

Spring 5-21-2012

Estimating land surface temperature using a thermal sharpening technique

Yitong Jiang
Indiana State University

Qihao Weng
Indiana State University

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Recommended Citation

Jiang, Yitong and Weng, Qihao, "Estimating land surface temperature using a thermal sharpening technique" (2012). *Symposium 2012*. 13.
<https://scholars.indianastate.edu/symposium/13>

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The Needs for Thermal Infrared Data

High spatial resolution thermal infrared imagery is needed in routine environmental assessment in both urban and suburban areas. Due to the tradeoff between temporal and spatial resolution in currently available thermal infrared data, thermal sharpening technique is desirable.

Table 1. Resolutions of thermal bands (Agam et al., 2007)

Sensor	Spatial resolution	Temporal resolution
TM	120m	16 days
ETM+	60m	16 days
ASTER	90m	on demand
MODIS	1,000m	1-2 per day
AVHRR	1,000m	2 per day
GOES	5,000m	15 minutes

Land Surface Temperature (LST) and Vegetation Abundance

We Assume that vegetation cover amount is the primary driver of temperature variation and heat exchange.

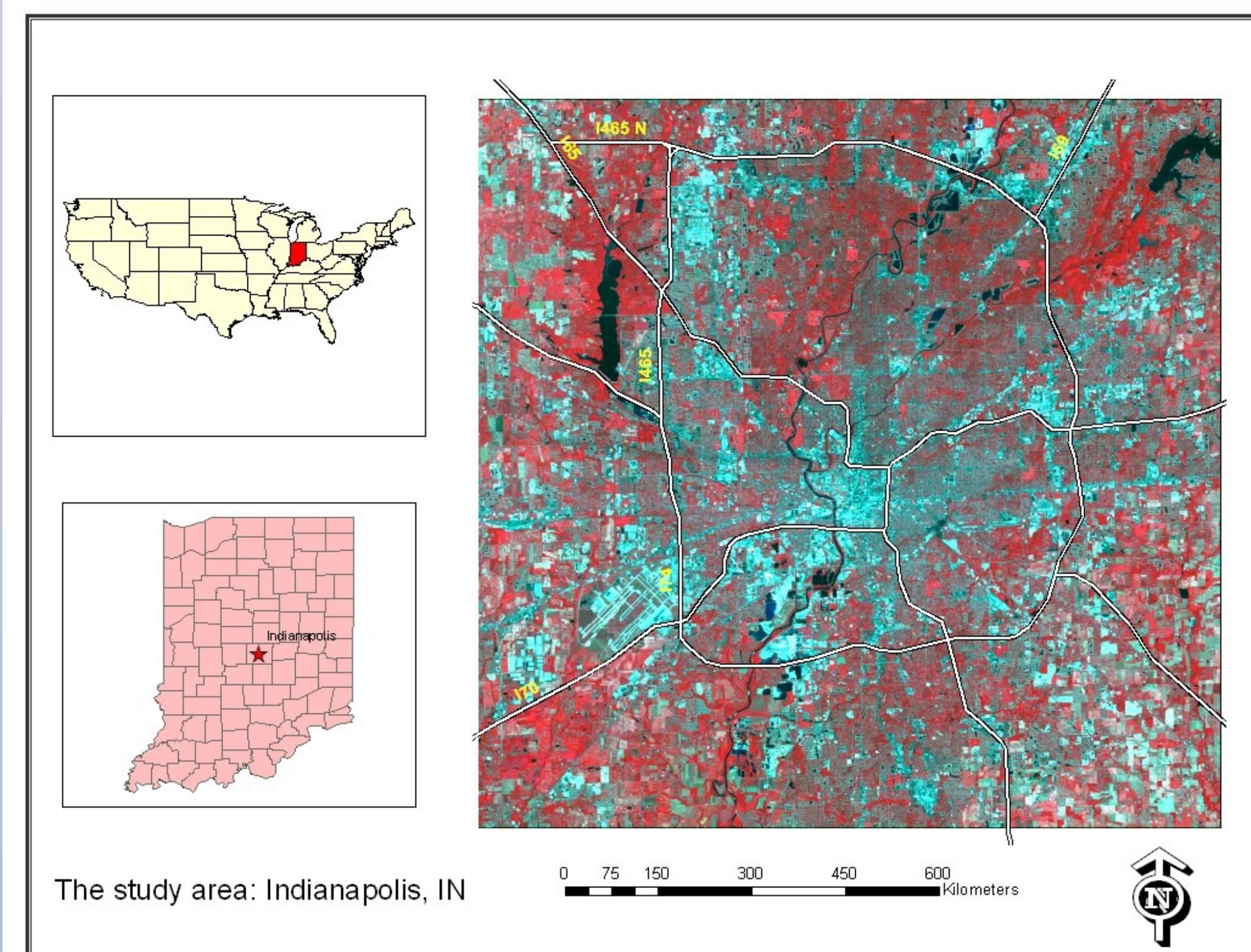
Both Normalized Difference Vegetation Index (NDVI) and fractional vegetation cover can be used as indicators for estimating LST.

NDVI could provides general vegetation growing condition. It can be calculated from red and NIR band with higher spatial resolution than thermal infrared band.

Considering the characteristics of urban surface feature, sub-pixel techniques, may further improve the accuracy of the temperature estimation in urban areas.

Data and Study Area

Landsat TM image (path 21, row 32) that was taken on July 6th, 2002.



Objective

This project compared the prediction of LST using NDVI and fractional vegetation cover as the indicators in urban and suburban areas in Indianapolis, IN.

Method

Kustas (2003) three-step LST estimation method was adopted.

$$\text{Step 1: } \hat{T}_R(VC_{120}) = f(VC_{120}) \quad (1)$$

$$\text{Step 2: } \Delta \hat{T}_{R120} = T_{R120} - \hat{T}_R(VC_{120}) \quad (2)$$

$$\text{Step 3: } \hat{T}_{R30}(i) = \hat{T}_R(VC_{30}(i)) + \Delta \hat{T}_{R120} \quad (3)$$

Where VC means vegetation cover. Both NDVI and fractional vegetation cover were tested. In equation (1), both linear and polynomial regression were tested. In equation (3), $\hat{T}_{R30}(i)$ means the estimated temperature of each i^{th} 30m pixel in 120m pixel.

The sample points for generating both LST-NDVI regression and LST-vegetation fraction regression are the same, including impervious surface, urban and suburb residential, agricultural fields with or without vegetation, and forestry.

Interstate Highway 465 were used to divide urban and suburban areas. Urban and suburban areas were processed separately.

Due to the assumption that vegetation cover is the primary driver of temperature variations, water bodies were masked out.

Results

Step 1: perform the regression between LST and vegetation cover at coarser resolution

(1) Regression LST vs. NDVI

- Urban
 - Linear: $y = -14.565x + 34.419$ ($R^2 = 0.56$)
 - Polynomial: $y = -30.9x^2 + 3.6116x + 32.557$ ($R^2 = 0.68$)
- Suburb
 - Linear: $y = -19.661x + 37.071$ ($R^2 = 0.75$)
 - Polynomial: $y = -28.836x^2 + 5.3342x + 32.22$ ($R^2 = 0.81$)

(2) Regression LST vs. vegetation fraction

- Urban
 - Linear: $y = -12.079x + 33.937$ ($R^2 = 0.51$)
 - Polynomial: $y = -19.003x^2 + 0.7568x + 32.363$ ($R^2 = 0.59$)
- Suburb
 - $y = -11.495x + 34.048$ ($R^2 = 0.70$)
 - $y = -10.219x^2 - 2.3244x + 32.57$ ($R^2 = 0.77$)

Step 2: Calculate the residual at coarser resolution

Table 2. Mean and standard deviation of difference between observed LST and estimated LST from NDVI and vegetation fraction.

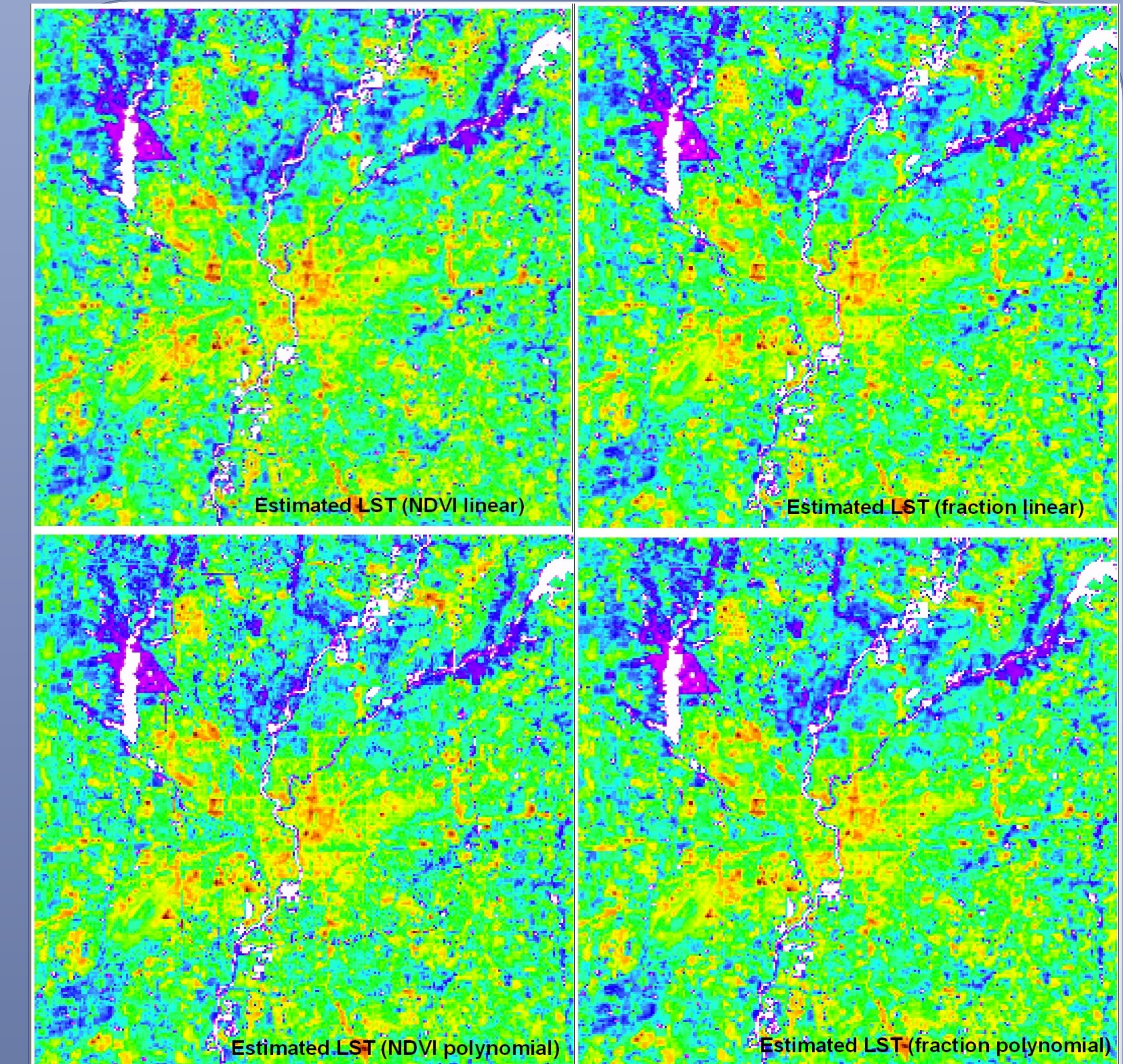
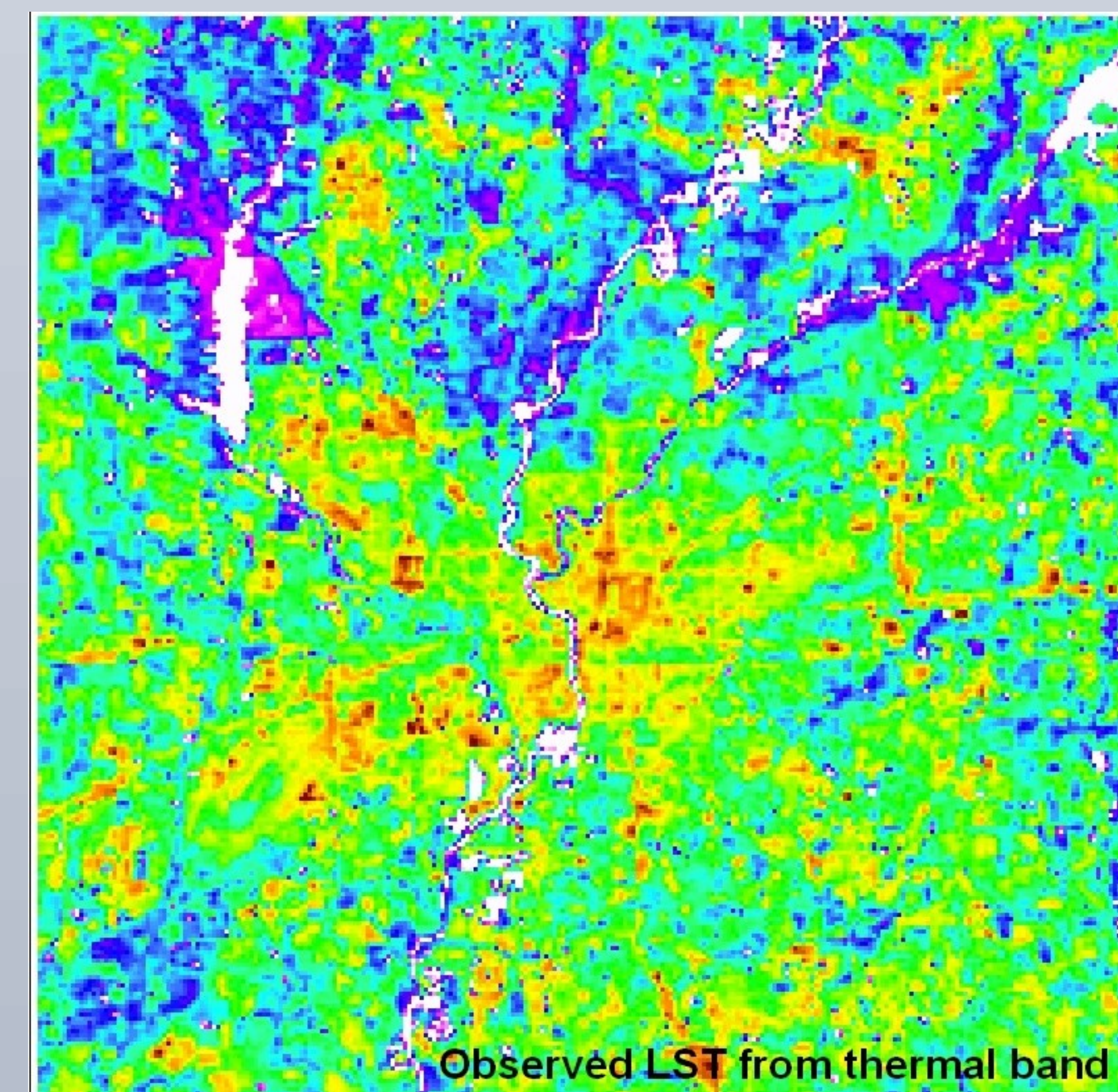
Indicator	Regression	Area	Mean	Std.Dev
f(NDVI)	Linear	urban	-0.112	1.146
		suburban	-0.611	2.143
	polynomial	urban	-0.097	1.775
		suburban	-0.477	2.064
f(fraction)	Linear	urban	-0.096	1.166
		suburban	-0.499	2.046
	polynomial	urban	0.031	1.270
		suburban	0.509	2.509

Step 3: perform the regression between LST and vegetation cover at finer resolution, and the residual were added back.

Table 3. RMSE between observed LST and estimated LST from NDVI and vegetation fraction.

Indicator	Regression	Area	RMSE (°C)
f(NDVI)	Linear	urban	0.937
		suburban	1.468
	polynomial	urban	1.960
		suburban	1.380
f(fraction)	Linear	urban	0.880
		suburban	1.441
	polynomial	urban	1.152
		suburban	1.459

Where M_i is modeled $\hat{T}_R$ and O_i is observed T_R .
 $RMSE = \sqrt{\frac{\sum_{i=1}^n (M_i - O_i)^2}{n}}$



Conclusions and Discussions

This study uses NDVI and fractional vegetation cover as indicators to estimate the land surface temperature.

Vegetation fraction method did reduce RMSE in the urban area in both linear (from 0.937 to 0.880) and polynomial (from 1.960 to 1.152) regression, which proved that the subpixel technique is more suitable for observing and extracting urban surface features.

Vegetation fraction application in the suburban area did not improve much the result over the NDVI method. Considering the size of individual agricultural fields in this region, 30m resolution is good enough for LST estimation in the suburban area.

Generally, linear regression worked better than polynomial regression, for it is less sensitive to outliers.

Future Work

The accuracy of the fraction image needs to be improved.

Further investigation under different vegetation and climate conditions is needed.

More resolution variation is expected to be tested.