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A scale self-adapting segmentation approach and knowledge transfer for automatically updating land use/cover change databases using high spatial resolution images

Zhihua Wang[a,b], Xiaomei Yang[a,c,*], Chen Lu[a,b], Fengshuo Yang[a,b]

[a] State Key Laboratory of Resources and Environmental Information System, Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, 11A Datun Road, Chaoyang District, Beijing, 100101, China
[b] University of Chinese Academy of Sciences, Beijng, China
[c] Jiangsu Center for Collaborative Innovation in Geographical Information Resource Development and Application, Nanjing, China

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ABSTRACT

Automatic updating of land use/cover change (LUCC) databases using high spatial resolution images (HSRI) is important for environmental monitoring and policy making, especially for coastal areas that connect the land and coast and that tend to change frequently. Many object-based change detection methods are proposed, especially those combining historical LUCC with HSRI. However, the scale parameter(s) segmenting the serial temporal images, which directly determines the average object size, is hard to choose without experts' intervention. And the samples transferred from historical LUCC also need experts' intervention to avoid insufficient or wrong samples. With respect to the scale parameter(s) choosing, a Scale Self-Adapting Segmentation (SSAS) approach based on the exponential sampling of a scale parameter and location of the local maximum of a weighted local variance was proposed to determine the scale selection problem when segmenting images constrained by LUCC for detecting changes. With respect to the samples transferring, Knowledge Transfer (KT), a classifier trained on historical images with LUCC and applied in the classification of updated images, was also proposed. Comparison experiments were conducted in a coastal area of Zhujiang, China, using SPOT 5 images acquired in 2005 and 2010. The results reveal that (1) SSAS can segment images more effectively without intervention of experts. (2) KT can also reach the maximum accuracy of samples transfer without experts' intervention. Strategy SSAS + KT would be a good choice if the temporal historical image and LUCC match, and the historical image and updated image are obtained from the same resource.

1. Introduction

Land Use/Cover Change (LUCC) plays an important role in forest monitoring (Gomez et al., 2011; Van Lier et al., 2011), urban sprawl (Huang et al., 2017), and environmental evaluation (Kennedy et al., 2009; Gao and Liu 2010; Brink et al., 2014; Spiekermann et al., 2015). The timely updating of existing LUCC, such as the LUCC of coastal areas that connect the land and sea and that tend to change frequently (Chen et al., 2013), is critical for policy making (Zhang et al., 2014a,b). Remote sensing techniques, especially high spatial resolution satellite images (Blaschke et al., 2014; Cheng and Han 2016), are widely adopted for LUCC mapping because of their frequent broad coverage and low cost. Under the concept of Object-based Image Analysis (Hay and Castilla 2008; Blaschke et al., 2014), lots of object-based change detection (OBCD) methods have been proposed (Chen et al., 2012; Hussain et al., 2013; Tewkesbury et al., 2015).

However, the scale parameter(s) segmenting the images often needs experts' intervention. The scale parameter directly determines the average size of the segmented objects, thus greatly influences the following change detection accuracy (Tewkesbury et al., 2015). Currently, the simplest but still widely adopted solution for the selection of the scale parameter is qualitative visual selection (Aguirre et al., 2012; Laliberte et al., 2012; Vieira et al., 2012). Although this subjective visual selection can result in high accuracy, it requires high time and labor costs. Some studies also provided quantitative solutions using a supervised strategy that selected scale parameter(s) alongside shape and compactness parameters according to the similarity measurement between corresponding trial-and-error segmentations and reference

* Corresponding author at: State Key Laboratory of Resources and Environmental Information System, Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, 11A Datun Road, Chaoyang District, Beijing, 100101, China.
E-mail addresses: zhwang@lreis.ac.cn (Z. Wang), yangxm@lreis.ac.cn (X. Yang).

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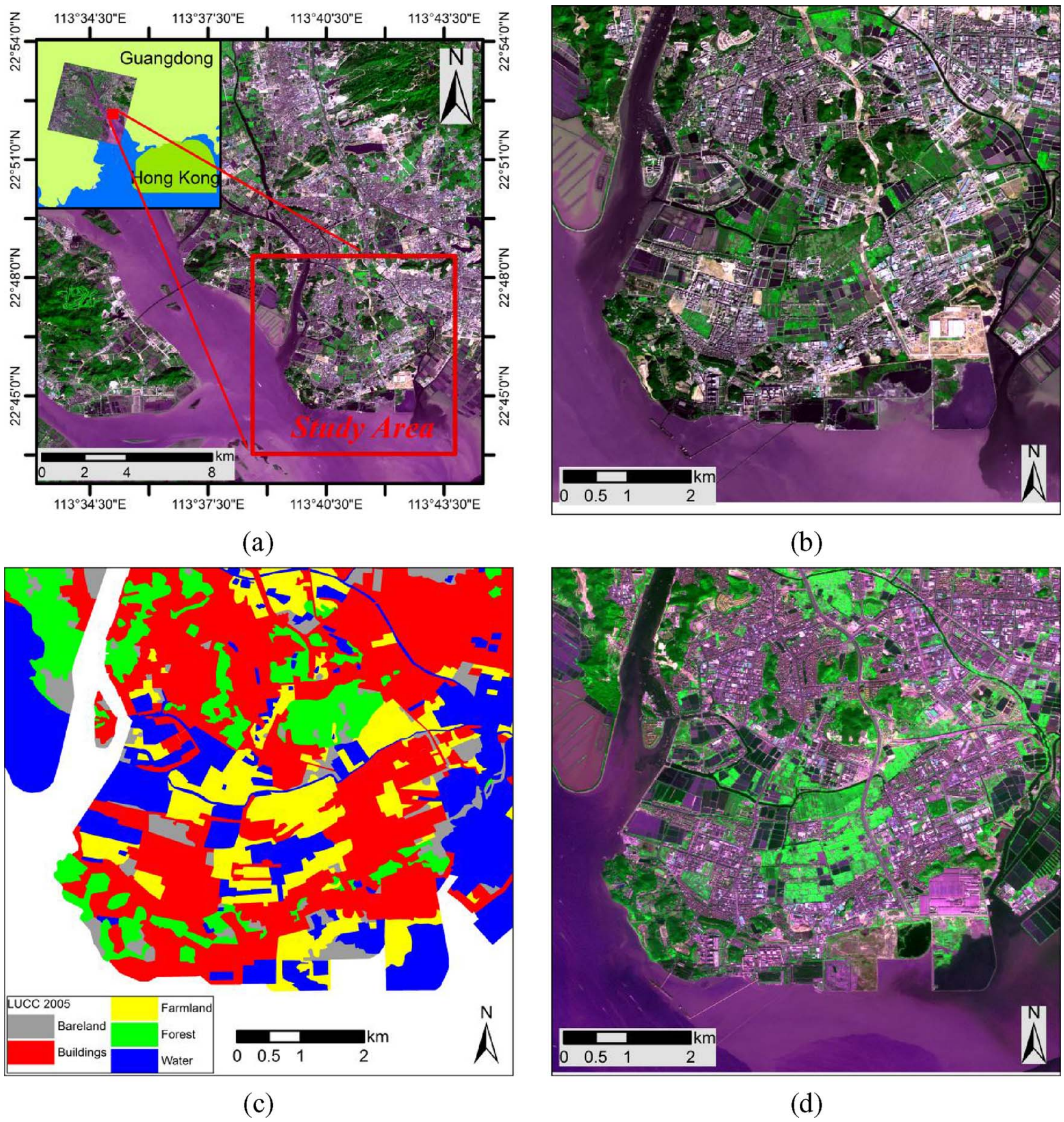

Fig. 1. Location and data of the experimental area: (a) shows the location of the experimental area; (b) is the SPOT 5 image from 2005; (c) is the corresponding LUCC interpreted based on the 2005 image; and (d) is the 2010 SPOT 5 image used for updating. (*Color should be used*).

segmentation (or reference data) (Smith and Morton 2010). The similarity measurement were based on area overlap (Carleer et al., 2005; Möller et al., 2007; Tian and Chen 2007; Clinton et al., 2010; Liu et al., 2012; Montaghi et al., 2013; Witharana and Civco 2014; Yang et al., 2015; Zhang et al., 2015a,b), border fitness (Lucieer and Stein 2002; Neubert et al., 2008), object location (Möller et al., 2007; Clinton et al., 2010; Montaghi et al., 2013), correctly matched object numbers (Carleer et al., 2005; Marpu et al., 2010; Liu et al., 2012; Witharana and Civco 2014), spectral discrepancy (Anders et al., 2011), or a combination of these (Clinton et al., 2010; Liu et al., 2012; Witharana and Civco 2014; Zhang et al., 2015a). However, the optimal scale parameter is not only one in most cases, even for a same kind of land cover, which makes the supervised strategy impractical in most cases (Drăguţ et al., 2014). There are also studies that provide solutions based on an unsupervised strategy that directly compares corresponding segmentations of sequential sampling scale parameters (Espindola et al., 2006; Drăguţ et al. 2010,2014; Yang et al., 2014; Ming et al., 2015; Liu et al., 2017). Most of them rely on metrics considering intra-object homogeneity and inter-object heterogeneity based on the properties of a good segmentation, proposed by Levine and Nazif (1985) and Haralick and Shapiro (1985). Although three scale parameters can be selected using Estimate Scale Parameters (ESP) proposed by Drăguţ et al. (2014), ESP still depends on the human parameter set, such as the increment of the sampling scale parameter. More than this, scale selection using methods such as ESP is aimless, which means we do not know which scale is suitable for a specific land cover. So method that could adapt the scale parameter according to the image content is urgent (Tewkesbury et al., 2015; Wang et al., 2018).

Another important and often the most costly prerequisite of applying machine learning algorithms to recognize the specific change type is the collection of samples for training. Obviously, the historical LUCC can help in this regard (Walter 2004; Wasige et al., 2013; Lark et al., 2017). The sample transfer strategy is the most widely used, where part or whole labels of LUCC are assigned to the new images when training classifiers. If changes are seldom, samples by the whole transfer can also be used to train a set of fine classifying rules because of the generality of machine leaning algorithms, such as the application of a frequent update (Walter 2004). However, if too many areas are changed, this strategy would be ineffective. To avoid wrong samples, part transfer strategy can be used, where binary change detection