

**Delhi**
- Night lights
- Backscatter power

Plan view: 21x21 grid cells (0.05°)

Frolking et al. 2013 _ERL_
Manila, Philippines

Jakarta, Indonesia
Beijing 2002-2009: monthly data trends

Seasonal Decomposition of Time Series by Loess in R ("stl")

Strong trend in Quikscat backscatter
Weak trends in UHI

Hypothesis not supported.