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# Remote sensing of impervious surface growth: A framework for quantifying urban expansion and re-densification mechanisms

Amir Reza Shahtahmassebi[a,*], Jie Song[a], Qing Zheng[a], George Alan Blackburn[b], Ke Wang[a], Ling Yan Huang[a], Yi Pan[a], Nathan Moore[c], Golnaz Shahtahmassebi[d], Reza Sadrabadi Haghighi[e], Jing Song Deng[a]

[a] *Institute of Remote Sensing and Information System Application, Zhejiang University, Hangzhou 310058, China*
[b] *Lancaster Environment Centre, Lancaster University, Lancaster LA1 4YQ, UK*
[c] *Department of Geography, Michigan State University, East Lansing, MI 48823, USA*
[d] *School of Science & Technology, Nottingham Trent University, UK*
[e] *Department of Agronomy and Plant Breeding, Mashhad Branch, Islamic Azad University, Iran*

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ABSTRACT

A substantial body of literature has accumulated on the topic of using remotely sensed data to map impervious surfaces which are widely recognized as an important indicator of urbanization. However, the remote sensing of impervious surface growth has not been successfully addressed. This study proposes a new framework for deriving and summarizing urban expansion and re-densification using time series of impervious surface fractions (ISFs) derived from remotely sensed imagery. This approach integrates multiple endmember spectral mixture analysis (MESMA), analysis of regression residuals, spatial statistics (Getis_Ord) and urban growth theories; hence, the framework is abbreviated as MRGU. The performance of MRGU was compared with commonly used change detection techniques in order to evaluate the effectiveness of the approach. The results suggested that the ISF regression residuals were optimal for detecting impervious surface changes while Getis_Ord was effective for mapping hotspot regions in the regression residuals image. Moreover, the MRGU outputs agreed with the mechanisms proposed in several existing urban growth theories, but importantly the outputs enable the refinement of such models by explicitly accounting for the spatial distribution of both expansion and re-densification mechanisms. Based on Landsat data, the MRGU is somewhat restricted in its ability to measure re-densification in the urban core but this may be improved through the use of higher spatial resolution satellite imagery. The paper ends with an assessment of the present gaps in remote sensing of impervious surface growth and suggests some solutions. The application of impervious surface fractions in urban change detection is a stimulating new research idea which is driving future research with new models and algorithms.


## 1. Introduction

### 1.1. Background

Remote sensing of impervious surfaces has been the subject of research in urban remote sensing in recent years partly because it is an indicator of the degree of urbanization, and partly because it is a major indicator of environmental quality (Weng, 2012). Growth of impervious surfaces (e.g. via the construction of highways, industrial regions and residential areas) presents serious challenges in terms of the environment, climate, urban planning, population health and natural resources (Elvidge et al., 2007; Parece and Campbell, 2013). Timely and accurate information about the spatial distribution of impervious surface changes will, thus, be a key resource for dealing with such challenges and it needs to be applicable to the diversity of the world's urban areas.

Since the 1970s, airborne and satellite sensor imagery have been utilized for mapping impervious surfaces and its changes (Weng, 2012). The earlier techniques for impervious surface change detection from remotely sensed imagery were based on the comparison of spectral responses (e.g. image to image comparison or map to map comparison) (Yang and Liu, 2005; Lu et al.,2011). These techniques detect the conversion of previous lands into impervious

* Corresponding author.
*E-mail addresses:* amir511@zju.edu.cn, kwang@zju.edu.cn (A.R. Shahtahmassebi).

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**Table 1**
Synoptic of most important impervious surface change detection techniques.

(A) Hybrid techniques

| Categories | Change detection approach | Change detection task | Number of input ISF | Final result | Reference |
|---|---|---|---|---|---|
| 1. Hybrid technique | Visual interpretation and image subtraction | Monitoring spatio-temporal of impervious surface | Two images | Urban change maps at two dates | Yang et al. (2003), Yang and Liu (2005), Nowak and Greenfield (2012), Wilson and Brown (2015) |
| | Rule based technique along with Pixel by pixel comparison | Urban change detection | Two images | Change matrices; urban change maps at two dates | Alberti et al. (2004), Alberti et al. (2007) |
| | Change vector analysis(CVA) and post mapping analysis | Updating impervious surface map | Two images | A single updated map | Xian and Homer (2010) |
| | Geographic information system | Spatiotemporal | Three images | A single map | Ma et al. (2014) |

(B) Time Series

| Categories | Change detection approach | Change detection task | Number of input ISF | Final result | Reference |
|---|---|---|---|---|---|
| 2. Time series | Multi-date classification based on the temporal rule | Leveraging the temporal information from the 34 year Landsat | More than two images | A change difference map | Powell et al. (2008) |
| | Write memory function (RGB-impervious surface) | Urban change detection; reducing amount of data | Three images for per process | A single change map at three dates | Shahtahmassebi et al. (2012) |
| | Image comparison | Detecting exurban and quantifying change;produce a time series of consistent impervious surface maps; summarizing information | More than two images | Urban change maps(more than two) | Michishita et al. (2012), Sexton et al. (2013), Suarez-Rubio et al. (2012), Gao et al. (2012) |
| | Per pixel level comparison | Modeling urban growth | More than two images | Urban change maps; Simulation of urban growth | Jantz et al. (2003), Xian and Crane (2005), Shao and Liu (2014), Sunde et al. (2014) |

(C) Modeling

| Categories | Change detection approach | Change detection task | Number of input ISF | Final result | Reference |
|---|---|---|---|---|---|
| 3. Modeling | Conjunction of VIS model with Fuzzy technique | Measuring neighborhood effect; Quantifying magnitude of change | Two images | Map of magnitude change at two dates | Rashed et al. (2005), Rashed (2008) |
| | Vegetation-impervious surface-soil(VIS) model | Urban change detection; Proofing strength of VIS model | Two images | Ternary plots/urban change maps at two dates | Weng and Lu (2009), Lu et al. (2011), Phinn et al. (2002), Madhavan et al. (2001) |
| | Spatial variance, logistic function and classification | Characterizing morphology urban growth/urban metrics/spatial pattern of impervious surface | Two images | Urban change maps at two dates | Van de Voorde et al. (2011) |

(D) Spatial Metrics

| Categories | Change detection approach | Change detection task | Number of input ISF | Final result | Reference |
|---|---|---|---|---|---|
| 4. Spatial metrics | Developing metrics | Analyzing pattern of change | More than two images | Graph | Zhou et al. (2012), Kuang et al. (2013), Kuang et al. (2014), Wu and Thompson (2013), Nie et al. (2015a,b) |

surfaces at the pixel level, i.e. between-class changes. About two decades ago, researchers began to realize that such methods could not identify sub-pixel changes (i.e. within-class changes or re- densification) of impervious surfaces (Ridd, 1995). In addition, the presence of mixed pixels within urban landscapes can adversely affect the performance of traditional techniques (Wu et al., 2003). This is a common problem in images with medium spatial resolution imagery (e.g. Landsat ETM+)(Demarchi et al., 2012).

The existence of these two problems led to the development of a sub-pixel framework. This framework emphasizes that quantification should be employed for monitoring change in impervious surfaces in order to preserve heterogeneity of impervious surface land cover, characterize impervious surface land cover independent from analyst-imposed definitions, and more accurately capture change through time (Ridd, 1995; Mather, 1999; Weng and Lu, 2009). This framework can be broken down into two main stages. Firstly, sub- pixel approaches are used to estimate the proportion of impervious surface within each pixel (i.e. impervious surface fraction, ISF). Examples of sub-pixel techniques applied to remotely sensed imagery include regression (Yang and Liu, 2005), regression trees (Yang et al., 2003; Xian, 2007), neural networks (Sun et al., 2011), spectral mixture analysis (Wu and Murray, 2003) and multiple endmember spectral mixture analysis (MESMA) (Rashed et al., 2003). Reviews of these techniques have been given by Slonecker et al. (2001) and Weng (2012). Secondly, the outputs from the sub-pixel techniques (ISFs) are subjected to change detection analysis, which is focus of this paper.

In most cases, change-detection based on impervious surface fraction images is appropriate and informative since it measures between-class change, within-class change and degree of urban-