MAPPING URBAN AREAS BY FUSING MULTIPLE SOURCES OF COARSE RESOLUTION REMOTE SENSED DATA

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ABSTRACT:

The main objective of this research is to improve understanding of the methodological and validation requirements for mapping urban land cover over large areas from coarse resolution remotely sensed data. A technique called boosting is used to improve supervised classification accuracy and provides a means to integrate MODIS data with the DMSP nighttime lights data. Results indicate that fusion of these two data types improves urban classification results by resolving confusion between urban and other classes that occurs when either of the data sets is used alone. Traditional measures of accuracy assessment as well as new, maplet-based methods demonstrate the effectiveness of the methodology for creating maps of cities at continental to global scales.

1. INTRODUCTION

Urban land cover presently accounts for less than one percent of the Earth's land area, although this proportion is growing rapidly as more and more cities expand into natural ecosystems and agricultural areas (Douglas, 1994). Identifying and anticipating the location and growth rate of urban areas is an important component to understanding and mitigating many aspects of global population growth, and by extension global change.

Previous studies of urban areas from remote sensing have consistently relied on fine resolution data (Landsat, SPOT), which limits these studies to small areas. The only existing global maps of urban areas are the Digital Chart of the World (DCW) urban layer (Danko, 1992), and maps derived from the Defense Meteorological Satellite Program Operational Linescan System (DMSP-OLS), or nighttime lights data (Elvidge et al., 1996). While the DCW urban data is valuable, it was compiled from 1960s Operational Navigation Chart data and no longer provides an accurate representation of city size. The nighttime lights data has produced stunning images for several years, however for mapping purposes the data possesses coarse (2.7 km) resolution, is poorly registered, and exhibits blooming effects that inflate city boundaries (Elvidge et al., 1996).

Recent coarse resolution land cover mapping efforts from remote sensing data have not included cities because of the limitations of Advanced Very High Resolution Radiometer (AVHRR) imagery and inadequacies of traditional classification algorithms (Loveland et al., 1999; Hansen et al., 2000; Friedl et al., 2002). Data from NASA's recently launched Terra platform offer a new opportunity for mapping urban areas, providing the potential to transform such studies from local to global scales. In particular, Terra's Moderate Resolution Imaging Spectroradiometer (MODIS) acquires multispectral data with high temporal frequency, and is designed specifically to monitor land properties at global scales.

Unfortunately, classifications based on MODIS data alone result in confusion between urban and barren areas.

The primary goal of this paper is to describe and assess a methodology for mapping urban land cover at 1 km spatial resolution by fusing two sources of coarse resolution data. Two major tasks were involved in this study. First, a supervised decision tree classification method was developed by fusing 1 km MODIS data and an ancillary sources, the nighttime lights data (Elvidge et al., 1996). The second task was to establish the best means for evaluating the accuracy of urban land cover maps produced over large regions, an issue that is especially problematic when the class of interest is a small fraction of the total area mapped.

2. METHODOLOGY

2.1 Overview

The method involved three main steps. In the first step, the nighttime lights data was used in a logistic regression model to produce a probability surface for urban areas. In the second step, a decision tree algorithm was trained using a global set of training sites for 17 land cover classes (including urban) defined by the International Geosphere-Biosphere Program (IGBP), and the trained tree was applied to the MODIS data. The output from this first stage provided a map of per-pixel probabilities for each of 17 classes. The class probabilities and the probability surface were then used as input to the third step, where Bayes' Rule was applied at every pixel. To do this, the probabilities of urban areas derived from the logistic regression were used as prior probabilities, and the final pixel label was assigned based on the maximum likelihood derived from the posterior probabilities. In this way, information from both data sources was fused to create a final map of urban areas.

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2.2 Data

The 1 km nighttime lights data (Elvidge et al., 1996) was used as input to a logistic regression model to create a map of "prior probability" for urban areas for each continent. A sample of 4000 1 km^2 pixels was selected randomly from the nighttime lights data and the DCW (the latter serving as the dependent variable to train the logistic model) to produce a binary urban/non-urban class map for each continent. The urban class defined in the DCW maps, although out of date, is considered a consistent source of data to sample city cores.

The classification stage employed a full year of MODIS imagery acquired between October 15, 2000 and October 15, 2001. These data included seven bands of Nadir-corrected BRDF Adjusted Reflectance values, and the MODIS Enhanced Vegetation Index (EVI) composited over 32 day periods. The decision tree algorithm was trained using 1800 training sites 1 to 100 km^2 in area, obtained by manual interpretation of Landsat data. Urban training sites were selected from cities using the criteria that the area must be composed of greater than 50 percent urban land cover.

2.3 Logistic Regression

The logistic model of urban/non-urban areas possessed the form:

$$P(urban) = \frac{\exp(U_i)}{1 + \exp(U_i)} \quad (1)$$

where *P(urban)* is the probability that a pixel is urban or non-urban. The value of U_i is provided by a conventional linear regression model. The model using the nighttime lights to predict urban/non-urban is:

$$U_i = \beta_0 + \beta_1 lights_i + e_i \quad (2)$$

where $lights_i$ is the value of the nighttime lights data at the *i*th pixel, the β coefficients are determined empirically using the logistic regression routine in SAS, and e_i is the random error term. The model results for each continent show that each of the coefficients was significant at $p < 0.05$.

2.4 Decision Trees

The method employed to compute conditional probabilities of IGBP land cover classes relies on a supervised decision tree classification algorithm, C4.5 (Quinlan, 1993). Decision trees have been especially effective for coarse resolution classifications because they are able to handle noisy or missing data, they require no *a priori* assumptions regarding the distribution of the input data, and they can handle complex, nonlinear relations between features and classes (Fayyad and Irani, 1992).

The technique of "boosting" has been widely shown to increase classification accuracies using supervised algorithms (McIver and Friedl, 2001). Boosting improves accuracy by estimating multiple classifiers while systematically varying the training sample. At each iteration of the classifier, the training sample is modified to focus the classification algorithm on examples that were difficult to classify in the previous iteration. The final classification is then produced by an accuracy weighted vote across all of the classifications (Quinlan, 1996).

Recently, a statistical examination of boosting has shown that it is equivalent to a form of additive logistic regression (Friedman et al., 2000). As a result, probabilities of class membership can be assigned for each class at every pixel. Using these probabilities, it is possible to calculate posterior probabilities of urban areas with the aid of ancillary information. For this work, Bayes' Rule was applied at every pixel to combine the probability surface (prior information) with the conditional probabilities derived from the boosted decision trees.

3. RESULTS

While it is difficult to assess the quality of the results at continental scales, Fig. 1 presents five panels showing the urban class at the scale of the city. Fig. 1a presents Landsat TM imagery, where settlement patterns can be seen intermixed with forested and agricultural areas. Similar patterns can be seen in the MODIS imagery in Fig. 1b, but with less spatial detail. Fig. 1c presents the DCW data, which characterizes the core urban area but fails to capture new growth. Fig. 1d presents the nighttime lights data set. While these maps appear reasonable at continental scales, Fig. 1d clearly illustrates how this data set leads to overestimation of urban areas. Finally, Fig. 1e presents the results achieved by fusing MODIS data with nighttime lights data (hereafter the fusion map). (Additional results available at http://duckwater.bu.edu/urban.)

4. ACCURACY ASSESSMENT

The conventional approach to accuracy assessment is to compare an independent, random sample of "ground truth" points to the classified map (Card, 1982). Representative results for North America were evaluated using an independent test set of 400 1 km^2 pixels. Producer's accuracy was used because the urban class represents only one percent of the total land area. When prior probabilities were included, the
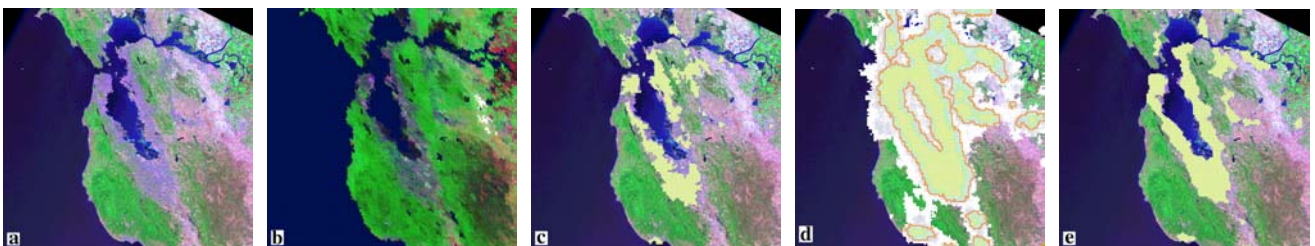

Figure 1: The San Francisco Bay area showing (a) 30m Landsat imagery (urban areas appear purple); (b) 1 km MODIS data (urban also appears purple), (c) the urban data from the DCW (note misregistration); (d) the nighttime lights data (orange boundary represents commonly used threshold); and (e) the fusion map of urban areas produced in this research.

producer's accuracy increased from 39 to 79 percent.

The fusion map of urban land cover was also compared against the DCW data, the nighttime lights data, and a regional, fine resolution map of the U.S., the National Land Cover (NLC) data (Vogelmann et al., 1998). Three maplet-based methods were used to supplement the overall accuracy statistics (Stoms, 1996), which serve to highlight the strengths and weaknesses of each for representing current urban land cover. Results of the method comparing city sizes obtained from the 30m NLC data against estimates from the DCW, the nighttime lights data, and the fusion map are shown in Fig. 2.

5. CONCLUSIONS

The main objective of this research was to improve understanding of the methodological and validation requirements for mapping urban areas over large areas. Urban areas were mapped on a continental scale by fusing MODIS data and the nighttime lights data. Decision trees used in association with prior probabilities were particularly effective for resolving confusion between urban areas and other land cover types. This result reflects a trend towards increased fusion of different data types to provide more representative characterization of land cover qualities. This is especially true for urban areas, where high levels of within-region and between-region variability make classification especially difficult. Finally, this research explored a variety of avenues for map accuracy and assessment.

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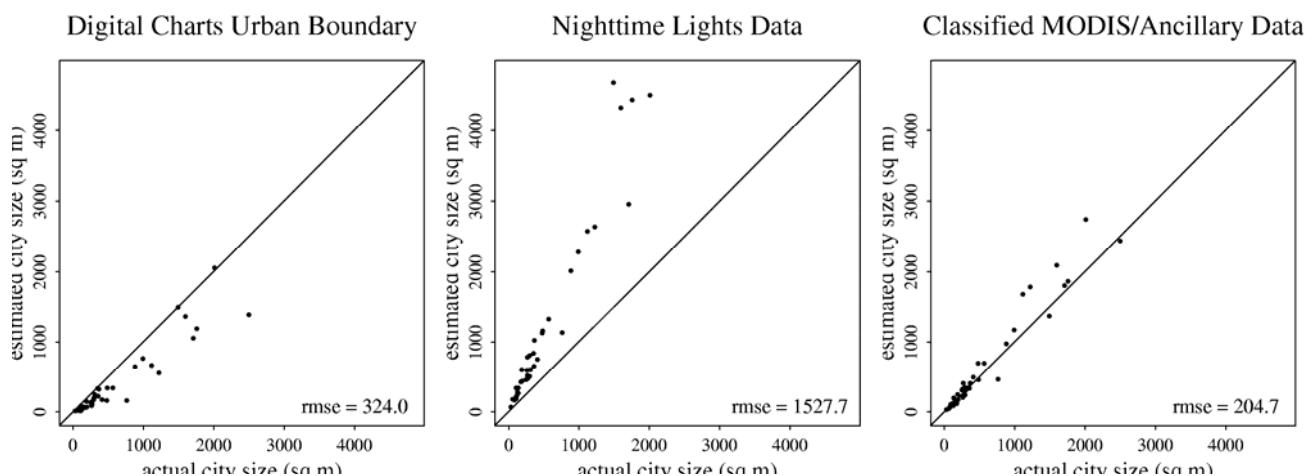
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Figure 2: A comparison of city size in continental scale maps of urban areas (vertical axis), using the urban areas defined by the 30 m NLC data to represent "true" city size (horizontal axis). The DCW data systematically underestimate city size (a), the nighttime lights data systematically overestimate city size (b), and the map produced from the combination of MODIS, nighttime lights and population data (c) achieves the closest and least biased fit to the "true" city size.