Modeling the Land Surface Temperature of the Kansas City Metro Area

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Geo 578 GIS Applications
Capstone Statement

We will determine the relationship between land surface characteristics and land surface temperature in and around Kansas City. We will then create a predicted surface temperature map and assess the strength of our models.

Introduction

The relationship between land cover patterns and materials of urban areas with an increase of temperatures within urban areas has become increasingly important to understand due to the impacts on the environment, as well as human health (Stone, 2001). Elevated air temperatures are known to help induce the chemical reactions that produce ozone. The increases in air temperatures also create higher demand for air conditioning, which requires a large amount of energy consumption and produces additional waste heat (Cardelino and Chameides 1990).

The phenomenon of the urban heat island (UHI) may become even more severe in the future due to the estimated increase in average temperature by 1.1 to 6.4 °C for the continental U.S. (U.N. Intergovernmental Panel on Climate Change, 2007). Urban areas have already been measured to be as much as 3.3 to 4.4 °C warmer than surrounding rural areas (U.S. Department of Energy, 1996). The effects of the UHI may also be felt more in Kansas City than other cities because it currently surpasses 32 °C (90 °F) on 44 days per year (Climatography of the U.S. 1971-2000). The UHI effect is also particularly important for planners and developers in the Kansas City metro to understand because the city is projected to grow by 750,000 people in the next thirty years (Mid-America
Regional Council 2011). This growth will entail the creation of more impervious surfaces and the removal of more vegetative areas in the cities periphery.

**Conceptualization**

**Study Area**

In order to see the effects of urban surface temperature and develop a spatial pattern it was important to include some rural area that surrounds the Kansas City Metro Area, as well as the downtown and suburban sections in the study area. For this reason the Landsat data was clipped to include the 6 metro counties of Kansas City (Figure A1). This resulted a study area of approximately 6625 square miles. The Landsat 5 image that was selected was for June 9, 2006. This time was selected as optimal because this study is most concerned with temperature patterns in the summer.

**Land surface Temperature vs. Air Temperature**

While the urban heat island is generally thought to be a phenomenon of urban air temperature, it can also be understood as a surface temperature phenomenon (Stone, 2001). Furthermore, it has been shown that there is “reasonable agreement” between land surface temperature and near surface air temperature (Roth et al. 1989). For this reason the authors of this study feel it is appropriate to use land surface temperature as an approximation for air
temperature. Using land surface temperature also has the considerable advantage over air temperature because surface temperature can be observed from satellite sensors. Monitoring the physical processes of UHI from in-situ instruments proves to be quite difficult because of the time and money required to collect air temperature readings in a multitude of locations at the same time. Remotely sensed thermal land surface data was a better choice for this study because rather than a few hundred observations, collected in-situ to record air temperature, four hundred and fifty thousand independent thermal land surface temperature observations were collected from the Landsat 5 satellite sensors used in our study at no monetary cost.

**Causes of Urban Heat Island**

The UHI effect of cities is largely caused from the fact that the primary building materials of cities such as concrete, asphalt, and brick have a high heat capacity. The urban building materials absorb the thermal energy of sunlight all day and then re-emit that energy through the afternoon and evening. In large cities the amount of land cover that is forested, or plant covered is quite small. Plants have a natural cooling mechanism known as evapotranspiration. This is the process by which plants use incoming solar radiation to transform water into water vapor. Plants reduce the amount of solar radiation which is absorbed by the ground and re-emitted as heat (Stone, 2001). Other processes that contribute to the urban heat island effect are the multiple surfaces buildings have to absorb heat and the waste heat generated from energy use (air conditioning, energy loss from buildings, power
plants)[Ibid]. There is a greater amount of this waste heat generated in the cities than in rural areas do to the larger populations.

Land Surface Characteristics as variables

The goal of this study was to establish a relationship between various land surface characteristic and land surface temperature. In order to be able define this relationship land surface characteristics need to be used as independent variables with land surface temperature used as a dependent variable in regression. The choice of what variables to include was undertaken by identifying the major causes of UHI. The major causes that have been identified are albedo, heat capacity, and lack of evapotranspiration (Ibid). One minor cause that is not addressed in this study is the change to radiant flux caused by the geometry of urban design and anthropogenic heat (Dousset and Gourmelon, 2003).

These major causes of UHI were then approximated in this study by using the independent variables: Normalized Difference Vegetative Index (NDVI) as a measure of vegetative cover, brightness for albedo, and percent impervious surface as heat capacity/ albedo. NDVI has a long history of use as a measure of vegetation cover and the percent impervious service is a very logical variable to approximate heat capacity and albedo as impervious surfaces reflect brightly in the visible and near infrared wavelengths. Brightness was used as an approximation for albedo as was done by KIage et. al (2006). It would have been preferable to use actual albedo
values, but unfortunately these are calculated with MODIS data and the spatial resolution was much too coarse to be of use for our study.

Each independent variable was regressed on the dependent variable ‘land surface temperature’ which was calculated from the thermal Landsat 5 band. In order to calculate land surface temperature most accurately the emissivity values for the each land cover type needed to be factored into the calculation. Classifying the land cover types allowed each land cover type to be paired with its emissivity value. While an easier method would be to use pre-established land cover data, the classification method provided land cover identification at the exact instant that the rest of the data was captured. This was especially important because a substantial portion of the study area is agricultural area where capturing fallow fields and leafed out vegetation is important because of the different emissivity values associated with each.

In an ideal study where land surface temperature is derived from the Landsat thermal band an atmospheric correction should be undertaken to correct for scattering and absorption by gases and aerosols while the electromagnetic energy travels through the atmosphere from the Earth’s surface to the sensor (Song et al., 2000). However, in this study the atmospheric correction algorithm MODTRAN was attempted and was unsuccessful. Overall, this is not seen as a major problem because it is apparent from the image that the atmosphere is clear and the relationships between the variables that are established, as well as the spatial pattern of surface temperature, should remain intact despite any small amount of
atmospheric interference.

**Statistical Analysis**

All independent variables were checked for multicollinearity. Then land surface temperature was regressed on impervious surface, NDVI, and brightness univariately. NDVI was cubed and regressed on land surface temperature in an attempt to explore a non-linear relationship through polynomial regression. Next we regressed land surface temperature on all three independent variables to attempt to raise the value of the correlation coefficient. Then, geographically weighted regression was attempted. This is a process by which a local model of the relationship that one is trying to predict is created by fitting a regression equation, which takes into account the dependent and independent variables, to every pixel in the image.

**Comparing with Another Year**

Lastly, the model created using multivariate regression on the 2006 image was used to predict land surface temperatures on a June 11, 2001 image using the independent variables derived from that image. The model was tested in this manner because it was deemed necessary to use independent data to see what other factors remained to explain the land surface temperature pattern other than the independent variables used in the 2006 image. The 2001 image was chosen because it is very close in time of year to the original 2001 image (with similar sun angle, similar time of day, and similar place in the agricultural cycle). Also, the mean daily temperatures are nearly the

Implementation

Deriving the variables

*Land surface temperature.* In our regression models, land surface temperature is the independent variable. While raw Landsat data does include a thermal infrared (11.5 µm) reflectance value, the scale is predominately for display purposes. Thus, it was essential to take the thermal digital numbers and transform them into standardized temperature values (citation - Landsat webpage). The first step in this process is to obtain true thermal radiance of a pixel. While the Landsat thermal band does not have the convenience of continual and precise sensitivity calibration like the other Landsat bands, the literature suggests it is acceptable to use the pre-launch gain and offset calibration coefficients (Chander et al., 2009). The calculation of temperature follows the method of Zhou and Wang (2010). The equation to convert to thermal radiance is:

\[
\text{Radiance} = \text{gain} \times \text{DN} + \text{offset}
\]

where the DN is the original, uncorrected thermal reflectance value. Gain and offset values are given by NASA in their Landsat science manual (USGS, 2011).

The true radiance is then used to find each pixel’s brightness temperature, or uncorrected temperature value. The equation for brightness temperature is:
where $L_3$ is the radiance value calculated above, in units of $K_1 = 607.76 \text{ Wm}^{-2} \text{ sr}^{-1} \text{ mm}^{-1}$ and $K_2 = 1260.56 \text{ K}$. Calibration coefficients are $K_1 = 607.76 \text{ Wm}^{-2} \text{ sr}^{-1} \text{ mm}^{-1}$ and $K_2 = 1260.56 \text{ K}$. While the output of this equation is a temperature value in Kelvin it fails to account for the emissivity values of the land cover types that are found in our study area. Emissivity is the measure of how efficiently an object radiates energy at a given temperature compared to a blackbody at the same temperature. A blackbody is a theoretical object absorbs and then emits all incident energy at all wavelengths. The measure of emissivity is a dimensionless number that ranges from 0 – 1, where 1 is a blackbody and 0 emits no energy. This is important because if a land cover type has lower radiation emissivity (than 1), an uncorrected temperature calculation would lead to an underestimation of that objects true temperature. The MODIS satellite has established a library of emissivity values for common land cover types (MODIS UCSB Emissivity Library).

For these reasons, a supervised classification was performed on the Landsat image using a maximum likelihood classifier. Predominant land cover types and their emissivites were urban (0.95), residential suburban (0.96), cropland (0.975), bare ground (including fallow cropland, 0.975), forest (0.98), and water (0.99). This dataset needed to be resampled (using the majority filter) to match the 120m resolution of the thermal band. The final surface temperature calculation was:
\[ T_s = \frac{T_b}{1 + (\lambda \times T_b/\alpha) \ln \varepsilon} \]

where \( T_s \) is the LST in K; \( \lambda \) is the wavelength of emitted radiance (\( \lambda = 11.5 \mu m \)) (Markham and Barker, 1985); \( \alpha \) equals \( 1.438 \times 10^{-2} \) mK, calculated as \( \alpha = \frac{hc}{s} \), with \( h \) as the Planck constant (\( 6.626 \times 10^{-34} \) Js), \( c \) as the velocity of light (\( 2.998 \times 10^8 \) m s\(^{-1} \)), and \( s \) as the Boltzmann constant (\( 1.38 \times 10^{-23} \) J/K); \( \varepsilon \) is the surface emissivity derived from the land cover classification map (MODIS UCSB Emissivity Library) (Zhao and Wang 2010).

**The independent variables.** Because the continuous dependent variables derived from the Landsat data (NDVI and brightness) and the ISA dataset all had 30m spatial resolution, they needed to be resampled to match the thermal resolution. Unlike the categorical resampling of the land cover dataset, the average value of the 120m neighborhood was used to assign each pixel of the dependent variables a resampled value.

The calculation of NDVI from the Landsat 5 2006 image was done by \((\text{near IR band} - \text{red band}) / (\text{near IR band} + \text{red band})\). This results in a value between -1 and 1, with typical vegetated values being between .1 - .7. NDVI can be used as an indicator of relative biomass and greenness (Boone et al. 2000, Chen 1998)

Brightness was calculated as the weighted sum of all spectral bands. The weights to the individual Landsat 5 bands are brightness = 0.29(band1) + 0.25(b2) + 0.48(b3)+0.56(b4) + 0.44(b5) + 0.17(b7). Brightness was used in the study as an
approximation for albedo. While it is not the same it is reasonable to assume that land cover types that have high levels of albedo will also have high levels of brightness.

Regression Analysis

*Checking for multicollinearity.* In order to avoid creating a multivariate regression model with inflated, erroneous strength, all independent variables (NDVI, ISA, and brightness) were compared to each other, both quantitatively and qualitatively. Regression analysis was performed to obtain an $R^2$ value, and the scatter plots were investigated to check for clear visual trends.

*Univariate regression.* All independent variables were then individually compared to the land surface temperature. Like in the multicollinearity check, $R^2$ values were calculated and scatter plots were inspected. In addition, model residuals were calculated. We define the residual as the difference between actual temperature (calculated directly from the Landsat image) and the predicted temperature (based on the univariate regression equations). Maps of the model residuals were produced. Because an attempted calculation of spatial autocorrelation would have taken many days to complete, visual inspections of the maps were performed to see if specific land cover types systematically were associated with unique residual values.

In order to determine if any variables had a polynomial relationship with land surface temperature, we performed the regression on the variables raised to the power
of 1-4. For each variable, the power with the highest $R^2$ and least predictable was used in the later multivariate regression.

*Multivariate and geographically weighted regression.* The multivariate and GWR models received the same treatment as the univariate regression (recording of $R^2$ and visual residual map inspection). In addition, to estimate the relative contributions of the different land cover types, the average residual and the average absolute residual were calculated. The average residual made it possible to see which land cover types were typically over- and under-estimated, and the absolute residuals was a measure of how closely the model predicted the values for each land cover type.

**Comparing to another image**

In order to assess the applicability of the derived model to other situations, the final multivariate regression was applied to the independent variables of another Landsat image (June 11, 2001). Root mean square error and $R^2$ were calculated, and the best fit line of the scatter plot (of actual surface temperature compared to predicted surface temperature) was considered for systematic deviation from expected temperature.

**Results and Discussion**
The map of land surface temperature in the study area is shown in Figure 1. Surface temperatures at the time of the image range from 12.8°C to 47.7°C. Since this transformation was based mostly on the thermal reflectance band of the Landsat image, the distribution of the temperature values to be consistent with those one would expect on a summer afternoon. For example, when comparing the land surface temperature map to the land cover map, the highest temperatures tend to occur in the downtown core and the bare ground and fallow fields near the Missouri River; these materials have a high heat capacity that can absorb large amounts of solar radiation. In contrast, regions of surface water are associated with the lowest surface temperatures.

The test for multicollinearity between the brightness layer and the impervious layer resulted in a coefficient of determination ($R^2$) value of 0.049, or a nearly insignificant relationship. The correlation between brightness and NDVI was stronger with an $R^2$ of 0.228; imperviousness and NDVI were similarly associated, resulting in an $R^2$ value of 0.189. Although a relationship exists among some of the variables, we felt that the measures of correlation were minimal enough such that all three variables could be utilized in a prediction model of land surface temperature without complications due to collinearity.

Once the interrelation among the explanatory variables was deemed to be satisfactory, univariate regressions were performed in order to assess the strength of each predictive characteristic in estimating land surface temperature in the study area. A simple least-squares regression relating brightness to temperature resulted in a
coefficient of determination of 0.33; in other words, if all explanatory variables are assumed to be independent, brightness values account for 33 percent of the variation in land surface temperature in the image. A scatter plot comparing the brightness and land surface temperature values can be seen in Figure 2. Using the observed relationship between brightness and land surface temperature, the model builds a regression equation to predict the temperature of each pixel as a function of the brightness value for that pixel. For example, in this case, temperature in degrees Celsius is equal to 20.832 plus a function (0.075) of the brightness value. The map of residual errors resulting from the difference between actual land surface temperatures calculated from thermal reflectance and predicted land surface temperatures using the regression model equation are shown in Figure 3. Significant clustering of residuals is apparent; actual surface temperature is much higher than the model predicted in the urban core and fallow fields, but much lower in regions of rural agriculture and open water. Because of the spatial distribution of error that can be seen, we can conclude that the relationship between brightness and land surface temperature is not constant across the image or across varying land cover types.

A least-squares regression comparing impervious surface percentage to land surface temperature resulted in a $R^2$ value of 0.18, which is significantly lower than either of the other explanatory variables and is well lower than expected. The scatter plot depicting the two variables (Figure 4) indicates a very linear trend even though the correlation is low. However, we feel that the low correlation is due to the study extent and the land cover types in the area rather than an indication of a weak relationship. In
urban areas, land surface temperature is strongly related to imperviousness; however, this model includes larger areas of agriculture, forest, bare ground, and water. These classes are all considered completely non-impervious but have very different thermal reflectance characteristics, meaning that impervious surface has no relationship to temperature in those areas, weakening the predictive power of the regression model. Had these classes been excluded or the study area been narrowed to the immediate Kansas City metropolitan area, we feel that the correlation between imperviousness and temperature would be much stronger. The map of residuals shown in Figure 5 supports this theory; the clustering of error in the downtown area is significantly reduced, while the predicted temperature of fallow fields and open water is noticeably inaccurate.

The least-squares regression relating NDVI to land surface temperature resulted in an $R^2$ value of 0.40, indicating that this is the strongest relationship and that NDVI is the best predictor of temperature in our study area. This relationship can be seen in Figure 6, where it is notable that unlike the previous variables, presence of NDVI has an inverse relationship to temperature. The map of residuals (Figure 7) shows that actual temperatures in the urban core were higher than predicted, while actual temperatures were much lower in agricultural and water areas. A similar trend in residuals was seen in the regression model between brightness and temperature; the similarity may be partially explained by the collinearity between brightness and NDVI measured earlier. All three independent variable regressions resulted in a Jarque-Bera probability p-value of 0, indicating that none of the residuals are normally distributed.
Exponential increases to brightness and imperviousness only weakened the relationship between each variable and land surface temperature. However, cubing NDVI values and comparing them to temperature resulted in an $R^2$ value of 0.44 (Figure 8), which was slightly better than the previously observed correlation of 0.4. The map of NDVI$^3$ residuals can be seen in Figure 9, and compared to the residuals of the linear NDVI regression. A visual comparison shows that the NDVI$^3$ model effectively reduces some of the highest error values; the number of pixels with a predicted value of five or more degrees Celsius different than the actual derived land surface temperature is noticeably lower. Due to this increased predictive power, NDVI$^3$ was used in place of NDVI for the multivariate regressions.

The linear regression based on brightness, impervious surface percentage, and NDVI$^3$ values resulted in predicted surface temperature values that showed a correlation value of 0.57 with the actual temperature, which is significantly better than that of any individual explanatory variable. The plot of these predicted values compared to actual values is shown in Figure 10. The number of pixels predicted to be within a degree of the actual temperature is notably greater using a multivariate regression. However, the same trends common to the univariate regressions appear. The high surface temperatures in the Kansas City downtown area and the fallow fields within the bends of the Missouri River are still not entirely accounted for by the multivariate model, and the temperature of water is much lower than anticipated.
The geographically weighted regression operation ran into problems when trying to incorporate all three explanatory variables. The problem was most likely caused by a high amount of local collinearity between some of the variables. When NDVI was an input in the GWR, the model failed to run; therefore, the geographically weighted regression was run with only brightness and impervious surface percentage as explanatory variables. Nevertheless, this model resulted in the best $R^2$ value of all with a correlation of 0.67 when comparing its predicted temperatures to the actual land surface temperature. The scatter plot of this relationship can be seen in Figure ??. Not only is the overall prediction power greater using this model, but the clustering of errors resulting from the model is greatly reduced (Figure 11). This is due to the nature of geographically weighted regressions; pixels tend to be closely related to nearby pixels, and since the GWR takes into account the characteristics of neighboring pixels, it has the ability to deal with localized disparity from other areas. This is especially useful with groupings of land cover types that have unique thermal properties, such as large lakes. As the map of residuals shows, this method of regression resulted in both the highest amount of pixels predicted to be within one degree Celsius of the actual surface temperature as well as the fewest number of extreme errors.

The equation for land surface temperature derived from the multivariate least-squares regression model is as follows: \[ \text{LST} = 0.04(\text{brightness}) + 0.03(\text{ISA}) - 12.6(\text{NDVI}^3). \]
Using the same coefficients but replacing the independent variables with values from 2001, we compared the predicted values to a new set of land surface temperature obtained using the thermal band of the 2001 image. The $R^2$ correlation coefficient of this
relationship is 0.57, which happens to be the same correspondence of the same relationship using 2006 values. Although the likeness is encouraging that these relationships may be constant over time, an examination of the residuals shown in Figure 12 raises a caveat to that theory. Land surface temperatures are almost universally lower than the predicted values in the 2001 image. To explore possible explanations for this disparity, atmospheric conditions for the two dates were examined. At the time of the 2006 image, the air temperature in Kansas City, MO was 91°F with a relative humidity of 35% (Weather Underground). The air temperature during the 2001 image was roughly the same at 90°F, but the relative humidity was higher at 57%. Since these images are not atmospherically corrected, it is feasible that the relationship between the explanatory variables and surface temperature was skewed by interference with atmospheric water vapor.

Conclusion

Of the three independent variables examined, NDVI had the strongest relationship to land surface temperature, while the scope of the study caused impervious surface percentage to have a comparatively minor influence on surface temperature. NDVI was also the only variable that had a non-linear relationship with temperature. The multivariate model combining all three explanatory variables was a better predictor of surface temperature than any individual variable, but the geographically weighted regression resulted in both the strongest correlation and the
least spatial autocorrelation of residuals, even though the only inputs were the two weaker independent variables. Had the GIS software been able to process a GWR of all three explanatory variables, the predictive power would have been even higher.

The strength of the relationship between land surface temperature and the other variables derived from the 2006 image also applies to the 2001 image; however, some level of absolute atmospheric correction needs to be applied for any single model to be able to accurately predict temperatures at more than one time period.

As the results have shown, different land cover types have distinct thermal reflectance properties. These classes may also respond to the explanatory variables in different ways. Therefore, one way to increase the strength of our models would be to examine each land cover type individually and create a model based on its characteristics. This would help account some of the extreme variations in land surface temperature from one area to the next. Had the data been more readily available, it would have been desirable to examine the relationship of these variables to air temperature rather than land surface temperature. Air temperatures should be less affected by land cover than surface temperatures, and some of the extreme land surface temperatures observed in this exercise would be minimized.
Bibliography


Figure A1 (above): Study Area
Figure 1: Map of land surface temperatures calculated from the thermal band of the Landsat image. The Kansas City downtown area is just east of the center of the image, and the Missouri River runs southeast and east through the study area.
Figure 2: Scatter plot showing the relationship of brightness to land surface temperature. The resulting $R^2$ value was 0.33.

Figure 3: Map of residuals resulting from least-squares regression model relating land surface temperature to brightness. Red pixels indicate a higher actual land surface temperature than the predicted value based on brightness, and the reverse is true for
blue pixels. The urban core is higher in temperature than the model predicted, while rural areas are lower in surface temperature than the model accounts for.

Figure 4: Scatter plot showing the relationship of imperviousness to land surface temperature. The resulting $R^2$ value was 0.18.
Figure 5: Map of residuals resulting from least-squares regression model relating land surface temperature to imperviousness. This regression does a better job of predicting the land surface temperature of urban areas, but fallow fields are significantly underpredicted in temperature while open water and rural fields are overpredicted.

Figures 6 and 8: Scatter plots of both NDVI and NDVI$^3$ in relation to surface temperature. Cubing the NDVI values increased the $R^2$ from 0.40 to 0.44.

Figures 7 and 9: Map of residuals comparing the relationships of NDVI to land surface temperature and NDVI$^3$ to land surface temperature, respectively. High residual errors are significantly reduced when NDVI$^3$ is related to temperature rather than the true NDVI values.
Figure 10: Map of residuals from a least-squares regression relating brightness, ISA, and NDVI\(^3\) to land surface temperature. There are more areas with predicted values within a degree Celsius (yellow pixels) resulting from this regression than any univariate regression. \(R^2 = 0.57\).
Figure 11: Map of residuals resulting from a geographically weighted regression relating only brightness and imperviousness to surface temperature. Even with only two explanatory variables, the $R^2$ value is the highest (0.67) and the spatial correlation of error values is significantly reduced.

Figure 12: Map of residuals resulting from a model using the coefficients from the least-squares regression using 2006 independent variables, but replaced with 2001 values. The $R^2$ value of 0.57 matched the 2006 image and the spatial clustering is similar, but actual surface temperatures were almost universally lower than the predicted temperature using these values.
Conceptualization Diagram (figure 13)

Goals

- Convert thermal reflectance to land surface temperature
- Establish relationship between land surface temperature and other variables

Key Concepts

- Land surface environment
- Surface thermal properties

Variables

- Land surface temperature
- Impervious surface percentage
- Brightness
- NDVI

Operationalize

- Univariate and multivariate least-squared regressions
- Geographically weighted regression

Data Layers

- Landsat 5 image
- Land cover classification map
- NDVI
- Brightness
- Impervious surface percentage
Implementation Diagram (Figure 14)

Landsat 5 thermal June 9, 2006

Landsat 5 Optical and NIR June 9, 2006

NLCD 2006 Impervious Surface Area

Landsat 5 optical and NIR June 9, 2006

Maximum Likelihood Classification

Land Cover Types (30m)

Resample (Majority)

Land Cover (120m)

Field Calculation

Land Cover Specific Emissivity

Raster calculation

Impervious Surface Area %

NDVI (120m)

Brightness (120m)

Raster calculation

NDVI (30m)

Brightness (30m)

(average)

(average)
Land Surface Temperature

NDVI

Brightness

ISA

Correlation and regression

Multicollinearity

Univariate

Multivariate

Least squares

Least squares

Geographically weighted regression

Land Cover and Land Use - Surface Temperature Relationships

Compute

Predicted Land Surface Temperature

Actual Land Surface Temperature

Raster difference

Map of Residuals
Appendices (MetaData)

Identification Information:

Citation:

Citation Information:

Originator: UW-Madison Geog 578 course

Publication Date: May 13, 2011

Title: Geographically weighted regression of land surface temperature

Geospatial Data Presentation Form: raster digital data

Online Linkage: \discovery\classes\g578\DBs\UHI\2006\images\georegressraw

Description:

Abstract: This is a map of the residuals between actual land surface temperature (as calculated by the method of Zhou and Wang 2010) and predicted land surface temperature (as calculated from a geographically weighted regression model containing ISA, and brightness).

Purpose: Visualize the magnitude and spatial configuration of the model's strengths and weaknesses. Places where the values are far from 0 show that the model is a poor predictor of land surface temperature in that region. This will help determine additional variables that will help increase the strength of future models.

Supplemental Information: This geographically weighted regression is based on a Landsat 5 image taken at 4:00 p.m. on June 9, 2006. ISA was taken from the 2006 NLCD developed by the
MLRCC. Brightness was a transform of the original Landsat bands. Land surface temperature was calculated from the Landsat thermal band and corrected using emissivity values of a supervised classification of land cover types.

Time_Period_of_Content:

Time_Period_Information:

Single_Date/Time:

Calendar_Date: April 26, 2011

Time_of_Day: 4 a.m.

Currentness_Reference: publication date

Status:

Progress: Complete

Maintenance_and_Update_Frequency: Continually

Spatial_Domain:

Bounding_Coordinates:

West_BoundingCoordinate: -95.204274
East_BoundingCoordinate: -94.162266

North_BoundingCoordinate: 39.545923

South_BoundingCoordinate: 38.729197

Keywords:

Theme:

Theme_Keyword_Thesaurus: Hot ground?

Theme_Keyword: Land Surface Temperature

Access_Constraints: Anyone who can handle the truth can view this dataset.

Use_Constraints: If you make any money from using this map, Tyler, Paul, and Nate should get at least half of it.

Point_of_Contact:

Contact_Information:

Contact_Person_Primary:

Contact_Person: Paul Gottinger, Tyler Stenz, Nate Stewart

Contact_Organization: UW-Madison
Contact Position: Remote sensing specialists

Contact Address:

Address Type: physical address

Address: 300 N Park St

City: Madison

State or Province: WI

Postal Code: 53703

Contact Voice Telephone: 9999

Contact Electronic Mail Address: njstewart@wisc.edu

Security Information:

Security Classification System: Padlock

Security Classification: Top secret

Security Handling Description: You might explode if you look without permission.
Native Data Set Environment: Microsoft Windows XP Version 5.1 (Build 2600) Service Pack 3; ESRI ArcCatalog 9.3.1.1850

Cross_Reference:

Citation Information:

Originator: UW-Madison

Publication_Date: Unknown

Publication_Time: Unknown

Title: Land Surface Temperature

Edition: 1st

Publication Information:

Publication Place: Tokyo

Publisher: Remote Sensing of Environment

Data Quality Information:

Lineage:

Source Information:
Source_Citation:

Citation_Information:

Title: Glovis

Source_Information:

Source_Citation:

Citation_Information:

Title: MLRCC

Spatial_Data_Organization_Information:

Direct_Spatial_Reference_Method: Raster

Raster_Object_Information:

Raster_Object_Type: Grid Cell

Row_Count: 742

Column_Count: 737

Vertical_Count: 1
Spatial_Reference_Information:

Horizontal_Coordinate_System_Definition:

Planar:

Grid_Coordinate_System:

Grid_Coordinate_System_Name: Universal Transverse Mercator

Universal_Transverse_Mercator:

UTM_Zone_Number: 15

Transverse_Mercator:

Scale_Factor_at_Central_Meridian: 0.99960

Longitude_of_Central_Meridian: -93.000000

Latitude_of_Projection_Origin: 0.000000

False_Easting: 500000.000000

False_Northing: 0.000000

Planar_Coordinate_Information:
Planar Coordinate Encoding Method: row and column

Coordinate Representation:

Abscissa Resolution: 120.000000

Ordinate Resolution: 120.000000

Planar Distance Units: meters

Geodetic Model:

Horizontal Datum Name: D_WGS_1984

Ellipsoid Name: WGS_1984

Semi-major Axis: 6378137.000000

Denominator of Flattening Ratio: 298.257224

Distribution Information:

Resource Description: Downloadable Data

Standard Order Process:

Digital Form:
Digital Transfer Information:

Transfer Size: 2.204

Metadata Reference Information:

Metadata Date: 4-26-2011

Metadata Contact:

Contact Information:

Contact Person Primary:

Contact Person: Paul Gottinger, Tyler Stenz, Nate Stewart

Contact Organization: UW-Madison

Contact Position: Remote sensing specialists

Contact Address:

Address Type: mailing address

Address: 300 N Park St.

City: Madison
State_or_Province: WI

Postal_Code: 53703

Country: Dane

Contact_Voice_Telephone: 9999

Hours_of_Service: 24/day

Metadata_Standard_Name: FGDC Content Standards for Digital Geospatial Metadata


Metadata_Time_Convention: local time

Metadata_Security_Information:

Metadata_Security_Classification: Top secret

Metadata_Extensions:

Online_Linkage: http://www.esri.com/metadata/esriprof80.html

Profile_Name: ESRI Metadata Profile