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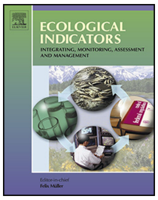

# A geospatial approach to monitoring impervious surfaces in watersheds using Landsat data (the Mondego Basin, Portugal as a case study)

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## ABSTRACT

The urbanization of watersheds is a highly dynamic global phenomenon that must be monitored. With consequences for the environment, the population, and the economy, accurate products at adequate spatial and temporal resolutions are required and demanded by the science community and stakeholders alike. To address these needs, a new Impervious Surface Area (ISA) product was created for a Portuguese Watershed (Mondego river) from Landsat data (a combination of leaf-on multispectral bands, derived products, and NDVI time series), using Regression Tree Models (RTM). The product provides 30-m spatial resolution ISA estimates (0–100%) with a Mean Average Error (MAE) of 1.6% and Root Mean Square Error (RMSE) of 5.5%.

A strategy to update the baseline product was tested in earlier imagery (2001 and 2007) for a subset of the watershed. Instead of updating the baseline product, the strategy seeks to identify stable training samples and remove those where change was detected in a time series of Change Vector Analysis (CVA). The stable samples were then used to create new ISA models using RTM. The updated maps were similar to the original product in terms of accuracy metrics (MAE: 2001: 2.6%; 2007:3.6%).

The products and methodology offer a new perspective on the urban development of the watershed, at a scale previously unavailable. It can also be replicated elsewhere at a low cost, leveraging the growing Landsat data archive, and provide timely information on relevant land cover metrics to the scientific community and stakeholders.

## 1. Introduction

More than half of the world's population inhabits urban areas (U.N., 2014). In Europe, this figure is even higher, with 75% of the population (80% by 2020) living in cities (EEA, 2006). A similar urbanization trend was observed in Portugal in recent decades, where the urban population now reaches 42% of the total (INE, 2014).

In fact, urbanization is a global phenomenon that affects ecosystems, climate and the livelihood of human communities. In the United States alone, from 1982 to 2010, 17 million hectares of non-federal land were developed (USDA, 2013) and in Germany, 100 ha of land are transformed into built-up/transportation classes every day (DESTATIS, 2007). The overwhelming pace of urbanization in the second half of the 20th century changed the face of European cities, with the emergence of 'sprawling' phenomena and profound transformations in the overall urban growth patterns (EEA, 2006).

This seemingly irreversible trend is not always accompanied by the development of efficient urban planning policies that could emerge from modern science and technology (Marinoni et al., 2013). Therefore, it is urgent to develop environmental indicators that can be employed routinely in the monitoring of urbanized ecosystems on a regional and global scale and at a rate consistent with that of development (Tiner, 2004). These rapid mutations of the landscape led to a profound change in the science of urban ecology (Pickett et al., 2008), which became increasingly integrated, with contributions from ecology, physical, social, and economic sciences (Grimm et al., 2000). This "human-environment system" calls for new perspectives (Turner et al., 2007), to foster the development of original management policies focused on sustainability, while

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accommodating growth and the population's legitimate aspirations (Marques et al., 2009).

Land Use and Land Cover (LULC) dynamics translate an otherwise abstract concept of change into measurable metrics, which can be objectively monitored to assess the impact over the health of land and aquatic ecosystems, the climate, and the territory (Loveland et al., 2002; Grove and Burch Jr., 1997). However such monitoring is not without challenges, as the urban and peri-urban space is inherently complex and highly heterogeneous, truly a patchwork of multiple LULC classes (Xian, 2008a,b; Bauer et al., 2008; Andrieu and Chocat, 2004). This complexity is the source of a multidimensional reality, with direct and indirect impacts over multiple biotic and abiotic variables, which may then influence social dynamics and interactions.

Stream hydrology and function are especially vulnerable to LULC (Morisawa Marie and Ernest LaFlure, 1979) and the concept of 'urban stream syndrome' was devised to describe the set of changes associated to streams draining developed lands (Walsh et al., 2005). Streams in urbanized catchments are characterized by channel instability (Bledsoe and Watson, 2001), changes in the volume and duration of surface runoff (Weng, 2001), channel incision, loss of large wood and sediment load (Vietz et al., 2014). Furthermore, the increased input of pharmaceuticals (Veach and Bernot, 2011), change in the nutrient load (Carey et al., 2013; Marinoni et al., 2013) and nonpoint-source pollution (Hurd and Civco, 2004; Brabec et al., 2002), or the change in sediment respiration rate (Feio et al., 2010) and in the benthic macroinvertebrate communities (del Arco et al., 2012) can also be attributed to urbanization and imperviousness. In fact, urban riparian areas can lose the ability to act as nitrate sinks (Groffman et al., 2003) or even foster nitrification (Pickett et al., 2008).

Land development is thus tied to an intricate, complex web of stressors that are hard to replicate in a controlled setting and are specific to each water body (Feio et al., 2010).

Adding to the aforementioned effects of imperviousness, the urbanization of watersheds has been suggested to influence litter breakdown rates and species richness. This relation can be explained by the increased flow of watersheds with higher levels of imperviousness, which may promote the physical degradation of litter (Chadwick et al., 2006; Paul et al., 2006). In fact several papers address the impact of imperviousness over invertebrate and fish populations (e.g. Chadwick et al., 2006; Roy et al., 2003; Miltner and White, 2004; Klein, 1979), vegetation structure and health (White and Grier, 2006; Song et al., 2015), and bird populations, which are negatively associated to the presence of paved surfaces (McClure et al., 2015).

However, the impact of urbanization goes beyond the deterioration of water quality, and it is directly connected to a decrease in the distribution and fragmentation of natural vegetation. In turn, the new urban environment influences the thermal conditions, originating the Surface Urban Heat Island (SUHI) (Yuan and Bauer, 2007; Xian, 2008b) even in shrinking cities (Emmanuel and Krüger, 2012). The SUHI consists in the increase of the surface temperature, observed in urban areas and that is strongly connected to the type of development and materials used (e.g. asphalt, rooftops) (Stathopoulou and Cartalis, 2007). The SUHI is the result of an accumulation of a significant amount of thermal energy, which may, in turn, generate a "thermal runoff response" (Kim et al., 2008) adding thermal pollution to the plethora of aforementioned stressors.

Interestingly, and despite the increasing global urban population, wide swaths of Europe and North America are subject to widespread shrinkage phenomena (Panagopoulos and Barreira, 2013). In the case of Portugal, by 2060, the population is projected to fall to 8.6 million, from the current 10 million (INE, 2014). In parallel, and even prior to the country's population decline, changes at the city level led to the relocation of the inhabitants to peripheral communities. Portuguese municipalities tend to react to the decline through investment, especially when the decline is associated to the young population (Panagopoulos and Barreira, 2013), which means that urbanization may not decline on par with population, but instead accelerate. This means that over the long term, in Portugal and elsewhere, the existing (or growing) infrastructure will have to be supported by a smaller population. This is thus a moment of particular importance in Europe, where the development of integrated monitoring strategies dedicated to developed lands takes center stage.

This reality is in contrast with that presented by many previous studies, which often focused on megacities (Duh et al., 2008; Grimm et al., 2008; Kraas, 2007) or regions of accelerated growth (Davis and Schaub, 2005) that may not be representative of the regional or even national realities within parts of continental Europe.

In face of the increasingly complex and challenging scenario, cities and communities are struggling to improve environmental standards through the establishment of urban sustainability goals (Duh et al., 2008). Information, namely regarding the sealed or impervious surfaces that characterize urban environments, becomes central to the development of such planning and mitigation strategies (Bauer et al., 2008; Young et al., 2013). This context of extremes is motivating an increased awareness to the fact that data users need timely land cover products capable of offering an accurate depiction of the urban environment (Xian and Homer, 2010). The widespread use of remote sensing and Geographic Information Technologies (GIT) opened a new chapter in the characterization of land cover trends, watershed planning, and modeling (Tiner, 2004; Brabec et al., 2002).

Ridd (1995) first described the Vegetation-Impervious-Soil (V-I-S) model as a possible answer to quantitatively describe the urban morphology and therefore fulfill the emerging promise of accurate land cover mapping brought by multispectral satellite imagery. In recent years, and especially after 2000, a growing number of studies addressing the use of remote sensing of developed lands have been published although significant challenges persist (Weng, 2012).

Yang et al. (2003) describe the "anthropogenic impervious surface" as an indicator of the spatial extent and intensity of urban development. Rooftops, roads, sidewalks, and compacted soil constitute examples of impervious surfaces (Arnold and Gibbons, 1996), which are ecologically important because of their nature and arrangement (Schwarz, 2010). The Impervious Surface Area (ISA) – the impervious fraction within a pixel – can thus become the "self-consistent metric" enabling accurate comparative analysis of urban extents in transboundary regions (Xian, 2008a,b).

Categorical classification systems (e.g. Anderson et al., 1976) can at times create artificial dichotomies between natural and developed lands, ignoring the continuum best described by pragmatic metrics that can be used in interdisciplinary studies (Cadenasso et al., 2007; Arnold and Gibbons, 1996). ISA does not describe function but only the amount of artificialization, which can be the driving force behind stream degradation and nonpoint-source pollution (Slonecker et al., 2001) at thresholds as low as 10% (Arnold and Gibbons, 1996). Although several authors suggest this threshold as key for stream degradation, permanent changes can be detected earlier, depending on the geographic context and parameter in analysis (Vietz et al., 2014; Chin, 2006; Bledsoe and Watson 2001).

Previous studies addressed the problem of ISA mapping using different or adapted strategies, sometimes relying in significant generalizations (Esch et al., 2009). Data sources range from optical sensors, RADAR, and LiDAR and techniques include Regression Analysis (Sexton et al., 2013; Bauer et al., 2008; Hodgson et al., 2003), Classification and Regression Trees (CART) (Jiang et al., 2009), Spectral Mixture Analysis (Li et al., 2015; Zhang et al., 2014a,b,c; Wu, 2004; Yuan and Bauer, 2007), Hyperspectral data