UAV-based Land Cover Mapping Technique for Monitoring Coastal Sand Dunes

Choi, Seok Keun1) · Kim, Gu Hyeok2) · Choi, Jae Wan3) · Lee, Soung Ki4) · Choi, Do Yoen5) · Jung, Sung Heuk6) · Chun, Sook Jin7)

Abstract

In recent years, coastal dune erosion has accelerated as various structures have been developed around the coastal dunes. A land cover map should be developed to identify the characteristics of sand dunes and to monitor the condition of sand dunes. The Korean Ministry of Environment’s land cover maps suffer from problems, such as limited classes, target areas, and durations. Thus, this study conducted experiments using RGB and multispectral images based on UAV (Unmanned Aerial Vehicle) over an approximately one-year cycle to create a land cover map of coastal dunes. RF (Random Forest) classifier was used for the analysis in accordance with the experimental region’s characteristics. The pixel- and object-based classification results obtained by using RGB and multispectral cameras were evaluated, respectively. The study results showed that object-based classification using multispectral images had the highest accuracy. Our results suggest that constant monitoring of coastal dunes can be performed effectively.

Keywords: UAV, Vegetation Classification, Random Forest, Sand Dune, Multispectral Image

1. Introduction

In recent years, coastal dunes have eroded at a very high rate. A coastal dune is regarded as a single system and organically related to a sandy beach. The sand in a dune is supplied to a sandy beach during the erosion of the sandy beach, and the sandy beach supplies the sand back to the dune. However, in the interests of the tourism industry, towns near coastal dunes often construct an artificial shelter belt to prevent sandy winds and protect coastal roads; this isolates the dunes, thereby making them unable to recover from erosion and accelerating the rate of erosion. Thus, it is very important to understand coastal dune characteristics to provide suitable recovery measures and prevent their further erosion.

Especially, sand sediments may vary greatly depending on the landscape connectivity, vegetation structure, and sand usage (Phi, 2015). To better understand and monitor the characteristics of coastal dunes, it is necessary to create an accurate cover map of the coastal dunes.

Lee and Kim (2000) studied the damage caused to coastal dunes by the development of coastal roads, agricultural land, and recreational facilities on beaches. Shin (1999) analyzed the effect of ecosystem cut-off after the construction of coastal roads in Sowon-myeon in Taean Peninsula. Kim et al. (2008) studied the damage caused to coastal dunes by the development of harbor facilities around Yeongnang Sokcho-si. Lee (2011) analyzed the loss of coastal dunes due to artificial development by investigating the land cover,
changes in sand beach shape, and changes in coastline in seven sand beaches in Gangneung. Choi (2012) developed a technique for assessing the damage caused to coastal dunes by human interference through analyzing the changes in five coastal dunes in Byeonsan Peninsula.

In order to monitor coastal dunes, a land cover map is necessary to understand the change of the various land cover. Currently, most studies have used land cover maps and vegetation maps, which were generated by the Korean Ministry of Environment. However, the former do not well reflect changes owing to the long renewal period and the latter are difficult to use because of their low spatial resolution. Therefore, in order to improve the classification accuracy, it is necessary to conduct a field investigation; however, this incurs much time and cost (Shin et al., 2015; Song et al., 2014).

Meanwhile, various studies have acquired high-resolution images using an UAV and perform monitoring after conducting accurate cover classification through multispectral analysis. Herwitz et al. (2004) studied growth and development monitoring in agriculture using a UAV, and Fuyi et al. (2012) and Hassan et al. (2011) studied high-resolution cover classification using a UAV. Among classification studies, Timm and McGarigal (2012) used Quickbird data with multispectral orthoimages to accurately map coastal dunes and salt marsh ecosystems at Cape Cod National Seashore. Shanmugam et al. (2003), Lucas et al. (2002), and Zhang and Baas (2012) used CASI (Compact Airborne Spectrographic Imager) data to map coastal dune vegetation in the Kenfig National Nature Reserve in the United Kingdom. They indicated that CASI provides coastal dune map of high classification accuracy, thus enabling classifiers to better discriminate between the unique spectral responses of the diverse habitats present within the coastal dune ecosystems. In Korea, many studies have used spatial information obtained using a UAV. Na et al. (2015) used a UAV for monitoring the growth of farm products, Shin et al. (2015) studied land cover classification using a UAV, and Kim (2014) generated 3D maps using a UAV and DSM (Digital Surface Model) by using a 3D map and extraction technique in a DEM (Digital Elevation Model). Multispectral images obtained using a UAV can be used for environmental monitoring and changes in land cover use in forest and agricultural areas. UAVs are advantageous for monitoring because they afford convenient data acquisition, require less time, and incur less cost. Choi et al. (2016) estimated the FVC (Fractional Vegetation Cover), namely, the vegetation per unit area, using a multispectral UAV and reported accuracy similar to that of field survey methods. However, few studies have focused on classifying vegetation and non-vegetation areas for coastal sand dune monitoring using a UAV and on a classification method for dune cover using vegetation indexes.

This study aims to produce a land cover map of coastal dunes in a small area with steep slope, which is difficult to perform using existing methods, by using a multispectral UAV. Pixel- and object-based classification were performed using the NDVI (Normalized Difference Vegetation Index), ExG (Excess Green) in order to evaluate the applicability of a multispectral UAV.

2. Study Area and Imagery

The study region was Pung Seong sand dune in U-I island, Docho-myeon, Sinan-gun, Jeollanam-do, Korea. Pung Seong sand dune is a representative sand dune that has been developed by sands transferred and accumulated by winds. Although most sand dunes in the area were destroyed by the construction of seawalls and reclamation, Pung Seong sand dune has survived.

![Fig. 1. Pung Seong sand dune: (a) Pung Seong sand dune in U-I island, and (b) panorama of Pung Seong sand dune](image)

In contrast with other dunes on the west coast, Pung Seong sand dune has a steep slope and narrow area. Therefore,
existing methods face limitations when used to determine the features of cover information. In an experiment, multispectral and RGB images based on a UAV were obtained two times on Oct. 17, 2015 and Sep. 24, 2016 in order to classify the land cover. Fig. 1 shows the location and front view of the experimental area. The senseFly eBee was used in this study, and images were acquired using MultiSPEC 4C sensors and IXUS 127 HS. Table 1 shows detailed information about each sensor.

Table 1. Characteristics of camera and dataset used

<table>
<thead>
<tr>
<th>Content</th>
<th>Specification/Parameter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensor size</td>
<td>4.8 × 3.6 mm (MultiSPEC 4C)/7.44 × 5.58 mm (IXUS 127 HS)</td>
</tr>
<tr>
<td>Altitude above ground</td>
<td>100 m (MultiSPEC 4C)/142 m (IXUS 127 HS)</td>
</tr>
<tr>
<td>GSD (Ground Sampling Distance)</td>
<td>10 cm/pixel (MultiSPEC 4C), 5 cm/pixel (IXUS 127 HS)</td>
</tr>
<tr>
<td>Longitudinal overlap</td>
<td>80%</td>
</tr>
<tr>
<td>Lateral overlap</td>
<td>80%</td>
</tr>
</tbody>
</table>

Considering the steep slope and beach in the Pung Seong sand dune, overlap was set to 80% in both the longitudinal and lateral directions, and the log file and image file were matched using the senseFly eBee’s eMotion program (SenseFly, 2016).

To process the acquired multispectral images, Pix4D software was used, and a value of the acquired ground control point was inputted to the software using real time kinematic global positioning system to perform geometric correction of the images (Pix4D, 2016). After geometric correction, the acquired images had a root mean square error within 0.5 GSD. The spectral information was corrected using the white reflectance panel provided by MultiSPEC 4C.

Table 2. Number of training and reference data in study area

<table>
<thead>
<tr>
<th>No.</th>
<th>Class name</th>
<th>Oct. 17, 2015</th>
</tr>
</thead>
<tbody>
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<td></td>
<td></td>
<td>Training</td>
</tr>
<tr>
<td>1</td>
<td>concrete road</td>
<td>159</td>
</tr>
<tr>
<td>2</td>
<td>deck</td>
<td>119</td>
</tr>
<tr>
<td>3</td>
<td>dry grass</td>
<td>277</td>
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<td>4</td>
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</tr>
<tr>
<td>5</td>
<td>rock</td>
<td>245</td>
</tr>
<tr>
<td>6</td>
<td>shrub</td>
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</tr>
<tr>
<td>7</td>
<td>tree</td>
<td>416</td>
</tr>
<tr>
<td>8</td>
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<td>324</td>
</tr>
<tr>
<td>9</td>
<td>wet sand</td>
<td>546</td>
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<table>
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</tr>
<tr>
<td>2</td>
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<tr>
<td>5</td>
<td>rock</td>
<td>380</td>
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<tr>
<td>6</td>
<td>shrub</td>
<td>333</td>
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<td>7</td>
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<td>1483</td>
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<td>8</td>
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<tr>
<td></td>
<td>Total</td>
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</table>
The training and reference data, selected as a homogeneous part that did not mix with other materials, were acquired manually based on RGB images. To distinguish between dry grass and shrub, area of low NDVI value among brown colored areas in the RGB image were selected as dry grass class, while area of high NDVI value among the green colored areas in the RGB image was selected as shrub. The number of training and reference data was adjusted to the ratio of classes present in the image, and the reference data was set to be several times in amount compared to the training data.

3. Methods

This study extracted ROIs (Regions Of Interest) from the RGB orthoimages. The ROI was applied to the RF (Random Forest) technique. To compare classification results, quantitative assessment based on a confusion matrix was applied by using ground truth data. Fig. 3 shows the workflow.

3.1 ExG

Woebbecke et al. (1995) developed a vegetation index derived using visible bands of green, red, and blue. The ExG vegetation index has been widely used and tested in previous studies (Giltelson et al., 2002; Mao et al., 2003). Mao et al. (2003) tested several indicators based on RGB images, such as ExG, normalized difference index, and modified hue, to separate plant material from different backgrounds. We choose the ExG index because of Mao et al. (2003) and Saberioona et al. (2014) found that the ExG index outperformed the other indexes tested in G band. ExG is calculated as follows:

\[
ExG = 2g - r - b
\]

\[
r = \frac{R}{R + G + B}, \quad g = \frac{G}{R + G + B}, \quad b = \frac{B}{R + G + B}
\]  

where R, G, and B refer to red, green, and blue bands, respectively, in the visible region band.

3.2 NDVI

NDVI is created using the optical property that the spectral reflectance of vegetation increases in the near infrared region. In this study, NDVI was used as input data to improve the classification accuracy between vegetation and non-vegetation classes and to overcome the limitation of the existing classification method using RGB image alone. Fig. 4 shows the resulting image. The NDVI is calculated as follows:

\[
NDVI = \frac{\rho_{nir} - \rho_{red}}{\rho_{nir} + \rho_{red}}
\]

where \(\rho_{nir}\) and \(\rho_{red}\) are the spectral reflectance of the near infrared and red band, respectively.
3.3 RF classifier

RF is a combination of predictors such that each tree predictor depends on the estimated values of a random sample independently for all trees in the group called forests. RF involves the use of hundreds of classifiers, and their decisions are combined based on votes. Combined set classifiers are often more accurate than a single classifier, because they avoid collisions between feature sets (Breiman, 2001; Chan and Paelinckx, 2008). As a result, RF classification is widely used to classify remotely sensed images. RF classifier consists of several trees that are organized by the pseudorandom selection of a subset of components of the feature vector, that is, trees are constructed in randomly chosen subspaces while maintaining the highest accuracy of training data and improving on the generalization accuracy as it grows in complexity (Ho, 1998). To apply the RF classifier, the number of decision trees is set to 100, and each class is selected by considering the spatial characteristics of the Pung Seong sand dune in the RGB images.

3.4 Object-based classification

Object-based classification techniques have already been used to extract information from very-high-resolution images (Giada et al., 2003; Benz et al., 2004). Object-based techniques recognize that important information is not always represented in a single pixel but in contextual relationships with meaningful image objects. Object-based classification consists of two steps: image segmentation and object classification. Image segmentation subdivides an image into groups of consecutive pixels called objects or segments that correspond to meaningful features or targets in a field (Blaschke and Strobl, 2001). The images are segmented into homogeneous objects based on spectral information and local pattern or texture information contained in adjacent pixel groups.

eCognition software was used in this study. eCognition uses a multi-resolution segmentation approach that is a bottom-up area merging technique that begins with a one-pixel object. Through many iterations, small image objects are merged into larger image objects. The results of the segmentation algorithm are controlled by the scale factor and heterogeneity criterion. The scale factor is indirectly related to the average size of the object to be detected. The heterogeneity criterion controls the merge decision process, and it is calculated using the spectral hierarchy (multispectral image) or non-spectral hierarchy (thematic data). The heterogeneity criterion contains two mutually exclusive attributes: color and shape. Color refers to the spectrum homogeneity, and shape takes into account the semantic properties of objects. Shapes are divided into two equivalent exclusive properties: smoothness and compactness.

The optimal segmentation parameters depend on the scale and characteristics of the features to be detected. These were determined using a systematic trial-and-error approach that was validated by visual inspection of the quality of the output image object. Once the appropriate scale factor was determined, the appearance of the image object was changed by modifying the color and shape criteria. Many previous studies have found that more meaningful objects are extracted using color criteria (Herold et al., 2002; Laliberte et al., 2004; Moffett and Gorelick, 2013).

4. Experiment Results and Analysis

In this study, the land cover map was classified using the orthoimage, DSM, and ExG and NDVI images obtained by UAV images. Because ExG is a vegetation index generated in the visible region, it was compared with NDVI that is generated from multispectral images. Therefore, the experiment was designed to analyze the influence of the input features. In addition, we tried to analyze the effect of classification results through pixel- and object-based classification in coastal dune monitoring. For this purpose,
we performed experiments of four cases according to the input feature and classification technique. The experimental methods are described below, and Figs. 5 and 6 show the land cover classification results. The parameters for object-based classification were set by referring to a previous study: shape: 0.2, compactness: 0.5, and scale: 45 (Moffett and Gorelick, 2013).

case 1. RF classification using RGB, DSM, and ExG images
  case 1-1. Pixel-based classification
  case 1-2. Object-based classification

case 2. RF classification using multispectral, DSM, and NDVI images
  case 2-1. Pixel-based classification
  case 2-2. Object-based classification

In case 1, the shadows in rock class, a non-vegetation region, was misclassified as vegetation. On the contrary, a part that should be classified as dry grass was misclassified as shrub. In case 2, the aforementioned misclassifications did not occur. Therefore, the classification result in case 2 was evaluated to be better than that in case 1. Classification result by NDVI obtained using a multispectral image was considered better for vegetation classification than that by ExG obtained using the RGB image. Furthermore, the salt-and-pepper error found in pixel-based classification was decreased in object-based classification.

![Fig. 5. Classification result using RF in 2015](image)

![Fig. 6. Classification result using RF in 2016](image)

![Fig. 7. Detailed classification results of 2015:](image)

(a) (d)
(b) (e)
(c) (f)

(a) orthoimage, (b) classification result by case 1-1, (c) classification result by case 1-2, (d) orthoimage, (e) classification result by case 2-1, and (f) classification result by case 2-2

Fig. 7 shows detailed images to show the characteristics of the pixel- and object-based classification results. A comparison of Fig. 7(a) and 7(b) indicates that the shadows on the road clearly show the characteristics of pixel- and object-based classification. The former classified roads with shadows as shadows, where the latter classified roads correctly. In addition, Fig. 7(c) shows that object-based classification reduces the salt-and-pepper error compared to that in Fig. 7(b). It means that the classification results are better when using multispectral images than when using RGB images. Fig. 7(e) and 7(f) show that the classification results using multispectral images are less affected by shadows.
compared with those using RGB images. Overall, the NDVI obtained from multispectral images more effectively improved the classification accuracy than the ExG obtained from RGB images, and object-based classification efficiently reduced errors such as salt-and pepper compared to pixel-based classification.

Table 3. Confusion matrix about classification result of case 1-1 in 2015

<table>
<thead>
<tr>
<th></th>
<th>dry sand</th>
<th>wet sand</th>
<th>dry grass</th>
<th>shrub</th>
<th>trees</th>
<th>deck</th>
<th>concrete road</th>
<th>rock</th>
<th>water</th>
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</thead>
<tbody>
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<td>18</td>
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<td>0</td>
<td>3</td>
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<td></td>
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<td></td>
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Table 4. Confusion matrix about classification result of case 1-2 in 2015

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<th>wet sand</th>
<th>dry grass</th>
<th>shrub</th>
<th>trees</th>
<th>deck</th>
<th>concrete road</th>
<th>rock</th>
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Table 5. Confusion matrix about classification result of case 2-1 in 2015

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<th>deck</th>
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<td>water</td>
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<td>0</td>
<td>0</td>
<td>0</td>
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<td>0</td>
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<tr>
<td>overall accuracy(%)</td>
<td>91.82</td>
<td></td>
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</table>

UAV-based Land Cover Mapping Technique for Monitoring Coastal Sand Dunes
Table 6. Confusion matrix about classification result of case 2-2 in 2015

<table>
<thead>
<tr>
<th>Reference data</th>
<th>dry sand</th>
<th>wet sand</th>
<th>dry grass</th>
<th>shrub</th>
<th>trees</th>
<th>deck</th>
<th>concrete road</th>
<th>rock</th>
<th>water</th>
</tr>
</thead>
<tbody>
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<td>dry sand</td>
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<td>0</td>
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</tr>
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<td>0</td>
<td>17</td>
<td>0</td>
</tr>
<tr>
<td>shrub</td>
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<td>Overall accuracy (%)</td>
<td>94.57</td>
<td>kappa coefficient</td>
<td>0.936</td>
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</table>

Table 7. Confusion matrix about classification result of case 1-1 in 2016

<table>
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<th>dry sand</th>
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<th>dry grass</th>
<th>shrub</th>
<th>trees</th>
<th>deck</th>
<th>concrete road</th>
<th>rock</th>
<th>water</th>
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<td>Overall accuracy (%)</td>
<td>84.59</td>
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</table>

Table 8. Confusion matrix about classification result of case 1-2 in 2016

<table>
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<th>dry sand</th>
<th>wet sand</th>
<th>dry grass</th>
<th>shrub</th>
<th>trees</th>
<th>deck</th>
<th>concrete road</th>
<th>rock</th>
<th>water</th>
</tr>
</thead>
<tbody>
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<td>0</td>
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<td>0</td>
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<td>0</td>
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</tr>
<tr>
<td>dry grass</td>
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<td>628</td>
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<td>0</td>
<td>56</td>
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</tr>
<tr>
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</tr>
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<td>Overall accuracy (%)</td>
<td>94.33</td>
<td>kappa coefficient</td>
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</tbody>
</table>
In order to evaluate the classification accuracy quantitatively, confusion matrix is used based on reference data. As shown in Table 3~10, the accuracy of the classification results was evaluated by kappa coefficient and overall accuracy using confusion matrix (Jensen, 2015). In Table 3~6, case 2 shows significantly higher classification results than case 1 owing to the misclassification occurring of vegetation (trees and shrub) and non-vegetation (rocks and sand). In addition, Table 7~10 shows that the accuracy of case 2 is higher, although the difference in accuracy is reduced. Meanwhile, in Table 8 and 10, object-based classification result by multispectral image (case 2-2) is slightly higher than that by RGB image (case 1-2). However, in case 1-2, some shrub class is classified dry grass. These results show that the results by RGB image vary depending on the obtained image conditions in the classification between vegetation and non-vegetation classes, compared with that by multispectral image. Therefore, it indicates that the object-based classification result based on multispectral image had the highest accuracy.

**5. Conclusion**

In this study, land cover was classified using RGB images and multispectral images obtained using a UAV to produce a land cover map of coastal dunes. In the experiment, the classification results obtained using RGB, DSM, and ExG images showed some errors when images contained similar colors or when one class contained various other classes; in comparison, the classification results obtained using multispectral, DSM, and NDVI images did not contain these errors. Quantitatively, object-based classification in case 2-2 in 2015 showed overall accuracy of 94.57% and that in case...
2-2 in 2016 showed overall accuracy of 94.39%; these were the highest accuracies obtained in the experiment. This indicates that object-based classification has higher accuracy than pixel-based classification for each period. Although object-based classification with ExG shows accuracy similar to that of case 2-2 in 2016, which indicates the classification results obtained using RGB images, many reliability problems were faced because the results vary according to the conditions. Therefore, the use of object-based classification with NDVI is the most effective method for monitoring, and it will be least affected by the conditions in the obtained image.

Object-based classification with NDVI needs to be evaluated further by being applied to other coastal dunes in different regions. In addition, the development of additional input data in accordance with a target region should be studied by identifying various factors that affect the classification.

Acknowledgment

This work was supported by academic research support project of Chungbuk National University in 2015 and the National Research Foundation of Korea (NRF) grant funded by the Korea government (MEST) (No. NRF-2015R1D1A1A01061058 and No. NRF-2013R1A1A1060343).

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