Support Vector Machines for Landscape Mapping from Remote Sensor Imagery

Dee Shi and Xiaojun Yang

ABSTRACT: Landscape mapping is an important activity leading to the generation of various geospatial products in support of sustainable land use planning and environmental management. A variety of pattern recognition techniques have been identified to automate this process from remote sensor imagery. Support vector machines (SVM) as a group of relatively novel statistical learning algorithms have demonstrated their robustness in mapping homogeneous and heterogeneous landscape types from remote sensor imagery. In this paper, we review the status and potential challenges in the implementation of SVM for landscape mapping. The paper is organized into two major parts. The first part reviews the research status of using SVM for landscape mapping from remote sensor imagery, focusing on some comparative studies that demonstrated the effectiveness of SVM over other conventional classifiers. We identify several areas for additional research, which are mostly related to appropriate treatments of some parametric and non-parametric factors in order to achieve improved mapping accuracies particularly for heterogeneous landscape types and for large datasets. Then, we implement the support vector machine technique to map various land cover types from a remote sensor image covering an urban area, and demonstrate the robustness of this geospatial technique for mapping heterogeneous landscapes.

KEYWORDS: Landscape mapping, geospatial analysis, support vector machines, heterogeneous landscape types, urban environment

Introduction

Landscapes provide the living space and resources for human beings. Physically, a landscape is a hybrid scene that is composed of a mosaic of heterogeneous land use and land cover types that are shaped by human activities and ecological processes (Alberti, 2008). Landscape mapping is an important activity that can generate various geospatial products in support of sustainable land use planning and environmental management.

Landscape mapping aims to inventory various landscape elements that are commonly described in an aggregated way, as land cover classes. Remote sensor data have been used to map land cover types through digital image classification techniques. While conventional classifiers (e.g., maximum likelihood) have been widely used, they generally work well with medium-resolution images and in relatively homogeneous areas rather than highly heterogeneous areas (Jensen, 2005). A variety of machine learning and pattern recognition techniques have been developed to improve land cover mapping in heterogeneous areas, and support vector machines (SVM) are found to outperform most of the conventional classifiers (Huang et al., 2002; Keuchel et al., 2003; Kavzoglu and Colkesen, 2009; Su and Huang, 2009). Moreover, SVMs were found to even outperform some novel pattern recognition methods, such as neutral networks (Huang et al., 2002; Foody and Mathur, 2004 a, 2004b). Nevertheless, there are some parametric and non-parametric factors that can affect the performance of SVM, and there is a need to

investigate them so that SVM could be used with improved performance (Yang, 2011).

In this paper, we examine the utilities of support vector machines (SVM) as a promising pattern recognition technique for landscape mapping particular for heterogeneous areas. It is organized into two major parts, beginning with a brief introduction of some basic knowledge on SVM and a review on the research status and possible challenges of using SVM for landscape mapping. The review focuses on some comparative studies that demonstrated the effectiveness of SVM over other conventional classifiers. Based on the review, we further discuss several areas that need additional research in order to improve SVM classification accuracies and reduce computational burdens, which are mostly related to appropriate treatments of some parametric and non-parametric factors. The second part of the paper discusses our implementation of SVM to map various land cover types from a remote sensor image covering an urban area, demonstrating the robustness of this type of pattern recognition technique for mapping heterogeneous landscapes.

Support Vector Machines

Basics

Support vector machines (SVM) are a group of relatively novel statistical learning algorithms that have not been extensive exploited in the geospatial science community. Their basic idea is to construct separating hyperplanes between classes in feature space through the use of support vectors which are lying at the edges of class domains. SVM seek the optimal hyperplane that can separate classes from each other with the maximum margin (Vapnik, 1995).

SVM were originally designed as a binary linear classifier, which assumes two linearly separable classes to be partitioned. In most cases, the best separable hyperplane may not be located exactly between two classes. To account for this, an error item is introduced to manipulate the tradeoff between maximizing the separation margin and minimizing the count of training samples that locates on the wrong side. SVM are further extended to deal with non-linear classification by using a non-linear kernel function to replace the inner product of optimal hyperplane. Several commonly used kernel functions include linear kernel, polynomial kernel, radial basis function (BRF), and sigmoid kernel (Haykin, 1999). Each of these kernel functions is constructed with multiple parameters, and how these parameters are setting can influence the performance of a specific support vector machine (Yang, 2011).

Moreover, SVM have been used for multi-class mapping through reducing the multi-class problem into a set of binary problems so that the basic SVM principles can be still applied. Two commonly used strategies for this purpose include one-against-one and one-against-all (Foody and Mathur, 2004b; Kavzoglu, 2009). The later is generally preferred because of its less computational intensity. However, this method can result in unbalanced class sizes (Huang et al., 2002).

SVM for landscape mapping

The performance of SVM has been assessed by comparing with other pattern recognizers for various landscape types (e.g., Huang et al., 2002; Foody and Mathur, 2006; Keramitsoglou et al., 2006; Su and Huang, 2009). Huang et al. (2002) found that SVM substantially outperformed maximum likelihood (MLC) or decision tree (DC) in terms of classification accuracy and even surpassed multilayer perceptrons (MP) neural networks. Su and Huang (2009) implemented SVM and MLC on a Multi-angle Imaging SpectroRadiometer (MISR) image to differentiate eight semi-arid vegetation types, and found that SVM significantly outperformed MLC. Keramitsoglou et al. (2006) mapped various vegetation types using IKONOS data, and compared the performance of SVM with radial basis (RBF) neural networks. They found that SVM had strengths in terms of classification accuracy and training time. Foody and Mathur (2006) also found that SVM can produce a more accurate classification of cultivated landscape types. Dixon and Candade (2008) compared SVM, MLC, and backpropagation neural networks (NN) for classifying a Landsat scene, and found that SVM and NN performed identically in the classification accuracy but SVM was more efficient in the training phase. They also noted that SVM can be quite attractive when working with high dimensionality data. This seems to be in line with an earlier work conducted by Huang et al. (2002) who found that SVM performed better for an image with 7 bands than with 3 bands. The effectiveness of SVM for working with high dimensional data classification was also confirmed by several other studies (e.g., Bazi and Melgani, 2006; Camps-Valls et al., 2007), indicating that they could provide a solution to dealing with the problem of "curse-of-dimensionality" (Hughes, 1968). Although SVM have demonstrated strengths when comparing with other classifiers, their performance can vary across different landscape types (Foody and Mathur, 2004 a,b; Keramitsoglou et al., 2006; Su and Huang, 2009).

The performance of SVM can be affected by both parametric and non-parametric factors (Foody and Mathur, 2006; Yang, 2011). Existing studies on SVM classification have largely concentrated on either improving classification accuracy on specific landscape types or reducing computational burdens, both of which can be manipulated at the SVM configuration stage and at the training stage. The inner-product kernel between the support vectors in feature space and in input space largely determines the separability of optimal separable hyperplane (Haykin, 1999). While introducing non-linear kernel functions could help deal with complex, non-linear classification, it can also lead to the difficulty in choosing the most appropriate kernel type and in the subsequent kernel parameterization (Huang et al., 2002; Kavzoglu and Colkesen, 2009; Yang, 2011). Yang (2011) conducted an empirical study assessing the performance of several most commonly used kernel types, along with their internal parameterization, and found that the kernel type and error penalty can substantially affect image classification accuracy. Some customized kernels, particularly those incorporating both spatial and spectral information, were found to be quite promising when comparing with spectral-based kernel types (Camps-Valls et al., 2006, 2007; Plaza, 2009).

Since SVM are a type of supervised classifiers by nature, both the size and quality of training sample can affect the classification accuracy (Foody and Mathur, 2006). Bazi and Melgani (2006) suggested that feature selection can be implemented at three different

stages: independent selection by technicians, training sample detection and optimization based on the fitness criteria, and signature selection totally embedded in classification. The selection of training data should be different by specific classifiers used. For statistically based classifiers, training samples should consist of relatively pure pixels, and should be identified from homogeneous areas in large fields, which can be applicable for a variety of classifiers (Foody and Arora, 1997). A minimum of 10- 30 pixels per class per waveband should be used to meet the assumption of normal distribution and be representative of the subclass (Foody and Mathur, 2004a,b; Foody and Marthur, 2006).

Since only the support vectors are actually needed in constructing separate hyperplanes for SVM, it may be highly possible to reduce training sample size to a small number of the most informative samples that are used to fit the decision hyperplanes. Accordingly, there is no need to maintain normal distribution in training samples. Several studies have been conducted to identify these critical samples. For example, Foody and Marthur (2004a,b, 2006) incorporated ancillary information of soil types and geographical boundary pixels of mixed spectral characteristics of two crop types in the selection of useful training samples, which dramatically reduced training samples before being applied to classification. They also examined the usefulness of applying other ancillary information (e.g., landform, moisture, and spatial texture) in targeting support vectors. Various techniques have been identified to automatically reduce the training sample size and hence help reduce the computational burden for SVM. For example, Demir and Ertürk (2009) used a clustering-based k-mean algorithm in training pattern selection to remove samples locating at the high density regions or to detect support vectors at the clustering centers. With these support vectors obtained from clustering preprocessing, the computational load has been substantially reduced, while the classification accuracy was much higher than using the full training samples. Other techniques to automatically optimize the feature detection or selection include the genetic algorithm (GA), the steepest ascent algorithm, the recursive feature elimination technique and radius margin bound minimization (Pal and Mather, 2005; Bazi and Melgani 2006; Ghoggali et al. 2009; Mukhopadhyay and Maulik, 2009).

Research Methods

In order to demonstrate the effectiveness of SVM for heterogeneous landscape mapping, we implemented SVM to map landscape types in an urban area. In this section, we will discuss the specific procedures, including the study site and data acquisition, classification scheme desicgn, SVM configuration, and classification and accuracy assessment.

Study site and data acquisition

The study site covers the entire Gwinnett County, a suburban county located at northeastern Atlanta metropolitan area, Georgia, USA (Figure 1). The county has an area of about 1,122 square kilometers and its population was 805,321 according to the 2010 census survey. The majority of topography is relatively flat and has primarily a humid

subtropical climate. Gwinnett has been one of America's fastest-growing counties and the second most populated county in Georgia. Its landscape is characterized by a mosaic of complex land use and land cover types, and therefore Gwinnett is an ideal site to examine the effectiveness of SVM for heterogeneous landscape mapping.
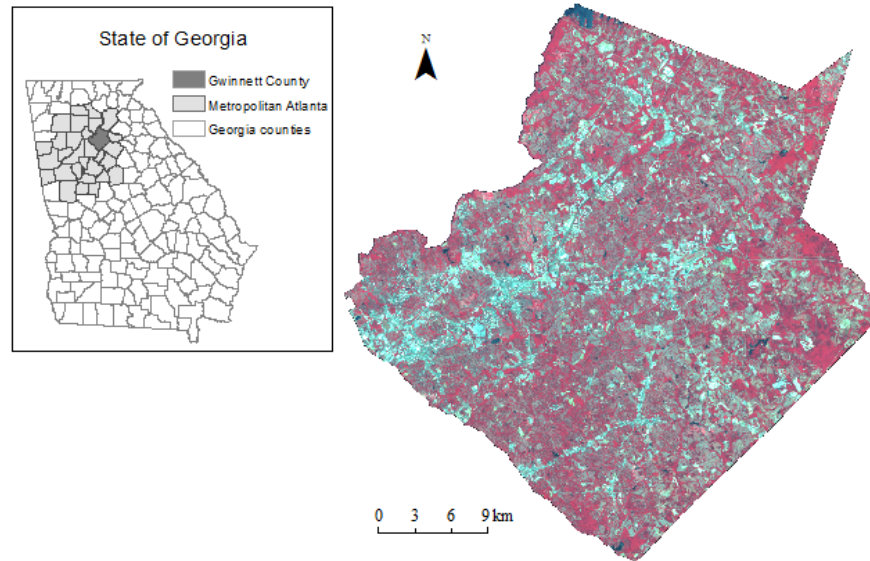
Figure 1: Location of the test site. The image used covers the entire area of Gwinnett County.

A cloud-free Landsat-5 Thematic Mapper (TM) image dated on 19 May 2007 was acquired from USGS EROS Data Center, and a subset of this scene covering the entire Gwinnett County was actually used in our study. The image has been geometrically corrected at the EROS data center, and no further preprocessing was conducted. The spatial resolution of this image is 30 m for all six non-thermal infrared bands, and 120 m for the thermal band. It was projected into the Universal Transverse Mercator Zone 16N with NAD 83 as the horizontal datum.

Classification scheme and training samples

We designed a land use/cover classification scheme based on the Anderson scheme (Anderson et al., 1976) and our field surveys across the Atlanta metropolitan area. The study area covers a mosaic of different land use cover types, and our classification system includes ten major categories: high-density urban, low-density urban, barren or fallow land, pasture and cropland, grassland, shrub and scrub, evergreen forest, deciduous forest, mixed forest, and water (Table 1).

After the classification scheme was adopted, we carefully selected training samples for each of the ten major categories by using several reference sources such as the high-resolution images from Google Earth and the 2006 National Land Cover Data (NLCD). Note that each information class listed in Table 1 may include multiple spectral classes. For the information classes with multiple spectral classes, we collected at least one training set with 25-35 pixels for each spectral class. Specifically, eight information

Table 1: Land-cover classification system, training sample size and reference data size

No	Class name	Description	Training sample size (in pixels)	Reference sample size (in pixels)
1	High-density urban	More than two-thirds impervious surfaces, mainly commercial, industrial, institutional facilities with large roofs, and public retail buildings, large transportation facilities	60	52
2	Low-density urban	Residential areas with impervious surfaces account for lower than two-thirds of total cover, including residential developments, smaller urban service buildings, such as detached stores and restaurants, state highways	54	84
3	Barren or fallow land	Urban areas with low percentages of constructed materials, vegetation, and low level of impervious surfaces, including bare soil lands, small amount fallow lands, exposed rock, mines and quarries	71	48
4	Grassland	Herbaceous cover, trees and shrub less than 10%. Parks, lawns and golf courses.	55	86
5	Pasture and cropland	Grazing area, field crops, horticulture, and vegetable.	41	52
6	Shrub and scrub	Residential and agricultural shrub, scrub, orchards, groves, and transitional vegetation areas.	27	47
7	Evergreen forest	Trees remain green throughout the year, wetland evergreen forests included, mainly cedar and pine trees.	47	55
8	Deciduous forest	Trees lose their leaves when the dry or cold season, wetland deciduous forests included, mainly oak, maple, elm, and hickory.	31	50
9	Mixed forest	Either evergreen or deciduous trees also mixed with shrub and scrub less than 10%.	49	114
10	Water	Rivers, streams, lakes, reservoirs	125	54

classes, namely, high-density urban, low-density urban, barren or fallow land, pasture and cropland, grassland, evergreen forest, mixed forest, and water, are comprised of training

data from multiple spectral classes. For the high density urban class, training samples were collected for three spectral classes with one for large roofs and the other two for parking lots with various pavement materials. For grassland, training samples were collected for two spectral classes with one for golf course with a bright color and the other for urban green spaces with low woody cover. Two spectral classes were defined for evergreen forest with one for highland evergreen forest and the other for wetland evergreen forest. For mixed forest, training samples were collected for two spectral classes that are various due to soil types. We calculated the spectral separability for each pair of the spectral classes, and finally selected 20 classes for use in the training phase of the SVM classification that will be discussed later.

SVM configuration and classification

As discussed before, SVM parameter settings can affect the classification performance (Huang et al., 2002; Kavzoglu and Colkesen, 2009; Yang, 2011). Among them, the kernel type, error penalty, and Gamma term are the three most critical parameters. We configured a support vector machine with radial basic function as the kernel type, a moderate error penalty value (C=100), and a Gamma term equaling to 0.143 (Yang, 2011). We used this SVM configuration to classify the Gwinnett subset of the 7-band TM imag with the training samples described above. For comparison purpose, we also used the same training samples to classify the same image by using the maximum likelihood classifier (MLC) that has been widely used. After the implementation of SVM and MLC, we combined the 20 spectral classes into 10 information classes prior to the accuracy assessment.

Accuracy assessment

The accuracy assessment was conducted by using visual interpretation and the error matrix approach. The visual interpretation is qualitative by nature, while the error matrix approach is a quantitative method that compares the classification map with the ground reference information (Congalton, 1998). A total of 498 reference samples were generated through the randomly stratified method (Table 2). The identity of each sample was determined by the combined use of high spatial resolution data from Google Earth, USGS 2006 National Land Cover Data, and our field survey data. Kappa coefficients were calculated to quantify the overall and categorical accuracies (Congalton, 1998).

Results and Analyses

The classification maps from SVM and MLC were visually displayed in Figure 2. Both maps were geographically linked with the original remote sensor image, and specific land cover categories were further checked. In general, both maps show an overall correct land cover classification but misclassified areas or pixels can be clearly observed. While the two maps do not show much different large landscape patches, the one from SVM shows many scattered, isolated patches being correctly classified. In terms of specific classes, grassland and low density urban are classified differently, as shown on the two maps (Figure 2). Some grassland patches on the map from SVM were misclassified as low density urban class on the other map. And some mixed forest patches were classified as low density area, and some small patches of evergreen forests and

shrubs were classified as mixed forest. Thus, if the spectral characteristics of a class are similar to other classes or if a class is dominated by mixed pixels, SVM clearly performed better than MLC.
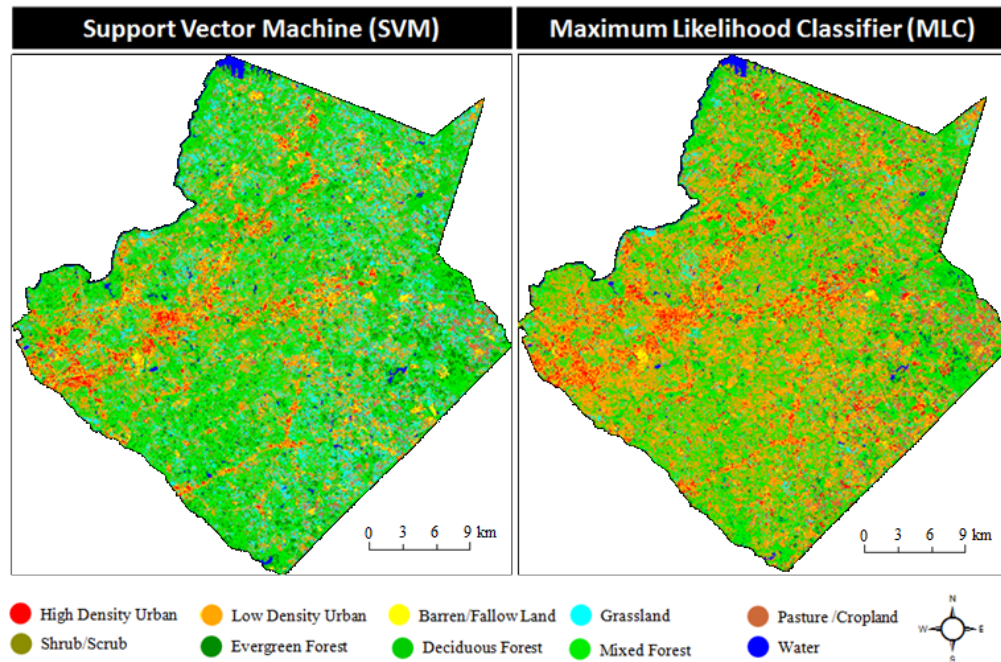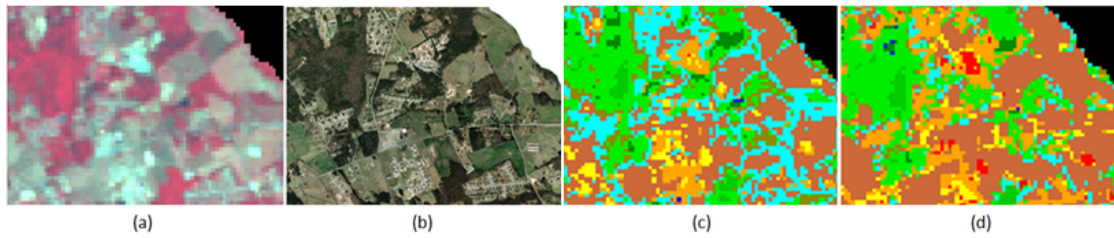

Figure 2: Visual comparison of the classification maps by SVM and MCL, respectively.

To further assess the performance of SVM when separating spectrally complex landscape categories, several sites were selected for a closer look. Figure 3 illustrates the original TM image, high resolution image from Google Earth, the two classified maps from SVM and MLC, for each of the three sites. For the two spectrally complex categories, namely, low density urban and mixed forest, MLC tended to include more neighboring pixels into these classes. MLC also misclassified some evergreen forest patches into water, barren land patches into high density urban, and grassland patches into low density urban and cropland. Contrastingly, SVM seemed to have done a better job in mapping spatially scattered patches. And SVM had correctly classified the residential patches on all the three sites and the pasture patches on Site 2.
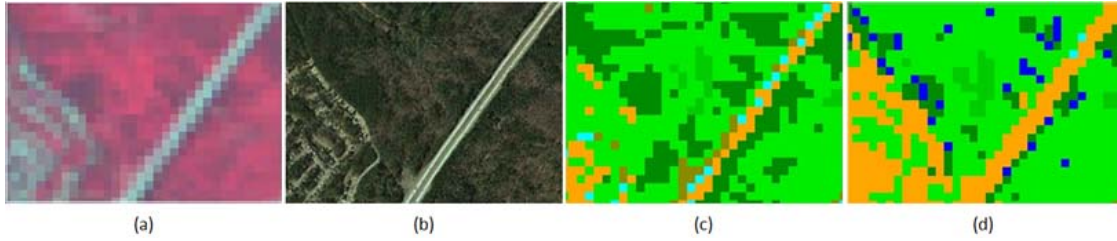
For quantitative accuracy assessment, Kappa coefficient and conditional Kappa coefficients were calculated and summarized in Table 2. If judging by the overall Kappa coefficient, SVM significantly outperformed MLC. As for specific classes, SVM significantly surpassed MLS in terms of classification accuracy for most classes, except evergreen forest and water. And the largest improvements were with the categories of high density urban, low density urban, pasture, and mixed forest, of which the second and last classes are most spectrally complex. SVM also showed a moderate improvement for grassland. However, SVM and MLC had almost identical classification accuracies for several relatively homogenous classes, such as evergreen forest and water.

Site 1:

Site 2:

Site 3:

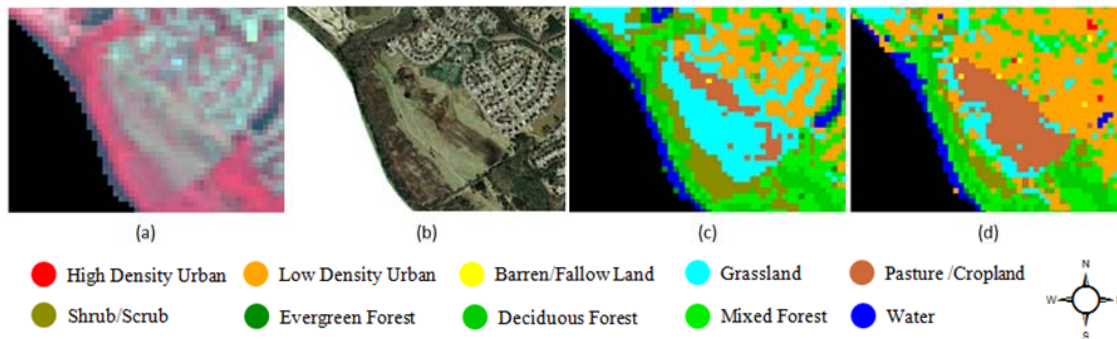| ● High Density Urban | ● Low Density Urban | ● Barren /Fallow Land | ● Grassland | ● Pasture /Cropland |
| ● Shrub/Scrub | ● Evergreen Forest | ● Deciduous Forest | ● Mixed Forest | ● Water |

Figure 3: Visual comparison at three selected sites: (a) TM Image in false color composite; (b) High-resolution image; (c) SVM classification; and (d) MLC classification.

Table 2: Summary of the image classification accuracies by SVM and MLC, respectively.

Class Name	Kappa Coefficient		$(K_{SVM}-K_{MLC})/K_{MLC}$
	Support Vector Machines (SVM)	**Maximum Likelihood Classifier (MLC)**	
High Density Urban	**0.80**	0.57	**0.40**
Low Density Urban	**0.69**	0.39	**0.77**
Barren/ Fallow Land	0.71	0.80	-0.11
Grassland	**0.70**	0.55	0.27
Pasture	**0.81**	0.56	**0.45**
Shrub/Scrub	0.76	0.69	0.1
Evergreen Forest	0.94	0.94	0
Deciduous Forest	0.95	0.88	0.08
Mixed Forest	**0.77**	0.55	**0.4**
Water	1.00	1.00	0
Overall Kappa	0.80	0.58	0.38

Conclusions

In this paper, we have reviewed the research status of using support vector machines (SVM) for landscape mapping with special attention on heterogeneous landscape types. Then, we have implemented this technique to map various land cover types in an urban area from a remote sensor image. Our studies further confirm that SVM can significantly outperform the maximum likelihood classifier (MLC), the most widely used pattern recognition method in the remote sensing community. We found that SVM can significantly improve mapping accuracy, particularly for spectrally and spatially complex landscape categories.

Acknowledgements

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