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Mapping oak decline through long-term analysis of time series of satellite images in the forests of Malekshahi, Iran

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ABSTRACT

The Zagros Mountains forests extend across 11 provinces in Iran and constitute approximately 40.0% of the country’s woodlands. These forests have important soil conservation and water regulation functions. Over the last decade, these forests have been declining in oak populations in many places, triggered by factors such as drought, pathogens like the fungus Biscogniauxia mediterranea, and pests such as borer beetles. Mapping the regions that show such a decline is the first step to addressing and managing the risks posed by this environmental calamity. In this research, we focus on the forests surrounding Malekshahi city in the Ilam province of Iran. Using Landsat data from the years 2000 to 2016, we determined the spatial distribution of oak decline in the region. After applying a forest/non-forest classification, appropriate spectral indices including Enhanced Vegetation Index (EVI), Normalized Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI) were selected. Together with ground truth data, two regression methods (linear regression and support vector regression (SVR)) were used to model the decline score of each pixel based on the slope of variation of selected spectral indices during the observed 17 years. The oak forests were then classified into four categories: healthy forests, low-severity-declined forests, mid-severity declined forests, and high-severity declined forests, based on the respective estimated decline scores. SVR mapped different severities of oak decline with an overall accuracy of 51%, which appears to be due to the dependency of the method on the time of decline during the 17-year timeframe. However, in a binary classification mode – meaning classifying decline score to be either ‘Healthy’ or ‘decline’ – both regression methods were able to detect declined pixels with a producer’s accuracy of 100%.

1. Introduction

Forests cover 31.0% of the global land area while only 7.40% of Iran is covered by forests (Keenan et al. 2015; Gooshbor et al. 2016). The per capita forest area in Iran is only 0.15 ha (FAO 2015), against a world average of 0.64 ha, which means that maintaining forest resources in the country is especially important. The Zagros Forest, with an area of about...
five million hectares, constitutes about 40.0% of all of Iran’s forests (Heshmati 2007; Salehi, Wilhelmsson, and Söderberg 2008; Valipour et al. 2014), and spans 11 provinces (Badian and Azim Nejad 2016).

Available data indicate that the global forest area declined by 3% from 1990 to 2015 (Keenan et al. 2015). Also in Iran, there have been alarming reports about the health of oak trees, which are the dominant tree species in the Zagros Forest. The first worrying reports came from Ilam province in 2009, where the status of the forest health was more alarming than in other provinces of Iran (Imanyfar and Hasanlou 2017). Symptoms of a serious disease called ‘oak decline’, including unusual leaf colour change, leaf loss and sap secretion from infected parts of the trees could be observed (Mirabolfathy 2013). The disease is triggered by factors such as drought, dust, pathogens like the fungus *Biscogniauxia mediterranea* and pests such as borer beetles (Mattson and Haack 1987; Vannini and Valentini 1994; Vannini, Paganini, and Anselmi 1996; Hoseiny 2011; Pirouzi and Tavakoli 2015) and now extends across about 1.5 million hectares – constituting a major ecological disaster (Zakeri, Hojjati, and Kiadaliri 2013).

Mapping the declining regions is the first step towards addressing and managing the risk posed by this environmental calamity (Imanyfar and Hasanlou 2017). To that end, the importance of mapping is already well recognized as part of the Food and Agriculture Organization (FAO) of the United Nations experts’ recommendations, as well as relevant instructions from the Forests, Range and Watershed Management Organization (Forests, Range and Watershed Management Organization of Iran 2011). There are different ways to produce such a map, but considering the large extent of the Zagros Forest, remote sensing (RS) methods should be particularly suitable and cost-effective provided that relevant phenomena can be detected with these. In RS research, numerous studies have been carried out using satellite imagery to monitor forest health and growth (J. Wang et al. 2010; Lambert et al. 2013; Meng et al. 2016; Lewińska et al. 2016; Housman et al. 2018). For example, Lambert et al. (2013) extracted vegetation activity variations using a 12-year time series of Moderate Resolution Imaging Spectroradiometer (MODIS) data and, as a result, remarkable relationships were found between the indicator of spring vitality derived from remote sensing images and the observed status of forest stands (Lambert et al. 2013).

Diseases affecting Oak species are nothing new and have occurred in several countries before, such as Japanese Oak Wilt (JOW) in Japan and Sudden Oak Death (SOD) in the United States of America (USA) (Imamura et al. 2017; Kozanitas et al. 2017). It should be noted that these diseases differ from those affecting the Zagros trees, at least in terms of the fungus species involved. Many researchers have investigated the phenomena using different kinds of RS data, including medium resolution optical imagery, e.g., Landsat data, high-resolution optical imagery, e.g., IKONOS data, and hyperspectral data (Komura et al. 2005; Weissling, Xie, and Jurena 2005; Wang, Lu, and Haithcoat 2007; Wang, He, and Kabrick 2008; Uto et al. 2008; Gillis 2014; Mahdavi et al. 2015; Rostamnia and Akhoondzadeh Hanzaei 2016). In the following paragraphs, selected research efforts related to the study of oak disease using each of these satellite data types will be discussed.

Wang, Zhenqian, and Haithcoat (2007) investigated the detection of an oak decline in the Mark Twain National Forest, in the Ozark Highlands, Missouri, USA. They applied the Normalized Difference Water Index (NDWI) to map the continuous forest dynamics
associated with oak decline. Landsat 5 Thematic Mapper (TM) imagery from 1992 and Enhanced Thematic Mapper plus (ETM+) imagery from 2000 were processed to compute the differential NDWI (DNDWI). A simple thresholding method was used to map oak dieback, recovery, and stable areas. Although the overall accuracy was found to be relatively high (76%), this approach was not fully validated because of limitations in ground data collection (Wang, Zhenqian, and Haithcoat 2007). In another study, a risk rating system based on a series of biophysical variables was developed for the same geographical region (Wang, He, and Kabrick 2008).

In another study (Gillis 2014), a method was proposed for mapping SOD in the Santa Cruz Mountains in central California. In that research, TM imagery was used. It should be noted that regions, where trees were destroyed for certain other reasons (such as fire), were determined using auxiliary data. The researchers calculated some vegetation indices and examined them to determine which of them to apply, and what threshold value to use in order to separate declined regions from healthy ones. The ratio of the Short Wave Infrared (SWIR) to the Near Infrared (NIR) proved most useful for this task. An accuracy evaluation shows that the method identified pixels containing dead trees with 24% accuracy, which, as the author pointed out, makes the results rather unreliable (Gillis 2014).

Landsat data were used in research to study the part of the Zagros Forest located in Ilam province (Rostamnia and Akhoondzadeh Hanzaei 2016). In this study, the effect of dust and rainfall on the oak decline was investigated using linear regression. Results indicate that the effects of dust and rainfall are 38% and 62%, respectively. This study did not, however, consider mapping the oak decline (Rostamnia and Akhoondzadeh Hanzaei 2016).

In another study (Mahdavi et al. 2015), the effects of physiographic factors (terrain relief), forest cover density, and soil on the severity and distribution of oak decline were evaluated using a logistic regression model. The results showed that with increasing altitude in the western and southern aspects, and with increasing forest cover density and in areas with shallow soils and steep terrain, the severity and distribution of the decline in oak trees increased. Although this research did produce a prediction map for the oak decline, only one of the input parameters was influenced by the spectral behaviour of the forest, while the soil data were supplied by an external source (Mahdavi et al. 2015).

Other researchers have used high-resolution satellite imagery (HRSI) to detect diseases affecting oak trees. Using high-resolution imagery can be useful in detecting phenomena at the individual tree scale. Komura et al. (2005) used high spatial resolution images acquired by IKONOS and proposed a method to identify individual dead trees killed by JOW. In this study, orthophoto imagery was transformed into both Hue Intensity Saturation (HSI) and Normalized Difference Vegetation Index (NDVI) datasets. Individual dead tree crowns were recognized by cluster analysis, using datasets of H, S, and NDVI. Comparing the final map with training data indicated that the recognition rate using HRSI was overestimated (Komura et al. 2005).

In another research (Karami et al. 2017), oak decline was mapped into four levels of severity for some parts of Ilam forests using Worldview-2 satellite data. Several methods including; Maximum likelihood, naive Bayes, K-nearest neighbours, and artificial neural network classification algorithm were applied to the image and the results showed that the artificial neural network classification algorithm provided the highest overall accuracy of 73% (Karami et al. 2017).
Early detection of oak diseases is very important from a managerial point of view. For this reason, there has been a tendency to use hyperspectral imagery in some studies because of their greater spectral resolution. In a study by Weissling, Xie, and Jurena (2005), a great amount of in-situ hyperspectral data from different parts of a tree for discriminatory signatures of the disease in different stages of pathology were collected, processed, and analysed. The output led to the development of classification methods that can be applied to hyperspectral imagery from the Hyperion satellite obtained over the study area in a scheduled acquisition for early disease detection (Weissling, Xie, and Jurena 2005). Other researchers have investigated whether or not symptoms of JOW in early stages could be detected using hyperspectral sensor data. Model trees suffering from JOW were created and observed until their death using multi-spectral cameras as well as spectrometers (Analytical Spectral Devices (ASD) FieldSpec HandHeld). The results showed that the difference spectrum changed after beetle infestation, which is a possible warning symptom of JOW (Komura et al. 2005).

The research of Gillis (2014) did not produce reliable results, and although the method proposed by Wang, Zhenqian, and Haithcoat (2007) achieved relatively high overall accuracy, it was not fully validated. Mahdavi et al. (2015) modelled oak decline, but the modelling inputs were not completely based on RS products. The research of Rostamnia and Akhoondzadeh Hanzaei (2016) was not focused on oak decline map production. In this paper, a method is proposed which uses time series of medium-resolution Landsat data to map oak decline and which is validated using ground truth data (field data and Google-Earth-based data). Figure 1 illustrates the workflow of the proposed method. The method involves three steps. First, a binary classification is applied to extract forest regions from non-forest ones. In the second step, three spectral indices are then selected according to ground truth data, rainfall data, and the results of previous research including Enhanced Vegetation Index (EVI) (Huete, Justice, and Leeuwen 1999), NDVI (Rouse 1974), and NDWI (Gao 1996). A time series of the indices is calculated for each pixel, and a sequence of values is accessible from each index point. The trend of each index is examined by fitting a linear equation. During the third step, two different regression models use slope values of fitted lines to estimate a decline score for each pixel. Decline scores are classified into four categories: healthy, low-severity, mid-severity, and high severity. The support vector regression (SVR)-based method is found to be able to detect different severities of decline with an overall accuracy of more than 50%.

2. Study area
Malekshahi county, with an area of 180,000 ha, lies at the geographic centre of Ilam province in Iran and is located between 46.2708° – 46.8800° East and 32.0844° – 32.5150° North. Malekshahi county is considered part of the arid and semi-arid regions of the Zagros Mountains. Its altitude ranges from 330 m to 2,737 m above sea level. In addition to forest, there are several other land covers including urban area, waterbody, farmland and rangeland. The location of the case study is shown in Figure 2.

The dominant oak species same as whole Zagros ecological region is Persian oak or *Quercus persica* (Salehi, Wilhelmsson, and Söderberg 2008). One of the forest regions of
Malekshahi, which is denser than others, is called Bivareh. It extends from the centre of Malekshahi to the southwest for more than 10 km and is indicated in green colour in Figure 2(d).

3. Data and pre-processing

3.1. Satellite data

This research used Landsat data of medium (30 m) resolution. Ordinarily, it would not be possible to detect individual declined oak trees at this resolution (as can be seen in Figure 7(b)); however, if a method could be developed to map oak decline using these data, that would have two important advantages. Firstly, these data are available free of charge, which means the method would be more practical for routine application. Secondly, the results could be used as a guide for other, more expensive, methods using HRSI.

Landsat satellite imagery from the years 2000 to 2016 was used (Table 1). The best time of the year for annual time series production was selected based on phenological studies. The criterion was rangeland dryness and forest greenness. To this aim, 16-year time series of MODIS 16 day composite NDVI data of rangeland and forest pixels were analysed using TIME-series of SATellite (TIMESAT) software (Zhang et al. 2003; Hmimina et al. 2013). The output of
TIMESAT was several phonological parameters of each land cover, including the beginning and end of the growth season (Jönsson and Eklundh 2004; Eklundh and Jönsson 2017).

The date of the higher peak of the NDVI values of the forest (which is expected to be more useful) is strongly correlated with the peak of rangeland (as can be visually observed by the red line in Figure 3). This causes inaccurate results if it is selected as the best date. According to phenological parameters of forest and rangeland, the best time of the year is determined based on the lower peak of forest cover which is the second half of September and the first half of October (or the 18th 16-day period

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Date</th>
<th>Sensor</th>
<th>Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>ETM+ (SLC -on)</td>
<td>11 October 2000</td>
<td>ETM+ (SLC-off)</td>
<td>4 October 2009</td>
</tr>
<tr>
<td>(Single Line Corrector)</td>
<td>14 October 2001</td>
<td></td>
<td>23 October 2010</td>
</tr>
<tr>
<td></td>
<td>1 October 2002</td>
<td></td>
<td>10 October 2011</td>
</tr>
<tr>
<td>ETM+ (SLC-off)</td>
<td>20 October 2003</td>
<td></td>
<td>26 September 2012</td>
</tr>
<tr>
<td></td>
<td>20 September 2004</td>
<td></td>
<td>24 September 2014</td>
</tr>
<tr>
<td></td>
<td>9 October 2005</td>
<td>OLI</td>
<td>7 October 2013</td>
</tr>
<tr>
<td></td>
<td>26 September 2006</td>
<td></td>
<td>13 October 2015</td>
</tr>
<tr>
<td></td>
<td>15 October 2007</td>
<td></td>
<td>14 October 2016</td>
</tr>
<tr>
<td></td>
<td>17 October 2008</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 2. Geographical location of the study area; (a) Iran is highlighted in the world map with red colour, (b) Ilam province is highlighted in the map of Iran’s provinces, (c) Malekshahi county is highlighted in the map of Ilam’s counties, and (d) Malekshahi county. Bivareh forest is highlighted with green colour.
of the year which is indicated by the green line in Figure 3(b); green line). Table 1 shows all dates for when the images were acquired.

Products and services provided by the United States Geological Survey (USGS) Earth Resources Observation and Science (EROS) Centre’s Science Processing Architecture (ESPA) on-demand interface were used in this research (Jenkerson 2013). Landsat ETM+ and Operational Land Imager (OLI) images were atmospherically corrected using the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) (Masek et al. 2013) and Landsat Surface Reflectance Code (LaSRC) (Vermote et al. 2016), respectively, and they were clipped to the area of Malekshahi county. The pixels were evaluated in terms of quality based on the ‘Pixel_qa’ data layer. In this step, all pixels covered by snow, ice, clouds, cloud shadows, and water were masked out.

3.2. Ground truth data

Calibrating oak decline models as well as evaluating the accuracy of the results requires ground truth data. The ground truth of this research is a combination of field data and Google-Earth-based data. We selected two small parts of Bivareh forest, which based on preliminary studies, were known to have suffered more decline. Fieldwork was performed on 9 September 2016 and on 12, 19, 20, and 21 October 2016. The health condition of all trees in both parts of Bivareh forest was measured visually and classified into four categories (Table 2). Their location was determined using smartphone Global Positioning System (GPS) data with
a positional accuracy of about 3 m. Figure 4 shows an example of the collected field ground truth data. Figure 5 shows different parts of declined oak trees observed in the field.

Field data alone, however, is not sufficient as ground truth data for our time series method, because a tree may simply have declined or have been felled before the fieldwork took place. Operators consequently would not be able to observe and measure its health condition, and would instead consider its former location as a spot that never held a tree. From the point of view of satellite imagery acquired as early as the year 2000, however, it is clear that there was indeed a tree in this spot that had simply declined in the meantime. This discrepancy causes a problem because it leads to inconsistencies between images and ground truth data. The problem can be solved using historical images of Google Earth. By comparing images from 2006 and 2017, vanished trees are easily detected. These missing trees are then classified as the highest level of decline, because they are already dead.

There still remain, however, some other inconsistency problems which should be solved with a few pre-processing steps. The first problem is that ground truth data (aside from felled trees) are independent of the area of tree canopies. The more area a tree canopy covers, the more it will affect pixel values, but the area of canopy does not affect ground truth data at all, because collected data are not considered as a polygon layer but a point layer. To solve this

<table>
<thead>
<tr>
<th>Tree status</th>
<th>Assigned code</th>
</tr>
</thead>
<tbody>
<tr>
<td>Healthy forest (declines less than 25.00%)</td>
<td>1</td>
</tr>
<tr>
<td>Low-severity declined (declines between 25.00% and 50.00%)</td>
<td>2</td>
</tr>
<tr>
<td>Mid-severity declined (declines between 50.00% and 75.00%)</td>
<td>3</td>
</tr>
<tr>
<td>High-severity declined (declines more than 75.00%)</td>
<td>4</td>
</tr>
</tbody>
</table>

Figure 4. Field collected data.
problem, Google Earth images were used once again. First, the canopy layer of those two parts of the Bivareh forest was drawn manually, and then a matching between this polygon layer and the field-data-based point layer was performed. Next, the decline information of the collected points was assigned to polygons. The output of this step can be seen in Figure 6.

The second pre-processing step is co-registration between the Google Earth image (canopy layer) and the satellite image. The final problem is that our algorithm produces a raster map of oak decline, and cannot detect individual trees, but the ground truth data does include individual trees. For this stage of pre-processing, it was decided to assign each pixel a score that describes the severity of its decline. This solution can be considered a kind of weighted averaging. Each tree in a pixel will affect the score of that pixel according to two factors: (1) the area of its canopy, and (2) the severity of its decline (Table 3).

Two kinds of ground truth data are needed to implement the method. Ground truth data related to oak decline are needed for the third step (of ground truth data pre-processing) and also for effective spectral index selection (which is the second step of the proposed method). The second necessary ground truth data are related to canopy cover, which is used in the forest/non-forest classification (first step of the proposed method).

The forest canopy cover, also known as crown cover, is defined as the ratio of the forest floor covered by the vertical projection of the tree crowns (Azizi, Najafi, and Sohrabi 2008). Figure 7(a,b) show the true colour of a part of Bivareh forest and its
equivalent forest/non-forest classified data (based on Google Earth data), respectively. As shown in Figure 7(b), Landsat data are also superimposed over the forest/non-forest classified data. Each pixel of the canopy cover data layer – coinciding with the Landsat data pixel – indicates how many percent of it is covered by the forest canopy.

Ground truth data of canopy cover assigns a value between 0.00 (empty of tree cover) and 1.00 (fully covered by the tree) to a pixel, applying unsupervised classification methods (k-means and Iterative Self-Organizing Data Analysis (ISODATA)) to Google Earth images. For example, pixels of green and red boundaries have values of about 0.50 and 0.00, respectively. According to the Forests, Ranges, and Watershed Management Organization of Iran, for the Zagros ecological region, the canopy cover should be higher than 0.05 in order for it to be classified as forest. This kind of ground truth data was prepared for 307 pixels.
To achieve objectives of this study, a method is proposed which includes three steps; (1) forest/non-forest classification, (2) effective spectral indices selection, and (3) oak decline modelling.

### 4.1. Forest/non-forest classification

Forest pixels should be determined via a binary classification. In addition to forest, there are several other land covers including urban area, waterbody, farmland and rangeland. The existence of land covers that are spectrographically similar to forest may be detrimental to the quality of the final results, and so it seems useful to apply a binary classification to reduce probable inaccuracies.

A decision tree classifier containing two internal decision nodes was used (Lu, Di, and Ye 2014). First, the NDVI value of each pixel is calculated at the right time of the year, when trees show high photosynthetic activity. All pixels with an NDVI value less than $T_0$ are considered non-forest. Then, if the difference between the NDVI values of early autumn and winter is...
higher than \( T_1 \), they are classified as forest. For the purpose of determining \( T_0 \) and \( T_1 \), ground truth data related to canopy cover was used.

### 4.2. Effective spectral indices selection

Selection of indices was done based on three criteria. The first criterion, according to experts on the oak decline, relates to the fact that the less it rains, the more trees are prone to decline. This means that an index should be chosen that contains sufficient information on rainfall data. Precipitation data measured at meteorological stations is needed to evaluate correlations with different indices. As mentioned previously, one of the symptoms of oak decline is an irregular loss of leaves, which affects the density of canopy layer. Another criterion for index selection, therefore, is related to canopy layer density. The third criterion is the extent of sensitivity to oak decline. Oak decline ground truth data were prepared and used to determine the degree of sensitivity to oak decline across different indices.

### 4.3. Oak decline modelling

The oak decline phenomenon was modelled based on the slope values of the fitted line of the selected indices. Two different regression methods, linear regression and SVR, are used and compared with each other. Conventional regression techniques like linear regression are more appropriate for data that are clearly linear or exponential, whereas machine-learning techniques are usually better suited to modelling strong nonlinearity between biophysical and biochemical parameters and reflection spectra (Liang et al. 2015; Yue et al. 2018). Input features of regression methods are the general trend of selected indices during the period, including NDVIs, NDWIs, and EVIs.

In RS studies, the linear regression method has been used for different purposes, from spectral unmixing (Theys et al. 2009) to determining relationships between primary and auxiliary variables (Haack and Rafter 2010). A mathematical model of linear regression can be seen in Equation (1). In this equation, \( a, b, c, \) and \( d \) are regression coefficients and \( S \) is the output parameter which is to be estimated, meaning in our case, the decline score.

\[
S = a(\text{NDVI})_s + b(\text{NDWI})_s + c(\text{EVI})_s + d
\]

On the other hand, it has been proven that SVR can be used for several applications (Kazuhi et al. 2017; Okujeni et al. 2017; Rosentreter et al. 2017). Parameters of SVR include kernel parameter and penalty coefficient. Equation (2) shows a mathematical model of the radial basis function (RBF) kernel used in this research. \( ||x_i - x_j||^2 \) may be recognized as the squared Euclidean distance between the two feature vectors and is the \( \gamma \) kernel parameter.

\[
k(x_i, x_j) = \exp\left(-\gamma ||x_i - x_j||^2\right), \gamma > 0
\]
5. Results and discussion

The year selected for applying the classification was 2001. The parameters of the decision tree classifier ($T_0$ and $T_1$) should be determined using canopy cover ground truth. Seventy percent of ground truth data are then selected for training the classifier, while the remaining 30% is set aside for test purposes. After training, 0.145 and 0.020 were assigned to $T_0$ and $T_1$, respectively. Using these two parameters, each pixel of interest was classified. Figure 8 shows the results of the classification. Using test data, classification accuracy was then evaluated. Table 4 shows the confusion matrix. According to the Table 4, an acceptable overall accuracy of 88% was obtained for forest/non-forest classification map.

For the first part of the second step, monthly precipitation data were obtained from Ilam meteorological station for the years 2000 to 2014. By normalizing precipitation values at a given timescale, the Standard Precipitation Index (SPI) (McKee, Doesken, and Kleist 1993) was obtained at the same timescale, which is one of the most useful indices for drought monitoring. Five indices, namely EVI, NDVI, NDWI, Soil-Adjusted Vegetation Index (SAVI) (Hongrui Ren, Zhou, and Zhang 2018) and Adjusted Transformed Soil-Adjusted Vegetation Index (ATSAVI) (H. Ren and Feng 2015) were investigated to find the one that most correlated to precipitation data using simple linear regression. The average value of these

![Forest map of study area. Black regions indicate the forest.](image)

**Figure 8.** Forest map of study area. Black regions indicate the forest.

<table>
<thead>
<tr>
<th></th>
<th>Non-forest</th>
<th>Forest</th>
<th>Producer's accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-forest</td>
<td>4</td>
<td>10</td>
<td>0.28</td>
</tr>
<tr>
<td>Forest</td>
<td>1</td>
<td>76</td>
<td>0.99</td>
</tr>
<tr>
<td>User's accuracy</td>
<td>0.80</td>
<td>0.88</td>
<td>Overall accuracy = 0.88</td>
</tr>
</tbody>
</table>

**Table 4.** Confusion matrix of forest/non-forest classification.
indices over the forest pixels of Malekshahi was computed for each year. The rainfall value for each year was the average of monthly precipitation data from the start of autumn of the year to the end of spring of the next year. The greater coefficient of determination ($R^2$) is, the more representative the index is of rainfall data. $R^2$ values can be seen in Table 5. According to the listed $R^2$ values, EVI is the best index on the list.

For the second criterion of step two, we need to find the index most correlated with canopy cover density. Results of previous studies indicate that NDVI is a suitable index for this purpose (Larsson 2002; La et al. 2013). Considering the final criteria, five indices were computed for each image, namely EVI, NDVI, SAVI, ATSAVI and NDWI. For each pixel, 17 values (or less, if the Digital Number (DN) of a pixel is invalid for some years because of clouds or other factors) are then available for each index. The general trend of each index was examined by fitting a linear equation. Figure 9 is the visual explanation of the process. To make it clearer, the slope image of the NDVI is shown in Figure 10, which also can give a visual impression of decline. Although using NDVI or even false colour composite (FCC) images for some years of research time frame can give a better visual impression, in our view this method may be even misleading for the readers, because of two reasons; the case study is a sparse forest and used satellite data is of medium resolution.

Such an image (Figure 10) was produced for each selected index. A possible result of non-random patterns of Figure 10 is the possibility of oak decline detection using

Table 5. The coefficient of determination values between rainfall time series and spectral indices time series.

<table>
<thead>
<tr>
<th>Spectral index</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>NDVI</td>
<td>0.50</td>
</tr>
<tr>
<td>NDWI</td>
<td>0.21</td>
</tr>
<tr>
<td>SAVI</td>
<td>0.42</td>
</tr>
<tr>
<td>EVI</td>
<td>0.59</td>
</tr>
<tr>
<td>ATSAVI</td>
<td>0.47</td>
</tr>
</tbody>
</table>

Figure 9. Time series of NDVI, (a) the plot of how NDVI values change for an arbitrary pixel during 17-year time series, and (b) the red line is the fitted line which its slope is used in the following steps.
30 m satellite imagery. For example, the red-bounded region experienced deterioration during research time frame.

According to the ground truth data on oak decline, the number of pixels with a decline score higher than 1.00 is 104. The correlation between these two sets of values (decline scores and linear equation slope) was measured for each of the indices. The results are shown in Table 6.

Low correlation values were unexpected. One of the probable reasons was due to the time frame of the study. If the time frame is not selected appropriately then forest spectral changes caused by the disease are less effective on the slope value and consequently a lower correlation will be obtained. The probability of that assumption increased in accordance with the first years of oak decline outbreak, which were in the middle of the time frame of our research. This hypothesis was examined, and the result showed that the most appropriate time frame is a 9-year period: from 2008 to 2016. Correlation values – for ground truth pixels with a declining score higher than 5.00 – were computed and indicated the correctness of the assumption, are shown in Table 6. It becomes clear that NDWI is more sensitive to oak decline.

Table 6. Correlation values between decline score and fitted line slope for 16 year and 9 year time frames.

<table>
<thead>
<tr>
<th>Time frame</th>
<th>NDVI</th>
<th>EVI</th>
<th>NDWI</th>
<th>SAVI</th>
<th>ATSAVI</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000–2016</td>
<td>−0.19</td>
<td>−0.13</td>
<td>−0.04</td>
<td>−0.06</td>
<td>−0.06</td>
</tr>
<tr>
<td>2008–2016</td>
<td>−0.57</td>
<td>−0.56</td>
<td>−0.63</td>
<td>−0.56</td>
<td>−0.60</td>
</tr>
</tbody>
</table>

Figure 10. Slope image of NDVI index. The redder colour is, the higher the severity of decline occurred in NDVI’s point of view.
In total, NDWI, EVI, and NDVI were considered as effective indices in relation to the oak decline phenomenon. For the purpose of modelling, approximately one-third of the ground truth pixels – related to oak decline – was used to test the results (30 pixels out of 104 pixels), while the remainder was used for the modelling process. The linear regression method was trained first. The results of solving the system of equations are shown in Table 7.

The model is then validated using test data. The results indicate that the root-mean-square error (RMSE) for estimating the decline score is 3.41. It should be noted that the score (output of regression) is a continuous quantity, but after the regression, the estimation (output) can be classified into several categories. Boundary values for those categories were computed using a simulation of some hypothetical pixels (to consider all possible levels of decline severity which may not happen in the ground truth data). The results are shown in Table 8.

According to the boundary values presented in Table 8, the Landsat data were classified for the oak decline phenomenon (Figure 11).

**Table 7.** Coefficient parameters for linear regression.

<table>
<thead>
<tr>
<th>Model parameter</th>
<th>( a )</th>
<th>( b )</th>
<th>( c )</th>
<th>( d )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value</td>
<td>(-0.0220)</td>
<td>(-0.0007)</td>
<td>(-0.0270)</td>
<td>(5.2500)</td>
</tr>
</tbody>
</table>

**Table 8.** Separating score values of different classes of oak decline severity using simulated declined pixels.

<table>
<thead>
<tr>
<th>Decline severity</th>
<th>Low</th>
<th>Mid</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Decline score range</td>
<td>(0.3–4.0)</td>
<td>(4.0–7.0)</td>
<td>(&gt; 7.0)</td>
</tr>
</tbody>
</table>

**Figure 11.** Oak decline map based on linear regression method.
In the process of validation, the accuracy of the classifications should also be evaluated. This is achieved through two modes. In the first mode, the model’s ability to identify declined pixels against healthy ones is evaluated. In other words, in this step, the accuracy of a binary classification (declined/healthy) is evaluated using 85 pixels of the ground truth data. The results show that the method can identify a declined pixel with a producer’s accuracy of 100% (but with lower user’s and overall accuracy). Of course, since healthy forest pixels were not available in the ground truth data, this would be ‘producer’s accuracy’, this means that all declined regions, in reality, are classified as declined in the final map. In the second mode, the success rate of the method to examine and distinguish different severities of decline was evaluated. The error matrix can be seen in Table 9.

A second regression method for modelling oak decline is SVR. First, all three indices were scaled. In this research, the RBF kernel function was used. Then RBF parameter ($\gamma$) and penalty factor ($C$) were optimized using grid search. $C$ and $\gamma$ were equal to $10^4$ and $2^{-13}$, respectively. Then the model was validated using test data. The RMSE was equal to 3.39. As in the previous regression method, the oak decline was classified and the resulting map is shown in Figure 12.

Table 9. Confusion matrix of oak decline classification, based on linear method.

<table>
<thead>
<tr>
<th>Ground truth</th>
<th>Low-severity</th>
<th>Mid-severity</th>
<th>High-severity</th>
<th>Total</th>
<th>Producer’s accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low-severity</td>
<td>8</td>
<td>9</td>
<td>6</td>
<td>23</td>
<td>0.35</td>
</tr>
<tr>
<td>Mid-severity</td>
<td>12</td>
<td>17</td>
<td>5</td>
<td>34</td>
<td>0.50</td>
</tr>
<tr>
<td>High-severity</td>
<td>2</td>
<td>9</td>
<td>17</td>
<td>28</td>
<td>0.60</td>
</tr>
<tr>
<td>Total</td>
<td>22</td>
<td>35</td>
<td>28</td>
<td></td>
<td>Overall: 0.49</td>
</tr>
</tbody>
</table>

User’s accuracy = 0.36, 0.48, 0.60

Figure 12. Oak decline map based on SVR regression method.
Next, the accuracy of the classification was also evaluated. SVR, like linear regression, detected declined pixels (in the first mode) with a producer’s accuracy of 100% (but with lower user’s and overall accuracy). In the second mode, Table 10 shows the confusion matrix of the classification.

Before proceeding with different regression methods, it was expected that SVR would provide better results because it is less dependent on training data. Validation outcomes indicate the correctness of the expectation. It is worth noting that modelling oak decline using the SVR method results in a more pessimistic outcome than modelling with the linear method.

Irrespective of which regression method is used, there might be a defect in the time-series method considering the overall accuracy of about 50%. According to the analysis of the authors, the output of the method depends on the time of decline in the 17-year time frame of the research, but the ground truth data are independent of that. In other words, if trees are declined in a late section of the time frame, they are less likely to be detected by the method.

The study tried to make a step forward in the domain of oak decline related researches. The study of Gillis (2014) did not produce reliable results, and although the method proposed by Wang, Zhenqian, and Haithcoat (2007) achieved relatively high overall accuracy, it was not fully validated. Mahdavi et al. (2015) modelled oak decline, but the modelling inputs were not completely based on RS products. The research of Rostamnia and Akhoondzadeh Hanzaei (2016) was not focused on oak decline map production. The method proposed here in this study maps oak decline based on only remote sensing data and validated using ground truth data.

In spite of the probable defect of the method, the results still seem to be useful for relevant organizations, because of the high producer’s accuracy in detecting declined regions. So the products can be used as a guide for optimizing other methods (like forest inventory or aerial imagery), which are time-consuming and costly. Another advantage of the method is that it is based only on the satellite imagery and it does not need any other auxiliary data. Also, it should be noted that the used satellite imagery is provided free of charge. Another point of the study was the approach used to select effective spectral indices, which is based on physical parameters (rainfall, etc.) instead of only mathematical approaches.

### 6. Conclusion

Over the last few decades, RS techniques have been used to monitor forest health. Zagros Forest, as the most extensive ecological region of Iran, has faced harsh conditions during recent years. In this research, a method was proposed to map oak decline using Landsat data. In this method, after applying a forest/non-forest classification, three optimum spectral indices

<table>
<thead>
<tr>
<th>Ground truth</th>
<th>Low-severity</th>
<th>Mid-severity</th>
<th>High-severity</th>
<th>Total</th>
<th>Producer accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low-severity</td>
<td>10</td>
<td>7</td>
<td>6</td>
<td>23</td>
<td>0.43</td>
</tr>
<tr>
<td>Mid-severity</td>
<td>12</td>
<td>17</td>
<td>5</td>
<td>34</td>
<td>0.50</td>
</tr>
<tr>
<td>High-severity</td>
<td>4</td>
<td>8</td>
<td>16</td>
<td>28</td>
<td>0.57</td>
</tr>
<tr>
<td>Total</td>
<td>26</td>
<td>31</td>
<td>27</td>
<td></td>
<td>Overall accuracy = 0.51</td>
</tr>
</tbody>
</table>

User accuracy: 0.38, 0.55, 0.59
including EVI, NDVI, and NDWI were selected. These indices were selected considering rainfall data, canopy cover, and oak decline, respectively. Then two regression methods were used to model the phenomena: SVR and linear regression. The regression methods modelled a decline score for each pixel. The oak forest was classified into four categories: healthy forest, low-severity declined forest, mid-severity declined forest, and high-severity declined forest. The classification was validated using ground truth data. SVR was more successful than linear regression. SVR mapped oak decline with an overall accuracy of more than 51%. However, both methods were able to detect declined regions with a producer’s accuracy of 100% if the decline score was classified as binary healthy/declined categories (but with lower user’s and overall accuracy). It seems that the method suffers a defect because of a dependence on the time of decline during the study period. Considering the objectives of the study, mapping oak decline was performed using free satellite data and without using any other auxiliary data and also the products seem to be useful for time and cost reduction of other complementary oak decline monitoring methods. However, the overall accuracy of the products – especially for classifying declined region to different decline severities – means that there is still a need to research for the development of higher performance algorithms.

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Disclosure statement

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