Journal of Zhejiang University SCIENCE A
ISSN 1673-565X (Print); ISSN 1862-1775 (Online)
www.zju.edu.cn/jzus; www.springerlink.com
E-mail: jzus@zju.edu.cn

Environmental impact prediction using remote sensing images

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Received Oct. 20, 2007; revision accepted Dec. 10, 2007; published online Jan. 27, 2008

Abstract: Environmental impact prediction is an important step in many environmental studies. A wide variety of methods have been developed in this concern. During this study, remote sensing images were used for environmental impact prediction in Robatkarim area, Iran, during the years of 2005~2007. It was assumed that environmental impact could be predicted using time series satellite imageries. Natural vegetation cover was chosen as a main environmental element and a case study. Environmental impacts of the regional development on natural vegetation of the area were investigated considering the changes occurred on the extent of natural vegetation cover and the amount of biomass. Vegetation data, land use and land cover classes (as activity factors) within several years were prepared using satellite images. The amount of biomass was measured by Soil-adjusted Vegetation Index (SAVI) and Normalized Difference Vegetation Index (NDVI) based on satellite images. The resulted biomass estimates were tested by the paired samples *t*-test method. No significant difference was observed between the average biomass of estimated and control samples at the 5% significance level. Finally, regression models were used for the environmental impacts prediction. All obtained regression models for prediction of impacts on natural vegetation cover show values over 0.9 for both correlation coefficient and *R*-squared. According to the resulted methodology, the prediction models of projects and plans impacts can also be developed for other environmental elements which may be derived using time series remote sensing images.

Key words: Environmental impact, Remote sensing, Prediction, Vegetation, Biomass
doi:10.1631/jzus.A072222 **Document code:** A **CLC number:** X9

INTRODUCTION

Prediction of plans and projects impacts on environmental elements is an important step in every environmental assessment. Commonly used prediction models may be qualitative or quantitative. Qualitative methods are fully dependent on experts' judgments, whereas quantitative methods are related to broad mathematical models (Arts and Morrison-Saunders, 2004). The most common remote sensing applications in environmental assessment are environmental inventory and monitoring studies (Ustin, 2004; Treweek, 1999). Satellite imagery has provided a valuable source of information on topography, land use, vegetation cover and habitat destruction. It has also enabled us to quantify the rate of global and regional habitat destruction which would otherwise be an incredibly difficult task (Milesi *et al*., 2003; Veitch *et al*., 1995). Remotely sensed images have played a key role in ecosystem classifying and mapping, particularly for regional and national applications. Ecosystem classifications are used to derive homogenous map units with predictable characteristics (Treweek, 1999). Remotely sensed images have

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also been used for mapping habitat potential of wildlife (Treweek, 1999).

Lunetta *et al.*(2004) used satellite images for detection of land-cover (LC) change by an identical change vector analysis (CVA) technique. Overall results indicate that a minimum of 3- to 4-year temporal data acquisition frequency was required to monitor LC change events in a study area. Svoray *et al.*(2004) presented a model to assess herbaceous plant habitats in a basaltic stony environment in a Mediterranean region. The model was based on geographic information systems (GIS), remote sensing and fuzzy logic.

Nautiyal and Kaechele (2007) used an integrated approach to study the impact of Natural Resource Management Plan (NRMP) in the protected areas of Himalayas of India. Satellite data and GIS were used to develop a land cover map of the area to detect landscape changes through the time span after the NRMP was implemented. Harvey and Hill (2003) investigated the feasibility of the integration of the remotely sensed data and other spatial information in a GIS to model habitat suitability for nesting by saltwater crocodiles (*Crocodylus porosus*). This methodology effectively identified the known suitable nesting areas of *C. porosus* by analyzing the environmental parameters, such as distance to water and vegetation type, which have an influence on selection of nesting habitat. The findings of this research demonstrated the utility of remote sensing and GIS for mapping nesting habitat of *C. porosus* at a range of scales, and provided guidelines for application of the approaches at the regional or state level.

Commonly used methods for prediction of biological environmental impacts are either descriptive or involving very complex quantitative procedures. Most of the quantitative methods are not applicable in EIA (Environmental Impact Assessment) due to their complexity and time-consuming nature (Canter, 1996). In order to predict environmental impacts by remotely sensed images, it is required to extract the expected environmental element data from images, and prepare the data of plan or project components affecting the environmental elements. Then the models for predicting impacts are created by regression equations. The significant point of time series satellite images application is that these images should be radiometrically corrected (Farzadmehr *et al.*, 2005). Atmospheric and radiometric corrections become necessary as the study involves multi-sensor and multi-temporal images. Radiometric normalization is an important factor when different images of different dates are compared.

The study aims to introduce time series remote sensing images to predict the environmental impacts and changes (Fig.1) and to propose a new and effective methodology to predict impacts of development plans and projects. The study was conducted in Robatkarim area, Iran, as a case study in 2005~2007. Natural vegetation as an environmental element was considered.

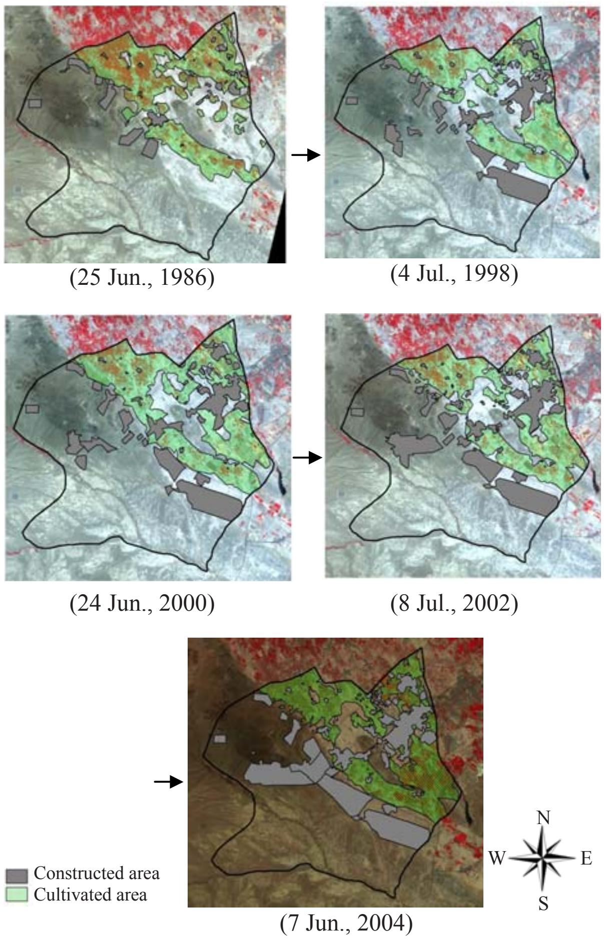

Fig.1 Presentation of land use types in the study area in time series images (Landsat images, RGB-432). The hypothesis of the research is that it is possible to predict environmental impacts using time series changes in remotely sensed images in quantitative way

MATERIALS AND METHODS

The case study conducted in Robatkarim area located in southwest of Tehran Province, Iran. Robatkarim township runs from 50°53′E to 51°13′E longitude and from 35°20′N to 35°35′N latitude (Fig.2).

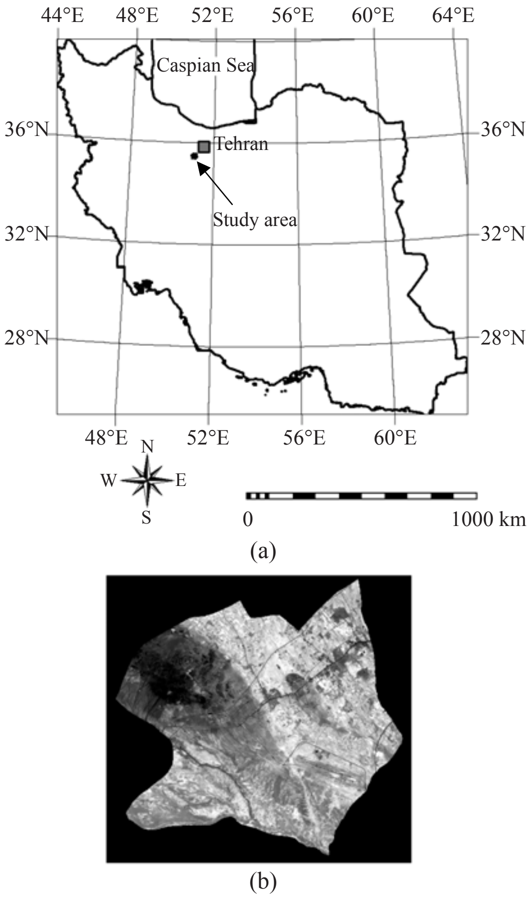

Fig.2 (a) Geographical location of the case study area (Robatkarim township), Iran; (b) Landsat ETM+ image of Robatkarim township (near-infrared band). Light color can be vegetation cover

Providing and preparing images

TM and ETM+ images were used to study vegetation cover changes and development impacts throughout the time. Two scenes (165-35 and 164-35) of satellite images belonging to July and August of the years of 1986, 1998, 2000, 2002 and 2004 were selected for this purpose.

CORRECTING REMOTELY SENSED IMAGES

Geometric correction

Remote sensing data usually have some distortions, so they cannot match maps. Some of these distortions are due to sensor failure, scanner and platform turbulences, earth curvature, etc. Geometric correction compensates image distortions caused by the mentioned factors. The topographic maps of Army Geographic Organization of Iran (1:50000) were used as reference map to do geometric corrections. The images were geo-referenced by using ground control points with *RMSE*=0.5. The images were then geometrically corrected by re-sampling. All images were geometrically corrected using the same method.

Radiometric correction

Since the images are from different times and may have various radiometric properties, so they needed to be corrected radiometircally and atmospherically. The errors of recorded digital number (*DN*) for a certain pixel affected by satellite temperatures, Sun elevation and angle, Sun-Earth distance and atmospheric conditions should be removed. To correct radiometrically, digital numbers were first changed into radiance. This was performed by using calibration coefficients of sensor and the following relation (Farzadmehr *et al.*, 2005):

$$L=Gain\cdot DN+offset, \tag{1}$$

where, L is radiance (W/(m^2·Ster·μm)), DN is pixel digital number (0 to 255), and $Gain$ and $offset$ are calibration coefficients of sensor. The radiance value is changed into reflectance by

$$\rho=\frac{\pi L d^2}{ESUN\cdot\cos(SZ)}, \tag{2}$$

where ρ is unitless planetary reflectance (spectral unit); π is 3.14; L is spectral radiance at the sensor's aperture; d is Earth-Sun distance in astronomical units from nautical handbook; $ESUN$ means solar exoatmospheric irradiances; SZ is solar zenith angle in degrees.

By changing radiance to reflectance, the impacts of the changed shining, season, geographical latitude and climate conditions are removed from the images, so the results are standard and can be applied directly to compare phenomenon reflectance between various images and an image in different times. All above steps were performed using ENVI (The Environment for Visualizing Images) software.

Enhancement of remote sensing images

In order to detect vegetation cover changes in the area and to prepare a regression model to predict development impacts, it was necessary to prepare land use and land cover maps in different years. False color composites (FCC) were used for images enhancement purpose. They were applied in classification land use classes as ETM+ 4-3-2 (R-G-B) and ETM+ 3-4-7 (R-G-B), which were prepared for remotely sensed images of 1986, 1998, 2000, 2002 and 2004. The two false color composites were used because vegetation cover has the most absorption and reflection in Band 3 and Band 4 in Landsat images. Combination of the two bands has the most information about vegetation cover. ETM+ 3-4-7 (FCC) was used for separation of vegetation cover from other land uses (Aronoff, 2005).

The important step in land use/land cover classification is to determine the land cover categories. The decision of which land or land cover categories to use depends on several factors. A consideration is that land use and land cover categories should generally conform to standard categories. The USGS (United States Geological Survey) land cover and land use classification has been widely adopted in remote sensing and GIS communities, because it is specially designed to use with remotely sensed data (Aronoff, 2005). The USGS land cover and land use classification is a hierarchical system in which land use and land cover categories are classified on different levels. In the present study, only part of the first level of the classification was used. Land cover/land use classes include constructed lands, agriculture land, rangeland, forest land, water, wetland, barren land, tundra and perennial snow or ice.

Then land use and land cover types of Robatkarim area were determined by visual image interpretation methods. In visual interpretation, classification relies on landscape specifications, size, pattern and color of the features. The interpretation strategies included field observation, direct recognition and photomorphic regions analysis. Obtained classes were agricultural lands (cultivated and fallowed lands), constructed lands (residential and industrial lands), and natural vegetation covered lands (rangeland) (Table 1). In the studied area, the natural vegetation of lands was rangeland with steppe type cover.

Also, vegetation cover was studied in respect with canopy and biomass covers. The two parameters mentioned indicating the quality of vegetation cover were selected for further impact assessment. The biomass is a very vital factor because its amount indicates the impacts resulted from all natural and human activities imposed on vegetation cover. The multi-temporal satellite images were used in preparing regression model in order to predict vegetation cover changes. SAVI (Soil-adjusted Vegetation Index) and NDVI (Normalized Difference Vegetation Index) were used to study the percentage of vegetation canopy and biomass to achieve a regression model for predicting development impacts. It is an approved rule that vegetation indexes are the best application for the study of vegetation cover in the most cases (Ustin, 2004). Because of vegetation cover has the most reflection in NIR (near infrared) channel (Band 4) and the most absorption in red channel (Band 3), a combination of two channels was used for vegetation cover studies.

SAVI was used because of low vegetation canopy (about 30%~40%) in the study area. Therefore, soil reflectance affects the amount of vegetation cover index. This index minimizes spectral variance from surface soil changes as much as possible. The soil adjustment factor was considered for surface soil changes.

NDVI is another vegetation cover index. This index is prepared by using red bands (Band 3) and NIR band (Band 4).

Table 1 Elements of land use and land cover types and other relative data in Robatkarim township

Biomass (kg/ha)	Time length from starting the study (year)	Area of natural vegetation (ha)	Area of constructed lands (ha)	Area of agricultural lands (ha)	Roads length (km)	Number of livestock	Population	Christian year
1078.9	1	39300.0	2092	8887	91.2	68938	24235	1986
1083.9	13	34768.0	6747	13019	153	46660	422211	1998
1070.1	15	33210.5	7251	14060	165	43283	488541	2000
1077.0	17	32910.0	8687	12914.5	175	36398	554871	2002
1069.0	19	30987.5	10722	12797.5	180	36398	621199	2004

$$NDVI=(NIR-Red)/(NIR+Red), \quad (3)$$
$$SAVI=(NIR-Red)(1+L)/(NIR+Red+L), \quad (4)$$

where, L is soil correction factor (for dense vegetation cover, L=0.25; for thin vegetation cover, L=1; for semi-dense vegetation cover, L=0.5); NIR is reflectance in NIR band; Red is reflectance in red spectral band.

Field measurements

The canopy percentage and biomass were measured in lands containing natural vegetation cover. Sampling was performed within 35 pixel frames selected randomly (30 m×30 m). The sample coordinates were taken by GPS. Vegetation canopy and biomass were measured and recorded by using 10 plots (1 m^2 each) on the square diagonals in every pixel frame randomly (totally 350 plots). The average of biomass values in 1 m^2 plots was considered as biomass amount in each pixel by generalizing it in 30 m×30 m area. Fig.3 shows the plot locations for every pixel.

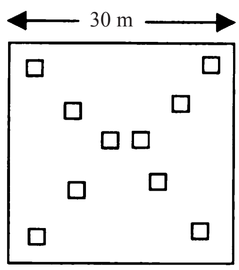

Fig.3 Sampling plots in every pixel (ten plots 1 m×1 m). The size of pixel samples is such as pixels of Landsat images (30 m×30 m)

Field measurements were performed in order to find the relation between plant indicators (biomass and canopy) and image extracted indexes such as NDVI and SAVI (remote sensing images). Therefore, by obtaining correlation and regression equations between biomass and the percentage of vegetation canopy in an actual environment (samples) and vegetation cover indexes of the remote sensing images (NDVI, SAVI), biomass and percentage of canopy cover could be estimated in total area. Since the radiometric characteristics of every image differs from one place to another or in the same place in different time according to variations in scene illumination (e.g., areas in shadow), atmospheric conditions, sensor characteristics and viewing geometry, vegetation cover samples from specified region were obtained to improve the results.

Regression

Regression models are usually employed to predict those dependant variables (Y) from independent ones (X), so they were used to predict development impacts on vegetation cover during this study. In order to obtain the regression relations of vegetation cover changes, we needed to obtain other variables which could affect quality and quantity of vegetation cover within the studied years. Other variables logically assumed to affect vegetation cover changes were determined as shown in Table 1. The more variables were obtained on the base of a pre-research result that the destructing and changing factors of rangeland and forest resources were determined in the study area (Roudgarmi, 2003). It is also possible that other variables are considered on the base of other development plans or projects with different factors. These variables include Christian year, township population, number of livestock, length of roads, time length from the beginning of study (year), and the data obtained from classifying satellite images (Table 1). The Christian year and time length from the beginning of study were used in the regression model as independent parameters to predict development impacts, because time is an important parameter in impacts prediction and environmental assessment. Sometimes, it is needed to predict future changes and impacts according to a determined date.

The statistical software SPSS11.5.0 was used in this study, and all data obtained from satellite images, field and statistical calculations were inserted in the software. In regression model, Y is dependent variable or response and X is independent or predicting variable.

RESULTS

Classification accuracy assessment

Classification accuracy was calculated using ILWIS3.2 (Integrated Land and Water Information System) software. This matrix can identify classification errors and their amounts. The 1:25000 National

Cartographic Center (NCC) topographic maps (in the year 2000) was used to estimate classification accuracy and to compare the classification results (in the year 2000) which had been provided almost at the same time with the mentioned NCC maps. The following measures were taken:

(1) The classified map was prepared as a raster model including certain features in a geographical data system. (2) A test set map was prepared as a raster model including certain features in geographical data system. The 1:25000 topography maps of NCC were used as test set map as well as accurate and actual data. (3) The classification map was crossed to the test set map. (4) Crossing of those two maps led to the preparation of the Crossing Table, which helped us to obtain the confusion matrix.

The studied classes were lands with natural vegetation cover (grassland), constructed lands and cultivated lands (Table 2). In confusion matrix, the rows indicate the present actual classes, and the columns indicate classification result. In accuracy column, the percentage of pixels belonging to a certain class which was correctly classified is presented. The average accuracy was 84.10% which describes the total values in accuracy column to the number of classes in test set. The overall accuracy was 86.51%, which reflects the ratio of the total correctly classified pixels to the total number of pixels. According to confusion matrix results and the related results of other researches, the classification of satellite images is helpful (Darvishsefat and Zare, 1998; Darvishsefat, 2000; Alavipanah, 2000).

Regression models for prediction of impact on vegetation cover area

According to input variables in Table 1, regression equations defining the quantitative changes in vegetation cover were provided for the study area. The used variables were vegetation cover area in hectares (dependant), Christian year, time length from the beginning of study, population (in individuals), area of constructed lands in ha, number of livestock, road length in km, and area of the agricultural lands in ha. Entered into regression equation by SPSS software were only some parameters, and the selection was based on the correlation between dependant and independent variables, and the number of observations of variables.

In Eq.(5), a regression model with the most significant levels is presented on R and R^2 basis, including the requirements for prediction of impacts such as predicting the future and time significance.

y=147303.53–2.37 (Area of constructed lands in ha)–738.29 (Roads length in km)+3291.60 (Time length from the beginning of study in year)–0.57 (Number of livestock), (5)

where y is area of natural vegetation cover (ha).

In Eq.(5), independent variables are regional development factors affecting environmental elements. For new proposed projects or plans, it is possible to insert the activity factors in prediction regression models as independent variables, or use these factors to create a new prediction regression model. Also, it is possible to completely apply these models for impact prediction in non-action alternative (environmental impact assessment).

Biomass estimation by remote sensing images

To study the development impacts on plant biomass and the vegetation canopy percentage, 35 samples of biomass and canopy percentage were obtained. After excluding useless samples, 30 were then used to obtain regression models to estimate biomass and canopy cover percentage. The vegetation indexes were SAVI and NDVI. The regression results were calculated for 1986, 1998, 2000, 2002 and 2004. The

Table 2 Confusion matrix which was resulted by crossing both the classified images and the reference classifier (test set)

	Cultivated area	Constructed area	Natural vegetation cover	Unclassified	Accuracy
Cultivated area	47782	4025	6691	0	0.82
Constructed area	2757	19743	1857	0	0.81
Natural vegetation cover	8885	5255	121479	0	0.90
Reliability	0.80	0.65	0.93		

Average accuracy=84.10%; average reliability=80.62%; overall accuracy=86.51%

regression results of 1986 between biomass in kg/pixel and percentage of vegetation canopy were studied by SAVI and NDVI. The highest correlation coefficient between biomass amount and SAVI for 1986 image was 0.538, and *R*-squared was 0.289. This correlation coefficient is placed in a significance level of 0.01. In 1998, the highest regression model between biomass (kg/pixel) and NDVI was obtained, whose *R*, R^2, and *Sig*. were 0.340, 0.115, and 0.97, respectively. SAVI regression models worked poorly in calculating biomass amount and the percentage of canopy cover. NDVI and canopy cover percentage show a meaningful correlation at 95% confidence level. Therefore, considering *Sig*.=0.035, there was relatively a proper regression between these two indexes.

In the established regression models of year 2000, a good correlation existed between SAVI and biomass amount. The correlation coefficient between these two parameters was 0.310, which was significant at level 10%. In this year, other regression models were low in view of accuracy and correlation. In 2002 there was a proper regression between SAVI and biomass. The correlation coefficient (*R*), R^2, and *Sig*. were 0.522, 0.304, and 0.002, respectively. The correlation was significant at 1% level. Correlation was significant at 10% level between biomass (kg/pixel) and NDVI. In the established regression models of year 2004, a good correlation existed between SAVI and biomass amount. The correlation coefficient (*R*), R^2, and *Sig*. were 0.547, 0.30, and 0.002, respectively. The correlation was significant at 1% level.

According to regression models, no significant results were obtained between SAVI and NDVI, and canopy cover; but some proper regression equations were obtained between SAVI and NDVI, and biomass. Thus, no estimation was made for the vegetation canopy percentage and no prediction models were developed for it. The total amount of biomass (in kg) in each pixel of satellite image (900 m^2) was obtained in regression relations. The best regression models of biomass with SAVI and NDVI were as follows:

$$\text{in 1986: } y=163.664+13180.912\ (\text{SAVI}), \tag{6}$$

$$\text{in 1998: } y=365.439+1851.378\ (\text{NDVI}), \tag{7}$$

$$\text{in 2000: } y=327.099+6995.789\ (\text{SAVI}), \tag{8}$$

$$\text{in 2002: } y=471.580+11489.680\ (\text{SAVI}), \tag{9}$$

$$\text{in 2004: } y=495.948+12629.775\ (\text{SAVI}). \tag{10}$$

where *y* is biomass amount (kg/pixel).

Then, SAVI 1986, NDVI 1998, SAVI 2000, SAVI 2002 and SAVI 2004 maps were inserted in resulted regression equations in ILWIS3.2 software in order to obtain vegetation biomass maps (in township). Afterwards, cultivated, residential, industrial and servicing lands and water resources were subtracted from the whole area so that only the naturally covered areas remained for calculating biomass. The total amount of biomass was calculated in kg/pixel, and then biomass amount in kg/ha was obtained for 1986, 1988, 2000, 2002 and 2004, and was used along with independent parameters to prepare regression models for predicting development impacts. The average biomass values in the area were obtained for 1986, 1998, 2000, 2002 and 2004 as 1078.9, 1083.9, 1070.1, 1077.0 and 1069.0 kg/ha, respectively.

In order to assess the accuracy of regression models in estimating biomass amount in 2004, 2002, 2000, 1998, and 1986, 10 samples were measured as control of biomass in kg/pixel (30 m×30 m) by field measurements. *t*-test paired samples method was used to determine the significance of the difference between the estimated and measured values (control samples). Here, the null hypothesis was: there is no significant difference between biomass averages. The rejected hypothesis was: there is significant difference between biomass averages. Obtained results for this test are presented as control samples and estimated values by regression models in Table 3. The accuracy level in this test was significant at 0.05 levels. As observed in Table 3, the amount of 0 is placed between confidence interval of the difference. So null hypothesis is accepted which indicates no difference between estimated biomass average from regression models and actual environment.

Regression models for prediction of impacts on biomass

Using independent parameters as development factors (Table 1), the prediction of regional development impacts on vegetation biomass was carried by regression models. All related parts such as time length from the beginning of study (year), Christian year, population of township, number of livestock, roads length (km), area of cultivated lands (ha), con-

Table 3 Results of paired samples *t*-test between samples of control and estimated biomass

Compared samples		Paired differences: Mean	Std. deviation	Std. error mean	95% confidence interval of the difference: Lower	Upper	*t*	*df*	*Sig.* (2-tailed)
Pair 1	Control of biomass and estimating biomass amount in 1986	9.4400	28.72982	9.08517	−11.1121	29.9921	1.039	9	0.326
Pair 2	Control of biomass and estimating biomass amount in 1998	22.6400	37.12212	11.73904	−3.9156	49.1956	1.929	9	0.086
Pair 3	Control of biomass and estimating biomass amount in 2000	17.9400	36.59922	11.57369	−8.2415	44.1215	1.550	9	0.156
Pair 4	Control of biomass and estimating biomass amount in 2002	−14.1360	29.34156	9.27862	−35.1257	6.8537	−1.524	9	0.162
Pair 5	Control of biomass and estimating biomass amount in 2004	20.1400	35.85862	11.33949	−5.5117	45.7917	1.776	9	0.109

structed lands in ha and natural vegetation cover lands in ha (Table 1) were used as input in SPSS software. These parts were considered as independent parameters (X). Dependant parameter was the biomass (kg/ha) in Robatkarim area. Independent parameters were entered into regression process in SPSS software and four parameters (time length from the beginning of study, roads length in km, population and area of natural vegetation cover in ha) were selected by the software. R and R^2 were considered as 1. The regression model for the prediction of development impacts on natural vegetation cover concerning biomass is defined as follows:

$$y=599.43-1.43\ (\text{Roads length in km})-2.55\ (\text{Number of human population})+13.57\ (\text{Time length from the beginning of study in year})+0.02\ (\text{Area of natural vegetation cover in ha}), \quad (11)$$

where y is biomass of vegetation cover (kg/ha).

Other equations may be developed that can be used in the prediction of environmental impacts on the basis of the needs of assessors and the kind of projects.

DISCUSSION

In comparison with other studies and available methods, the main point in this method is its quantitative prediction capability of the environmental impacts while most available methods for environmental impacts assessment in biotic group are descriptive (Treweek, 1999; Marriott, 1997). Commonly used methods assess environmental impacts on the basis of expert knowledge. In comparison with habitat-based prediction methods, such as habitat evaluation system (HES) and quantitative ecosystem models (Canter, 1996), the proposed methodology is more applicable and less time consuming. Walters (1993) identified four possible approaches for modeling the environmental management as Dogmatic, Empiricist, Reductionist and Experimentalist (Treweek, 1999). On the basis of the classification, the resulted methodology in this study can be classified in both Experimentalist approach, e.g., designs that will reveal the best option, and Empiricist approach, e.g., examination of past results in similar situations.

In vegetation cover studies, the most common application of remotely sensed images is in the field of biometry and monitoring of vegetation cover changes. There have been no studies before that applied satellite images for environmental impacts prediction. The results of this study are applicable to impacts prediction. Over the past three decades, the commonest application of remotely sensed images in the field of vegetation cover was mapping of vegetation cover and their characteristics (Hansen and Reed, 2000; Hansen *et al*., 2002), monitoring and mapping of forest and rangeland fires (Li *et al*., 2000; Conard *et al*., 2002), determining forest composition (species composition) and structures (canopy cover, stem density, tree size, age and successsional stage) (Underwood *et al*., 2003; Gemmell *et al*., 2001; Ustin and Xiao, 2001), vegetation cover biophysical studies-leaf area index, albedo, net primary production, growth (Roderick *et al*., 2001; Choudhury, 2001), forest biochemistry (Serrano *et al*., 2002; Sims and Gamon, 2002), forest health (Zarco-Tejada *et al*., 2003), effects of disease, pests and pollution (Albrechtova *et al*., 2001; Carter and Knapp, 2001), monitoring timber harvest and forest clearing (Woodcock *et al*., 2001), monitoring canopy defoliation and mortality (Collins and Woodcock, 1999; Radeloff *et al*., 1999), and estimating above ground biomass (Davidson and Csillag, 2001).

The present study reveals that combination of different approaches may even work better than the individual one to predict environmental impacts. The attempt of this study was to combine different approaches that present a methodology or process for prediction of environmental impacts. Remote sensing images and techniques were used to obtain environmental time series data. Regression models were employed for modeling of the impacts to obtain quantitative prediction results. Our recommended methodology can also be developed for other environmental elements (Fig.4).

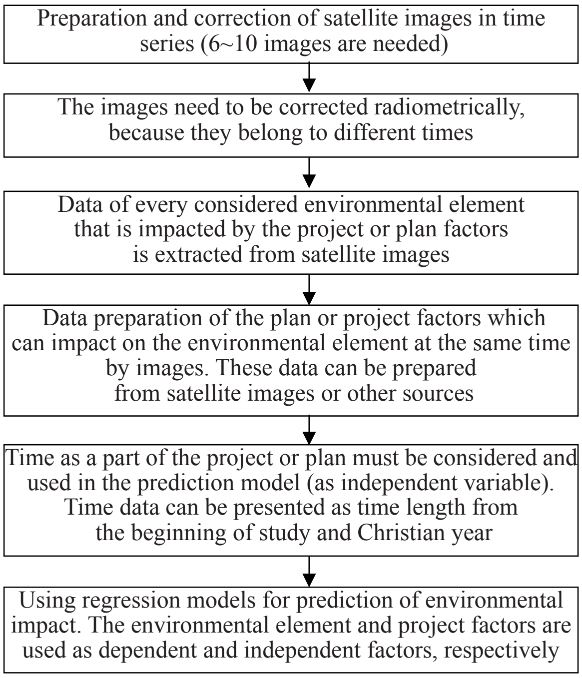

Fig.4 Presentation of the resulted methodology for prediction of environmental impacts by using satellite images

CONCLUSION

The results of present study revealed that time series remotely sensed data could be used to predict environmental impacts. The following steps were taken to predict the environmental impact: preparing remote sensed images, enhancing image, extracting the environmental data using satellite images (as dependent variables), preparing the data of regional development factors (as independent variables) and finally preparing the regression models. These steps can also be used for other environmental impacts prediction and assessment study. It is possible that other proposed development plans or projects factors are inserted in regression models to predict new environmental impacts such as resulted regression equations. These factors can be considered as independent variables in regression models.

Prediction of biological impacts is usually done by expert knowledge, but the stated strategies and creativities in this respect made quantitative predictions and determination of impacts possible. These results are derived from a new approach and methodology for environmental impacts prediction; therefore, the methodology is suggested for environmental impacts prediction studies in other regions and also for other elements.

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