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Detection of the Dry Trees Result of Oak Borer Beetle Attack Using Worldview-2 Satellite and UAV Imagery an Object-Oriented Approach

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Abstract

In Iran, forest inventory information has been essential with respect to land management because 10% of Iran is composed of forests. Therefore, accurate forest information such as tree counts, height, DBH, and volume are critical for forest management. While such data traditionally have required labor intensive and time consuming field measurement, new technologies such as remote sensing have supplemented and supplanted some of these field measurements. Although different types of sensors have been used to extract individual trees information, WorldView-2 (WV-2) has been used recently to extract surface information because WV-2 have high spatial and spectral resolution. In this study, object base classifiers (with KNN way) were used to classify WV-2 satellite and do assessment accuracy with UAV image in study sites. the study indicate that the classification accuracy of Object-based algorithm was best for extraction of dry trees. This study is conducted to evaluate the possibility of WV-2 data to extract forest characteristics from identifying and measuring individual trees. Our results demonstrate that WV-2 data, NDVI with object-based classification can be used to detect tree mortality resulting from numerous causes and in several forest cover types.

Keywords: Extraction of individual trees; Tree crown; Dry trees; Remote sensing; Classifiers; Zagros forests; Haft Barm Shiraz

Introduction

Forest inventory is traditionally a useful and accurate way of monitoring forest coverage, but it is very expensive and its updating cycle is relatively expensive because of its cost [1-3]. Wide range of forest can be rapid changes, forest inventory traditionally does not respond adequately to the development of change [4]. Climate warming and recent severe droughts have resulted in vegetation mortality in various woody biomes across the globe [5-9]. The outbreak of insects requires a quick way to monitor forestry. As soon as information is provided, monitoring and reducing activities can be effectively implemented. Because insects, with their effects, change the spectral response pattern of trees and allow us to monitor forest disturbances using remote sensing data [10,11].

So, the forest inventory was traditionally combined with satellite and aerial mapping in the Haft Barm forest of Shiraz, so that we could obtain documents of oak dryness. Given the severe forest areas, it is possible to identify trees under the pest attack with remote sensing imagery.

The traditional per-pixel classification provides sufficient results for medium-resolution images [1]. But with access to high-resolution images (VHRs), with increasing spectral capabilities within objects on the map, the demand for ground object techniques has increased [12-15].

The concept of the base object classification is that the information needed to interpret the image in a separate pixel is not provided, but rather in meaningful image objects. Segmentation is the first step in the base object method with a certain heterogeneity. Compared to pixels, image objects have very useful information, so we can use pure spectral information to distinguish between features, such as texture, neighborhoods, or content. In the second step, this information is used to classify by deciding the base law on fuzzy concepts [16-19].

Materials and Methods

Study of dry forest areas with eCognition

The development of the base object model consists of two steps: segmentation and classification. Image objects are extracted from the image in the fragmentation process that takes place before the classification. The method is described in detail in the next section.

Segmentation

The first step in the eCognition chart is the image segmentation that creates image objects (pieces) of "similar" pixels. The idea behind this is the Fractal Net Evolution Algorithm (Fractal Net Evolution Algorithm), which brings the weighted heterogeneity of the image objects. At each step, the matching objects defined are merged with the smallest growth in heterogeneity, but only if the growth of heterogeneity is smaller than the user-defined scale parameter. This process is similarly used throughout the image to obtain objects of a size and desirable quality [17].

Creating a parameter for fragmentation is determined in the bottom-up method. The scale parameter defines the size of the image objects to be repeatedly increased, preserving the parameter color; shape, softness and compression in the default values (see Table 1). In the parameter of scale 20, the created well-sized objects showed the size of the crown of individual dried trees. In the living masses, especially from broad-leaved trees, several tree crowns were combined

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in one piece. The shadows were extracted very clearly from the image. Changes in parameters such as color, shape, softness and compression did not result in significant changes in the pieces, so the default settings were maintained. The size of the very small objects is compared with the size of the image set under the image, they have little variation. For the final classification of non- woodland levels, the GIS thematic layer was used to represent the boundaries of these levels within the plotted image from the Haft-Barm "reference GIS" forest including roads, structures, etc., as shown in Figure 1.

Workflow	Description of work; in/output	Parameter settings/variables
Step 1	Segmentation	Level 1
Method	Multiresolution segmentation	Scale parameter 20, color/shape 0.8/0.2; smoothness/ compactness 0.9/0.1
	Masking of “non-woodland areas”"	ReferenzGIS layer
Deliverables	“Object primitives fitting dead trees”	
Step 2	Classification 1: “object primitives”	Level 1
Methodology	1. Ratio and pseudo NDVI calculation	Index values, thresholds
	2. Training sample collection	
	3. Classification with nearest neighbor	
Deliverables	Map with classified object primitives	“Non-woodland”, dead tree, vital vegetation, shade within dead trees, shade within vital trees
Quality check	Accuracy assessment	Overall accuracy: 82%, k-index 89.7%
Step 3	Classification 2: “objects of interest”	Level 2
Methodology	Neighborhood relationships	
Deliverables	Map with classified “objects of interest”	“Dead trees”, “vital trees”, “non-woodland areas”
Step 4	Accuracy assessment	
Methodology	Visual examination using a UAV airborne image	300 samples
Results	Contingency matrix (Table 2)	Overall accuracy: 91,5%, k-index 89.77%

Table 1: Image analysis chart.

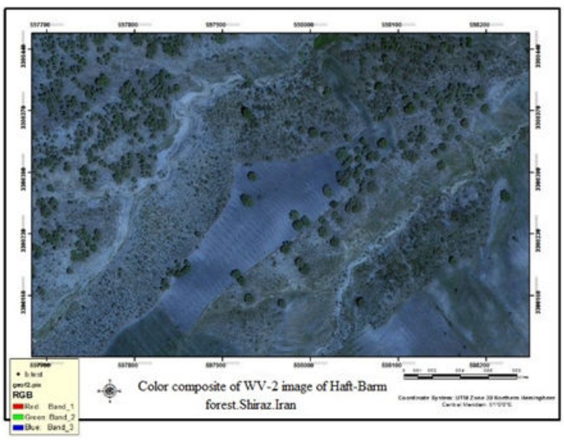

Figure 1: The color image of the WV-2 from the studied area. Haft-Barm forest, Shiraz, Iran.

The purpose of the classification is to label all objects as "dry tree surfaces", "live vegetation" or "non- woodland surfaces". This process starts with the "First Objects" classification based on image objects created in the segment. The third class required for classifying the levels is a non- woodland class that represents surfaces such as forest roads, water, wetlands that masks with the help of the thematic of the Haft-Barm forest "GIS Reference". Two additional classes are introduced as a temporary class or auxiliary classes: "Shadows between dry trees" and "Shadows among the living trees." These are needed for the correct assessment of the final classes.

Classification strategy

We used "spectral" information from RGB bands to extract trees.

Two spectral indexes were calculated: the "ratio" algorithm provided by the eCognition software and the NDVI. For the ratio function in eCognition, the average value of the channel is divided by each object by the average value of the remaining bands.

$$r_L = \frac{\bar{C}_L}{\sum_{i=1}^{n_L} \bar{C}_i} \qquad (1)$$

RL: L band ratio; CL: Average value of the object observed in the image in the band L.

The NDVI also provides a good syllabus for separating classes. NDVI is one of the most common indicators in remote sensing for vegetation identification. This makes it possible to distinguish between plants with active and non-vegetative photosynthesis.

$$NDVI = \frac{NIR - \text{Red}}{NIR + \text{Red}} \quad (2)$$

Similar to this process, to calculate the ratio, NDVI was not computed by pixels, but instead, the average values of pixels from each channel were calculated in image objects.

$$i_{veg} = \frac{\bar{C}_{L(1)} - \bar{C}_{L(2)}}{\bar{C}_{L(1)} + \bar{C}_{L(2)}} \quad (3)$$

i_{veg}: vegetation index; $\bar{C}_L(1)$: average value of the channel (1) image of the image object; $\bar{C}_L(2)$: average value of the channel (2) image of the image object.

With the ratio of all three channels and NDVI, the series of data used for classification includes four channels. Based on the data extracted from the data series, not only live vegetation can be identified, but also shadows on living vegetation can be separated from shadows in dry trees. Therefore, the initial classes of "living trees", "dry trees", "shadows between dry trees" and "shadows among living trees" were classified with "fractal closest standard neighbors". For this purpose, the algorithm is first required to be calibrated with known educational objects.

This process, output and product are multidimensional communication. The smaller distances between objects in the feature space, give a greater degree of dependence to the class. Details of this method are described by Baatz et al. [20]. Classification is based on the "nearest neighbor of the standard"; that is, a small number of objects are first selected as prototypes for each class, then the initial classification is performed. The classification result is gradually improved by introducing more instances gradually and step by step.

The next class required for the region statistics is "Non- woodland " class, showing the levels of forest roads, water structures, wetlands that are classified by thematic attachments of the GIS layer used for segmentation.

The overall result of the objects is to add more "dry surfaces" and "live vegetation" by adding two temporary classes. Individual objects, which can be identified directly, not as "dry tree surfaces", but rather as "living vegetation", are enclosed by objects of one of these classes, were assigned to the corresponding class By Neighborhood Communications. There are such levels, for example, the massive cover of the earth's surface within a dry forest floor, which is classified as "living vegetation." This is achieved with the help of membership functions. The rules for these are as follows:

"Other Dry Areas": If more than 60% of the environment from these boundaries of the surface is dry on the forest surfaces, they will be awarded to dry forest levels. "Other Living Vegetation": If more than 90% of the environment is alive from the boundaries of these surfaces on vegetation, they will be assigned to the class.

The first classified objects are subsequently combined into "desired objects" over a higher level of width by "base class classification". The final classes are "dry forest levels", "live vegetation", and "other levels" (non- woodland levels).

The main step of this classification process is shown in Figure 2 and is described in Table 2.

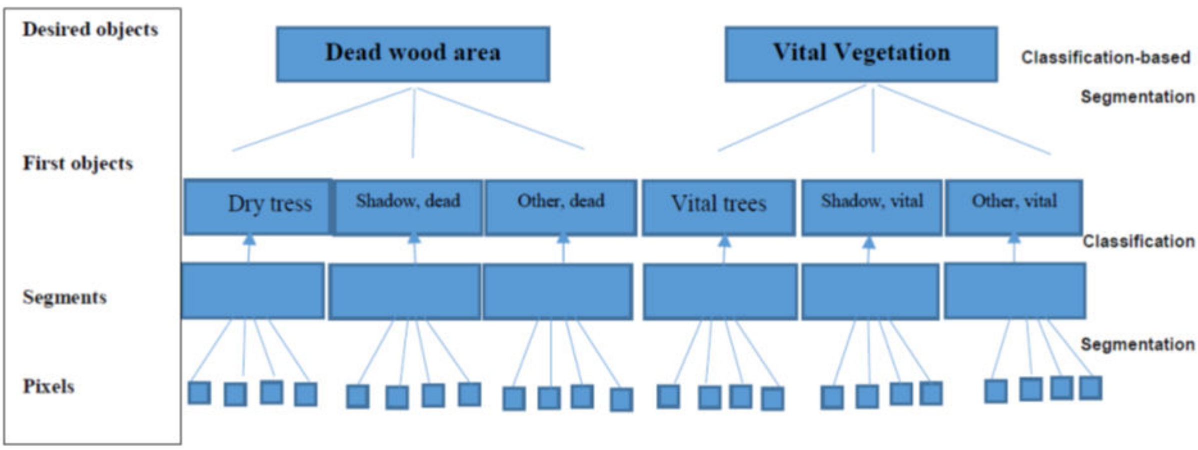

Figure 2: Schematic image analysis with eCognition.

Class	Object feature	Function
Dead trees	Ratio (1, 2, 3), NDVI	Standard-Nearest-Neighbor
Shadow among dead trees	Ratio (1, 2, 3), NDVI	Standard-Nearest-Neighbor
Other dead	Relative border to dead trees>0.6	Membership Function

Vital trees	Ratio (1, 2, 3), NDVI	Standard-Nearest-Neighbor
Shadow among vital trees	Ratio (1, 2, 3), NDVI	Standard-Nearest-Neighbor
Other vital	Relative border to vital trees>0.9	Membership function
Non-woodland	Thematic attribute of GIS layer	Masking

Table 2: The complication of objects and functions in the classification process.

Accuracy assessment

Theories and methods have been developed to evaluate the classification result in pixel-based image processing. In contradiction to traditional methods, the results of the object- oriented classification strategies are evaluated on an object-level basis. As previously stated by Schneider et al., Tiede and Hoffmann, Schopfer and Lang [14,21,22], object-oriented methods require an adapted accuracy assessment strategy to fully access the extensions options offered by the feature tables automatically created by the eCognition classification process. In the present study, we decided to limit the accuracy assessment to the final plot results. The most common processes use the results of the mapping method as a reference. In the present study, the standard mapping method of visual interpretation was identified as the correctness of the present. Two more independent mapping methods have more credibility than others. The solution to assess both methods versus visual interpretation is the use of vision that is derived from the analysis.

For this, 300 reference objects were randomly identified on UAV images and assigned to the classes by visual interpretation. Tree crowns were independently selected from the 2018 UAV image, thus providing a total of 300 tree crowns (150 live, 150 dead). False-color display (NIR, red, and green bands) of pan-sharpened images (0.6 m spatial resolution) facilitated visual selection of live and dead tree crowns and clusters in the imagery (Figure 3).

The result of the error matrix is evaluated based on overall accuracy, producers accuracy, user accuracy and classification accuracy [23-27].

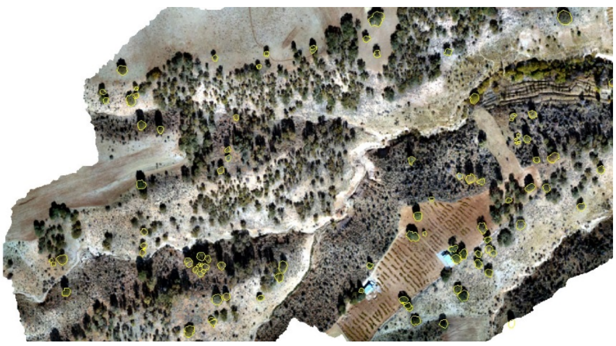

Figure 3: Training points on the UAV image.

Apart from these quantitative markers of a classification, focusing especially on the detection of areas with dead trees, three qualitative aspects were checked to assess the success of the evaluation strategy:

The transferability of the rule bases to images of the same flight ("Detection of areas with dead trees and transferability of the rule bases to images of the same flight")

(2) The transferability of the rule bases to images with other recording conditions and "change detection" ("Transferability of the rule bases to images with other recording conditions and "change detection")

(3) Comparison of the results of mapping obtained with the semi-automatic method developed with the results of conventional methods by GIS activities ("comparison with the results of the conventional method with the use of visual interpretation").

Results

Discovering surfaces with dry trees and the transferability from the rule bases to images of the same flight.

The base object method is well characterized by dry trees (Figure 4). The overall classification for dry forests, dry shade, live vegetation and live vegetation shades was 82.0%. The Kappa index was 89.77%. The most misunderstanding has occurred in the classification of shadows. These are clearly not clear in the shade class of vegetation, because they are often mixed with living vegetation cover classes. This is different for the shade of the dry forest. Here, 35% of the tested objects are dedicated to living vegetation classes and live vegetation shadows. Considering the final results, this related to the classification is wrong. If each class pair, dry forest and dry shade, and live vegetation and shade of living vegetation combine together and create a distinct class, the final production of the classification output will obtain a total accuracy of 82% (Table 3). Therefore, the established rule of law is for a fairly consistent separation between the dry forest and living vegetation. The capability of the base law for the other part of the same imaging also does not have existing problems.

Method	Object Based. KNN
Coefficient of Kappa	89.77
Overall Accuracy	82
User Accuracy Class "Other"	96.2
Precision Producer Class "Other"	83
User Accuracy Class "Live Trees"	56.2
Precision manufacturer Class "Live Trees"	70
precision user "Live trees"	85.6
Precision producer of "Live trees" Class	79.5
User-class accuracy "Dry tree shades"	51

Class accuracy "Dry shade trees"	92.5
Precision of User-class accuracy "Dry trees"	97.6
Precision of class producer "Dry trees"	83.5

Table 3: The results of the classification of dry trees with eCognition.

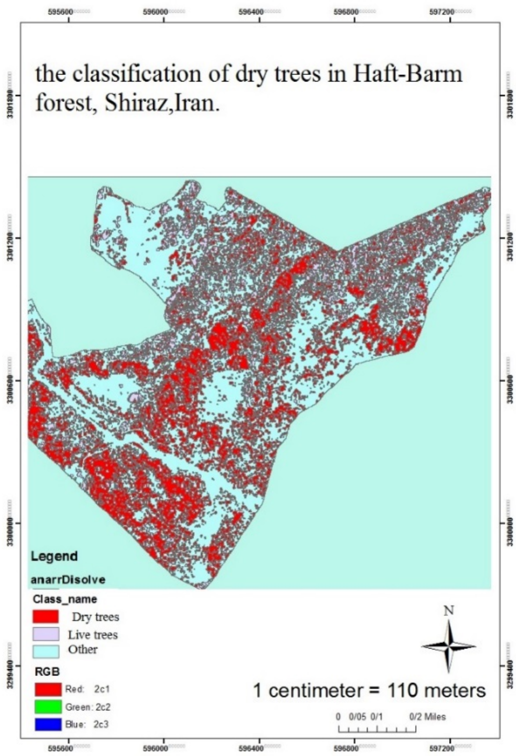

Figure 4: Classification of surfaces with dry trees with eCognition.

Discussion and Conclusion

In the present study, the object-oriented model was developed using high resolution images to map the trees that were dried by pests. The results confirm that this may identify the dried surfaces with precise detail and high by the object-oriented method. Detecting and periodically publishing periodic pest-dried levels from remote sensing tasks.

Examining the error matrix shows that the main source of errors starts with the status of objects in comparison with the definition of the class of objects. For example, the observed complexity between dry forest levels and living vegetation is due to the presence of shoots and vegetation regenerations in the forest floor at these levels, which leads to mistakes in the identification of dry trees. In such a situation, regeneration is successful, and for classification clarity, the class name should change to "successful regeneration" in future work.

Contrary to the visual method, the object-oriented method has many advantages:

(1) Requires a very small amount of human intervention, except in very few situations.

(2) The basic rules are the important codification for image interpretation and can be adapted to a small extent with the new data set.

(3) These maps provide precise details of the distribution of dry forest surfaces.

(4) Single trees, which are very important for the strategy of the continuity model, can be identified.

Given the high radiometric resolution of the WV-2 images (11 bits), it is possible to distinguish dry trees easily from the available data.

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