Assessment of Landsat 8 Data and the Urban Heat Island Effects in Connecticut

Zhiyuan Yang
Department of Natural Resources and the Environment
University of Connecticut

INTRODUCTION

- Extensively urbanized surfaces modify the energy and water balance processes and influence the movement of air, resulting in a warmer thermal climate than the surrounding rural areas, known as an urban heat island (UHI). This phenomenon can not only influence the comfort and health of urban dwellers, but also alters environmental conditions, such as biodiversity, air quality and energy consumption.
- Remote sensing data can provide the spatial distribution of temperature within a large area. They have widely been used to monitor urban heat island effect across the globe and have been a very hot topic among researchers. Landsat data is one of the most widely used satellite images for environmental monitoring because they are readily accessible and available free of charge. Landsat-8 carries two sensors, i.e., the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS).
- Based on the data from U.S. Census Bureau, a study area in Connecticut was chosen that includes 117 towns distributed along the Connecticut River, high traffic U.S. highways (US-6, US-44), and Interstate highways (I-95, I-84). Also, the area was enlarged by the inclusion of rural areas (developed or not) around the towns, the area of which is approximately 8400 square kilometers. The study area covers up to 60% of Connecticut.

METHODS

1. Data

- Landsat Science Data Products were ordered from https://espa.cr.usgs.gov/ (account needed, EarthExplorer works also) Imagery was filtered by Cloud Cover (less than 10%).
- Shapefiles of census (by tracts) and boundaries (by towns) from UConn Map And Geographic Information Center (MAGIC).
- 2011 edition: NLCD2006 Percent Developed Imperviousness and NLCD 2006 Land Cover from https://www.mrlc.gov/ (National Land Cover Database).

2. Methodology

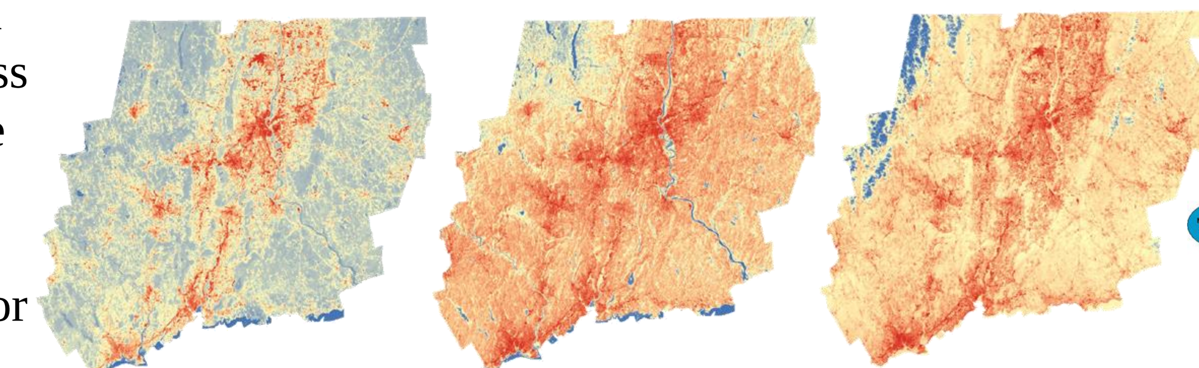
- **Imagery Processing**
- **NDVI value**, Normalized difference vegetation index maps were derived for all four images as follows:
  NDVI=(NIR - RED)/(NIR+RED) Tool: ERDAS Imagine, ArcGIS
- **Land Surface Temperature**, Tool: ArcGIS, Toolbox by Dr. Daniel Civco Parameters to input: NDVI, Landsat 8 Band 10 & 11 (Thermal Bands)
- **Percent Impervious Surface Area**, Tool: ArcGIS, Impervious Surface Analysis Tool (NOAA) Parameters to input: Raster-based land cover or land use grid (NLCD); Polygon data set for which percentage of impervious surface is to be calculated (Towns); Land cover impervious surface coefficients (NLCD); Population density theme (Census by tracts)*

* required for imperviousness coefficient derivation process

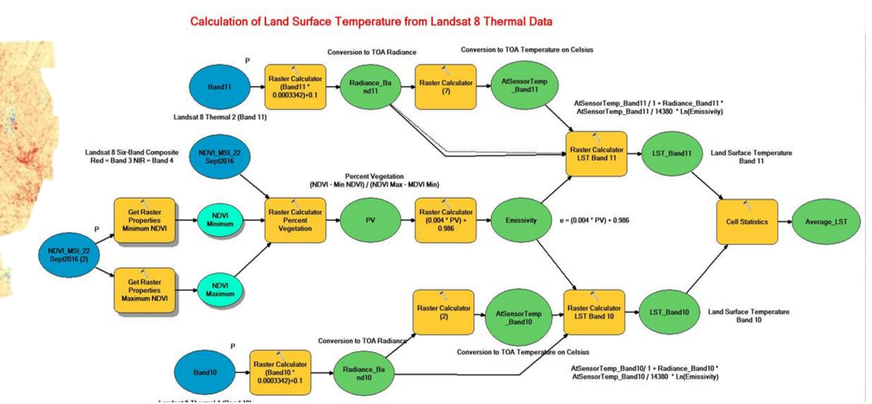
RESULTS

- LST patterns and statistics

For summer, the 2016 LST map had a range of 281-324 K with the highest surface temperatures. The September LST values displayed a range comparable to that of the April LST map, but their thermal patterns were different, especially in rural areas with deciduous forests showed more significant difference from the apparent hot spot than April.



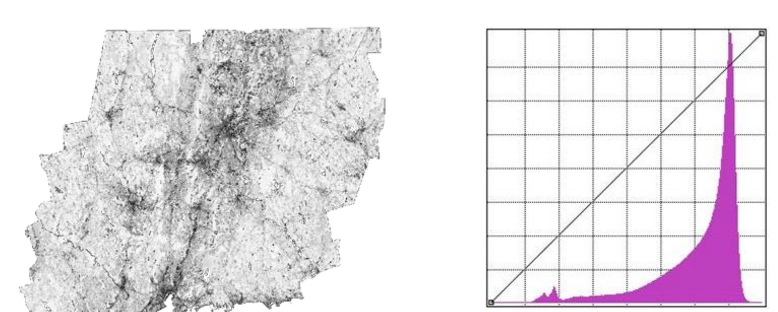
June 19, 2016 April 10, 2014 Sept. 30, 2013



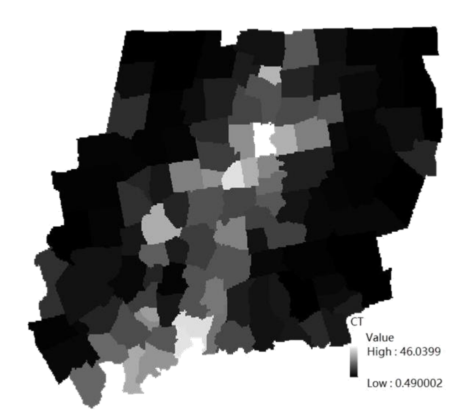
Flow chart of the LST model

- NDVI and Percent Impervious Surface Area

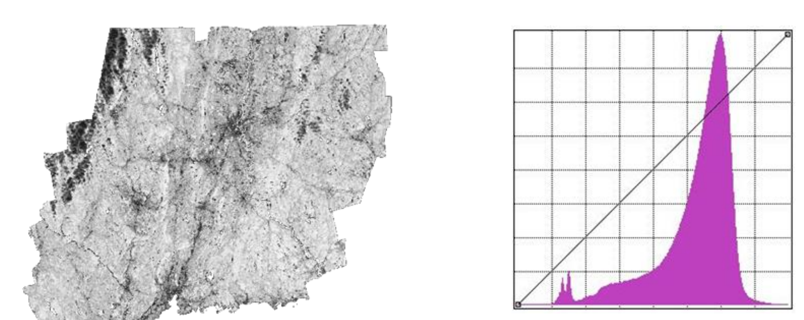
While there was a large variation (−0.25–0.69), the summer NDVI had the highest average value of 0.48 among all dates. Compared to the skewed histogram of summer NDVI, the fall NDVI had an approximate normal distribution with a mean of 0.35 and standard deviation of 0.12, indicating a clear greenness decrease from June to September.



NDVI and histogram of 2016 Summer



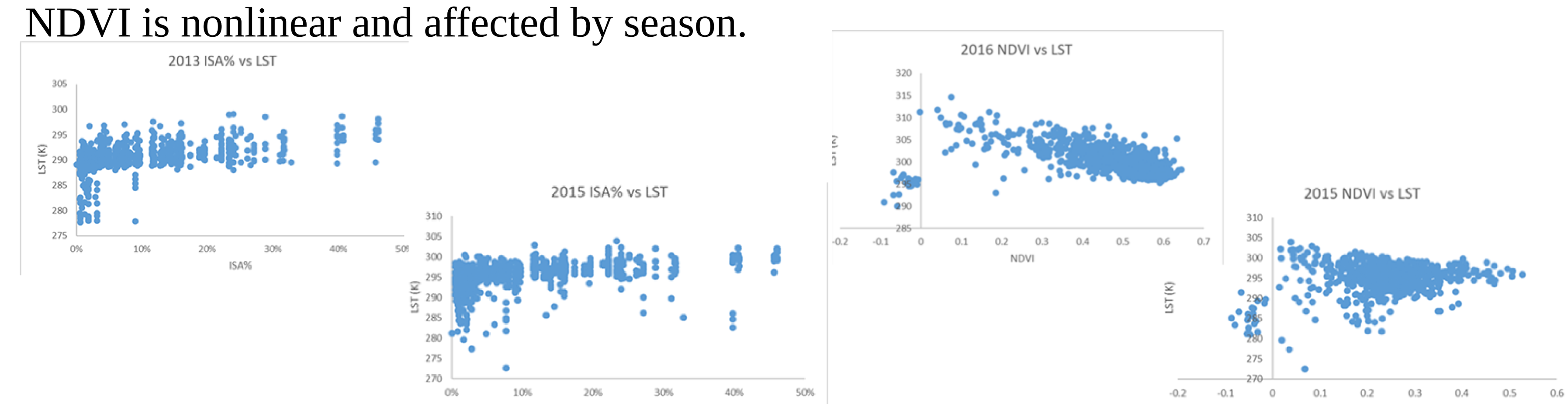
Percent Impervious Surface Area Map



NDVI and histogram of 2013 September

- Relationships of LST to NDVI and Percent Impervious Surface Area

A sample with 1000 randomly generated points was created for each date.
For all the seasons, figures indicate consistent linear patterns between LST and percent impervious surface. On the other hand, the relationship between LST and NDVI is nonlinear and affected by season.



CONCLUSIONS

- The study investigated the relationships between the LST, %ISA, and NDVI in an area covering most of Connecticut. Results indicate %ISA is an accurate indicator of Urban Heat Island (UHI) effects with strong linear relationships between LST and %ISA for all the four seasons, whereas the relationship between LST and NDVI suffers from evident seasonal changes and it is better restricted to analysis of UHI effects during summer and early autumn.
- From the imagery, we can easily identify the UHI condition during different seasons. Winter data was eliminated to avoid the effect of snow cover. Apparently areas with large population and high urbanization show intense UHI effects in relation with surrounding areas with relatively more vegetation cover and lower levels of development. Such developed urban areas like Hartford, Waterbury and New Haven are good examples for the vary effect.
- According to the study, the variations in surface temperature can be better accounted for by differences in imperviousness than by the commonly used NDVI. However, admittedly the conclusion is based on only one area and four different dates. Although the overpass time (around 10:30 AM) and 16-day revisit interval (which means we cannot collect the night data) of Landsat are not ideal for dynamic surface heat island analysis, the data nevertheless provide useful information for measuring and understanding urban heat island effects based on seasonal changes. Further studies of additional metropolitan areas and different satellite data such as MODIS can be used as complement.

REFERENCES

1. Chen, W., Zhang, Y., Gao, W., & Zhou, D. (2016). The Investigation of Urbanization and Urban Heat Island in Beijing Based on Remote Sensing. Procedia - Social and Behavioral Sciences, 216, 141 – 150.
2. Hunga, T., Uchihama, D., Ochi, S., & Yasuoka, Y. (2006). Assessment with satellite data of the urban heat island effects in Asian mega cities. International Journal of Applied Earth Observation and Geoinformation, 8, 34–48.
3. Rozenstein, O., Qin, Z., Derimian, Y., & Karnieli, A. (2014). Derivation of Land Surface Temperature for Landsat-8 TIRS Using a Split Window Algorithm. Sensors 2014, 14, 5768-5780.
4. Scarano, M., & Sobrino, J. A. (2015). On the relationship between the sky view factor and the land surface temperature derived by Landsat-8 images in Bari, Italy. International Journal of Remote Sensing, 36:19-20, 4820-4835.
5. Wu, C. (2004). Normalized spectral mixture analysis for monitoring urban composition using ETM+ imagery. Remote Sensing of Environment, 93(4), 480−492.
6. Wu, C., & Murray, A. T. (2003). Estimating impervious surface distribution by spectral mixture analysis. Remote Sensing of Environment, 84, 493−505.
7. Yu, X., Guo, X., & Wu, Z. (2014). Land Surface Temperature Retrieval from Landsat 8 TIRS—Comparison between Radiative Transfer Equation-Based Method, Split Window Algorithm and Single Channel Method. Remote Sens. 2014, 6, 9829-9852.
8. Yuan, F., & Bauer, M. E. (2007). Comparison of impervious surface area and normalized difference vegetation index as indicators of surface urban heat island effects in Landsat imagery. Remote Sensing of Environment, 106, 375–386.

UCONN UNIVERSITY OF CONNECTICUT

Connecticut View http://ctview.uconn.edu

AmericaView http://americaview.org