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A NEW APPROACH FOR MODELING UNCERTAINTY IN REMOTE SENSING CHANGE DETECTION PROCESS

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Abstract

Land use/cover change mapping is one of the basic tasks for environmental monitoring and management. Since the change maps are usually utilized in the planning and decision-making processes, therefore identification of the certainty and reliability of these maps is very important in many applications. Unfortunately in many studies only the pixel-based spectral and probabilistic measures as obtained from the classification approaches such as the maximum likelihood algorithm are used for uncertainty estimation. In this work, a new approach has been developed which is based on the pixel-based and object-based probability information as well as the spatial parameters including the distance, neighborhood, region size and the type of change. Two Landsat TM images of Isfahan urban area (Iran), acquired in 1990 and 1998 have been co-registered using the first order polynomial and the nearest neighbor resampling approaches .The registered images have been classified using the Maximum Likelihood Classification Algorithm (MLC) and the probabilistic measures have been generated. Using different spatial analysis functions, for modeling the change of agriculture to urban areas the relevant spatial parameters have been extracted. The probabilistic and spatial parameters have been integrated through the logistic regression modeling approach to model uncertainty of change of agriculture to urban areas. The Relative Operating Characteristics (ROC) index has been used for validation of the model and it has been estimated to be 0.9944, which is an indicator of the good model fitting. Further test and development of the proposed approach is under investigation.

INTRODUCTION

Change detection based on remotely sensed data is an important component of environmental and resource monitoring programs. Because of the regular imaging capabilities, satellite data plays a unique role for mapping and monitoring of land use/cover changes. However, many sources of errors can influence the reliability of the change maps resulting from the analysis of remotely sensed data. Inherent radiometric and geometric errors of the multi-temporal data together with the errors introduced during the processing stages particularly the classification and change detection operations can have very significant effects on the reliability and accuracy of the land use/cover change maps.

Although many works have been completed on the remote sensing change detection techniques (e.g. Awaya and Tanaka, 1993; Gong, 1993; Lunetta and Elvidge., 1999), few works have been concentrated on evaluation and mapping of the uncertainty in the remote sensing land use/cover change products. The existing approaches for mapping of the uncertainty mostly rely on the pixel-based spectral and probabilistic data resulting from the classification approaches such as the maximum likelihood algorithm (e.g. Shi and Ehlers, 1996). Valuable role of the spatial data as a source of significant information for uncertainty mapping has not been carefully explored.

In this work, a new approach based on the extraction of the useful probabilistic and spatial measures and their combination by using the logistic regression modeling approach has been proposed. Usefulness of the approach has been tested in land use/cover change mapping of Isfahan urban areas located in Isfahan Province, central parts of Iran.

OUTLINE OF THE PROPOSED APPROACH

The proposed approach for uncertainty mapping in change detection is mainly based on the probabilistic and spatial data. Spectral similarity between classes is an important source of uncertainty, therefore in addition to spectral data, the use of spatial data can play significant role for modeling of the uncertainty in the change detection process. Because of the variation of uncertainty in mapping of the change of different class pairs, separate models of uncertainty are required to be developed for each class pair.

Let U_{ij} be the uncertainty of change from class i to j expressed as:

$$\mathbf{U}_{ij} = f(S_{ij}, P_{ij})$$

where P_{ij} is the probabilistic measure of uncertainty in change from i to j and it can be modeled from the following function

$$P_{ij} = \frac{Pe(i \mid j)}{Pc(i \mid j)}$$

where Pe(i|j) is the probability of confusion between the two classes i and j and Pc(i|j) is the probability of change from i to j.

S_{ij} is the spatial measure of uncertainty in change from i to j and it is expressed as:

$$S_{ij}=f(D_{ij}, R_{ij}, \overline{P}ij, N_{ij})$$

where D_{ij} is the nearest distance of i from j in the starting time (t1) of change studies, R_{ij} is the size of the region of change from i to j, Pij is the mean probability of change of i to j in R_{ij} and N_{ij} is the number of neighbor pixels of i in t1 with labels j.

PRACTICAL EVALUATION OF THE PROPOSED APPROACH

For practical evaluation of the proposed approach , Landsat-TM data of the Isfahan Urban Areas (Latitude of 52.02 and Longitude of 39.33 decimal degrees), Isfahan Province, Iran, acquired in years 1990 and 1998 were used. A window of 700 by 700 pixels (about 21 by 21 kilometers) was selected for this test. The study site is highly populated and has shown rapid physical growth of urban areas during the course of previous studies (Rabiei, 2004).

After radiometric normalization of the satellite data ground control points and linear functions were used to geometrically correct the data to the 1:50000 topographic maps of the area. Mean errors (RMS) of image to image registration of the data of two dates were estimated as 0.38 pixel size, showing a good match between the data.

Well represented training sites for the existing land use/cover types in the area including ten classes (Table 1) were identified and maximum likelihood classification approach was used for classification of the data of each date. In addition to the classified data, data of the posterior probability of each class were produced and used as indicators of confusion between classes and as well as the pixel-based measures of uncertainties in the classifications. Post-classification comparison approach was used to produce the change maps and data of change regions as required for the modeling processes. The spatial measures of uncertainty as required for the modeling approach were calculated.

Table 1: Discriminated land use/cover types of the study site.

Land use/cover	Numerical code
Water	1
Range lands	2
Industrial sites	3
Shaded areas	4
Orchards & Green spaces	5
Green agricultural lands	6
Roads	7
Residential areas	8
Bare lands	9
Non-green farms	10

Because of the importance of mapping and monitoring the change of agricultural and vegetated lands to urban areas, modeling of the uncertainty of detected changes between the above mentioned land cover types were investigated.

Although other approaches such as the use of neural networks or mathematical techniques may be employed for integration of the spatial and probabilistic data, the logistic regression approach has been adopted in this study. The main reason for selection of this approach at this stage was due to its simplicity, ease of use and adoption for modeling the binary response problems (Alimohammadi and Turner, 1994). Sample areas from the changed and unchanged pixels (from agriculture & orchards to urban areas) were carefully selected by using the available sources of data including the aerial photographs, the existing land use/cover maps, visual interpretation of the multi-temporal TM data and field checking. The resulting data of change and no-change samples were used as the training data for development of the logistic regression model. Quality of the resulting model of uncertainty was evaluated by using the ROC approach (Pontius and Schneider, 2001).

DISCUSSIONS AND CONCUSIONS

Land use/cover maps of the area in 1990 and 1998 and the land use/cover change maps resulting from the comparison of two classifications are shown in Figures 1 to 3. Conversion of the agricultural lands (displayed as the green pixels in Figures 1 and 2) to urban areas during the time period of 1990- 1998 is visually observable by the significant decrease of green pixels in Figure 2 as compared to data of Figure 1. Coefficients of different variables in the resulting logistic regression model are listed in Table 2.

Table 2: Coefficients of probabilistic and spatial variables in the logistic regression model of the uncertainty.

Variable	Coefficient
Intercept	3.058
P(agr90) (posterior probability of agriculture in 1990)	0.063
P(urban98) (posterior probability of urban areas in 1998)	-3.455
$\overline{P}ij$	0.002
D_{ij}	0.004
N_{ij}	0.004
R_{ij}	-0.002

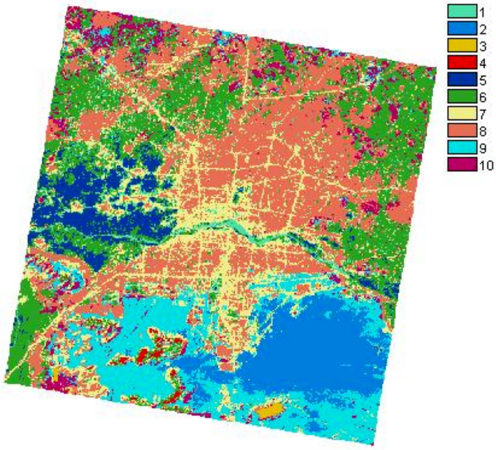

Figure 1: Land use/cover map of the Isfahan urban area in 1990 (for numerical codes see Table 1).

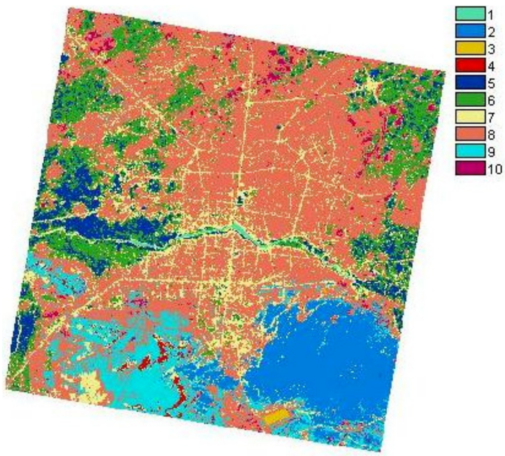

Figure 2: Land use/cover map of the Isfahan urban area in 1998 (for numerical codes see Table 1).

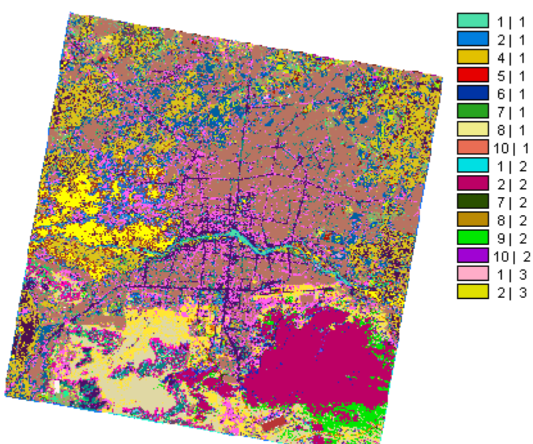

Figure 3: The map resulting from the crosstabulation of land use/cover maps of the Isfahan urban area in 1990 and 1998 (for numerical codes see Table 1).

Because of the high spectral contrast between the two classes of interest (agricultural and urban areas), the probabilistic measures indicated by the probability of urban area in 1998 (see Table 2) displays the highest contribution for modeling of uncertainty in change detection. Negative sign for the probability of urban area in 1998 is an indicator of the higher uncertainty for lower values of this measure.

Although because of the higher discriminatory role of probabilistic measures in this case study, the proposed spatial data do not show major contribution in the model , the signs of coefficients for spatial data are in good agreements with those of the theoretical expectations (Table 2). Negative sign for the coefficient of R_{ij} is an indicator of larger uncertainties for the regions with smaller sizes. In contrast, positive signs for the other three spatial variables shows the complementary effect and usefulness of combination of spatial and pixel-based probabilistic data for modeling of the uncertainty.

In the case of the discrimination of the change of spectrally less distinct classes such as the conversion of bare lands to urban areas which is the subject of this continuing research, spatial data would show more important discriminatory role.

The resulting data of uncertainty for change from the agriculture & orchards to urban areas are shown in Figure 4. Higher rates of uncertainty in change are displayed as the green and yellow colors and mostly include no-change pixels far from the urban areas. In contrast, the changed pixels are displayed with darker tones and they are mostly include the change pixels located in the vicinity of urban areas.

Validity of the developed uncertainty model. is confirmed by the considerably high and very closeness of the calculated ROC measure to one (ROC = 0.9944).

Development of more efficient approaches for quantification of the spectral and spatial measures as well as investigation of the other integration approaches and extension of the approach for modeling of multiple classes are the topics of higher priority in this continuing research programs.

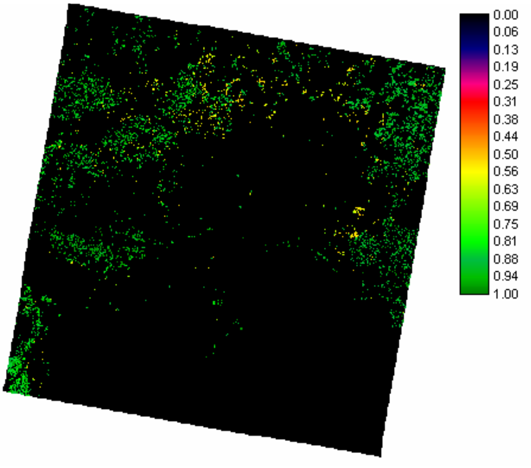

Figure 4: Probability of uncertainty in change of agricultural lands to urban land uses in Isfahan City (Iran) resulting from the integration of the probabilistic and spatial data by the logistic regression modeling approach. Higher rates of uncertainty are highlighted by the green and yellow colors.

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