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Continuous Mapping and Monitoring Framework for Habitat Analysis in the United Arab Emirates

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Abstract: In 2015, the Environment Agency - Abu Dhabi has developed an extensive Abu Dhabi Habitat, Land Use, Land Cover Map based on very high resolution satellite imagery acquired between 2011 and 2013. This was the first integrated effort at such a scale. This information has greatly helped in assisting in environmental conservation and preservation activities along with future infrastructure planning. This map has created an excellent baseline and provides a great opportunity for efficient monitoring. In this work, we aim to establish a framework for short term updates to the maps to quickly enable efficient planning. We make use of the spectral-spatial approaches based on object-based image analysis to adapt the classification scheme. Training examples from the baseline maps and field surveys are used to train classifiers such as support vector machines (SVM) to build the updated maps. Eventually, the goal is to develop a consistent classification approach first and then adapt automatic change detection approaches to extend the baseline maps temporally.

Keywords: United Arab Emirates; Landcover; Mapping; Monitoring

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1. Introduction

The United Arab Emirates (UAE) has seen a tremendous growth in the last decades developing advanced urban centers in the world. Such a rapid development can put the environment under significant stress. This creates a need for continuous monitoring of the landcover and landuse to make informed decisions. With this exact motivation, Environment Agency- Abu Dhabi (EAD) has developed a detailed Habitat, Land Use, Land Cover Map based on very high resolution satellite imagery acquired between 2011 and 2013 [1]. A total land area of 60,000 km^2 and a marine area of 30,000 km^2 has been mapped at 1:10,000 scale with an accuracy of around 87% on an average. It was the first integrated effort at such scale in the country and has created a very good baseline for future mapping activities in the country. Banking on the effort of the EAD, there is an ongoing effort to extend the process to cover the entire UAE with key stakeholders like UAE Space Agency and Ministry of Climate Change and Environment leading the initiative. This work summarizes the pilot study that is being carried out to extend the mapping workflow to develop land use, land cover maps of the UAE.

Globally, there are active programs for development and frequent updation wide area land cover maps. The Coordination of Information on the Environment (CORINE) Land Cover (CLC) project is a great example of such initiatives. Initiated in 1985 and widely implemented over the complete European Union, updates have been produced in 2000, 2006 and 2012 by definining 44 land use, land cover classes with 25 ha minimum mapping unit. The CLC maps have proven to be important resources for several sectors such as risk management [3] environmental impact assessment [4], life cycle analysis [5], biodiversity conservation [6], urban heat island studies [7], etc. In the United States of America, a consortium known as Multi-Resolution Land Characteristics Consortium (MRLC) was formed in 1992 with the goal of generating consistent and relevant land cover information [8]. The first National Land Cover Dataset (NLCD) was produced in 1992 and updates were produced in 2001 [9], 2006 [10] and 2011 [11]. It provides a nationwide classification of 16 classes at a spatial resolution of 30 meters.

Compared to the above initiatives, UAE aims to generate a highly detailed classification with over 55 classes and at a spatial resolution of less than 5 m for the entire country. In this work, as a part of the ongoing project, a pilot project is being carried out to improve the maaping accuracy obtained by the previous mapping project of the EAD and also formulate a methodology to extend the mapping exercise to the entire UAE. The work also aims to develop a methodology to perform updates to the maps in short intervals of less than 2 years as against 5-6 years which is normally accepted globally. Such a rapid update of maps is crucial for the UAE which is developing at a higher rate.

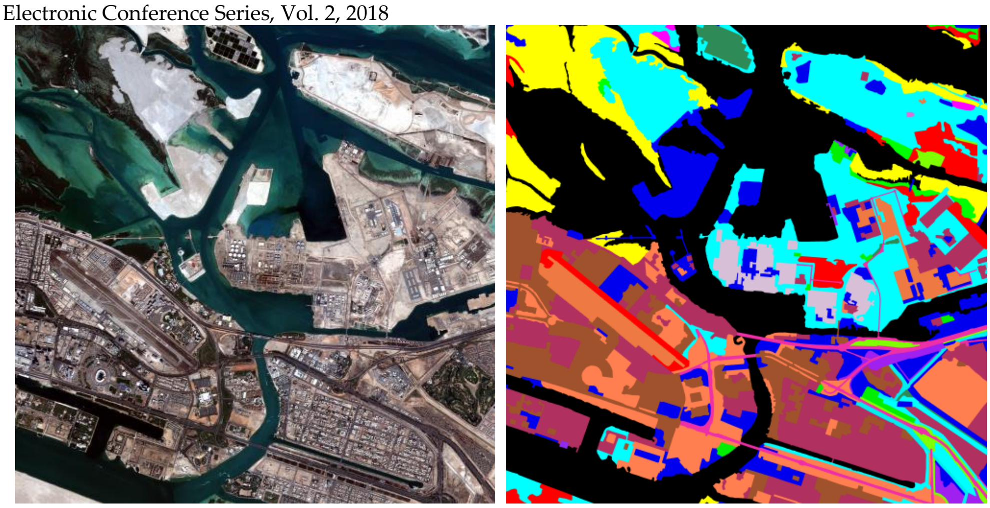
2. Experiments

2.1. Study Area

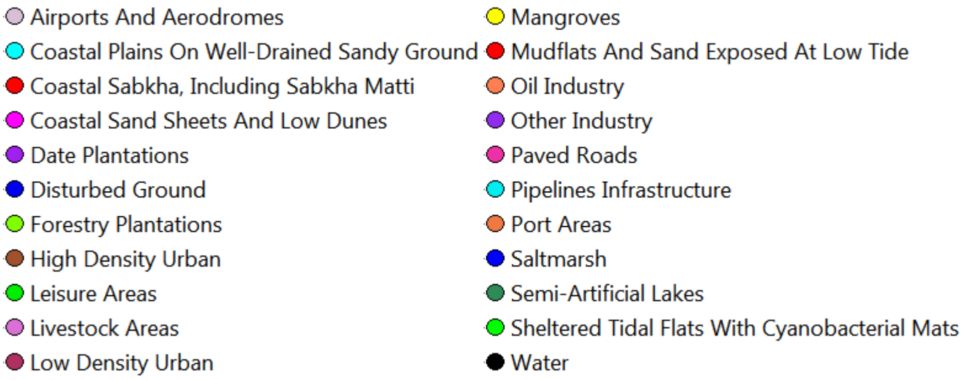
In this study, we consider a study area in Abu Dhabi as shown in Fig. 1. The area is represented by 22 landcover/land use classes out of the 54 classes defined by the EAD. It consists of a diverse setting with part of Abu Dhabi city in the south and various islands in the north with significant human activity. The region also consists of part of mangroves along the Abu Dhabi coast.

Figure 1. Location of the study area in Abu Dhabi

The image is acquired by WorldView-2 satellite in 2012 and consists of data acquired in 8 bands in visible, near-infrared (NIR) and shortwave infrared (SWIR) regions at a spatial resolution of 2 1.85 m for the multispectral images and 46 cm for the panchromatic image. The panchromatic image consists of 20000 X 20000 pixels. A snapshot of the image and the corresponding land use/landcover map from the EAD database is shown in Fig. 2. The corresponding legend shows the 22 classes considered in the study. It can be clearly observed that several of these classes are highly heterogenous spatially e.g., Airports and Aerodromes, Disturbed Ground, Industry classes, urban classes, etc., as they correspond to land use rather than land cover.



(a) **(b)**



(c)

Figure 2. (a) RGB image of the WorldView-2 image; (b) Land use/land cover map of the area of study; and (c) List of Classes identified in the map.

2.2. Materials and Methods

As a part of our initial efforts to experiment with the methods, the first step is to develop a reliable classification approach. Our aim is to see if we can develop a method which makes use of the spatial information to deduce the heterogenous land use classes as well. Recently, several authors have successfully demonstrated the superiorty of spectral - spatial approaches such as geographical object-based image analysis (GEOBIA) [12, 13], morphological and attribute profiles [14,15], convolutional neural networks (CNNs) [16], etc. Embedding spatial information in the modeling of classes is shown to significantly improve the classification accuracy especially when dealing with highly heterogenous classes. In this work, as the first attempt, we employ a segmentation based approach similar to the method that was successfully utilized to map the coral reef environment in the UAE [16]. The flowchart of the proposed method is shown in Fig. 3. The lower resolution multi-spectral image is first geometrically and radiometrically corrected and pan-sharpened using the higher resolution panchromatic image to enhance the spatial information while preserving the spectral information. In this work Gram-Schmidt method [17] is employed for pansharpening. The pan-sharpened dataset is used to derive the normalized difference vegetation index (NDVI) and normalized difference water index (NDWI). Principal component analysis (PCA) is performed to extract the top three components accounting for the majority of variance. These five components are stretched and normalized to the same range (0- 1000) and stacked to be used in segmentation. The reason behind this processing step is to enhance the contrast between the image segments for an accurate segmentation of the image. Also, NDWI is used to mask the water regions with a threshold of 0.7. The image is segmented into multiple levels to capture the fact that different objects appear at different scales in the images. Subsequently, object features (e.g., mean value, texture features calculated using gray level co-occurrence matrix, shape features, relational features, etc. [13]) are calculated for all the objects at the identified segmentation levels. All the features are stacked and are used as inputs for classification using non-linear classifiers such as Random Forest (RF) [18] or Support Vector Machines (SVM) [19]. In this work SVM is employed.

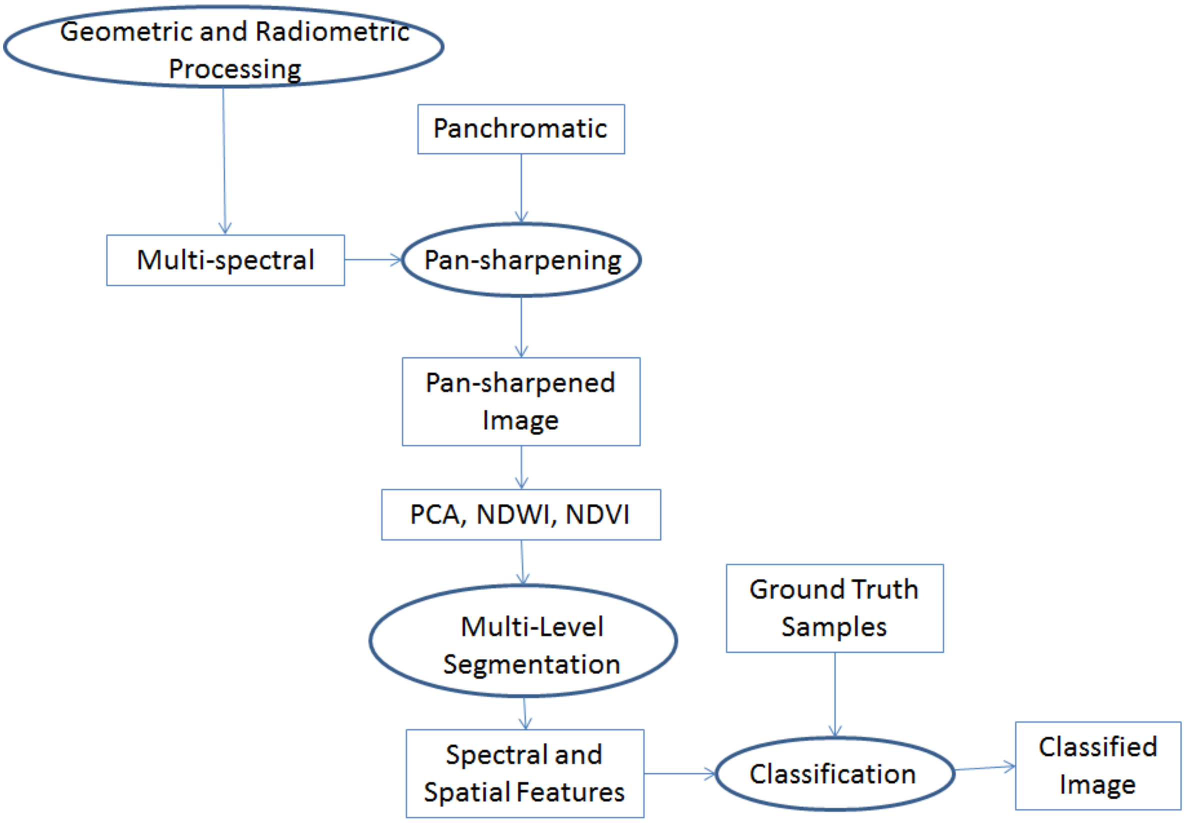


Figure 3. Flowchart showing the spectral-spatial approach employed in this work.

3. Results

The proposed approach is applied on the dataset shown in Fig. 2. Multi-resolution segmentation in eCognition software [20] is used in this work for segmentation. Three segmentation levels are used with scale parameters of 100, 200 and 400 respectively based on visual inspection of the segmentation result. The key to choose the scale parameter is to abstract land use classes which are often represented at larger scales. Only the layer means and GLCM Mean features were used as features in this initial study, where the GLCM features embed the texture information that could be related to the land use classes. The segmentation profiles are formed by stacking all the features at all segmentation levels and are used as input to the SVM classifier. Ten percent of the pixels are randomly selected from the map in Fig. 2 (b) for the purpose of training the classfier and the rest are used for testing. Fig. 4 shows the result of the classification using the proposed method. An overall accuracy of 82.76% was achieved. However, some classes with highest ambiguity such as disturbed ground, mud flats and industry areas could not be identified properly. This can be due to the high heterogeneity and low number of samples for the classes.

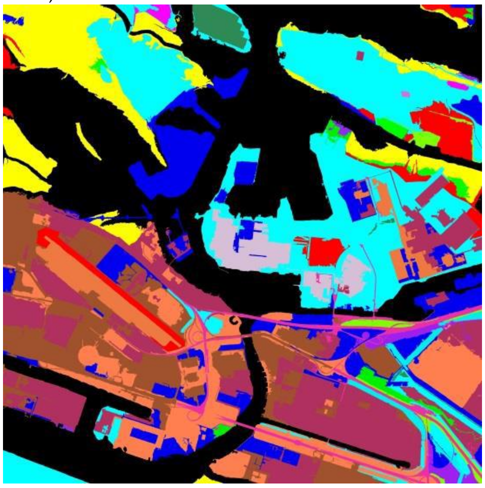


Figure 4. Classification Result using the proposed approach.

4. Discussion

In this work, an initial result of the spectral-spatial approach using segmentation is presented. The approach seems to be in general adaptive to deal with wide areas even with high heterogeneity. However, there are some issues that have to be optimized. It is crucial to identify the segmentation parameters correctly for the subsequent steps to achieve higher accuracy. At the same time, the classification seems to be biased towards the classes with higher number of samples. Despite these shortcomings, it presented an acceptable overall accuracy which is comparable to what was achieved during the extensive campaign to produce the Abu Dhabi habitat maps. We intend to extend this work to optimize the framework while also exploring other approaches like the CNNs. The ongoing work will also explore automatic change detection methods. The idea behind this is to apply change detection to identify no-change regions. These no-change regions can then be used as training samples for the new dataset to update the classification model. This will help in developing a framework for updating landcover maps in shorter time intervals.

5. Conclusions

As a part of the pilot project funded by the UAE Space Agency, there is an ongoing effort to establish the methods that could be used in the development of UAE nationwide landcover maps and also to continuously monitor the changes to update the maps in shorter time intervals. This paper presents the results of the first case study using a spectral-spatial approach for classification of highly heterogenous areas. The method which uses GEOBIA framework is able to achieve around 83% accuracy. This work is now being extended to study different approaches such as convolutional neural networks (CNNs) for classification and also change detection for continuous monitoring applications.

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