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Monitoring land cover change in urban and peri-urban areas using dense time stacks of Landsat satellite data and a data mining approach

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ABSTRACT

Given the pace and scale of urban expansion in many parts of the globe, urban environments are playing an increasingly important role in daily quality-of-life issues, ecological processes, climate, material flows, and land transformations. Remote sensing has emerged as a powerful tool to monitor rates and patterns of urban expansion, but many early challenges – such as distinguishing new urban land from bare ground – remain unsolved. To deal with the high temporal and spatial variability as well as complex, multi-signature classes within settlements, this paper presents a new approach that exploits multi-seasonal information in dense time stacks of Landsat imagery using a multi-date composite change detection technique. The central premise of the approach is that lands within/near urban areas have distinct temporal trajectories both before and after change occurs, and that these lead to characteristic temporal signatures in several spectral regions. The method relies on a supervised classification that exploits training data of stable/changed areas interpreted from Google Earth images, and a 'brute force' approach of providing all available Landsat data as input, including scenes with data gaps due to the Scan Line Corrector (SLC) problem. Three classification algorithms (maximum likelihood, boosted decision trees, and support vector machines) were tested for their ability to monitor expansion across five time periods (1988–1995, 1996–2000, 2001–2003, 2004–2006, 2007–2009) in three study areas that differ in size, eco-climatic conditions, and rates/patterns of development. Both the decision trees and support vector machines outperformed the maximum likelihood classifier (overall accuracy of 90–93%, compared to 65%), but the decision trees were superior at handling missing data. Adding transformed features such as band metrics to the Landsat data stack increased accuracy 1–4%, while experiments with a reduced number of features (designed to mimic noisy or missing data) led to a drop in accuracy of 1–9%. The methodology also proved particularly effective for monitoring peri-urbanization outside the urban core, capturing >98% of village settlements.

1. Introduction

During the last two decades, we have made important strides toward developing remote sensing methods that allow for the accurate characterization of land cover change (Rogan & Chen, 2004), including urban expansion (Chan et al., 2001). Mapping urban areas remains a complex challenge, however, because of the many combinations of materials present and the variations in size/shape of urban features that can lead to different 'mixtures' within pixels (Small & Lu, 2006). Particularly troublesome is the fact that newly developed urban areas typically appear identical to fallow farmland at any given time, since both exhibit high reflectance in the visible-infrared wavelengths. These issues are further compounded in developing countries such as China and India, since new development is often small, patchy in nature, and located in peri-urban areas up to 100 km from the urban core (Long et al., 2009; Webster, 2002).

The new wave of very high spatial resolution (VHR) data (1–4 m) holds tremendous promise for resolving these issues, and methods have emerged to characterize urban features with increased spatial detail (Ban et al., 2010; Del Frate et al., 2007). However, the sparse coverage, limited scene availability, and lack of data prior to 2000 make routine use of VHR data to map *change* impractical, and in some locations, impossible. Currently, medium resolution (20–30 m) datasets such as Landsat and SPOT remain the best option for balancing the trade-offs involving spatial detail, areal coverage, and availability of historical data. The dense archives as well as routine collection of these data (as opposed to VHR 'on-demand' collection) are also advantageous when the rate of change is particularly rapid; in cities in China, for instance, the scale and pace of urbanization must be monitored on the order of years rather than on decades (Ma, 2004). Moreover, studies that have moved beyond mapping to link social and economic processes to land use have shown that monitoring change for multiple periods (i.e. three or more) is pivotal to understand the complex drivers of urban morphology through space and time, and to forecast future land use trends (Seto & Kaufmann, 2003).

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With the opening of the Landsat archive and new data sources coming online, it is now possible to take advantage of the temporal dimension of satellite data to map urban change. The central premise of the approach presented here is that the confusion between new urban land and other land cover types can be resolved by including images (a) from multiple seasons, as well as (b) from multiple years. While there is likely to be confusion between bare ground and urban areas during the course of one year, there is often a high probability that nearby fields or open areas will be vegetated during at least one season of a given year, and thus be 'separable' from built-up areas that are predominantly non-vegetated year round. The temporal information from multiple years (case b) is also beneficial: expansion of built-up lands is often unidirectional (i.e. once land is converted to urban uses, it is unlikely to be converted back to farmland or forest), and thus images that follow the date of change actually 'confirm' that an area has been developed. Despite the clear advantage of seasonal, multi-year information, few studies have exploited a multi-temporal approach to resolve urban remote sensing issues.

The primary goal of this research was to develop, test, and validate a multi-date composite change detection technique that is effective in complex, heterogeneous urban and peri-urban environments. The multi-date composite approach was specifically chosen because of its superior accuracy for difficult change detection problems (Coppin et al., 2004; Rogan & Chen, 2004), and because it provided a means to exploit dense time stacks of Landsat data now freely available from the U.S. Geological Survey (USGS, 2011). Because of the complexity and size of the datasets for a given study area (~35–50 Landsat scenes), three supervised classification algorithms were tested: a traditional maximum likelihood (ML) classifier, and two machine learning algorithms, boosted decision trees (DT) (Quinlan, 1993), and support vector machines (SVM) (Chang & Lin, 2001). The methods were tested for their ability to isolate and correctly classify urban expansion for five time periods spanning 1988 to 2009. To prevent the methodology from being applicable in only one study area, the algorithms were tested on three cities (Fig. 1) with different city sizes, diverse ecosystem characteristics, as well as differential rates/patterns of urban development. Specifically, the following questions guided this research:

(1) Which supervised classification algorithm performs best for change detection in urban environments given dense temporal data stacks?
(2) Does the addition of transformed features increase overall accuracy?
(3) What is the impact of data quality and quantity on classifier performance? and
(4) How well do multi-date change detection approaches work in peri-urban environments given the small size/scale of settlements (e.g. built-up areas ~1800 km^2)?

To address these questions, the three algorithms were evaluated using multiple criteria through a series of experiments that provided different combinations of data features as input to the classifiers. Recent applications that exploit dense, multi-temporal datasets have benefitted from the inclusion of transformed data such as band maxima, minima and means (Friedl et al., 2010; Hansen et al., 2008), thus question 2 was designed to test whether the addition of these features was beneficial for monitoring urbanization. Question 3 was included to specifically test feature selection. While machine learning algorithms can now handle any number of input features, feature selection remains an important concern if reduced-quality data are used as input (e.g. data with clouds or missing observations), or if insufficient imagery is available to create a dense stack. In the context of these issues, it is important to understand which features may or may not be necessary to achieve high accuracy results. Finally, question 4 was designed to test the ability of this approach to characterize small, piece-meal land development and village settlements outside the city core.

2. Background: remote sensing of urban change, 1970s to today

Characterizing cities and towns with remotely sensed data has been challenging since the field of Earth observation began nearly 50 years ago. As medium resolution satellite data (Landsat MSS) became available in the 1970s, early applications relied on simple band ratios, image thresholding, and image differencing to discern broad-scale changes at the urban–rural fringe (Friedman & Angelici, 1979; Howarth & Boasson, 1983; Jensen & Toll, 1982; Todd, 1977). Despite the apparent success of early approaches, the potential user community – urban planners, developers, land managers, and social scientists – did not immediately embrace the new technology. Relatively few applications appear in the urban planning literature, due in large part to the lack of spatial detail and thus inferior information content of satellite data relative to aerial photos or ground surveys (Michalak, 1993; Ryznar & Wagner, 2001). While GIS technology has been widely adopted in urban planning, the lack of reliable, easy-to-use methods and dearth of remote sensing data with sufficient spatial resolution continue to impede widespread use of satellite-based maps of urban change.

A second user community of remote sensing-based maps of urban change emerged in the 1990s–2000s, however. Disciplines such as climatology (Romero et al., 1999), hydrology (Carlson & Arthur, 2000), ecology (Robinson et al., 2005), and public health (Tatem & Hay, 2004) have embraced satellite data to understand the impacts of urban expansion on environmental systems, as well as human health and well-being. Moreover, there is a growing body of work looking at urbanization and its effects from a regional to global perspective (Mills, 2007; Pataki et al., 2006) which requires medium to coarse resolution large-area maps of urban extent and urban change (Schneider et al., 2009, 2010). With these needs in mind, it is critical that the remote sensing community continues to develop efficient methods and to explore data sources for mapping urban growth and sprawl.

Although the user community has varied widely, the methods to generate maps of urban growth have not deviated significantly from early approaches that exploited spectral profiles of built-up areas and newly developed land (Ehlers et al., 1990; Jensen & Toll, 1982; Ulbricht & Heckendorff, 1998; Yang & Lo, 2002). Multi-date composite approaches – those using images of two dates that are combined during processing to produce a map of change – began to be used for urban applications in the 1990s (Ridd & Liu, 1998). Early multi-date techniques included stacked principal component analysis (Deng et al., 2008; Li & Yeh, 1998), change vector analysis (Chen et al., 2003), or stacked multi-date composite classification (Schneider & Woodcock, 2008). To handle the complexity of the urban environment, machine learning approaches were adopted in the late 1990s, including neural networks (Dai & Khorram, 1999; Liu & Lathrop, 2002), boosted/bagged decision trees (Rogan et al., 2003; Schneider et al., 2003, 2005), and support vector machines (Griffiths et al., 2010; Nemmour & Chibani, 2006). While these algorithms provided increased class accuracies, isolating distinct spectral signatures from the inherently mixed pixels in urban environments has remained problematic.

It is becoming increasingly clear that resolving class confusion in urban change detection applications requires taking advantage of 'domains' of remote sensing beyond spectral information, such as temporal, spatial, or polarimetric domains. In this regard, data fusion approaches – those that combine spectral profiles with either spatial information or radar responses – have shown great potential. Spatial information has been exploited through contextual classification and object-oriented processing (An et al., 2007; Li et al., 2009), which tackle the urban problem by using patches to reduce the variability in the urban spectral response. Textural information has also been tested widely for urban change detection, but with minimal improvement in detection of built-up areas (Gluch, 2002; Moller-Jensen, 1990). Data fusion has also included merging multispectral and radar data: visible to near-infrared wavelengths are used to reveal the *composition* of the land, while the high backscatter of human-made objects in radar data is used to discern settlement *structure*