Journal of Applied Sciences

ISSN 1812-5654

science alert

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Journal of Applied Sciences 11 (17): 3089-3103, 2011
ISSN 1812-5654 / DOI: 10.3923/jas.2011.3089.3103
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Monitoring the Impacts of Drought on Land Use/Cover: A Developed Object-based Algorithm for NOAA AVHRR Time Series Data

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Abstract: This project was implemented on Zayandeh-Rud basin which is one of the most important and strategic regions of Iran. The main goal of the research was to monitor and evaluate the temporal land use/cover changes affected by drought episodes over a 10-year period (1992-2003). Primarily, raw weather data preparation activities were carried out to produce Standard Precipitation Index (SPI) spatial point thematic layer as a base map, then, satellite image pre-processing works applied on the remotely sensed data to generate the time series land use/cover maps. As a novel idea in this study, it developed a new object-based classification algorithm for AVHRR (Advanced Very High Resolution Radiometer) data. The model works based on the seasonal values of Normalized-difference Vegetation Index (NDVI) in the study area. The algorithm was statistically compared with maximum likelihood supervised classification method. Results demonstrated an increase in overall accuracy from 74.34 to 90.07% and the Kappa index from 70.58 to 88.8%. Based on the statistical analysis results, drought had not statistically significant effect on the land use/cover changes. Therefore, there are more important factors other than natural weather drought in the study area and these could be summarized as a term of disorder on land management in the Zayandeh-Rud river basin. Results of the investigation provide a scientific tool enabling governmental land and water managers to monitor, make decision and manage the water crises due to drought upon the catchment.

Key words: Land use/cover, change detection, drought periods, SPI, NOAA AVHRR, spatial interpolation

INTRODUCTION

In the recent decades, among the natural incidents that affected human populations, drought have been higher in number and frequency in comparison to other events (Bryant, 2005). Humans are usually affected by the impacts of the drought. The recent droughts have had economic drawbacks, environmental consequences and personal burdens both in the developed and in the developing countries (UNISDR, 2009). All of them have caused the vulnerability of the societies to this devastating phenomenon to be taken into consideration.

The Zayandeh-Rud is one of the most important and strategic river basins in central Iran. The basin covers an area occupied by more than three million people and it is a cornerstone in Iran's agriculture and industry. The continuing growth of urban population and the recent, rapidly increasing demand on water for industrial uses have led to a competition on water between the industrial and the agricultural sectors. Recently, droughts were claimed to be the most serious factor leading to substantial land use changes and posing negative effects on water resources, especially groundwater aquifers in the basin (Foltz, 2002).

Satellite systems with good temporal resolution are the best tools for mapping and monitoring the earth surface environment (Friedl *et al*., 2002; Salim *et al*., 2008; Washington-Allen *et al*., 2004) specially for the vegetation cover investigations and land use/cover mapping along the time scale (Reddy *et al*., 2008a, b) and natural resources change detection (Kumar, 2011). Many of the researches like Tonkaz (2006) have been done in order to define and study the drought periods. However, this investigation put together geospatial data analysis techniques, to produce spatio-temporal SPI index data set and multi-temporal image processing analysis, to create a multi-temporal change detection data set, in order to ultimately identify the effects of drought on land use/cover change in the study area.

The main goal of the investigation was to find a new, highly accurate algorithm for the very high resolution data, such as NOAA AVHRR (National Oceanographic and Atmospheric Administration-Advanced Very High Resolution Radiometer) images, that will enable users to

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map the land use/cover changes in arid and semi-arid areas. The second goal of the research was to monitor and evaluate the temporal land use/cover changes affected by drought episodes over a 10 year period (1992-2003). AVHRR Satellite sensor, with four spectral bands, was launched into space by satellite Tiros-N series in 1978 and is now taking films. In the next generation, the number of the spectral bands has increased to 5. It was launched into space by satellite NOAA-7 in 1981, which had already sent back its images (Earth Observation and Satellite Imagery, 2011; Kidwell, 1995). The last series of this sensor is AVHRR-3, with 6 spectral bands, which was launched into space from the platform NOAA-15 and put on the orbit in 1998 (Evans and Greer, 2004; Jiang *et al*., 2008). The main characteristics of the sensor are summarized in Table 1. As it show the table, the most important sensor channels which are suitable in environmental and natural resources studies are channel 1 (red) and channel 2 (Near infra-red). Other channels can be used in hydrological and oceanographic studies, as well as, climatic and weather investigations.

MATERIALS AND METHODS

Zayandeh-Rud basin is one of the most important, strategic and tourist attractive areas in central Iran. Therefore, the river basin selected as the research area in this project. Zayandeh-Rud river basin, is shown in Fig. 1. The area of the basin is 105,000 km^2. Precipitation varies in intensity, volume and rates from the western; over 1400 mm year^{-1}, to the eastern parts of the basin; less than 300 mm year^{-1}.

Methodology: In order to make a better understanding of all the details of the plan, it is better to look at Fig. 2. The flowchart shows the whole activities and the techniques which are done from the data sources selection, in the start of the work, via used modules and functions which are practically utilized as the heart of a GIS activity and the resulted outputs which lead to a reliable and logical hypothesis judgment at the end of project. Technically, it is possible to describe the processes shown in Fig. 6 in three main steps, i.e., from data preparation to post processing and accuracy assessment, as the following steps:

Preparation of the meteorological data:

- Determining the period of the research and a temporal basis for the preparation of necessary data for the research (which included the satellite data from 1992 to 2002 in order to learn about the land use/land cover change and the data from 1972 to 2002 to determine the meteorological drought index and the climatic analysis of the area under study)
- Collection, completion, efficacy and accuracy test and completion of the climatic data

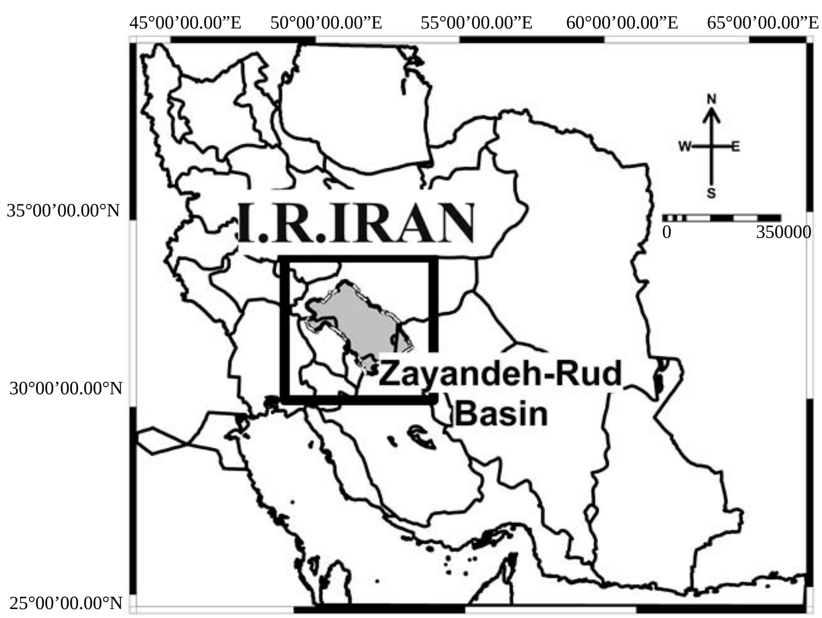

Fig. 1: Research area location

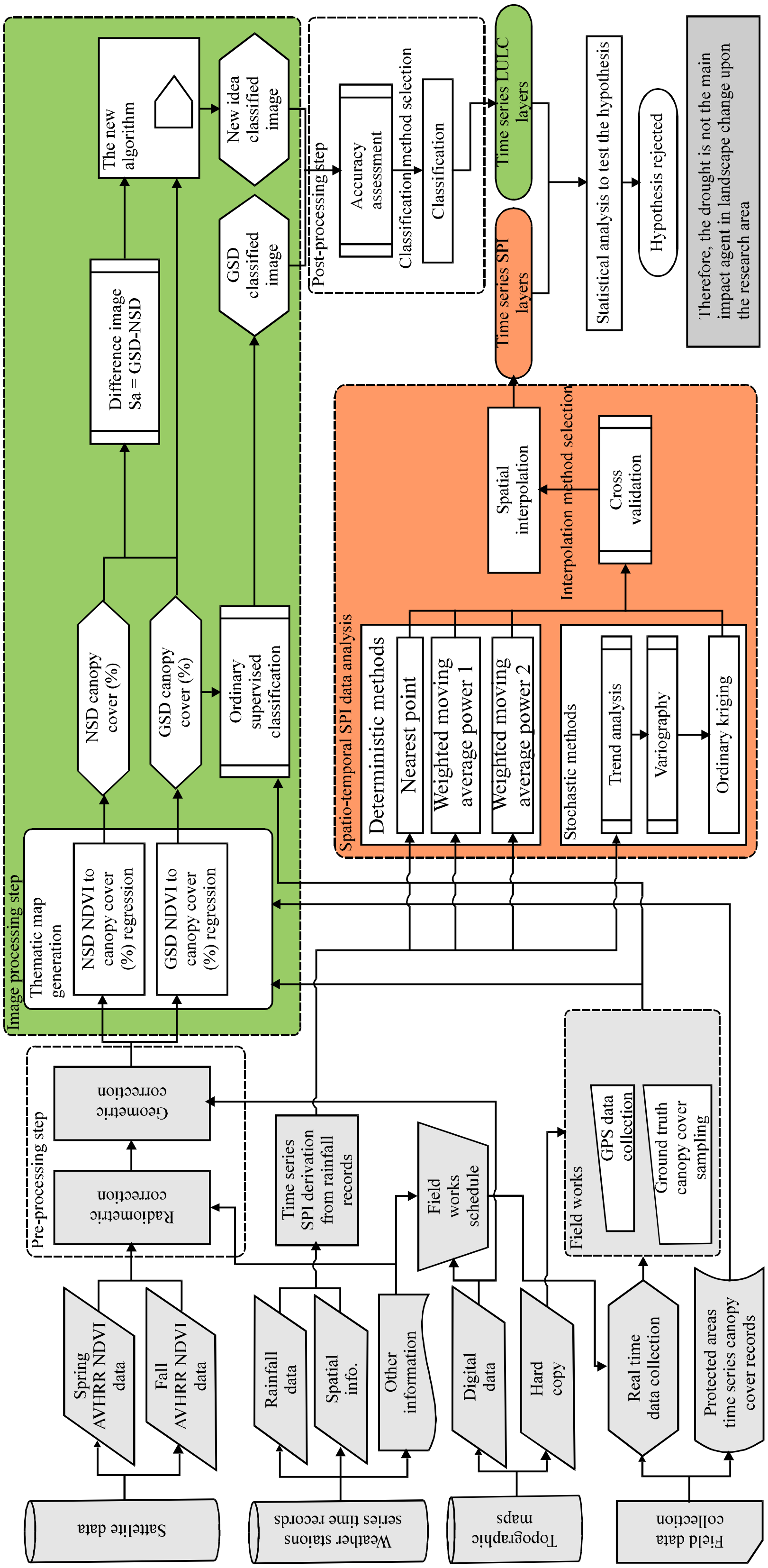

Fig. 2: Full extent flowchart of the project

Table 1: Characteristics of the AVHRR Sensor reference: (Earth Observation and Satellite Imagery, 2011)

Channel	Wavelength (nm)	IFOV (milliradians)	At nadir resolution (km)	Primary uses
1	0.58-0.68	1.39	1.09	Daytime cloud/surface and vegetation mapping
2	0.725-1.00	1.41	1.09	Surface water, ice, snow melt and vegetation mapping
3a	1.58-1.64	1.3	1.09	Snow and ice detection
3b	3.55-3.93	1.51	1.09	Sea surface temperature, night-time cloud mapping
4	10.30-11.30	1.41	1.09	Sea surface temperature, day and night cloud mapping
5	11.50-12.50	1.30	1.09	Sea surface temperature, day and night cloud mapping

Drought index (SPI) spatio-temporal analysis:

- Computing SPI for each time and station and determining the condition of the temporal changes of the data
    - Modelling on the basis of choosing 2/3 of the stations with suitable dispersion within the area
    - Testing the derived spatial models and choosing the best model for every one of the times on the basis of choosing 1/3 of the stations with suitable dispersion within the area
- Producing spatio-temporal SPI layers according to the best methods

Pre-processing the data:

- Collecting the field data
- Preparing the information vector layers. This includes georeferencing and coordinating all the available information layers on the basis of a suitable coordinate system
- Preparing the remote sensing data
    - Radiometric corrections
    - Geometric corrections
    - Coordinating the NOAA and MODIS coordinate data

Processing the data:

- Processes of GIS-level 1
    - Preparing the maps of the work units (the hydrological units of the area) to determine the degree of aridity on the basis of one of the famous methods. This is necessary to determine the information layers of the severity of the drought in different areas
    - Remote sensing the MODIS data in order to classify the land use/cover by means of the collected field data
    - Analysing the relationship between MODIS and NOAA to determine the land use/cover of the years of research
- Processes of GIS-level 2
    - Overlaying the map related to SPI of each year on the map of land use/cover of the same year and analysing the diagram of the changes of the two factors during the years of the research in the sub-watersheds of the watershed of Zayandeh-Rud River

Preparation of the meteorological data: A 30 year precipitation data record covering the time period from 1972 to 2003 and derived from 74 weather stations (Fig. 3) was used to create the spatiotemporal SPI Index dataset. Two thirds of the stations were used in the geospatial analysis and interpolation modeling. The stations were selected randomly in such a way as to ensure uniform, representative spatial distribution in the region. The rest of the data was reserved to be used in cross validation so as to determine the best interpolation method which will allow preparation of a map of SPI spatial variation for each study year. The study period of concern in this research was the years from 1992 to 2003.

Drought index (SPI) spatio-temporal analysis: As precipitation is an important water resources supply component, an analysis of the characteristics of precipitation is a critical step in drought risk assessment. However, if we wish to compare climatic conditions in different areas characterized by varying hydrological balances, we need to employ a standardized variable that is capable of objectively capturing the dominant drought conditions of the target region (Hayes *et al*., 1999). For this purpose, the Standardized Precipitation Index (SPI) appears to be the most powerful drought index. Its main features are that it is based only on the precipitation field; it is standardized; and can be computed at different time scales, thus allowing for monitoring of different kinds of drought and wetness conditions (Keyantash and Dracup, 2002).

For evaluation of the level of the deficit/excess of precipitation, we employed the SPI computed for each point of the network. The SPI represents the number of standard deviations by which the observed values deviate from the long-term means of a normally distributed

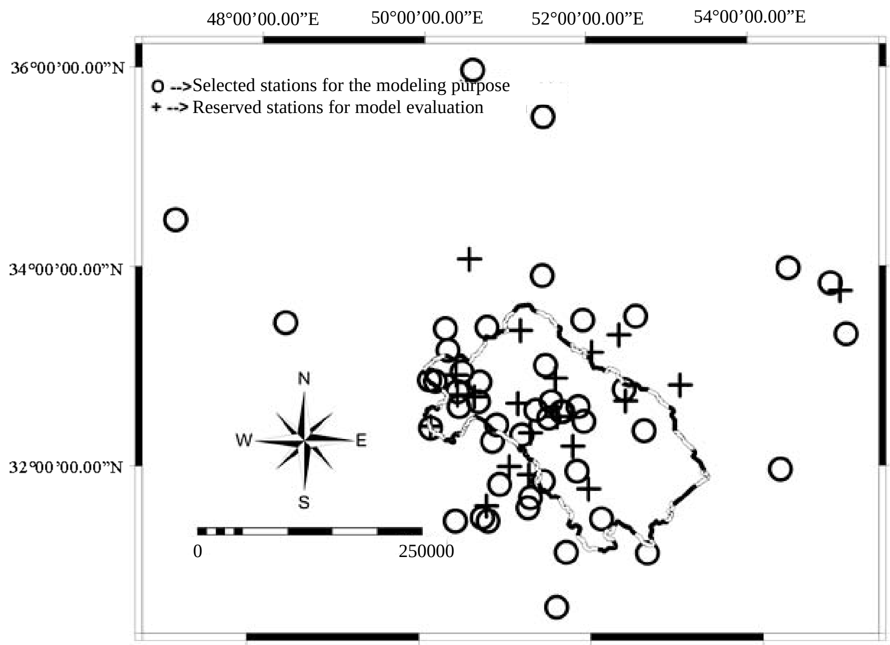

Fig. 3: Spatial distribution of the Stations upon the region of study

Table 2: Geostatistical methods were applied to the data set

Method	Map ID
Nearest Neighbor	Nearest
First Order Weighted Moving Average	WMA_P1
Second Order Weighted Moving Average	WMA_p2
Kriging method	Kriging

random variable. For computing the SPI, we used Eq. 1, assuming normal distribution of the precipitation variable:

$$SPI = \frac{P_i - P_m}{SD_i} \quad (1)$$

where, P_i is Precipitation registered in the period i (1...12 months). P_m is Mean of precipitation in the period i. SD_i is standard deviation of mean precipitations in period i.

Transforming the SD into coefficient of variation was done using Eq. 2:

$$S\% = \frac{SD}{P_m} \times 100 \quad (2)$$

By developing Eq. 1, which is based on a single-date data set and two spatial dimensions (x, y), the SPI can be computed by Eq. 3 for the third dimension, which in this investigation was time (z):

$$SPI = \frac{\frac{P_i - P_{mi}}{P_{mi}}}{s_i} \quad (3)$$

By using this simple formula, it was possible to estimate the SPI for every point of the land on the basis of the precipitation measured in the period i, the multi-annual mean values of precipitations (P_{mi}) and the coefficient of variation estimated for the territory and mapped for different periods (Barbu and Popa, 2004).

Different geostatistical methods were applied to the data set and these are summarized by Table 2, which displays the spatial interpolation method used in tracking the spatial variations in the drought index. By use of the cross validation table (Wang *et al*., 2010; Willmott and Matsuura, 2005), the best fit model for each year was selected in light of the Mean Absolute Error (MAE) and the Mean Bias Error (MBE) indices to produce the SPI drought index map of each study year.

Image processing and time series change detection: Satellite images time series analysis was the other part of the project which is done based on the visual interpretation and digital image processing concepts. Table 3 introduces the types and main features of the satellite images used in this investigation. This step of the analysis consisted of different parts.

First, pre-processing procedures such as radiometric and geometric corrections for NOAA AVHRR images, was carried out. Then, in order to generate canopy cover percentage thematic map, ground truth sample point data is regressed to the NDVI values of the image in the same point.

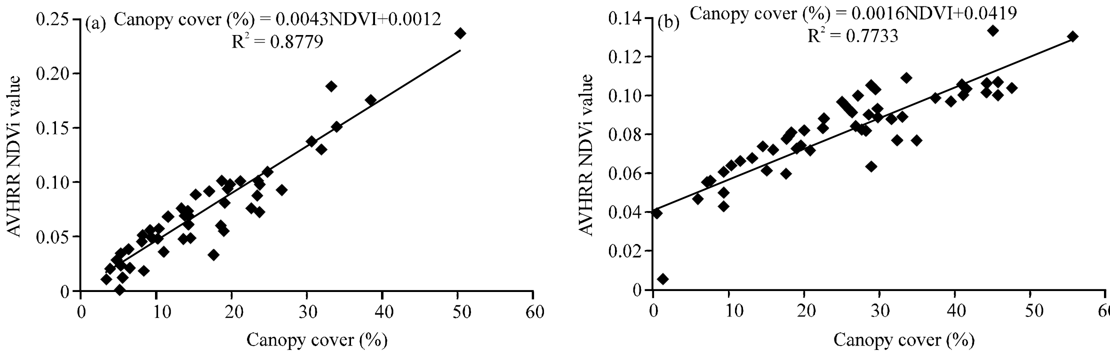

Fig. 4 (a-b): Canopy cover and NDVI value regression analysis for summer (a) and autumn (b) 2003

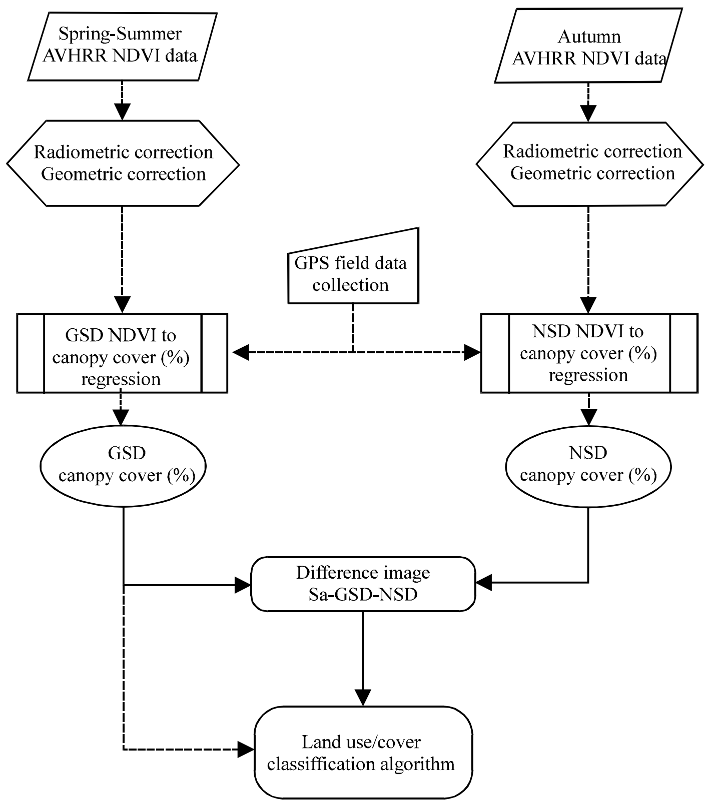

Fig. 5: Data preparation and pre-processing schematic

Table 3: The used satellite images information

Sensor	Platform	Year
AVHRR	NOAA	2003*
AVHRR	NOAA	2002*
AVHRR	NOAA	2001*
AVHRR	NOAA	2000*
AVHRR	NOAA	1999*
AVHRR	NOAA	1998*
AVHRR	NOAA	1997*
AVHRR	NOAA	1996**
AVHRR	NOAA	1995**
No Data	No Data	1994
AVHRR	NOAA	1993**
AVHRR	NOAA	1992**

* Single date from Iran space agency, ** 10 days composite NDVI image from: http://edc2.usgs.gov/1KM/comp10d.php

Field data collection for Canopy cover percentage information was estimated via the line transacts approach, which is a better method for the fast estimation of canopy cover percentage (Hanley, 1978; Marsett *et al*., 2006; Sankey *et al*., 2009) in a large NOAA ground pixel area. In Fig. 4a and b it is shown that the NDVI values were regressed to the ground samples of canopy cover percentage of closest dates in summer and autumn of the year 2003, respectively.

Next, the first processing step as it showed in Fig. 5, is carried out. In the flow chart of the Fig. 5, the NDVI images of the AVHRR data is generated for the spring and

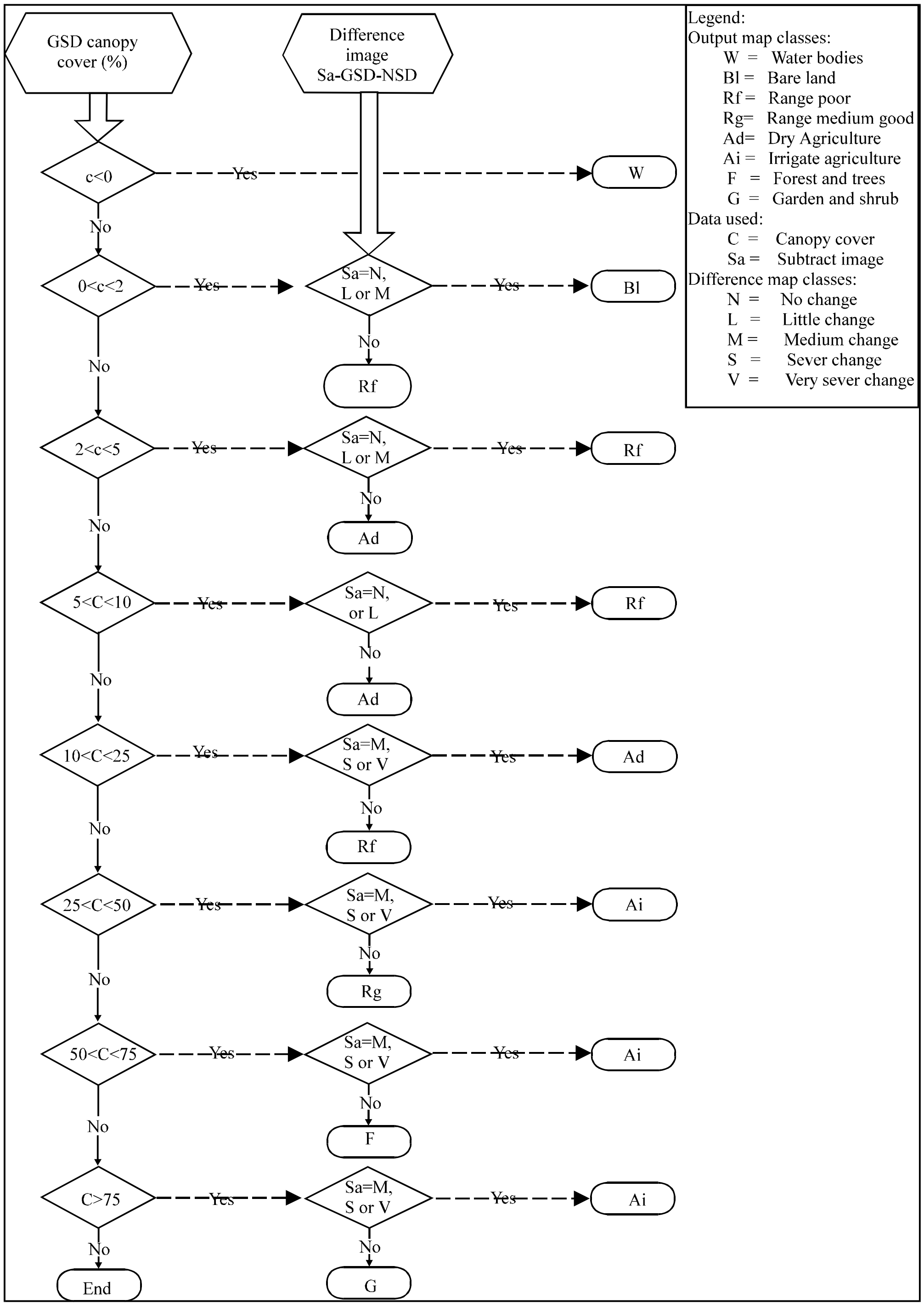

Fig. 6: Schematic flowchart of the decision making algorithm for land use/cover classification

fall in order to Produce Growth Season (GSD), Non-growth Season (NSD) and the difference (Sa) images.

Finally, based on a simple algorithm which is shown schematically in Fig. 6, an accurate land use/cover classification map was prepared in such a way as to be useable in a time series comparison of SPI and land use/cover for the study area during the study period (1992-2003).

In other words, this part, which can be named as the static step of image processing, comprised use of seasonal NDVI values and seasonal differences in NDVI values in each year. On account of this, the canopy cover which correlated well with the NDVI values, both for GSD and NSD, was change from late spring-early summer; which can be a growing, or before-harvest, season (GSD), to autumn: which can be a non-growing, or after-harvest, season (NSD). This produced a difference in canopy cover map derived from the NDVI images. So, the difference generated image can be used in a change-detection algorithm for each year.

RESULTS

Temporal drought variations were defined by using the SPI at a yearly scale (Table 4). As it mentioned before, the closer the MAE value is to zero, the higher is the model accuracy and vice versa. On the other hand, the closer is the MBE to zero, the less is the bias in the estimations and vice versa. Accordingly, the model with the least MAE and lowest absolute value of MBE is the best model to choose (Willmott and Robeson, 1995).

The result of applying the selected method of yearly interpolation, in Table 5, is presented in Fig. 7. In the Fig. 7, variations of drought over the study area in the study period are illustrated from year to year by the classified values of the SPI index. Interestingly, with a look at the Table 5, it can be infer that, in the years when the water shortage and drought were happened (1993, 1995 and1997) the appropriate model changed from Stochastic Kriging method to a deterministic model of weighted moving average with the power 1. The reason can be explain based on the difference and variation on the rain fall amount during the wet and dry years. In the drought years, usually, there is less difference in amount of the precipitations all over the study area; however, the condition is different in the wet periods. In the years with the good weather condition, the variation of rainfall can be very significant from station to station specially from west parts with the wetter climatic condition to drier east basin parts.

Ground truth information for the study area were collected via a set of field works and a good accuracy (5-10 meter) handheld GPS. In order to get the best approximation to the ground canopy cover percentage in the very big ground pixel size of the AVHRR (around 1.1 km), the assessments were conducted by the random line transect approach with at least four points with the maximum variation in canopy cover in each selected pixel for canopy cover estimation. In Fig. 8, the status of the sampled points is illustrated. The point selection, that is illustrated in the Figure was done based on a GIS approach model to choose the NOAA AVHRR pixels which are closer to the access main roads and well distributed on all the observed land use/cover units for supervised classification.

Table 4: Cross validation table to identify the more accurate method

	Kriging		Nearest		WMA_P1		WMA_P2	
Year	MAE	MBE	MAE	MBE	MAE	MBE	MAE	MBE
2003	0.86	-0.22	1.23	-0.39	0.78	-0.24	0.84	-0.27
2002	0.76	0.18	1.02	0.12	0.77	0.12	0.77	0.09
2001	0.73	-0.06	1.03	-0.20	0.70	0.00	0.75	-0.06
2000	0.71	-0.33	0.80	-0.37	0.69	-0.38	0.70	-0.36
1999	0.70	-0.19	0.96	-0.36	0.70	-0.22	0.79	-0.24
1998	0.45	0.03	0.57	-0.13	0.45	0.02	0.44	0.01
1997	0.78	0.45	1.03	0.50	0.78	0.46	0.79	0.44
1996	0.68	-0.23	0.87	-0.30	0.68	-0.24	0.69	-0.28
1995	0.95	-0.61	1.06	-0.60	0.89	-0.54	0.89	-0.56
1994	0.75	0.05	1.10	0.12	0.58	0.11	0.73	0.09
1993	0.88	-0.01	1.15	-0.03	0.79	0.01	0.86	-0.02
1992	0.57	-0.06	1.10	0.01	0.57	0.02	0.58	0.02

Table 5: Selected Interpolation methods to model spatio-temporal SPI Index

Year	Method	Model	Sill	Range (m)	Nugget
2003	Kriging	Exponential	0.72	100,000	0.06
2002	Kriging	Exponential	0.70	100,000	0.15
2001	Kriging	Exponential	0.83	100,000	0.30
2000	Kriging	Exponential	0.48	100,000	0.03
1999	Kriging	Exponential	0.49	152,500	0.12
1998	Kriging	Exponential	0.45	175,000	0.05
1997	WMA_P1	-	-	-	-
1996	Kriging	Exponential	0.58	100,000	0.08
1995	WMA_P1	-	-	-	-
1994	Kriging	Exponential	1.00	100,000	0.02
1993	WMA_P1	-	-	-	-
1992	Kriging	Exponential	1.30	100,000	0.06

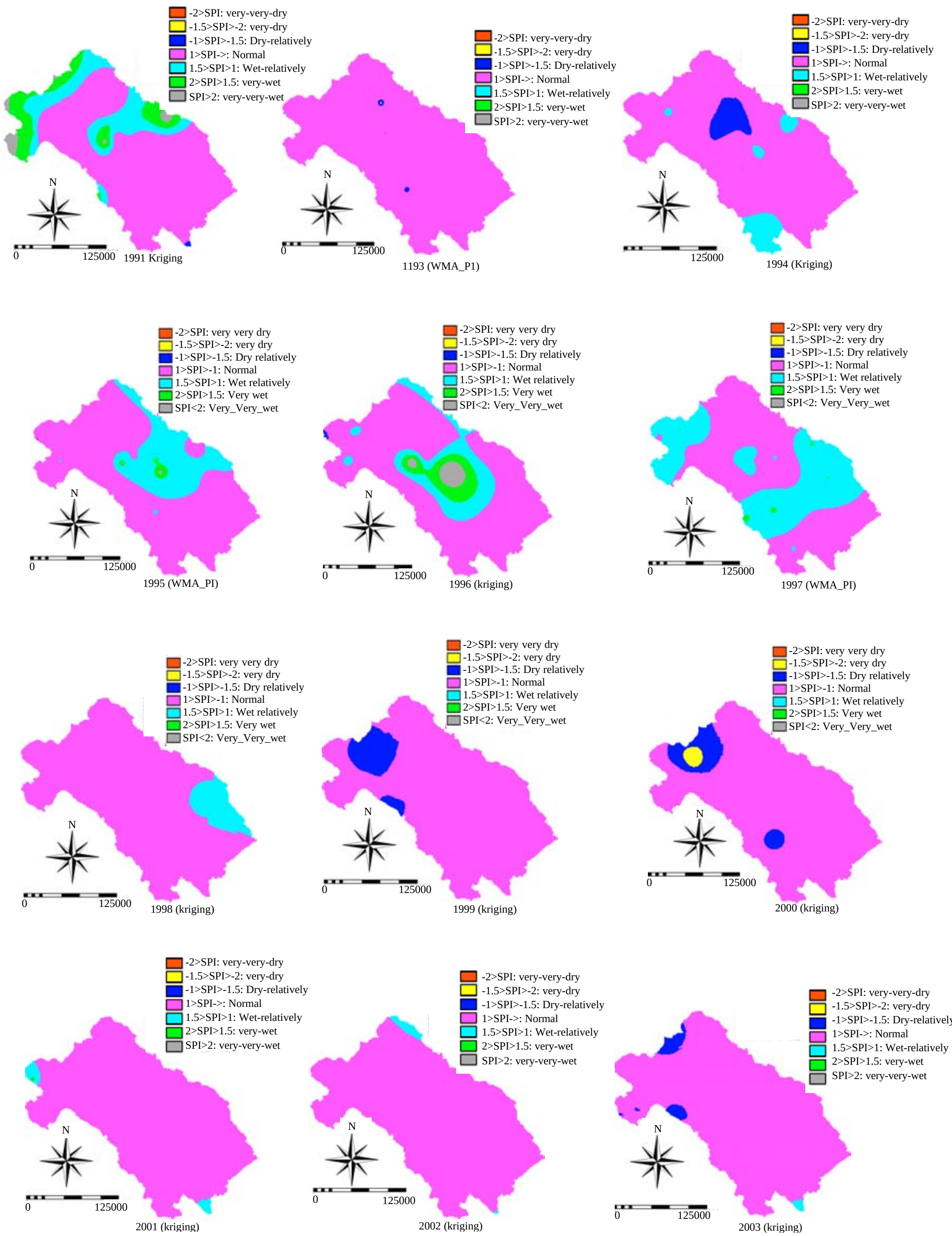

Fig. 7: The best methods selected to create continuous map for each study years

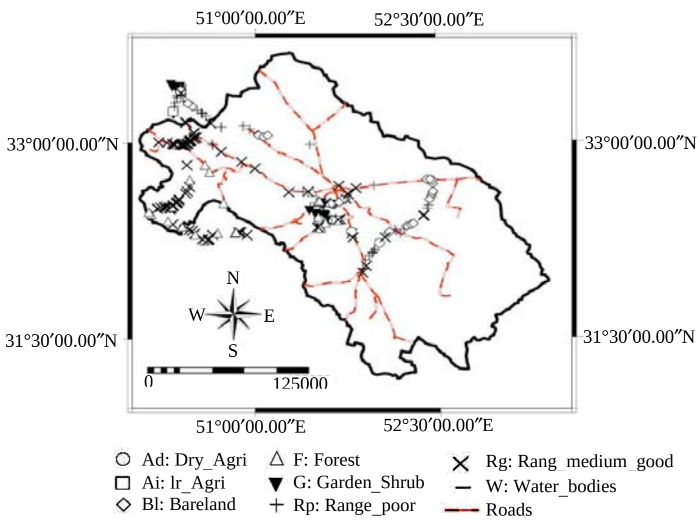

Fig. 8: Ground Truth Sample Point Locations via GPS field survey

Figure 9 shows the generated land use/cover map for the 1992-2003 period based on the novel, proposed method. As an example the GSD image of year 2003 is dated 12/07/2003 (summer) and the NSD image was the image captured on 26/10/2003 (autumn).

A general degradation in land use/cover could be seen by only visual interpretation and comparing the year to year images in the Fig. 9. The most important point, which is highlighted via time series image visualization, is the removing and degradation of Gavekhooni swamp in south east of the basin. The swamp, which is the most important vital ecological part of the east and south east of the basin, can clearly be seen in a red color on the images from 1992 to 2000 but there is no indication of such a marsh after that. Although, it is possible to interpret the change in swamp area as a large water body in the south east of the basin based on the 1993 or even 1996-1997 drought period but dismissing the same large water body cannot be explained based on the drought seasons in the following years, when the wet years frequently happened. As it can be seen in the images, from 1998, gradually, the swamp area is replaced by the poor land use/cover units like bare land and poor range lands.

In order to identify the advantages of the new algorithm in comparison with the ordinary methods, a supervised classification using the maximum likelihood classifier algorithm was done for the GSD of the year 2003. Accuracy assessment was carried out on the basis of reserved GPS ground samples, both for the supervised classification image and the image of the proposed algorithm. The confusion matrices of the supervised classification and the seasonal-based new algorithm are given by Table 6 and 7, respectively.

As it shows in the tables, although a negligible decrease in accuracy are happened for the Dry_Agri and Forest classes, which are changed from 0.77 to 0.76 and 0.88 to 0.82 respectively, other land use/cover classes accuracy had a significant growth in the accuracy. For example, maximum accuracy rise could be seen in the case of Garden_Shrub and Rang_med_good by 0.56 (from 0.37 to 0.93) and 0.46 (from 0.48 to 0.94), respectively. Reliability generally shows an upturn in all the classes when the new seasonal algorithm is applied instead of maximum likelihood supervised classification method. As it clearly presented in the Table 8, the overall accuracy and the Kappa index revealed an increase from 74.3 to 90.07% and from 70.58 to 88.8%, respectively.

In the last step, the Geostatistically-generated, yearly spatial SPI maps were compared with the land use/cover images of each year of concern. The effects of the drought on the land use/cover unit areas compared and proved to be helpful for interpretation and decision making. The graph presented by Fig. 9 which was derived from the analysis of time series SPI and the land use/cover images, introduces the final result of the current investigation.

As shown in Fig. 10, there was a decrease with severe fluctuations in the general trend of the SPI changes in the comparison period of comparison of 1992

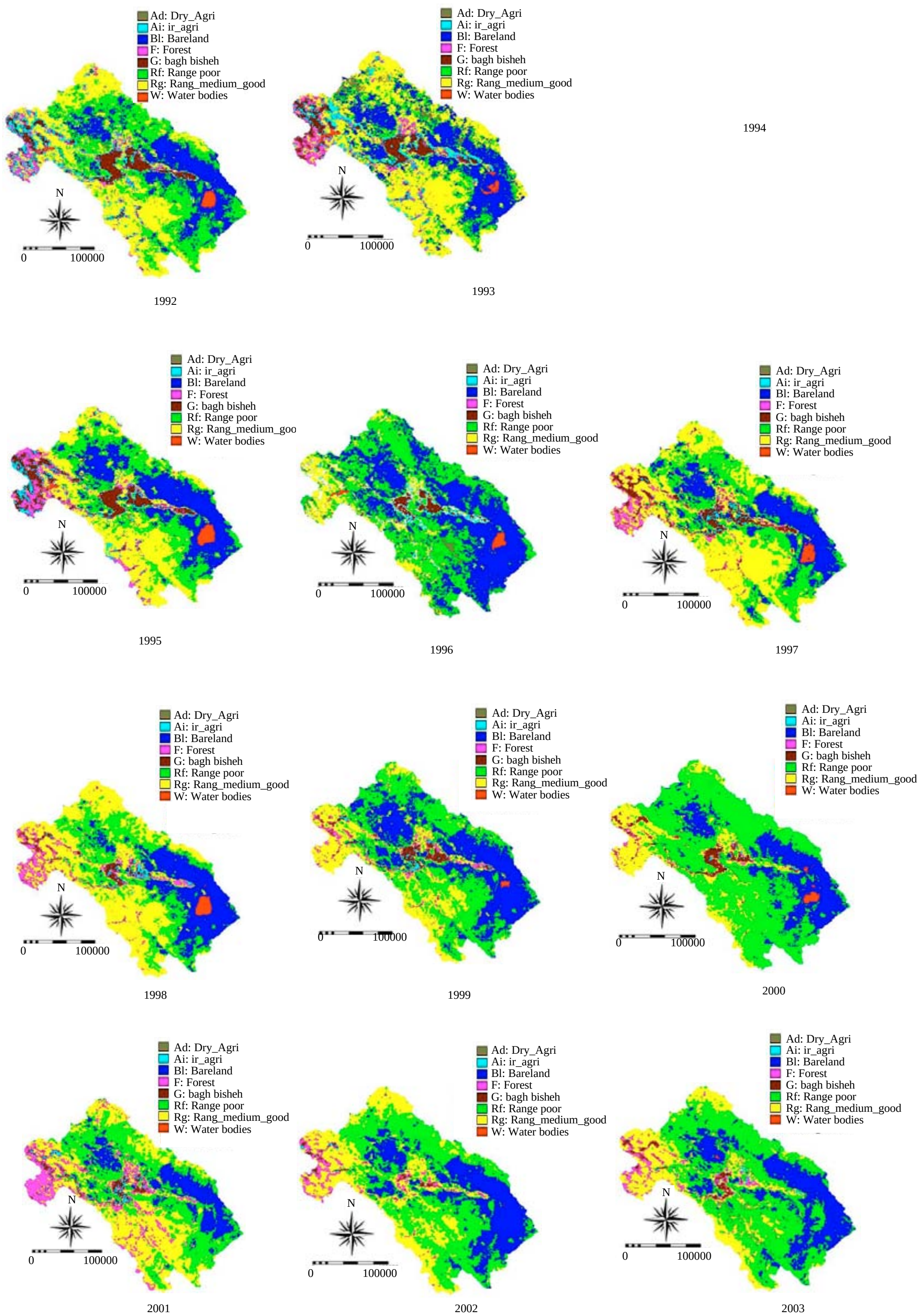

Fig. 9: New-algorithm classification Maps for each of the study years

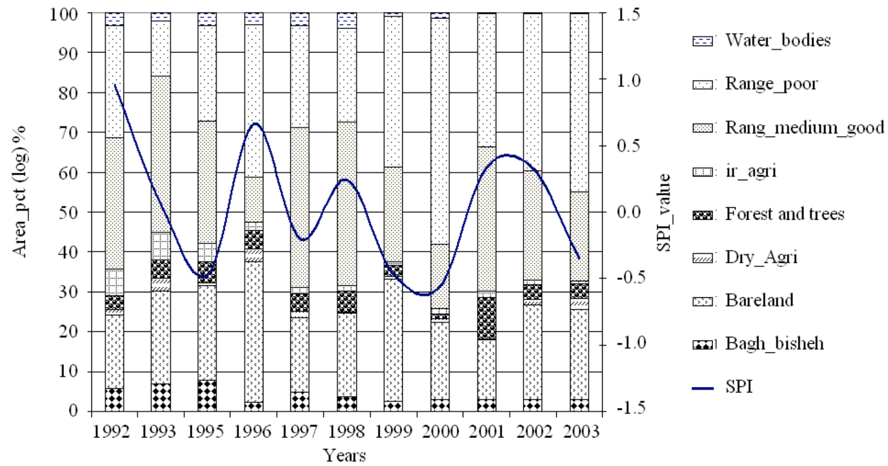

Fig. 10: Time series SPI and land use/cover variation

Table 6: Confusion matrix for supervised classification method

	Dry_Agri	Ir_Agri	Bareland	Forest	Garden_Shrub	Rang_med_good	Range_poor	Water_bodies	Accuracy
Dry_Agri	103	5	0	13	6	5	0	2	0.77
Ir_Agri	8	138	0	0	10	0	0	0	0.88
Bareland	3	0	165	0	0	0	2	12	0.91
Forest	18	0	0	155	0	3	0	0	0.88
Garden_Shrub	53	16	1	6	56	15	0	3	0.37
Rang_med_good	24	0	9	29	4	78	20	0	0.48
Range_poor	0	0	7	0	0	5	133	0	0.92
Water_bodies	2	0	19	2	1	5	3	73	0.70
Reliability	0.49	0.87	0.82	0.76	0.73	0.70	0.84	0.81	

Table 7: Confusion matrix for new Idea Seasonal Based algorithm

	Dry_Agri	Ir_Agri	Bareland	Forest	Garden_Shrub	Rang_med_good	Range_poor	Water_bodies	Accuracy
Dry_Agri	81	2	1	1	0	16	5	0	0.76
Ir_Agri	0	105	0	4	0	2	0	0	0.95
Bareland	0	0	114	0	0	0	7	0	0.94
Forest	0	0	0	106	15	8	0	0	0.82
Garden_Shrub	0	0	0	8	123	1	0	0	0.93
Rang_med_good	0	0	0	4	1	126	3	0	0.94
Range_poor	3	0	1	0	0	2	130	0	0.96
Water_bodies	1	0	2	0	0	0	2	22	0.81
Reliability	0.95	0.98	0.97	0.86	0.89	0.81	0.88	1.00	

Table 8: Accuracy comparison for supervised classification and New Idea classification

Classification method	Overall accuracy (%)	Kappa (%)
Supervised classification	74.34	70.58
New Idea classification	90.07	88.80

to 2003. At that time, the percentage of the area of the Range_Poor, Dry_Agri and Bareland units had an increasing trend, while the bagh_bisheh, Water_bodies, Ir_Agri and Range_medium_good units possessed a falling trend and the Forest unit had an approximately fixed trend without any noticeable changes, although, some remarkable fluctuations were also observed.

In general, the Zayandeh-Rud River watershed underwent short-term dry and wet fluctuations at the time of comparison but on the whole, this region experienced a period with relatively abundant water at the beginning of the period and a drought at the end of the period. The graph reveals that the units of land use/cover with different time delays in comparison to SPI were in alignment with the changes and probably because of the coming effects of the drought with a short time distance, the SPI increase led to the increase of level (the reduction of SPI of the level reduction). Thus, it is necessary to explain that the most severe droughts during the research project occurred in 2000, while the year 1992 enjoyed a period of abundant water in this term.

As a tool to investigate on the drought period in the research and the yearly land use/cover changes in the percentage of the whole catchment, the SPI was assessed. The statistical analysis carried out using the statistical software showed very interesting results. A part of the

Multiple Regression-SPI
Dependent variable: SPI
Independent variables:
bagh_bisheh
Bareland
Dry_Agi
Forest_trees
it_agri
Range_medium_good
Range_poor
Water_bodies

p-value	T Statistic	Standard Error	Estimate	Parameter
0.2566	1.57176	0.942899	1.48201	Contant
0.1617	-2.17437	0.00465688	-0.0107846	bagh_bisheh
0.3769	-1.12662	0.000446123	-0.00050261	Bareland
0.4413	-0.95284	0.0167752	-0.0159798	Dry_Agi
0.8709	0.184178	0.00225753	0.000415786	Forest_trees
0.1139	2.70367	0.00472624	0.0127782	ir_agi
0.1624	-2.16855	0.000351701	-0.00076268	Range_medium_god
0.4371	-0.963101	0.000231518	-0.000222975	Range_poor
0.1184	2.64108	0.0100849	0.026635	Water_bodies

Analysis of variance

p-value	F-ratio	Mean square	Df	Sum of squares	Source
0.2507	3.34	0.0769349	8	0.61548	Model
		0.0230282	2	0.0460564	Residual
			10	0.661536	Total (Cror)

R-squared	=	90.038%
R-squared (adjusted for df.)	=	65.1898%
Standard error of Est	=	0.15175
Mean absolute error	=	0.0482191
Durbin-Watson statistic	=	2.55823 (p = 0.7903)
Lag 1 residual autocorrelation	=	-0.364996

Fig. 11: Results of the statistical data analysis using Statgraphics

statistical analysis results can be seen in Fig. 11, which is the output of Statgraphics statistical software.

Based on the Statistical analysis results, drought did not have a statistically significant effect on the land use/cover changes at 90%, or higher, while the confidence level was observed on the wet to clod-wet upstream areas in west of the catchment. However, the same analysis showed no significant relationship between the drought variations and the changes in the land use/cover upon the downstream arid and semi-arid areas in the central and eastern parts, as well. Therefore, it could be inferred from the results that, there are more important and effective factors other than natural weather drought in the study area and these could be summarized as a term of land management in the Zayandeh-Rud river basin.

DISCUSSION

In order to compare the resulted output of the research, in fact, too many related articles were found even in the internet search engine resulted pages or library material reviews. Finding a Huge number of articles and materials, not only, in the field of land use/cover change in the environmental sciences but also, in the field of local and global impact of drought shows the increasing attention of the scientists and researchers to the main focal subjects of this research. Although, several materials were found, which made attention to the time series analysis of the drought and landscape change in parallel, however, few of them really pointed such a goal to find and highlight relationship between drought periods and landscape changes. However, addressing the main factors which are strongly effective on landscape change is really few among the cited references. In compare to results of this research, three journal articles show conformity with the output results.

In the first case, Campbell *et al.* (2003), found an interaction between the biophysical and social progress in land use/cover dynamics in Kenya. Without any year to year mathematical or statistical analysis, they claim in the results that the drought was not the main factor to land use/cover change in the research area.

Second article in this relation published by Hirche *et al*. (2010). They monitored a set of time series phytoecological factors via a drought period in the Algerian High plateau. Based on the observation and analysis, the research group detected a severe drought effect on landscape change, in addition to a human acceleration impacts via high pressure livestock grazing upon the study area. Unfortunately, they didn't do any further analysis to declare the main root factors of landscape change to highlight the natural crisis or human activities effects.

Thirdly, in conformity with the research result, Kamusoko and Aniya (2009) utilized a hybrid classification algorithm with supervised and unsupervised approach to monitor the land use/cover change in Bindura district/Zimbabwe. They numbered the human activities, in the form of agriculture practices, as the first main factor of landscape change. Moreover, their investigation result shows the effect of other factors such as wildfire and drought to be the main agents in land use/cover changes.

However, many materials and articles are found in contrast with the present research results, which two of them were more interestingly related to the subject and can be discussed here.

Firstly, the work of Asner and Alencar (2010) would be named as the first case. A remote sensing and GIS based project has done in their work in order to assess ecological impacts on Amazon basin during the drought period. As the interesting part of the final results of the research they mentioned that: hydrological function including land use/cover in the floodplain area is significantly affected by drought which is completely in opposite with the result of present study.

In second contradiction case (Volcani *et al*., 2005), integrated remote sensing and GIS in order to spatio-temporal analysis of the physiological state of a semi-arid forest with respect to drought years. They utilized the Normalized Difference Vegetation Index (NDVI) for Landsat-TM and ETM+data. Moreover, NDVI Image Differencing technique was applied for assessing seasonal and inter-annual variations in vegetation. They found considerable NDVI decline between 1995 and 2000 due to the drought events during these years; therefore, they expressed the drought as the main factor of change in land use/cover upon the study area surface.

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