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New landscape ecology approach to the assessment of land degradation

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ABSTRACT:

Land degradation, as a long-term decline in the ecosystem services, is one of the most important environmental problems especially in the arid and semi-arid regions of the world. Quantitative assessment of land degradation is a prerequisite to its control and management. This paper proposes a new approach to land degradation assessment that considers all dimensions of ecological status and trends of the area of study. Due to the limitation of data collection and the lack of sufficient information about ecological trends, this method can be used as an effective tool in environmental assessments. This paper proposes a new approach for assessing the land degradation that uses landscape ecology concepts and theories, focusing on landscape structure and functional relationships. The approach is based on a conceptual model that is expressed in a methodological framework developed for land degradation assessment in the Lake Urmia basin, as a case study. The results showed that landscape ecology concepts and theories can be useful in establishing the links of causality that are often missed in degradation assessments, thereby improving the available methodology for land degradation assessment, especially in regions with high level of chorological relationships.

Keywords:

Land degradation, landscape ecology, Lake Urmia

Abbreviations

CGL- Changes in Groundwater Level; **CP**- Climatological Parameters; **DEM**-Digital Elevation Model; **DPSIR**- Driver-Pressure-State-Impact-Response; **HC**- Homogeneity Criterion; **IAA** - Irrigated Agricultural Area; **GWR**- Geographic Weighted Regression; **LWM**- Land and Water Mask; **MIR**- Mid-Infrared Reflectance; **MCM**- Millions of Cubic Meters; **MS**- Multiresolution Segmentation; **NIR**- Near-Infra-Red reflectance; **NDVI**- Normalized Difference Vegetation Index; **OBC**- Object-Based Classification; **OBIA**- Object-Based Image Analysis; **OLS**- Ordinary Least Squares; **PBC**- Pixel-Based Classification; **RUE**- Rain Use Efficiency; **SP**- Scale Parameter; **TAWM**- Thiessen-Area Weighted Mean; **UTM**-Universal Transverse Mercator; **UA**- Urban Area

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INTRODUCTION

Land degradation is understood as the long-term decline in ecosystem services. It is one of the most important contemporary environmental problems especially in arid and semi-arid regions of the world where it can lead to desertification (Luo *et al.,* 2005). Desertification is a process resulting from disturbances in the hydrological, biogeochemical and ecological regimes. Environmental managers require quantitative measures of land degradation to make the best decision for their health of the environment (Dent and Bai, 2008; Makhdoum, 2002). Quantitative assessment of land degradation is a prerequisite to manage the desertification process in arid and semi-arid regions (Wu and Ci, 2002).

Many methods have been developed to assess land degradation from local to global scales. Field measurements, expert opinions, field observations, land user's judgments, productivity changes, remote sensing and modeling methods are the main approaches for the quantification of land degradation. In these approaches, mainly topological information is used and no attention has been paid to invaluable chorological data derived from the study of, causal relationships between geographical phenomena occurring within the region. Landscape system is an open system, so a single unit is well described only if the influences of other horizontal components are also considered (Baudry *et al.*, 1990). Landscape ecology takes vertical heterogeneity as an holistic object of study and also considers the chorological pattern as a whole.

Landscape ecology focuses on the reciprocal relationships between spatial structure and ecological functions. Different landscapes have different structures and functions. Variety in distribution and composition of the landscape elements and the flow of material and energy leads to deferent levels of ecosystem functions (Fu *et al.,* 2010). Accordingly, it could be noted that landscape structure changes were likely comprehensive indicators of ecosystem function decline or land degradation. Ecological consequences such as biodiversity loss, soil erosion and soil productivity decline can be quantified by comprehensive measuring

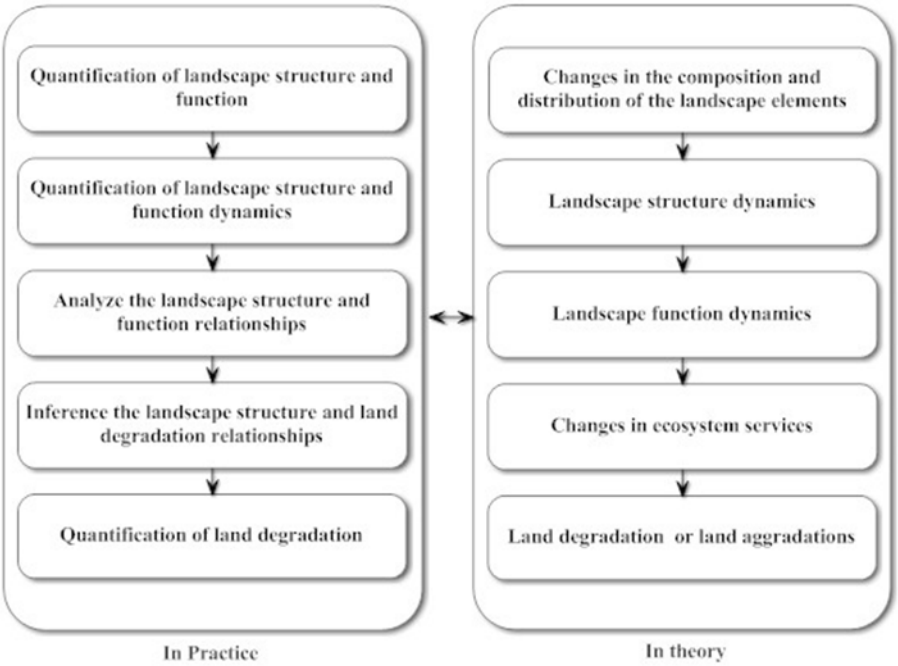

Figure 1. Conceptual model of land degradation assessment based on the landscape ecology approach

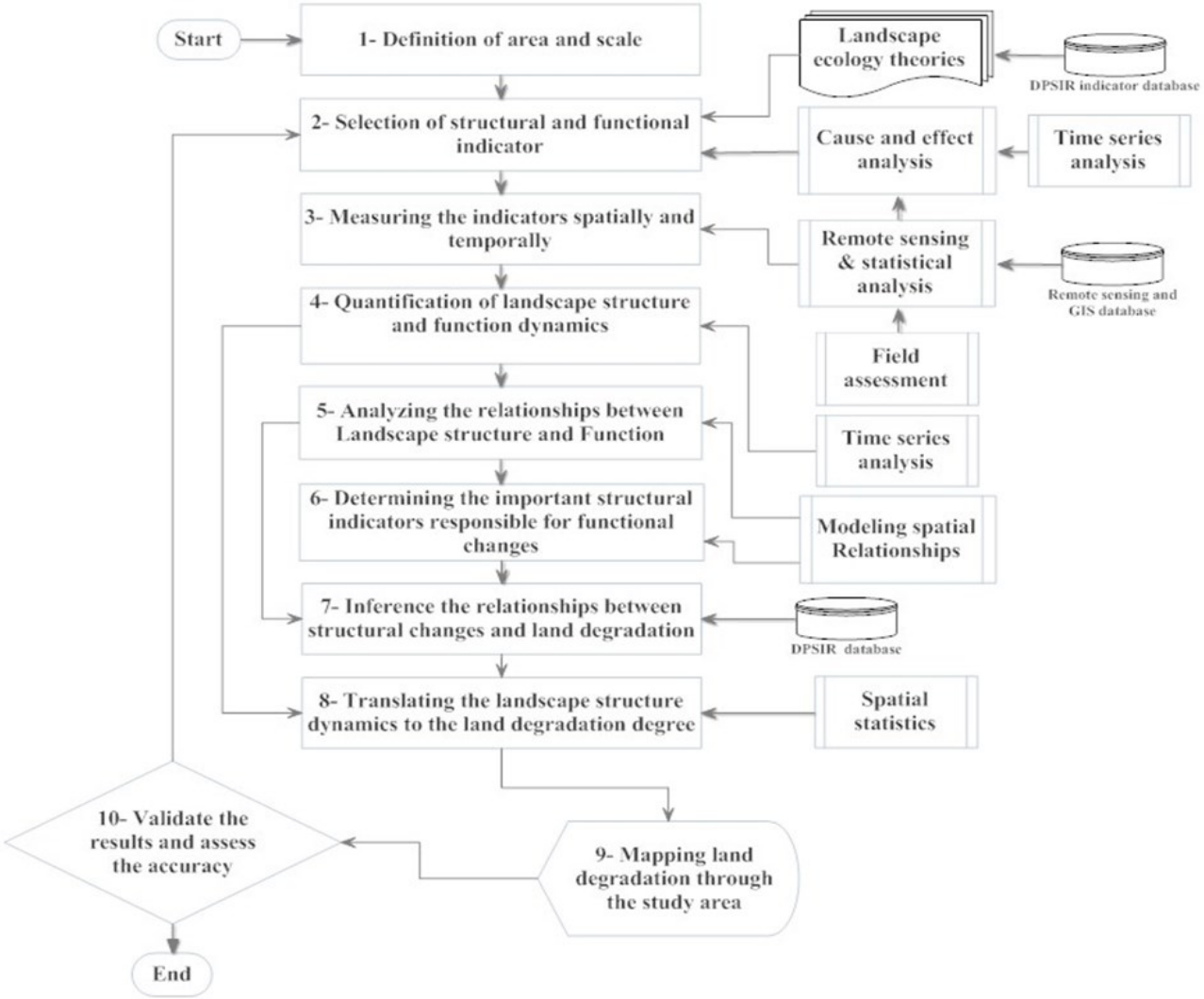

Figure 2. Methodological framework for land degradation assessment using a landscape ecology Approach

and analyzing of landscape structure changes and causes (Plieninger, 2006).

Monitoring and assessing of ecological processes is difficult due to the complexity of ecosystems. To determine the degree of land degradation, various factors such as soil stability, vegetation cover, the status of nutrients cycling need to be survey and assess. Due to the limitations imposed on data collection and the lack of sufficient information about ecological trends, the development of a land degradation index that includes all dimensions of ecological situation can be used as an effective tool in environmental assessments.

This study introduces a new approach to land degradation assessment using landscape ecology concepts and theories focusing on structure and functional relationships with a view to put together a methodological framework based on such approach. The Lake Urmia basin is selected as a case study in order to implement that approach and test the resulting methodology. The Urmia Lake plays a vital role in the environment and the economy of the Azerbaijan region, Iran. But unfortunately in recent years, this region is in the danger of extinction. The lake is becoming a salty desert. Apparently, the increasing demand for groundwater resources due to the expansion of agricultural fields and cities is the main cause of this phenomenon (Hassanzadeh *et al.,* 2012; Moghtased-Azar *et al.,* 2012).

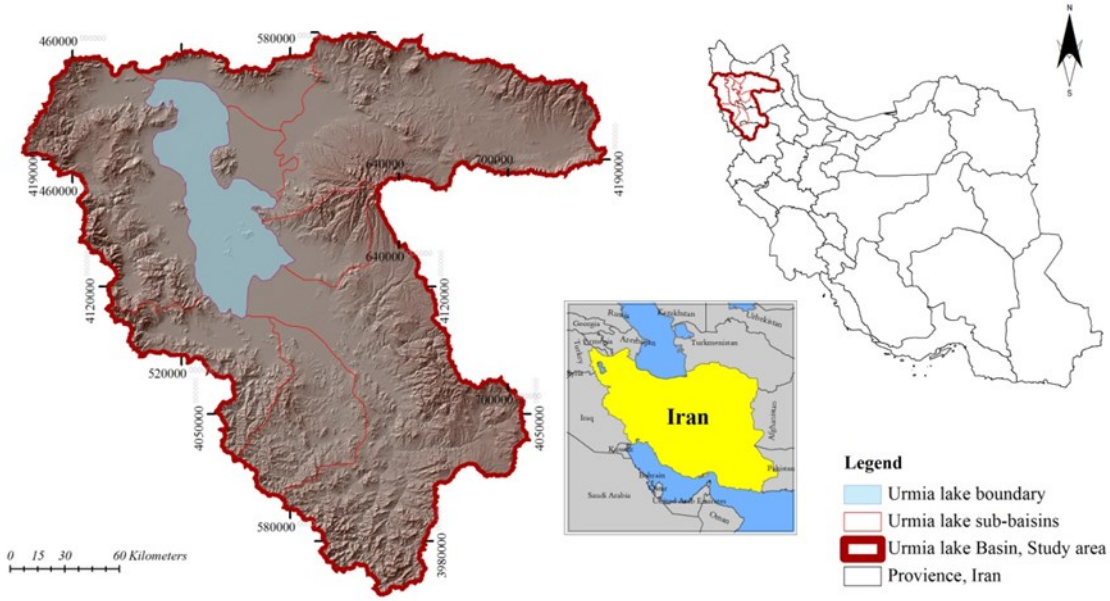

Figure 3. The study area

MATERIALS AND METHODS

Conceptual model and methodological framework

Landscape structure, function, and change are three useful characteristics examined in the landscape ecology approach. "Structure" is made by the component ecosystems that regulate the distribution of energy and materials. "Function" describes the flow of energy and materials among the component ecosystems and "change" refers to alteration in the structure and function of the ecological mosaic through time. The broad-scale metrics of landscape structure may be appropriate indices for revealing regional ecological changes (Turner, 1989). Nowadays, the field of remote sensing provides sufficient tools, techniques and data for broad-scale change detection and assessment of ecosystem disturbance and degradation. By developing a suitable model considering the knowledge of the structure-function relationships, functional changes can be inferred from broad-scale structural changes.

Considering the central concepts in the landscape ecology described above and by joining these with reviewed land degradation assessment methods, it was possible to develop a conceptual model for land degradation assessment using the landscape ecology approach (Figure 1). Theoretically, changes in composition and configuration of the landscape elements as landscape structure dynamics result in landscape function dynamics which lead to changes in ecosystem services that are reflected in land degradation or aggradation. Practically, by measuring the landscape structure and function through time, the dynamics of the landscape structure and function can be quantified.

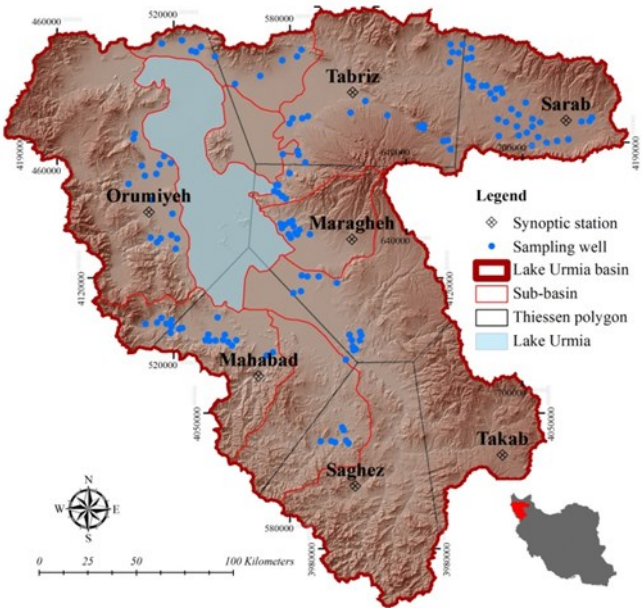

Figure 4. Locations of the sampling wells and synoptic stations in the study area.

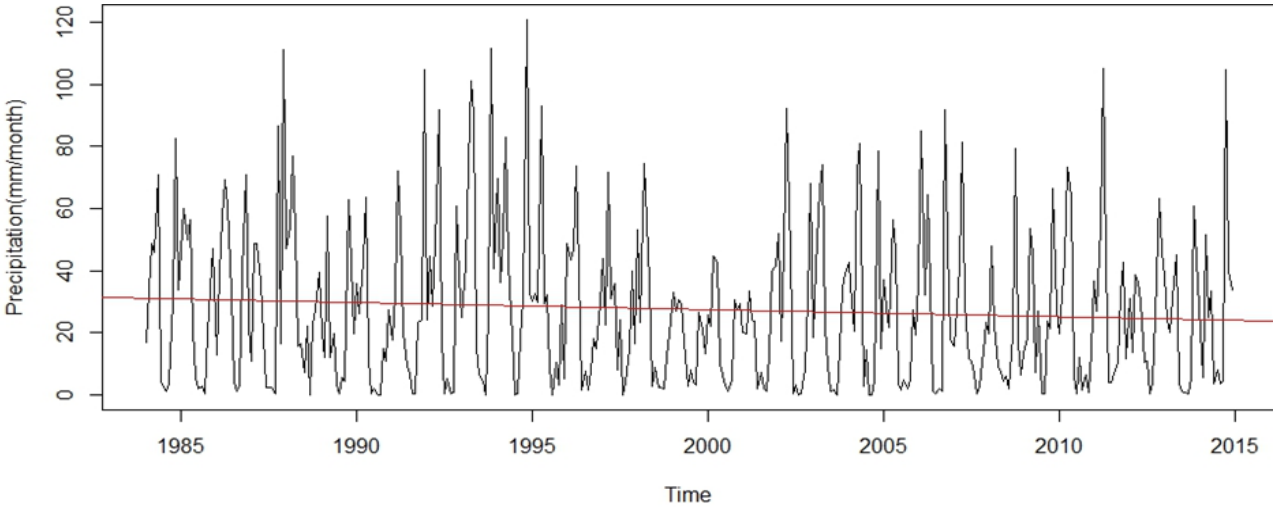

Figure 5. Thiessen-Area Weighted Mean (TAWM) of precipitation data of all stations as the precipitation time series of the whole basin, and corresponding linear trend line.

Furthermore, by analyzing the relationships between the landscape structure and function, landscape structure dynamics can be translated into degree of land degradation.

Based on the conceptual model a methodological framework was developed. The essence of the proposed methodological framework involves ten core steps (Figure 2), namely:

1) Definition of area and scale;
2) Selection of structural and functional indicators;
3) Measuring the spatial and temporal manifestation of these indicators;
4) Quantification of the landscape structure and function dynamics;
5) Analysis of the relationships between the landscape structure and function;
6) Identification of the important structural indicators responsible for functional changes;
7) Inferences involving the relationships between structural changes and land degradation;
8) Translating the landscape structure dynamics into the degree of land degradation;
9) Mapping land degradation throughout the study area;
10) Validation of results and assessment of accuracy.

Study Area

The Urmia lake basin, northeast part of Iran, stretches over an area of 51974 km^2 and lies between latitude 35° 40'to 38° 29' and longitude 44° 14' to 47° 53' (Figure 3).

In the last decades, the declining of the Urmia lake level and the increase of land degradation in its basin have been the most important environmental challenges in Iran. Agricultural and urban areas in the Lake Urmia basin have been increased sharply. Total water consumption for industrial, domestic and agricultural uses have ranged 400 and 3482 Millions of Cubic Meters (MCM) in 2003, and it is expected consumption level will increase up to 619 and 4300 (MCM) by 2020, respectively (WRI, 2006).

To determine the accurate boundary of Lake Urmia basin as the study area, a hydrological analysis was conducted using a Digital Elevation Model (DEM) of the three provinces surrounding the lake. Arc Map software (ESRI, 2004) was used to execute this process.

Data Used

To reveal the lake area changes (from 1974 to 2014, at time steps of each 4 years), images of MSS, TM, ETM and ORI and TIRS sensors on Landsat satellites were used. In order to detect the changes in landscape structure of the whole basin area 21 satellite images for

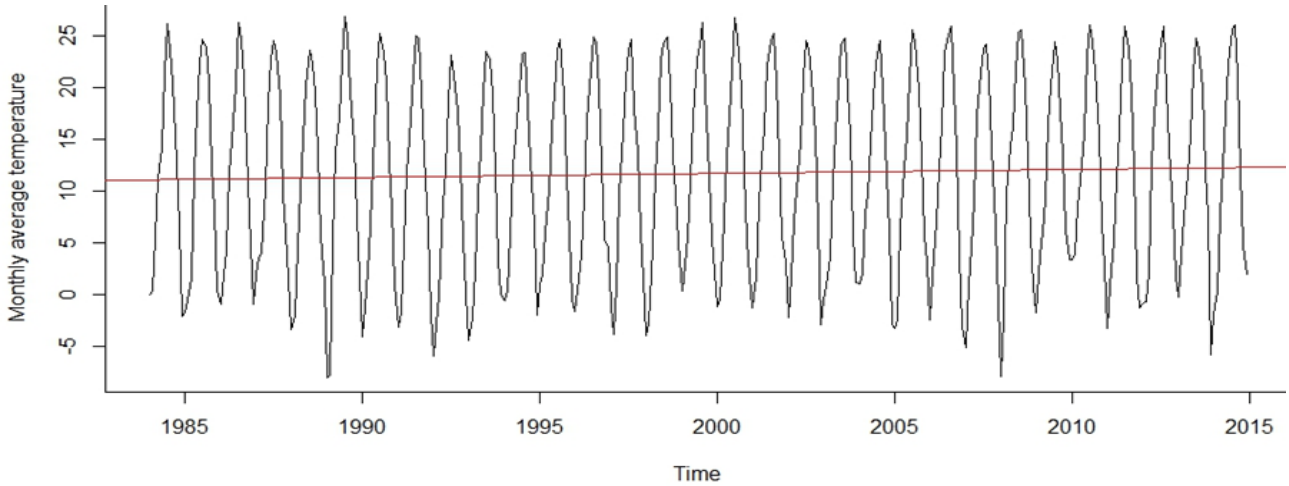

Figure 6. Thiessen-Area Weighted Mean (TAWM) of temperature data of all stations as the temperature time series of the whole basin with a corresponding linear trend line

1984, 1999 and 2014 have been processed. The satellite images were Pre Georeferenced; however to ensure of their accuracy, all images were examined and corrected geometrically and projected in the Universal Transverse Mercator (UTM) coordinate projection before being processed. To minimize the depiction of false changes due to atmospheric conditions and sensor differences, the images underwent radiometric corrections.

Climatological data, including monthly precipitation and mean temperatures, were gathered from all synoptic stations existing in the Lake Urmia basin to examine climatological trends.

Quantitative data of groundwater level changes for 150 agriculturally active wells which was used as a functional indicator in the agricultural and urban areas. Figure 4 shows the locations of these wells in the study area.

Other data used in this study are ancillary data such as DEM, shape files (vector data sets) of boundaries, cities, synoptic stations, existing land cover maps of the study area and other supplemental data.

Data processing

A Driver-Pressure-State-Impact-Response (DPSIR) approach (Assessment MEA, 2003, Ponce-Hernandez and Koohafkan, 2010) was applied to determine the primary structural and functional indicator list. Based on expert judgment, changes in the area of the Lake Urmia surface was selected as the main structural indicator. Lake Urmia functions as a support system to provide different kinds of ecosystem services, and changes in the surface area covered by this lake affects the whole area of the basin. Therefore the surface area can be a functional as well as a structural indicator.

In order to find more related indicators for land degradation the causality of important drivers of these effect was analyzed. Based on the DPSIR approach, it was determined that the likely cause and the main reason of the descending trend of the Lake Urmia surface is anthropogenic activities in the lake basin. However, climate change is a factor that merits examination. In this regard, the changes in Irrigated Agricultural Area (IAA), Urban Area (UA) and Climatological Parameters (CP) were selected as variables to be analyzed using remote sensing and time series analysis. Changes in Groundwater Level (CGL) is also a good functional indicator which is related to structural indicators and therefore it must be analyzed.

All satellite image processing was undertaken in the eCognitionDeveloperTM software (Definiens, 2005) which is a powerful environment for Object-Based Image Analysis (OBIA). It is increasingly acknowledged that an Object-Based Classification (OBC) yields higher

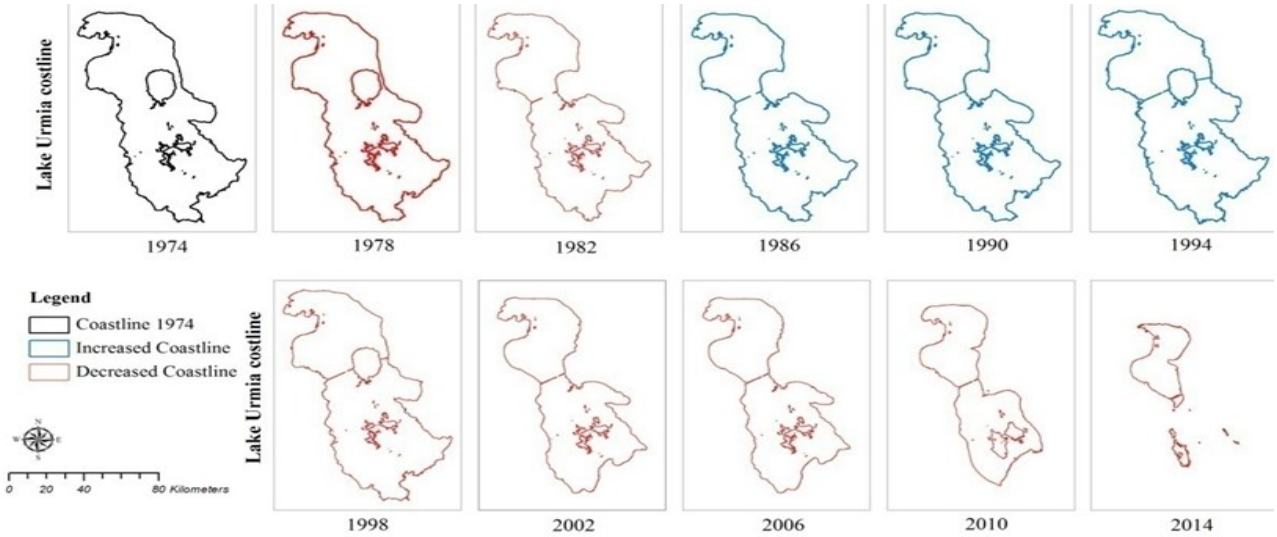

Figure 7. Lake Urmia surface change detection during the past 40 years (from 1974 to 2014)

accuracy than the traditional Pixel-Based Classification (PBC) approach (Cleve *et al.,* 2008). This is mainly due to the inclusion of cognitive spatial information from the analyst perspective, which can be made in the OBC approach, such as image texture, geometric attributes of features and contextual information (Blaschke, 2010; Burnett and Blaschke, 2003). Time series analysis of all data was conducted with the "R" software (R Development Core Team, 2005).

The relationship of CGL with structural indicators was explored by Geographic Weighted Regression (GWR) in GWR4 software. GWR is an advanced model of Ordinary Least Squares (OLS) by allowing local statistics, which can estimate a set of local parameters and present the relationship variance over space (Fotheringham *et al.,* 2001).

Precipitation and temperature Analysis

Based on data availability and location of weather stations in the basin, monthly precipitation and temperature data of seven synoptic stations were analyzed to examine the trend of climatological factors over the basin area. Precipitation and temperature data for each station from 1984 to 2014 were imported into the 'R' software environment as time series data separately. Thiessen polygons were computed and drawn for weather stations using ArcMap software (ESRI, 2004) in order to determine their spatial domains (Figure 4). Thiessen-Area Weighted Mean (TAWM) of precipitation and temperature data for all stations was calculated separately to obtain a precipitation and a temperature time series for the whole basin area. Figure 5 and 6 show the plots of the precipitation and temperature time series (monthly from 1984 to 2014) of the basin area respectively.

In order to examine the trend of precipitation and temperature over time, a Mann-Kendall test (Kendall, 1948, Mann, 1945) was used. Mann-Kendall is a rank-based non-parametric statistical test which has been commonly applied to assess the significance of trends in precipitation and temperature data over time (Hamed and Rao, 1998; Yue *et al*., 2002). This test, as a non-parametric method, has the advantage of being insensitive to the form of the frequency distribution of the data (Serrano *et al*., 1999). In other words, it does not have to comply with "normality". The null hypothesis (H0) test establishes that there is no statistically significant trend among the observations. In order to ignore the seasonal trend in trend analysis the annual aggregation of precipitation and the annual mean of temperature were used as input data.

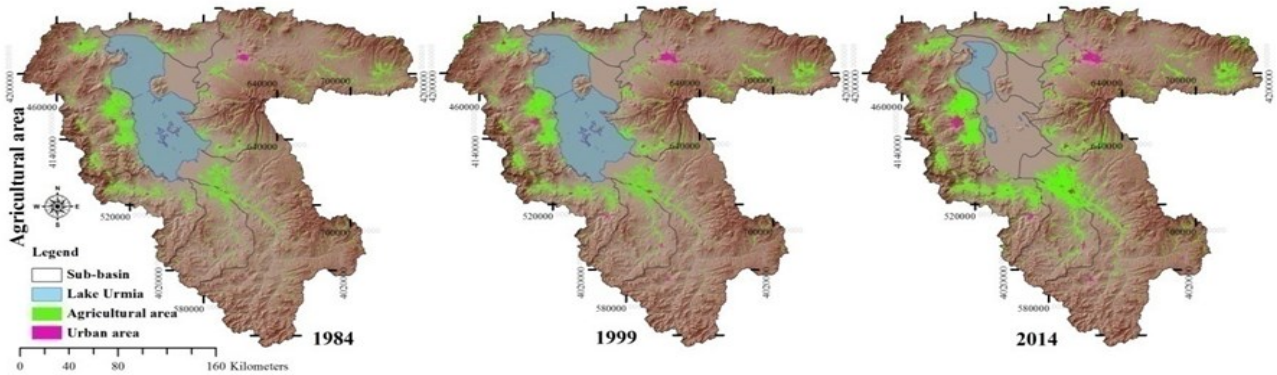

Figure 8. Irrigated agricultural area and urban area in 1984, 1999 and 2014

Landscape Structure Dynamics

In order to obtain the thematic maps of the surface occupied by Lake Urmia, the irrigated agricultural and the urban areas were identified and mapped from satellite images using the OBC approach. Eight steps were applied:

1) Determining the optimal parameters for segmentation in each satellite image;
2) Applying segmentation;
3) Classification;
4) Editing the classification results manually using a manual tool embedded in the eCognition software;
5) Merging the objects assigned to each class;
6) Importing the results as vector layers to ArcGIS software;
7) "Mosaicing" the thematic maps of same years into a single thematic map covering the whole basin;
8) Accuracy assessment.

Segmentation groups the pixels of an image into objects based on spectral behaviour, shape and context (Benz *et al.,* 2004). In this study, Multiresolution Segmentation (MS) which is a bottom-up region-merging technique (Darwish *et al.,* 2003), was used for image segmentation. The merging process in MS is based on the Homogeneity Criterion (HC) and the Scale Parameter (SP). HC is a combination of spectral values and shape properties (smoothness and compactness), and SP is a threshold to terminate the process of merging (Darwish *et al.,* 2003).To obtain meaningful objects, The HC and SP for segmentation in different satellite images from different sensors, were determined by using an empirical approach supported by visual interpretation.

In all image segmentation processes, the weight of spectral values and shape properties were 0.9 and 0.1 respectively. The shape factor was divided between compactness and smoothness equally. SP for images of MSS, TM, ETM+ and OLI and TIRS sensors were chosen to be 12, 20, 53 and 122 respectively. This difference in SP is due to the differences in image resolutions.

To classify irrigated agricultural area and water body (the lake area), A Normalized Difference Vegetation Index (NDVI) (Equation1) and Land and Water Mask (LWM) (Equation 2) were applied. NDVI is the ratio of the difference between Near-Infra-Red reflectance (NIR) and red visible reflectance to their sum (Deering, 1978). In recent decades, NDVI has been widely used as an indicator of plant photosynthetic activity and efficiency, which has become a standard vegetation index in applications such as detecting green biomass and vegetation productivity (Benedetti and Rossini, 1993; Tucker *et al.,* 1986; Tucker *et al.,* 2005). LWM is a ratio of Mid-Infrared Reflectance (MIR) to the green visible band. To calculate these indices for each object, the mean of pixel values within the object, was applied.

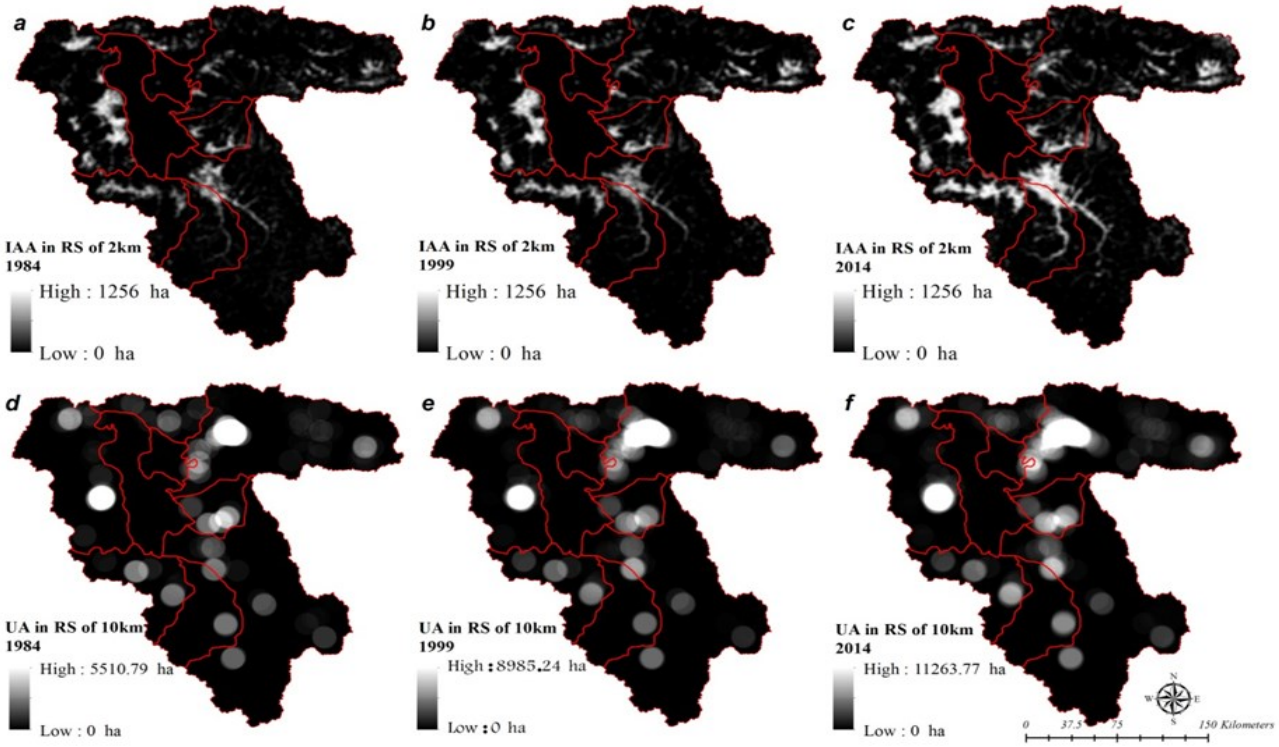

Figure 9. Results of moving window using a circular (r = 2km for IAA, and r = 10 km for Urban area): a) IAA (1984); b) IAA (1999); c) IAA (2014); d) UA (1984); e) UA (1999); f) UA (2014).

$$NDVI = \frac{NIR_{mean} - red_{mean}}{NIR_{mean} - red_{mean}} \quad (1)$$

$$LWM = \frac{MIR_{mean}}{green_{mean} + 0.0001} * 100 \quad (2)$$

In this study, irrigated agriculture including orchard or crop fields is considered as part of the areas located in the agricultural zone with high level of NDVI. Every object with an NDVI value of more than 0.22 was assigned to irrigated agriculture, except for the objects that were not located in the agricultural zone. To extract the lake surface area, a threshold value of 49 in LWM was used. For MSS images without MIR band, the object of the lake surface was selected manually based on a visual interpretation in different color composites. The thresholds were determined based on an empirical approach based on successive approximations. The classification of the urban area required experimentation with different classification methods. The manual assignment of objects to urban areas based on visual interpretation gave the best results. To find the location of each city on the images, a point-shape file of cities of the basin was used.

Figure 7 represents the maps of changes in the Lake Urmia coastline from 1974 to 2014 at 4 year intervals. In this map, the increased and decreased of lake shorelines in each 4 years are highlighted by blue and red colors. The irrigated agricultural and urban area for 1984, 1999 and 2014 are illustrated in Figure 8.

In order to internalise the chorological relationships, a moving window analysis was executed on the maps of urban and irrigated agricultural areas. Urban (UA) and Irrigated Agricultural Area (IAA) in 1984, 1999 and 2014 were computed for each pixel (30*30 m) of the basin using a circular (r = 2km for IAA, and r = 10 km for UA) overlapping moving window. Figure 9 shows the outputs of this operation, these maps are raster data sets with a pixel size of 30 m and the pixel's values are the area of IAA (Figures 9a,b and c) in a radius search of 2km and Urban area (Figures 9d,e and f) in a radius search of 10km of each pixel.

Table 1 Changes in the area of the Lake Urmia, mean annual temperature and precipitation in the basin

year	Lake Urmia surface (ha)	Changes in 4 years Area (ha)	Area (%)	4 years-mean of climatological parameters in the basin Precipitation (mm)	Temperature (ºc)
1974	543555.36	_	_	_	_
1978	529233.84	-14321.52	-2.63	_	_
1982	494818.92	-34414.92	-6.58	_	_
1986	508298.4	13479.48	2.72	377	11.74
1990	510816.9375	2518.5375	0.49	315	11.49
1994	584266.373	73449.4355	14.37	444	10.45
1998	554294.1825	-29972.1905	-5.12	310	11.58
2002	424120.545	-130173.6375	-23.48	263	12.31
2006	412073.325	-12047.22	-2.84	337	11.81
2010	301242.825	-110830.5	-26.89	270	12.16
2014	102247.083	-198995.742	-66.06	327	11.72

The Relationship between Changes in Groundwater Level (CGL) and Landscape Structure Dynamics (LSD)

In order to gain a better understanding of the relationship between the CGL and LSD, a GWR model was developed. The GWR model used in this part of data processing can be written as:

$$y_j = \beta_0(u_j, v_j) + \sum_{i=1}^{p} \beta_i(u_j,\ v_j)x_{ij} + \varepsilon_j \qquad (3)$$

where y_j is a dependent variable, (u_j, v_j) if is the x-y coordinate of each location j, εj is the Gaussian error at location j, β_i (u_j, v_j) and β_0 (u_j, v_j) are, respectively the local parameter estimate for independent variable xi at location j and the intercept for location j. The vector of parameters $\beta_i = (\beta_1, \beta_2, .. , \beta_p)$ is computed for each sample point. Based on an exponential distance-decay function, all observations around a sample point are weighted. Therefore, the closer observations have higher impact on the local parameter measures. The function for weighing the observations are stated as:

$$w_{ij} = \exp(\frac{-d_{ij}^2}{b^2}) \qquad (4)$$

where wij is the weight of observation j for sample point i, dij is the distance from sample point i to j and b is the kernel bandwidth. In this study, an adaptive kernel bandwidth was used. This algorithm includes the bandwidth in size as a function of the density of sample point and it varies locally.

An important assumption in the GWR model is homoscedasticity of the disturbances; spatial autocorrelations can lead to statistical invalid inference. Therefore, Moran's index was applied to measure and test the strength of autocorrelations, statistically.

In building the regression model, CGL was assigned as the dependent variable, IAA changes and UA changes were used as explanatory variables. For each sample point (i. e. the location of each observation well) (Figure 4), CGL was calculated by subtracting the annual average of groundwater depth for 2014 from 1999. For IAA and UA , changes in IAA from 1999 to 2014 in a radius search of 2 km (of each sample point), and changes in UA in a radius search of 10 km from 1999 to 2014, were computed.

RESULTS AND DISCUSSION

The results of the landscape structure analysis indicated a significant increase in urban and irrigated agricultural areas and a resulting significant decrease in lake area. The area of irrigated agricultural land increased by 9.5 % from 3035 km^2 in 1984 to 3324 km^2 in 1999 and 53 % from 3324 km^2 in 1999 to 5086 km^2 in 2014. Moreover, the area of urban land increased by 81% from 173 km^2 in 1984 to 314 km^2 in 1999 and 77 % from 314 km^2 in 1999 to 559 km^2 in 2014

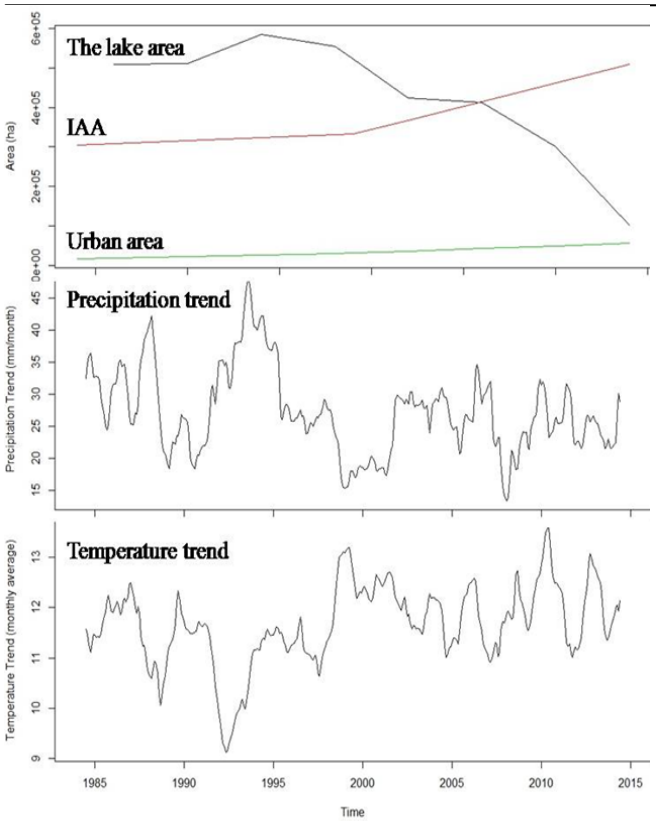

Figure 10. The multiple time series of structural and CP from 1984 to 2014 in Lake Urmia basin

Table 1 shows the changes in the Lake surface area from 1974 to 2014 (in each of 4 year intervals). The lake decreased by almost 9 % from 1974 to 1982; increased by 17.5% from 1982 to 1994; and decreased by 82% from 1994 to 2014.

The results of the Mann-Kendall test for precipitation and temperature data in each station and the TAWM of each of them show that in precipitation data, only for one station (Maragheh) there is a significant trend which is a descending one. Concerning the TAWM in precipitation data for all stations, the results indicate that there is no significant change in the basin from 1984 through 2014.

According to the results of Mann-Kendall test for temperature data, ascending significant trends were observed in Tabriz, Orumiyeh, Maragheh and Mahabad stations. In the three other stations (Sarab, Takab and Saghez), there are descending trends but these are statistically insignificant. The temperature trend for the whole basin, based on the TAWM of all stations is significant at the alpha level $\alpha = 0.05$, and not significant at the alpha level $\alpha = 0.01$. It should be noted that the four stations with ascending significant trend in temperature are the closest ones to the location of the lake and the three others with descending insignificant trend are the most remote ones to the the lake. In view of all of the facts shown above and considering the significant descending trend of the lake surface area, it can be concluded that the lake dry-out is likely to have an influence on the increases of temperature in the area near and around the lake.

In order to show a more comprehensive and better view of changes in the Lake Urmia basin, Figure 10 shows the multiple time series of structural and climatological parameters in a single picture.

Before 1999 the irrigated agricultural area has experienced slight increases with a low rate of change. In this period, the Lake surface changes have been mainly due to the changes in the precipitation amounts. From 1974 to 1998 the lake surface increased by two percent. It can be mentioned that increases in the lake area by 14 % from 1990 to 1994 can be attributed to the high level of precipitation in 1990 to 1994 with an annual mean of 444 mm in this period. After 1999, the irrigated agricultural area grew with a high rate. In this period, even with continuous increases of precipitation amounts in some periods (in the basin) the lake surface is still shrinking. For instance, the lake surface decreased by 2.84% from 2002 to 2006 while the mean annual precipitation in this period increased by 74 mm comparing to the last period (1998 to 2002); and the lake area decreased by 66.06 % from 2010 to 2014 while the mean annual precipitation in this period increased by 57 mm comparing to the last period (2006 to 2010).

Considering the results of both, the Mann-Kendal test for precipitation in which no significant descending trend in precipitation could be found, including the annual mean (for each 4 years) of precipitation data

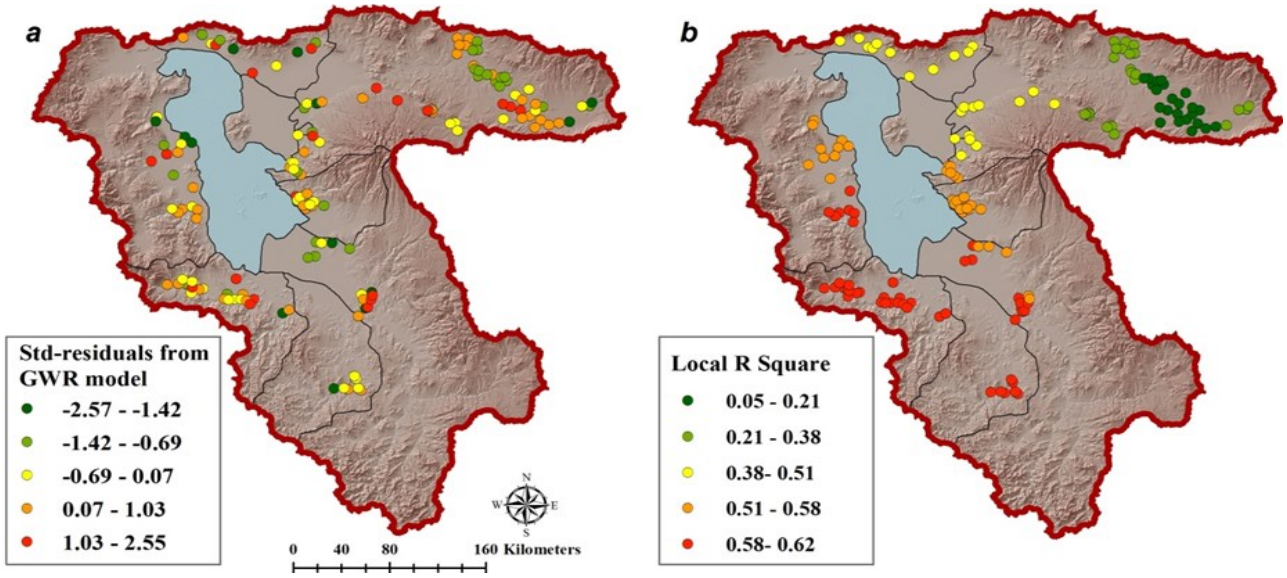

Figure 11. Results of the GWR model: a) Std-residual; b) local R^2.

(Table 1), it can be concluded that precipitation and temperature changes are not significantly contributing to the drastically descending trend of the lake dry out. Based on the results, it seems logical to conclude that the massive expansion of irrigated agricultural area and the increases in urban area in the Lake Urmia basin especially after 1999, particularly considering their enormous water demands, are the main and most plausible explanations of the severe descending trend of the lake surface.

Based on the results from the time series analysis of climatological parameters and landscape structural dynamics, it can be considered that changes in IAA and UA from 1999 to 2014 are appropriate structural indicators of land degradation, and that their spatially explicit measures can be translated into a measure of the degree of intensity of land degradation. However, in order to establish this link, the spatial relationships between these structural indicators and the functional indicators through the area of the basin must be examined. To this effect, the spatial relationships of changes in IAA and UA with CGL have been modeled through a GWR analysis.

The outputs of the GWR model include local parameter estimates, t-test scores, local residual and the local R^2 values. Using these local factors, the spatial relationships could be properly explored. As illustrated in Figure 11b. The value of the explanatory power of the model (R Squared) changed spatially in a range from 0.05 to 0.62 from southwest of the basin to northeast, R Squared value of the model decreases. It means that except for the northeastern part of the study area, CGL is well predicted by changes in IAA and UA.

To statistically test the autocorrelations, a global Morans's I was calculated on the standard deviation of the residuals (Figure 11a); and these results (Moran's I index=0.039, z-score=0.76, p-value=0.446) showed that there is no significant autocorrelations in the residuals ($P<0.01$).

In order to explore the relationships separately, local parameter estimates and their values of t-test for changes in IAA and in UA as explanatory variables are mapped and presented in Figure 12. In most of the sample points, parameter estimate for changes in IAA is more than 0.50 (Figure 12a) and considering the t-test values (Figure 12b), in only 30 samples located in the northeastern part of the basin, there is no significant relationship between the changes in IAA and CGL. The same results for the changes in UA indicate that the relationship between the changes in UA and CGL

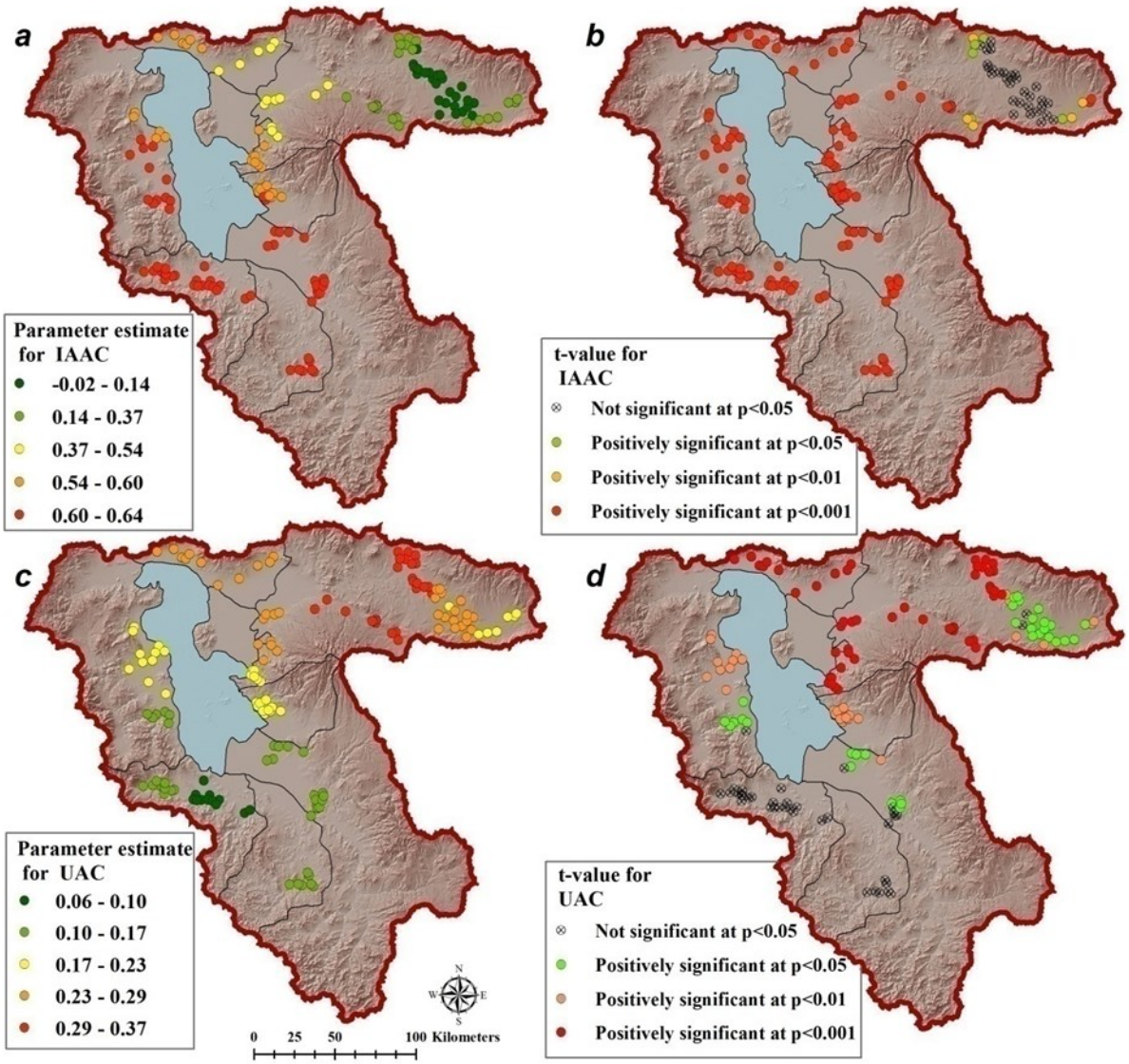

Figure 12. Results of the GWR model: a) Parameter estimates for changes in IAA; b) Local t-value for changes in IAA; c) Parameter estimates for changes in UA; d) Local t-value for changes in UA.

(ranged from 0.06 to 0.37) is considerably less than the relationship between the changes in IAA and CGL, but it is still significant in the most of sample points (Figure 12c, d).

The results of the GWR model, showed that there is a significant and spatially varying relationship between changes in urban and irrigated agricultural area and changes in groundwater level. Therefore, these two structural indicators can be translated into the intensity of land degradation. To achieve this, the spatial differences in the coefficients of relations must be considered. In this regard, raster surfaces of the coefficients were produced for independent variables.

By subtracting the raster data sets resulting from the moving window analysis in 2014 (Figure 9c and 9f) the same results we get in 1999 (Figure 9b and 9e), the maps depicting the changes in area of IAA and UA were produced. Figures 13a and 13b shows the changes in IAA and UA maps respectively, the data structure of these maps is raster (with 30 m resolution) and the pixel

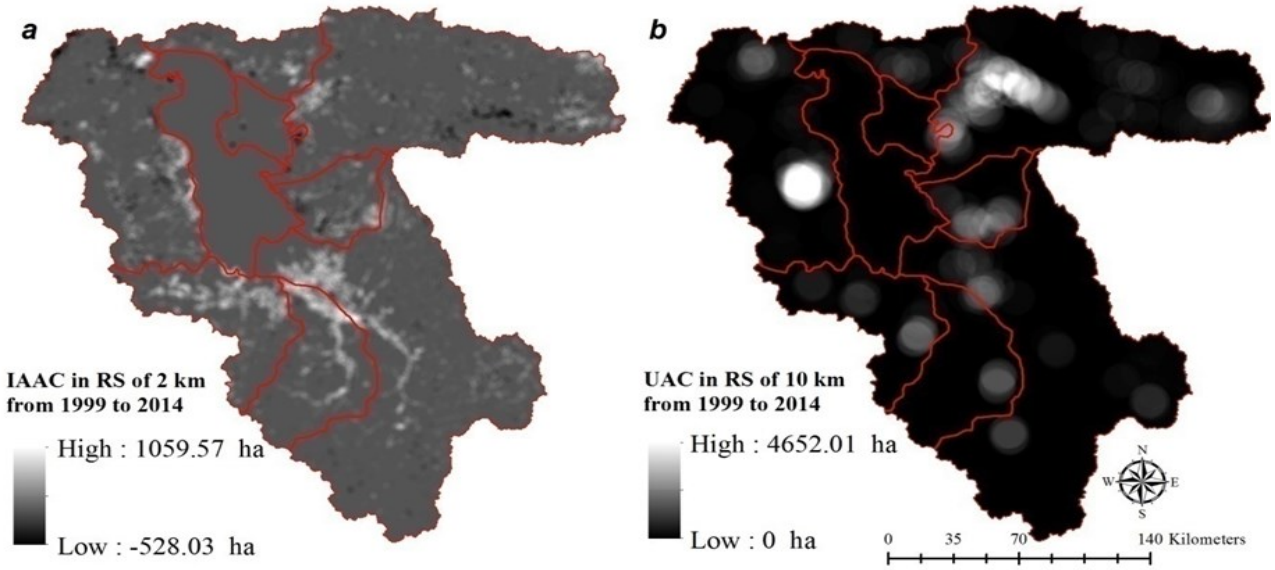

Figure 13. Changes (in search radius of each pixel) in landscape structural indicators: a) changes in IAA (SR of 2km); b) changes in UA (SR of 10 km).

values show the changes in IAA (in a search radius of 2km from the pixel) and UA (in a search radius of 10km from the pixel) from 1999 to 2014.

Changes in IAA and UA layers were separately multiplied by their corresponding coefficient surfaces resulting from the GWR model to achieve the final image of spatial effective changes of landscape structural indicators. Figure 14 represents the spatial effective changes of urban and irrigated agricultural area in the basin separately. Areas with higher values in these maps indicate more depletion in the groundwater level and consequently land degradation as a result of IAA and UA expansion from 1999 to 2014. Land degradation in the northern parts of the basin is the result of the urban development area and in central parts of the basin is the result from the expansion of the irrigated agricultural area after 1999.

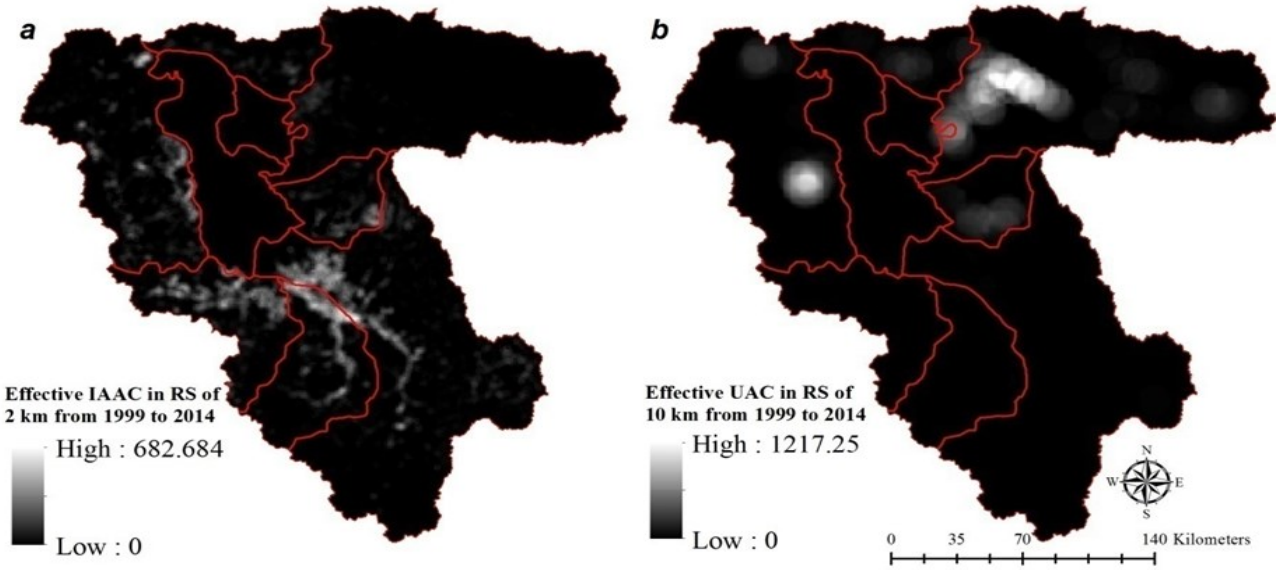

Figure 14. Spatial effective changes of landscape structural indicators: a) Effective IAAC (SR of 2km); b) Effective UAC (SR of 10 km).

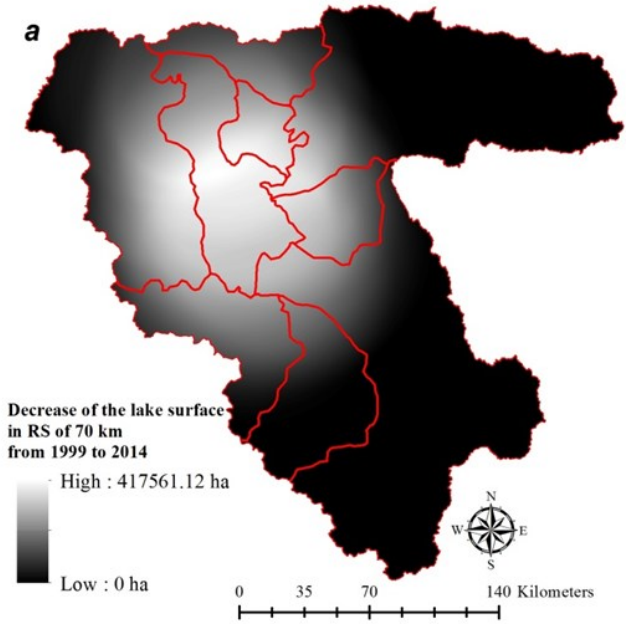

Figure 15. Spatial changes of landscape structural indicator: decrease of the lake surface in a search radius of 70-km from 1999 to 2014.

Another structural indicator that can be translated into the intensity of land degradation is the changes in the Lake Urmia surface from 1999 to 2014. Surface water bodies especially in dry lands have a basic role in supporting ecosystem services. Shrinkage of Lake Urmia can lead to diverse environmental impacts. For instance, the dry part of the lakebed is a major source of salinity and saltating particles transported long distances. According to the results of the analysis of climatological parameters jointly with expert judgment, it was determined that areas within a distance of 70-km from the Lake boundary are directly influenced by the lake dry out.

To map the severity of the harmful impacts of the lake dry out, a raster map showing the changes of water surface area in a search radius of 70km from 1999 to 2014 in each pixel (30*30m) was produce using moving window analysis and the raster calculator (Figure 15). Pixels with high values in this map are more affected by the consequences of the lake dry out. Therefore, according to this indicator the level of land degradation in these pixels are higher.

To obtain a single map of the degree of land degradation, different maps of structural indicators were standardized on a 0-10 scale (10 indicate high degradation) and overlaid together in Arc Map software (Figure 16). The southern parts of the lake are degraded mostly as a result of agricultural expansion. In the western and eastern parts of the lake both agricultural and urban development is the main reason for land degradation.

The proposed method compared to other methods of land degradation assessment (Bai *et al*., 2008; ISRIC, 2008; Oldeman *et al*., 1990; Lynden *et al*., 2003) is more sensitive of ecological concepts, such as carrying capacity and ecosystem services, rather than the soil productivity. For instance, 'Rain Use Efficiency' (RUE) is a well-known index of land degradation; it is claimed that reduction in vegetation cover is land degradation if it is not related to precipitation. According to the RUE index, in an area with no changes in precipitation, only a decrease in the primary productivity of land is considered as degradation. The results of remote sensing analysis for the Urmia basin have shown that from 1999 to 2014 the

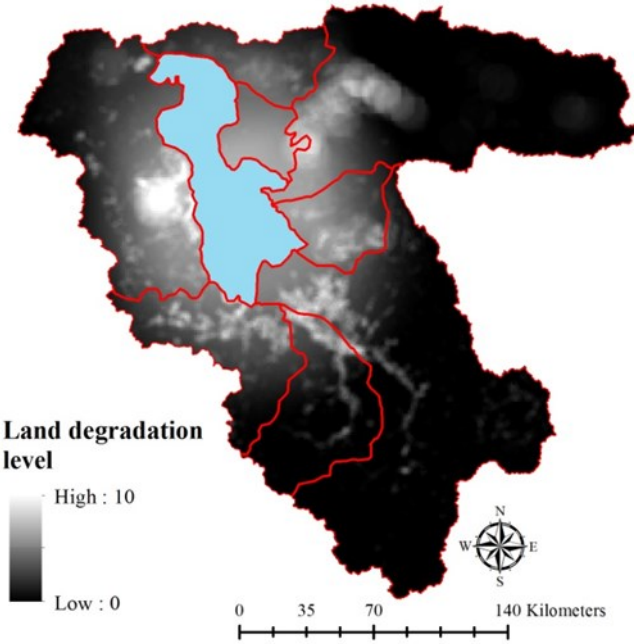

Figure 16. Final land degradation map

IAA is increased by 53 %, which is non-precipitation related, and is a massive increase in primary production. However, the huge expansion in IAA and UA has resulted in over-extraction of groundwater and construction of numerous dams across the rivers feeding the Lake Urmia. Consequently, in recent years the presence of an extended dried salt lake significantly increased concentration of salt aerosols in the atmosphere (Delju *et al*., 2013); and major depletion in groundwater resources significantly affected the efficiency of land to support different kind of ecosystem services.

CONCLUSION

Using a landscape ecology approach, land degradation was mapped in the Lake Urmia basin. A conceptual model and a methodological framework were developed and different techniques including spatial and statistical analysis were used in the proposed methodology. The chorological relationships were modeled by defining a search radius for each structural indicator and the spatial relationships between structural and functional indicators were estimated using a GWR model.

The results showed that landscape ecology concepts and theories can be useful for improving the methodology of land degradation assessment especially in regions with high level of chorological relationships. They also showed that the most likely causes of the lake drying out and of the intensity of land degradation in the region are the reason for expansion of irrigated agriculture together with the expansion of the area occupied by urban settlements. Considering the availability of remotely sensed data with multiple spatial and temporal resolutions, the proposed method can be properly applied in different scales.

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