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## Integration of Remote Sensing data and GIS for prediction of land cover map

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### ABSTRACT

Satellite remote sensing and geographic information system (GIS) have been widely applied in identifying and analyzing land use and land cover change. In this study, aerial photos and MSS, TM and ETM<sup>+</sup> images of Isfahan and its environs were used to provide maps of land cover for 1955, 1972, 1990 and 2001. A hybrid method was used for image classification: a combination of supervised and unsupervised classification. Cellular automata filter facilities and Markov model were used together in a CA-Markov model for predicting land cover maps. To study the accuracy of the predicted maps and validation of the CA-Markov model, three methods were used: a calculating agreement and disagreement table, a chi-squared goodness-of-fit test and an error matrix. The results indicate that if land cover change processes are constant, the CA Markov model predicts land cover changes for the following years, for which agreement between predicted maps with actual map is less than 70% in this study area.

**Key words:** Change detection, CA-Markov model, Land cover

### 1. Introduction

Satellite remote sensing and geographic information system (GIS) have been widely applied in identifying and analyzing land use and land cover change (Jensen and Cowen, 1999; Hathout 2002). In recent years, these methods have progressed and have been used widely in management of natural resource and urban planning. Techniques based on multi-temporal, multi-spectral, satellite-sensor acquired data have demonstrated potential as a means to detect, identify, map and monitor ecosystem change, respective of the casual agents (Coppin et al., 2004). Land cover and land use change analyses and projection provide a tool to assess ecosystem changes and their environmental implication at various temporal and spatial scales (Lambin, 1997). There are a lot of methods for land cover change detection such as image rationing, image difference, change vector analysis, image regression, composite analysis and post-classification (Coppin et al., 2004). Detecting past changes and predicting these kinds of changes in the future play a key role in decision making and long term planning. Modeling is the main tool for studying land use and land cover change (Schneider and Pontius, 2001).

There are a lot of methods for land cover and land use change modeling that include mathematical equation based, system dynamic, statistical, expert system, evolutionary,

cellular, and hybrid models. Cellular models (CM) include cellular automata (CA) and Markov models. In CA, each cell exists in one of a finite set of states, and future states depend on transition rules based on a local spatiotemporal neighborhood (Parker, 2002). Markov chain analysis is a convenient tool for modeling land cover and land use changes when changes and processes in the landscape are difficult to describe. Markov chains model is able to predict land use and land cover changes from one period to another and use this as the basis to project future changes (Estmen, 1995). Since first introduced by Ulam (1976) in 1948, cellular automata (CA) have been widely used to simulate nonlinear complex systems (Wolfram, 1984). CA-based models have a strong ability to represent non-linear spatial and stochastic processes (Batty et al., 1997). Recently, cellular automata (CA) models have been applied in urban growth and land use change prediction (Yang et al., 2008).

To validate the simulations of land cover maps by a model, it should be calibrated with additional previous information to create a reference map for the simulated time (Pontius and Spencer, 2005). There are many techniques for validation; including the calculation of that one of them is budgets sources of agreement and disagreement between the prediction map and the reference map (Pontius et al., 2004). The percentage correct is budgeted by three components: agreement due to chance, agreement due to the predicted quantity of each land category, and agreement due to the predicted location of each land category. The percentage error is budgeted by two components: disagreement due to the predicted location of each land category and disagreement due to the predicted quantity of each land category. Therefore users can survey error sources and evaluate accuracy of model (Pontius and Spencer, 2005).

Detection of land cover change and prediction of future changes by CA-Markov models have been reported in several studies discussed in the following paragraphs.

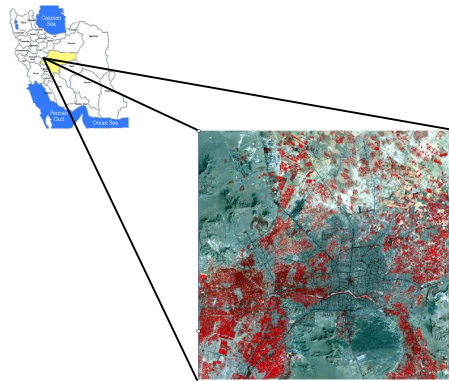
Wijanarto (2006) investigates change detection and prediction of changes in land use in Serang, Indonesia by using ETM<sup>+</sup> (Enhanced Thematic Mapper) images from April 2000 and August 2001. Cheng-Liang Chang and Jui-Chin (2006) used SPOT data of Jiou Jiou Mountain from four different periods (March 1999, October 1999 and November 2002 & 2005) to study vegetation cover in 2006. Finally, they use Markov chain analysis and Cellular automata to predict temporal and spatial changes of vegetation cover. The paper concludes that CA Markov model is a more suitable method than others for the simulation of vegetation cover changes. Ayodeji Opeyemi (2006) detects land cover and land use changes of the Ilorin region in Kwara state by using GIS technology and remote sensing between 1972 and 2001 with the help of ETM<sup>+</sup>, TM and MSS data. After change detection in recent years he predicts land cover and land use changes for the next 14 years by using Markov and Cellular automata models.

The purpose of the current study is to prediction of land cover maps using CA Markov model in the study area and investigation of validation maps by comparing land cover maps produced by a hybrid method of image classification and prediction maps generated by the Markov model.

## 2. Material and Method

### 2.1 Study area

The study area covers the city of Isfahan, Iran and its environs. Covering a total of 115567 ha, the area is bounded by 51° 26' 27" and 51° 49' 58" eastern longitude and 32° 40' 49" and 32° 32' 38" northern latitude. The location of the area is shown in the Fig 1. The study area has arid and semi-arid weather and it is in the neighborhood of Zayandehrood River. In recent years, because of industrial and economic growth on one hand and special historical and cultural conditions on the other, Isfahan city has experienced a high immigration rate from suburbs and other cities, and a significant change in land use and land cover. Because of rapid urban expansion and other changes, predicting future changes in the area and accurate planning to protect existing resources seems essential.



**Figure 1:** False color composite from ETM<sup>+</sup> of Isfahan

### 2.2 Datasets

Aerial photos and images of different sensors of Landsat satellite were used in the current study to produce land cover maps and change maps in various years. Characteristics for each image are shown in Table 1. Ancillary data layers include 1:50000 scale topographic maps in 1967, 1991 and 2002 and large scale aerial photos at 1:6000 and 1:25000 scale in 1955 and 1967, respectively.

**Table 1:** The data used in this study

Image	Year	Scale/ Spatial Resolution	Number of Bands
Aerial Photos	1955	1:50000	----
MSS	1972	57	4
TM	1990	28.5	7
ETM <sup>+</sup>	2001	28.5	8

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### **3. Methodology**

#### **3.1 Geometric correction**

A first-order polynomial method and nearest neighbor image re-sampling algorithm was applied for the geometric correction of aerial photos and satellite images. The RMS error of the aerial photos was in a range of 0.1 to 0.45 pixels. Then the georegistered aerial photos were mosaiced together. The RMSe of the transformation of MSS, TM and ETM<sup>+</sup> was 0.73, 0.68 and 0.6 pixels respectively. Rees et al. (2003) reported that RMSe in geometric correction of TM and ETM<sup>+</sup> images which were georeferenced to a topography map with 1:20000 scale were less than 1 pixel. Coppin et al. (2004) noted that an RMSe of less than 1 pixel for geometric correction of satellite images in a change detection process is acceptable.

#### **3.2 Aerial photointerpretation**

Aerial photointerpretation was carried out using standard photographic keys (tone, texture, pattern, shape and size). Interpretation of aerial photos was performed in mach line. We used a Stereomicroscope for accurate interpretation.

#### **3.3 Image classification and accuracy assessment**

To make the best false color composite, the Optimal Index Factor (OIF) was used. The OIF value is based on the amount of total variance and correlation between various band combinations. In this study, the supervised classification was performed using the maximum likelihood method and five land cover classes were identified including mountain, barren land, urban, green cover and river. Unsupervised classification was done with iterative self organizing data analysis (Isodata). NDVI and principal component analysis were used to separate the green cover and barren land respectively. The classification accuracy can be assessed by an error matrix. Many measurements have been proposed to improve the interpretation of the error matrix, among which the Kappa coefficient is one of the most popular measures. It is a discrete multivariate technique used in accuracy assessment (Congalton, 1988). The reference data are collected from large-scale aerial photos and topographic maps.

#### **3.4 Change Detection**

Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different times (Singh, 1989). It involves independently produced spectral classification results from each end of the time interval of interest, followed by a pixel-by-pixel or segment-to-segment comparison to detect changes in cover type. The principal advantage of post classification comparison lies in the fact that the two dates of imagery are separately classified; thereby minimizing the problem of radiometric calibration between dates (Copping, 2004).

### 3.5 Land Cover Prediction

Markov chains have been widely used to model land use and land cover changes (Bell, 1974; Jahan, 1978; Robinson, 1978). Markov change models have several assumptions. One basic assumption is that land use and land cover is regarded as a stochastic process, and different categories are as the states of a chain (Weng, 2002); that is, it is only the most recent state (or link) that affects the transition to the next state: it is independent of prior history. The Markov chain can be expressed as

$$P(X_t = j \mid X_0 = i_0, X_1 = i_1, \dots, X_{t-1} = i_{t-1}) = P(X_t = j \mid X_{t-1} = i_{t-1}) \quad (\text{Equation } 1)$$

(Fan et al., 2008).

This model is stochastic as opposed to dramatic, because model output, which is the distribution among states, is based on the probability of transition,  $P_{ij}$ , between state  $i$  and  $j$ . Since the transitions are probabilities, it follows that:

$$\sum_{j=1}^m P_{ij} = 1 \quad i=1, 2, 3 \dots m \quad (\text{Equation } 2)$$

The transition probability is usually derived from a sample frequency of the transition occurring during some time interval (Baker, 1989). This is accomplished by developing a transition probability matrix of land use change from time one to time two, which will be the basis for projecting to a later time. The transition probabilities matrix records the probability that each land cover category will change to each other category. This matrix is the result of cross tabulation of two images adjusted by the proportional error (Estmen, 1995).

A CA model is a set of identical elements, called cells, each one of which is located in a regular and discrete space. Each cell can be associated with state from a finite set. The model evolves in discrete time steps, changing the state of each cell according to a transition rule homogeneously applied at every step. The new state of a certain cell depends on the previous states of a set of cells. Integrating a Markov chain model and a CA model provides a means of predicting temporal and spatial changes of land cover (Fan, 2008). In this study, we use a CA-Markov model for producing 1990 and 2001 maps and then compare them with the 1990 and 2001 maps produced by the hybrid method to study the capabilities of a CA-Markov model in predicting land cover changes.

### 3.6 Validation

As it is very important to validate model predictions, users need some powerful tools to measure the accuracy of predicted changes in land use models (Pontius, 2001). In this paper, in order to calculate the accuracy of prediction maps and validate the CA-Markov model three methods were used:

- An agreement and disagreement table

- A chi-squared goodness-of-fit test
- An error matrix

#### *An agreement and disagreement table*

To measure validation of predicted maps by the CA-Markov model, the VALIDATE function of Idrisi Kilimanjaro was used. VALIDATE provides a method to measure agreement between two categorical images, a "comparison" map and a "reference" map. The comparison map will usually be the result of a simulation or classification model whose validity is being assessed against a reference map that depicts reality (Estman, 1995).

#### *A chi-square goodness-of-fit test*

This statistical test judges whether or not a particular distribution adequately describes a set of observations by making a comparison between the actual land-cover area of observations and the expected land-cover area of observations. The statistic is calculated from the relationship  $\chi^2 = \sum(O_i - E_i)^2 / E_i$

Where  $O_i$  is the observed and  $E_i$  the expected land cover area in 1990 and 2001. Hypotheses tested were:

$H_0$ : There are no significant differences between the observed areas (by means of hybrid classification) and the predicted areas (from CA-Markov model).

$H_1$ : The above-mentioned differences are significant at  $\alpha=0.05$ .

#### *Error matrix*

The error matrix and kappa coefficient are used to assess the accuracy of the classification procedure undertaken and may suggest ways to improve the classification.

A method flow diagram of the process used is given in Figure 2.

## **4. Result and Discussion**

### **4.1 Image Classification**

The 1955 land cover map was produced by visual interpretation of aerial photos. The false color composites were generated from bands 3, 2 and 4 for MSS and 3, 4 and 7 for TM and ETM<sup>+</sup> by using the OIF index. Land cover classes in 1972, 1990 and 2001 were mapped from digital remotely sensed data though a hybrid process combining a supervised and unsupervised digital image classification. For accuracy assessment of the 1955 map, large scale aerial photos with a 1:6000 scale from the same year were used. For accuracy assessment of the 1972, 1990 and 2001 reference maps, aerial photos at a scale 1:25000 for 1967 and updated digital topography maps for 1991 and 2002 were

used respectively, and then the kappa coefficient and overall accuracy was calculated for all produced maps. The results show that overall accuracy of the hybrid method of land cover classification used in this study achieve accuracies of 99.77%, 90.27%, 91.65% and 93.19% and kappa values of 0.98, 0.87, 0.88 and 0.91 for the 1955, 1972, 1990 and 2001 reference maps respectively. The accuracy of the post-classification comparison is totally dependent on the accuracy of the initial classifications.

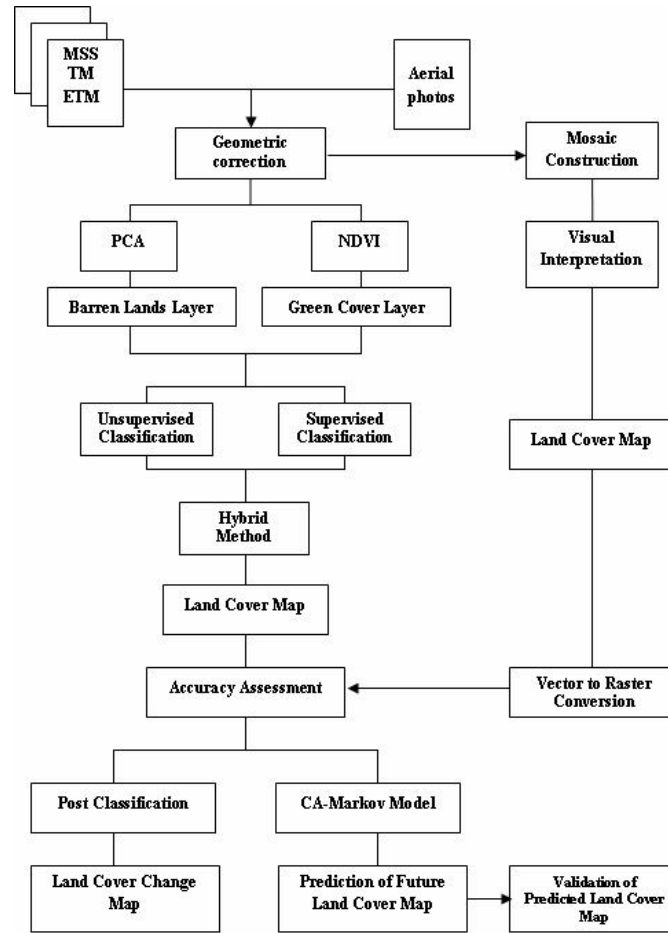


Figure 2: Flowchart of Methodology

#### 4.2 Land Cover Change Detection

Cross tabulation is a means to determine quantities of conversions from a particular land cover to another land cover category at a later date (Alphan, 2008). The change matrices based on post classification comparison were obtained and are shown in Tables 2, 3 and 4.

The nature of the changes of different the land cover classes can be examined in Tables 2 and 3. For example, urban covered 3127 ha in 1955 and 8321 ha in 1972, while the green cover class covered an area of 65019.1 ha in 1955 and 44808.8 ha in 1972. 36307 ha of

the area which was green cover in 1955 was still green cover in 1972, but 5461.3 ha had been converted to urban use by 1972. As can be seen in Table 3, between 1972 and 1990, 7293.3 ha of green land was depredated and converted to urban use. During the same time period, 19453.3 ha of barren land were restored to green cover. 20% was changed to green cover. This occurred in the north of the study area and shows that aerial photos have a greater ability than MSS image data for separating urban area from other covers. Spectral mixing and spectral confusion between different land cover such as urban and barren land or urban and fallow agriculture fields are one of the most prevalent errors in image classification (Guindon et al. 2004).

The result of change detection from 1990 to 2001 shows that 7436.1 ha of green cover and 1991.1 ha of barren land were converted to urban use. At the same time the increase in green cover, from 1990 to 2001, was 2873.1 ha from urban and 4634.2 ha from barren land. During 1990-2001, 15% of the urban class was changed to green land. These changes may seem to be a classification error, but green land is among some of the urban areas for developing new housing. Streets and highways were generally classified as urban, but when urban tree canopies along the streets grow and expand, the associated pixels may be classified as green cover. We note that the changes from urban to green land occurred almost entirely near highways and streets: for example Chaharbagh bala and Charbagh paein streets. Yuan et al (2005) obtained the same results in their study. Converting river to urban and inverse change is most likely associated with omission and commission errors in the Landsat classification change map. Registration errors and edge effects can also cause apparent errors in the determination of change vs. no-change.

**Table 2:** Post-classification matrix of study area from 1955-1972 (ha)

		1955					
		Mountain	Barren land	Urban	Green cover	River	Total
1972	Mountain	10573.7	0	0	0	0	10573.7
	Barren land	0	27818	441.3	23069.2	20.2	51199.6
	Urban	0	664.3	2140.7	5461.3	46.7	8321
	Green cover	0	7446.1	564.9	36307	474.5	44808.8
	River	0	26.6	9.9	181.4	351.3	568
	Total	10573.7	35955.1	3127	65019.1	892.5	115567.7

**Table 3:** Post-classification matrix of study area from 1972-1990 (ha)

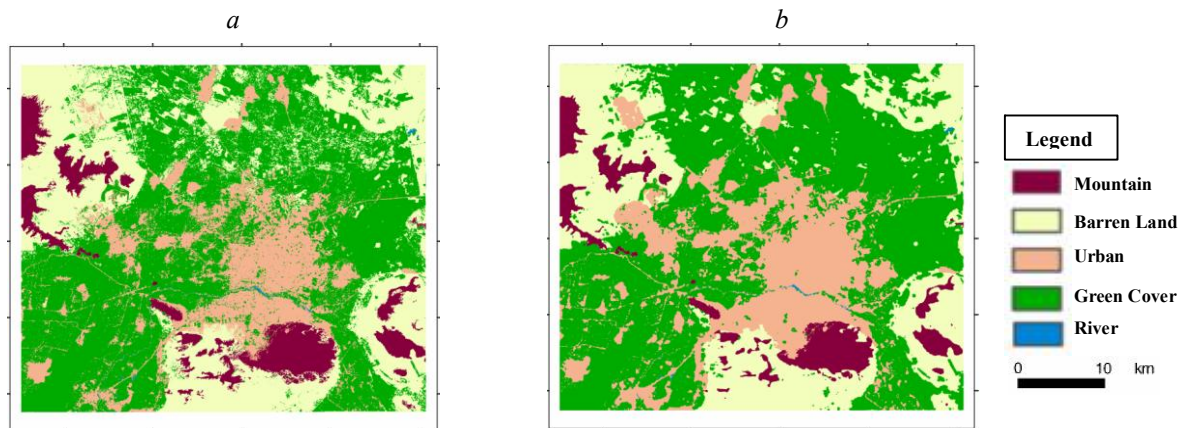
		1972					
		Mountain	Barren land	Urban	Green cover	River	Total
1990	Mountain	10573.7	0	0	0	0	10573.7
	Barren land	0	27209.7	176	4560.5	9.8	33694.4
	Urban	0	4499.7	6444.9	7239.3	128.4	18599.1
	Green cover	0	19453.4	1692.6	32969	369.2	54529.2
	River	0	28.5	7.3	39.8	60.5	136.2
	Total	10573.7	51199.6	8321	44808.8	568	115567.7

**Table 4:** Post-classification matrix of study area from 1990-2001 (ha)

		1990					
		Mountain	Barren land	Urban	Green cover	River	Total
2001	Mountain	10573.7	0	0	0	0	10573.7
	Barren land	0	25275.8	1741.4	11904.9	22	40201.4
	Urban	0	1991.1	13898.1	7436.1	14.4	23441
	Green cover	0	4634.2	2873.1	34969.1	32.6	42495.7
	River	0	6.3	86.3	137.8	67	297.1
	Total	10573.7	33694.4	18599.1	54529.2	136.2	115567.7

### 4.3 Land Cover Prediction

A Markov model result is a transition matrix which shows the probability of changes from each class of land cover or land use to each other class in the future. But the output of a CA-Markov model is images produced by the software. Each image shows the probabilistically determined land cover for future years. Tables 5, 6 and 7 are the probability transition matrix of different land cover types of Isfahan during the periods 1955-1972, 1972-1990 and 1990-2001 respectively. In this research, we use the 1955 and 1972 land cover maps to predict the 1990 land cover map and then use the 1972 and 1990 land cover maps to predict the 2001 land cover map. In this study, the maps produced for 1990 and 2001 by the hybrid method were considered to be reference map and the maps predicted by the CA-Markov model in the same years were considered to be comparison maps.



**Figure 3:** The 1990 land cover map produced by the hybrid method (a) and the CA-Markov model (b)

According to Table 5, green cover has been transformed into urban with a transformation probability of 0.1; at the same time (1955-1972) barren land greatly decreased, transformed into green cover and urban with probabilities of 0.02 and 0.26 respectively. During the 1972-1990 period, green cover is transformed into urban with the probability of 0.14 (Table 6). Table 7 shows that green cover and barren land have been transformed

into urban with the probability of 0.11 and 0.05 respectively between 1990 and 2001. In the all of years the most consistent classes were mountain, barren land and urban area.

**Table 5:** Probability transition matrix for changes of land cover from 1955 to 1972

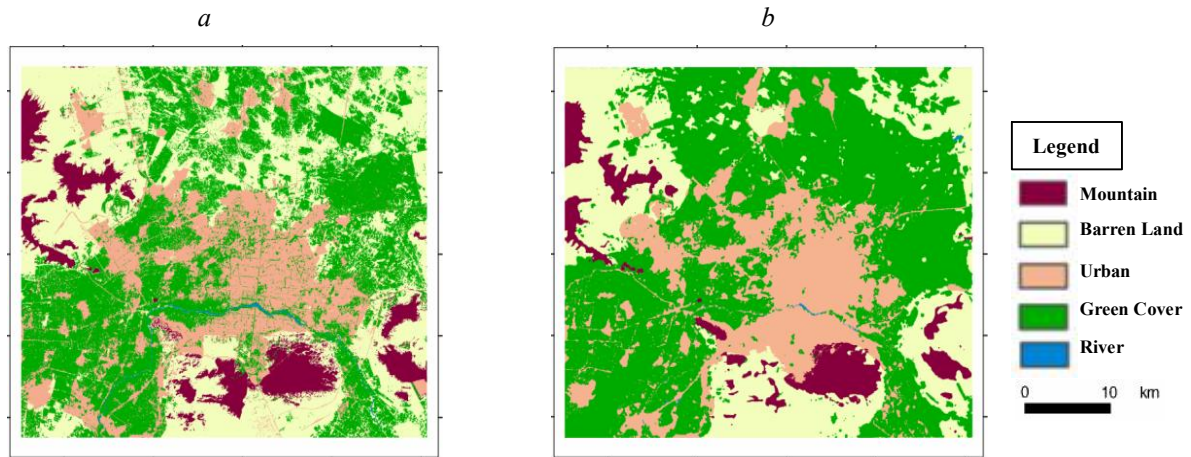
		1972				
1955		Mountain	Barren land	Urban	Green cover	River
	Mountain	<b>1</b>	0	0	0	0
	Barren land	0	<b>0.7137</b>	0.021	0.2644	0.0009
	Urban	0	0.1688	<b>0.612</b>	0.215	0.0042
	Green cover	0	0.4299	0.1019	<b>0.4648</b>	0.0034
	River	0	0.0331	0.0645	0.6235	<b>0.2789</b>

**Table 6:** Probability transition matrix for changes of land cover from 1972 to 1990

		1990				
1972		Mountain	Barren land	Urban	Green cover	River
	Mountain	<b>1</b>	0	0	0	0
	Barren land	0	<b>0.6081</b>	0.0528	0.3386	0.0005
	Urban	0	0.0121	<b>0.8008</b>	0.1862	0.001
	Green cover	0	0.1012	0.1388	<b>0.7591</b>	0.001
	River	0	0	0.182	0.6606	<b>0.1573</b>

**Table 7:** Probability transition matrix for changes of land cover from 1990 to 2001

		2001				
1990		Mountain	Barren land	Urban	Green cover	River
	Mountain	<b>1</b>	0	0	0	0
	Barren land	0	<b>0.8278</b>	0.0451	0.1272	0
	Urban	0	0.0701	<b>0.7838</b>	0.1416	0.0046
	Green cover	0	0.1866	0.1147	<b>0.6965</b>	0.0022
	River	0	0.1204	0.0785	0.212	<b>0.5892</b>



**Figure 4:** The 2001 land cover map produced by the Hybrid method (a) and the CA-Markov model (b)

#### 4.4 Validation of Predictive Land Cover

Results of the agreement and disagreement components relating the prediction maps of 1990 and 2001 and reference maps according to the VALIDATE function were produced as shown in Tables 8 and 9. According to Table 8, the agreement of the 1990 maps is 0.6052 and the disagreement is 0.3948. These results for overall agreement of maps of the year 2001 is 0.6944 (Table 9) and overall disagreement for these two maps is 0.3056.

**Table 8:** A Table of agreement and disagreement of hybrid reference map and predictive map based on CA-Markov model (year 1990)

	No[n]		Medium[m]		Perfect[p]	
Perfect[P(x)]	P(n)	0.6366	P(m)	0.7764	P(p)	1
MediumGrid[M(x)]	M(n)	0.4371	M(m)	<b>0.6052</b>	M(p)	0.6105
No[N(x)]	N(n)	0.2	N(m)	0.3127	N(p)	0.3391

**Table 9:** Table of agreement and disagreement of hybrid and predictive maps based on CA-Markov model (year 2001)

	No[n]		Medium[m]		Perfect[p]	
Perfect[P(x)]	P(n)	0.6816	P(m)	0.872	P(p)	1
MediumGrid[M(x)]	M(n)	0.4946	M(m)	0.6944	M(p)	0.6701
No[N(x)]	N(n)	0.2	N(m)	0.3099	N(p)	0.3036

The second method of model validation is the chi-squared goodness-fit test. This test is based on the number of pixels in each class or in the area of each class in the land cover map, and also compares the reference map and comparison map. The computed value of

$\chi^2$  is 25642 and 36915 for the 1990 and 2001 land cover maps which predicting by CA-Markov respectively (with 4 degree-of-freedom at  $\alpha=0.05$ ) for above the accepted is threshold value of 0.711. The null hypothesis is rejected. Lopeza *et al.* (2001) used goodness-fit test to quantitatively assess the capabilities of Markov models in predicting different land use classes, and reported a value of 6677 for  $\chi^2$ , also showing that the land use areas predicted by Markov models have a statistically significant difference at  $\alpha=0.05$  when compared with land use areas of maps from aerial photo interpretation.

To calculate kappa coefficient and overall accuracy of all land cover maps, ground control points were used error matrix was calculated for land cover maps produced by both the hybrid method and the CA-Markov model. The kappa coefficient of prediction maps for the years 1990 and 2000 are 0.64 and 0.84 respectively, which are smaller than the hybrid method maps with kappa coefficients of 0.93 for the year 1990 and 0.92 for the year 2001 (Tables 10, 11, 12 and 13).

**Table 10:** Error matrix of land cover map produced by the CA-Markov method in 1990

	Mountain	Barren land	Urban	Green cover	River	Total	Commission error
Mountain	2587	238	53	0	0	2878	0.1011
Barren land	110	5988	1485	2441	7	10031	0.4036
Urban	0	0	1738	15	0	1753	0.0086
Green cover	0	105	501	4342	9	4957	0.1241
River	0	0	0	0	0	0	0
Total	2697	6331	3777	6798	16	19619	
Omission error	0.0408	0.0542	0.5398	0.3613	1		0.253

Kappa coefficient: 0.64

Overall accuracy: 74.69%

**Table 11:** Error matrix of land cover map produced by the hybrid method for 1990

	Mountain	Barren land	Urban	Green cover	River	Total	Commission error
Mountain	2269	0	0	0	0	2269	0
Barren land	406	5945	1	12	0	6364	0.0658
Urban	0	0	3744	32	0	3776	0.0085
Green cover	22	386	32	6754	0	7194	0.0612
River	0	0	0	0	16	16	0
Total	2697	6331	3777	6798	16	19619	
Omission error	0.1587	0.061	0.0087	0.0065	0		0.0454

Kappa coefficient: 0.93

Overall accuracy: 95.45%

**Table 12:** Error matrix of land cover map produced by CA-Markov model for 2001

	Mountain	Barren land	Urban	Green cover	River	Total	Commission error
Mountain	2631	0	0	0	0	2631	00
Barren land	436	6111	112	139	0	6798	0.1011
Urban	0	4	3784	15	78	3881	0.025
Green cover	4	885	219	2721	7	3836	0.2907
River	0	0	0	0	94	94	0
Total	3071	7000	4115	2875	179	17240	
Omission error	0.1433	0.127	0.0804	0.0536	0.4749		0.1102

Kappa coefficient: 0.84

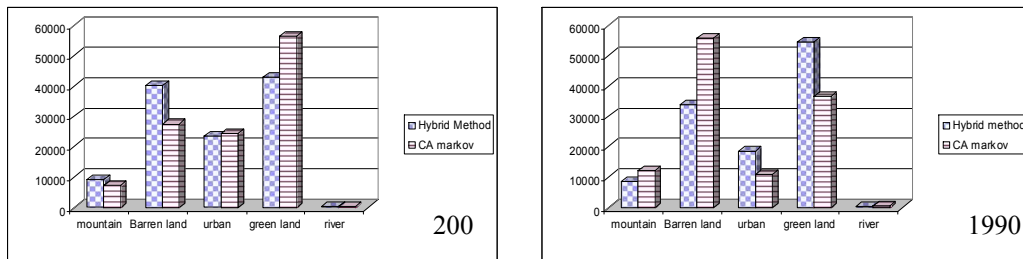
Overall accuracy: 88.98%

**Table 13:** Error matrix of land cover map produced by Hybrid method for 2001

	Mountain	Barren land	Urban	Green cover	River	Total	Commission error
Mountain	2846	6	0	0	0	2852	0.0021
Barren land	151	6983	10	103	0	7247	0.0364
Urban	72	0	3600	13	24	3709	0.294
Green cover	2	11	505	2759	1	3278	0.1583
River	0	0	0	0	154	154	0
Total	3071	7000	4115	2875	179	17240	
Omission error	0.0731	0.0024	0.1252	0.0403	0.1397		0.0521

Kappa coefficient: 0.92

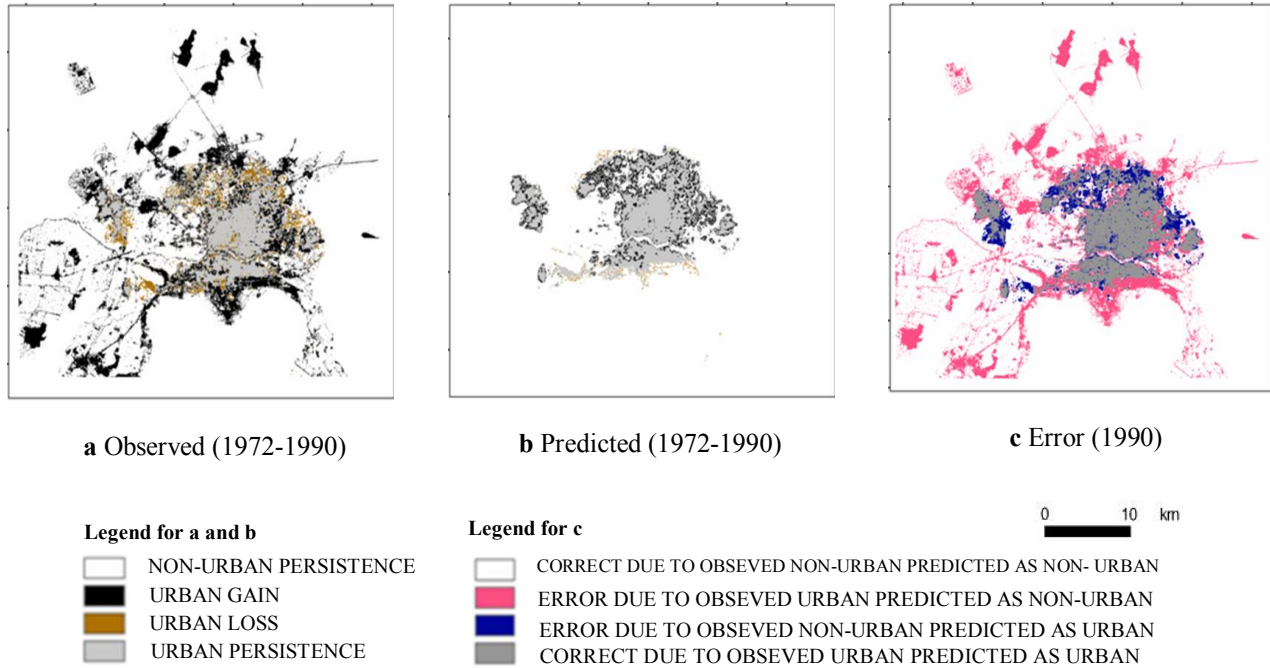
Overall accuracy: 94.79%



**Figure 5:** Comparison of total area of different land cover classes by the hybrid and Markov model classifications methods for 1990 and 2001

#### 4.5 Prediction Error

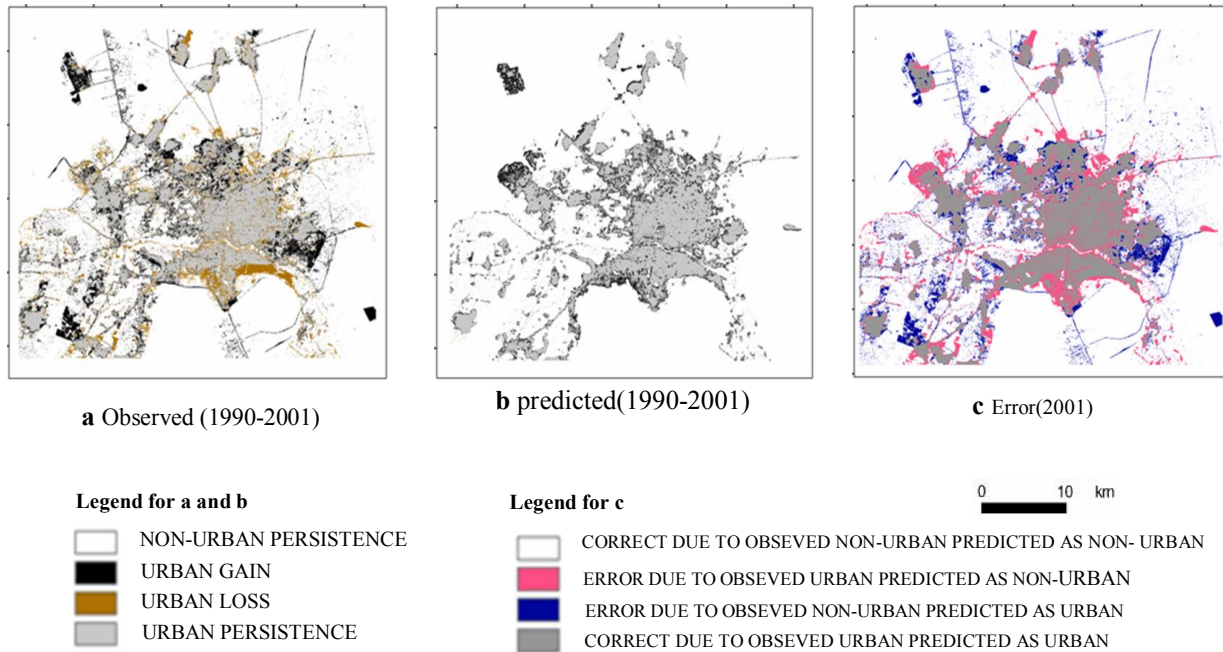
In this research, we would like to describe or understand our prediction errors. Therefore, the urban class (the most important class in our study) was separated from the other land cover classes to produce maps with only two land use classes: urban and non-urban maps. Given two times, a reference map for each and a prediction map for the second time, there are three possible two-map comparisons.



**Figure 6:** The urban class of Isfahan map: a observed change 1972-1990, b predicted change 1972-1990, c prediction error 1990

A comparison between the reference map of time 1 and the reference map of time 2 characterizes the observed change in land use for the area. A comparison between the reference map of time 1 and the prediction map of time 2 characterizes the model's predicted change, which reflects the behavior of the model. A comparison between the reference map of time 2 and the prediction map of time 2 characterizes the accuracy of the prediction. This third two-map comparison is most productively interpreted by considering the first two two-map comparisons (Pontius et al. 2008).

The three possible two-map comparisons were performed for the periods 1972-1990 and 1990-2001 and the relative maps are given in Figures 6 and 7. The prediction error maps (the third map) for 1990 and 2001 have four classes: error due to observed non-urban areas predicted as urban, correct due to observed urban predicted as urban, correct due to observed non-urban predicted as non-urban and error due to observed urban predicted as non-urban.



**Figure 7:** The urban class of Isfahan map: a observed change 1990-2001, b predicted change 1990-2001, c prediction error 2001

## 5. Conclusion

Land cover mapping and change detection have increasingly been recognized as one of the most effective tools for environmental resource management. Isfahan and its environs are undergoing a fast, unplanned development, where urban area is growing without any consideration of the landscape types that are being transformed. If we suppose that processes like political policy, social and economical factors and also population factors which can change land cover and land use were constant across time, we would assume that model prediction results would be in agreement with past change trends. In the real world, these changes are not constant over long periods, so it is difficult to assume that future changes are the same as those which have gone before, potentially violating the Markov assumptions and therefore affecting the results of the predicting model. Finally, we can conclude that if processes of land cover change remain fixed and constant, CA-Markov model predicts land cover changes with validation for the following years which agreement of predicted map with real map would be less than 70% for this study area.

## 6. References

1. Alphan H., Doygan H., and Unlukapman YI, (2008), Post-classification of land cover using multitemporal Landsat and ASTER imagery: the case of Kahramanmara, Turkey, Environmental Monitoring and Assessment, 10,pp 1-10.

2. Ayodeji Opeyemi Z., (2006), Change detection in land use and land cover using remote sensing data and GIS, (A case study of Ilorin and its environs in Kwara State). The Department of Geography, University of Ibadan in Partial Fulfillment for the award of Master of Science.
3. Batty M., Couclelis H., and Eichen M, (1997), Urban system as cellular automata. *Environment and Planning*, 24(2),pp 159-164.
4. Bell E.J, (1974), Markov analysis of land use change: an application of stochastic processes to remote sensed data, *Socio-Economic Planning Sciences*, 8,pp 311-316.
5. Congalton, R.G, (1988), Using spatial autocorrelation analysis to explore the error in maps generated from remotely sensed data, *Photogrammetric Engineering and remote sensing*, 54,pp 587-592.
6. Coppin P., Jonckheere I., Nackaerts K., and Muys B, (2004), Digital change detection methods in ecosystem monitoring: a review, *International Journal Remote Sensing*, 25,pp 1565-1596.
7. J.R.Estmen., (1995), *Idrisi for windows user guide version 1/0*. Clark University.
8. Chang C.L., and Chang, J.C, (2006), Markov model and cellular automata for vegetation, *Journal of Geographical Research*, 4,pp 45-57.
9. Fan F., Wang Y., and Wang Z, (2008), Temporal and spatial change detecting (1998-2003) and predicting of land use and land cover in core corridor of Pearl River delta (China) by using TM and ETM<sup>+</sup> images, *Environmental Monitoring and Assessment*, 137,pp 127-147.
10. Guindon B., Zhang Y., and Dillabaugh, C, (2004), Landsat urban mapping based on a combined spectral- spatial methodology, *Remote sensing of environment*, 92,pp 218-232.
11. Hathout S, (2002), The use of GIS for monitoring and predicting urban growth in East and West St Paul, Winnipeg, Manitoba, Canada,. *Journal of Environmental Management*, 66,pp 229-238.
12. Jahan S, (1986), The determination of stability and similarity of Markovian land use change processes: a theoretical and empirical analysis, *Socio-Economic Planning Sciences*, 20,pp 243-251.
13. Jensen J.R., and Cowen D.C, (1999), Remote sensing of urban suburban infrastructure and socio-economic attributes, *Photogrammetric Engineering and Remote Sensing*, 65,pp 611-622.

14. Lambin E.F, (1997), Modeling and monitoring land-cover change processes in tropical regions, *Progress in phys. Geography*, 21(3),pp 375-393.
15. Lo'peza E., Bocco G., Mendoza M., and Duhau E, (2001), Predicting land-cover and land-use change in the urban fringe: a case in Morelia city, Mexico, *Landscape and Urban Planning*, 55,pp 271-285.
16. Parker D.C., Manson S.M., Janssen M.A., Hoffmann M.J., and Deadman, P, (2002), Multi agent systems for the simulation of land use and land cover change: a review, 43.
17. Pontius Jr R.G., and Schneider L.C, (2001), Land-cover change model validation by an ROC method for the Ipswich watershed, Massachusetts, USA, *Agriculture, Ecosystems and Environment*, 85,pp 239-248.
18. Pontius Jr R.G., Huffaker D., and Denman K, (2004), Useful techniques of validation for spatially explicit land change models. *Ecological modeling*, 179,pp 445-461.
19. Pontius Jr R.G., and Spencer J, (2005), Uncertainty in extrapolations of predictive land cover models. *Environment and Planning B: Planning and Design*, 32,pp 211-230.
20. Pontius Jr R.G., Boersma W., Castella J.C., Clarke K., Nijs, T.D., Dietzel C., (2008), Comparing the input, output, and validation maps for several models of land change, *Annals of Regional Science*, 42,pp 11-37.
21. Rees W.G., Williams M., and Vitelosc P, (2003), Mapping land cover change in a reindeer herding area of the Russian arctic using Landsat TM and ETM+ imagery and indigenous knowledge, *Remote sensing of environment*, 85,pp 441-452.
22. Robinson V.B, (1978), Information theory and sequences of land use: an application, *The Professional Geographer*, 30 (2), 174-179.
23. Singh A, (1989), Digital change detection techniques using remotely-sensed data, *International Journal of Remote Sensing*, 6,pp 989-1003.
24. Schneider L.C., and Pontius JR R.G, (2001), Modeling land use change in the Ipswich watershed Massachusetts, USA, *Agriculture, Ecosystems and Environment*, 85,pp 83-94.
25. Weng Q.H, (2002), Land use change analysis in the Zhujiang Delta of China using satellite remote sensing, GIS and stochastic modeling, *Journal of Environment management*, 64,pp 273-284.

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26. Wijanarto A.B, (2006), Application of Markov change detection technique for detecting Landsat ETM derived land cover change over Banten Bay, Journal Ilmiah Geomatika, 12(1),pp 11-21.
  27. Wolfram S, (1984), Cellular automata as models of complexity, Nature, 31,pp 419-424.
  28. Wu Q., Li H.Q., Wang S., Paulussen J., He Y., Wang M., Wang B.H, and Wang, Z, (2006), Monitoring and predicting land use change in Beijing using remote sensing and GIS, Landscape and Urban Planning, 78,pp 322-333.
  29. Yang Q., Li X., Shi X, (2008), Cellular automata for simulating land use changes based on support vector machines, Computers & Geosciences, 34,pp 592-602.