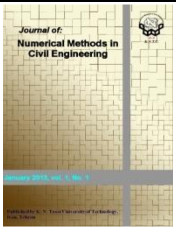

Numerical Methods in Civil Engineering

Integration of SimWeight and Markov Chain to Predict Land Use of Lavasanat Basin

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Abstract:

Production and prediction of land-use/land cover changes (LULCC) map are among the significant issues regarding input of many environmental and hydrological models. Among various introduced methods, similarity-weighted instance-based machine learning algorithm (SimWeight) and Markov-chain with lower complexity and proper performnce are frequently used. The main aim of this study is utilizing SimWeight along with Markov chain to predict land-use map of Lavasanat basin located in north-east of Tehran for the year 2018. In this regrad, eight driver variables and two land-use maps of the sudy area which were created from two Landsat-5 TM image sensor for the years 2000 and 2011 were considered as input. To evaluate the result of SimWeight, Receiver Operating Characteristic was used. The Land-use map of year 2018 was predicted using the proposed method. To evaluate this map, a land-use map of 2018 was produced using classification of a Landsat-8 OLI image. The results of model and value of area under curve (AUC) for transition potential map was about 0.78, which indicated good performance. Furthermore, the comparison of two produced and predicted land-use maps of 2018 shows great similarity. Generally, the results indicated the proper performance of the propsed method to predict LULCC.

1. Introduction

Land-Use/Land Cover Changes (LULCC) has major effects on a number of factors of ecological-environment like ecosystem functioning, climate change, deforestation etc. (Li et al., 2015)[12]. To understand the process of LULCC, such as deforestation or continuous urbanization, modeling can inform scientists and policymakers about the possible future conditions under different scenarios (Zadbagher et al., 2018)[25]. The overall procedure of land change modeling include the past land-use analysis and evaluation, finding the connection of changes and driver variables to find out suitability maps (potential of transition from one LULC to another), determining the total amount of land that will change (demand), and eventually allocation of each category of LULC (Murayama, 2012)[15]. There are many different methods used to model LULCC, of which, some of more important ones are introduced in the following.

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Among the most important methods to point out can refer to Artificial neural network multi-layer perceptron (Taud and Mas, 2018)[23], which uses a supervised training procedure by taking advantage of examples of data with known outputs of data (Bishop, 1995)[2].The course of action produces a nonlinear function model, which can predict the output of the data from the dataset. Cellular Automata -Markov chain (CA-Markov) (Ghosh et al., 2017)[10, Eastman, 2015)[5], which uses Markov chain model to analyze the probability of change of one state (the first land-use map) to another one (the second land-use map) is another example of LULC models (Moghadam and Helbich, 2013)[13]. In CA, the model is implemented to consider the spatial nature and also direction of data; In other words, CA considers the neighborhood of cells by defining spatial filter as well as previous state of each cell.

Dinamica EGO (EGO stands for Environment for Geo-processing Objects) is a flexible software for environmental modeling (Soares-Filho et al., 2009)[22]. Using software interface, users can design their model with a complete series of spatial algorithms for the simulation of space-time phenomena like LUCC models (Rodrigues and Soares-Filho, 2018)[18]. The renowned Weights of

Evidence (WoE) is a quantitative method that is based on conditional probabilities (Soares-Filho et al., 2010)[21]. In LULCC modeling, this method is applied to create layers of change probability, taking into account spatial variables such as distance, slope, and so forth.

Researches in recent years can mention the study by (Li et al., 2015)[12] which used CA-Markov model to predict spatiotemporal change of LULC in a watershed with a lake. They used high resolution satellite images of 2006 and 2009 years as input data and then made a prediction for LULC for the year 2014. The overall accuracy estimated from quantitative comparison was about 88 percent.

Gago-Silva et al. (2017)[9] used Bayesian method with a weight of evidence approach. They modeled the probability of LULCC in an area in Switzerland and utilized CA for spatial allocation of land-use classes. They investigated three different scenarios (business, liberalization, and lowered agriculture production) in Dinamica EGO model and evaluated the impact of each scenario on LULCC for the year 2050. Tran et al. (2017)[24] used MLP method to investigate changes in LULC and characterize impacts of these changes on urban heat with Land surface temperature (LST) index. Results from this work provided a new method for Urban Heat Island (UHI) effects and indicated that LST depends on LULC types in a nonlinear manner.

One of the useful methods to model LULCC is SimWeight. This method is an instance-based machine learning algorithm (Sangermano et al., 2010)[19]. The procedure of transition potential prediction is based on driver variable of land-use change without defining complex parameter. This method is used in many different areas and for various purposes. We can refer to the following studies which used SimWeight method. Mozumder et al. (2016)[14] compared SimWeight model with logistic regression and MLP methods to evaluate their applicability for built-up transitions. They simulated land-use changes for the 1989-2001 period to produce transition potential maps for 2011 and validated their results with multi-regression validation method. Results indicate that SimWeight and MLP method predicted changed areas with more accuracy than logistic regression method. Bununu (2017)[3] simulated urban expansion in Nigeria. They used SimWeight to calculate transition potential maps. Satisfactory outcomes from relative operating characteristic and kappa index of agreement demonstrated ability of method to model transition potential. Shrestha et al., (2018)[20] employed SimWeight model to calculate land-use change maps and evaluated these changes on streamflow and sediment in a basin. They concluded that land-use transition potential modeling can result in spatial variations of change. Therefore, land use demand uncertainty causes the highest streamflow and sediment load changes.

As the previous studies demonstrate, different methods were developed to model and predict LULCC. Among those methods SimWeight is a frequently used method with acceptable performance. In this study, SimWeight method is used to produce the transition potential map of Lavasanat basin located in north-east of Tehran. In this regard, different driver variables were standardized and applied as input of method to produce transition potential maps. Three satellite images (from Landsat 5 TM and Lansat 8 OLI of the years 2000, 2011, and 2018) and other information layers were used to create land use images. Markov chain was used to calculate the transition probability matrix of 2018 from land use of years 2000 and 2011. Afterwards, land-use map of 2018 was predicted. The predicted land-use of 2018 was compared with the land-use map that was created from Support Vector Machines (SVM) classification of satellite image. Receiver Operating Characteristic (ROC) was calculated to evaluate the efficiency of SimWeight method.

2. Material and Methods:

2.1 Study area and used data

Lavasanat basin (Figure 1a) with an area about 995 km^2 is located in the north-east of Tehran metropolis. Jajrood River located in the study area emerges from Alborz Mountains with more than 4000 m elevation height (Figure 1b). Based on statistics from Statistical Centre of Iran for 5 years, from 1996-2001, the population of the area increased about 37.5 percent and average population growth for each year was about 7.5 percent. These accelerated changes indicate a pivotal role of evaluation and assessment of LULCC in Lavasanat basin.

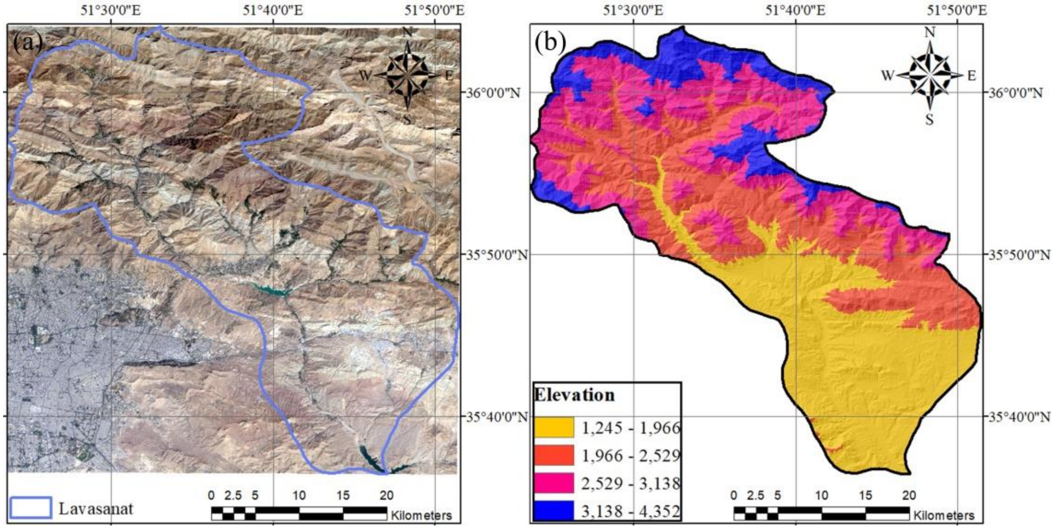

Fig. 1: Study area Maps of a) Lavasanat basin, and b) Elevation ranges

In this study, three satellite images were used including Landsat-5 TM of June 8, 2000 and July, 9, 2011, and Landsat-8 OLI image of September 14, 2018. These mentioned images were used to produce land-use image of Lavasanat study area. Moreover, Digital Elevation Model of Shuttle Radar Topography Mission (SRTM-DEM) data of the study region was prepared from Earthexplorer 2018. Furthermore, digital maps of open street, roads, and land-use of study area were gathered from (Download.geofabrik.de, 2018)[4] data server.

2.2 Pre-processing of data and driver variables

In order to calculate the transition potential map, eight information layers were produced. The selected layers include DEM, slope, focal statistic, inverses distance to settlement areas, inverse distances to rivers and tributaries, inverse distance to roads, evidence likelihood transformation of pixels which change to built-up class, and evidence likelihood transformation of pixels which changes to Vegetation cover class. Focal statistic layer (annulus type) was created from land-use map considering land-use classes. Undoubtedly, this analysis shows neighborhoods with many types of existing land-uses. This analysis can be useful to identify the locations with lack of variability in the distribution of land-use. Since different driver variables have different variable space, their values should be standardized. To do this, the evidence of likelihood transformation was applied to the categorical explanatory variable (changes of other classes–to built-up from) and changes to vegetation cover from 2000 to 2011). For other driver variables, the linear standardize method is chosen. Based on Eastman, (2015)[6], evidence likelihood transformation is a very effective means of incorporating categorical variables in a set of Boolean variables.

2.3 SimWeight method

SimWeight method which originated from K-nearest neighbor technique (Fix and Hodges Jr, 1951)[8] is an instanced-based machine learning algorithm. In this method, weighted-distances are computed in a changeable space to known instances for the classes. In creation of transition potential maps for LULCC modeling, each transition can have two positions: change or persistence. To evaluate each pixel, SimWeight extracts the K-nearest neighbors and afterwards computes the distance in variable space to the instances of change that falls in the range of k (Figure 2).

To produce a continuous surface of class membership, the distance is inputted in an exponential weighting function. Then, the following equation (Soares-Filho et al., 2010)[21] is used to calculate the class membership of each pixel:

$$Membership_{change} = \frac{\sum_{i=1}^{c}\left(1.0 - \frac{1}{1+e^{1/d_i}}\right)}{k} \qquad (c \le k) \qquad (1)$$

In this equation, k is the number of adjacent pixels (change + persistence), c shows the number of change pixels within the k nearest neighbours, and d denotes the distance to a change instance i. Large value of membership would convey that a pixel has similar environmental condition to those that have already changed (Eastman, 2015)[5]. Therefore, higher membership indicates high transition potential.

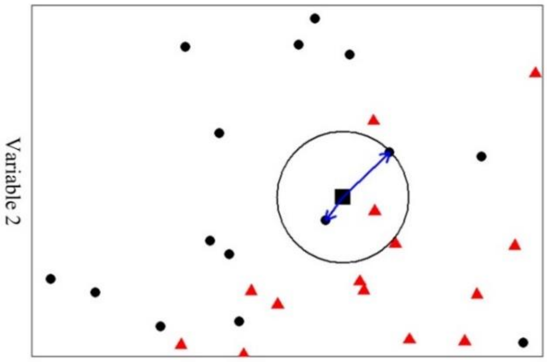

Fig.2: Variable space produced by two variables Triangles shows persistence and Circles that represent the change. The solid squares represent evaluation pixels with undetermined transition potential. In the circle there are two change samples and two persistence samples, therefore k=4. Arrows represents the vector of distance in the variable space.

The SimWeight is different from the K-Nearest Neighbor (KNN) in two aspects. The former, SimWeight, estimates a continuous statement of class membership rather than a crisp assignment. The latter method obtains its value only from instances of change because instances of persistence are certainly not examples of locations that will remain unchanged. Nevertheless, instances of change are clear.
One of the advantages of this algorithm is that it needs just one parameter k. Furthermore, using subset of training data for validation over a range of values for k, the ideal k can be estimated. In this study the ideal k=300. The k parameter controls the degree of generality of the solution. Setting k to a very low value will result in over-training. Setting it to a very high value will result in over-generalization. Finally, it is essential to mention that algorithm is distribution free and is easy to control interconnections that are non-linear and multi-modal (Sangermano et al., 2010)[19].

2.4 Relevance weight

To estimate the degree of importance of each driver variables, weights should be determined by comparing standard deviation of the variable inside the areas that have changed, to standard deviation of the variables of the study region. Equation 2 indicates the relevance weight.

$$\text{RelevanceWeight} = 1-(SD\ of\ Change\ /\ SD\ of\ Study\ Area) \tag{2}$$

The standard deviation of the variable inside the changed pixels will be smaller than standard deviation of the whole study area, if the variable is relevant for discriminating change. After determination of the weights for each driver variable, in order to discriminate change, standardized driver variables are multiplied by the weights that affect the scaling of each variable. These weights are used in the SimWeight method. In fact, by multiplying weight of each information layer (driver variable) to pixels of the regarding layer, the impact of each layer will change, which is effective on the final map.

2.5 Markov chain to calculate transition probability matrix

To produce probability of land-use change, Markov chain was used. This model is a stochastic process that describes how likely one state alters to another one. It has a key-descriptive tool, which is the transition probability matrix. The basis for producing transition probability matrix is that the prior condition of land-use can be used to predict present and future land-use. (Bell and Hinojosa, 1977)[1] reported that transition probability of LULCC in each specific time by having all prior land-use maps is related to nearest elapsed period. In the first step, the following equation is used to determine transition probability matrix:

$$P = (P_{ij}) = \begin{vmatrix} P_{11} & P_{12} & \dots & P_{1n} \\ P_{21} & P_{22} & \dots & P_{2n} \\ \dots & & & \\ P_{n1} & P_{n2} & \dots & P_{nn} \end{vmatrix} \tag{3}$$

where P_{ij} indicates transition probability from i to j (first stage to second one). In other words, the term on the subscript is derived from the observed data by counting the number of the changes from i to j (n_{ij}) and the number of occurrences of the n_i . n represents the number of classes in a land-use map. $\mathrm{P_{ij}}$ must incorporate the subsequent conditions:

$$\begin{cases} 0 \le P_{ij} \le 1 & (i, j = 1, 2, 3, \dots, \mathrm{n}) \\ \sum_{i=1}^{n} P_{ij} = 1 & (i, j = 1, 2, 3, \dots, \mathrm{n}) \end{cases} \tag{4}$$

Based on Markov algorithm and Bayesian probability, the prediction Markov model is computed using the following equation:

$$P_{(n)} = P_{(n-1)} P_{ij} \tag{5}$$

where n denotes a specified time period. The prediction of transition probability can be performed by analysis of two land-use maps of different dates (Hyandye and Martz, 2017)[11]. Accordingly, two images of years 2000 and 2011 were selected and were classified using SVM method. The land-use map contains four classes (Built-up, Water bodies, Vegetation cover, and Rangeland). In the final stage, a list of host classes which include categories that will lose area in rows, and ones that will gain area (claimant classes), was created using Multi-objective Land Allocation (MOLA). Eventually, MOLA algorithm solves the conflicts using the weighted ranks based on a minimum distance to ideal point rule. The allocation is performed for all claimant classes of each host class, but some pixels could transit to more than one claimant category. Therefore, the MOLA algorithm solves the conflicts based on a minimum-distance-to-ideal-point rule using the weighted ranks. Then, the final results is the overlay of each host class reallocation (Olmedo, 2018)[16]. Finally, the predicted land-use map is created.

2.6 Receiver Operating Characteristic (ROC)

In order to assess and validate the performance of LULCC model, the ROC analysis can be used to compare a map of actual change to maps of modeled suitability for LULCC (Pontius Jr and Schneider, 2001)[17]. To evaluate the agreement between the predicted and true transition, the probability map is compared with the true binary map of transition by making a curve, called the ROC curve. In such a curve, the horizontal axis indicates the proportion of not changed cells predicted as changed (false positive rate), and the vertical axis shows the portion of truly determined changed pixels (true positive rate). The Area Under Curve (AUC) of ROC is a good index to evaluate the performance of the method. The AUC statistic values varies from 0 to1 where a value of 0.5 represents no skill, a value of 1 indicates perfect skill, and values between 0 and 0.5 represent no calibration of the model (Fielding and Bell, 1997)[7].

In this study, four allowable transitions were contemplated; the allowable changes and main steps to predict land-use of 2018 are represented in figure 3.

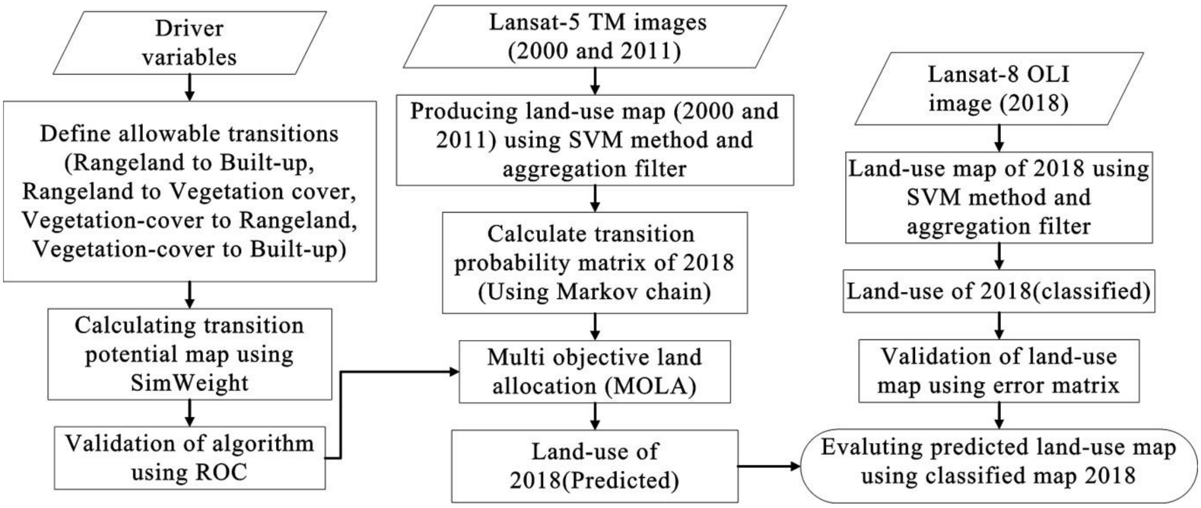

Fig. 3: The overall procedure of LULC prediction of this study

3. Results and discussion

As mentioned earlier, to calculate the transition potential map, 8 driver variables were selected. Figures 4a and b represent inverse standardized Digital elevation model and slope of the study area. Considering higher values in both of the figures, it can be deduced that the southern region has lower elevation and slope and the study area of this region has greater potential to city expansion as a result of anthropogenic activities due to lower slope and elevation.

Figure 4c shows the focal statistic layer which was created from annulus neighborhood filter of focal statistic. This map represents pixels, which have neighbor pixels with different land use category. Hence, it is expected that the pixels with higher values have greater potential to change. Figure 4 d, e, and f are created from inverse Euclidean distance from settlements, roads, and tributaries. As it is evident in this figure, higher distance from these classes can result in lower potential to changes. As illustrated in these maps, two other layers (figures 4g and h) are created from evidence likelihood transformation which shows pixels changes from 2000 to 2011. Accordingly, changed pixels have lower probability to change in the future.

Figure 5 represents the land-use maps of 2000 and 2011 produced from SVM method. Moreover, Table 1 shows count of changes from each class to another one. As it is evident in this table, most of the changes are from rangeland to built-up. This change demonstrates the expansion of urbanization and construction which might cause high instability in environmental conditions. Also, most changes are in the southern areas. Consequently, it can be concluded from this figure and previous figures that the southern region of the study area has greater potential compared with the northern parts.

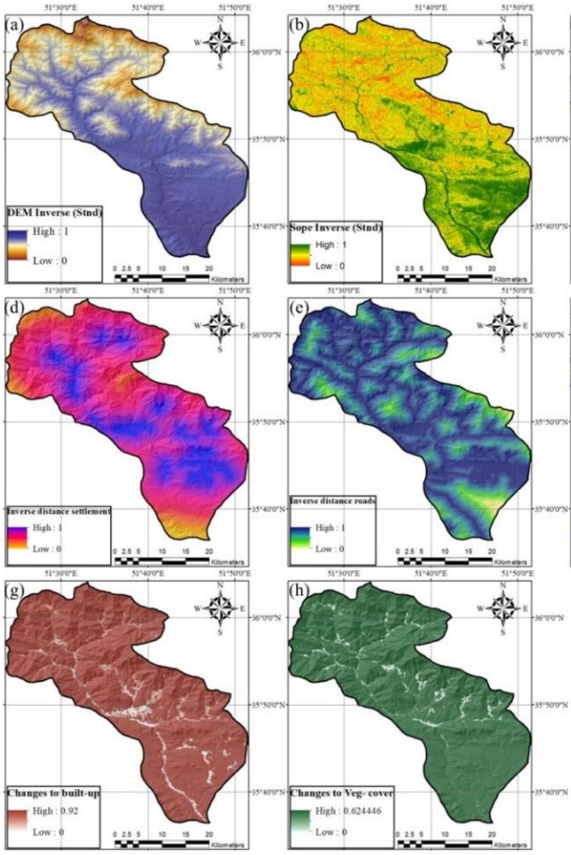

Fig.4: The driver variables used in SimWeight method

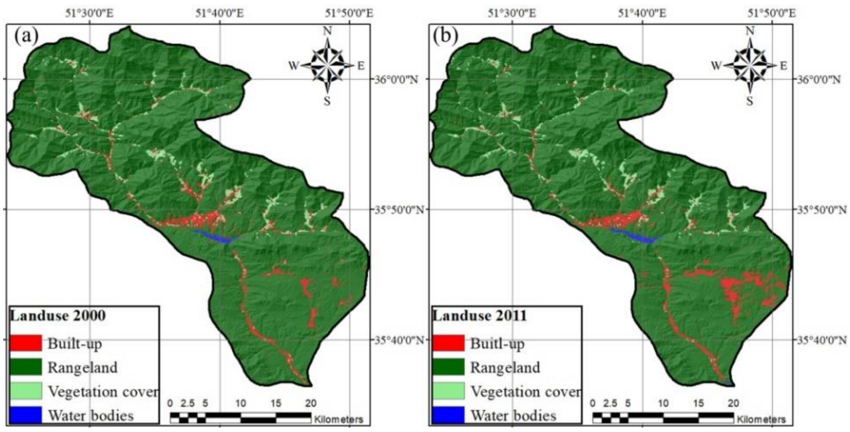

Fig.5: The land-use images of a) 2000 and b) 2011

The transition potential image which was produced by SimWeight method is shown in Figure 6a. The pixels which are portrayed in light black and white tones are more likely for changes; therefore, the southern areas are more prone to alter. The plot of estimated ROC to evaluate the performance of model in study area is represented in Figure 6b. The value of AUC statistic was about 0.78 which demonstrates a good value for the model. Moreover, as can be seen in the Figure 6b, the values of true positive are greater than false positives which indicate that the model is capable of prediction in a proper way. Furthermore, Figure 7a represents the produced land-use map of year 2018 created using SVM classification of Landsat 8-OLI sensor image. Figure 7b represents the predicted land-use map by the proposed method of this study. The differences between the produced and the predicted land-use maps are indicated in Figure 7c. The values of 1 to 4 correspond to water-bodies, built-up, vegetation cover, and rangeland classes, respectively. For instance, 2|3 represents pixels that are built-up in predicted image but in classified image, they were classified as vegetation cover. Moreover, Table 2 represents error matrix, Kappa coefficient, and overall accuracy of this map. As can be seen in Table 2, the accuracy of image is acceptable (both kappa coefficient and overall accuracy are more than 0.95).

Table 1. The land-use changes from 2000 to 2011

Class name	Count (Pixels)	Areas (km2)
Water bodies to Water bodies	2582	2.3238
Built-up to Water bodies	203	0.1827
Vegetation cover to Water bodies	13	0.0117
Rangeland to Water bodies	633	0.5697
Built-up to Built-up	22339	20.1051
Vegetation cover to Built-up	2619	2.3571
Rangeland to Built-up	20701	18.6309
Built-up to Vegetation cover	3346	3.0114
Vegetation cover to Vegetation cover	24967	22.4703
Rangeland to Vegetation cover	3709	3.3381
Water bodies to Rangeland	18	0.0162
Built-up to Rangeland	11650	10.485
Vegetation cover to Rangeland	3344	3.0096
Rangeland to Rangeland	1009016	908.1144

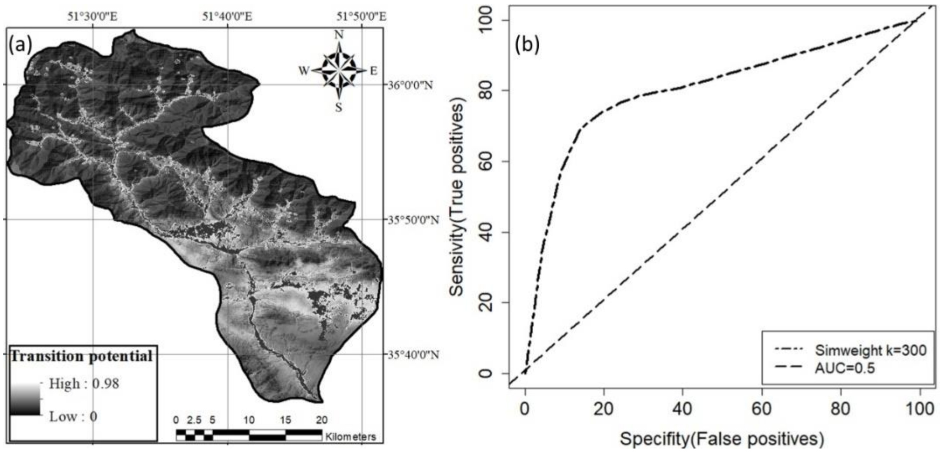

Fig. 6: a) The transition potential produced by SimWeight method, and b) the ROC curve for SimWeight (K=300)

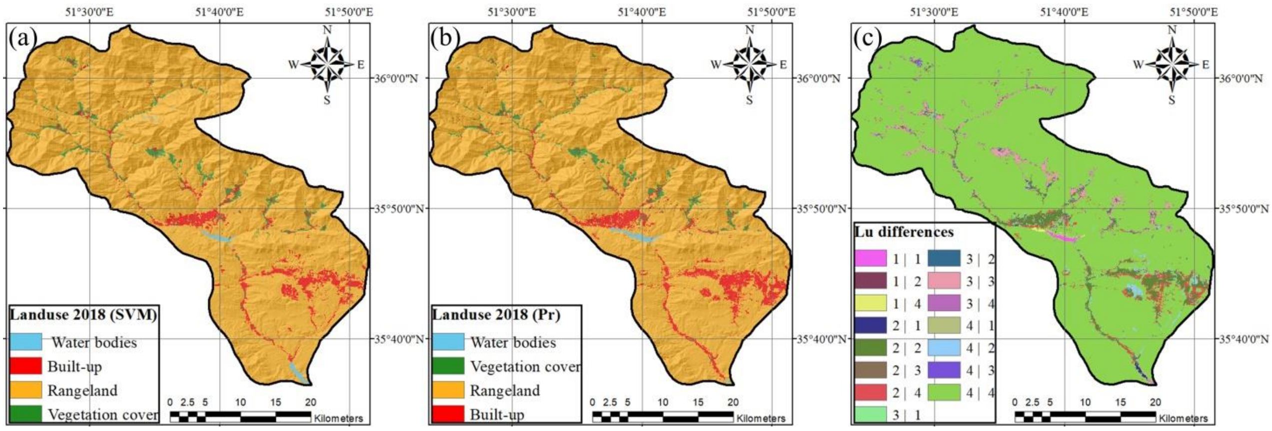

Fig. 7: The map of a) land-use of 2018 produced from SVM classification of Landsat-8 OLI image sensor, b) predicted land-use of 2018, and c) difference between created image and predicted in which 1=water-bodies, 2=Built-up, 3=Vegetation-cover, 4=Rangeland

Table 2. The error matrix of the produced land-use map of year 2018

Ground Truth (Percent)	Waterbodies	Built-up	Vegetation-cover	Rangeland	Kappa Coefficient = 0.9502
Water bodies	100	0	0	0.61	Overall Accuracy = 97.4104%
Built-up	0	88.59	0	0	
Vegetation-cover	0	2.17	98.91	0	
Rangeland	0	9.24	1.09	99.39	
Total	100	100	100	100	

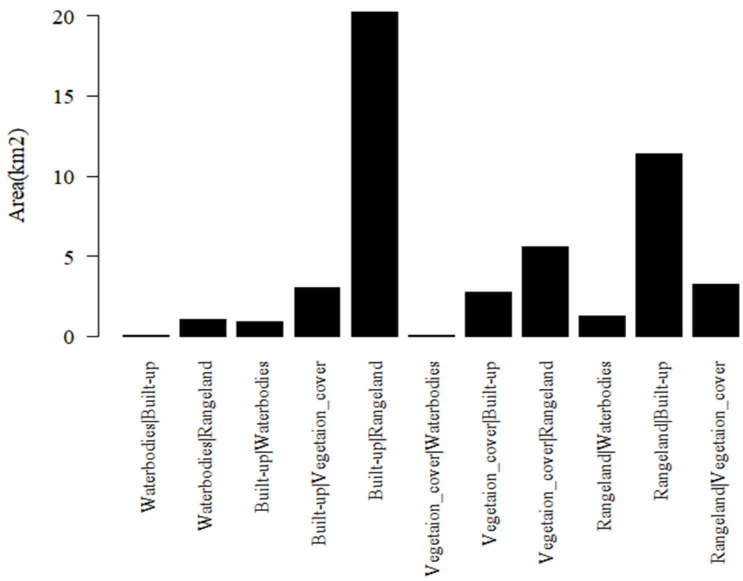

Fig. 8: The differences between two predicted and produced land-use of 2018 based on area (km2)

Figure 8 indicates the differences between two predicted and produced images (km2). The most significant difference belongs to Rangeland and built-up classes. In other words, some areas that are classified as built-up in predicted image are considered as rangeland in produced image and conversely.

In general, the results indicate proper performance of the model to predict land-use changes. The changes in Lavasanat basin indicate that civic development is the prime concern in the study area.

4. Conclusion

LULC and its changes are among the most important issues which can be used as input of many environmental models. Therefore, prediction of LULCC in an area can inform us about the changes. To predict land-use maps, different models are developed. However, many of them are so complicated and need many input parameters. Among the LULCC models, SimWeight algorithm is a machine learning algorithm without defining complex parameters. Subsequently, the objective of this study was utilizing SimWeight algorithm to produce Transition potential maps of Lavasanat basin. To do this, eight information layers were employed as input layers (driver variable). Then, land-use map of 2000 and 2011 were created using Markov chain to estimate transition probability matrix. Afterwards, Multi-objective Land Allocation (MOLA) was utilized to predict land-use map of 2018. ROC and AUC methods were used to evaluate the performance of SimWeight method in estimation of the transition potential map of study area. The results of ROC and AUC depicted the proper accuracy and performance of the proposed method. Furthermore, the land-use map of 2018 was produced using a Landsat-8 OLI image to compare this map with the output of the model. The results revealed that the most predominant changes are from rangeland to built-up classes that can be a result of expansion of urbanism. Additionally, the maximum difference between the produced and the predicted image are in changes from rangeland to built-up and conversely. In general, the results revealed the satisfactory performance of the SimWeight and Markov Chain to predict land-use of Lavasanat basin.

References

[1] BELL, E. J. & HINOJOSA, R. 1977. "Markov analysis of land use change: continuous time and stationary processes", Socio-Economic Planning Sciences, 11**,** 13-17.

[2] BISHOP, C. M. 1995. "Neural networks for pattern recognition", Oxford university press.

[3] BUNUNU, Y. A. 2017. "Integration of Markov chain analysis and similarity-weighted instance-based machine learning algorithm (SimWeight) to simulate urban expansion", International Journal of Urban Sciences, 21, 217-237.

[4] DOWNLOAD.GEOFABRIK.DE 2018. "Geofabrik Download Server. [online] Available at: http://download.geofabrik.de/ [Accessed 4 Dec. 2018]",

[5] EASTMAN, J. 2015. "TerrSet: Geospatial Monitoring and Modeling Software", Clark Labs, Clark University.

[6] EASTMAN, J. R. 2015. "TerrSet manual", Accessed in TerrSet version, 18, 1-390.

[7] FIELDING, A. H. & BELL, J. F. 1997. "A review of methods for the assessment of prediction errors in conservation presence/absence models", Environmental conservation, 24, 38-49.

[8] uthor 1951. "Discriminatory analysis-nonparametric discrimination: consistency properties". California Univ Berkeley.

[9] GAGO-SILVA, A., RAY, N. & LEHMANN, A. 2017. "Spatial Dynamic Modelling of Future Scenarios of Land Use Change in Vaud and Valais, Western Switzerland", ISPRS International Journal of Geo-Information, 6, 115.

[10] GHOSH, P., MUKHOPADHYAY, A., CHANDA, A., MONDAL, P., AKHAND, A., MUKHERJEE, S., NAYAK, S., GHOSH, S., MITRA, D. & GHOSH, T. 2017. "Application of Cellular automata and Markov-chain model in geospatial environmental modeling-A review", Remote Sensing Applications: Society and Environment.

[11] HYANDYE, C. & MARTZ, L. W. 2017. "A Markovian and cellular automata land-use change predictive model of the Usangu Catchment", International Journal of Remote Sensing, 38, 64-81.

[12] LI, S., JIN, B., WEI, X., JIANG, Y. & WANG, J. 2015. "Using Ca-Markov Model to Model the spatiotemporal change of land use/cover in Fuxian Lake for decision support", ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 2, 163.

[13] MOGHADAM, H. S. & HELBICH, M. 2013. "Spatiotemporal urbanization processes in the megacity of Mumbai, India: A Markov chains-cellular automata urban growth model", Applied Geography, 40, 140-149.

[14] MOZUMDER, C., TRIPATHI, N. K. & LOSIRI, C. 2016. "Comparing three transition potential models: A case study of built-up transitions in North-East India", Computers, Environment and Urban Systems, 59, 38-49.

[15] MURAYAMA, Y. 2012. "Progress in geospatial analysis", Springer Science & Business Media.

[16] OLMEDO, M. C. 2018. Multi-objective land allocation (MOLA). Geomatic Approaches for Modeling Land Change Scenarios. Springer.

[17] PONTIUS JR, R. G. & SCHNEIDER, L. C. 2001. "Land-cover change model validation by an ROC method for the Ipswich watershed, Massachusetts, USA", Agriculture, Ecosystems & Environment, 85, 239-248.

[18] RODRIGUES, H. & SOARES-FILHO, B. 2018. A short presentation of dinamica ego. Geomatic Approaches for Modeling Land Change Scenarios. Springer

[19] SANGERMANO, F., EASTMAN, J. R. & ZHU, H. 2010. "Similarity Weighted Instance-based Learning for the Generation of Transition Potentials in Land Use Change Modeling", Transactions in GIS, 14, 569-580.

[20] SHRESTHA, B., COCHRANE, T. A., CARUSO, B. S. & ARIAS, M. E. 2018. "Land use change uncertainty impacts on streamflow and sediment projections in areas undergoing rapid development: A case study in the Mekong Basin", Land Degradation & Development, 29, 835-848.

[21] SOARES-FILHO, B., MOUTINHO, P., NEPSTAD, D., ANDERSON, A., RODRIGUES, H., GARCIA, R., DIETZSCH, L., MERRY, F., BOWMAN, M. & HISSA, L. 2010. "Role of Brazilian Amazon protected areas in climate change mitigation", Proceedings of the National Academy of Sciences, 107, 10821-10826.

[22] SOARES-FILHO, B. S., RODRIGUES, H., COSTA, W. & SCHLESINGER, P. 2009. "Modeling environmental dynamics with Dinamica EGO", Centro de Sensoriamento Remoto. Universidade Federal de Minas Gerais. Belo Horizonte, Minas Gerais, 115.

[23] TAUD, H. & MAS, J. 2018. Multilayer perceptron (MLP). Geomatic Approaches for Modeling Land Change Scenarios. Springer.

[24] TRAN, D. X., PLA, F., LATORRE-CARMONA, P., MYINT, S. W., CAETANO, M. & KIEU, H. V. 2017. "Characterizing the relationship between land use land cover change and land surface temperature", ISPRS Journal of Photogrammetry and Remote Sensing, 124, 119-132.

[25] ZADBAGHER, E., BECEK, K. & BERBEROGLU, S. 2018. "Modeling land use/land cover change using remote sensing and geographic information systems: case study of the Seyhan Basin, Turkey", Environmental monitoring and assessment, 190, 494.