



Performance Comparison of Random Forest and Support Vector Machine Algorithms for Land Use Change Monitoring in the Samian Watershed (2015–2024) Using Remote Sensing Data in Google Earth Engine

Sayyad Asghari Saraskanroud^{1*} , Fatemeh Samadi Shalveh Alia²

¹ Professor, Department of Physical Geography, Faculty of Social Sciences, University of Mohaghegh Ardabili, Ardabil, Iran

² MSc Student Remote Sensing and Geographic Information Systems (GIS) Department of Physical Geography, Faculty of Social Sciences, University of Mohaghegh Ardabili, Ardabil, Iran

Received Date: 11 May 2025

Accepted Date: 12 September 2025

Abstract

Background and Objective: Land use changes represent a critical environmental challenge, significantly impacting natural resources, ecosystems, and hydrological processes. This study aims to comparatively evaluate the performance of two machine learning algorithms—Random Forest (RF) and Support Vector Machine (SVM)—for land use mapping and analyzing temporal changes between 2015 and 2024 in the Samian Watershed, Ardabil Province, with an approximate area of 4236 km².

Methodology: Satellite imagery from Landsat 8 and 9, along with Sentinel-2, were utilized within the Google Earth Engine platform for land use classification. The RF and SVM classifiers were applied to produce land use maps consisting of eight classes: water, residential, irrigated agriculture, rainfed agriculture, snow, forest, dense rangeland, and sparse rangeland. Accuracy assessment was conducted using confusion matrices and related accuracy metrics. Global datasets (Dynamic World and GHSL) were employed for sampling and model training.

Results and Findings: Comparative analysis revealed that the RF algorithm outperformed SVM, achieving an overall accuracy and Kappa coefficient exceeding 99%. Significant land use changes were observed during the study period, including a notable increase in irrigated agriculture and residential areas, alongside a decrease in rainfed lands, snow cover, and surface water bodies. Overall, due to its high accuracy and stable performance, RF is recommended as the superior method for monitoring land use changes within big data environments such as Google Earth Engine.

Keywords: Land Use, Watershed, Samian, Landsat, Sentinel, Machine Learning.

Corresponding Author Email: s.asghari@uma.ac.ir

Cite this article: Asghari Saraskanroud, S. and Samadi Shalveh Alia, F. (2026). Performance Comparison of Random Forest and Support Vector Machine Algorithms for Land Use Change Monitoring in the Samian Watershed (2015–2024) Using Remote Sensing Data in Google Earth Engine. *Journal of Sustainable Urban & Regional Development Studies (JSURDS)*, 7(1), 355-379.

Extended Abstract

Introduction:

Since the beginning of time, humans have experienced significant transformations across the Earth's surface. One of the main drivers of global environmental change is the conversion of natural landscapes into a wide range of anthropogenic uses (Taloor et al., 2020). The term *land use* refers to the way in which people utilize land and its resources (Esfandiari Darabad et al., 2021). This concept encompasses activities that alter the composition of soil, water, vegetation, and other natural resources (Jahdi, 2023). In comparison to previous states, lands that undergo changes in climate, topography, soil, and land use are considered to have experienced *land use/land cover change* (Mazaheri et al., 2013). Land use change is recognized as one of the most critical environmental issues and global challenges today (Asghari Saraskanroud, 2017). The main objective of this study is to utilize Landsat satellite imagery and the SVM and RF classification algorithms within the Google Earth Engine platform to analyze land use/land cover change trends in the Samian watershed between 2015 and 2024.

Methodology:

To investigate land use/land cover (LULC) changes in the Samian watershed, satellite imagery from Landsat 8, Landsat 9, and Sentinel-2 for the years 2015 and 2024 was utilized within the Google Earth Engine (GEE) platform. Cloud and shadow noise were removed using the 'CLOUD_COVER' filter, and a median composite was generated. To enhance land use classification separability, spectral indices including NDVI (Normalized Difference Vegetation Index), NDBI (Normalized Difference Built-up Index), and MNDWI (Modified Normalized Difference Water Index) were calculated. Additionally, elevation data was incorporated to provide topographic context to the dataset. Eight land use/land cover classes were defined: irrigated agriculture, rainfed agriculture, water bodies, dense rangelands, sparse rangelands, forest, snow cover, and residential areas. For training data extraction, the Global Human Settlement Layer (GHSL) and the Dynamic World pre-classified product were employed. Two machine learning algorithms—Random Forest (RF) and Support Vector Machine (SVM)—were implemented for supervised classification.

Accuracy Assessment of Classification:

To evaluate the accuracy of the classified maps and compare the performance of the two employed algorithms, a confusion matrix and its derived indices were utilized. These indices include Producer's Accuracy, User's Accuracy, Overall Accuracy, and the Kappa Coefficient, each reflecting a different aspect of classification quality. Training and validation datasets were generated using a random sampling approach based on the final land use/land cover (LULC) map. In this process, a specified number of samples were uniformly selected from each class to provide a representative subset of all categories. However, due to computational constraints and the temporal complexity of the Support Vector Machine (SVM) algorithm, the sample size for this method was reduced, and a subset of the original dataset was employed for training and evaluation. This adjustment was essential to prevent errors and to enhance the efficiency of the classification procedure.

Results and Discussion:

Land use classification results

The classification results obtained using the Smile Random Forest and Support Vector Machine (SVM) algorithms indicate significant changes in land use/land cover (LULC) patterns over the study period. Both algorithms revealed substantial increases in classes such as irrigated agriculture, tree cover, sparse rangelands, and residential areas. These changes

may be attributed to the expansion of agricultural infrastructure, urban growth, afforestation programs, shifts in resource utilization strategies, and climatic variations. The increase in irrigated agriculture observed in both classifications reflects a shift toward more efficient water resource use and efforts to enhance regional food security. The considerable growth in tree cover may suggest the success of reforestation projects, orchard development, or potentially classification errors at the boundaries between dense vegetation and rangelands. Conversely, noticeable declines were detected in rainfed agriculture, dense rangelands, water bodies, and especially snow cover. These reductions are likely driven by prolonged droughts, decreasing surface water availability, climate change, unregulated urban sprawl, and a decline in traditional agricultural practices. The near-complete loss of snow cover in both classifications serves as clear evidence of global warming and reduced snowfall in the region. Additionally, the transformation of dense rangelands into sparse rangelands may indicate gradual degradation of natural resources due to overgrazing, anthropogenic pressure, and precipitation variability. Minor discrepancies between the results of the two algorithms can be attributed to their differing sensitivities to spectral features and classification methods. Overall, the classification analysis reveals a concerning trend of natural resource depletion and expansion of anthropogenic land uses, highlighting the urgent need for comprehensive land management and environmental planning strategies in the study area.

Comparison and Overall Performance Analysis of the Algorithms

The comparative results demonstrate that the Random Forest (RF) algorithm outperformed the Support Vector Machine (SVM) in land use/land cover (LULC) classification within the study area. The RF algorithm not only provided higher overall accuracy and Kappa coefficient values but also delivered more consistent and reliable classification performance across all classes. Specifically, the overall accuracy of RF exceeded 0.99 in both study years, with a Kappa coefficient of approximately 0.99. In contrast, the SVM algorithm achieved a lower overall accuracy of 0.75, with a corresponding Kappa coefficient of around 0.71, indicating weaker agreement with the reference data. At the class-specific level, RF exhibited superior performance, particularly in classes characterized by dense or spectrally similar vegetation, such as irrigated agriculture and sparse rangelands, which are typically more challenging to discriminate. Conversely, SVM showed reduced accuracy in differentiating these categories and maintained higher accuracy only in spectrally distinct classes such as water and snow. This limitation is likely attributable to the high sensitivity of SVM to boundary data and spectral overlaps. From a computational standpoint, RF also demonstrated greater efficiency due to its tree-based structure and capacity for parallel processing, making it faster and more stable for large-scale datasets. These advantages, combined with its superior classification accuracy, establish RF as a more suitable approach for scientific applications and the generation of accurate LULC maps within the Google Earth Engine environment.

Overall, the findings highlight that the SmileRandomForest algorithm is a more effective choice for monitoring land use changes in the Samian watershed, owing to its enhanced capability in class discrimination. These results are consistent with Avaji (2023), who emphasized the superior performance of RF compared to SVM in LULC classification. However, they contrast with the findings of Ghodsi et al. (2020), who reported that SVM achieved higher overall accuracy (91.36%) and a Kappa coefficient of 0.8927, thereby outperforming RF in producing more precise LULC and agricultural product maps.

Evaluation of Cross-Tabulation Results

The cross-tabulation analysis highlighted significant patterns of stability and transition across land use/land cover (LULC) classes for both the Random Forest (RF) and Support Vector

Machine (SVM) algorithms. For RF, high stability was observed in dryland agriculture (947.9 km²), irrigated agriculture (859.7 km²), and sparse rangelands (516.6 km²), demonstrating the algorithm's strong capability to accurately classify these categories within the Samian watershed. The most pronounced transition involved the conversion of dryland agriculture to irrigated agriculture (473.6 km²), likely reflecting shifts in land management practices and a preference for higher-value crops. Dense rangelands largely remained stable (324.1 km²), though portions transitioned to sparse rangelands (86.3 km²) and irrigated agriculture (38.4 km²), indicating partial degradation of natural vegetation and expansion of human land use. Residential areas were predominantly stable, with minor conversions from dryland (17.7 km²) and irrigated agriculture (22.6 km²) suggesting urban and rural development. Forested areas were mostly correctly classified (71.1 km²), yet notable conversions to irrigated agriculture (11.7 km²) and dense rangelands (10.7 km²) reflect spectral similarities and potential forest clearance for agricultural purposes. The snow class exhibited the highest misclassification rate, frequently confused with forest or irrigated agriculture due to seasonal variability and lower spectral separability. SVM results revealed comparable stability in dryland agriculture (966.6 km²), irrigated agriculture (871.9 km²), and sparse rangelands (546 km²), aligning with RF observations. Major transitions, such as dryland to irrigated agriculture (552.9 km²), mirrored RF patterns, indicating the substantial expansion of irrigated farming from 2015 to 2024. Dense rangelands experienced partial conversion to sparse rangelands (102.1 km²), reflecting gradual vegetation degradation potentially driven by overgrazing, drought, or climatic factors. Forested areas largely remained stable (72.5 km²), though minor conversions to irrigated agriculture (9.5 km²) and dense rangelands (9 km²) were detected. Residential areas demonstrated relatively high stability (178.8 km²), with minimal encroachment from other classes. Notably, SVM exhibited improved discrimination between boundary classes such as dense and sparse rangelands, resulting in reduced class confusion compared to RF, although misclassification persisted in classes such as water and snow due to spectral overlaps under specific conditions.

Overall, both algorithms effectively captured the primary LULC change patterns, with RF excelling in overall stability and classification consistency, while SVM provided better performance in differentiating challenging boundary classes. These findings offer a comprehensive understanding of land use dynamics in the Samian watershed during the study period and inform the selection of suitable classification algorithms for similar remote sensing applications.

Conclusion:

The findings of this study demonstrate that leveraging remote sensing data within the Google Earth Engine platform, combined with advanced machine learning algorithms such as Random Forest (RF) and Support Vector Machine (SVM), provides a robust and efficient tool for monitoring land use/land cover (LULC) changes at the watershed scale. The comparative analysis of the two algorithms indicates the superior performance of RF over SVM in discriminating between different LULC classes, particularly in spectrally similar categories such as irrigated agriculture, rangelands, and forested areas. RF consistently achieved high overall accuracy and Kappa coefficients exceeding 0.99 for both 2015 and 2024, reflecting its reliability, whereas SVM exhibited lower performance across these metrics. This difference was especially pronounced in classes with overlapping spectral characteristics, such as rangelands and irrigated croplands.

From a spatial change perspective, key patterns identified include a substantial increase in irrigated agriculture (up to 35% for SVM and 24% for RF), growth of human settlements (13–16%), and a marked decline in dryland areas (approximately 30–35%). Additionally, reductions in snow cover exceeding 96% and shrinkage of water bodies across both

algorithms highlight the impacts of climatic changes in the Samian watershed between 2015 and 2024, posing significant concerns for water resources and ecological sustainability. The consistency of conversion patterns observed in the Cross-Tab results for both algorithms underscores the stability of certain classes, such as dryland and irrigated agriculture, while simultaneously revealing the concerning degradation of dense rangelands, predominantly converted to irrigated agriculture and sparse rangelands.

Overall, the results suggest that RF, particularly within the cloud-based processing environment of Google Earth Engine, represents a powerful and suitable approach for classifying and monitoring LULC changes at the watershed scale. For future research, the integration of seasonal datasets or composite indices is recommended to enable more precise trend analysis and the modeling of potential future scenarios.

Declarations

Funding

The article is extracted from a research project supported by the Vice President of Research and Technology of University of Mohaghegh Ardabili.

Authors' Contribution

Authors contributed equally to the conceptualization and writing of the article. All of the authors approved the content of the manuscript and agreed on all aspects of the work declaration of competing interest none.

Conflict of Interest

The authors declare no conflict of interest.

Acknowledgments

We are grateful to all the scientific consultants of this paper.

References

- Acharya, S., Hori, T., & Karki, S. (2023). Assessing the spatio-temporal impact of landuse landcover change on water yield dynamics of rapidly urbanizing Kathmandu valley watershed of Nepal. *Journal of Hydrology: Regional Studies*, 50, 101562. <https://doi.org/10.1016/j.ejrh.2023.101562>
- Aşci, E., & Genç, L. (2024). Determination of the Effects of Various Spectral Index Combinations on Seasonal Land Use and Land Cover (LULC) Changes Using Random Forest (RF) Classification Case Study: Southeast Marmara Region 2016-2020. *Türkiye Uzaktan Algılama Dergisi*, 6(1), 12-25. <https://doi.org/10.51489/tuzal.1395189>
- Asghari Saraskaneroud, S., & Sharifi Toularod. (2023). Detecting land use and forest area changes using remote sensing (Case study: Astara County). *Land Management Journal*, 11(2), 195–208. <https://doi.org/10.22092/lmj.2023.362257.332> (in Persian)
- Asghari Saraskaneroud, S., Aghayari, L., & Pirouzi, E. (2017). Land use changes and their effect on erosion using RS and GIS (Case study: Nir County). *Remote Sensing and GIS in Natural Resources*, 8(4), 49–62. (in Persian)
- Asghari Saraskaneroud, S., Pasandeh, A. H., & Khavarian, [Initials]. (2024). Detecting land use changes during 2013–2024 using Landsat 8 image processing and impact analysis (Case study: Miandoab City). *Journal of Urban and Regional Sustainable*

- Development Studies*, 5(4), 330–346. (in Persian)
https://www.srds.ir/article_222189.html?lang=fa
- Avcı, C., Budak, M., Yağmur, N., & Balçık, F. (2023). Comparison between random forest and support vector machine algorithms for LULC classification. *International Journal of Engineering and Geosciences*, 8(1), 1–10. <https://doi.org/10.26833/ijeg.987605>
- Brandolini, F., Domingo-Ribas, G., Zerboni, A., & Turner, S. (2021). A Google Earth Engine-enabled Python approach for the identification of anthropogenic palaeo-landscape features. *Open Research Europe*, 1, 22. [10.12688/openreseurope.13135.2](https://doi.org/10.12688/openreseurope.13135.2)
- Chandra, M. A., & Bedi, S. S. (2021). Survey on SVM and their application in image classification. *International Journal of Information Technology*, 13(5), 1–11.
- Ebrahimi, B., Pasandi, M., & Neil Foroushan, H. (2023). Estimating land use changes under traditional irrigation in Khansar County. *Water and Soil Science*, 27(4), 77–91. <https://doi.org/10.47176/jwss.27.4.27532> (in Persian)
- Esfandiari Darabad, & Nezafat Takleh. (2025). Analysis of the impact of E and L indices on water sustainability and security in the Samian watershed. *Journal of Urban and Regional Sustainable Development Studies*, 6(4), 15–30. (in Persian)
https://www.srds.ir/article_216659.html?lang=en
- Esfandiari Darabadi, R., Rafiei, M., & Farzaneh, H. (2021). Land use/cover changes in Zarrineh River Basin and their impact on soil erosion using the WLC hydrogeomorphology model. *Hydrogeomorphology*, 8(29), 45–68. <https://doi.org/10.22034/hyd.2021.47572.1600> (in Persian)
- Farkhzadeh, B., Nour, G., & Aghabigi, A. (2023). Modeling land use change trends in Gahvareh region, Kermanshah Province. *Journal of Rainwater Catchment Systems*, 11(2), 48–62. <https://doi.org/10.1001.1.24235970.1402.11.2.4.2> (in Persian)
- Fazeli Farsani, A., Ghazavi, R., & Farzaneh, M. R. (2015). Performance assessment of land use classification algorithms using image fusion techniques (Case study: Beheshtabad sub-basin). *Remote Sensing and GIS Applications in Natural Resources*, 6(1), 91–105. (in Persian)
- Ghodsi, K., Kheirkhah Zarkesh, M., Mir Masoud, Q., & Baghershameh, B. (2020). Comparing SVM and Random Forest methods for land use and crop mapping using multi-temporal Sentinel-2 images. *Iranian Journal of Remote Sensing and GIS*, 12(4), 73–92. <https://doi.org/10.52547/gisj.12.4.73> (in Persian)
- Golshan, M., Kaviani Ataollah, A., Esmaeili Ouri, A., & Ziegler, A. D. (2018). Modeling runoff and sediment yield using hydrogeomorphic characteristics in Samian watershed, Ardabil Province. *Watershed Science and Engineering*, 12(43), 117–126. <https://doi.org/10.1001.1.20089554.1397.12.43.13.6> (in Persian)
- Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote sensing of Environment*, 202, 18–27. <https://doi.org/10.1016/j.rse.2017.06.031>
- Guo, F., Fan, L., Zhang, C., & Xue, S. (2024). A novel space–spectrum array tile probability random-forest model enhances LULC mapping accuracy on Google Earth Engine: An experiment in Ordos, China. *Ecological Informatics*, 81, 102607. <https://doi.org/10.1016/j.ecoinf.2024.102607>
- Gupta, R. P. (2017). *Remote sensing geology*. Springer.
- Haji Elyasi, N., Naseri, B., Badi'i, & Seyed Peyman. (2024). Evaluating land use changes based on integration of machine learning and spectral angle mapper using variable training samples: Case study Anzali wetland watershed. *Journal of Natural Geography Research*, 56(4), 39–56. <https://doi.org/10.22059/jphgr.2025.384462.1007848> (in Persian)

- Hasan, R., Kapoor, A., Singh, R., & Yadav, B. K. (2024). A state-of-the-art review on the quantitative and qualitative assessment of water resources using google earth engine. *Environmental Monitoring and Assessment*, 196(12), 1266. doi: [10.1007/s10661-024-13315-5](https://doi.org/10.1007/s10661-024-13315-5)
- Hezbavi, A., & Nazila. (2024). Assessment and optimization of hydrological connectivity for water resources management in Samian watershed. *Spatial Planning*, 14(3), 115–138. <https://doi.org/10.22108/sppl.2024.139234.1749> (in Persian)
- Irani, A., Hiraad, & Rasouli, [Initials]. (2024). Analyzing the relationship between land use changes and landscape metrics: Case study of Godarchai watershed. *Spatial Geography Journal*, 14(1), 165–188. (in Persian)
- Izadi Fard, H., Rathi Nezami, M. R., & Khavarian, [Initials]. (2024). Urban development and characteristics of short- and medium-term hydrological drought in Samian watershed, Ardabil Province. *Geography and Environmental Studies*, 51(46), 46. <https://doi.org/10.71740/ges.2024.979123> (in Persian)
- Izadi Fard, H., Rathi Nezami, M. R., & Khavarian, [Initials]. (2023). Relationship between surface runoff coefficient changes and land use/cover changes in Samian watershed, Ardabil Province. *Journal of Dryland Geographical Studies*, 14(51), 24–41. <https://doi.org/10.22034/jargs.2023.373960.0> (in Persian)
- Jahanbakhshi, F., & Ekhtesasi, M. R. (2018). Evaluating the performance of three image classification methods (Random Forest, Support Vector Machine, and Maximum Likelihood) in land use mapping. *Journal of Remote Sensing and GIS in Iran*, 22(4), 235–247. <https://doi.org/10.1001.1.24763594.1397.22.4.29.4> (in Persian)
- Jahdi, [Initials]. (2023). Modeling land use changes and future predictions using CA-ANN simulation in Shenarood watershed, Siahkal. *Geography and Environmental Studies*, 12(46), 164–179. (in Persian)
- Jiang, M., Cheng, T., Dong, K., Xu, S., & Geng, Y. (2020). Fault diagnosis method of submersible screw pump based on random forest. *Plos one*, 15(11), e0242458. <https://doi.org/10.1371/journal.pone.0242458>
- Karimzadeh Motlagh, L., Lotfi, M., Pour Manafi, & Ahmadi Zadeh, S. (2022). Assessment and prediction of land use changes using CA-Markov model. *Geography and Environmental Planning*, 33(2), 67–84. <https://doi.org/10.22108/gep.2022.130601.1458> (in Persian)
- Khalaji, & Saba. (2021). Effects of land use changes on land use planning. *Journal of Space and Place Research*, 19(1), 5–18. <https://doi.org/10.1001.1.25386050.1400.1400.19.1.2> (in Persian)
- Kuemmerle, T., Levers, C., Erb, K., Estel, S., Jepsen, M. R., Müller, D., ... & Reenberg, A. (2016). Hotspots of land use change in Europe. *Environmental research letters*, 11(6), 064020. doi:10.1088/1748-9326/11/6/064020
- Lin, C., & Doyog, N. D. (2023). Challenges of retrieving LULC information in rural-forest mosaic landscapes using random forest technique. *Forests*, 14(4), 816. <https://doi.org/10.3390/f14040816>
- Loukili, I., Laamrani, A., El Ghorfi, M., & El Moutak, S. (2025). Monitoring land changes at an open mine site using remote sensing and multi-spectral indices. *Heliyon*, 11(2). doi:10.1016/j.heliyon.2025.e41845
- Mazaheri, M. R., Esfandiari, M., Masih Abadi, M. H., & Kamali, A. (2013). Monitoring temporal land use changes using remote sensing and GIS techniques (Case study: Jiroft, Kerman Province). *Remote Sensing and GIS Applications in Natural Resources*, 4(2), 25–39. (in Persian)
- Moradzadeh, H., Hezbavi, A., Esmaeili Ouri, A., Mostafazadeh, R., ... & Nazila. (2022). Assessing spatial heterogeneity of hydro-erosion disturbance index in Samian sub-

- watersheds. *Hydrogeomorphology*, 9(31), 117–136. <https://doi.org/10.22034/hyd.2022.51186.1634> (in Persian)
- Noszczyk, T. (2019). A review of approaches to land use changes modeling. *Human and Ecological Risk Assessment: An International Journal*, 25(6), 1377-1405. [doi:10.1080/10807039.2018.1468994](https://doi.org/10.1080/10807039.2018.1468994)
- Noubaharan, K., Abtahi, A., & Mahmoudi, S. (2019). Trends of land use changes in Marvdasht plain, Fars Province. *Water and Soil Conservation*, 8(3), 68–82. (in Persian)
- Rana, V. K., & Suryanarayana, T. M. V. (2020). Performance evaluation of MLE, RF and SVM classification algorithms for watershed scale land use/land cover mapping using sentinel 2 bands. *Remote Sensing Applications: Society and Environment*, 19, 100351. <https://doi.org/10.1016/j.rsase.2020.100351>
- Rathi Nezami, H., Izadi Fard, H., Khavarian, [Initials], & Mofateh, R. (2023). Land use/cover changes in Samian watershed and their relationship with surface water quality. *Environmental and Water Engineering*, 9(3), 413–426. <https://doi.org/10.22034/jewe.2022.341548.1783> (in Persian)
- Sellami, E. M., & Rhinane, H. A. S. S. A. N. (2023). A new approach for mapping land use/land cover using google earth engine: a comparison of composition images. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 48, 343-349. doi.org/10.5194/isprs-archives-XLVIII-4-W6-2022-343-2023
- Shekrian, F., & Soleimani, K. (2024). Land use changes based on satellite imagery in Haraz plain. *Iranian Journal of Remote Sensing and GIS*, 16(1), 113–128. <https://doi.org/10.48308/gisj.2023.232979.1176> (in Persian)
- Taloor, A.K., Kumar, V., Kumar, S.G., Singh, A.K., Kale, A.V., Sharma, R., Khajuria, V., Raina, G., Kouser, B., & Chowdhary, N.H. (2020). Land use land cover dynamics using remote sensing and gis techniques in western doon valley uttarakhand India. *Geocology of Landscape Dynamics, Advances In Geographical And Environmental Sciences*, 4(1), 37-51.
- Tavakoli, M., & Naeem Abadi, N. (2019). Urban sprawl and land use changes in peri-urban areas of Nishapur. *Peri-urban Space Development*, 1(2), 151–165. <https://doi.org/10.1001.1.26764164.1398.1.2.12.4> (in Persian)
- Tesfaye, W., Elias, E., Warkineh, B., Tekalign, M., & Abebe, G. (2024). Modeling of land use and land cover changes using google earth engine and machine learning approach: implications for landscape management. *Environmental Systems Research*, 13(1), 31.
- Van Asselen, S., & Verburg, P. H. (2013). Land cover change or land-use intensification: simulating land system change with a global-scale land change model. *Global change biology*, 19(12), 3648-3667. <https://doi.org/10.1111/gcb.12331>
- Wang, J., Bretz, M., Dewan, M. A. A., & Delavar, M. A. (2022). Machine learning in modelling land-use and land cover-change (LULCC): Current status, challenges and prospects. *Science of the Total Environment*, 822, 153559. <https://doi.org/10.1016/j.scitotenv.2022.153559>
- Wang, Y., & Ling, J. (2024). Analysis of spatio-temporal evolution and influencing factors of land dividends in China. *PloS one*, 19(11), e0309786. <https://doi.org/10.1371/journal.pone.0309786>
- Wu, J., Qin, C. X., Yue, Y., Cheng, S. P., Zeng, H., & He, L. Y. (2024). Comprehensive effects of climate, land use/cover and management practices on runoff and nutrient variations in a rapidly urbanizing watershed. *Chemosphere*, 349, 140934. <https://doi.org/10.1016/j.chemosphere.2023.140934>

- Younesazadeh, S., Salajeghe, S., Mesbahzadeh, T., Tajrishi, [Initials], Khalighi, S., & Taheri Shahraini. (2020). Evaluating the capability of Dyna-CLUE model in analyzing and predicting future land use patterns in Siminerud watershed. *Ecohydrology*, 8(1), 73–87. <https://doi.org/10.22059/ije.2020.309703.1381> (in Persian)
- Yousefi Taleghani, M., Molaei Heshjin, R., Nasrollah, & Rezaei, [Initials]. (2022). Explaining factors affecting land use changes in peri-urban villages of Rasht. *Peri-urban Space Development*, 7(4), 47–66. <https://doi.org/10.1001.1.26764164.1401.4.1.3.4> (in Persian)
- Zarei, H., Hezbavi, A., Mostafazadeh, R., Roouf, & Esmaeili Ouri, A., & Abazar. (2020). Comparing vulnerability of sub-watersheds of Samian based on changes in climatic components. *Journal of Natural Geography Research*, 52(2), 217–236. <https://doi.org/10.22059/jphgr.2020.283909.1007406> (in Persian)
- Zhu, L., Suomalainen, J., Liu, J., Hyyppä, J., Kaartinen, H., & Haggren, H. (2018). A review: Remote sensing sensors. *Multi-purposeful application of geospatial data*, 19, 19-42.