IJST (2015) 39A2: 123-127
Iranian Journal of Science & Technology

http://ijsts.shirazu.ac.ir

The relationship between the satellite-based index and standard precipitation index, on different land covers

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Abstract

The Normalized Difference Vegetation Index (NDVI) derived from the SPOT 4 satellite has been widely used to monitor moisture-related vegetation condition. The relationship between vegetation and climate index, however, is complex and has not been adequately studied with satellite sensor data. To better understand this relationship, an analysis was conducted on time series of monthly NDVI (1999–2009) during the growing season in the Semnan province. The NDVI was correlated to the Standardized Precipitation Index (SPI), a multiple-time scale meteorological-drought index based on precipitation. The 3 and 24 month SPI were found to have the best correlation with NDVI, indicating lag and cumulative effects of precipitation on vegetation, but the correlation between NDVI and SPI varies significantly between months. Results show that combining NDVI and a climatic index is a suitable method for estimating land cover changes. Steppe range land or class 7 in all stations had a higher correlation between NDVI and SPI. Land covers with vegetation have significant correlations in spring and summer months. The highest correlations occurred during the middle of the growing season, and lower correlations were noted at the beginning and end of the growing season in most of the area. A stepwise regression model showed that the relationship between the NDVI and SPI was significant in both rangelands and forest.

Keywords: Land covers change; NDVI; SPI; stepwise regression; Semnan province

1. Introduction

Both remote sensing data and drought indices have been found useful for crop prediction. However, until recently both approaches have been used independently. In this paper, NDVI data and drought indices have been combined to attempt predict crop production at fine spatial resolution. The analysis has been done in the northernmost semi-arid region of Europe, the Centre of the Ebro valley. In this area droughts are very frequent and severe and crop production has an important inter-annual variability (Vicente-Serrano *et al* 2003; Vicente-Serrano *et al.* 2004). Therefore, an early predictor of crop production would be very useful in this region. Over the past few decades, land cover change has taken place in the study area. During this process, many rural land areas, such as forests and wetlands, have been transformed to human settlements. Initially, forest areas were reforested rather than converted to agricultural areas, however, agricultural land finally opened for urban settlements. (Karatepe and Ikiel, 2013) The complex phenomenon of drought can be simplified into a drought index, which is a single number assimilating a large amount of water supply data. The index allows scientists to quantify climate anomalies in terms of intensity, duration, and spatial extent, making it easier to communicate the information to diverse users. A variety of drought indices have been developed in the United States (Heim, 2000) and the most widely used are the Palmer Drought Severity Index (PDSI). The Crop Moisture Index and the Standardized Precipitation Index (SPI) developed the SPI based on precipitation only The SPI is calculated by fitting historical precipitation data to a Gamma probability distribution function for a specific time period and location, and transforming the Gamma distribution to a normal distribution with a mean of zero and standard deviation of one. Since the SPI is equal to the z -value of the normal distribution, McKee et al. proposed a seven-category classification for the SPI: extremely wet (z >2.0), very wet (1.5 to 1.99), moderately wet (1.0 to 1.49), near normal (0.99 to -0.99), moderately dry (-1.49 to -1.0), severely dry (-1.99 to -1.5), and extremely dry (<-2.0 (McKee et al., 1995). The number of applications using the Standardized Precipitation Index (SPI) around the world continues (Hayes, 2000). The Semnan province is one of the provinces in the north of Iran with different forms of land cover that include forest, rangelands and desert (Arastoo, 2013). The present study evaluates the relationship between the

Received: 13 November 2013 / Accepted: 7 October 2014

satellite-based Normalized Difference Vegetation Index (NDVI) and Standard Precipitation Index, within the land covers of Semnan province.

2. Material and Methods

2.1. Study area

Semnan Province is one of the 31 provinces of Iran. It is in the north of the country, and its center is Semnan. The province of Semnan covers an area of 96,816 square kilometers and stretches along the Alborz mountain range and borders to Dasht-e Kavir desert in its southern parts.

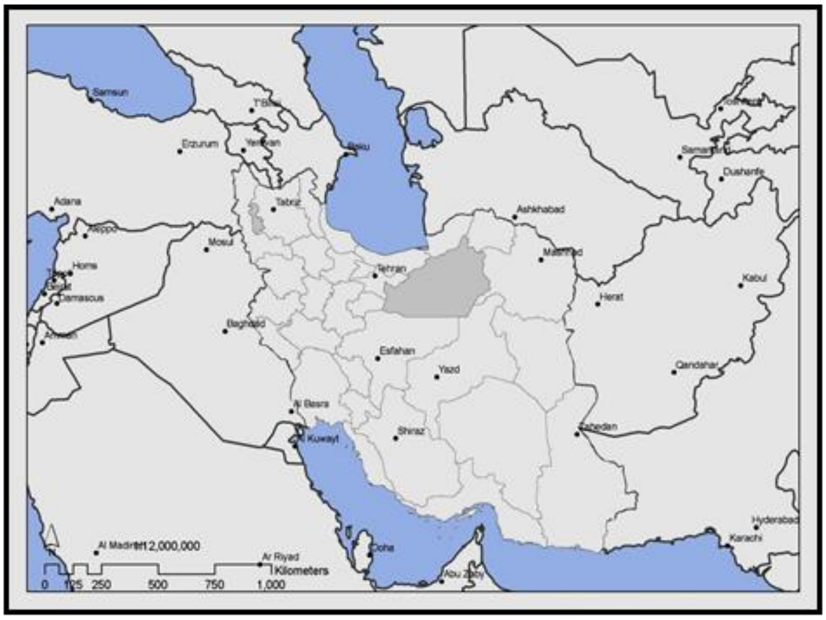

Fig. 1. Semnan province location

2.2. Data and methodology

The Vegetation sensor onboard the Spot 4 satellite provides global coverage on an almost 10 day basis at a spatial resolution of 1 kilometer. The SPOT-VEG spectral bands were designed specifically to study vegetation cover and its temporal dynamics; red (0.61 to 0.68 µm), near-infrared (0.78 to 0.89 µm), short-wave infrared (1.58 to 1.75 µm); with a blue band (0.43 to 0.47 µm) for atmospheric corrections. The red and near-infrared bands were used for calculating maximum value Normalized Difference Vegetation Index (NDVI) composites every 10-days. Data used for this part of the study were geo-referenced and de-clouded SPOT4 Vegetation 10-day composite NDVI images (S10 product) at 1km resolution taken from April 1999 till 2009 as obtained from www.VGT.vito.be. De-clouded means using only pixels with a 'good' radiometric quality for bands 2 (red; 0.61-0.68 µm) and 3 (near IR; 0.78-0.89 µm) (Arastoo, 2013).The Iterative Self Organizing Data Analysis Technique (ISODATA) method used a set of rule-of-thumb procedures that have been incorporated into an iterative classification algorithm. Many of the steps used in the algorithm are based on the experience obtained through experimentation. The ISODATA algorithm is a modification of the k-means clustering algorithm. This algorithm includes the merging of clusters if their separation distance in multispectral feature space is less than a user-specified value and the rules for splitting a single cluster into two clusters. This method makes a large number of passes through the dataset until specified results are obtained (Arastoo et al., 2013). After unsupervised classification and storage legend in signature file, select the optimal number of classes (Arastoo et al., 2013).

3. Result and Discussion

3.1. Correlation Coefficient between SPI and NDVI

Correlation Coefficient was calculated between SPI and NDVI related parameters to indicate the dependency level of land cover and vegetation on the related precipitation.

$$r = \frac{\sum Z_X Z_Y}{n-1} \quad (1)$$

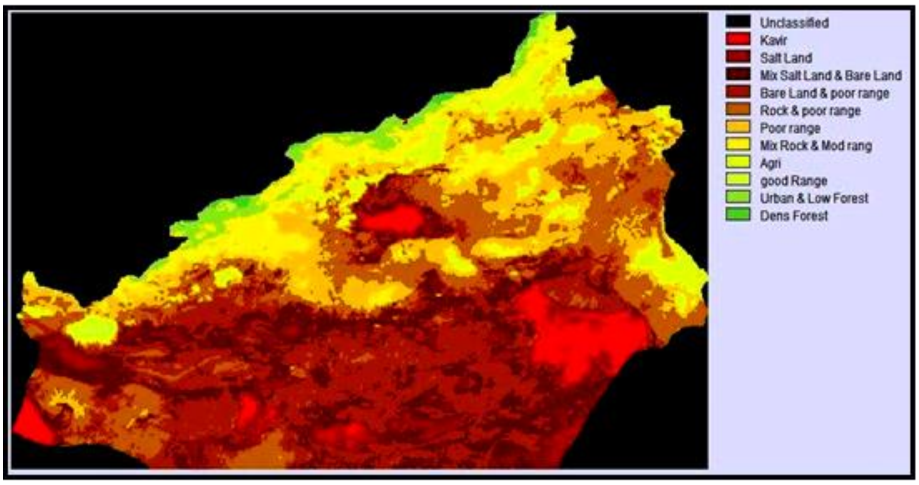

Fig. 2. land cover map of Semnan province

Pearson correlation analyses were conducted for the NDVI in 11 classes of land cover vs. 3-, 6-, 12 and 24-month SPIs. Because the relationship between vegetation and precipitation varies within a growing season, each month and station were analyzed separately.

3.1.1. Semnan station

This station located near Semnan city and in the land cover map is classified in desert range land (class 7). The highest correlation equal to 0.898 was in May between SPI 24 and NDVI of class 7 also high correlations equal to 0.821 were observed in September between SPI 24 and NDVI of class 3.

3.1.2. Shahrud station

In the east of Semnan province near the most populous city located in desert range land (class 7), the highest correlations in class 7 and SPI 3 equal 0.834 in September, while the next best correlations were SPI 6, 24 at 0.826 and 0.826 was observed for the duration of study. Finally, SPI 24 class 7 correlated with NDVI equaled 0.816 in October.

3.1.3. Biarjomand station

Biarjomand station is located in desert range land (class 7). The highest correlation of 0.943 was observed in June between SPI 12 and NDVI of class 7. Then in order of importance, SPI 6, 24 were correlated with desert rangeland. There were high correlations in July, August and September but less than in June. Data collected in this station also show us salt land in September and low forests in June have high correlation with SPI 6, 12 and 3.

3.1.4. Garmsar station

This station is located near salt land in the desert rangeland. The highest correlation of 0.750 was in June between SPI 24 and NDVI of class 2. The next best correlation was SPI 6 with salt land.

3.1.5. Damghan station

In this station, only in June was a high correlation of 0.773 observed between desert rangeland and SPI 24.

3. 2. Selection of independent variables

Strong correlations were found among NDVI of land cover classes and SPI at the four time scales, for each month period, from May to October. The 3-months, 6-months and 24 SPI in May for Semnan site, both for desert range land, semi steppe rangeland and Steppe rangeland NDVIs showed correlations higher than 0.8. Moreover, for periods of August, correlations higher than 0.8 have been found between the 3 and 6-months SPI for Kavir and mix of bare land & desert rangeland NDVIs. (Table 1)

In Shahrud, correlations of NDVI land cover classes and 3, 6 and 24 month SPI were also significant for the periods of May and July for semi steppe rangeland and for steppe rangeland in Augst with a R2 higher than 0.75 (Table 2).

In Biarjomand, high correlations were found among steppe rangeland, the 24 month SPI and the NDVI of class 7 in June. The highest Biarjomand correlations were between salt lands, bare land and 24 month SPI in September. In October Kavir land covers NDVIs had high correlations with 3, 24 month SPI (Table 3).

Table 1. Stepwise regression analysis on Semnan site for selective months

Month/classes		**class1**	**class2**	**class3**	**class4**	**class5**	**class6**	**class7**	**class8**	**class9**	**class10**	**class11**
May	R^2	0.508	0.099	0.139	0.252	0.305	0.816	0.806	0.328	0.864	0.529	0.301
	F	6.188	0.657	0.971	2.026	2.632	11.116	24.935	2.932	15.847	6.751	2.587
	Pr > F	0.047	0.449	0.363	0.204	0.156	0.014	0.002	0.138	0.007	0.041	0.159
	Input model						SPI6-SPI3	SPI24		SPI6-SPI3		
August	R^2	0.907	0.137	0.455	0.808	0.155	0.233	0.27	0.244	0.297	0.219	0.175
	F	24.375	0.949	5	10.513	1.103	1.823	2.22	1.938	2.532	1.683	1.269
	Pr > F	0.003	0.368	0.067	0.016	0.334	0.226	0.187	0.213	0.163	0.242	0.303
	Input model	SPI6-SPI3			SPI6-SPI3							

Table 2. Stepwise regression analysis in site of Shahrud for selective months

Month		**class1**	**class2**	**class3**	**class4**	**class5**	**class6**	**class7**	**class8**	**class9**	**class10**	**class11**
May	R^2	0.181	0.072	0.043	0.011	0.057	0.078	0.775	0.046	0.079	0.266	0.028
	F	1.325	0.463	0.267	0.065	0.366	0.504	8.632	0.289	0.518	2.174	0.172
	Pr > F	0.294	0.521	0.624	0.807	0.567	0.504	0.024	0.61	0.499	0.191	0.692
	Input model							SPI24 SPI3				
July	R^2	0.657	0.455	0.264	0.111	0.125	0.122	0.792	0.055	0.795	0.191	0.029
	F	4.793	5.012	2.151	0.748	0.855	0.834	9.497	0.35	9.71	1.42	0.178
	Pr > F	0.069	0.066	0.193	0.42	0.391	0.396	0.02	0.576	0.019	0.278	0.688
	Input model							SPI24 SPI12		SPI24 SPI3		
August	R^2	0.19	0.387	0.202	0.161	0.276	0.187	0.356	0.035	0.766	0.04	0.076
	F	1.403	3.786	1.516	1.149	2.293	1.377	3.324	0.218	8.197	0.252	0.492
	Pr > F	0.281	0.1	0.264	0.325	0.181	0.285	0.118	0.657	0.026	0.634	0.509
	Input model									SPI24 SPI3		

Table 3. Stepwise regression analysis in site of Biarjomand for selective months

Month		**class1**	**class2**	**class3**	**class4**	**class5**	**class6**	**class7**	**class8**	**class9**	**class10**	**class11**
June	R^2	0.357	0.069	0.533	0.085	0.605	0.355	0.889	0.419	0.393	0.691	0.719
	F	3.336	0.442	6.841	0.561	9.202	3.299	47.856	4.329	3.88	13.445	15.336
	Pr > F	0.118	0.531	0.04	0.482	0.023	0.119	0	0.083	0.096	0.01	0.008
	Input model							SPI24				
September	R^2	0.566	0.928	0.851	0.581	0.242	0.497	0.492	0.542	0.607	0.176	0.237
	F	7.831	31.985	14.269	8.33	1.911	5.94	5.804	7.103	9.258	1.284	1.859
	Pr > F	0.031	0.001	0.009	0.028	0.216	0.051	0.053	0.037	0.023	0.3	0.222
	Input model		SPI24 SPI6	SPI24 SPI3								

October	R^2	0.898	0.312	0.137	0.538	0.379	0.342	0.298	0.321	0.503	0.213	0.191
	F	21.995	2.719	0.949	6.975	3.661	3.119	2.544	2.832	6.075	1.624	1.413
	Pr > F	0.003	0.15	0.368	0.038	0.104	0.128	0.162	0.143	0.049	0.25	0.279
	Input model	SPI24 SPI3										

In Garmsar Kavir, bare land & desert rangeland and Semi steppe rangeland, had R2s higher than 0.8 3, 6 and12 month SPI only in June. (Table 4)

Table 4. Stepwise regression analysis in site of Garmsar for selective months

Month		class1	class2	class3	class4	class5	class6	class7	class8	class9	class10	class11
June	R^2	0.871	0.263	0.121	0.822	0.037	0.158	0.82	0.152	0.457	0.161	0.893
	F	16.876	2.137	0.825	11.582	0.233	1.124	11.411	1.077	5.048	1.152	20.85
	Pr > F	0.006	0.194	0.399	0.013	0.646	0.33	0.014	0.339	0.066	0.324	0.004
	Input model	SPI12 SPI3			SPI6 SPI3			SPI6 SPI3				SPI6 SPI3

Conclusion

Our study analyzed the relationship between NDVI and SPI in Semnan province on different land cover types during the growing season. The combination of remote sensing NDVI vegetation data and climatic index are suitable for estimation of land cover changes. Steppe range land or class 7 in all stations had higher correlations between NDVI and SPI. Land cover with vegetation had the best correlations during the spring and summer months. NDVI predicted by regression fit the observed NDVI very well in most cases. This implies that the NDVI can be a good indicator of moisture condition and can be used as an important data source for detecting and monitoring drought in the arid and semiarid areas. SPIs from 3 to 24 months, had the highest correlation to NDVI. This was probably because of a time lag in vegetation response to precipitation and that the impact of water deficits on vegetation is cumulative. Our results suggest that the 3-24 month SPI is best for determining drought severity and duration in vegetation cover. Seasonality has a very significant effect on the relationship between NDVI and SPI because the highest correlations occurred only in the middle of the growing season, and were much lower during greenup and senescence. This was likely due to plants being more sensitive to water availability during their reproductive growth stage. When regression techniques are used to quantify the NDVI and SPI relationship, this seasonal effect needs to be taken into account.

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