Synergy of Satellite Image and Volunteered Geographic Information to Change Analysis of Impervious Surface

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***Abstract*—China is experiencing a rapid urbanization process and impervious surface is an important indicator to urban sprawl and its related economic and environmental issues. Multi-temporal remote sensing, with the auxiliary of change detection methods, provides an efficient, consistent and economical means to monitor the impervious surface change. Traditional change detection methods require prior information to produce the change of impervious surface change, which is time consuming and labor cost. To tackle this issue, this paper presents an integrated approach to detect impervious surface change using satellite image (i.e., Landsat 8) and volunteered geographic information (i.e., Open Street Map). The presented approach was applied to map the impervious surface change in the city of Hefei, China. The results show that the presented approach was able to produce a satisfactory compared to supervised classification methods. The presented approach sheds new light to automatically map and estimate impervious surface change in a reliable and efficient way.**

***Index Terms*—Volunteered geographic information, satellite image, impervious surface, change detection**

I. Introduction

China has experienced explosive urban growth over the last 40 years [1], [2]. With the urbanization process, the natural landscape is replaced by impervious surfaces (ISs), such as buildings, parking lots and roads. As a key component of urban landform, impervious surface is not only an important indicator of the urbanization degree, but also a key urban ecological environment sensitive factor, which is the basic geographic information data for urban research [3]- [5]. It therefore follows that impervious surface distribution and change information is critical for a wide range of studies, such as urban flooding, urban ecosystem, and urban heat island.

Remote sensing, with the auxiliary of change detection methods, provides an efficient, consistent and economical means to monitor the IS spatial distribution and temporally change information. Research on impervious surface extraction from remotely sensed data has attracted interest since the 1970s [6]- [8]. Many methods have been developed for mapping impervious surfaces with different spatial resolution images (e.g., vegetation-impervious surface-soil (V-I-S) model [9], stratified spectral mixture analysis [10], combinational build-up index [11]). Once the impervious surface is extracted from satellite images, change detection methods are subsequently applied to extract IS change information. Existing change detection methods can be grouped into two main categories: 1) unsupervised change detection [12]- [14], and 2) supervised change detection [15]- [17]. Compared to unsupervised change detection, supervised change detection can provide explicit labelling of change and class transitions. However, supervised change detection methods require sufficient and timely in-situ data, which is time consuming and labor costive when the study area is at regional/global level. Therefore, to balance the efficiency and accuracy, a novel IS change detection method is required.

In recent years, volunteered geographic information (VGI) has received increasing attention in field of remote sensing. For instance, The work by Cervone et al. [23] suggests that social media can be used for tasking satellite image collection for damage assessment. This method is developed and tested on the 2013 Colorado floods and well demonstrates its practicability. Similarly, researchers in Japan find that a sudden increase in social media could be used to monitor quake striking in real-time [24], [25] and provide earthquake early warning.

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Hou et al. [26] have exploited web crawler to collect geo-location data from real estate websites to validate classification accuracy of GlobeLand30. Their study tested the feasibility of using geo-location data collected from Internet to identify land uses. Along similar research lines, the works in [27]- [30] have examined the relationship between land use classes and geo-tagged information that one can extract from social media data. Yue et al. [31] contends that the integration of scientific and social media data can support timely decision. They find that the haze-related event detection from social media is comparable to that from satellite image (i.e., MODIS). Although massive data from VGI are often published without scientific intent, often carry little scientific merit, and the use of VGI tools is not uniformly distributed across the world [32], they provide a source of useful information that may help to avoid, for instance, long and expensive in situ data collection for remote sensing image classification [33]. However, the synergic study of VGI and satellite image is only in its infancy and further research is deserved.

Based on aforementioned analysis, the objective of this paper is to explore an automatic training sample generation strategy to map, estimate and analysis the change information of impervious surface from satellite images. The remainder of this paper is organized as follows. Section II introduces the presented approach. The experimental results are given in Section III while Section IV concludes the paper.

II. An approach to map impervious surface change jointly exploiting Landsat and VGI

A. *A strategy of generating training samples*

This paper selects Open Street Map (OSM) as the only source of volunteered geographic information (VGI). The OSM was firstly converted to the same coordinate system of satellite image, followed by co-registered to satellite image. After that, OSM was converted to a raster image with the same spatial resolution of satellite image. The rasterized OSM was then overlaid with satellite image and pixel that contains an OSM point is taken as the training sample of impervious surface class. Although simply linking OSM and satellite images seems to be simple, there is no pre-processing or post-processing steps required and the computation efficiency is high.

Prior to further processing, it is worth noting that training samples derived from the aforementioned strategy present label noise. Existing research suggests that label noise adversely influence the classifier performance. To tackle this issue, this study presents a strategy of weighting training samples, including impervious surface percentage and intra-class concentration.

To compute impervious surface percentage of a pixel, we first rasterize OSM into an image $\mathcal{I}$ with a spatial resolution of 1m. For a 30m Landsat pixel, it would cover an area of 30 pixels by 30 pixels (i.e., totally 900 pixels) on an image

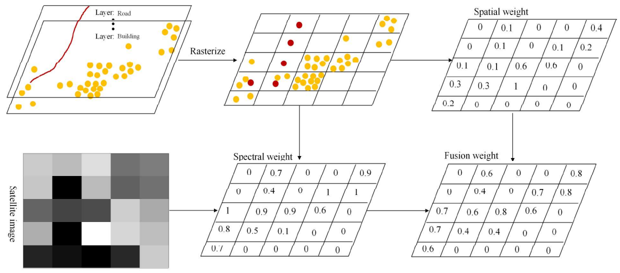

Fig. 1. The computation of weight of training sample derived from VGI automatically.

with a spatial resolution of 1m. Thus, the impervious surface percentage PF of i-th training sample is defined as:

$$PF_i = \frac{T_i}{900}, \;\; i = 1, \dots, L \tag{1}$$

where T_i is the total number of impervious pixels in an area of $\mathcal{I}$ that is equivalent to i-th 30m Landsat image pixel.

The intra-class concentration (ICC) of the i-th training sample can be measured by:

$$ICC_i = (\boldsymbol{x} - \hat{\boldsymbol{\mu}})^T \hat{\boldsymbol{\Sigma}}^{-1} (\boldsymbol{x} - \hat{\boldsymbol{\mu}}) \tag{2}$$

where $\hat{\boldsymbol{\mu}}$ and $\hat{\boldsymbol{\Sigma}}$ are the sample mean and the sample covariance matrix, respectively. The small value of ICC_i means the i-th training sample has a high probability to be located in urban area.

By fully consideration of impervious surface percentage and intra-class concentration, the weight w_i for the i-th training sample is defined as:

$$w_i = \frac{e^{PF_i}}{ICC_i} \tag{3}$$

Fig. 1 illustrates steps of computing training sample weight.

B. *Impervious Surface Probability Computation*

This study introduces one class classifier to classify Landat images to measure impervious surface probability. It should be noted that only training samples of impervious surface class is derived from OSM and the negative examples (i.e., pervious surface class) are absent during training. To tackle this issue, this study exploits one class support vector machine (OCSVM) to complete classification task. OCSVM presentd by Schölkopf et al. [37] may be taken as a special case of the standard two-class SVM where all training samples are from the positive class. In contrast with the standard SVM that finds an optimal boundary separating two classes, the OCSVM fits a hyper-sphere with minimum volume that contains the maximum number of training samples of a single class [38]. The distance of any additional sample to the sphere can be interpreted as a similarity score, and provide a measure about whether that sample belongs to the considered class or not. The OCSVM therefore solves a constrained convex optimization problem [39]:

$$\underset{R,\mathbf{a},\xi_1,\ldots,\xi_l}{\arg\min}\ R^2 + C\sum_{i=1}^{l} w_i\xi_i \tag{4}$$

subject to $\|\mathbf{x}_i - \mathbf{a}\|^2 \leq R^2 + \xi_i$, and $\xi_i \geq 0, i = 1, \ldots, l$. Here, $\mathbf{a}$ and R are the center and radius of the hyper-sphere, respectively; ξ_i are slack variables, C is a trade-off parameter controlling how much the slack variables are penalized, and w_i is the weight of the $i-$th training sample. The dual form of Eq. 4 is:

$$\min_{\alpha_1,\ldots,\alpha_l} \sum_{i=1}^{l} \alpha_i K\langle \boldsymbol{x_i}, \boldsymbol{x_j}\rangle - \sum_{i=1}^{l}\sum_{j=1}^{l} \alpha_i\alpha_j K\langle \boldsymbol{x_i}, \boldsymbol{x_j}\rangle \tag{5}$$

subject to $0 \leq \alpha_i \leq w_i C, i = 1, \ldots, l$, and $\sum_{i=1}^{l} \alpha_i = 1$. Here, $K\langle \boldsymbol{x_i}, \boldsymbol{x_j}\rangle$ is the kernel function and this paper uses a Gaussian radial basis function (RBF) kernel. We adopt a five-fold cross-validation to tune the best parameters.

Once WOCSVM was conducted on satellite images over two time periods, the impervious surface probability change f is computed by:

$$f = p_1^{\mathrm{IS}} - p_2^{\mathrm{IS}} \tag{6}$$

where p_1^{IS} and p_2^{IS} are two impervious surface probability maps derived from WOCSVM.

III. Experimental Results

The study area is located in Hefei, the capital of Anhui province, China. Like many cities of China, Hefei has witnessed a prolonged period of rapid urban growth. Two Landsat 8 OLI images taken in March 14, 2014 and January 23, 2019 with relatively small cloud coverage (less than 5% of the whole scene) were collected. The building layers of OSM were overlaid with Landsat images, see Figs. 2(a) and 2(b). It can be seen that the building amount of 2014 is limited as OSM was just released at that year. Typical land covers in the study area include farm land, water, forest, bare soil, and low to high density developed lands. The cloud and cloud shadow areas were manually digitized to create a cloud mask. All pixels within the cloud mask will be taken as no change. Two Landsat images were pre-processed, including data calibration and co-registration.

Figs. 2(c) and 2(d) show the probability maps of impervious surface derived from WOCSVM of 2014 and 2019 in Hefei, respectively. To evaluate WOCSVM classification performance, we compare it with the impervious surface probability map produced by supervised SVM classification. To this end, we randomly selected 100 pixels for each land cover class and totally 500 pixels were generated. SVM model was trained on these 500 sample pixels and the corresponding impervious surface probability maps are shown in Figs. 2(e) and 2(f).

Figs. 2(g) and 2(h) report the agreement between two impervious surface probability maps derived from unsupervised WOCSVM and supervised SVM. Agreement between impervious surface probability maps derived from automatic

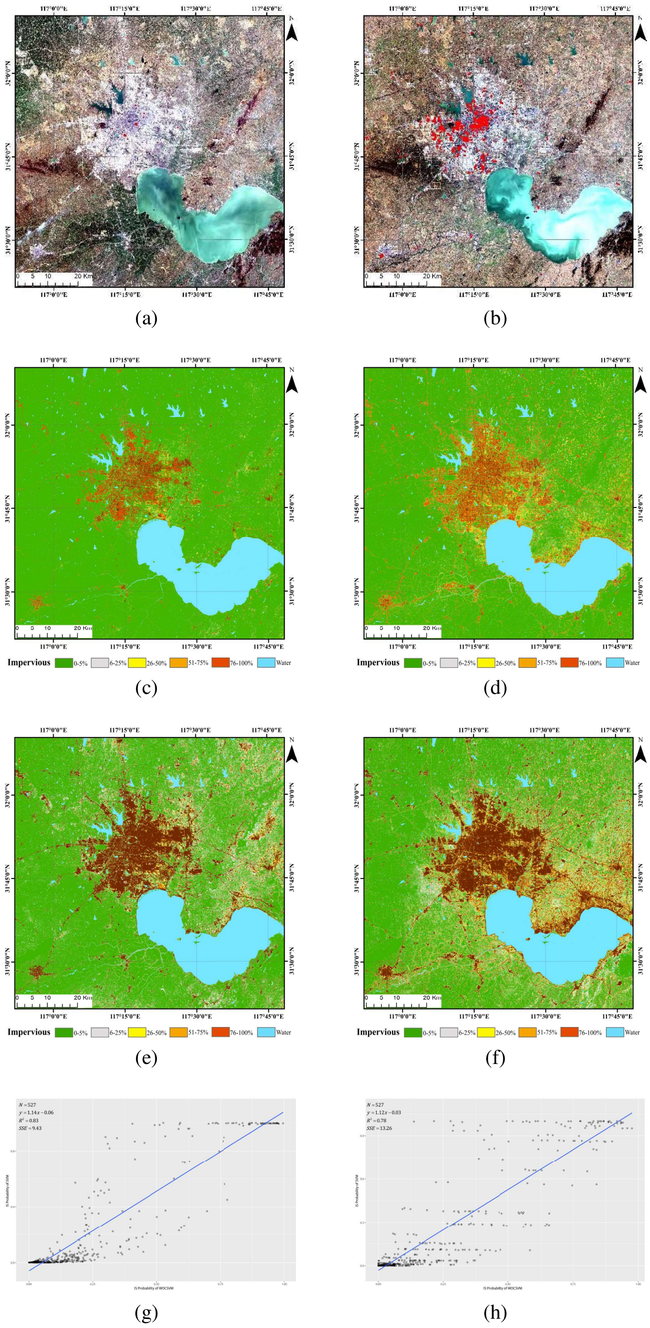

Fig. 2. (a) and (b) show the overlay images of Landsat image and building layers of OSM of Hefei for 2014 and 2019, respectively. The building layer is shown in red. (c) and (d) show the probability maps of impervious surface of Hefei for 2014 and 2019, respectively. The impervious surface probability images for two periods are shown in (e) and (f), respectively. (g) and (h) report the agreement between two impervious surface probability maps derived from unsupervised WOCSVM and supervised SVM.

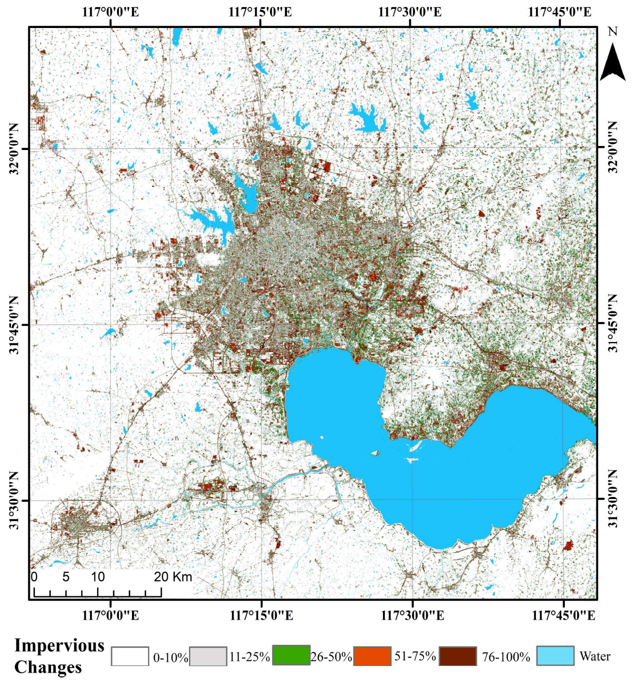

Fig. 3. The change map of impervious surface probability values of Hefei for 2014 and 2019.

WOCSVM and supervised SVM was very high for both two time periods with R^2 values ranging from 0.78-0.83 and with sum of squared errors (SSE) of 9.43 to 13.26. This suggests that WOCSVM based on OSM is capable to produce a comparable performance to traditional supervised classification method.

Fig. 3 presents the change image of impervious surface probability maps over two time periods for Hefei. It can be seen that Hefei city is experiencing significant growth. The impervious surface change of Hefei is spatially distributed on both directions, suggesting the urban sprawl has a radial pattern. Meanwhile, a large amount of impervious surface change is occurring near to the lake and reservoir, posing a significant influence on water quality.

IV. Conclusions

This paper proposes a novel method for change detection of impervious surface by jointly use of satellite images and volunteered geographic information. The findings show that VGI is capable to automatically generate training samples to train classifier to produce the impervious surface (IS) probability map from satellite image (i.e., Landsat 8 used in this study). A strong relationship of the impervious surface probability maps derived from the present approach and traditional supervised classification was identified. Therefore, the proposed approach is capable to produce satisfactory impervious surface change detection performance, making it a suitable method to monitor the IS change at the large scale.

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