

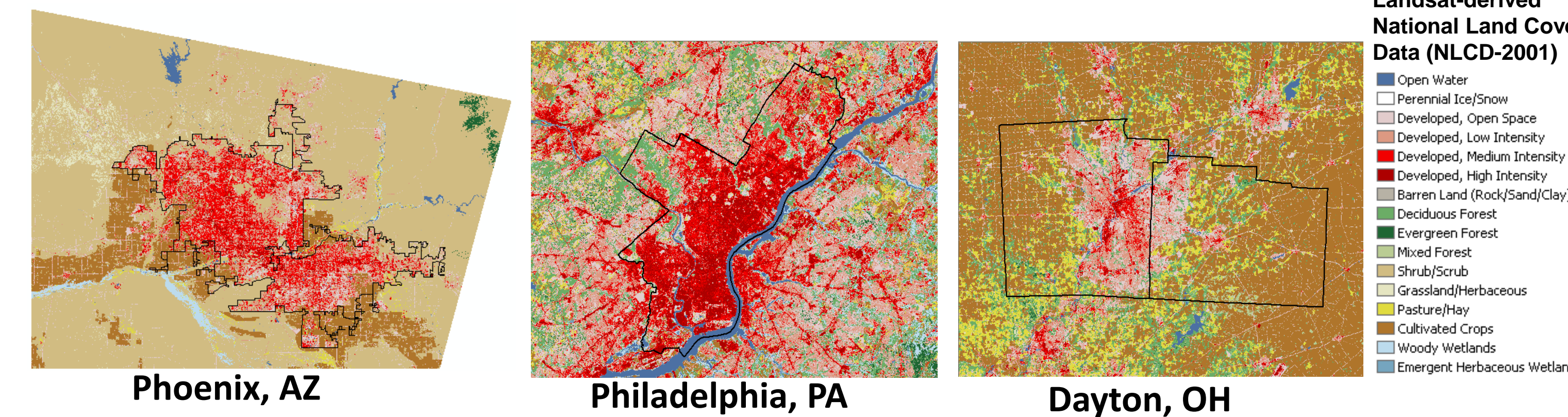
1. Overview

This study is part of a project funded by the NASA Applied Sciences Public Health Program, which focuses on Earth science applications of remote sensing data for enhancing public health decision-making. Heat related death is currently the number one weather-related killer in the United States. Mortality from these events is expected to increase as a function of climate change. This activity sought to augment current Heat Watch/Warning Systems (HWWS) with NASA remotely sensed data, and models used in conjunction with socioeconomic and heat-related mortality data. The current HWWS do not take into account intra-urban spatial variations in risk assessment. The purpose of this effort is to evaluate potential methods to improve spatial delineation of risk from extreme heat events in urban environments by integrating sociodemographic risk factors with land surface temperature (LST) estimates derived from thermal remote sensing data. In order to further improve the assessment of intra-urban variations in risk from extreme heat, we developed and evaluated a number of spatial statistical techniques for downscaling the 1-km daily MODerate-resolution Imaging Spectroradiometer (MODIS) LST data to 60 m using Landsat-derived LST data, which have finer spatial but coarser temporal resolution than MODIS. These techniques have been demonstrated and validated for Phoenix, AZ; Philadelphia, PA; and Dayton, GA using data from the summers of 2000-2006.

2. Goals/Objectives and Motivation

This overall goal of this project, which this study is part of, is to augment current Heat Watch/Warning Systems (HWWS) with NASA remotely sensed data, and models used in conjunction with socioeconomic and heat-related mortality data. The objectives of this study is to develop and evaluate a number of spatial statistical techniques for downscaling the 1-km daily MODIS LST data to 60 m using Landsat-derived LST data, which have finer spatial but coarser temporal resolution than MODIS. This will improve the assessment of intra-urban variations in risk from extreme heat, which is something that current HWWS do not take into account.

3. Study Areas



4. Methods Development and Applications

A. Deriving LST from Landsat thermal data

We followed the Weng et al. (2004)* procedure to derive land surface temperature (LST) from Landsat thermal data, which involves three steps:

1. Converting the digital number of Landsat TM or ETM+ TIR band into spectral radiance

$$\begin{aligned} \text{Radiance} &= 0.0370588 \times \text{DN} + 3.20 && \text{(For Landsat7 ETM+)} \\ \text{Radiance} &= 0.0553760 \times \text{DN} + 1.18 && \text{(For Landsat5 TM)} \end{aligned}$$

2. Converting the spectral radiance to at satellite brightness temperature (i.e., blackbody temperature, T_B)

$$T_B = K_2 / [\ln(K_1 / \text{Radiance} + 1)]$$

Where "ln" is Natural Logarithm, and K_2 and K_1 are pre-launch calibration constants (For Landsat7 ETM+, $K_2=1282.71$ K, and $K_1=666.09$ W/(m² sr um)) (For Landsat5 TM, $K_2=1260.56$ K, and $K_1=607.76$ W/(m² sr um))

3. Converting the blackbody temperature to land surface temperature (LST) which involves correcting for spectral emissivity according to the nature of land cover. We identified the land cover land use (LCLU) classes using the Landsat-derived NLCD-2001 data. Each of the LCLU classes was assigned an emissivity value by reference to the emissivity classification scheme by Snyder et al. (1998)**. The emissivity corrected LST was computed as follows (Artis & Carnahan, 1982)**:

$$\text{LST} = T_B / [(1 + (\lambda \times T_B / \rho) \times \ln(\epsilon))]$$

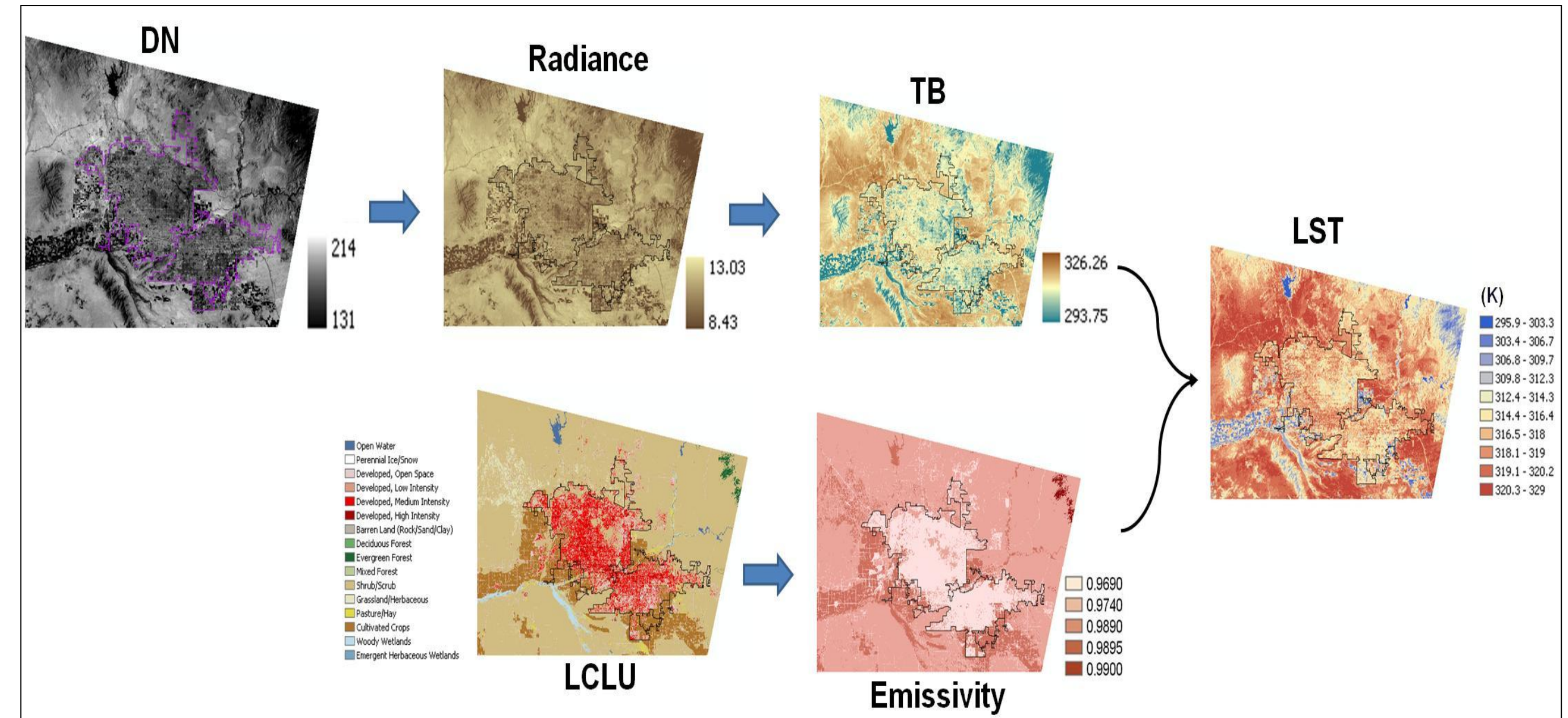
where: λ = wavelength of emitted radiance ($\lambda = 11.5$ um), $\rho = hc/\sigma = 1.438 \times 10^{-2}$ m K, σ = Boltzmann constant (1.38×10^{-23} J/K), h = Planck's constant (6.626×10^{-34} J s), and c = velocity of light (2.998×10^8 m/s).

*Weng, Q. H., Lu, D. S. and Schubring, J. (2004) Estimation of land surface temperature-vegetation abundance relationship for urban heat island studies. *Remote Sensing of Environment*, 89, pp. 467-483.

**Snyder, W. C., Wan, Z., Zhang, Y., & Feng, Y. -Z. (1998). Classification based emissivity for land surface temperature measurement from space. *International Journal of Remote Sensing*, 19, 2753-2774.

***Artis, D. A., & Carnahan, W. H. (1982). Survey of emissivity variability in thermography of urban areas. *Remote Sensing of Environment*, 12, 313-329.

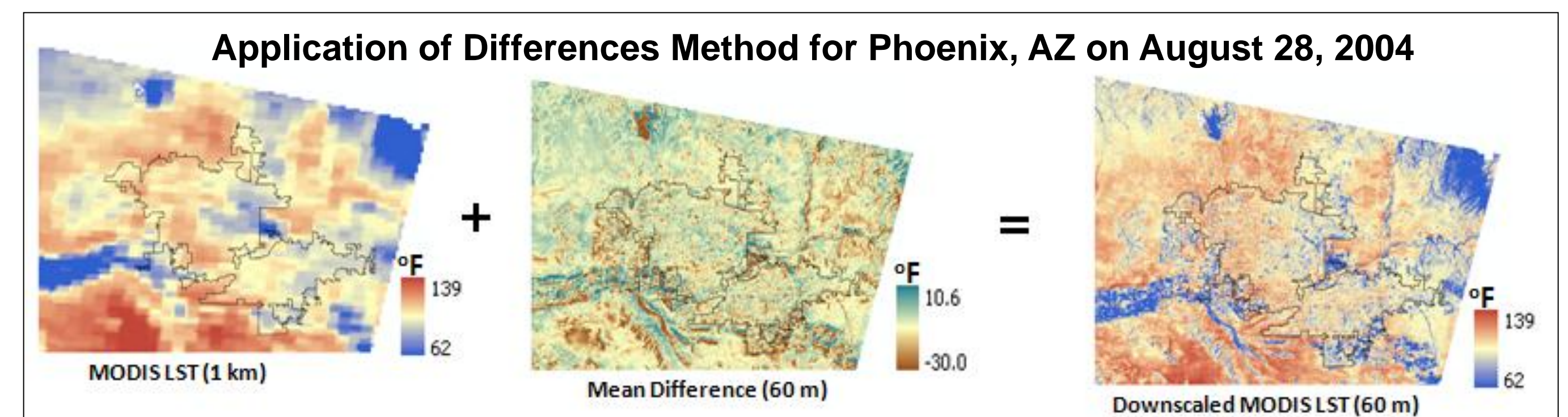
B. Downscaling MODIS LST



1. Differences Method (illustrated for Phoenix, AZ)

$$\frac{\sum_{i=1}^{10} (\text{Landsat}_{60m_i} - \text{MODIS}_{1km_i})}{10} = \bar{\Delta}_{60m} \quad \text{Adjustment Factor Development}$$

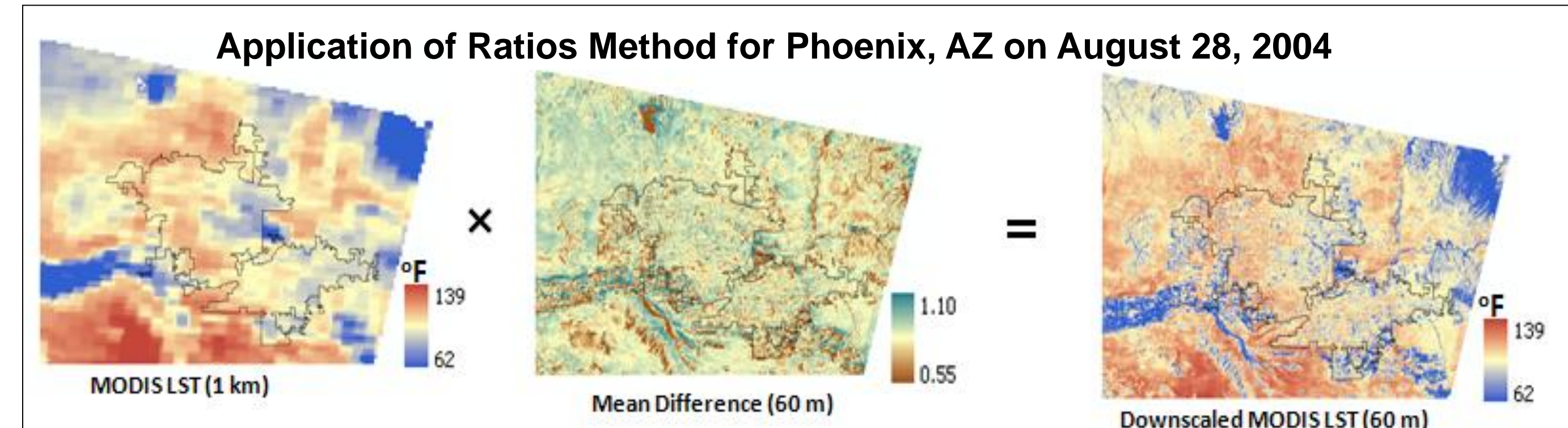
$$\text{MODIS}_{1km_j} + \bar{\Delta}_{60m} = \text{MODIS}_{60m_j} \quad \text{Model Application/Validation}$$



2. Ratios Method (illustrated for Phoenix, AZ)

$$\frac{\sum_{i=1}^{10} (\text{Landsat}_{60m_i} / \text{MODIS}_{1km_i})}{10} = \bar{R}_{60m} \quad \text{Adjustment Factor Development}$$

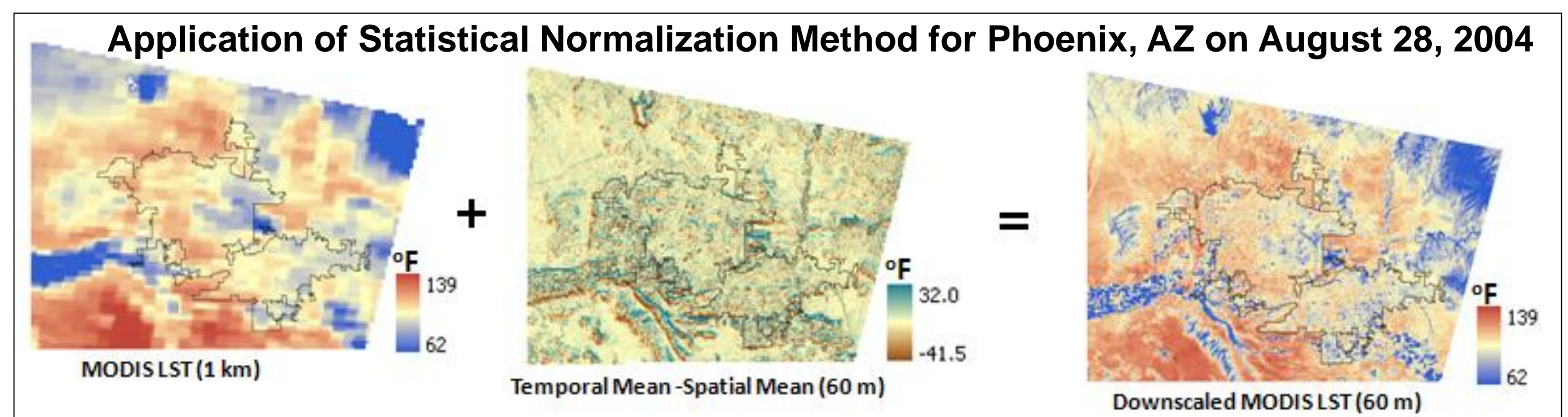
$$\text{MODIS}_{1km_j} \times \bar{R}_{60m} = \text{MODIS}_{60m_j} \quad \text{Model Application/Validation}$$



3. Statistical Normalization Method (illustrated for Phoenix, AZ)

$$\frac{\sum_{i=1}^{10} (\text{Landsat}_{60m_i} - \text{Landsat}_{1km_i})}{\sigma_{\text{Landsat}_{1km}}} = \bar{\Delta}_{60m} \quad \text{Adjustment Factor Development}$$

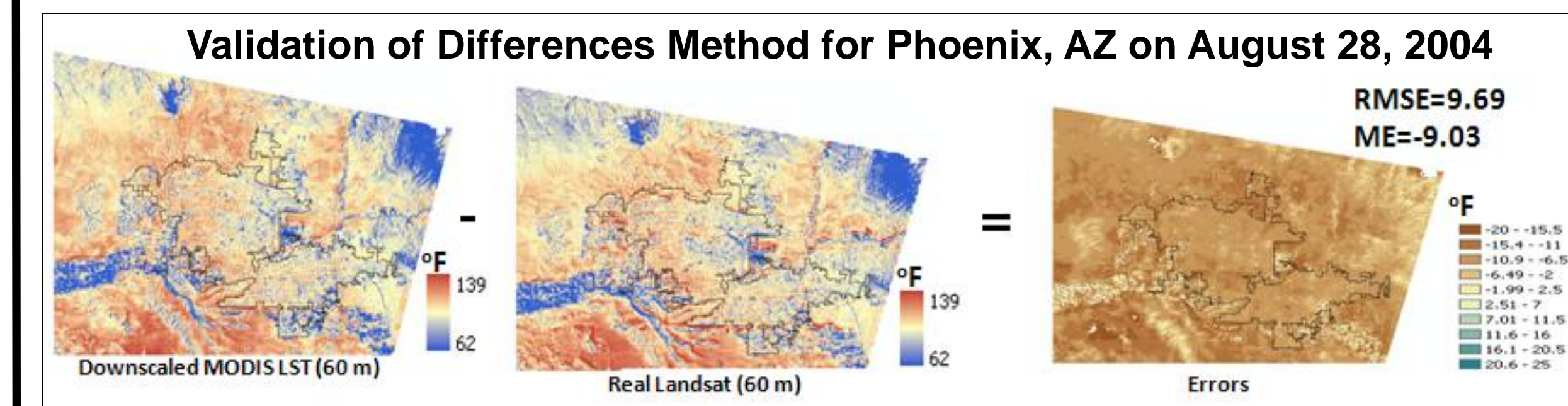
$$\text{MODIS}_{1km_j} + (\bar{\Delta}_{60m} \times \sigma_{\text{Landsat}_{1km}}) = \text{MODIS}_{60m_j} \quad \text{Model Application/Validation}$$



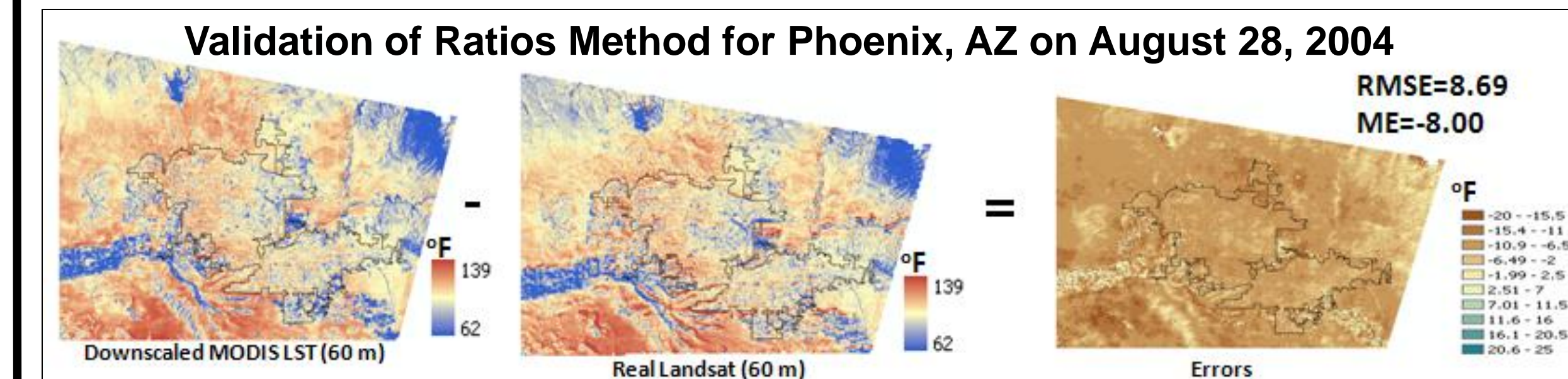
*For sharper rendering, a two-standard deviation stretch was applied for all the rasters mapped in sections 4-5.

5. Methods Validation

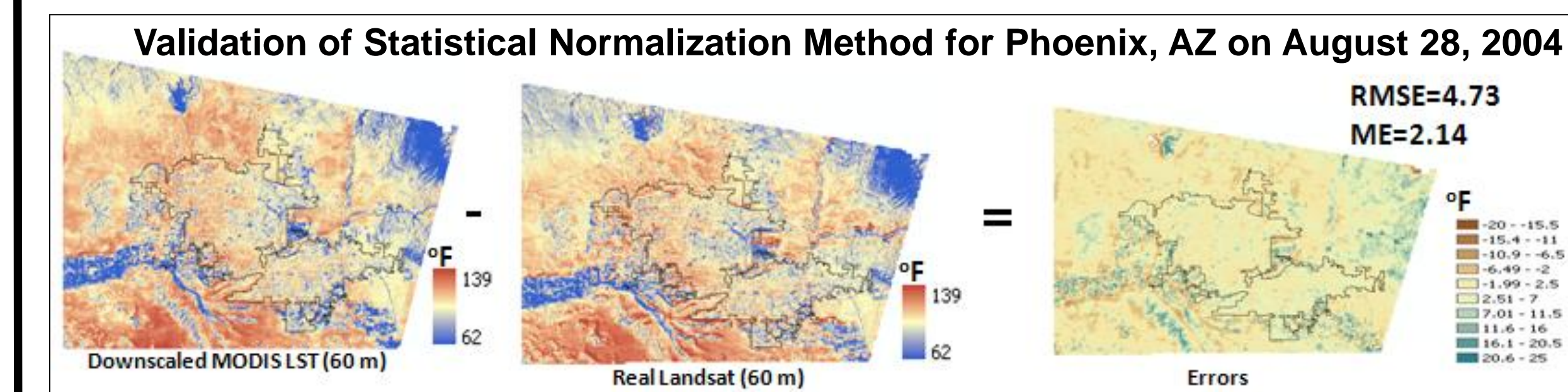
1. Differences Method (illustrated for Phoenix, AZ)



2. Ratios Method (illustrated for Phoenix, AZ)

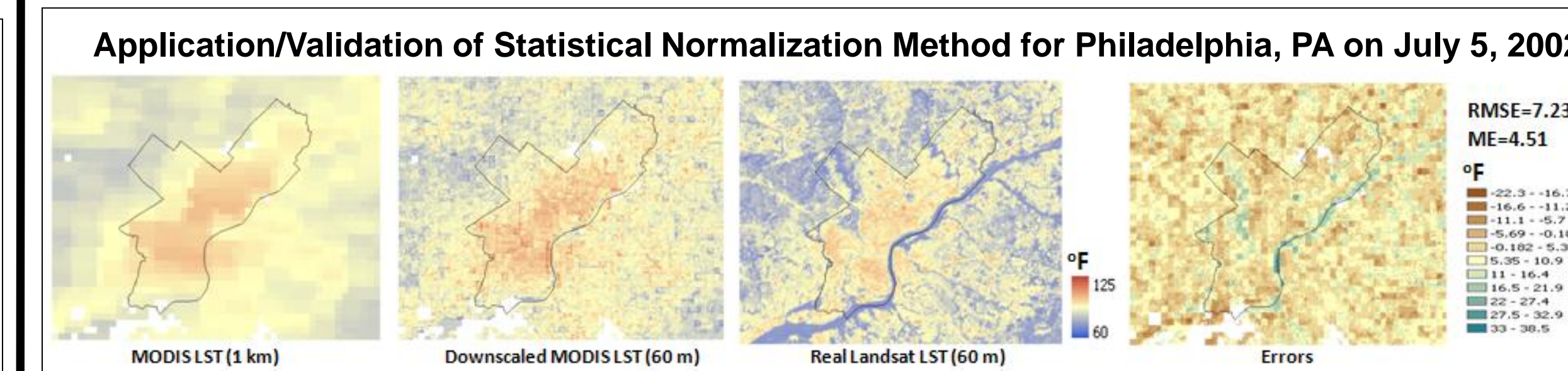
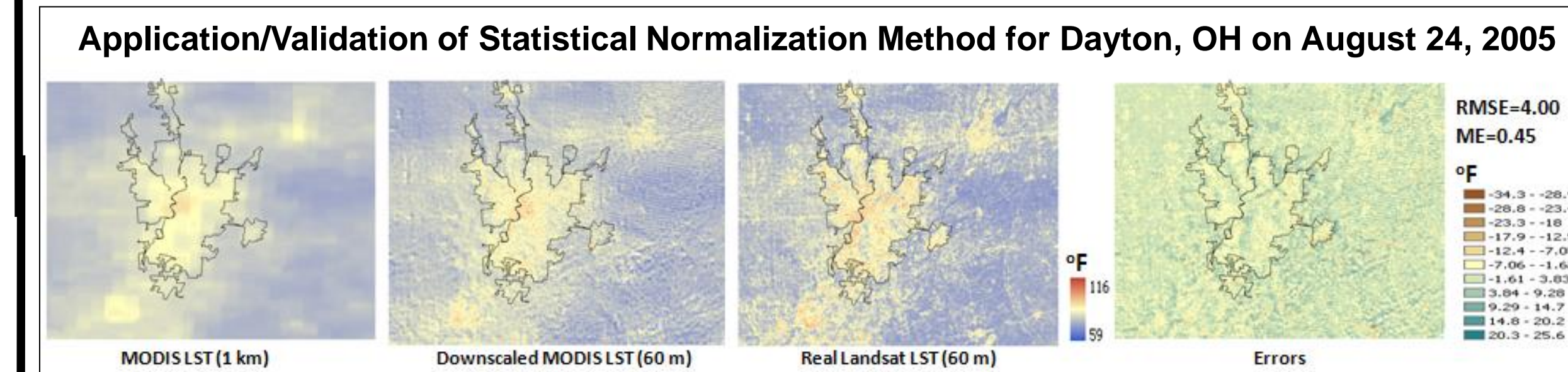


3. Statistical Normalization Method (illustrated for Phoenix, AZ)



6. Results for more Dates/Cities

Since the statistical normalization method had the lowest errors, it was applied and validated for other cities and dates.



Validation Results for all the Tested Methods/Cases (ME, RMSE)						
Downscaling Method	Phoenix, AZ (Whole Domain)	Phoenix, AZ (City Limit)	Dayton, OH (Whole Domain)	Dayton, OH (City Limit)	Philadelphia, PA (Whole Domain)	Philadelphia, PA (City Limit)
Differences	(-9.03, 9.69)*	(-8.85, 9.08)*	N/A	N/A	N/A	N/A
Ratios	(-8.00, 8.69)*	(-7.84, 8.09)*	N/A	N/A	N/A	N/A
Statistical Normalization	(2.14, 4.73)**	(2.43, 3.76)**	(0.45, 4.00)	(-1.25, 4.24)	(4.51, 7.23)	(4.59, 7.93)

* August 28, 2004, ** June 25, 2004

6. Summary

In this project, we developed and evaluated a number of spatial statistical techniques for downscaling the 1-km daily MODIS LST data to 60 m using Landsat-derived LST data, which have finer spatial but coarser temporal resolution than MODIS. This will improve the assessment of intra-urban variations in risk from extreme heat, which is something that current HWWS do not take into account. Three methods were first developed and validated for Phoenix, AZ, among which the Statistical Normalization Method showed the lowest errors, followed by the Ratios Methods and the Differences Method that had the highest errors. Thus, the Statistical Normalization Method was applied and validated for other dates/cities. Validation results from two different dates for Phoenix, AZ were generally similar to each other, which is a positive sign for the model's robustness. Results from Dayton, OH were also generally similar to those from Phoenix, AZ. However, results from the Statistical Normalization Method application and validation for Philadelphia, PA showed higher errors than the other two cities, which could be due to the fact that there are lots of water bodies within the urban area, maximizing the mixed pixel effect and increasing the discrepancy between the MODIS and Landsat LST estimations.

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