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Investigation on Zagros forests cover changes under the recent droughts using satellite imagery

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Abstract: Oak decline phenomenon has recently led to considerable dieback within Zagros forests, western Iran. In the present study, Landsat imagery (2005 to 2016) and synoptic station data were used to study the forest dieback in Dorood, Lorestan province. Sixteen vegetation indices were calculated and values in each year were obtained. The correlations between the index and climatic parameters of rainfall, temperature and relative humidity were investigated. Results showed that the correlation of some indices with rainfall and the correlation of other indices with temperature were more than 70%. Optimized soil adjusted vegetation index had 80% correlation with annual rainfall and the modification of normalized difference water index was correlated with average annual temperature by 75%. Using the numerical value changes of the indices, a map of forest cover change was prepared in four classes; healthy, weak, moderate and severe dieback and the process of its change were compared with the trend of variations in regard with rainfall values in the study period. There was a close relationship between changes in the area of forest cover dieback and rainfall and temperature values.

Keywords: oak; decline; Landsat; Lorestan; vegetation index

Oak decline phenomenon has recently led to considerable dieback within Zagros forests, western Iran. In general, factors involved in the decline of forest trees include predisposing factors, contributing or inciting factors (Sallé et al. 2014). Contributing factors act as the main factor of forest decline. These factors are severe and intense disorders that can occur as biological factors such as severe drought (Andersson et al. 2011).

These factors are themselves either directly affected by climate change or indirectly influenced by the conditions of their host trees. According to the fifth report of the Intergovernmental Panel on Climate Change (IPCC 2014), in future, many natural ecosystems affected by climate change will undergo major structural changes. Generally, the results of the findings suggest that climate change, especially rainfall reduction and increasing temperatures around the world, has led to the loss of forest cover (Azizi et al. 2015; Thiele et al. 2017). Some factors such as drought cause severe and short-term damage, but if two contributing and predisposing factors are in the same line, then improvement will be slower very much (Prieto-Recio et al. 2015).

The Zagros forests of Iran with the main species of oaks are semi-arid and occur over an area of about six million ha and account for almost 44% of Iran's forests (Sagheb Talebi et al. 2014). These forests were affected by oak decline phenomenon during the past decade. This issue has become a topic of numerous researches in many scientific resources as one of the critical issues in forests of Iran (Hosseinzadeh,

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Pourhashemi 2015; Zandebasiri et al. 2017). For sustainable management and conservation of forest resources, it is necessary to know the amount and location of deforestation, its speed and area, and monitoring of the effects of drought on forest cover reduction.

Monitoring of the effects of drought with regard to high economic costs, the extent of natural areas and the impassable regions create many problems, since the preparation of information through field operations requires a huge amount of time and costs, usually alternative approaches with lower costs and acceptable accuracy level are used.

Considering the above-mentioned issues and the change in climate parameters as well as the published reports on oak forest decline in the Zagros region, it seems that monitoring of forest cover health change, which is the goal of this research, is necessary.

MATERIAL AND METHODS

The study area. The study area is located in Dorood forests, a part of Zagros forests, in the southeast of Lorestan province, Iran (48°59'54''E to 49°07'54''E and 33°23'36''N to 33°28'24''N; Fig. 1). The minimum and maximum elevations were 1,054 and 3,075 m a.s.l., respectively. The study area covers 660 km^2 of mountainous stands with average slope of 38%. Approximately 50% of the area is covered by forests, most of which are pure Brant's oak (*Quercus brantii* Lindley) stands.

Satellite data and preliminary preprocessing. Eight consecutive images of August from 2005 to 2012 from ETM + Landsat 7 and four OLI Landsat 8 image data from 2013 to 2016 were downloaded from the United States Geological Survey (https://earthexplorer.usgs.gov/). All images were acquired in the second half of the summer season. The initial errors including atmospheric (FLAASH algorithm), radiometric (radiometric calibration) and SLC-off gap-fill algorithm were corrected by the ENVI program (Version 5.3, 2015) (Safari et al. 2018).

Land use classification. Supervised classification methods including maximum likelihood (Morgan et al. 2015) and the three linear, radial, and polynomial kernels of the support vector machine (Ustuner et al. 2015) were used to classify the land use of satellite images of 2005.

During the summer of 2016, 45 field samples were collected. 30 samples were used for training in the supervised classification methods and 15 samples were used for accuracy assessment. Overall accuracy and Kappa index were calculated from the confusion matrix, and the method with smaller error was used as a suitable method for land use classification.

Vegetation indices used. Vegetation reflectance in the range of near and mid-infrared op-

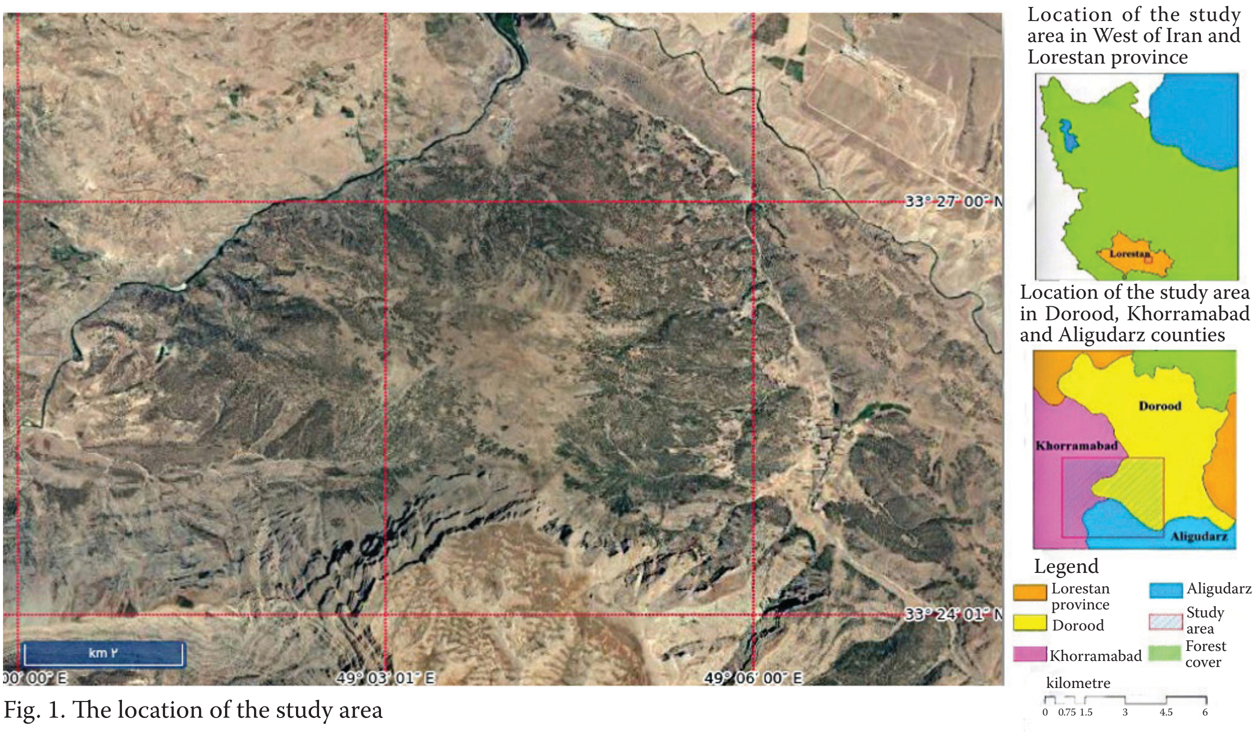

Fig. 1. The location of the study area

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Table 1. Indices used in the present study

Vegetation index	Equation	Reference
Difference vegetation index (DVI)	$\mathrm{DVI} = \mathrm{NIR} - \mathrm{Red}$	Tucker (1979)
Enhanced vegetation index (EVI)	$\mathrm{EVI} = 2.5 \times \frac{(\mathrm{NIR} - \mathrm{Red})}{(\mathrm{NIR} + 6 \times \mathrm{Red} - 7.5 \times \mathrm{Blue} + 1)}$	Huete et al. (2002)
Normalized difference vegetation index (NDVI)	$\mathrm{NDVI} = \frac{(\mathrm{NIR} - \mathrm{Red})}{(\mathrm{NIR} + \mathrm{Red})}$	Rouse et al. (1973)
Green difference vegetation index (GDVI)	$\mathrm{GDVI} = \mathrm{NIR} - \mathrm{Green}$	Sripada et al. (2006)
Green normalized difference vegetation index (GNDVI)	$\mathrm{GNDVI} = \frac{(\mathrm{NIR} - \mathrm{Green})}{(\mathrm{NIR} + \mathrm{Green})}$	Gitelson and Merzlyak (1998)
Green ratio vegetation index (GRVI)	$\mathrm{GRVI} = \frac{\mathrm{NIR}}{\mathrm{Green}}$	Sripada et al. (2006)
Green vegetation index (GVI)	$\mathrm{GVI} = (-0.2848 \times \mathrm{TM1}) + (-0.2435 \times \mathrm{TM2}) + (-0.5436 \times \mathrm{TM3}) + (0.7243 \times \mathrm{TM4}) + (0.0840 \times \mathrm{TM5}) + (-0.1800 \times \mathrm{TM7})$	Kauth and Thomas (1976)
Infrared percentage vegetation index (IPVI)	$\mathrm{IPVI} = \frac{\mathrm{NIR}}{\mathrm{NIR} + \mathrm{Red}}$	Crippen (1990)
Leaf area index (LAI)	$\mathrm{LAI} = 3.618 \times \mathrm{EVI} - 0.118$	Boegh et al. (2002)
Modification of normalized difference water index (MNDWI)	$\mathrm{MNDWI} = \frac{\mathrm{Green} - \mathrm{MIR}}{\mathrm{Green} + \mathrm{MIR}}$	Xu (2006)
Modified triangular vegetation index (MTVI)	$\mathrm{MTVI} = \frac{1.5[1.2(\rho_{800} - \rho_{550}) - 2.5(\rho_{670} - \rho_{550})]}{\sqrt{(2 \times \rho_{800} + 1)^2 - (6 \times \rho_{800} - 5 \times \sqrt{\rho_{670}}) - 0.5}}$	Haboudane et al. (2004)
Soil adjusted vegetation index (SAVI)	$\mathrm{SAVI} = \frac{1.5 \times (\mathrm{NIR} - \mathrm{Red})}{(\mathrm{NIR} + \mathrm{Red} + L)}$	Huete (1988)
Optimized soil adjusted vegetation index (OSAVI)	$\mathrm{OSAVI} = \frac{1.5 \times (\mathrm{NIR} - \mathrm{Red})}{(\mathrm{NIR} + \mathrm{Red} + 0.16)}$	Rondeaux et al. (1996)
Renormalized difference vegetation index (RDVI)	$\mathrm{RDVI} = \frac{(\mathrm{NIR} - \mathrm{Red})}{\sqrt{\mathrm{NIR} + \mathrm{Red}}}$	Roujean and Breon (1995)
Sum green index (SGI)	mean of reflectance across 500 to 600 nm	Lobell and Asner (2003)
Transformed difference vegetation index (TDVI)	$\mathrm{TDVI} = \sqrt{0.5 + \frac{(\mathrm{NIR} - \mathrm{Red})}{(\mathrm{NIR} + \mathrm{Red})}}$	Bannari et al. (2002)

Band: NIR – near-infrared, Red, Blue, Green, MIR – mid-infrared; ρ – wavelength, L – soil brightness correction factor

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tical spectrum has been widely used in the vegetation cover studies. Indices extracted from this spectrum range are attributed to a wide variety of plant growth and plant abilities associated with water content, pigments, sugars, and carbohydrates (Batten 1998; Foley et al. 1998; Safari et al. 2017). In this study, 16 well-known vegetation indices were used for the purpose of studying forest cover changes (Table 1).

The principal component analysis was used to reduce the number of indices into some components. For selecting a suitable number of components, those components with eigenvalue greater than one were selected. Those indices which had the highest correlation with the derived components were considered as the most important indices for land use classification. Climate data were also acquired from a local climate station regarding the time interval of the study. The time interval between two sequential imaging dates was considered for extraction of annual rainfall, average annual temperature and annual relative humidity.

Preparation of forest cover health change map and assessing the impact of climate parameters. To derive the cover change layer, the pixel values of selected indices were sequentially subtracted from 2005 to 2016, as well as in four periods of 2005 to 2007, 2005–2010, 2005–2013, and 2005–2016. The pixels with positive subtraction are considered as healthy forests and zeros are considered as no change. Pixels with negative values were divided into three categories, including weak, moderate, and severe dieback. In this way, the map of forest cover change during the study time interval was developed. The value of climate parameters in these intervals was also extracted and interpreted by the results of forest cover change.

RESULTS

Different supervised classification methods were used for land use classification. Table 2 represents the results of comparing the classification methods. The overall accuracy of the methods ranged from 84 to 92% while Kappa index ranged between 83 and 91%. The most accurate method was maximum likelihood which was selected to derive the land use map for the next analyses.

After deriving the land use map (in 2005), using the map, a spatial subset of all images was extracted and forest changes were assessed only in the subset. Then, the average value of each vegetation index was extracted for each year in the forest subset (Table 3).

Table 2. Overall accuracy and Kappa ratio evaluation of classification methods

Classification method	Overall accuracy (%)	Kappa index (%)
Maximum likelihood	92.02	91
Linear kernel – support vector machines	86.90	86
Polynomial kernel – support vector machines	84.62	83
Radial basis kernel – support vector machines	84.33	83

The results of Pearson correlation matrix showed a high correlation between the studied indices (Table 4), so that the two indices – green vegetation index (GVI) and optimized soil adjusted vegetation index (OSAVI) with 13 others had the highest correlation coefficient.

Table 5 shows the share of each index in the first and second factor. With respect to the higher weight of more variables, the 90.0 criterion was considered as the threshold for selecting variables. Accordingly, OSAVI, renormalized difference vegetation index, soil adjusted vegetation index, GVI and modified triangular vegetation index were placed in the first group and sum green index and modification of normalized difference water index (MNDWI) were placed in the second group.

Using the principal component analysis, 16 study indices were reduced to seven indices including five indices belonging to the first group and two indices belonging to the second group. Investigating the relationship between the indices and climatic parameters showed that the indices which lie in the first group had a high correlation with annual rainfall and indices in the second group had a high correlation with the average annual temperature (Table 6).

According to the results, OSAVI and MNDWI indices were selected to study the forest cover changes in the study area. The OSAVI value change map was prepared for the periods 2005–2007, 2005–2010, 2005–2013, and 2005–2016 and the numerical value of the index was distinguished in four classes of a healthy forest, a forest with weak, moderate and severe dieback (Figs 2a–d).

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Table 3. Average values of the study indices in each year

Vegetation index	Year											
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
DVI	0.069	0.074	0.073	0.066	0.067	0.069	0.062	0.072	0.065	0.069	0.064	0.073
EVI	0.097	0.102	0.103	0.092	0.094	0.100	0.087	0.099	0.095	0.099	0.094	0.106
GDVI	0.091	0.097	0.095	0.089	0.089	0.091	0.084	0.096	0.086	0.090	0.084	0.094
GNDVI	0.414	0.429	0.439	0.405	0.413	0.419	0.431	0.426	0.440	0.407	0.441	0.424
GRVI	2.461	2.561	2.631	2.403	2.448	2.485	2.573	2.530	2.631	2.417	2.643	2.525
GVI	0.031	0.035	0.036	0.028	0.031	0.032	0.030	0.034	0.033	0.030	0.032	0.035
IPVI	0.645	0.651	0.655	0.638	0.643	0.647	0.644	0.647	0.654	0.645	0.655	0.653
LAI	0.291	0.309	0.310	0.272	0.280	0.300	0.255	0.297	0.282	0.298	0.279	0.321
MNDWI	–0.405	–0.412	–0.425	–0.407	–0.400	–0.413	–0.435	–0.418	–0.439	–0.420	–0.452	–0.417
MTVI	0.055	0.059	0.060	0.049	0.052	0.055	0.047	0.056	0.054	0.056	0.053	0.062
NDVI	0.290	0.302	0.311	0.275	0.285	0.294	0.288	0.295	0.308	0.290	0.310	0.306
OSAVI	0.129	0.135	0.138	0.122	0.126	0.130	0.124	0.132	0.132	0.129	0.132	0.136
RDVI	0.196	0.207	0.209	0.186	0.191	0.197	0.184	0.202	0.196	0.195	0.195	0.208
SAVI	0.107	0.113	0.114	0.102	0.105	0.108	0.101	0.111	0.107	0.107	0.106	0.114
SGI	0.066	0.066	0.062	0.067	0.065	0.064	0.057	0.066	0.056	0.067	0.054	0.065
TDVI	0.888	0.894	0.899	0.880	0.885	0.890	0.887	0.891	0.898	0.887	0.899	0.897

DVI – difference vegetation index, EVI – enhanced vegetation index, GDVI – green difference vegetation index, GNDVI – green normalized difference vegetation index, GRVI – green ratio vegetation index, GVI – green vegetation index, IPVI – infrared percentage vegetation index, LAI – leaf area index, MNDWI – modification of normalized difference water index, MTVI – modified triangular vegetation index, NDVI – normalized difference vegetation index, OSAVI – optimized soil adjusted vegetation index, RDVI – renormalized difference vegetation index, SAVI – soil adjusted vegetation index, SGI – sum green index, TDVI – transformed difference vegetation index

Table 4. Results of factor analysis (eigenvalues and corresponding variance of factors)

Initial eigenvalues			Extraction sums of squared loadings			Component
Total	percentage of variance	cumulative percentage	total	percentage of variance	cumulative percentage	
62.00	62.00	9.92	62.00	62.00	9.92	1
95.98	33.98	5.44	95.98	33.98	5.44	2
99.01	3.03	0.48	–	–	–	–

Subsequently, the map of the change process created with the OSAVI index was compared with the process of rainfall change during the above-mentioned periods, which is shown in Table 7.

After preparing the map of forest cover changes using the MNDWI index, the forest health status was evaluated over the period 2014–2015 (Fig. 3a). At this period, the greatest difference in the average annual temperature occurred between two consecutive years in the studied 12 years. So that, the temperature in 2015 increased by about 1.7°C compared to 2014. On the other hand, the average three-year temperatures in the 12-year period of the study have an increasing trend. Therefore, the effects of the temperature rise process in the form of a map of forest cover changes in the period of 2005–2016 were investigated (Fig. 3b).

The changes in the area of forest cover health due to the influence of the average annual temperature change are summarized in Table 8.

DISCUSSION

The study of forest cover change showed that forest dieback is related to changes in climate parameters. As the highest average annual rainfall occurred in the period 2005–2007, the OSAVI index change did not show much dieback in this period. However, in the period 2005–2010 with a decline

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Table 5. Weight of matrix indices

Vegetation index	Component 1	Component 2
DVI	0.798	0.587
EVI	0.868	0.441
GDVI	0.680	0.663
GNDVI	0.530	–0.810
GRVI	0.520	–0.818
GVI	0.961	–0.029
IPVI	0.827	–0.547
LAI	0.868	0.440
MNDWI	–0.118	0.929
MTVI	0.942	0.284
NDVI	0.827	–0.547
OSAVI	0.992	–0.120
RDVI	0.980	0.193
SAVI	0.966	0.255
SGI	0.082	0.991
TDVI	0.828	–0.546

DVI – difference vegetation index, EVI – enhanced vegetation index, GDVI – green difference vegetation index, GNDVI – green normalized difference vegetation index, GRVI – green ratio vegetation index, GVI – green vegetation index, IPVI – infrared percentage vegetation index, LAI – leaf area index, MNDWI – modification of normalized difference water index, MTVI – modified triangular vegetation index, NDVI – normalized difference vegetation index, OSAVI – optimized soil adjusted vegetation index, RDVI – renormalized difference vegetation index, SAVI – soil adjusted vegetation index, SGI – sum green index, TDVI – transformed difference vegetation index

in rainfall, there was a 19% decline in the area of healthy forests. With the continuation of the decline in rainfall in comparison with the average annual long-term interval, in the period from 2005 to 2013, although rainfall slightly increased in this period in comparison with the previous one, we still witness a continuing drought. This greatly affected the dieback of trees at this time interval, so that the area of the healthy forest decreased about 45% in 2005–2007 and about 25% in 2005–2010. In the period 2005–2016, rainfall increased significantly in comparison with the previous two periods. Therefore, in this period, the forest cover health condition improved significantly in the period from 2005 to 2013, with the healthy forest area rising by about 35% in the period from 2005 to 2013.

The results showed that with increasing rainfall in the last three years from 2005 to 2016, the condition of forest trees improved in comparison with the previous period (2005 to 2013). However, when tree dieback is once affected by contributing factors, this increases their susceptibility to pests and other diseases. For this reason, despite the improvement of the forest cover condition in the last three years, we still see the dieback of oak trees in some areas. Some of the contributing and inciting factors cause severe and short-term damage, and if they stop, trees can recover relatively quickly, but if

Table 6. Correlation coefficients of the selected indices with climatic parameters

Vegetation index	Relative humidity		Average temperature		Precipitation	
	6 months	annual	6 months	annual	6 months	annual
GVI	0.59	0.52	0.32	0.07	0.43	0.71
MTVI	0.64	0.67	0.67	0.19	0.38	0.76
OSAVI	0.63	0.64	0.13	0.05	0.50	0.80
RDVI	0.62	0.61	0.30	0.17	0.40	0.76
SAVI	0.62	0.61	0.34	0.22	0.38	0.75
MNDWI	0.00	0.00	0.63	0.75	0.32	0.12
SGI	0.07	0.06	0.53	0.71	0.25	0.00

GVI – green vegetation index, MTVI – modified triangular vegetation index, OSAVI – optimized soil adjusted vegetation index, RDVI – renormalized difference vegetation index, SAVI – soil adjusted vegetation index, MNDWI – modification of normalized difference water index, SGI – sum green index

Table 7. The trend of forest cover health change affected by rainfall in the studied periods

Period	Average precipitation (mm)	Average precipitation since 2005 (mm)	Healthy forest area		Area of forest cover decline					
					low severity		moderate severity		high severity	
			(km^2)	(%)	(km^2)	(%)	(km^2)	(%)	(km^2)	(%)
2005–2007	769.38	769.37	327.96	97.23	7.85	2.33	1.31	0.39	0.18	0.05
2005–2010	485.18	627.27	262.29	78	47.53	14.13	21.87	6.50	4.6	1.37
2005–2013	513.16	589.24	175.31	52.56	82.29	24.67	60.71	18.2	15.24	4.57
2005–2016	670.59	609.58	292.68	87.76	30.59	9.17	8.74	2.62	1.51	0.45

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Table 8. The trend of forest cover health change under the influence of temperature during the studied periods

Period	Average temperature (°C)	Increase of temperature in the period (°C)	Healthy forest area		Area of forest cover decline					
					low severity		moderate severity		high severity	
			(km^2)	(%)	(km^2)	(%)	(km^2)	(%)	(km^2)	(%)
2014–2015	17.02	1.1	244.71	72.47	76.89	22.77	14.07	4.14	2	0.59
2005–2016	17.65	1.7	326.84	96.04	11.39	3.35	1.47	0.43	0.17	0.6

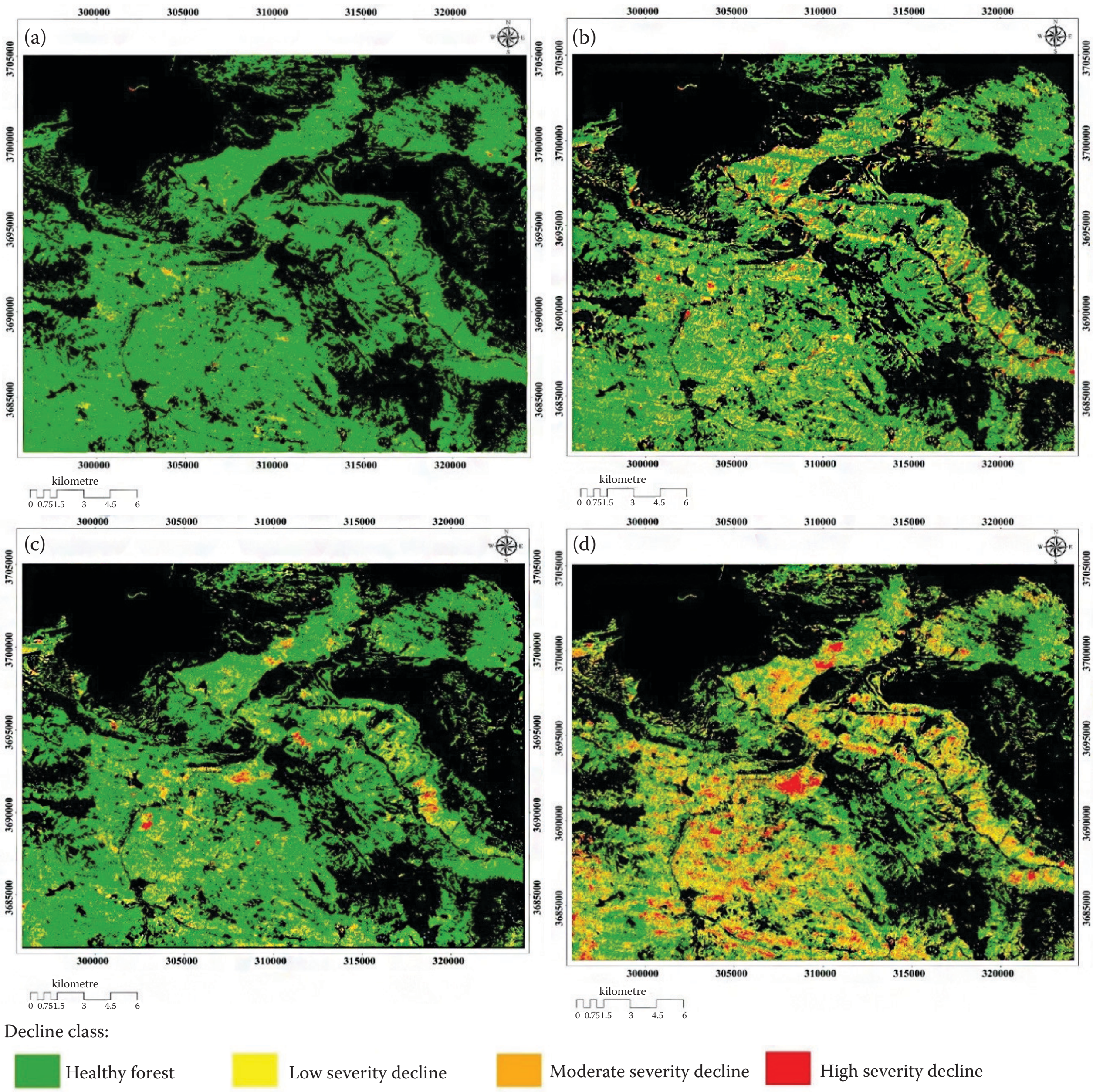

Fig. 2. Forest cover health change using the optimized soil adjusted vegetation index for the periods 2005–2007 (a), 2005–2010 (b), 2005–2013 (c), 2005–2016 (d)

the predisposing, contributing and inciting factors are aligned, then the recovery will be much slower (Prieto-Recio et al. 2015). Hence in the study area, due to the absence of proper management and underlying planning, oak forests face many problems and the lack of necessary studies and investigations in this area increases the above problems. Since knowing the amount and location of dieback,

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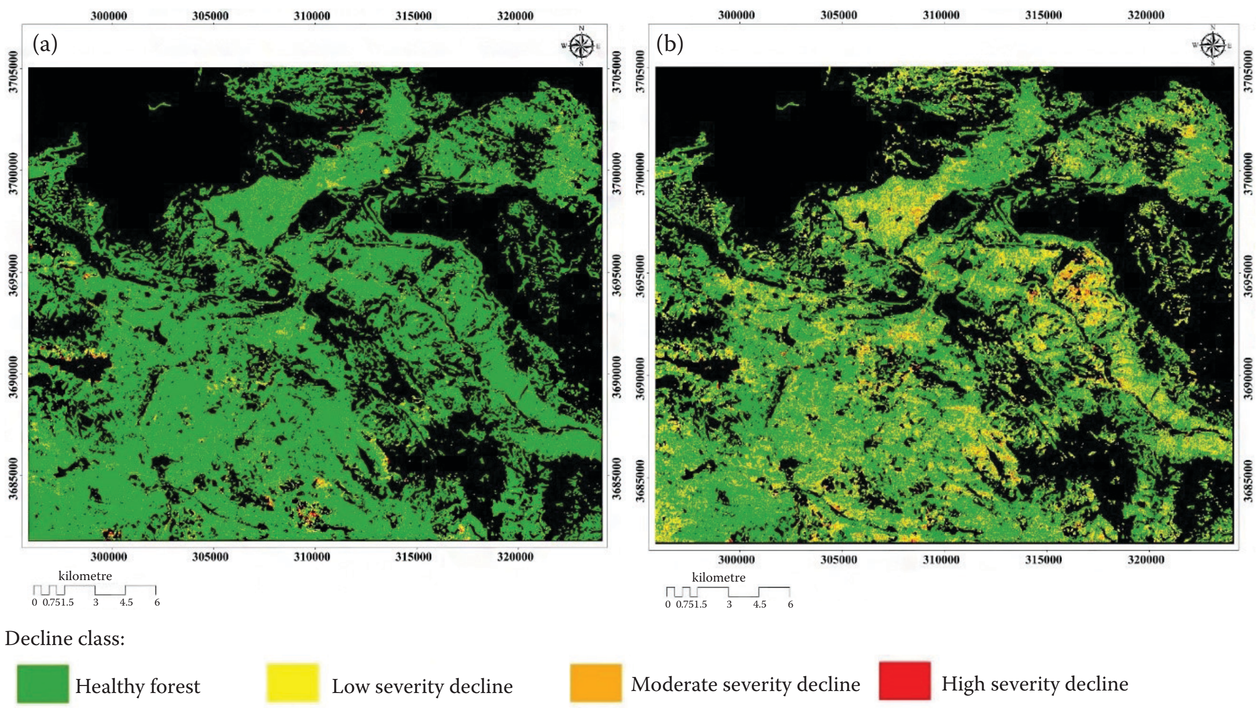

Fig. 3. Forest cover health change using the modification of normalized difference water index for the periods 2014–2015 (a), 2005–2016 (b)

its speed and area and its causes and reasons is essential; the results of this research can be of great help for the sustainable management and conservation of forest resources in the study area.

CONCLUSIONS

The correlation analysis of the selected indices with climatic parameters at the annual and 6-month scale showed that the OSAVI index and annual rainfall had a correlation of about 80% and the MNDWI index was correlated about 75% with average annual temperature. Furthermore, the correlation of indices with the desired climate parameters in the 6-month interval is less than annual. This means that the effects of climate factors in the long run are more tangible. Based on the prepared map of the forest cover health changes, a close relationship between changes in the dieback of forest cover area and changes in rainfall and temperature values was observed.

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