

Evaluation of the effects of minimum winter temperatures on changing the type of cultivation and changing the use of agricultural lands. (Case study: Urmia county)

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Abstract

Land use and land cover change (LULC) and climate change are among the major threats to the global environment. Assessing the causes of land use change and its relationship with climate change is one of the important issues that understanding its process can help better human interaction with the environment. Therefore, the purpose of this study is to evaluate the effects of climate change on changing land use and land cover. The indicators used to achieve the mentioned goal are: ((average minimum winter temperatures), Number of days ($\leq 0^{\circ}\text{C}$), Number of days ($\leq -10^{\circ}\text{C}$) and 30-year Landsat satellite images)), CMIP5(CanESM2) model was used to predict temperature changes and CA-MARKOV model was used to predict land use changes and finally Pearson correlation coefficient test was used to measure the correlation. The results of the study indicated that, there is a direct relationship between changes of minimum winter temperatures and changing the type of cultivation and land use in Urmia city. Also, simulation of temperature changes showed that there is the highest (> 0.8) correlation between rcp4.5 scenarios and land use changes, which indicates a high probability of changes in the specified time period (2018–2033).

1 Introduction

Over the past century, global warming has been closely related to human activities, Climate change is expected to increase future temperatures, potentially resulting in change and reduced crop production in many key production regions. Temperature changes are one of the most important factors that affect climate changes; eventually, this also impacts land use/land cover (LULC) changes (Zoran, 2010). Change detection is useful in many applications related to land use and land cover (LULC) changes, such as shifting cultivation and landscape changes (Imbernon, 1999; Serra, Pons, & Saurí, 2008), land degradation and desertification (Adamo & Crews- Meyer, 2006; Gao & Liu, 2010),

Changes in LULC are one of the fundamental concerns associated with changes in the global environment and sustainable development. Rapid worldwide population growth, accompanied by economic activities causing urban agglomeration and subsequent construction and land expansion, has led to rapid LULC changes (Guan et al., 2011; Halmy et al., 2015; Zheng et al., 2015). Although, different studies have been conducted in the field of climate change and land use change, in most of these studies, the most important factor of land use change (climate change) has been given less value or most studies have focused on the effects of land use change on small-scale temperature changes. For example, (Darvishi 2018) examines the relationship between land use change and land surface temperature in Marivan and shows that increasing the area of residential land and reducing vegetation and agricultural land has increased the temperature in the study period. (pielke et al., 2011; Oleson et al., 2004). Other studies assessed land use change scenarios and modeling (Gollnow et al., 2018; Nazar Nezhad et al., 2018; Rajabzadeh, 2016; Prestele et al., 2017) or scenarios of climate change using simulation models (KyunPark et al., 2015; Huang et al., 2015; (Weinberger et al., 2017; Fix et al., 2018; Barredo et al., 2018). As mentioned, so far there have not been many specialized studies on the effects of climate change on changes of agricultural land use. Climate change and its effects on Urmia city,

especially Lake Urmia and also increasing the area of orchards in the region are among the most important reasons for this study. Therefore, the present study is based on the hypothesis that the reduction of glacial periods and winter frosts has led to the expansion of orchards.

Accordingly, the purpose of this study is to evaluate the rate of winter temperature changes ((1. Minimum winter temperature (Average) 2. The number of days ($\leq 0^{\circ}\text{C}$) 3. The number of days ($\leq -10^{\circ}\text{C}$)) changes in agricultural land use and type of cultivation in the town, simulate the future of these changes and finally to determine the degree of correlation between agricultural land use change and climate change.

2 Study Area

The Urmia County is located between longitude $37^{\circ} 04'N$ and $38^{\circ} 01'N$, and latitude $44^{\circ} 36'E$ and $45^{\circ} 16'E$ in West Azarbaijan Province in Iran. (Enayat Allah, 1988). In terms of its natural features, Urmia County encompasses an area of 1851.551 km², which is about 15.8% of the province. Its altitude ranges from 1000 m to 3500 m, and its average slope is 9%. Its political and administrative divisions are as follows: The Urmia county located is south of the city of Salmas, north of Naghda, east of Lake Urmia, west of Turkey, and southwest of Iraq. Urmia County is divided into five regions: Central, Anzal, Silivana, Somay Beraydost, and Nazlou; it has 20 rural districts (Ghesmati et al., 2015). Finally, according to statistics released by the Iranian Statistics Organization, in 2016, the county's population was 1,040,565 (www.amar.org.ir) (Fig. 1).

3 Methodology

3.1. LULC data

Five Landsat images of different Sensor (TM, ETM+, OLI) for study area were downloaded from the US Geological Survey Earth Explorer site (<https://earthexplorer.usgs.gov>). The acquisition dates with clear sky conditions for the Landsat data are presented in Table 1. We chose one scene study area close to summer to consider seasonal effects, such as the phenology of vegetation, and to increase classification accuracy, as found by Bechtel et al. (2015). All Landsat images were first clipped covering study area and then atmospheric-corrected into scaled reflectance data using ENVI Fast Line-of-sight Atmospheric Analysis of Hypercube (FLAASH). Nine of the 11 bands (bands 1-7, 10, and 11) in each Landsat 8 scene were used as input data. Based on the statistical characteristics of the different bands of the Landsat (TM, ETM+, OLI) images and a visual evaluation of selected band combinations, a false-color composite of (TM bands 5-4-3 and 4-3-2 (RGB)) and (ETM+ bands 3-4-7 and 4-5-7 (RGB)) was produced for the 1985-2010 images, also Seven of the 11 bands (bands 1-7) in Landsat 8 scene were used as input data for the 2018 image. Bands 1-7 in Landsat 8 sensor were the 30 m resolution Operational Land Imager (OLI) spectral bands.

3.1.1 LULC classification

Classification using satellite images is one of the current challenges in remote sensing. The use of remote sensing science has received a great deal of attention in areas where access to real data is difficult and impossible (Nogueira et al., 2017; Penatti et al., 2015; Xia et al., 2016). Recently, new algorithms and techniques have been introduced to categorize satellite imagery. It is important to examine and compare different classification algorithms in order to identify a suitable classification method in a particular region (Lu et al., 2007: 827). Currently, the support-vector machine (SVM) model is one of the methods most often used to classify images (Wang et al., 2013; Peng et al., 2017; Mirunalini et al., 2017). The SVM model finds a linear separating hyper plane with the maximal margin in this higher dimensional space. $C > 0$ is the penalty

parameter of the error term. Furthermore, $K(x_i; x_j) = \phi(x_i)^T \cdot \phi(x_j)$ is known as the kernel function. Although researchers are proposing new kernels, the following four basic kernels are listed in SVM books:

Linear: $K(x_i; x_j) = x_i^T x_j$

Polynomial: $K(x_i; x_j) = (\gamma x_i^T x_j + r)^d \quad \gamma > 0$.

Radial basis function (RBF): $K(x_i; x_j) = \exp(-\gamma \|x_i - x_j\|^2) = \gamma > 0$

Sigmoid: $K(x_i; x_j) = \tanh(\gamma x_i^T x_j + r)$ (Keerthi et al. 2003)

In this current study, a communally used radial basis function (RBF) kernel was recognized during image classification (Rimal et al. 2018). Finally, we used the Kappa coefficient to determine the accuracy of the classification.

3.1.2. LULC Simulation

Simulation of land use change is a process that predicts changes in the future based on older changes. There are several models for predicting future in land use changes. The most recent of these is the CA-Markov model (Rimal et al. 2018; Hernández-Guzmán et al. 2019; Surabuddin Mondal et al. 2016).

While the Markov model can quantitatively predict the dynamic changes of landscape patterns, it is not good at dealing with the spatial patterns of landscape change. On the other hand, the Cellular Automaton (CA) model has the ability to predict any transition among any number of categories (Gil et al., 2005). The important property of the CA model is that it demonstrates spatial and dynamic processes, which is why CA has been broadly used in land use simulations (Ye et al., 2008). Moreover, the state of each cell depends on the spatial and temporal state of its neighbors (Reddy et al., 2017). Combining the advantages of CA theory and the space layout forecast component of Markov theory, the CA-Markov model performs better than the Markov model or the CA model for modeling land cover changes for both time and spatial dimensions. At present, IDRISI software is one of the best platforms on which to run the CA-Markov model. That software was developed in the United States (US) by Clark Labs. Therefore, in the present study, the CA-Markov model in IDRISI software was used to predict the rate of land use change. Land uses are classified into seven categories (sandy soils, rocky soils, saline soils, residential and built-up lands, pastures, rainfed agriculture, irrigated arable lands, and orchards). The 18-year period of 2000-2018 was chosen to better and more accurately predict the amount of change in the period 2018-2033.

3.2. Climate change assessment

3.2.1 Historical climate data

To determine climate change we used the minimum temperature index. The minimum daily temperature data was obtained from the Urmia Synoptic Station for the period ranging from 1977 to 2017 (Mehrizi Zarea, 2018; Yousefi et al. 2018). Evaluating the region's Feature climate data was based on three indicators: 1. Minimum winter temperature (Average) 2. Number of days ($\leq 0^\circ\text{C}$) 3. Number of days ($\leq -10^\circ\text{C}$).

3.2.2 Climate change simulation

General circulation models are the most important methods for forecasting global and continental global climate variables. This study used the general circulation model to predict the climate variables of the Canadian model (CanESM2). This model is the only model that has the daily data available for SDSM software for three scenarios: RCP2.6, RCP4.5, and RCP8.5 (Thomson et al., 2011; IPCC, 2014) (Table 2).

Therefore, Canesm2 model in sdssm5.1 was used to predict changes in the minimum winter temperature in the period (2018-2033).

3.3 Correlation coefficient

A correlation coefficient is a numerical measure of some type of correlation, meaning a statistical relationship between two variables (Hoseini, 2003). Thus, we used the Pearson correlation coefficient in SPSS software because of the variables variety, (Van Loon and Laaha, 2015) (Figure 2).

4 Results And Discussions

4.1 Land use classification

In this study, satellite images from 1985, 1992, 2000, 2010, 2017 for seven land use categories: Sandy soils, Rocky soils, saline soils, built-up land, Pastures, rainfed agriculture, Orchards and Irrigated arable lands (Figure 3).

In the process of conducting the research study, the overall accuracy coefficient and the Kappa coefficient were used to determine the accuracy of the image classification (Table 3).

As seen in the information presented in Table 3, the overall accuracy of the classification and Kappa coefficient for all the studies years is >80%, and that result is confirmed. Accordingly, the rate of land use change during the studied years is shown in table 4.

The results of the land use change assessment show that most of the changes are related to Sandy soils and Orchards uses; the Sandy soils area decreased from 864 km² in 1985 to 460 km² in 2018, which represents a decrease of -0.077% of the area over a period of 33 years. In contrast, the use of Orchards increased from 131 km² in 1985 to 295 km² in 2018 (an increase of 0.032% in this area over a period of 33 years) Also, according to the classification, land use area of the built-up land and rainfed agriculture has increased, and Rocky soils and saline soils have decreased.

4.2 LULC Simulation

The CA-Markov model was used for land use and land cover changes simulation. A Transitional probability matrices produced by Markov model that prepare details on the probability of transition between LULC types during the periods 2000–2018 and 2010–2018 (Table 5). For example, the results of the model show that the probability of converting irrigated agricultural lands to orchards in the period 2000-2018 is about 25%, which has decreased by 2% in the period 2000-2018 to about 23%, and this shows that in the long run, the conversion rate of irrigated agricultural lands into orchards has been higher.

According to the prediction analysis, Rainfed agriculture areas will occupy 195.48 km² in 2025 and 196.74 km² in 2035. Rocky soils area is estimated to decrease to 176.54 km², and 166.36 km², in 2025 to 2033 (Fig 4). The results also show that Sandy soils and saline soils has been reduced by 28.20% and 1.23%, and the increased (Pastures, Built-up Land, Orchards, Irrigated arable lands) by (14.42%, 6.56%, 10.47%, 6.97%), respectively, in the period 2025-2033.

The results of land use changes in the period 1985-2003 showed that the area of three land uses (sandy soil, salty soil, and rocky soil) has decreased. (sandy soil = 7.7%) (Rocky soil = 2.7%) (Saline soils = 3.9%) While the increase 5 land use area (Built-up land =3.5%) (Pastures = 2.9%) (, Rainfed agriculture =3.2%) (Orchards = 4%) (Irrigated arable lands =0.06%) (Fig 5).

4.3 Assessment minimum temperature change

The observation data investigated at the time interval (1977-2017) shows an increase in the mean winter temperature (2.17° C), decreased the number of days ≤ 0 °C (80 days) and also decreased the number of

days ≤ -10 ° C (44 days). (Fig 6)

The analysis of observational data shows that the Minimum winter temperature (Average) from -5.36°C for the first 8 years of study (1977-1984) has fallen to -3.19°C , at 8 years end of study (2010-2017). This means that the average minimum winter temperature over a 40-year period has increased about 2.17°C . also, the number of days ≤ 0 ° C has decreased from 596 days in the period (1977-1984) to 516 days in the period (2010-2017) and the number of day's ≤ -10 ° C in the mentioned period has reduced from 141 days to 97 days.

4.4 Simulation minimum temperature change

After checking and controlling the quality of observational data, predictive CanESM2 variables were selected which most closely correlated with observational data.

According to Table (6), the RMSE coefficient (0.07%) is the representativeness of the model; this means that whatever approach to zero indicates the precision of modeling. Also, the Pearson correlation coefficient (0.94%), which indicates the correlation between observational data and predicted data

After modeling the temperature variable in the period (1961-2005) and evaluating the performance of the model, an attempt was made to simulate the temperature changes in the scenarios (RCP2.6, RCP4.5, RCP8.5) in the period (2006-2100). According to (Fig 7) the Minimum winter temperature variable will increase in the period of 2018-2025 under rcp2.6, rcp4.5, rcp8.5 scenarios (2.34 , 2.08 , 2.33°C) and for the period 2026-2033, (3.50 , 3.06 , 3.83°C) respectively. Also, the minimum winter temperature increased in the 2025-2033 period in comparison to the initial 1977–1985-time period (RCP2.6 = 5.67°C , RCP4.5 = 5.23°C , RCP8.5 = 6.002°C); moreover, the number of days $\leq 0^{\circ}\text{C}$ decreased (RCP2.6 = 260, RCP4.5 = 225, RCP8.5 = 286 days) and the number of days $\leq -10^{\circ}\text{C}$ also decreased (RCP2.6 = 132, RCP4.5 = 128, RCP8.5 = 131 days).

4.5 Correlation test between climate variables and land use and land cover change

According to Fig 8, there is a correlation between land use changes and variables (Minimum winter temperature (Average), number of days (≤ 0 ° C), and number of days (≤ -10 ° C)). More precisely, there is the highest correlation coefficient between changes in land use Rainfed agriculture, Orchards) and climate variables (Minimum winter temperature) with correlation coefficients (0.96%, 0.941%) and sig (0.001%, 0.002%) respectively. Also, there is an inverted correlation between the variables (Minimum winter temperature) and land use (Sandy soils, saline soils) with correlation coefficients (0.861%, 0.843%) and with sig (.013%, .017%) respectively. Finally, there is the highest correlation by correlation coefficient (0.867) and sig (0.012), between land use (Rocky soils) and (number of days (≤ -10 ° C) variable.

5 Conclusion

This study was conducted with the aim of evaluating the relationship between climate change (minimum winter temperatures) and change in type of cultivation and agricultural land use, using satellite images

classification and temperature data of Urmia Synoptic Station in the period (1977-2017) and simulating the rate of changes of agricultural land use and temperature patterns in the period (2018-2033). The results showed that the most land use changes include: increasing the land use areas of orchards and rainfed agricultural lands and reducing the land use areas of sandy and rocky lands. The study of temperature change scenarios also showed an increase in the average minimum winter temperature, so that the Rcp4.6 scenario had the highest correlation with a coefficient of more than 0.8% with land use changes. According to the proposed scenario, while the minimum winter temperature (average) has increased, the land use level (sandy, rocky, and saline soils) has decreased and the use of rainfed arable lands and orchards has increased. The increase in the average winter temperature in the study area has caused a large part of irrigated agricultural lands to be turned into orchards. Meanwhile, the average winter temperature has increased and the number of frost days (number of days (≤ 0 °C)) has decreased, which has led to a tendency to cultivate fruit trees, especially apple trees in the study area.

In addition, increasing the minimum winter temperature reduces the density of mountain glaciers and increases the permanent evolution of the snow line, and as a result, in the period 1977-2018, a large area of mountainous lands (pastures) turned into rainfed agricultural lands. Therefore, the most important results of surveys and forecasts of land use change and temperature change in the study area are:

1. Increasing the area under cultivation of orchards
2. Increasing the minimum winter temperature
3. Change in rainfall regime
4. Reducing the density of mountain glaciers

Therefore, in the near future, these changes are expected to lead to water shortages and water stress in the area. Hence, it is recommended to prevent floods and soil degradation by using sustainable agricultural patterns such as: drip irrigation, and river boundary determination.

Declarations

Conflict of Interest

It is the policy of the Journal *Theoretical and Applied Climatology* to ensure balance, independence, objectivity, and scientific rigor in the Journal. All authors are expected to disclose to the readers any real or apparent conflict(s) of interest that may have a direct bearing on the subject matter of the article. This pertains to relationships with pharmaceutical companies, biomedical device manufacturers or other corporations whose products or services may be related to the subject matter of the article or who have sponsored the study. The intent of the policy is not to prevent authors with a potential conflict of interest from publication. It is merely intended that any potential conflict should be identified openly so that the readers may form their own judgements about the article with the full disclosure of the facts. It is for the readers to determine whether the authors' outside interest may reflect a possible bias in either the exposition of the conclusions presented.

The corresponding author will complete and submit this form to the Editor-in-Chief on behalf of all authors listed below.

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Contributions

F.GH and KH.SH conceived and designed the research; F.GH. ran the model; F.GH. and GH.M. contributed materials/analysis tools; F.GH. and KH.SH. analysed the data/model outputs and wrote the paper; all authors commented on the manuscript.

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Data and code availability

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

The data for this project are confidential, but may be obtained with Data Use Agreements with Email to these project researchers. Researchers interested in access to the data may contact [Ghasem Farahmand] at [farahmand.geo@gmail.com], It can take some months to negotiate data use agreements and gain access to the data. The author will assist with any reasonable replication attempts for two years following publication.

Ethical Statement

I testify on behalf of all co-authors that the article was submitted:

- this material has not been published in whole or in part elsewhere;
- the manuscript is not currently being considered for publication in another journal;
- all authors have been personally and actively involved in substantive work leading to the manuscript, and will hold themselves jointly and individually responsible for its content.

Consent to participate

I Ghasem Farahmand, agree to participate or agree to participation of my child in the research project titled: Evaluation of the effects of minimum winter temperatures on changing the type of cultivation and changing the use of agricultural lands. (Case study: Urmia county). conducted by Shahriar khaledi and manijeh ghahroudi tali who has (have) discussed the research project with me.

I have received, read and kept a copy of the information letter/plain language statement. I have had the opportunity to ask questions about this research and I have received satisfactory answers. I understand the general purposes, risks and methods of this research.

I consent to participate in the research project and the following has been explained to me:

- the research may not be of direct benefit to me
- my participation is completely voluntary
- my right to withdraw from the study at any time without any implications to me
- the risks including any possible inconvenience, discomfort or harm as a consequence of my participation in the research project
- the steps that have been taken to minimise any possible risks
- public liability insurance arrangements
- what I am expected and required to do
- whom I should contact for any complaints with the research or the conduct of the research
- I am able to request a copy of the research findings and reports
- security and confidentiality of my personal information.

In addition, I consent to:

- audio-visual recording of any part of or all research activities (if applicable)
- publication of results from this study on the condition that my identify will not be revealed.

Name: Ghasem farahmand

Signature:

Date: 25/02/2021

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References

Adamo SB, Crews-Meyer KA (2006) Aridity and desertification: exploring environmental hazards in Jáchal, Argentina. *Applied Geography*, 26, 61-85.

Bonan GB (2008) Forests and climate change: forcings, feedbacks, and the climate benefits of forests. *Science* 320:1444–1449.

Barredo JI, Mauri A, Caudullo G, Dosio A (2018) Assessing Shifts of Mediterranean and Arid Climates Under RCP4.5 and RCP8.5 Climate Projections in Europe, *Pure and Applied Geophysics*, 175, 3955–3971.

Battisti A, Stastny M, Netherer S, Robinet ch, Schopf A, Roques A, Larsson S (2005) Expansion of geographic range in the pine processionary moth caused by increased winter temperatures, *Ecological Applications*, 15(6), 2084-2096

Bechtel B, Alexander PJ, Böhner J, Ching J, Conrad O, Feddema J, Mills G, See L, Stewart I (2015) Mapping local climate zones for a worldwide database of the form and function of cities. *ISPRS Int. J. Geo-Inf.* 4, 199–219.

Bonan GB (2008) Forests and climate change: forcing's, feedbacks, and the climate benefits of forests *Science* 320, 1444–1449.

Chang KP, Hi DB, Ravinesh D, Bo RL (2015) Drought prediction till 2100 under RCP 8.5 climate change scenarios for Korea, *Journal of Hydrology*, 526, 221-230.

Chou SCh, Lyra A, Chagas D, Dereczynski C, Gomes J, Tavares P (2018) Downscaling projections of climate change over South America and Central America under RCP4.5 and RCP8.5 emission scenarios, 20th EGU General Assembly, EGU2018, Proceedings from the conference held 4-13 April, 2018 in Vienna, Austria, p.8866. *Compute. Technol. Agric*, 1, 321–329.

Darvishi Sh, Rashidpour M, Soleimani K (2018) investigating the relationship between land use and surface temperature changes using satellite imagery. Case study: Marivan County, *Iranian Geography and Development Quarterly journal*, 54, 143-162.

Devaraju N, BalaGand-Nemani R (2015) Modeling the influence of land-use changes on biophysical and biochemical interactions at regional and global scales *Plant Cell Environ.* 38, 1931–46.

Enayatullah R (1988) *the Great Islamic Encyclopedia*, 10, 424.

Eshetu Y, Wu W, Xiaoping Sh, Habtamu T, Belew B (2017) Land Use/Land Cover Change Modeling and the Prediction of Subsequent Changes in Ecosystem Service Values in a Coastal Area of China, the Su-Xi-Chang Region, *journal of Sustainability*, 9, 2-17.

Farsi J, Yousefi M (2014) Detection of Land Use Change Using Remote Sensing Data Case Study of Bojnourd Plain, *Geography Quarterly and Environmental Studies*, 2, 95-106

Feddema JJ, Oleson KW, Bonan GB, Mearns LO, Buja LE, Meehl GA, Washington WM (2005) The importance of land-cover change in simulating future climates *Science* 310, 1674–8.

Gao J, Liu Y (2010) Determination of land degradation causes in Tongyu County, Northeast China via land cover change detection. *International Journal of Applied Earth Observation and Geo-information*, 12, 9-16

Ghesmati B, Manafi M, Dorostkar J, Karimi M, Karcher B (2015) *Protest West Azerbaijan*, Iran Educational books & Publishing Company, Fifth Edition, 1-49

Gollnow F, Goßpel J, DeBarros L, Hissa V, Schaldach R, Lakes T (2018) Scenarios of land-use change in a deforestation corridor in the Brazilian Amazon: combining two scales of analysis, *Reg Environ Change journal*, 18, 143–159.

- Gounaridis D, Chorianopoulos I, Symeonakis E, Koukoulas S (2019) A Random Forest-Cellular Automata modeling approach to explore future land use/cover change in Attica (Greece), under different socioeconomic realities and scales. *Science of the Total Environment* 646, 320–335.
- Guan DJ, Li HF, Inohae T, Su WC, Nagaie T, Hokao K (2011) Modeling urban land use change by the integration of cellular automaton and Markov model. *Ecol. Model.* 222, 3761–3772.
- Halmy MWA, Gessler PE, Hicke JA, Salem BB (2015) Land use/land cover change detection and prediction in the north-western coastal desert of Egypt using Markov-CA. *Appl. Geography* 63, 101–112.
- Hernández-Guzmána R, Ruiz-Luna A, González C (2019) Assessing and modeling the impact of land use and changes in land cover related to carbon storage in a western basin in Mexico, *Remote Sensing Applications: Society and Environment* 13, 318–327.
- Hosseini SY (2003) *Nonparametric statistics*, Iranian Allameh Tabatabaei University Publications.
- Huang Sh, Krysanova V, Hattermann F (2015) Projections of climate change impacts on floods and droughts in Germany using an ensemble of climate change scenarios, *Regional Environmental Change*, 15, 461–473.
- Imbernon J (1999) Changes in agricultural practice and landscape over a 60-year period in North Lampung, Sumatra. *Agriculture, Ecosystems and Environment*, 76, 61-66.
- IPCC (2013). Summary for policymakers: Stocker, T.F., Qin, D., Plattner, G.K., Tignor, M., Allen, S.K., Boschung, J., Nauels, A., Xia, Y., Bex, V., Midgley, P.M., the physical science basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, 3-29.
- IPCC (2014) Summary for policymakers, In: *Climate Change Impacts, Adaptation, and Vulnerability, Part A: Global and Sectorial Aspects*. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change: Field, C.B., Barros, V.R., Dokken, D.J., Mach, K.J., Mastrandrea, M.D., Bilir, T.E., Chatterjee, M., Ebi, K.L., Estrada, Y.O., Genova, R.C., Girma, B., Kissel, E.S, Levy, A.N., MacCracken, S., Mastrandrea, P.R., White, L.L., Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA: 1-32.
- Keerthi SS, Lin JCH (2003) Asymptotic Behaviors of Support Vector Machines with Gaussian Kernel, *Neural Computation*, 15, 1667 - 1689
- Liu P, Raymond-Choo KK, Wang L, Huang F (2017) SVM or deep learning? A comparative study on remote sensing image classification, *Soft Computing*, 21, 7053–7065.
- Loona AFV, Laahab G (2015) Hydrological drought severity explained by climate and catchment characteristics, *Journal of Hydrology*, 526, 3-14.

- Lu D, Weng Q (2007) A survey of image classification method a technique for improving classification performance, *remote sensing*, 28, 823-870.
- Liu J, Li S, Ouyang Z (2008) Ecological and socioeconomic effects of China's policies for ecosystem services. *Proc Natl Acad Sci U S A* 105(28):9477–9482
- Mahmood R (2014) Land cover changes and their bio geophysical effects on climate *Int. J. Climatol.* 34, 929–53.
- Mallampalli VR, Mavrommati G, Thompson J, Duveneck M, Meyer S, Ligmann Zielinska A (2016) Methods for translating narrative scenarios into quantitative assessments of land use change. *Environ. Model software*, 82, 7–20.
- Mehrizi-Zarezadeh SH, Khorani A, Bazrafshan J, Bazrafshan, U (2018) Assessment of Changes in Future Flows under Different Scenarios of Climate Change on Gamasiab River Basin, *Iranian Eco-Hydrology journal*, 3, 777-789.
- Miranda JF, Cooley D, Stephan RS, Tebaldi C (2018) A comparison of U.S. precipitation extremes under RCP8.5 and RCP4.5 with an application of pattern scaling, *Climatic Change*, 146, 335–347.
- Mirunalini P, Aravindan CH, Jaisakthi SM (2017) Automatic stenosis detection using SVM from CTA projection images, *Multimedia Systems*, 24, 1-11.
- Mondal S, Sharma N, Garg PK, Kappas M (2016) Statistical independence test and validation of CA Markov land use land cover (LULC) prediction results, *The Egyptian Journal of Remote Sensing and Space Sciences* 19, 259–272.
- Nogueira K, Penatti OA, Dos-Santos JA (2017) Towards better exploiting convolutional neural networks for remote sensing scene classification. *Pattern Recognition*, 61, 539–556.
- Oleson KW, Bonan GB, Levis S, Vertenstein M (2004) Effects of land use change on North American climate: impact of surface datasets and model bio geophysics *Clim, Dyn.* 23, 117–32.
- Penatti OA, Nogueira K, Dos-Santos JA (2015) Do deep features generalize from everyday objects to remote sensing and aerial scenes domains? In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops*, 44–51.
- Pielke RA (2005) Land use and climate change. *Science* 310:1625–1626
- Pielke RA, Pitman A, Niyogi D, Mahmood R, McAlpine C, Hossain F, Goldewijk KK, Nair U, Betts R, Fall S, Reichstein M, Kabat P, de-Noblet N (2011) Land use/land cover changes and climate: modeling analysis and observational evidence *Wiley Interdiscip. Rev.: Clim. Change*, 2, 828–850.

- Prestele R, Arneth A, Bondeau A, De-Noblet N, Pugh T, Sitch S, Stehfest E, Verburg PH (2017) Current challenges of implementing anthropogenic, Earth System Dynamics, 8, 369-386.
- Rajab-Zadeh F (2016) Land Use Change in Southwest of Tehran Using Remote Sensing and Markov Chain Technique, Iranian Journal of Water and Soil Conservation, 6, 60-71.
- Reddy CS, Singh S, Dadhwal VK, Jha, CS, Rao NR, Diwakar PG (2017) Predictive modeling of the spatial pattern of past and future forest cover changes in India Journal Earth System, 126, 1-16.
- Rimal B, Zhang L, Keshtkar H, Sun X, Rijal S (2018) Quantifying the spatiotemporal pattern of urban expansion and hazard and risk area identification in the kaski district of nepal. 7, 2-22.
- Serra P, Pons X, Saurí D (2008) Land-cover and land-use change in a Mediterranean landscape: a spatial analysis of driving forces integrating biophysical and human factors. Applied Geography, 28, 189-209.
- Titeux N, Henle K, Mihoub, JB, Regos A, Geijzendorffer IR, Cramer W, Verburg PH, Brotons L (2016) Biodiversity scenarios neglect future land-use changes. Glob. Chang. Biol. 22, 2505–2515.
- Thomson AM, Calvin KV, Smith SJ, Kyle GP, Volke A, Patel P, Delgado-Arias S, Bond-Lamberty B, Wise MA, Clarke LE, Edmonds JA (2011) RCP4.5: A pathway for stabilization of radiative forcing by 2100, Climatic Change, 109, 77-94.
- Wang F, Zuo W, Zhang L, Meng D, Zhang D (2013) A Kernel Classification Framework for Metric Learning, arXiv:1309.5823, 1, 1-11.
- Weinberger KR, Haykin L, Eliot MN, Schwartz JD, Gasparri A, Wellenius GA (2017) Projected temperature-related deaths in ten large U.S. metropolitan areas under different climate change scenarios, Environment International, 107, 196-204.
- Xia GS, Hu J, Hu F, Shi B, Bai X, Zhong Y, Zhang, L (2016) A benchmark dataset for performance evaluation of aerial scene classification. IEEE Transactions on Geoscience and Remote Sensing, 55, 3965-3981
- Ye B, Bai ZH (2007) Simulating land use/cover changes of Nenjiang County based on CA-Markov model, Computer and Computing Technologies In Agriculture, I, 321-329
- Yousefi H, Amini L, Ghasemi L, Amaraji N (2018) The Effectiveness of SDSM Model for Modeling the Parameters of Karaj Authors, Iranian Eco-Hydrology journal, 3, 957-968.
- Zheng HW, Shen GQ, Wang H, Hong JK (2015) Simulating land use change in urban renewal areas: A case study in Hong Kong. Habitat Int, 46, 23–34.
- Zoran M, Savastru D, Miclos S, Tautan MN, Baschir L (2011) Multisensory satellite remote sensing data for heat waves assessment in metropolitan region, journal of optoelectronics and advanced materials, 13,

Tables

Table 1 Details of satellite data used in the study.

Satellite	Sensor	Path/row	Data acquired	Spatial resolution (m)
LANDSAT-5	TM	169-34	05/08/1985	30
LANDSAT-5	TM	169-34	24/08/1992	30
LANDSAT-7	ETM+	169-34	22/08/2000	30
LANDSAT-7	ETM+	169-34	03/09/2010	30
LANDSAT-8	OLI/TIRS	169-34	16/08/2018	30

Table 2 CanESM2 Model features

Model	Atmospheric resolution	Oceanic resolution	Simulation period	Scenarios
CanESM2	2.81*2.81	.94*1.41	1850-2005,2006-2100	RCP2.6, RCP4.5, RCP8.5

Table 3 Accuracy assessments for 1985, 1992, 2000, 2010 and 2018 classification

Land Use/cover	Confusion Matrix				
	1985	1992	2000	2010	2018
Sandy soils	76.1%	73.3%	82.2%	90.2%	92.8%
Rocky soils	83.5%	76.1%	81.5%	78.9%	95.4%
saline soils	83.9%	89.2%	80.9%	98.3%	100%
Built-up Land	93.8%	91.6%	80%	77.1%	96.1%
Pastures	89.5%	90.4%	82.4%	89.1%	91.8%
Rainfed agriculture	98.5%	100%	92.9%	73.9%	95.6%
Orchards	92.2%	96.7%	87.8%	90.3%	95.2%
Irrigated arable lands	93.1%	95.8%	95.4%	90.2%	93.7%
Kappa Coefficient	0.847%	0.854%	0.848%	0.872%	0.944%
Overall Accuracy	87.06%	87.75%	87.87%	84.39%	95.35%

Table 4 LULC change (km²)

Land Use/cover	Lands area (km ²)				
	1985	1992	2000	2010	2018
Sandy soils	846.395	799.55	764.405	606.825	460.377
Rocky soils	306.247	392.526	254.154	240.772	226.791
saline soils	206.072	159.164	100.795	69.644	9.354
Built-up Land	48.153	68.949	74.02	118.356	191.783
Pastures	3098.108	2906.702	3116.064	3142.911	3323.68
Rainfed agriculture	30.573	21.863	32.125	83.8422	130.378
Orchards	131.921	133.6	178.3943	207.21	294.234
Irrigated arable lands	425.179	610.294	572.691	623.088	456.051

Table 5 Transition probability matrix of LULC classes for the periods 2000–2018, 2010–2018

2000-2018	Variables	sand	Rock	salt	Built	Pas	Rain	Orc	Irr
	sand	0.299%	0.039%	0.002%	0.033%	0.575%	0.010%	0.012%	0.026%
	Rock	0.206%	0.289%	0%	0.178%	0.166%	0%	0.010%	0.149%
	salt	0.005%	0.873%	0.034%	0.040%	0.045%	0%	0%	0%
	Built	0.111%	0.094%	0.002%	0.602%	0.064%	0.006%	0.019%	0.104%
	Pas	0.066%	0.014%	0%	0%	0.836%	0.046%	0.016%	0.014%
	Rain	0%	0%	0%	0%	0.785%	0.192%	0.015%	0.006%
	Orc	0.011%	0.006%	0.004%	0.025%	0.024%	0%	0.53%	0.396%
	Irr	0.041%	0.015%	0.003%	0.087%	0.099%	0.008%	0.25%	0.493%
2010-2018	sand	0.411%	0.042%	0.002%	0.027%	0.492%	0.001%	0.004%	0.017%
	Rock	0.23%	0.405%	0%	0.165%	0.054%	0%	0%	0.144%
	salt	0%	0.094%	0.056%	0%	0%	0%	0%	0%
	Built	0.098%	0.093%	0.031%	0.726%	0%	0%	0%	0.079%
	Pas	0.067%	0.01%	0%	0%	0.864%	0.047%	0.01%	0.005%
	Rain	0%	0%	0%	0%	0.711%	0.278%	0.01%	0%
	Orc	0%	0%	0.005%	0%	0%	0%	0.625%	0.369%
	Irr	0.033%	0.008%	0.003%	0.072%	0.052%	0.008%	0.237%	0.584%

Table 6 Evaluation of Model Performance (1961-2005)

Variables	SDSM					
	NSE	RMSE	R2	PBLAS	PSR	Pearson correlation
temperature	0.88%	0.07%	0.88%	6.8%	0.33%	0.94%

Figures

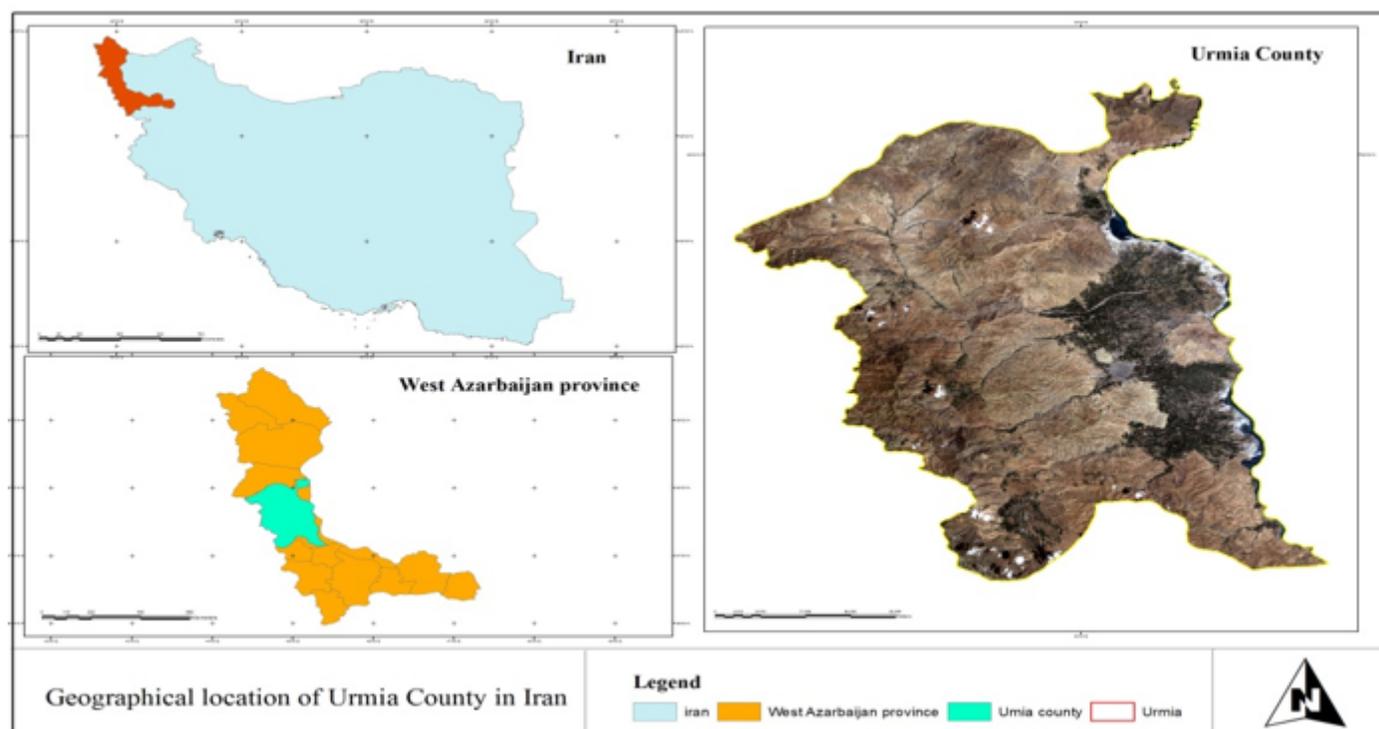


Figure 1

Location of study Area. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

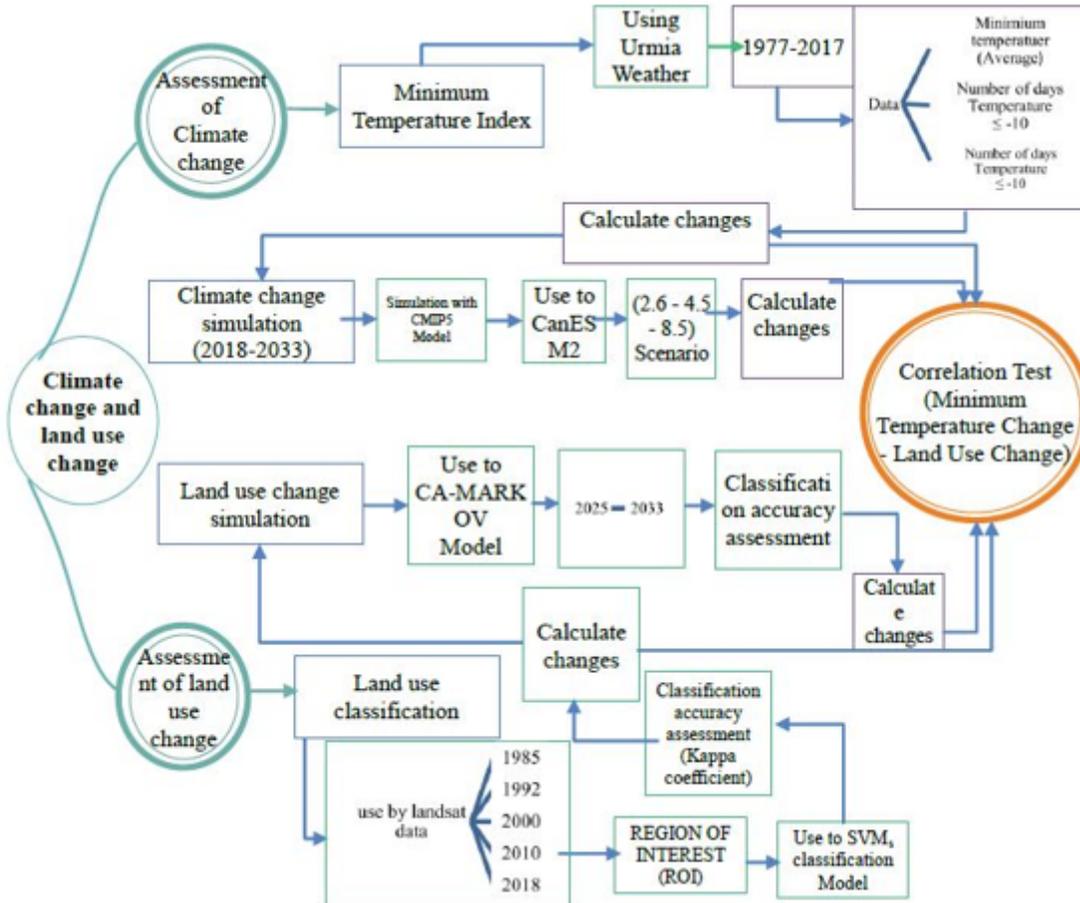


Figure 2

The framework of the study

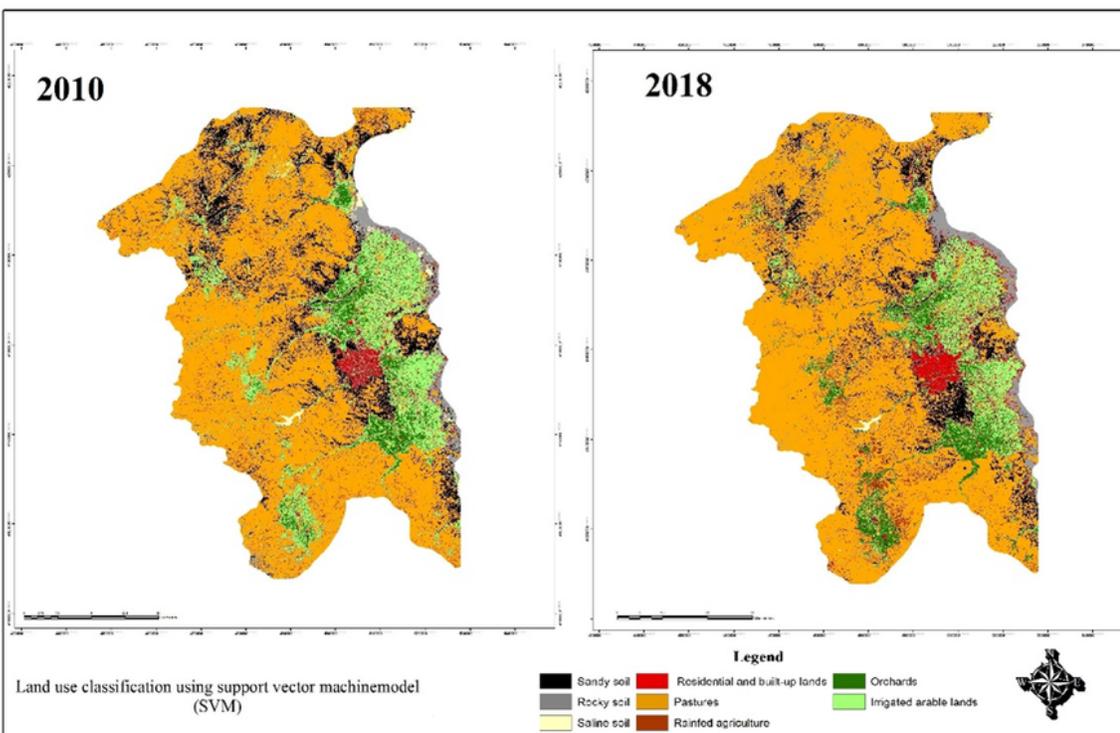
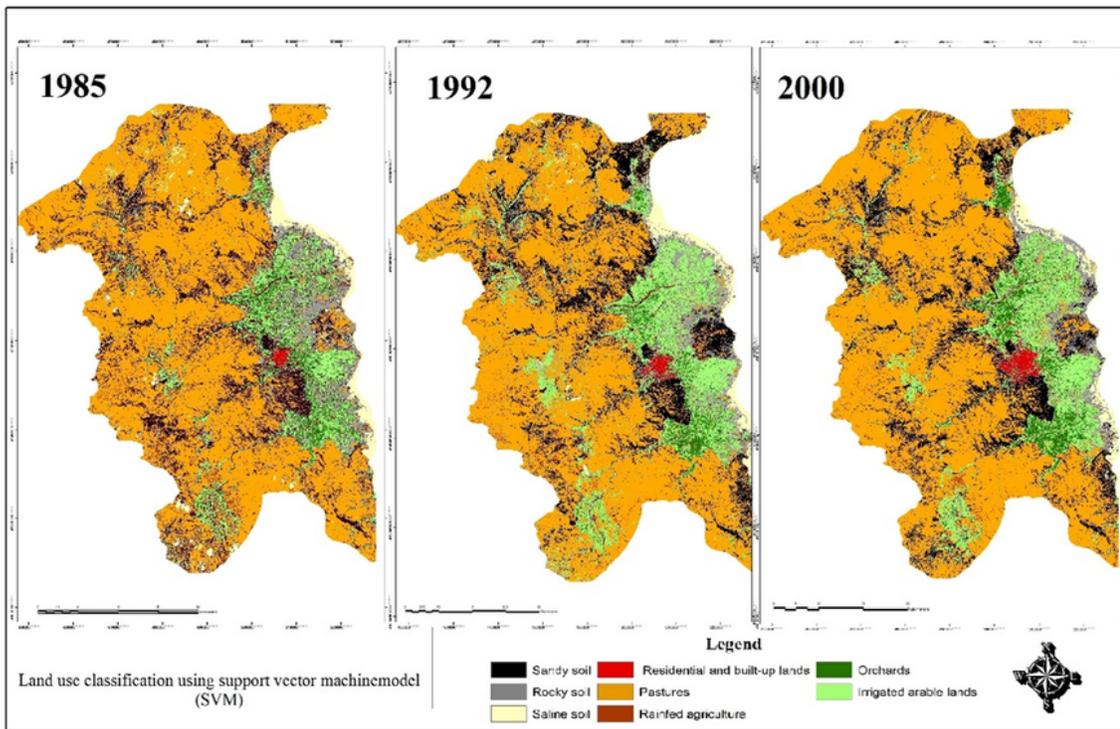


Figure 3

Land-use/land-cover (LULC) Map from 1985 to 2018. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

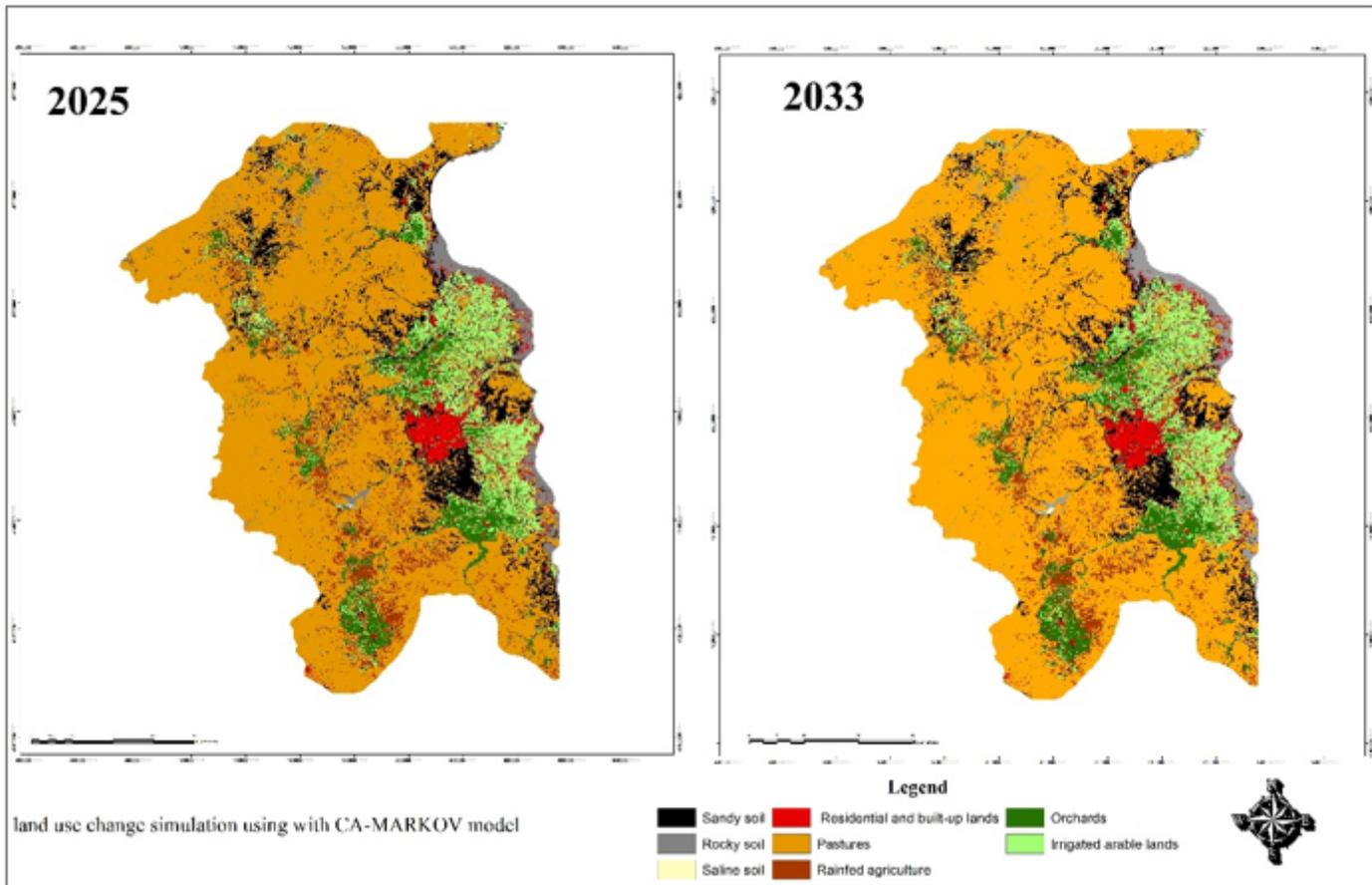


Figure 4

LULC maps: simulation map by CA-MARKOV model (2025-2033). Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

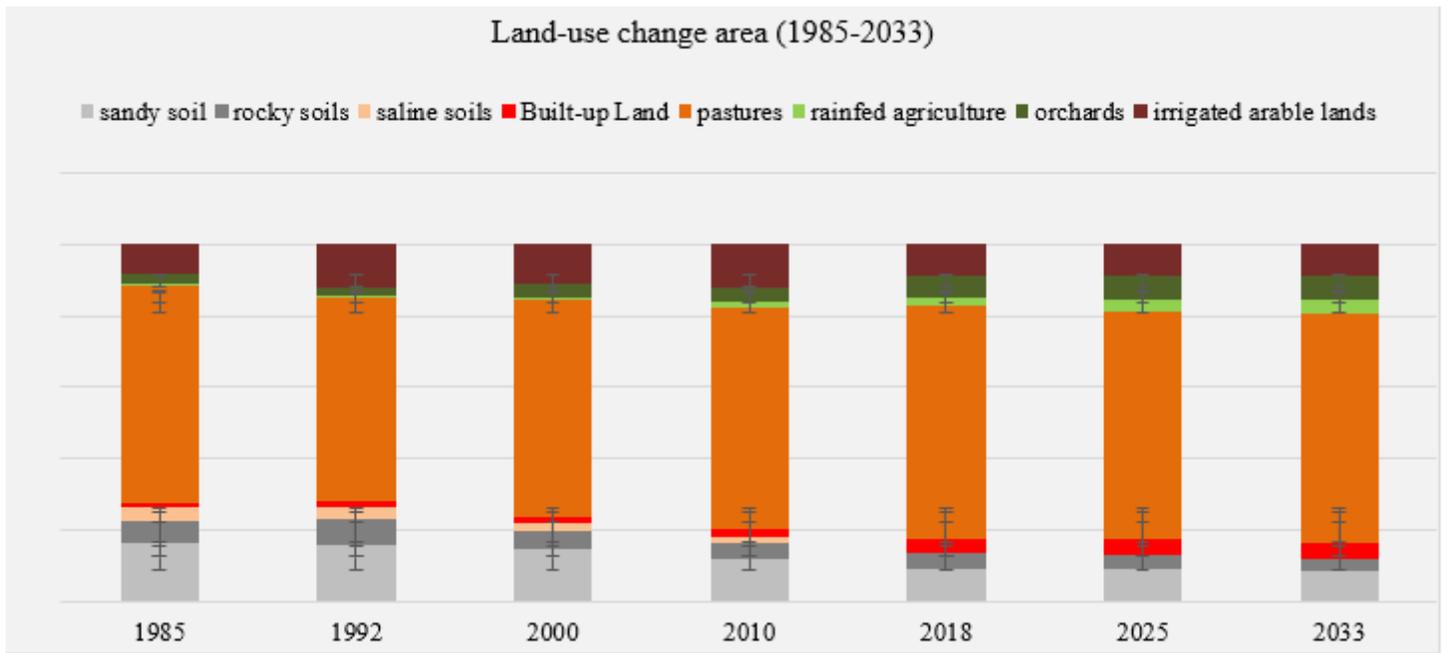


Figure 5

graph of LULC from 1985 to 2033

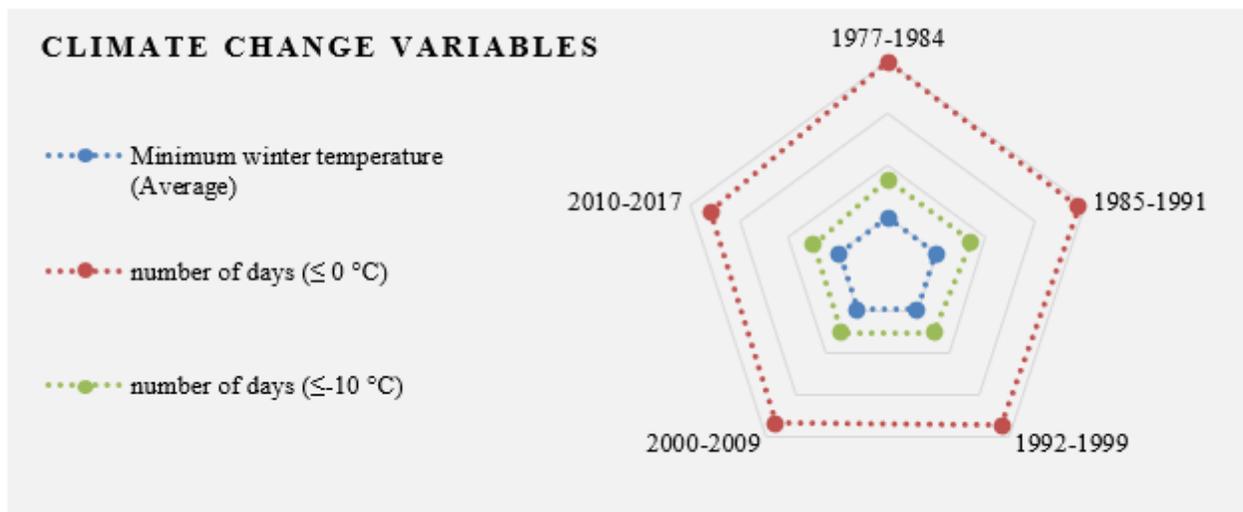


Figure 6

graph of three variables Changes (Minimum winter temperature (Average), number of days (≤ 0 °C), number of days (≤ -10 °C)) in the period 1977-2017

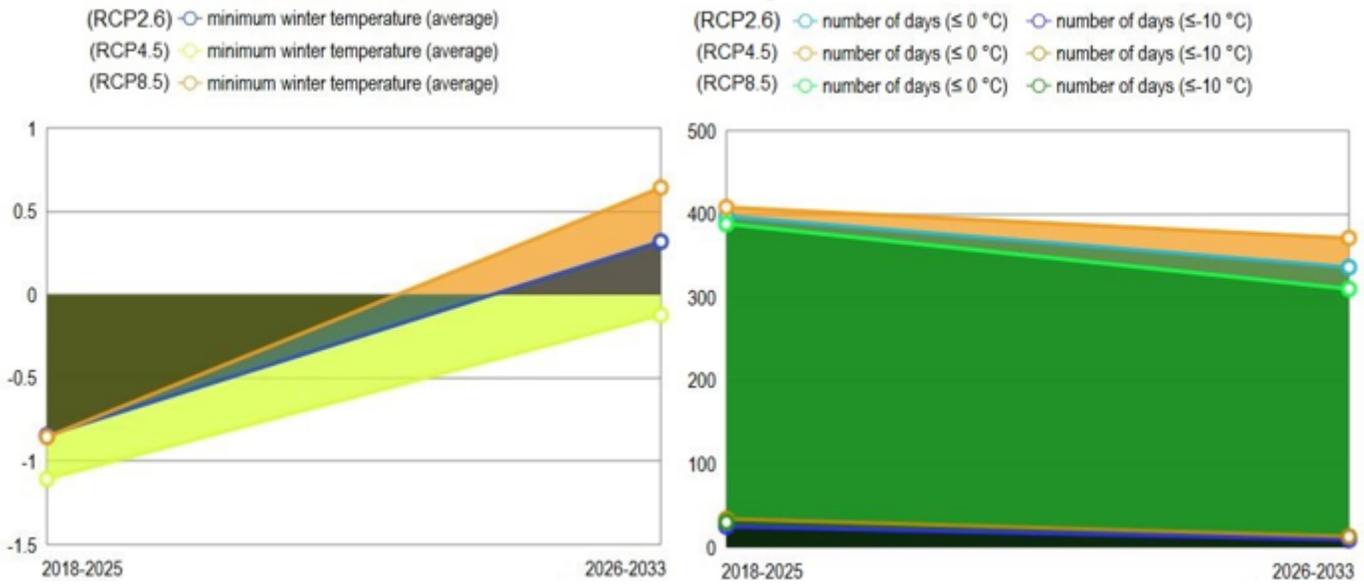


Figure 7

graph of variables Changes (Minimum winter temperature (Average), number of days ≤ 0 °C), number of days ≤ -10 °C) under scenarios (RCP2.6, RCP4.5, RCP8.5) in the period (2018-2025, 2026-2033)

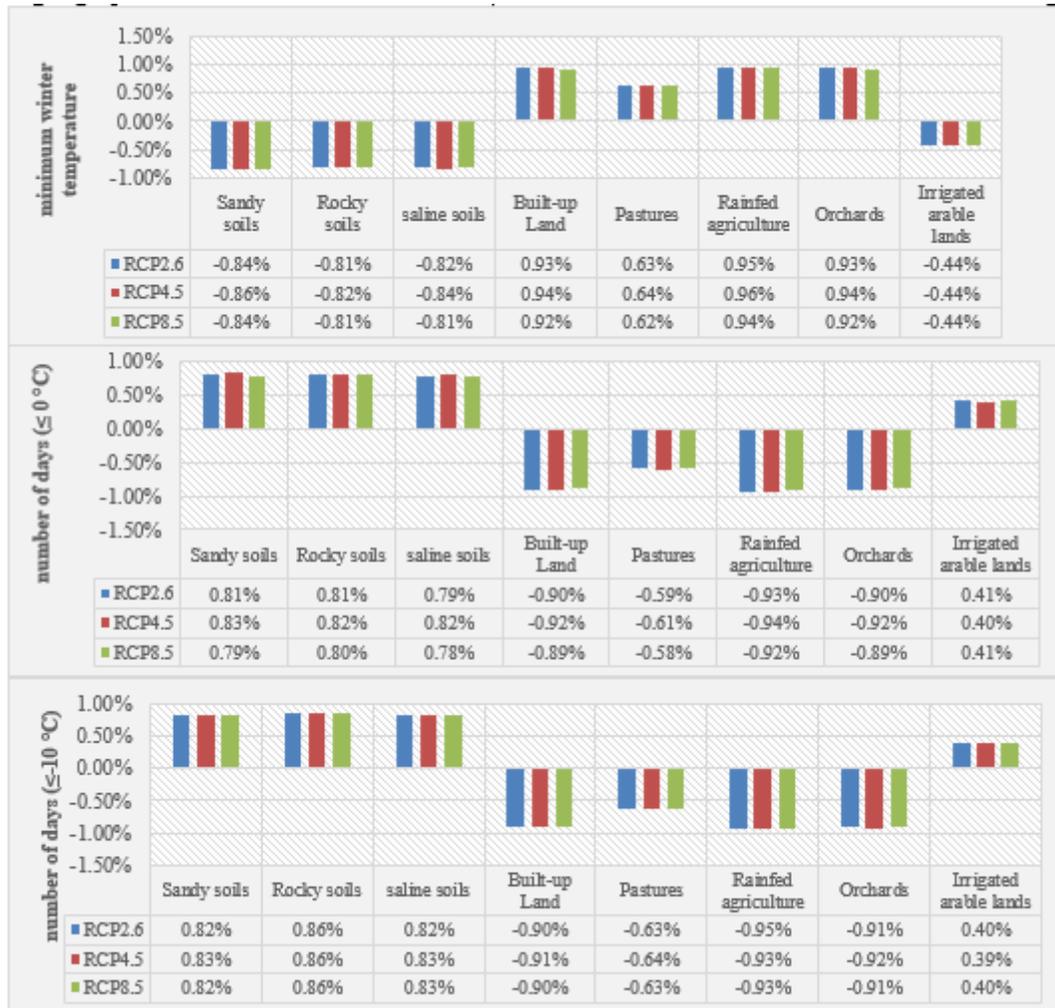


Figure 8

graph of Correlation test between climate variables and land use and land cover change