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Comparison between Land Surface Temperature Retrieval Using Classification Based Emissivity and NDVI Based Emissivity

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***Abstract*—Remote sensing of land cover has been widely used in order to understand the relationship between natural and anthropogenic changes occurring in the surface of the earth at a range of temporal and spatial scales. This study investigates the relationship between land cover changes and land surface temperature (LST) changes. This was accomplished by developing land surface classification images using a maximum likelihood algorithm that will be compared to images obtained using k-means unsupervised clustering method, and comparing these to land surface temperature retrieved from Landsat thermal band 6. In order to retrieve LST it is necessary to know the land surface emissivity values. For this reason, LST was retrieved using NDVI and Classification based emissivity values. Results show good agreement between LST images obtained using the two methods to derive land surface emissivity, and increase in LST from 1985 to 2011 is coincident with increase in percentage of urban and built up areas. Results also show good agreement between supervised and unsupervised classification for water and forestland. However, there is an underestimation of barren land cover category and an overestimation of urban areas category when using k-means clustering algorithm.**

***Keywords*— Landsat, Land cover, Land surface temperature; Land surface classification; Emissivity.**

I. INTRODUCTION

Land cover is an essential attribute in the surface of the earth that is shaped by geologic, hydrologic, climatic, atmospheric, and land use processes that occur at a range of spatial and temporal scales. In turn, land cover affects these processes through feedback mechanisms [1] such as the significant role that land cover plays in the global carbon cycle, both as a source and a sink [2]. In recent decades, the anthropogenic impact on land cover changes has unprecedentedly accelerated due to technological development and increase in human population [3].

Land cover changes can have positive and negative impacts on human well-being [4].

Tropical deforestation, conversion of forests to croplands, agricultural intensification and urbanization can provide fuel, food, fiber, shelter and a host of other products and services to increasing human population. However, these can also release carbon dioxide into the atmosphere, which in turn affect climate change and variability, as well as degrade watersheds, increase soil erosion, water pollution and air pollution [5].

On the other hand, the land surface temperature (LST) is a fundamental factor that regulates most physical, chemical and biological processes of the earth and is controlled by the surface energy balance, atmospheric state, thermal properties of the surface, and subsurface mediums [6]. The physical properties of different types of surfaces, such as color, sky view factor, street geometry, and anthropogenic activities are important factors that determine LSTs in the surface of the earth. Therefore, the LST corresponds closely to the land cover characteristics and their distribution [7, 8, 9].

Nowadays, it is possible to monitor and assess land cover and land surface temperature changes at multiple spatial and temporal scales. Remote sensing is practical a way to accomplish this, because it represents a relatively low cost and rapid method to acquire up-to-date information over a large geographical area, providing information about remote areas that wouldn't be possible to access otherwise, in several spectral ranges that are invisible to human eyes.

The focus of this study is to examine the relationship between land cover and land surface temperature defined by the temporal variations of both. An area located in Northeast region of the United States has been chosen as the case study. Four Landsat TM5 images will be utilized to quantify for the changes in land cover types and temperature. The objectives of this research are finding a relationship between LST and land cover type in order to assess the thermal condition of the land surface using satellite images.

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II. METHODOLOGY

For this project, four Landsat TM5 images were used in order to implement the land surface classification and land surface temperature retrieval. These images were acquired from the USGS Global Visualization Viewer (Glovis) site for the following dates: 1985-04-17, 1995-05-31, 2001-07-02, and 2011-07-14. The imagery corresponds to Landsat Thematic Mapper (TM) data, which is a sensor on board the Landsat 5 satellite. TM consists of seven spectral bands; six of them (1 to 5 and 7) are located in the visible and near infrared regions of the electromagnetic spectrum and with a spatial resolution of 30 meters, while band 6 is located in the thermal infrared (TIR) region of the spectrum and it was acquired at 120-meter resolution, but is resampled to 30-meter pixels for products processed after February 25, 2010 and to 60-meter pixels for products processed before this date.

The main classification steps include image preprocessing, unsupervised classification, and supervised classification. After performing land surface classification, two methods to retrieve LST using thermal infrared data acquired by band 6 of the TM sensor will be compared.

A. Study Area

The area that was chosen in order to analyze the relationship between land cover and land surface temperature changes is located in the Northeast region of the United States. The upper left coordinate corresponds to 40°58'38.35'' N and 75°48'35.53'' W. The lower right coordinate corresponds to 40°18'54.96'' N and 73°50'57.75'' W. The reasons behind the selection of the image is to assess the behavior of a very populated area as New York City in comparison with surrounding rural areas in order to identify differences in land cover types and LST between these areas.

B. Image Processing

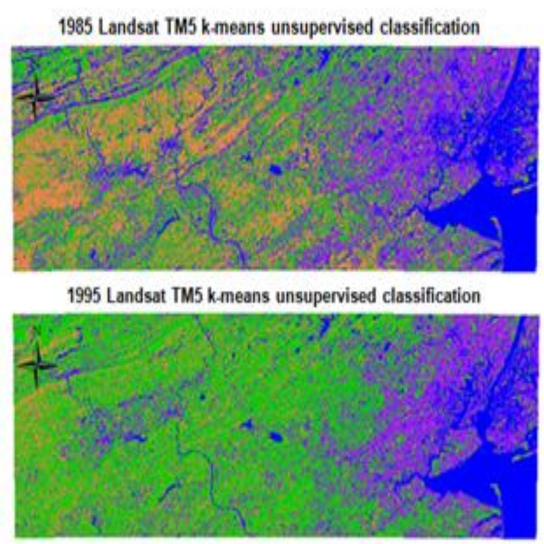
In remote sensing application, multi-temporal images obtained at high temporal and spatial resolution are an important tool for change detection and trends analysis [10]. In order to normalize the data, that is, to minimize the effects of bias arising from atmospheric conditions, solar illumination and view angles, atmospheric calibration is required. This would allow quantitative comparison between images taken at different times. In this project, atmospheric correction of the four Landsat images was applied to convert digital number (DN) of the sensor measurements into surface reflectance. After this, Dark object subtraction technique was used to remove the effects of scattering from the image data.

III. LAND SURFACE CLASSIFICATION

A vast amount of legends and classification systems have been developed throughout time in remote sensing applications for monitoring land cover. A land cover classification that has been used for many years is the Anderson Classification System (ACS) developed by Anderson et al. (1976). This classification scheme consists in four levels (I to IV) of increasing detail, which makes it easily adaptable to user demands [11]. For this project, the land cover classes were defined using four out of nine classes of Level I ACS, namely 1) Urban or built up, 2) Forestland, 3) Water, and 4) Barren land. These were chosen because they are the predominant land cover types in the study area. Furthermore, level I of ACS has been used for remote sensing data acquired at Landsat's spatial resolution of 30 m.

A. K-means Unsupervised Classification

K-means clustering is an algorithm typically used in an unsupervised manner to divide a data set into k groups or classes. The algorithm is initialized by selecting the number of initial class means and improves them by iteration. K-means was implemented in each of the four corrected Landsat TM5 scenes and the classification resulting from its application is shown in Figure 1.



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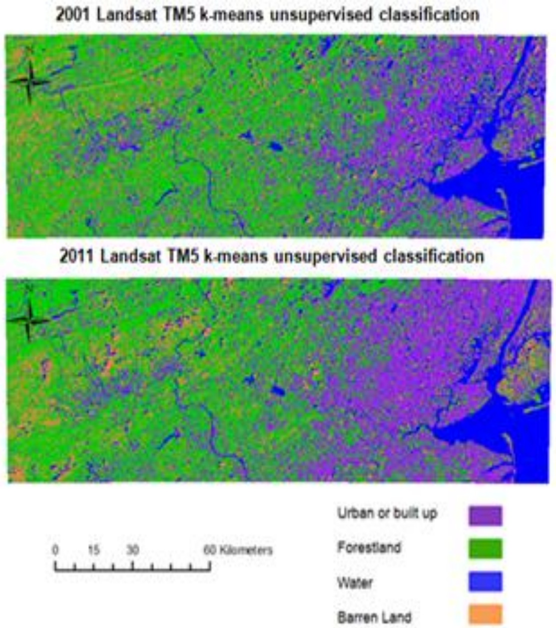

Figure 1. K-means unsupervised classification results

B. Supervised Maximum Likelihood Classification

Supervised maximum likelihood classification was performed over the 2011 corrected Landsat true color image using ENVI. This image was chosen because it is the most recent scene and aerial imagery for this day was available. The training samples were selected as representative of the class that was trying to be identified with the help of aerial imagery. Both the size of the training dataset and the strategy followed for the sampling, influence the classifier's performance. Sample size has been shown to have a relationship with classification accuracy. Thus, the higher the sample size, the higher the accuracy, until a saturation point where additional samples mean very little improvement [12]. The training samples obtained for the Landsat TM5 2011 scene were used for the rest of the images, as the spectral characteristics of the targets is supposed to remain the same throughout time.

The classification resulting from the application of the supervised maximum likelihood classification is shown in Figure 2.

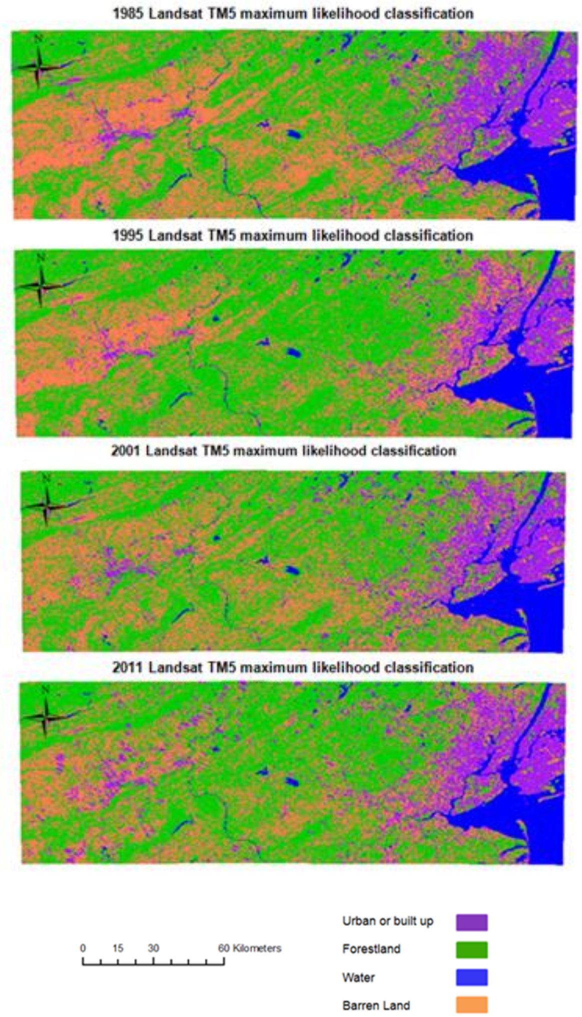

Figure 2. Results of the supervised maximum likelihood classification

IV. LAND SURFACE TEMPERATURE RETRIEVAL

Thermal Infrared (TIR) remote sensing has been used to study urban climate and environment, especially for assessing LST patterns and their relationship with surface characteristics [13]. The air temperature of the lower layer of the urban atmosphere is modulated by LST and is an essential part in the determination of surface radiation, energy exchange, human comfort in the urban areas, and climate of buildings [14].

The first step in the estimation of the LST from Landsat TM 5 using thermal band 6, was to convert the Digital Number (DN) of scene pixels into spectral radiance making use of sensor calibration data.

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The effective at-sensor (top of atmosphere) brightness temperature is obtained from the spectral radiance using Plank's inverse function. The brightness temperature is a reference blackbody temperature. Therefore, it is necessary to correct for spectral emissivity according to the nature of the surface in order to obtain LST [9]. For this reason, LST Retrieval using TIR data requires the knowledge of emissivity values of the surface. This study makes use of two different methods to obtain Land Surface Emissivity (LSE). The first approach utilizes a supervised classification image in order to obtain a LSE image, in which an emissivity value for each class is assumed. The second approach is to use NDVI to obtain the LSE image.

A. Classification based Emissivity

Land surface temperature retrieval from satellite images using classification-based emissivity has been done before and has proven to show high accuracy [15, 16]. This approach assigns a value of emissivity to each land cover class. For this project, the emissivity values assigned to forestland, water and barren land were derived from a previous study in which emissivity values were obtained with remote and contact measurements of surfaces using thermal radiometer and contact thermistors [17]. The pixels in the images resulting from the supervised maximum likelihood classification that represented forest land were given emissivity values of 0.96, pixels that represented water were assigned a value of 0.99, and barren land pixels were given a value of 0.92. For pixels representing urban areas or built up, emissivity values of 0.99 were given.

Once LSE images for the four different dates were obtained, LST was estimated and it was later converted from kelvin to degrees Celsius. The results are shown in the left-hand side of Figure 3.

B. NDVI based Emissivity

This research makes use of the NDVI method developed by Sobrino et al, (2004) [18]. The method obtains emissivity values from the NDVI image considering three different cases: (1) NDVI<0.2. The pixel is considered bare soil; (2) NDVI>0.5. The pixel is considered fully vegetated; and (3) NDVI between 0.2 and 0.5. The pixel is considered a mixture of bare soil and vegetation. Since the study area is a mixture of bare soil and vegetation, the third case applies.

After deriving LSE images for the four different Landsat scenes, LST was retrieved in degrees Celsius. The results are shown in the right-hand side of Figure 3.

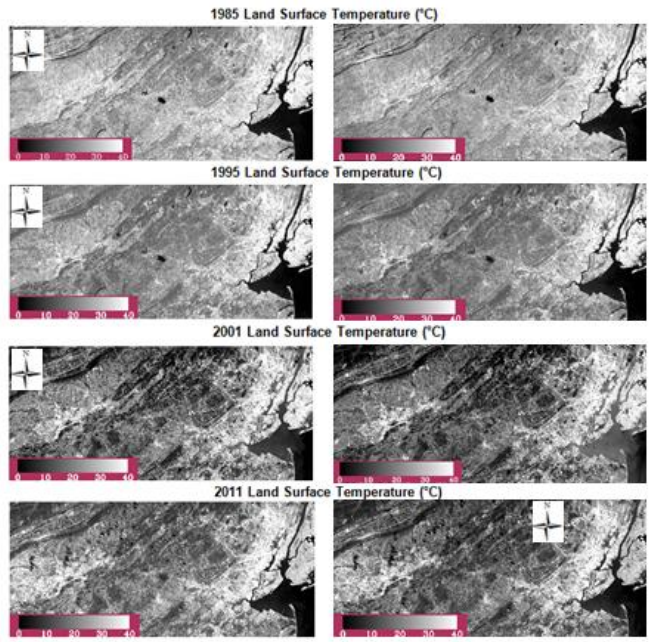

Figure 3. LST for four landsat scenes using classification-based emissivity and NDVI-based emissivity values (°C)

V. Results And Discussion

According to the percentages of each land cover type extracted after implementing maximum likelihood supervised classification algorithm, it is possible to see that urban class appears to have decreased from 1985 to 1995 (13% to 9%), but it increases again from 1995 to 2011 (9% to 15%). On the contrary, forestland seems to have increased from 1985 to 1995 (41% to 50%), but it decreases to 44% between 1995 and 2001 and remains very similar from 2001 to 2011 (44% to 46%). Barren land does not show a large change in percentage throughout time, going from 39% (1985) to 32% (2011). Finally, water remains constant. Urban class shows very little increase in percentage from 1985 to 2011 compared to what was expected. The original images show that indeed there has been an increase in urban and built up areas that are not reflected in the maximum likelihood algorithm results.

When comparing maximum likelihood classification with k-means clustering results, we can see that there is good agreement between both supervised and unsupervised classification for two land cover types; that is water and forestland. However, there is an underestimation of barren land cover type and an overestimation of urban or built up land cover type.

By analyzing the images generated implementing different classification techniques, it can be concluded that the method of supervised classification seems to reflect much more accurately what can be seen from Landsat scenes. Errors in identifying changes in urban areas, that increased just by 2% in 26 years (1985 to 2011), can be attributed to human error in digitizing, lack of sufficient knowledge of the study area, mixed pixels, need for further calibration of the scenes, among several factors that contribute to inaccurate results.

Results show that for the different dates, LST distribution appears to be very similar for both cases, NDVI and Classification based emissivity retrieval. There seems to be a 3°C offset between the LST retrieved from the NDVI-based emissivity and the classification-based emissivity.

LST increased by 7°C from 1985 to 1995 (18°C to 25°C and 21°C to 27°C respectively), which also occurred from 2001 to 2011 (21°C to 27°C and 24°C to 30°C respectively). However, there was a drop in the LST from 1995 to 2001 of 4°C. An examination between the Land Cover and LST results indicated that both NDVI and established emissivity values for a land cover type extracted using maximum likelihood classification scheme were effective for quantifying LST using Landsat imagery. The behavior of forestland is directly proportional to the behavior or LST, which is not accurate since more presence of vegetation, means lower values of LST. Results also indicate that urban areas increased throughout the 1995-2011 time period, as well as temperatures, which was expected because analysis from imagery indicates that urban areas have the highest temperatures of all land cover types considered in the study.

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REFERENCES

[1] Pouliot, D., Latifovic, R., Fernandes, R., Olthof, I., 2009. Evaluation of annual forest disturbance monitoring using a static decision tree approach and 250 m MODIS data. Remote Sensing of Environment 113, 1749–1759.

[2] Loveland, T.R. and Belward, A.S., 1997. The IGBP-DIS Global 1 km Land Cover Data Set, DISCover First Results. International Journal of Remote Sensing, v. 18, no. 5, p. 3,289-3,295.

[3] Meyfroidt, P., Lambin, E.F., 2011. Global Forest Transition: Prospects for an End to Deforestation. Annual Review of Environment and Resources 36, 343–371.

[4] Defries, R.S., Belward, A.S., 2000. Global and regional land cover characterization from satellite data: an introduction to the Special Issue. International Journal of Remote Sensing 21, 1083–1092.

[5] Giri, C., 2012. Brief Overview of Remote Sensing of Land Cover, in: Remote Sensing of Land Use and Land Cover, Remote Sensing Applications Series. CRC Press, pp. 3–12.

[6] Becker, F. and Z. L. Li. 1990. Towards a local split window method over land surfaces. Int. J. Remote Sensing, 11:369-393.

[7] Weng, Q., 2001. A remote sensing-GIS evaluation of urban expansion and its impact on surface temperature in the Zhujiang Delta, China. International Journal of Remote Sensing 22 (10), 1999_2014.

[8] Weng, Q., 2003. Fractal analysis of satellite-detected urban heat island effect. Photogrammetric Engineering and Remote Sensing 69 (5), 555_566.

[9] Weng, Q., Lu, D., Schubring, J., 2004. Estimation of land surface temperature vegetation abundance relationship for urban heat island studies. Remote Sensing of Environment 89, 467–483.

[10]El Hajj, M., Bégué, A., Lafrance, B., Hagolle, O., Dedieu, G., Rumeau, M., 2008. Relative Radiometric Normalization and Atmospheric Correction of a SPOT 5 Time Series. Sensors 8, 2774–2791.

[11] Martin Herold, Antonio Di Gregorio, 2012. Evaluating Land-Cover Legends Using the UN Land-Cover Classification System, in: Remote Sensing of Land Use and Land Cover, Remote Sensing Applications Series. CRC Press, pp. 65–90.

[12] Darren Pouliot, Rasim Latifovic, Ian Olthof, Robert Fraser, 2012. Supervised Classification Approaches for the Development of Land-Cover Time Series, in: Remote Sensing of Land Use and Land Cover, Remote Sensing Applications Series. CRC Press, pp. 177–190.

[13] Weng, Q. 2009. Thermal infrared remote sensing for urban climate and environmental studies: methods, applications, and trends. ISPRS Journal of Photogrammetry and Remote Sensing, 64(4): 335-344.

[14] Voogt, J.A., Oke, T.R., 1998. Effects of urban surface geometry on remotely-sensed surface temperature. International Journal of Remote Sensing 19, 895–920.

[15] 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.

[16] Nichol, J.E., 2005. Remote Sensing of Urban Heat Islands by day and night Photogrammetric Engineering & Remote Sensing. Vol. 71, No. 5, pp. 613–621.

[17]Artis, D.A., and W.H. Carnahan, 1982. Survey of emissivity variability in thermography of urban areas, Remote Sensing of the Environment, 12:313–329.

[18]Sobrino, J.A., Jiménez-Muñoz, J.C., Paolini, L., 2004. Land surface temperature retrieval from LANDSAT TM 5. Remote Sensing of Environment 90, 434–440.