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Using Landsat and nighttime lights for supervised pixel-based image classification of urban land cover

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ABSTRACT

Reliable representations of global urban extent remain limited, hindering scientific progress across a range of disciplines that study functionality of sustainable cities. We present an efficient and low-cost machine-learning approach for pixel-based image classification of built-up areas at a large geographic scale using Landsat data. Our methodology combines nighttime-lights data and Landsat 8 and overcomes the lack of extensive ground-reference data. We demonstrate the effectiveness of our methodology, which is implemented in Google Earth Engine, through the development of accurate 30 m resolution maps that characterize built-up land cover in three geographically diverse countries: India, Mexico, and the US. Our approach highlights the usefulness of data fusion techniques for studying the built environment and is a first step towards the creation of an accurate global-scale map of urban land cover over time.

1. Introduction

Urbanization has been a fundamental trend of the past two centuries and a key force shaping the development of the modern world. Between 1950 and 2014, the share of the global population living in urban areas increased from 30% to 54%, and in the next few decades is projected to expand by an additional 2.5 billion urban dwellers, primarily in Asia and Africa (Seto et al., 2011; UN, 2014). Urban population growth is accompanied by a dramatic increase in the land area incorporated in cities (Seto et al., 2011). While urbanization in rapidly growing nations is helping lift hundreds of millions of people out of poverty, it is also creating immense societal challenges by increasing greenhouse-gas emissions, destabilizing fragile ecosystems, and creating new demands on public services and infrastructure that impose significant burdens on the environment (Ban et al., 2015). Timely and reliable information on the extent of urban areas is fundamental for the support of sustainable urban development and management (Ban et al., 2015; Jacob and Ban, 2015). Despite the importance of understanding the drivers of urban growth, we are still unable to quantify the magnitude and pace of urbanization in a consistent manner at high resolution and global scale (Ban et al., 2015; Giri et al., 2013).

The revolution in geospatial data has transformed how we study cities. Previous approaches leveraged household surveys but these are expensive to collect, produced infrequently, and subject to measurement problems. Since the 1970s, however, terrestrial Earth-observation data have been continuously collected in various spectral, spatial and temporal resolutions. As improved satellite imagery becomes available, new remote-sensing methods and machine-learning approaches have been developed to convert terrestrial Earth-observation data into meaningful information about the nature and pace of change of urban landscapes and human settlements (Ban et al., 2015; Chen et al., 2015; CIESIN, 2005; Gaughan et al., 2013; Pesaresi et al., 2016; Potere et al., 2009; Seto et al., 2011; Taubenböck et al., 2012).

The availability of satellite data has triggered the development of new methods to map global land cover using remotely-sensed data such as Landsat (Chen et al., 2015; Gaughan et al., 2013; Goldblatt et al., 2016; Patel et al., 2015), MODIS (Moderate Resolution Imaging Spectroradiometer) (Schneider et al., 2009, 2010; Wan et al., 2015), DMSP-

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OLS (Elvidge et al., 2014; Liu et al., 2012; Xiao et al., 2014; Zhang and Seto, 2013) and other spaceborne High-Resolution (HR), Very-High-Resolution (VHR) and Synthetic-aperture radar (SAR) radar sensors (Ban et al., 2015; Gamba et al., 2011; Jacob and Ban, 2015). Recent studies have developed automated and semi-automated classification procedures to map global land cover at a 30 m resolution with high accuracy (Ban et al., 2015; Chen et al., 2015). Because Landsat satellites have been collecting data from Earth since 1972, Landsat data are often used for analysis of urban change (Patel et al., 2015), and are ideal for land cover mapping (Woodcock et al., 2008). Nighttime light data are also associated with developed land (Elvidge et al., 2014; Levin and Duke, 2012; Sutton, 2003) and can be used to infer the extent of urban areas (Bagan and Yamagata, 2015; Small and Elvidge, 2013; Zhang and Seto, 2013), as well as economic activity at the local, regional and national levels (Elvidge et al., 2014; Henderson et al., 2003; Keola et al., 2015). Sensors on board the Operational Line-scan System of the Defense Meteorological Satellite Program (DMSP-OLS) have captured artificial lighting since the early 1990's. A pixel's nighttime light value that exceeds a specified threshold, which may vary across regions or countries, signifies urban development (Henderson et al., 2003; Liu et al., 2016; Small and Elvidge, 2013; Su et al., 2015; Wei et al., 2014; Zhou et al., 2014, 2015). However, inference using nighttime-light data are often inaccurate, particularly in low-density urban areas (Zhang and Seto, 2013). DMSP-OLS can also exaggerate the extent of urban areas (Henderson et al., 2003; Small et al., 2005), while overlooking small or developing settlements. In addition, the extent and intensity of lit areas cannot directly delimit urban regions due to the “blooming” effect (Imhoff et al., 1997) and “saturation” of pixels (Hsu et al., 2015). Blooming refers to the identification of lit areas as consistently larger than the settlements with which they are associated (Small et al., 2005); saturation occurs when pixels in bright areas, such as in city centers, reach the highest possible digital number (DN) value (i.e., 63) and no further details can be recognized (Hsu et al., 2015).

Until recently, most remote sensing studies focused on local settings (Herold, 2009). Mapping land cover at a national or regional scale is challenging because of the lack of high-resolution global imagery, the heterogeneous and complex spectral characteristics of land, and the small and fragmented spatial configuration of many cities (Chen et al., 2015; Herold, 2009). In the case of mapping urbanization, existing maps of urban land show considerable disagreement on the location and extent of urbanization (Potere et al., 2009; Seto et al., 2011) and are limited across space and time. These inconsistencies arise in part because the delineation of urban land depends on the input data (Schneider et al., 2010), which may capture different dimensions of urbanization, such as built-up land cover or land use and population density (Bagan and Yamagata, 2014; Stevens et al., 2015; Tatem et al., 2007).

1.1. Detecting urbanization using machine learning

Urban areas can be detected in satellite imagery using various machine-learning approaches (e.g., supervised, unsupervised and semi-supervised). These approaches typically rely on reference data that mark urban features, either for training or validation. Reference data are fundamental not only for mapping urbanization across space, but also for classification over time (Boucher and Seto, 2009). Some of the reference datasets used for classification include Landsat-based urban maps (Potere et al., 2009), census-based population databases (Stevens et al., 2015), hand-labeled examples (Goldblatt et al., 2016), and data collected via crowd-source platforms, such as OpenStreetMap (OSM) (Belgiu and Drăguţ, 2014; Estima and Painho, 2015). However, because they are expensive to collect, reference datasets for large geographic scales are scarce (Miyazaki et al., 2011). Due to the scarcity of ground-reference data, it is often necessary to exploit existing global coarse datasets and classification products to create accurate higher-resolution maps of urban areas (Kasimu et al., 2009; Trianni et al., 2015). Moreover, mapping land cover at a global scale and with high precision requires effective, efficient and operational approaches to deal with a very large volume of data. For example, it is estimated that over 10,000 Landsat satellite images are required to cover the entire Earth at 30 m resolution (Chen et al., 2015). Until recently, the majority of studies that analyze urbanization have been limited in their geographic scale because of the lack of extensive high-resolution satellite data, scarcity of ground-reference data, and computational constraints. Emerging cloud-based computational platforms now allow for scaling analysis across space and time. Google Earth Engine (GEE) is one platform that leverages cloud-computing services to achieve planetary-scale utility. GEE has been previously used to map population (Patel et al., 2015; Trianni et al., 2015), urban areas (Goldblatt et al., 2016), and surface water (Pekel et al., 2016). This paper contributes to this literature by developing a machine-learning methodology for supervised high-resolution image classification of built-up areas using GEE's cloud-based computational platform.

1.2. Research objective and contribution

The use of nighttime remotely-sensed data to map urbanization is not new to the literature. Remotely-sensed data on artificial lighting has long been considered an economical way to map urbanization and development across the globe (Elvidge et al., 2009). By utilizing the distribution of vegetation land cover, the combination of nighttime and daytime data increases the heterogeneity of urban and suburban land cover (e.g., distinguishing between built-up land cover and vegetation in urban areas) and improves the characterization of inter-urban variability in nighttime luminosity (Zhang et al., 2013). This, in turn, improves the ability to detect urban features (Lu et al., 2008; Ma et al., 2014) including sub-pixel fractional urban land cover (Huang et al., 2016). Several spectral indices that combine nighttime light and vegetation spectral characteristics have been developed, including the Vegetation Adjusted NTL Urban Index (VANUI) (Jing et al., 2015; Zhang et al., 2013), the Normalized Difference Urban Index (NDUI) (Zhang et al., 2015) and the Normalized Difference Spectral Vector (NDSV) (Trianni et al., 2015). These indices increase the separability between urban and non-urban land cover.

We develop a methodology that combines nighttime and daytime remotely-sensed data. We collect training examples automatically using DMSP-OLS data, and use them for classification of built-up areas with daytime Landsat 30 m spatial resolution imagery. Previous studies that combine nighttime and daytime data have either been limited in their spatial application (i.e., the ability to generalize the method and to apply it over regions with heterogeneous land cover) or spatial resolution (i.e., many of the existing approaches, for example those that rely on MODIS or DMSP-OLS, are limited in their spatial resolution). In this study, we adopt a hexagonal tessellation mapping approach to handle large variation across regions (where we refer to each hexagon in the hexagonal grid as a hex-cell). We collect training examples from each hex-cell and classify the hex-cell as an independent unit of analysis.

Our methodology can be applied across heterogeneous land cover and across time and, crucially, does not rely on expensive hand-labeled examples. It requires minimal manual adjustments for training and classification, and does not require adjustments to local parameters. This feature makes the approach scalable across space and time. Importantly, the methodology is time-invariant and can be applied whenever Landsat and DMSP-OLS data are coincident. The robustness of the methodology lies in our approach to sample training examples (i.e., according to the relative intensity of the emitted light at night and the distribution of vegetation land cover) and on the per-hex-cell classification, which allows us to account for regional variations in the land cover. Finally, we assess the accuracy of the methodology using an extensive dataset of 84,564 hand-labeled polygons characterizing built-up (BU) and not built-up (NBU) pixels for each of the three study areas,

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