A Novel Semi-Supervised Method for Obtaining Finer Resolution Urban Extents Exploiting Coarser Resolution Maps

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***Abstract*—In this work, we present a new semi-supervised strategy for obtaining finer spatial resolution urban maps from coarser resolution satellite data. Our method first uses a coarse resolution map as a source of training data. Then, we use semi-supervised learning in order to refine the set of initial (labeled) training samples by the inclusion of additional (reliable) unlabeled samples at the finer resolution level, in fully automatic fashion. The new unlabeled samples are automatically generated by our proposed methodology, which only requires a limited number of initial labeled samples for initialization purposes. Then, we conduct land cover classification (at the finer spatial resolution level) using a probabilistic multinomial logistic regression (MLR) classifier—in both supervised and semi-supervised fashion—by considering different numbers of labeled and unlabeled samples. In order to exploit spatial information, we use a Markov random field (MRF)-based postprocessing strategy to refine the obtained classification results. In order to test our concept, we use a global dataset: the European Space Agency's GlobCover product, as the coarser resolution map (300-m spatial resolution). Our experimental evaluation is further conducted using Landsat data (30-m spatial resolution) collected over three different locations in the city of Sao Paulo, Brazil, and over two different locations in the city of Guangzhou, China. We obtain promising results in the generation of finer resolution urban extent maps using very limited training samples, derived in all cases from the GlobCover product. These experiments suggest the potential of GlobCover to provide reliable training data in order to support mapping of urban areas at a global scale.**

***Index Terms*—GlobCover product, Landsat data, Markov random fields (MRFs), multinomial logistic regression (MLR), semi-supervised learning, urban area mapping.**

I. Introduction

LAND COVER classification has been a very active area of research in remote sensing [1], [2]. Given a set of observations (e.g., pixel vectors in a multispectral image), the goal of land cover classification is to assign a unique label to each pixel so that it is well defined by a given land cover class [3]. Although techniques for unsupervised classification and/or clustering have been used for this purpose [4], supervised classification has been generally more successful [5], [6], including the development of methods able to work at a global scale [7], [8]. At the same time, supervised classification faces challenges related with the limited availability of labeled training samples in practice [9]. In order to address this issue, semi-supervised [10] and active [11]–[13] learning techniques have been developed in order to exploit the information carried out by additional (unlabeled) samples, which can be generated in order to complement the available labeled samples with a certain degree of confidence.

Several techniques have been used to perform supervised land cover classification [14]. The main problem of these supervised classifiers, however, is their sensitivity to the limited availability of training samples. Other classifiers have been developed to perform under limited training samples. Examples include kernel methods, such as the support vector machine (SVM) [15]–[17], or probabilistic classifiers, such as the multinomial logistic regression (MLR) [18], [19]. The MLR has been recently explored in remote sensing applications [20] as a technique able to model the posterior class distributions in a Bayesian framework, thus supplying (in addition to the boundaries between the classes) a degree of plausibility for such classes [21].

As mentioned before, a relevant challenge for supervised classification techniques is the limited availability of labeled training samples, since their collection generally involves expensive ground campaigns [22]. While the collection of labeled samples is generally difficult, expensive, and time-consuming, unlabeled samples can be generated in a much easier way [23]. This observation has fostered the idea of using both labeled and unlabeled samples for land cover mapping of large geographic areas [24]. In particular, semi-supervised techniques have been shown to be quite effective for the characterization of urban areas [25], [26]. The main assumption of such techniques is that the new (unlabeled) training samples can be obtained from a (limited) set of available labeled samples. In order for this strategy to work, several requirements need to be met. First and foremost, the new (unlabeled) samples should be obtained without significant cost/effort [22]. Second, the number of unlabeled samples required in order for the semi-supervised classifier to perform properly should not

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be too high [27]. Third, unlabeled samples should be reliable in order to avoid confusing the classifier, as they are generally derived from a limited set of initial labeled samples [28]. This is directly related with the quality of the labeled samples, which may directly influence the subsequently derived unlabeled samples.

Despite the success achieved by supervised and semi-supervised learning techniques in the task of land cover classification, it is now commonly accepted that using the spectral information alone may not be sufficient (in particular, if very limited training samples are available). For this purpose, including spatial and spectral information simultaneously can provide significant advantages in terms of improving the performance of classification techniques [5]. As a result, there is a clear need to integrate the spatial and spectral information to take advantage of the complementarities that both sources of information can provide [29]. Markov random fields (MRFs) [30], [31] have been a successful approach to jointly exploit spatial and spectral information in remote sensing applications. MRFs exploit the continuity, in probability sense, of neighboring labels [32]. In this regard, several techniques have introduced an MRF-based prior which encourages neighboring pixels to have the same label when performing land cover classification of remotely sensed datasets [33], [34].

Among land cover classification problems, urban extent mapping represents one of the most pressing challenges for generating global maps, as urban extents define areas affected by mankind, where population lives, and the most exposed places to risks and hazards. Currently, there are many ongoing activities funded by the European Space Agency, Google, and World Bank, among others, to extract human settlement extents at the global level. Urban extents also attract great attention from a research viewpoint. In [35]–[37], global urban extent maps were produced from MODIS data. In [38], robust extraction of urban extents for high resolution (HR) and very high resolution (VHR) images is performed. In [39], a fast and efficient method using synthetic aperture radar (SAR) data in wide swath mode is proposed to extract urban extents. In [40], PanTex [41] is considered in global scale for automatic recognition of human settlements. All these activities and works have shown that urban extents in a global script are very important. However, except the PanTeX [41] (which has no global validation) there are currently no methods working on HR or VHR images for extraction of urban extents.

Inspired by some of the aforementioned developments, in this work, we present a new strategy for obtaining finer spatial resolution urban maps from coarser resolution satellite data. Here, we aim at exploiting the available coarser classification to obtain a finer mapping of urban extents, with the ultimate goal of achieving an automatic framework to perform urban mapping on HR or VHR datasets from coarser classification maps in a global script, as Landsat covers most locations worldwide. To achieve this goal, it has been shown that supervised spectral classification is needed [35]–[37]. However, supervised classification of Landsat data for urban areas requires a highly specialized training set, which is heavily dependent on the geographical area of interest. An alternative solution is to use coarser classification maps to obtain a first (and inevitably highly approximated) training set followed by a semi-supervised methodology, so as to overcome the issue of manually labeling training sets in many different parts of the world. Concerning the coarser classification map and the HR or VHR datasets, we specifically use MEdium Resolution Imaging Spectrometer (MERIS)[1] and Landsat images which, respectively, refer to the coarser and finer datasets. Our reason for resorting to these specific datasets is two-fold. First and foremost, MERIS and Landsat provide global coverage of the world and are available for free, which is also the reason why all currently available global mapping projects use these data. Here, we use Landsat as our finer resolution data for extraction of urban extents as, for most regional or national (even subnational) analyses and models, a spatial resolution of 30 m (for the whole globe) is much finer than what available models can generally manage. A second reason is that, as we perform urban classification in a global script, a global classification map is important for generating the initial labeled training set. Since existing global urban maps have (at most) 300-m spatial resolution, the use of VHR data such as SPOT and IKONOS bring challenges since, on the one hand, they currently have no global coverage and, on the other hand, we need a significant change in the spatial scale, which makes the pixel selection in the finer dataset unfeasible. With Landsat and MERIS, the spatial scale factor is 10, which is quite affordable from the viewpoint of model complexity.

This work presents a new semi-supervised learning methodology, which consists of several steps. Our method first uses a coarse resolution map (e.g., a global product) as a source of training data. Then, we use semi-supervised learning in order to refine the set of initial (labeled) training samples obtained from the coarser resolution data by the inclusion of additional (reliable) unlabeled samples at the finer resolution level, in fully automatic fashion. That is, after obtaining an initial labeled training set from the coarser classification map, we iteratively include unlabeled samples for training. Due to the difference between the coarser classification map and the finer dataset and the limitations of the sampling approach for selecting labeled samples, the generalization of the initial labeled training set from the coarser map might be poor. Therefore, we use a self-learning procedure to actively select unlabeled samples from the classification results of the finer image, which are shown to be effective in our previous studies [28]. Here, we use the MLR classifier (in both supervised and semi-supervised fashion) by considering small training sets generated from the coarser resolution product, and further exploit spatial information by using an MRF-based postprocessing strategy to refine the classification results obtained by expanding the initial training set, using automatically derived unlabeled samples. We have selected the MLR classifier due to the following reasons.

1) First and foremost, MLR classifiers are able to learn directly the posterior class distributions and deal with ill-posed classification scenarios in a very effective way [19].
2) Second, the MLR used in this work adopts a sparsity-inducing prior on the estimated regressors in order to

[1] [Online]. Available: https://earth.esa.int/web/guest/missions/esa-operational-eo-missions/envisat/instruments/meris

obtain sparse estimates. This allows us to control the complexity of our proposed technique and its generalization capacity, which is important when dealing with very limited training sets.

3) Finally, the MLR provides a class posterior probability, which plays a crucial role when including the MRF spatial regularizer. As shown in previous studies, MRF-based spatial regularization is particularly appropriate when combined with a probabilistic classifier [42]–[44].

An important remaining remark is that, in this work, we choose MRF as our spatial regularizer since it can be easily combined with a probabilistic classifier in the proposed framework. Some other types of spatial features, such as morphological profiles, are more difficult to be integrated in the proposed framework in automatic fashion, despite the fact that they have been shown to be very effective for remote sensing classification in previous works [45].

Another important remaining aspect at this point, bearing in mind that this work focuses on urban area mapping, is the definition of "urban areas" adopted in this work. Here, we adopt the definition provided by one of the reference coarse datasets (in this case, the GlobCover[2] product that we use as a starting point and the dataset from which training points are selected). To be more precise, according to the GlobCover definition, the "urban class" is defined as "artificial surfaces and associated areas." Hence, the classification at the finer spatial resolution that we obtain follows the same definition provided by GlobCover. Should a different dataset (e.g., MODIS 500 m) be used, then the obtained results would follow the definition included in that dataset for the "urban class." In this sense, the procedure we developed is quite flexible. A final remark is that, to our best knowledge, this is the first work automatically generating finer urban extents from coarser classification maps which can be used in a global script.

The remainder of the paper is organized as follows. Section II presents the newly proposed methodology to obtain finer resolution urban extent maps from coarser resolution satellite data. Section III presents an experimental evaluation of the proposed approach using a global product as the coarser resolution dataset, and Landsat data (which represent the finer spatial resolution data considered in this work) collected over three different locations in the city of Sao Paulo, Brazil, and over two different locations in the city of Guangzhou, China. In our experiments, we specifically address the problem of how to effectively generate urban maps at finer spatial resolution than the one available in the global product. These experiments suggest the potential of the proposed method to support global urban mapping activities at finer spatial resolution levels. Section IV concludes the paper with some remarks and hints at plausible future research lines.

II. Proposed Methodology

Before introducing the proposed methodology, we emphasize that using supervised classifiers on Landsat data for urban areas requires a highly specialized training set, which is heavily dependent on the geographical area of interest. Therefore, an alternative solution to supervised classification of Landsat data is using coarser classification maps to obtain a first (and inevitably highly approximated) training set followed by a semi-supervised methodology, which is an efficient and effective way to overcome the issue of manually labeling training sets in many different parts of the world. Therefore, the proposed method aims at exploiting the prior information in the coarse classification maps for finer resolution image mapping, which consists of four main steps: 1) initial training sample generation from the coarser resolution data; 2) semi-supervised learning; 3) generation of unlabeled samples; and 4) MRF-based postprocessing. In the following, we describe these individual aspects that integrate the proposed framework.

A. Initial Training Sample Generation

We first illustrate the procedure for obtaining a set of initial labeled samples from the coarser resolution data. As shown by Fig. 1, let us assume that the spatial resolution of the finer resolution data available is 30 m/pixel, while the spatial resolution of the coarser resolution data available is 300 m/pixel. As a result, each label in the coarser resolution data corresponds to a 10×10 pixel area in the finer resolution data. In our proposed approach, we select the center pixel of the 10×10 area (corresponding to a pixel in the coarser resolution data) and use the same label, as illustrated in Fig. 1 for four different pixels with colors: 1) cyan; 2) red; 3) green; and 4) yellow. It should be noted that this is just a simple strategy but we empirically find out that this sampling approach leads to good performance. Another important reason is that the proposed sampling approach is easy to be implemented in automatic fashion, which brings good advantages from the viewpoint of global urban mapping. However, other sampling approaches such as random sampling or probabilistic approaches (able to obtain confident classification labels from the coarser resolution data) can be adopted in future developments to promote better initialization.

Once the initial labeled samples have been extracted, the unlabeled samples are derived from the finer resolution data. As a result, the coarser resolution data is used to provide an initial labeled sample selection, which is later refined by the generation of unlabeled samples in semi-supervised fashion, as it will be explained in Section II-C. It should be noted that, in our framework, the initial (labeled) training samples are randomly selected from the coarser resolution data, with approximately the same number of labeled samples per class. Furthermore, we only select samples which are not in the boundaries of classes of the coarser resolution data, in order to have higher confidence of the initial class label selection. This is because, as shown in Fig. 1, the spatial resolution of the coarser and finer spatial resolution data may be quite different. In fact, the samples away from the boundary can lead to high confidence of the initial labeled training samples.

At this point, it is important to note that there may be significant time lags between the coarser classification map (as the coarser product shown in Fig. 1) and the finer resolution images, i.e., the Landsat data. Therefore, the generalization of

[2][Online]. Available: http://due.esrin.esa.int/globcover

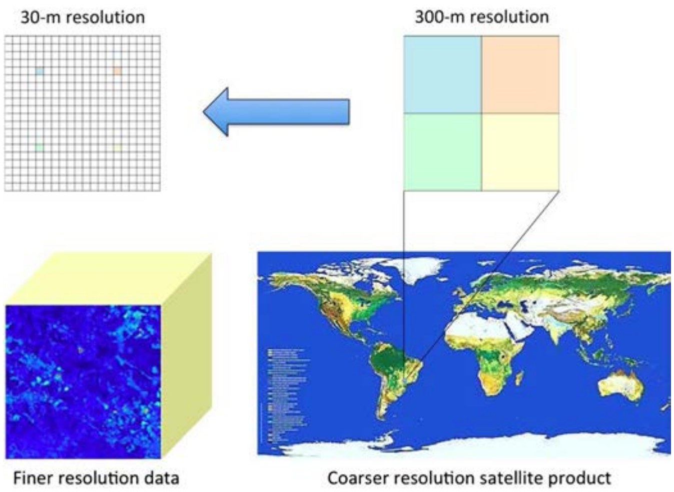

Fig. 1. Procedure for obtaining a set of training samples for the finer resolution data from a coarser resolution satellite data.

the initial training set might be poor for supervised classification. In order to refine the supervised classification performance, we propose to integrate the labeled samples from the coarser map and unlabeled samples obtained from the finer resolution data, to perform semi-supervised learning for accurate urban mapping. Nevertheless, we emphasize that, in this study, we consider problems in which both datasets are collected in the same year. Since urban area extents, according to all studies, can be conveniently studied on a yearly basis, we believe that we are within the boundaries of a sound and effective comparison.

B. Semi-Supervised Learning

Let $\mathbf{x} \equiv (\mathbf{x}_1, \ldots, \mathbf{x}_n) \in \mathbb{R}^{d\times n}$ be the finer resolution image, where d is the number of bands and n is the number of pixels; and let $\mathbf{y} \equiv (y_1, \ldots, y_n)$ be an image of class labels. In our approach, we use the MLR probabilistic classifier to model the class posterior density, for a given pixel $\mathbf{x}_i$, which is formally given by [18]

$$p(y_i = k|\mathbf{x}_i) = \frac{\exp(\boldsymbol{\omega}^{(k)^T}\mathbf{h}(\mathbf{x}_i))}{\sum_{k=1}^{K}\exp(\boldsymbol{\omega}^{(k)T}\mathbf{h}(\mathbf{x}_i))} \tag{1}$$

where K is the number of classes in $\mathbf{y}$; $\mathbf{h}(\mathbf{x}_i) = [h_1(\mathbf{x}_i), \ldots, h_l(\mathbf{x}_i)]^T$ is a vector of l fixed functions of the observation $\mathbf{x}_i$, often termed features; and $\boldsymbol{\omega} = [\boldsymbol{\omega}^{(1)^T}, \ldots, \boldsymbol{\omega}^{(K)^T}]^T$ are the regressors. Notice that the function $\mathbf{h}$ may be linear, i.e., $\mathbf{h}(\mathbf{x}_i) = [1, x_{i,1}, \ldots, x_{i,d}]^T$, where $x_{i,j}$ is the jth component of $\mathbf{x}_i$; or nonlinear, i.e., $\mathbf{h}(\mathbf{x}_i) = [1, K_{\mathbf{x}_i,\mathbf{x}_1}, \ldots, K_{\mathbf{x}_i,\mathbf{x}_l}]^T$, where $K_{\mathbf{x}_i,\mathbf{x}_j} = K(\mathbf{x}_i, \mathbf{x}_j)$ and $K(\cdot,\cdot)$ is some symmetric kernel function.

Kernels have been largely used because they tend to improve the data separability in the transformed space. In this work, we use a Gaussian radial basis function (RBF) $K(\mathbf{x}_i, \mathbf{x}_j) = \exp(-\|\mathbf{x}_i - \mathbf{x}_j\|^2/2\sigma^2)$ kernel (σ is a tunable parameter), which has been widely used in remote sensing applications [16]. We selected this kernel (after extensive experimentation using other kernels, including linear and polynomial kernels) because we empirically observed that it provided very good results in our context.

In order to learn the class densities, which amounts to estimating the logistic regressors $\boldsymbol{\omega}$, several strategies have been proposed in the literature. The sparse MLR in [19] introduces a Laplacian prior to control the sparsity of the regressors. In [46], Borges *et al.* proposed a fast SMLR (FSMLR) for the same purpose. However, most remote sensing datasets are beyond the reach of these algorithms, as their processing time becomes unbearable when the dimensionality of the input features increases. In order to address this issue, we take advantage of the logistic regression via variable splitting and augmented Lagrangian (LORSAL) algorithm in [47], which is able to manage large data volumes and training sets [21], [48]. This is important in our context, as the initial set of labeled samples is complemented by the generation of new unlabeled samples, using the procedure that is described in Section II-C.

C. Generation of Unlabeled Samples

Our proposed approach is based on the generation of unlabeled samples in the finer resolution data from a set of initial labeled training samples obtained from the coarser resolution data. In fact, the considered semi-supervised approach belongs to the family of self-learning approaches, where the initial labeled training set is incremented under the methodology described in [28], where we studied active learning for effective automatic selection of unlabeled samples, which aims at finding the most informative unlabeled samples for training purposes. The study in [28] concluded that semi-supervised active earning can bring great advantages for classification. Therefore, in this work, we follow the strategy presented in [28] to actively generate the unlabeled training samples in semi-supervised self-learning fashion. In the following, we revisit the aforementioned semi-supervised self-learning framework.

Let $(\widehat{y}_i, \mathbf{x}_i)$ be an initial labeled sample, in which the class label $\widehat{y}_i$ is derived from the coarser resolution data as explained in Fig. 1. Let $(\widehat{y}_j, \mathbf{x}_j)$ be a sample in the neighborhood $\mathcal{N}(i)$ of pixel i, where $\widehat{y}_j$ is estimated label from the MLR classifier. The criterion considered in this work is, if $\widehat{y}_j = \widehat{y}_i$, we increment the unlabeled training set by adding $(\widehat{y}_j, \mathbf{x}_j)$. This increment is reasonable due to the following considerations.

1) First, from a global viewpoint, samples which have the same spectral structure likely belong to the same class.
2) Second, from a local viewpoint, it is very likely that two neighboring pixels also belong to the same class. Therefore, the newly included samples are reliable for learning the classifier.

In this work, we run an iterative scheme to increment the training set as this strategy can refine the estimates and enlarge the neighborhood set such that the set of potential unlabeled training samples is increased. Once a candidate set is inferred using spatial information, we run standard active learning algorithms [49] on the previously derived candidate set, so that they are adapted to a self-learning scenario to automatically (and intelligently) select the most informative samples from the candidate set, as suggested in [28]. As a result, in the proposed semi-supervised self-learning scheme our aim is to select the most informative samples without the need for human supervision. Concerning the adopted active learning strategy, following [28], we use the breaking ties (BTs) algorithm [50] for unlabeled sample selection, which has shown to be effective for semi-supervised self-learning [28]. This algorithm relies on the smallest difference of the posterior probabilities for each sample. In a multiclass setting, the BT algorithm can be applied (independently of the number of classes available) by calculating the difference between the two highest probabilities. As a result, the algorithm finds the samples minimizing the distance between the first two most probable classes.

D. MRF-Based Spatial Postprocessing

In order to include spatial-contextual information in the considered approach, we use the MRF, a widely used contextual model and a classic probabilistic method to model spatial correlation of pixel neighbors. MRF assumes that neighboring pixels are likely to exhibit similar class labels, which matches the aforementioned local criterion according to which two neighboring pixels are likely to belong to the same class. Normally, the MRF-based classification approaches can be implemented in two steps. First, a probabilistic pixel-wise classification method (such as the MLR adopted as our baseline classifier) is applied to learn the posterior probability distributions from the spectral information. Second, contextual information is included by means of an MRF regularization to refine the classification. Here, we adopt an isotropic prior to model the image of class labels $\mathbf{y}$ (at the finer spatial resolution) by the following expression:

$$p(\mathbf{y}) = \frac{1}{Z} e^{\mu \sum_{(i,j)\in \mathcal{C}} \delta(y_i - y_j)} \tag{2}$$

where Z is a normalizing constant for the density, μ is a tunable parameter controlling the degree of smoothness, $\delta(y)$ is the unit impulse function,[3] and $\mathcal{C}$ is a set of cliques.[4] Notice that the pairwise interaction terms $\delta(y_i - y_j)$ attach higher probability to equal neighboring labels than the other way around. In this way, the adopted MRF prior promotes piecewise smooth segmentations, where μ controls the degree of smoothness. In our experiments, we have set empirically $\mu = 2$ as we observed that this parameter setting provides generally good results [51].

At this point, it is important to emphasize that, despite the availability of a large number of training samples in the coarser resolution satellite product, it is important to use unlabeled samples at the finer resolution level since these samples are more confident (and less sparsely distributed) than those available at the coarser resolution level. This is an important consideration when generating finer spatial resolution maps from the coarser resolution data. Finally, Fig. 2 illustrates the proposed semi-supervised framework for automatically generating a finer resolution map from a coarser resolution dataset. As inputs, we have the coarser and finer resolution data, while the output is the urban extent map at finer spatial resolution. In the processing, we use labeled samples (generated from the coarser data available) and unlabeled samples (actively selected from the finer resolution data as described in Section II-C). These samples are used to jointly learn the MLR classifier. The classification output obtained from the MLR classifier is refined by the MRF spatial regularizer. As we can observe in Fig. 2, the proposed framework is fully automatic and can be easily implemented in a global script. In Section III, we provide an experimental evaluation of our proposed approach which is focused on the generation of finer resolution urban maps from a global satellite product at coarser spatial resolution.

[3] That is, $\delta(0) = 1$ and $\delta(y) = 0$, for $y \neq 0$.

[4] A clique is a set of labels which are neighbors of each other.

III. Experimental Results

In this section, we perform an experimental validation of the proposed approach using the European Space Agency's GlobCover product at the coarser resolution level. The objective of the GlobCover project [35], [36] is the generation of a land cover map of the world using a fully automated processing chain for remote sensing data collected by MERIS [52], one of the main ones in Envisat platform, at 300-m spatial resolution per pixel. The GlobCover project has been carried out by an international consortium started in 2005 [53] and continued nowadays. This project provides a relevant source of information for land cover studies at a global level. Here, we use GlobCover as a reliable source of training data for finer resolution urban extent mapping purposes. In our context, GlobCover is used for obtaining training samples when no other training data may be available *a priori*. This allows for the generation of finer spatial resolution maps from the coarser resolution data. Here, we particularly evaluate the possibility to generate finer resolution urban extent maps. Although in this work we rely on the GlobCover product (at the coarse resolution level) to test our proposed concept, other global products can be used as well.

For the finer spatial resolution level, we have selected five datasets collected by Landsat (at 30-m spatial resolution) over three different locations in the city of Sao Paulo, Brazil, and over two different locations in the city of Guangzhou, China. It is important to point out that the GlobCover and Landsat datasets used in our experiments have the same time stamp. The GlobCover extraction refers to 2009, and the Landsat data are from the same year (different days). Since mapping of urban extents can be conveniently studied on a yearly basis, we are within the boundaries of a sound comparison. These areas have ground truth available in vectorial format. As a result, we can use the classification accuracy as a metric to evaluate the quality of the generated urban maps at the finer spatial resolution as compared to the available ground truth. At this point, we emphasize the final map that we are interested in is a binary one, containing information about urban/nonurban areas. Therefore, the maps are converted in our experiments to binary maps by clustering all nonurban classes into one. We also emphasize that, in our experiments, only those pixels that are not in the boundaries of each class in the GlobCover dataset are used for training purposes, as illustrated in Fig. 1. This allows us to conduct an extensive evaluation analyzing the accuracy of our proposed strategy in mapping urban versus nonurban land cover areas over different locations.

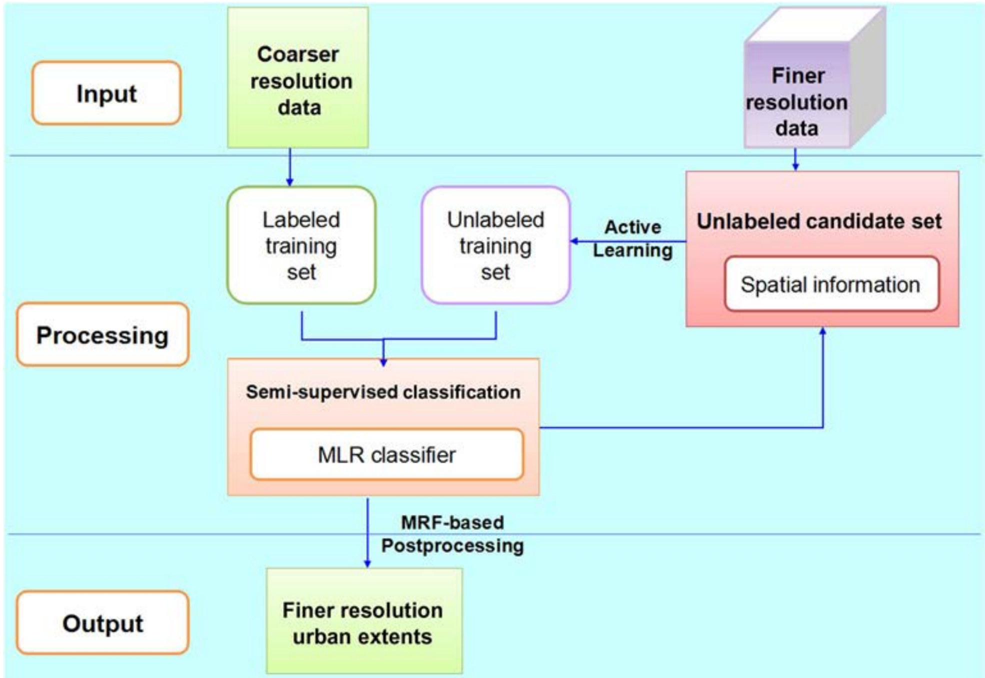

Fig. 2. Proposed semi-supervised framework for generating a finer resolution map from a coarser resolution dataset.

In our experiments, we also consider different numbers of labeled samples derived from the GlobCover product, in order to analyze the sensitivity of our method to the initial training samples. We perform five Monte Carlo runs for each experiment and report the average accuracy and the standard deviation of the results obtained for statistical consistency. Since the Landsat data covering the entire Sao Paulo city in Brazil and the city of Guangzhou in China are extremely large, we have selected three 500×500-pixel subscenes in Sao Paulo and two 500×500-pixel subscenes in Guangzhou for evaluation purposes. Furthermore, in all experiments we have considered the supervised version of the classifier (i.e., using only labeled information derived from the GlobCover product) and also the semi-supervised version of the classifier, in which both labeled and unlabeled samples are considered for mapping purposes. Similarly, we also report the results obtained by the MLR classifier with and without MRF spatial postprocessing. In the following, we report the results obtained for the two considered test sets.

A. Sao Paulo, Brazil

Fig. 3 displays a portion of the 2009 GlobCover map in which the city of Sao Paulo, selected as our first test site, is highlighted. As it can be seen in Fig. 3, this is a highly populated urban area. In order to analyze the accuracy of our proposed strategy, we have selected three 500×500-pixel Landsat subscenes [see plots (a) in Figs. 4–6], and evaluated the performance achieved in each test case. The first, second, and third test sets contain 12, 8, and 11 classes, respectively, according to the GlobCover map.

Figs. 4–6 present the obtained urban maps from the three considered datasets, respectively. For comparative purposes, we also run the same semi-supervised scheme by using the probabilistic SVM classifier. As shown by these figures, the proposed approach obtained very good mapping results according to the urban features displayed in the Landsat image [see Figs. 4(a)–6(a)]. It can be observed that, by including unlabeled samples and the MRF spatial regularizer, the proposed approach leads to very good extraction of urban extents. Furthermore, it can also be observed that the proposed approach (which uses the MLR classifier) generally outperforms the results obtained by using the probabilistic SVM, especially in the cases in which the MRF spatial regularizer is considered. This is due to the fact that the SVM is not a straightforward probabilistic classifier. Finally, when compared with the ground truth maps, it can be observed that the proposed approach captures more detailed urban extents. In fact, it can be seen that some details are missing in the ground truth images. For instance, the road information and some small urban extents are missing from the reference data. Therefore, if we use these ground truth maps for validation it can be expected that the obtained accuracy values may not be totally satisfactory. This is more related with an incomplete ground truth rather than with a poor performance of our proposed method. Still, we have decided to use the available reference information and move forward with the provision of a quantitative analysis as follows.

In order to provide a quantitative assessment of our proposed approach, we use the ground truth information given in plots (b) of Figs. 8 and 9 for validation. Specifically, Table I presents the obtained individual, overall accuracies and κ statistics. As mentioned before, due to the observed differences between

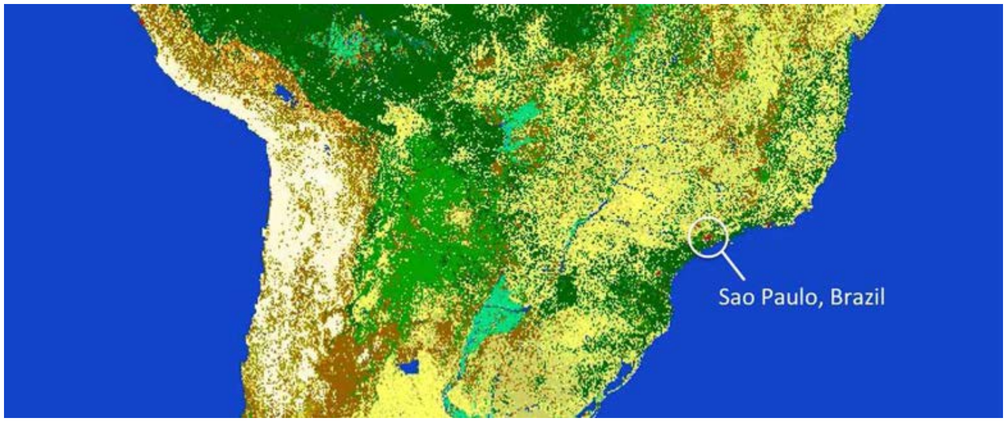

Fig. 3. Portion of the 2009 GlobCover map in which the city of Sao Paulo, Brazil, is highlighted.

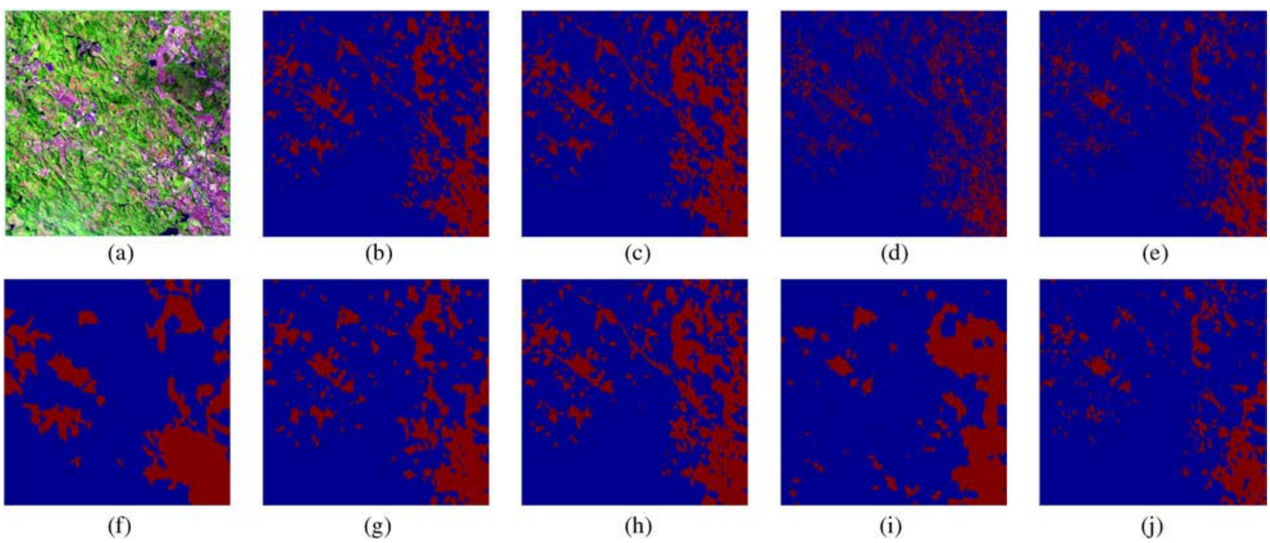

Fig. 4. Urban maps obtained for our first test case in Sao Paulo, Brazil, using 269 labeled samples and 298 unlabeled samples, where Sup. and Semi. denote supervised and semi-supervised, respectively. (a) Landsat image is composed by bands 5 (R), 4 (G) and 3 (B). (b) Supervised MLR. (c) Semi-supervised MLR. (d) Supervised SVM. (e) Semi-supervised SVM. (f) Ground truth. (g) Supervised $\mathrm{MLR}+\mathrm{MRF}$. (h) Semi-supervised $\mathrm{MLR}+\mathrm{MRF}$. (i) Supervised $\mathrm{SVM}+\mathrm{MRF}$. (j) Semi-supervised $\mathrm{SVM}+\mathrm{MRF}$.

the Landsat image and the ground truth map, it is expected that the obtained values are not fully representative, as shown in Table I. Another important observation is that, by including the unlabeled samples and the MRF spatial regularizer, the proposed approach obtained better individual class accuracies and κ statistic.

B. Guangzhou, China

Fig. 7 displays a portion of the 2009 GlobCover map in which the city of Guangzhou, China, selected as our second test site, is highlighted. As it can be seen in Fig. 7, this is also a highly populated urban area. In order to analyze the accuracy of our proposed strategy, we have selected two 500×500-pixel Landsat subscenes [see plots (a) of Figs. 8 and 9] and evaluated the performance achieved in each test case, in which the first and second test sets contain 13 and 15 classes, respectively, according to the GlobCover map. Based on the conclusion that MLR is always comparable or superior (in terms of classification accuracies) than SVM in the proposed semi-supervised framework, in this experiment we only consider the MLR classifier.

Figs. 8 and 9 present the obtained urban maps for the two considered datasets. As shown by these two figures, the proposed approach obtained good mapping results according to the urban features displayed in the Landsat image [see Figs. 8(a) and 9(a)]. In comparison with the ground truth maps, it can be again observed that the proposed approach captured more detailed urban extents. In fact, it can be seen that some details are missing in the ground truth images. For instance, for the first dataset there is a big urban area in the upper and middle area of the Landsat image which is not present in the ground truth map. On the other hand, for the second dataset there is an urban extent in the lower leftmost side in the Landsat

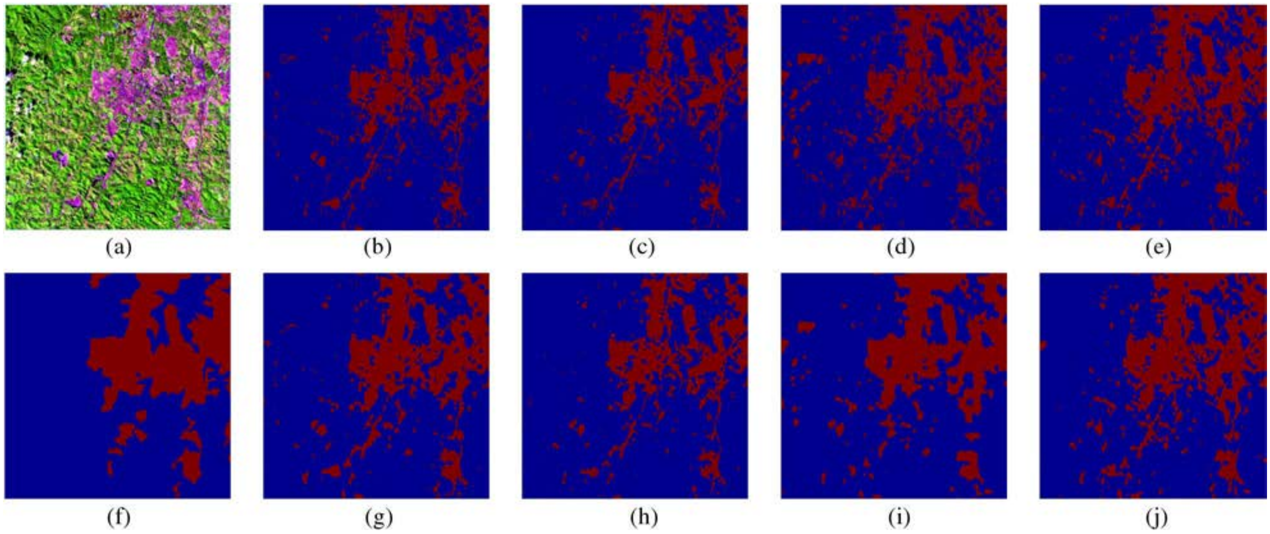

Fig. 5. Urban maps obtained for our second test case in Sao Paulo, Brazil, using 223 labeled samples and 300 unlabeled samples, where Sup. and Semi. denote supervised and semi-supervised, respectively. (a) Landsat image is composed by bands 5 (R), 4 (G) and 3 (B). (b) Supervised MLR. (c) Semi-supervised MLR. (d) Supervised SVM. (e) Semi-supervised SVM. (f) Ground truth. (g) Supervised $\mathrm{MLR} + \mathrm{MRF}$. (h) Semi-supervised MLR+MRF. (i) Supervised $\mathrm{SVM} + \mathrm{MRF}$. (j) Semi-supervised $\mathrm{SVM} + \mathrm{MRF}$.

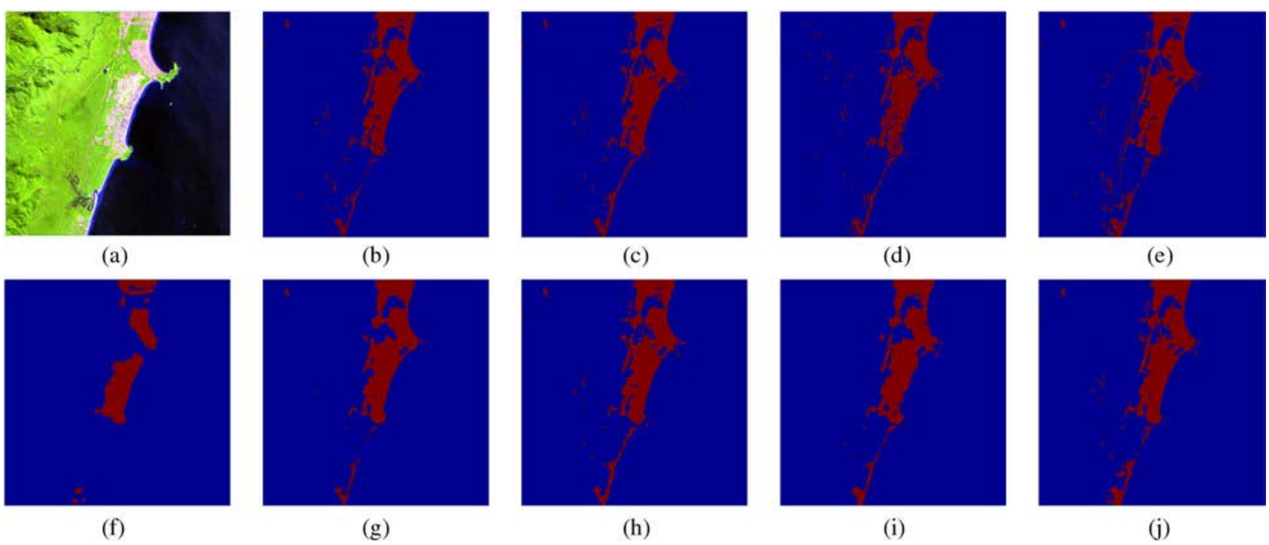

Fig. 6. Urban maps obtained for our third test case in Sao Paulo, Brazil, using 168 labeled samples and 301 unlabeled samples, where Sup. and Semi. denote supervised and semi-supervised, respectively. (a) Landsat image is composed by bands 5 (R), 4 (G) and 3 (B). (b) Supervised MLR. (c) Semi-supervised MLR. (d) Supervised SVM. (e) Semi-supervised SVM. (f) Ground truth. (g) Supervised $\mathrm{MLR} + \mathrm{MRF}$. (h) Semi-supervised $\mathrm{MLR} + \mathrm{MRF}$. (i) Supervised $\mathrm{SVM} + \mathrm{MRF}$. (j) Semi-supervised $\mathrm{SVM} + \mathrm{MRF}$.

image which is missing in the ground truth map. However, the proposed approach was able to detect these details, which reveal a good match between the obtained results and the Landsat data.

Despite the aforementioned issues and with the ultimate goal of providing a quantitative assessment of the obtained results, we use the ground truth information given in plots (d) of Figs. 8 and 9 for validation purposes. Table II shows the obtained individual and overall accuracies and κ statistics. Due to the differences between the Landsat image and ground truth map, as expected the values are not extremely good, as reported in Table II. An important observation, however, is that by including the unlabeled samples and MRF spatial regularizer, the proposed approach obtained good individual and overall accuracies, and κ statistic.

In summary, the experiments reported with three test cases in Sao Paulo, Brazil, and two test cases in Guangzhou, China, reveal that the proposed methodology can generate finer spatial resolution urban maps from the one available in the global product used as reference. Specifically, we can obtain the finer spatial resolution urban maps using a moderate number of labeled training samples (generated from the GlobCover product) plus

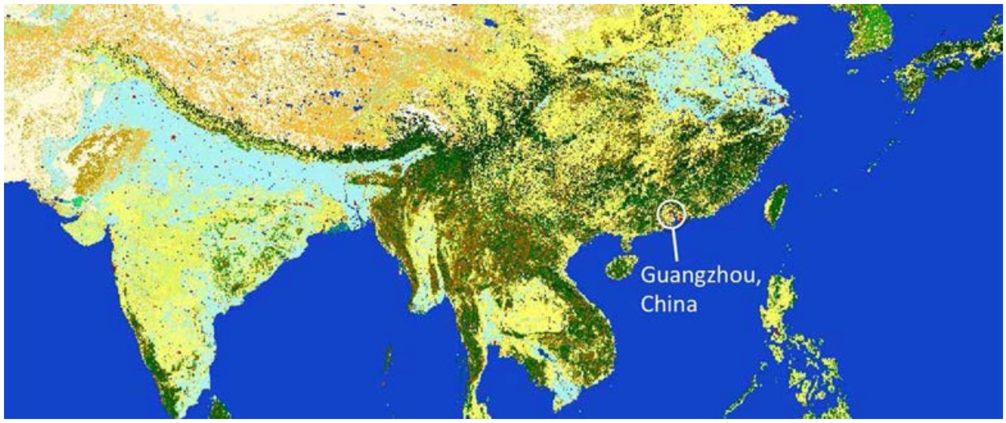

Fig. 7. Portion of the 2009 GlobCover map in which the city of Guangzhou, China, is highlighted.

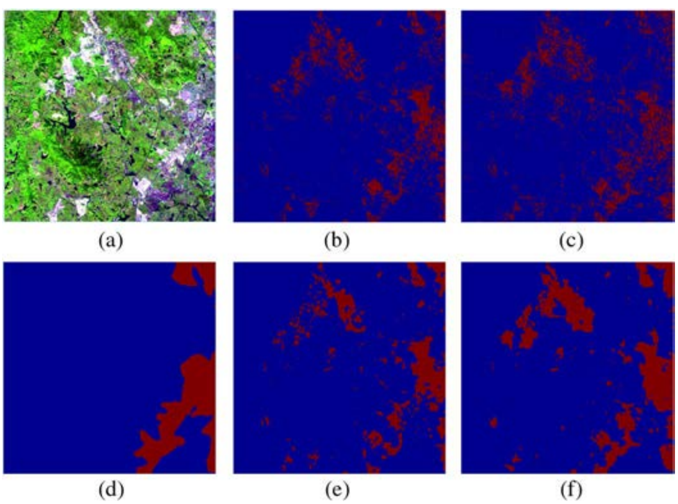

Fig. 8. Urban maps obtained for our first test case in Guangzhou, China, using 605 labeled and 302 unlabeled training samples. (a) Landsat image (R:5, G:4, B:3). (b) Supervised MLR. (c) Semi-supervised MLR. (d) Ground truth. (e) Supervised $\mathrm{MLR}+\mathrm{MRF}$. (f) Semi-supervised $\mathrm{MLR}+\mathrm{MRF}$.

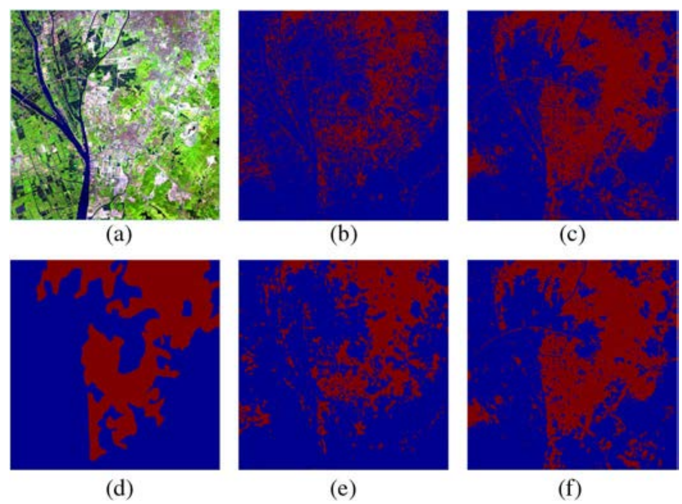

Fig. 9. Urban maps obtained for our second test case in Guangzhou, China, using 283 labeled and 199 unlabeled training samples. (a) Landsat image (R:5, G:4, B:3). (b) Supervised MLR. (c) Semi-supervised MLR. (d) Ground truth. (e) Supervised $\mathrm{MLR}+\mathrm{MRF}$. (f) Semi-supervised $\mathrm{MLR}+\mathrm{MRF}$.

additional unlabeled samples generated automatically (at the finer resolution level) by the proposed methodology, which also benefits from MRF-based postprocessing to increase the spatial consistency and the visual appearance of the final urban maps. These results can be readily extrapolated to other urban areas due to the global nature of the GlobCover product used to generate the initial labeled samples required by the proposed methodology.

IV. Conclusion and Future Research Lines

In this work, we have developed a new technique for the generation of finer spatial resolution urban maps from coarser resolution global maps. Our methodology is based on the probabilistic MLR classifier, embedded in a semi-supervised self-learning framework, and on the use of MRFs for spatial regularization. The proposed semi-supervised approach has been validated using the European Space Agency's GlobCover product to generate initial (labeled) training samples that are then complemented using automatically generated unlabeled samples at the finer spatial resolution level. In our context, the GlobCover data is injected into the training process of the classifier, more specifically to generate (with high confidence) the training samples required at the beginning of the process. Due to the global nature of the GlobCover product, this is considered a very important feature that ensures global applicability of the proposed approach, which can also take advantage of other similar global products.

Our experimental results suggest that the proposed methodology can be used to effectively generate good urban maps from coarser resolution satellite data. This is an important contribution, as the availability of global products providing coverage of the entire world is increasing, and these products can be exploited (by means of the proposed approach) to generate reliable maps at finer resolution. In this work, we have specifically demonstrated that GlobCover exhibits the potential to become

TABLE I
CLASSIFICATION ACCURACIES (%) OBTAINED IN OUR FIRST TEST CASE IN SAO PAULO, BRAZIL

	Without MRF				With MRF			
	Urban	Nonurban	Overall accuracy	κ statistic	Urban	Nonurban	Overall accuracy	κ statistic
Test set 1: 269 labeled training samples, 298 unlabeled samples								
Supervised MLR	90.53	50.98	80.95	43.90	91.64	50.63	81.71	45.15
Semi-supervised MLR	89.91	59.94	82.65	51.35	93.01	59.82	84.97	56.31
Supervised SVM	92.19	46.01	81.00	42.36	94.79	37.61	80.95	36.21
Semi-supervised SVM	90.15	45.85	79.43	39.05	96.25	50.19	85.10	53.11
Test set 2: 223 labeled training samples, 300 unlabeled samples								
Supervised MLR	97.14	36.48	81.72	39.18	97.62	36.55	82.10	40.06
Semi-supervised MLR	90.86	66.24	84.60	58.39	90.46	75.07	86.55	64.81
Supervised SVM	95.59	28.00	78.42	23.33	91.65	45.64	79.95	35.27
Semi-supervised SVM	90.46	54.38	81.29	44.35	88.77	82.13	87.09	67.55
Test set 3: 168 labeled training samples, 301 unlabeled samples								
Supervised MLR	98.28	56.29	96.01	58.21	98.04	62.25	96.11	60.63
Semi-supervised MLR	96.67	79.64	95.75	64.06	97.13	80.75	96.25	67.16
Supervised SVM	97.15	74.76	95.95	63.58	97.20	75.31	96.01	64.11
Semi-supervised SVM	95.71	86.93	95.24	63.98	97.20	86.82	96.64	71.97

TABLE II
CLASSIFICATION ACCURACIES (%) OBTAINED IN OUR FIRST TEST CASE IN GUANGZHOU, CHINA

	Without MRF				With MRF			
	Urban	Nonurban	Overall accuracy	κ statistic	Urban	Nonurban	Overall accuracy	κ statistic
Test set 1: 605 labeled training samples, 302 unlabeled samples								
Supervised	46.35	90.09	85. 24	32.76	54.76	92.31	88.14	43.91
Semi-supervised	49.48	91.21	86.58	37.61	55.59	92.25	88.19	44.62
Test set 2: 283 labeled training samples, 199 unlabeled samples								
Supervised	73.93	80.02	75.85	49.09	77.37	87.64	80.60	59.14
Semi-supervised	76.83	83.78	79.02	55.54	78.44	87.56	81.31	60.44

an important source of information for mapping urban area extents, in particular, when very limited labeled samples are available *a priori*.

As with any new technique, there are several unresolved issues that may present challenges over time. For instance, in the considered framework, we select the labeled samples far away from the boundaries of the classes in the GlobCover product, in order to avoid possibly negative effects associated to the very different spatial resolutions of the Landsat and MERIS data (used to generate the GlobCover product). However, it is well known that border training samples may convey very useful information for classification purposes [22]. As a result, a more detailed investigation of this issue is required in future developments of the method. Another relevant topic is to develop better sampling approaches for the generation of initial labeled training set and the active learning strategies for the selection of unlabeled samples. A possibility is to combine both in multiscale fashion [54]. Further experiments should also be focused on analyzing larger areas than the ones reported in this study, which have been confined to small 500×500 images due to computational requirements. In this regard, additional spatial features such as morphological profiles will be considered in future developments of the proposed approach. Focus will be on how to integrate the spatial feature extraction step into the proposed automatical framework. Computationally efficient implementations of the proposed methodology, using high performance computing architectures, are also currently being investigated. Last but not least, other global products in addition to GlobCover should be tested in future developments of the method, as well as other sources of finer spatial resolution data for the generation of the final maps.

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