Performance of ANN, SVM and MLH techniques for land use/cover change detection at Sultan Marshes wetland, Turkey

M. Hayri Kesikoglu, U. Haluk Atasever, Filiz Dadaser-Celik and Coskun Ozkan

ABSTRACT

Wetlands are among the most productive ecosystems that provide services ranging from flood control to climate change mitigation. Wetlands are also critical habitats for the survival of numerous plant and animal species. In this study, we used satellite remote sensing techniques for classification and change detection at an internationally important wetland (Ramsar Site) in Turkey. Sultan Marshes is located at the center of semi-arid Develi closed basin. The wetlands have undergone significant changes since the 1980s due to changes in water flow regimes, but changes in recent years have not been sufficiently explored yet. In this study, we focused on the changes from 2005 to 2012. Two multispectral ASTER images with spatial resolution of 15 m, acquired on June 11, 2005 and May 20, 2012, were used in the analyses. After geometric correction, the images were classified into four information classes, namely water, marsh, agriculture, and steppe. The applicability of three classification methods (i.e. maximum likelihood (MLH), multi-layer perceptron type artificial neural networks (ANN) and support vector machines (SVM)) was assessed. The differences in classification accuracies were evaluated by the McNemar’s test. The changes in the Sultan Marshes were determined by the post classification comparison method using the most accurate classified images. The results showed that the highest overall accuracy in image classifications was achieved with the SVM method. It was observed that marshes and steppe areas decreased while water and agricultural areas expanded from 2005 to 2012. These changes could be the results of water transfers to the marshes from neighboring watershed.

Key words | artificial neural networks, change detection, maximum likelihood, Sultan Marshes, support vector machines, wetlands

INTRODUCTION

Wetlands are among the most important natural resources on earth. Wetlands support rich biodiversity and are critical habitats for many plant and animal species (Mitsch & Gosselink 2000a). Wetlands also provide many ecosystem services (Hansson et al. 2005; Sierszen et al. 2012). They regulate ground water and surface water. By preserving a large amount of carbon dioxide gas from spreading to the atmosphere, they help prevent global warming. They also contribute to both a region’s and country’s economy by providing goods with economic value, such as reeds. Unfortunately, the majority of wetlands are threatened by human activities, including hydrologic alterations, water pollution, etc.

Remote sensing methods have been used in wetland studies for many years. A review conducted by Ozesmi & Bauer (2002) showed that remote sensing methods provide tools for monitoring, classification, and management of wetlands. Various techniques have been used for classification of wetlands including visual interpretation, unsupervised classification (clustering), principal component analysis, supervised classification, and hybrid classification (Ozesmi & Bauer 2002). Among these methods, supervised maximum likelihood classification technique (MLH) is the most common and it has successfully been used for wetland classification purposes in many previous studies (Munyati...
MLH is based on the assumption that data show normal distribution. This classifier also requires a large amount of data for definition of statistical properties of various classes. In recent decades, more computationally intensive methods have become available for classification of remote sensing imagery. These methods provide robustness, require less data, and provide better classification results. In this study, we selected two of these recent approaches, artificial neural networks (ANN) and support vector machines (SVM) and compared them with MLH in classification of wetlands.

ANN take the human brain system as an example to solve problems. An ANN consists of interconnected neurons that work together to classify input data into output classes. The use of ANN in remote sensing studies goes back to the early 1990s (Atkinson & Tatnall 1997). Since then, ANN have been used in various regions, including wetlands (Bao & Ren 2011; Qiang & Lam 2015). SVM method is one of the classification methods that defines a boundary allowing two or more classes to be separated from each other in the best way. The method is produced to solve pattern recognition and nonlinear function estimation problems (Sahu et al. 2015). The use of SVM method in wetland studies is comparatively lower than the other methods, except for a few recent studies (Singh et al. 2014; Mohammadpour et al. 2015).

In the literature, there are some studies which compared different classification techniques with respect to their mapping accuracies. Zeng et al. (2011) produced a few different procedures for determining land use/cover changes in the city of Wuhan in China. Each of the procedures included different classifiers such as K-Means, Isodata, MLH, and SVM. The most successful procedure was found to be post supervised classification scenario with MLH and SVM. Szantoi et al. (2015) performed wetlands mapping in the Everglades National Park in Florida by using high spatial resolution imagery. Classification accuracy of MLH, decision trees, and ANN were compared and it was shown that ANN provided the best results.

In this study, we aim to identify the changes at the Sultan Marshes wetland in the Develi Basin in Turkey from 2005 to 2012 based on analysis of ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) imagery. Sultan Marshes is one of the important wetlands of Turkey that has a complex structure consisting of freshwater marshes and salt water lakes surrounded by salt steppes, agricultural areas, and bare/sparsely vegetated soils. Therefore, it provides an interesting case study for evaluating the success of different methods. The Sultan Marshes is also a wetland that has a history of human intervention. From the late 1980s to the early 2000s, the wetland went through a drought period due to diversion of water from the wetlands to irrigation in the basin. Since the mid-2000s, water requirements of wetlands have been partially met by transferring water to the Develi Basin from another basin nearby (Zamanti Basin). The changes occurred in the Sultan Marshes from 1987 to 2003 were investigated previously by Dadaser-Celik et al. (2006). In that study, major decreases in water areas and wetlands were reported. The effects of recent management activities (i.e. water transfers), however, are unknown.

This study has two major objectives. First, we aim to update our knowledge about the Sultan Marshes and determine how the wetland responded to changes in water inflows by analyzing changes from 2005 to 2012. The changes were analyzed by classification of ASTER images acquired in 2005 and 2012. Post classification comparison technique was used to identify the nature and extent of changes. The second objective was to analyze the success of different supervised classification methods. Wetlands are complex ecosystems, which presents major challenges in image classification. We compared a widely used technique, MLH, with ANN and SVM for classification of wetlands. ANN and SVM are data driven techniques which have been used in different application areas, but their use in wetland studies are rather limited. In this study, we aim to determine the best classification technique for wetlands that have complex structures similar to the Sultan Marshes.

STUDY AREA

Sultan Marshes is located in the Develi Basin in the Central Anatolia region of Turkey (Figure 1) between 38° 12’ 14”–38° 25’ 49” N latitudes and 35° 09’ 20”–35° 22’ 20” E longitudes (GISM 2017). The area is important due to having more than 300 bird species, hosting numerous plant species, and very rich biological diversity (Dadaser-Celik et al. 2008). The wetlands are located on two important bird migration routes linking Asia to Europe (Dadaser-Celik et al. 2008; Orman et al. 2013). Sultan Marshes was declared a Nature Conservation Area in 1971 and a Ramsar site in 1994. In 2006, it was declared a National Park.
Sultan Marshes wetland consists of four interrelated systems including two fresh water marshes (Örtülüakar and Kepir) and two salt water lakes (Yay and Çöl) (Figure 1). The marshes are surrounded by steppe areas, agricultural areas, and bare/sparsely vegetated soils. For these reasons, monitoring changes in the Sultan Marshes is very important in order to take measures against any problem in advance. This can be achieved by classification of land use/cover and change detection analysis.

There are already some studies related with the Sultan Marshes in the literature. Dadaser-Celik et al. (2006) and Dadaser-Celik et al. (2007) examined the hydrological sustainability of the Sultan Marshes. The authors examined the relationships between surface and ground water inflows to the marshes and the wetland water levels. As a result of the examination, they determined that the changes in water level from 1993 to 2003 were not directly related to climate change but extensive use of surface and ground water resources. Dadaser-Celik et al. (2008) examined the changes in the Sultan Marshes from 1980 to 2003 to understand the effects of water diversions for irrigated agriculture. In this article, the authors used a hybrid classification system consisting of unsupervised ISODATA classification and MLH classifier. The analysis showed that the lake surface area decreased by 95%, the marsh area decreased by 50%
and, in some regions, marsh cover was turned into agriculture.

As can be seen from previous studies, no up-to-date information is available regarding the wetland. With this study, we will fill in this gap by producing land use/cover maps for 2005 and 2012 and examining the transformation in the wetland between these years.

MATERIALS AND METHODS

Data and software used

In this study, two multispectral ASTER images were used. ASTER is a sensor aboard on NASA’s Terra platform. ASTER has wide spectral coverage and provides data in 14 bands consisting of three visible-near infrared, six short-wave infrared, and five thermal infrared bands. Visible-near infrared bands provide a spatial resolution of 15 m, while short-wave infrared bands provide a spatial resolution of 30 m. An ASTER image covers an area of 60 km × 60 km, sufficient for studying large areas. In this study data from visible-near infrared bands (green, red, and near infrared) were used in the analysis. The ASTER images were acquired on June 11, 2005 and May 20, 2012 (Figure 2). Spatial and spectral resolution of ASTER imagery and areal coverage were the major reasons for selection of ASTER imagery rather than imagery from other sensors (i.e. Landsat).

We also used some ancillary data related to the study area. We obtained the topographic map data with a scale of 1:25,000 and a raster map showing National Park boundaries from the Ministry of Environment and Urbanization. We also obtained Land Cover Database of Turkey (LCDT) belonging to the Ministry of Forestry and Water Affairs (LCDT 2013). The topographic map data belonging to the study area provided by Kayseri Provincial Directorate of the Environment and Urbanization and the raster data from Sultan Marshes National Park Long-Term Development Plan were used in the determination of land use/cover classes.

All analyses were conducted using ArcGIS (ESRI, Redlands, CA, USA), ENVI (Harris Geospatial Solution, Boulder, CO, USA), ERDAS (Hexagon Geospatial, Norcross, GA, USA), and MATLAB (The Matworks Inc., Natick, MA, USA) software.

Image preprocessing

The satellite imagery and topographic map (with a scale of 1:25,000) data were transformed to WGS-84 datum. The study area, which consists of the national park area, was extracted from both images. The geometric correction of the imagery was undertaken using 24 well-distributed
Ground control points and the images were resampled with the cubic convolution method. The root mean square error in geometric correction of the two images was lower than 0.5 pixel.

Image classification

The applicability of three methods was assessed for image classification. First the training and test (region of interest) areas were selected on satellite images. After the ground truths of the classes were verified with several field trips, each satellite image was classified into four classes as water, marshes, agriculture, and steppe (Table 1). For each land use/cover class at least 500 pixels were selected. This resulted in 7,957 pixels for training and 7,902 pixels for testing process of 2005 image; 7,282 pixels for training and 3,186 pixels for testing process of 2012 image.

Image classification was done with the MLH, ANN, and SVM methods, all separately. Below information about these three methods were provided.

Maximum likelihood classification

Maximum likelihood method (MLH) is one of the most used methods in the satellite image classification. This method considers mean, variance, and covariance in class assignment. MLH method assumes normal distribution for statistics for each class in each band. It also assumes equal prior probability among the classes (Foody et al. 1992; Zhang et al. 2011). First, MLH method calculates the probability that a given pixel belongs to a specific class. Assignment process is carried out according to threshold value defined by users. The pixel is assigned to the class having the highest probability. Formulation of MLH can be defined as follow:

$$D = \ln(a_c) - (0.5 * \ln|\text{Cov}_c|)$$

$$- [0.5 * (X - \text{M}_c)^T * (\text{Cov}_c^{-1}) * (X - \text{M}_c)]$$  

(1)

In Equation (1), D is probability value, C is an any class, X is measurement vector of pixel to be examined, M_c is mean vector for class of C, a_c is belonging percentage of X and Cov_c is variance-covariance matrix of pixels in the class of C (ERDAS 1999; Otukei & Blaschke 2010).

Artificial neural networks

ANN simulate the human brain system to solve problems. An ANN consists of an input layer, one or more hidden layers, and an output layer. Each layer consists of many neurons. Each neuron symbolized a variable in the input layer. These input variables are converted to the outputs. Thus, ANN model contacts between inputs (x) and outputs (y). General form of ANN is illustrated in Figure 3.

After the connections are established, the ANN model produces new outputs in response to new input values. General formulation of ANN can be defined as follow:

$$y_k = Q \left( \sum_{l=0}^{n} W_{ki} \cdot X_l \right)$$  

(2)

In Equation (2) W_k is weight, Xis input and Q is the transfer function. Transfer function is a mathematical function which makes a non-linear structure created for ANN. In this way, ANN can be used to solve non-linear problems. ANN are widely used in variety of applications for pattern recognition, classification, optimization, etc. The method does not require any statistical acceptance. It is an

<table>
<thead>
<tr>
<th>Information class</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water</td>
<td>Open water areas such as lakes</td>
</tr>
<tr>
<td>Marshes</td>
<td>Wetlands covered by common reeds or other herbaceous vegetation</td>
</tr>
<tr>
<td>Steppe</td>
<td>Scrublands, poorly vegetated areas and bare soils</td>
</tr>
<tr>
<td>Agriculture</td>
<td>Crop fields or orchards</td>
</tr>
</tbody>
</table>

Table 1 | Descriptions of information classes

![Figure 3](https://example.com/fig3.png)  

Figure 3 | ANN structure with one hidden layer (Haykin 2001).
advantage but it is sensitive to parameter changes affecting the classification accuracy directly (Haykin 2001; Qiang & Lam 2015).

**Support vector machines**

The SVM method is one of the supervised classification techniques based on statistical learning. The basic working principle of this method is to determine the hyperplane (border) distinguishing the data belonging to two classes from each other optimally. The classification process is done by considering the situations if the data to be classified are separated as linear or not.

SVM works by separating the data into two classes as \((-1, +1)\) linearly. Afterwards, the training dataset is divided into classes, and the decision function is determined by using the training dataset. This decision function constructs a hyperplane which separates data into two optimal classes.

It is assumed that the dataset used for training is \(A = (x_i, y_i), i = 1, 2, \ldots, m\) and \(m\) is the number of elements. \(y_i \in \{-1, 1\}\) denotes the class labels and \(x_i \in \mathbb{R}^d\) is a feature vector having \(d\)-dimensions (Özkan 2008). The inequalities of the optimum hyperplane can be defined as follows:

\[
W \cdot X_i + b \geq 1, \quad y = +1 \tag{3}
\]

\[
W \cdot X_i + b \leq -1, \quad y = -1 \tag{4}
\]

where \(W\) is the weight vector and \(b\) is the bias value. The following inequality can be achieved by utilizing the two inequalities given in Equations (3) and (4):

\[
y_i(W \cdot X_i + b) - 1 \geq 0 \tag{5}
\]

The \(W\) and \(b\) values should be optimized to achieve the optimum hyperplane (Kavzoglu & Colkesen 2009). The value of \(||W||\) should be minimum to obtain the maximum value of the optimum hyperplane line. In this instance, the solution of the constrained optimization problem (Equation (6)) should be implemented to obtain the optimum hyperplane (Özkan 2008).

\[
\min \left[ \frac{1}{2} ||W||^2 + C \sum \xi_i \right] \tag{6}
\]

If the underlying structure of the data shows non-linear distribution, some of the training dataset remains on the other side of the hyperplane. In order to solve this problem, a positive slack variable defining error \(\xi_i, i = 1, 2, \ldots, m\) is added to the optimization model. With the help of the artificial variable, Equation (5) transforms into Equations (7) and (8):

\[
w \cdot x_i + b \geq 1 - \xi_i, \quad y_i = +1 \tag{7}
\]

\[
w \cdot x_i + b \leq -1 + \xi_i, \quad y_i = -1 \quad \xi_i \geq 0, \forall i \tag{8}
\]

In Equations (7) and (8), the situations of \(\xi_i = 0\) or \(0 < \xi_i < 1\) mean that data are classified correctly. However, \(\xi_i \geq 1\) means that data are classified incorrectly (Kavzoglu & Colkesen 2009).

In a system which cannot be separated linearly, the constrained optimization problem described in the following Equation (9) should be resolved to obtain the most suitable hyperplane, i.e., while the distances between hyperplanes become maximum, classification errors become minimum.

\[
\min \left[ \frac{1}{2} ||W||^2 + C \sum \xi_i \right] \tag{9}
\]

The \(C\) parameter in Equation (9) means the maximum value of the Lagrange multiplier.

The linear separation of data with non-linear structure is done by utilizing kernel functions. When we look at the studies done today, we see that the most frequently encountered kernel functions are the Linear Function Kernel, Polynomial Kernel, Radial Basis Function Kernel and the Pearson VII (PUK) Function Kernel. As a result of the analysis, among these kernel functions, the Radial Based Kernel is shown as the kernel giving the classification value with the highest accuracy (Kavzoglu & Colkesen 2009).

In the scope of this article, the Radial Basis Function was used while the images were being classified with SVM. When the Radial Based Kernel is used, there are two important parameters as \(C\) Value (Penalty Parameter) and Gamma to adjust. \(C\) is a balance between training errors and the edge of a class. Increasing the \(C\) parameter reduces training errors. The \(C\) parameter and Gamma value are greater than or equal to 0.01. The default value for gamma is calculated by taking the inverse of the number of bands in the input image and the default value for \(C\) parameter is 100 (ENVI 2019). In this study, we used the default values for both Gamma and \(C\), as 0.111 and 100, respectively.

**Statistical test: McNemar’s test**

McNemar’s test is based on the \(\chi^2\) test with one degree of freedom (Roggo et al. 2003). It is used to detect whether there is a significant difference between two situations.
Change detection

Change detection is the process of identifying the differences in nature or in the situation of an object as a result of the observations done at different times (Singh 1989). There are many change detection techniques described in the literature (Singh 1989; Coppin et al. 2004).

Post classification comparison was used as the change detection approach in this article. This technique is a comparative analysis of satellite images belonging to different times classified as independently from each other. The biggest known advantage of this method is that it gives information about the direction of the change. Another advantage is that it keeps the negations arising from atmospheric and environmental factors and the radiometric differences among the images belonging to different dates to a minimum (Coppin et al. 2004; Lu et al. 2004). Although both images come from the same sensor, spectral differences are expected to occur in the same land use/cover classes due to changes in atmospheric conditions, sun angle, etc. even if the time interval is very small in multi-time data (Munyati 2000). Also, there may be differences in spectral response of vegetation due to phonological differences between images from two different dates.

According to post classification comparison technique, the change is identified based on a pixel by pixel basis by overlapping land use/cover maps belonging to different dates obtained by the supervised classification technique. At the end of this process, the number of areas which have undergone change and which class has changed can be identified.

RESULTS AND DISCUSSION

In the first part of the analysis, we used three different image classification methods (MLH, ANN, SVM) to select the best method for further analysis. The comparison of these three methods was done using McNemar’s test at the 0.05 significance level. The results of the McNemar’s test were presented in Table 2. When the classification accuracies of two methods are different, the McNemar’s value is written in bold. When the McNemar’s values are greater than $\chi^2_{(1,0.05)}$ 3.8414, the classification accuracies are significantly different. As can be seen, both ANN and SVM produced results significantly different than MLH in both 2005 and 2012 classifications. The difference between classification accuracies of ANN and SVM methods was not statistically significant for the 2005 image. For the 2012 image, ANN and SVM produced different classification accuracies.

Table 3 provides the accuracies of classifications, overall accuracy (OA) and Kappa statistics, conducted with three methods (MLH, ANN and SVM) for 2005 and 2012 classifications. Overall accuracy is the ratio of correctly classified pixels to the total pixels in the images. The Kappa statistic shows the agreement between classified image and reference data.

ANN and SVM methods provided better results than MLH method for both 2005 and 2012 classifications. SVM method also provided higher accuracy than ANN in 2012 classification. The higher success rates with the SVM method were also detected in some other studies in

<table>
<thead>
<tr>
<th>Method</th>
<th>MLH</th>
<th>ANN</th>
<th>SVM</th>
</tr>
</thead>
<tbody>
<tr>
<td>2005 classification</td>
<td></td>
<td>555.66</td>
<td>495.50</td>
</tr>
<tr>
<td>MLH</td>
<td>NA</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ANN</td>
<td>NA</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SVM</td>
<td>NA</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2012 classification</td>
<td></td>
<td>263.72</td>
<td>571.84</td>
</tr>
<tr>
<td>MLH</td>
<td>NA</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ANN</td>
<td>NA</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SVM</td>
<td>NA</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 3 | Classification accuracies of classified ASTER images acquired in 2005 and 2012

<table>
<thead>
<tr>
<th>Method Year</th>
<th>MLH</th>
<th></th>
<th></th>
<th>ANN</th>
<th></th>
<th></th>
<th>SVM</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Overall accuracy</td>
<td>Kappa statistics</td>
<td>Overall accuracy</td>
<td>Kappa statistics</td>
<td>Overall accuracy</td>
<td>Kappa statistics</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2005</td>
<td>85%</td>
<td></td>
<td></td>
<td>95%</td>
<td></td>
<td></td>
<td>95%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2012</td>
<td>79%</td>
<td></td>
<td></td>
<td>88%</td>
<td></td>
<td></td>
<td>94%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

In Table 4, producer’s accuracy of a class is the ratio of correctly classified pixels to the total pixels assigned to that class in the reference data. User’s accuracy of a class is the ratio of correctly classified pixels to the total pixels assigned to that class in the classified map. Highest accuracy was achieved in both images for the water class, where the accuracies were 99–100%. The producer’s and user’s accuracy values were over 90% for steppe class and 88% for marsh class. The producer’s accuracy for agricultural areas was 64% in 2012 image. This can be due the complex nature of agricultural area class. This class consists of many different crop types, therefore it may be possible that some crop types were not sufficiently represented in the training data.

Post classification comparison was used as the change detection approach in this study. In post classification comparison, classified images are compared with each other. The areal coverage of different classes and change detection results are shown in Table 5 and classified imagery are presented in Figure 4. From 2005 to 2012, water areas increased 20 km², while the change in agriculture areas was negligible (0.4 km² change). Marsh areas decreased 16.1 km² and marsh coverage decreased from 17.3% to 10.7% in the study area. Steppe areas showed a 4.3 km² decrease.

From 2005 to 2012, the change in water areas was significant. This change is due to coverage of marsh areas with water during 2012. It is apparent that more water reached the Sultan Marshes in the year 2012. We examined in Table 3, accuracy assessment was also done based on particular classes. The producer’s and user’s accuracies are reported

Table 4 | Class based accuracy assessment of 2005 and 2012 classifications conducted with SVM

<table>
<thead>
<tr>
<th>Class</th>
<th>Producer’s accuracy (%)</th>
<th>User’s accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2005</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Agricultural area</td>
<td>93</td>
<td>89</td>
</tr>
<tr>
<td>Classified Marsh</td>
<td>88</td>
<td>92</td>
</tr>
<tr>
<td>Data</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Steppe</td>
<td>99</td>
<td>98</td>
</tr>
<tr>
<td>2012</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Agricultural area</td>
<td>64</td>
<td>100</td>
</tr>
<tr>
<td>Classified Marsh</td>
<td>100</td>
<td>91</td>
</tr>
<tr>
<td>Data</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Steppe</td>
<td>98</td>
<td>93</td>
</tr>
</tbody>
</table>
the climatic conditions in the selected years to understand if a wetter climate can be responsible for this change. As can be seen in Figure 5, annual precipitation was 375 mm and annual average temperature was 11.5 °C in 2005. In 2012, annual precipitation was 348 mm and annual average temperature was 12 °C. These data show that climatic conditions were not different in years 2005 and 2012. Another reason for the conditions in 2012 could be water diversions from Zamantı River. After 2010, we know that significant amounts of water were diverted to the basin from Zamantı Basin. Wetlands are dynamic systems and respond to changes in water inflows rapidly. They also react quickly to artificial interventions (Mitsch & Gosselink 2000). This can be seen in the study of Sultan Marshes wetland. Water flows to the marshes from Zamantı River could explain higher water levels in 2012. It shows us that wetlands will quickly regain their old natural structure when they are supported by different water sources.

**CONCLUSIONS**

Wetlands are important natural resources with complex land use/cover structure. Satellite remote sensing is suitable for gathering information and mapping of wetlands on large areas, particularly when field monitoring data were unavailable. However, analyzing wetlands with satellite images is also due to the spectral confusion with other land use/
cover classes. Therefore, the selection of a good classifier is very important in the classification of wetlands. In the study, the land use/cover change occurring in the Sultan Marshes National Park and Ramsar site was determined by using two ASTER satellite images belonging to the years 2005 and 2012. The images were classified to four information classes (water, agriculture, marsh, steppe) by the MLH, ANN and SVM methods. The post classification comparison method was used for change detection. The applicability of MLH, ANN and SVM methods to classify land use/cover types in a wetland area were evaluated.

The analyses showed that there were differences in classification accuracies obtained with different methods. SVM method produced remarkably better results than MLH and slightly better results than ANN. In general, SVM and ANN were better in representing the complex nature of the Sultan Marshes wetland.

The change detection analysis showed that there was an increase in water areas and a decrease in marsh and steppe areas from 2005 to 2012. The wetter conditions are most probably due to diversion of water from a nearby basin to the Sultan Marshes. From the water level rise, it can be concluded that the drought conditions reported by previous studies can be reversed once natural water inflows to the Sultan Marshes are restored. Attention should be paid to the wetlands not only because of their importance for world’s biological diversity but also as a healthy life needs a healthy environment.

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