The Potential of Machine Learning and Multi-Criteria Decision-Making for Data-Driven Land Policies in Türkiye

Okan Yılmaz[1*], Mehmet Alkan [1]

[1]Department of Geomatic Engineering, Faculty of Civil Engineering, Yıldız Technical University, Istanbul, Türkiye- (okanymz, alkan) @yildiz.edu.tr

Keywords: Land Management, Sustainable Land Policies, Policy-Making, Machine Learning, Multi-Criteria Decision-Making.

Abstract

Land management policies are shaped through diverse development processes and implemented via instruments such as legal regulations, incentives, and land development tools. Especially in urban areas, the complexity of social, economic, and environmental dynamics requires policy-making that is adaptive, predictive, and data-driven. Global agendas, including the UN's Sustainable Development Goals, highlight issues such as equitable land access, resource efficiency, and informal settlement upgrading. In this context, the success of policy-making depends on effectively managing uncertainty and utilizing both past experiences and real-time data. As decisions grow more complex and data volumes increase, advanced analytical tools become essential. Machine learning (ML) algorithms enable pattern recognition and prediction from large datasets, while Multi-Criteria Decision-Making (MCDM) methods offer structured evaluation of alternatives based on multiple criteria and stakeholder inputs. The integration of ML and MCDM provides a comprehensive framework to support dynamic, informed, and sustainable land policy development and implementation. This study aims to examine the potential application of machine learning and MCDM methods within the context of land management policies in Türkiye. This study suggests that ML and MCDM have high potential to support improvements in Türkiye's land management policies. The potential of these tools shows that policymakers can benefit from them to make more informed, data-driven decisions, ensure more efficient and equitable land management, and ultimately contribute to sustainable urban and rural development.

1. Introduction

Land management is a governance process that ensures the use of land and its resources within the framework of sustainable development principles through urban and rural planning, legal regulations, and institutional mechanisms, and it is where land policies are put into practice (Yomralıoğlu, 2011). Sustainable development, environmental protection, planned urbanization, agriculture, and property security are examples of land-based management policies (Lemmen, 2012). Such land management policies emerge in various forms through different policy development processes and are implemented using tools such as legal regulations, incentives, and land development. Each country employs different techniques and instruments to achieve its land policy objectives while managing its land and resources (Auzins et al., 2022).

Due to their socially, economically, and culturally complex and dynamic nature, cities are the focal point of many policies. In addition to national and local urban policies, the United Nations (UN) has addressed issues such as informal constructions, slum upgrading, access to basic services, and the provision of ownership and control over land in the policies and goals of many of its agencies (UN-Habitat, 2016, 2017). Furthermore, problems such as the overconsumption of resources, low quality of life, agricultural inefficiency, social problems, food insecurity, and inequitable income distribution—which provide justification for the mission of the Sustainable Development Goals—intersect with urbanization policies.

For a policy to be successful, it must produce positive outcomes in three main areas: the process (decision-making and legislation), the program (implementation and goal attainment), and the political dimension (McConnell, 2010). Given the existence of multiple plausible scenarios for the future, it may not be possible to develop a single static policy that performs well under all conditions. Therefore, uncertainties faced by policymakers are often addressed through past policy experiences or newly acquired information (Walker et al., 2001). Policy-making processes typically involve multi-dimensional decisions that require effective analysis of various data sources. In the face of growing data volumes and increasingly complex decision-making processes, contemporary tools are utilized to support data-driven decisions and solve complex problems in both the development and implementation phases of policy-making. The general process followed in policy-making is illustrated in Figure 1, outlining the key stages from problem identification to policy evaluation.

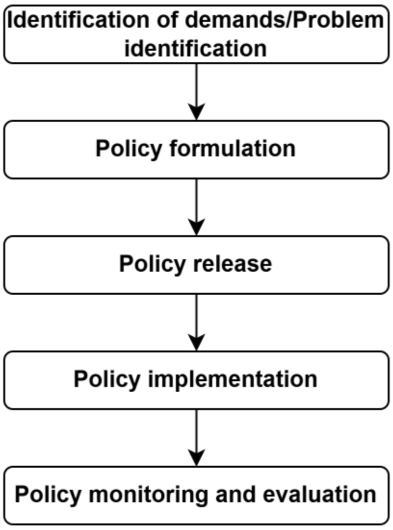

Figure 1. Policy-making processes (Wang et al., 2024).

Since policies are future-oriented, they are inherently predictive (Walker et al., 2001). The predictive accuracy of models trained on current conditions and evolving trends increases the likelihood of a policy's success. One of the techniques used to define, interpret, and analyze highly complex data structures and patterns is machine learning (ML), which can make predictions based on large datasets (Ati et al., 2024; Ngiam & Khor, 2019). In addition to ML algorithms, Multi-Criteria Decision-Making (MCDM) methods provide a decision-making framework for identifying the best alternatives by integrating diverse criteria and stakeholder interests (Cohen et al., 2019). Since land management policies inherently refer to spatial assets, a significant portion of the data guiding these policies is spatial in nature. Geographic Information Systems (GIS), with their capabilities for processing, analyzing, and visualizing spatial datasets, can enhance decision-making processes by providing interpretable data to both ML and MCDM methods.

When assessing the impacts of land-use-related policies, it is crucial to offer recommendations on how flawed policies can be modified or adjusted to ensure substantial development outcomes (Li et al., 2014). In this context, ML algorithms have been used in the literature to: propose a cost-effective mass appraisal policy methodology using only free and open data sources (Carranza et al., 2022); analyze the effects of greenbelt policies in the Seoul metropolitan area (Jun, 2023); examine the likelihood of land-use planning achieving its goals in Chongqing, China (Xu et al., 2019); and identify the most influential factors on per-square-metre land values in New York City (Ma et al., 2020). MCDM methods, on the other hand, have been applied in the literature for selecting suitable housing locations for low-income households in Iran (Sharghi et al., 2022) and for determining appropriate land-use types to support sustainable land-use policies (Topuz & Deniz, 2023). This study aims to analyze the policy-making phases of land management in Türkiye and to examine the potential use of machine learning algorithms and multi-criteria decision-making methods within these phases. Additionally, the study discusses the possible impacts of employing ML algorithms and MCDM methods on the effectiveness and success of land administration policies. In the second section of the study, the institutional structure and development process of land policies in Türkiye are explained. The third section explain the principles and capabilities of ML algorithms and MCDM methods. In the Results and Discussion section, the potential applicability of these methods for Türkiye is examined.

2. Land Policy-Making Framework in Türkiye

Land policy consists of established rules and guidelines that determine the governance, management, and administration of urban land (Koroso & Zevenbergen, 2024). A sound land policy is essential for effective land administration and management (Yomralıoğlu, 2011). In Türkiye, land policies are developed at both national and local government levels. At the national level, the most comprehensive policy documents are the development plans, prepared every five years since 1963, which aim to guide policies and decisions across a wide range of sectors including the economy, health, education, and transportation (Boğuşli & Oğuztimur, 2021). These development plans cover issues ranging from property ownership to urbanization and public investments, and they establish a five-year vision. They also serve as primary reference documents for executive institutions. During the problem-identification stage of policy formulation, special expert commissions and working groups are established with the contributions of private sector representatives, civil society actors, and the academic community. Participation is encouraged through meetings and surveys (Twelfth Development Plan (2024-2028), 2024). To ensure coordination between nationally produced policies and locally implemented activities, and to reduce regional development disparities, regional planning policies are developed by development agencies affiliated with the central government. While the central government formulates land policies at both national and regional levels, local governments are often the primary authorities responsible for designing and implementing policies related to urbanization, taxation, and spatial planning that address local needs. However, ministries under the central government possess broad supervisory and enforcement powers over local government activities. One of the key issues highlighted under the urbanization theme of the Eleventh Development Plan is the necessity of legal regulations that will clarify the distribution of authority and responsibility among institutions and enhance inter-institutional coordination (Batuhan & Kodaz, 2020).

Land policy can aim to ensure tenure security, support access to credit, guide land reform and titling processes, and address challenges related to traditional or customary tenure systems. It may also prioritise equitable land access for disadvantaged groups such as the poor, ethnic minorities, and women, while promoting effective land use and spatial planning, real property taxation, and the prevention of land speculation and disputes (FIG, 1996). One of the five strategic pillars defined to achieve the vision set out in Türkiye's Eleventh Development Plan is *"livable cities and sustainable environment."* Within this pillar, policy proposals and measures are outlined across various thematic areas, including regional development, urbanisation, housing, urban transformation, urban infrastructure, rural development, environmental protection, and disaster management (Batuhan & Kodaz, 2020). The Twelfth Development Plan, which covers the period from 2024 to 2028, continues to pursue similar policy objectives, particularly focusing on *disaster-resilient living spaces* and a *sustainable environment*. Table 1 presents selected targets and policy actions defined within the scope of the Twelfth Development Plan under the vision of disaster-resilient living spaces and a sustainable environment. It includes a subset of land-related policies embedded in the broader development strategy.

https://doi.org/10.5194/isprs-archives-XLVIII-4-W17-2025-339-2026 | © Author(s) 2026. CC BY 4.0 License.

Thematic Domain	Policies and Objectives
Disaster Management	Disaster hazards and risks will be prioritised during spatial planning processes, and enforcement and monitoring mechanisms will be strengthened to improve implementation. GIS-based decision support mechanism capable of effectively managing all resources during disasters will be developed and kept up to date.
Urban Renewal	Renewal addressing various problems will be developed through an integrated approach. Prioritization will be carried out based on criteria such as disaster and climate hazards, as well as economic and social challenges. The actual market values of properties will be determined to provide financial resources for renewal processes.
Urbanization	Public spaces will be planned to be accessible and inclusive. Green areas will be expanded based on population, climate, and accessibility criteria. A mechanism will be established for monitoring real (market) property values
Housing	Access to safe and affordable housing for all will be enhanced. Social housing will be provided for disadvantaged groups. Equitable solutions will be developed to meet post-disaster housing needs.
Environmental Protection	Infrastructure for the evaluation and management of environmental monitoring data would be developed
Urban Infrastructure	Water data will be improved, and climate impacts will be analysed. The impacts of climate change on water resources across Türkiye will be determined using up-to-date data sets and scenarios. In order to reduce fuel consumption in the planning of new settlement areas in cities, the capacity of rail systems will be utilized and mixed areas supporting pedestrian and bicycle use will be encouraged.
Regional Development	A statistical infrastructure will be developed to measure regional disparities. Strategies for green and digital transformation will be formulated based on the potential and needs of each region.
Rural Development	Public service delivery in rural areas will be improved by analysing region- and location-specific characteristics to enhance the quality of life. In the resettlement of expropriated areas, measures will be taken to minimise public expenditures in the selection of settlement locations. The attractiveness of rural areas will be increased through improved employment opportunities and diversification of the economy.

Table 1. Strategic goals and policies identified to achieve the vision of disaster-resilient living spaces and a sustainable environment

3. Machine Learning and MCDM Methods for Decision-Making Processes

The fundamental logic of ML algorithms is based on their ability to learn from data and use this learning to make predictions. ML algorithms are typically trained on a dataset referred to as training data. This dataset allows the algorithm to learn patterns and build a model that can be used for future decision-making (Zaki et al., 2022). For instance, a machine learning algorithm can be trained on data such as land parcel size, distance to existing infrastructure, topography, proximity to surrounding services, and environmental protection areas in order to predict land use types. By learning the relationships between land use and these features, the algorithm can estimate which use—such as agriculture, residential, commercial, or industrial—is more suitable for a given area. ML algorithms can be classified into three main categories depending on their learning styles: supervised learning, unsupervised learning, and reinforcement learning (Tchuente & Nyawa, 2022). In supervised learning, algorithms are trained on labelled data, which includes both input and output values. The algorithm learns to identify patterns from this data in order to make predictions about future events (Mayer et al., 2022). It can be applied for classification tasks or for regression tasks involving the prediction of continuous values. In contrast, unsupervised learning algorithms work with unlabelled data, which only contains input variables. The goal of the algorithm in this case is to discover hidden structures or patterns in the data. Unsupervised learning is commonly used for clustering and dimensionality reduction tasks (Jun, 2023). In reinforcement learning, the algorithm interacts with an environment and receives rewards or penalties based on the actions it takes. In the field of land policy, various algorithms have been applied depending on the intended objective. Multiple Linear Regression is commonly used to model linear relationships between predictor variables and the target variable. Support Vector Machines are preferred when modelling non-linear relationships, while the Random Forest method is often selected due to its ability to model complex relationships and its robustness to outliers. For property value prediction tasks, the Random Forest method is widely adopted due to its ease of optimal parameter selection, straightforward applicability in regression problems, provision of variable importance insights, and overall high model performance (Guliker et al., 2022; Şişman et al., 2023). There are also interpretability methods that

https://doi.org/10.5194/isprs-archives-XLVIII-4-W17-2025-339-2026 |

calculate each feature's contribution to model predictions, providing insights into overall feature importance and offering detailed explanations regarding how individual features contribute to specific predictions. These methods enhance the applicability of machine learning in spatial contexts by enabling the extraction of spatial effects using ML models (Zhang et al., 2024).

MCDM methods are techniques used to identify the most appropriate alternative among multiple, often conflicting, criteria (Fei et al., 2020; Torkayesh et al., 2021). MCDM methods vary depending on the mathematical models employed and the way criteria are addressed. Commonly applied methods include the Analytic Hierarchy Process (AHP), the Best-Worst Method (BWM), and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). The key differences among MCDM methods lie in how the problem is structured, how the criteria are handled, and the mathematical approaches used to reach a solution. AHP is suitable when criteria can be arranged in a hierarchical structure and when pairwise comparisons are needed to reduce subjectivity and ensure consistency (Kutlu Gündoğdu et al., 2021). BWM facilitates the comparison process when the best and worst criteria are known by requiring the decision-maker to compare all other criteria with only these two, thereby simplifying pairwise comparisons. TOPSIS, on the other hand, ranks decision alternatives based on their distance to the best and worst possible criterion values (Torkayesh et al., 2021). Unlike AHP, it does not involve pairwise comparisons between criteria. When the goal is to evaluate how close an alternative is to the ideal solution, TOPSIS is often the preferred method. Figure 2 presents the typical steps shared across MCDM methods in a sequential process.

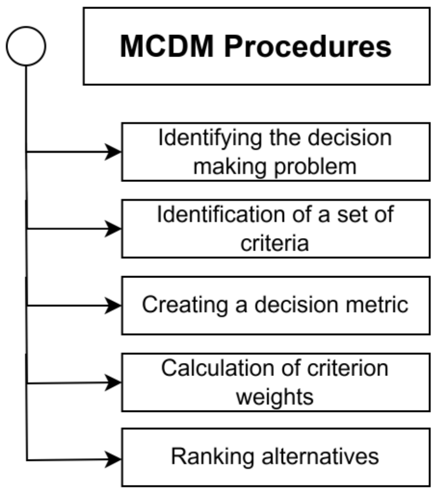

Figure 2. Stages of multi-criteria decision-making processes (Hasan et al., 2022).

As shown in Figure 2, the processes of problem identification and the determination of all key criteria influencing the problem are generally common across all MCDM methods. The step that varies depending on the specific method is the construction of the decision matrix. This step refers to the mathematical formulation that determines how alternatives are evaluated and ranked based on the criteria. At this stage, weights are assigned to indicate the relative importance of each criterion (Fei et al., 2020). The calculation of criterion weights also differs depending on the chosen method. While AHP employs pairwise comparisons, BWM requires the identification of the best and worst criteria, which are then compared to all others. A total score is computed for each alternative using the criterion weights and evaluation scores, and alternatives are subsequently ranked based on these scores—this is also carried out using different mathematical approaches depending on the method. ML algorithms can offer significant support in reducing subjective judgments, which are frequently encountered in traditional MCDM methods (Yalcin et al., 2022). ML algorithms can be used to objectively determine criterion weights by analysing patterns in large datasets. Furthermore, by revealing complex relationships within the data, ML enables a more accurate evaluation of alternatives (Yılmaz Balaban & Çalı, 2019). Thus, the integration of MCDM and ML methods can enhance the objectivity of weight determination and reveal hidden interdependencies among criteria. Even in cases where sufficient labelled data is not available for machine learning, MCDM methods can still be effectively utilised.

4. Results and Discussion

In the second section of the study, the process of formulating land policies in Türkiye and the country's current strategic land management objectives are discussed. The third section focuses on how data-driven foresight, particularly in problem identification, policy formulation, and monitoring policy impacts, can be integrated into decision-making processes. As shown in Table 1, an analysis of Türkiye's current land policies reveals that in the domains of disaster management and urban transformation, spatial planning policies prioritise disaster-prone areas and establish a hierarchy for urban renewal zones. While prioritising among alternatives based on various criteria involves a MCDM process, predicting disaster risk and estimating the value of urban transformation areas can be supported by ML solutions. Within the theme of urbanisation, the accurate identification of protected values and ML-based value estimation using market data and value-influencing criteria can offer analytical insights. The inclusive and accessible planning of public spaces, which involves forecasting future demand for certain services, represents a potential application area for ML in problem identification within the planning discipline. The selection of green space locations based on multiple attributes may also benefit from MCDM approaches to support evidence-based policy development. In the housing policy outlined in the development plan, identifying housing needs across different income groups is prioritised. Problem/requirement estimation for each group can be conducted by analysing socio-economic data, investment plans, and physical environment variables. The prioritisation of housing construction can then be aligned with urban development strategies. Urban infrastructure policies increasingly focus on impact estimation through scenario-based analysis of natural resources and transport systems. To support decision-making among potential policy alternatives generated through such scenarios, integrated ML and MCDM decision support systems can offer viable solutions. In the context of regional development policies, which aim to minimise regional disparities, explainable ML models can help identify patterns among regional data and reveal problematic areas. For rural development policies, ML can be utilised to identify key data points that enhance the attractiveness of rural areas, while investment planning and location selection for public services can be addressed through MCDM approaches.

By their very nature, land policies are closely linked to geographic features and are associated with numerous data sources. The integration of GIS is essential for both the generation of data to be analysed through ML and MCDM, and for the visualisation of analysis results. Within the framework of the INSPIRE Directive, Türkiye has developed a national data infrastructure known as the Turkish National Spatial Data Infrastructure (TUCBS), which establishes standards for the production and dissemination of spatial data required for policymaking. This infrastructure enables the use of developed prediction and prioritisation models across different domains for consistent policy requirements, offering a significant advantage in terms of interoperability and reusability.

5. Conclusion

The policy-making process inherently involves the design and implementation of scenarios. Data that guide policy formulation are evaluated through various tools to determine the most effective policy actions for achieving specific goals. In this context, understanding relationships among existing data during problem identification, generating policy alternatives based on predictive scenarios, and conducting in-depth evaluations of policy outcomes through monitoring can all benefit from the application of ML and MCDM methods. The Twelfth Development Plan, which is the focus of this study, demonstrates a strong alignment with the use of these tools in the context of land policies. Future research may investigate the performance of specific ML and MCDM methods tailored to particular problem areas in land policy development. Additionally, the inclusion of these data analysis and decision-support tools within the policy-making process can provide a basis for evaluating policy effectiveness.

References

Ati, A., Bouchet, P., & Ben Jeddou, R. (2024). Using multi-criteria decision-making and machine learning for football player selection and performance prediction: A systematic review. *Data Science and Management*, *7*(2), 79–88. https://doi.org/10.1016/j.dsm.2023.11.001

Auzins, A., Brokking, P., Jürgenson, E., Lakovskis, P., Paulsson, J., Romanovs, A., Valčiukienė, J., Viesturs, J., & Weninger, K. (2022). Land Resource Management Policy in Selected European Countries. *Land*, *11*(12), 1–32. https://doi.org/10.3390/land11122280

Batuhan, T., & Kodaz, İ. (2020). On Birinci Kalkınma Planında Kentleşme ve Çevre Politikaları. *Şehir ve Medeniyet Dergisi*, *6*(12), 75–94. http://www.sehirvemedeniyetdergisi.org

Boğuşli, Ö., & Oğuztimur, S. (2021). 2000 Sonrası Kalkınma Planlarının Ulaştırma Politikaları Bakımından İncelenmesi. *Kent Akademisi*, *14*(2), 452–467. https://doi.org/10.35674/kent.900606

Carranza, J. P., Piumetto, M. A., Lucca, C. M., & Da Silva, E. (2022). Mass appraisal as affordable public policy: Open data and machine learning for mapping urban land values. *Land Use Policy*, *119*(June). https://doi.org/10.1016/j.landusepol.2022.106211

Cohen, B., Blanco, H., Dubash, N. K., Dukkipati, S., Khosla, R., Scrieciu, S., Stewart, T., & Torres-Gunfaus, M. (2019). Multi-criteria decision analysis in policy-making for climate mitigation and development. *Climate and Development*, *11*(3), 212–222. https://doi.org/10.1080/17565529.2018.1445612

Fei, L., Lu, J., & Feng, Y. (2020). An extended best-worst multi-criteria decision-making method by belief functions and its applications in hospital service evaluation. *Computers and Industrial Engineering*, *142*(January), 106355. https://doi.org/10.1016/j.cie.2020.106355

FIG. (1996). *THE BOGOR DECLARATION*. United Nations Interregional Meeting of Experts on the Cadastre. https://fig.net/organisation/comm/7/library/reports/bogor/BogorDeclaration.html

Guliker, E., Folmer, E., & van Sinderen, M. (2022). Spatial Determinants of Real Estate Appraisals in The Netherlands: A Machine Learning Approach. *ISPRS International Journal of Geo-Information*, *11*(2). https://doi.org/10.3390/ijgi11020125

Hasan, M. G., Ashraf, Z., & Khan, M. F. (2022). Multi-choice best-worst multi-criteria decision-making method and its applications. *International Journal of Intelligent Systems*, *37*(2), 1129–1156. https://doi.org/10.1002/int.22663

Jun, M. J. (2023). Simulating Seoul's greenbelt policy with a machine learning-based land-use change model. *Cities*, *143*(December 2022), 104580. https://doi.org/10.1016/j.cities.2023.104580

Koroso, N. H., & Zevenbergen, J. A. (2024). Urban land management under rapid urbanization: Exploring the link between urban land policies and urban land use efficiency in Ethiopia. *Cities*, *153*(April), 105269. https://doi.org/10.1016/j.cities.2024.105269

Kutlu Gündoğdu, F., Duleba, S., Moslem, S., & Aydın, S. (2021). Evaluating public transport service quality using picture fuzzy analytic hierarchy process and linear assignment model. *Applied Soft Computing*, *100*, 106920. https://doi.org/https://doi.org/10.1016/j.asoc.2020.106920

Lemmen, C. (2012). A Domain Model for Land Administration. In *TU Delft* (Vol. 78, Issue June).

Li, Y., Liu, Y., Long, H., & Cui, W. (2014). Community-based rural residential land consolidation and allocation can help to revitalize hollowed villages in traditional agricultural areas of China: Evidence from Dancheng County, Henan Province. *Land Use Policy*, *39*, 188–198. https://doi.org/10.1016/j.landusepol.2014.02.016

Ma, J., Cheng, J. C. P., Jiang, F., Chen, W., & Zhang, J. (2020). Analyzing driving factors of land values in urban scale based on big data and non-linear machine learning techniques. *Land Use Policy*, *94*(April 2019), 104537. https://doi.org/10.1016/j.landusepol.2020.104537

Mayer, M., Bourassa, S. C., Hoesli, M., & Scognamiglio, D. (2022). Machine Learning Applications to Land and Structure Valuation. *Journal of Risk and Financial Management*, *15*(5). https://doi.org/10.3390/jrfm15050193

McConnell, A. (2010). Policy success, policy failure and grey areas in-between. *Journal of Public Policy*, *30*(3), 345–362. https://doi.org/10.1017/S0143814X10000152

Ngiam, K. Y., & Khor, I. W. (2019). Big data and machine learning algorithms for health-care delivery. *The Lancet Oncology*, *20*(5), e262–e273. https://doi.org/https://doi.org/10.1016/S1470-2045(19)30149-4

Presidency of the Republic of Türkiye Presidency of Strategy and Budget (2024). *Twelfth Development Plan (2024-2028)* (p. 253).

Sharghi, A., Nourtaghani, A., Ramzanpour, M., & Gorji, R. B. (2022). Low-income housing location based on affordable criteria Using AHP Model and GIS Technique (Case Study: Babolsar City). In *Environment, Development and Sustainability* (Vol. 24, Issue 8). Springer Netherlands. https://doi.org/10.1007/s10668-

021-01870-7

Şişman, S., Çağdaş AYDINOĞLU, A., & Tarihi, G. (2023). Toplu Taşınmaz Değerlemesi için Coğrafi Verinin İşlenmesi ve Rastgele Orman Makine Öğrenmesi Tekniğiyle Tahmin Modelinin Geliştirilmesi (Processing Geographical Data and Developing Prediction Model with Random Forest Machine Learning Technique for Mass Re. *Ocak*, *169*, 13–27.

Tchuente, D., & Nyawa, S. (2022). Real estate price estimation in French cities using geocoding and machine learning. In *Annals of Operations Research* (Vol. 308, Issues 1–2). Springer US. https://doi.org/10.1007/s10479-021-03932-5

Topuz, M., & Deniz, M. (2023). Application of GIS and AHP for land use suitability analysis: case of Demirci district (Turkey). *Humanities and Social Sciences Communications*, *10*(1), 1–15. https://doi.org/10.1057/s41599-023-01609-x

Torkayesh, A. E., Malmir, B., & Rajabi Asadabadi, M. (2021). Sustainable waste disposal technology selection: The stratified best-worst multi-criteria decision-making method. *Waste Management*, *122*, 100–112. https://doi.org/https://doi.org/10.1016/j.wasman.2020.12.040

UN-Habitat. (2016). Slum Almanac 2015/2016: Tracking improvement in the lives of slum dwellers. In *Participatory Slum Upgrading Programme*. https://unhabitat.org/slum-almanac-2015-2016-0

UN-Habitat. (2017). *Human Rights in Cities Handbook Serıes: The Human Rights-Based Approach to Housing and Slum Upgrading*. https://unhabitat.org/the-human-rights-in-cities-handbook-series-volume-i-the-human-rights-based-approach-to-housing-and-slum-upgrading

Walker, W. E., Rahman, S. A., & Cave, J. (2001). Adaptive policies, policy analysis, and policy-making. *European Journal of Operational Research*, *128*(2), 282–289. https://doi.org/https://doi.org/10.1016/S0377-2217(00)00071-0

Wang, Z., Xie, D., Yang, Y., & Liu, Y. (2024). A process-based evaluation framework for environmental impacts of policy making. *Environmental Impact Assessment Review*, *104*(November 2023), 107351. https://doi.org/10.1016/j.eiar.2023.107351

Xu, T., Gao, J., & Li, Y. (2019). Machine learning-assisted evaluation of land use policies and plans in a rapidly urbanizing district in Chongqing, China. *Land Use Policy*, *87*(June), 104030. https://doi.org/10.1016/j.landusepol.2019.104030

Yalcin, A. S., Kilic, H. S., & Delen, D. (2022). The use of multi-criteria decision-making methods in business analytics: A comprehensive literature review. *Technological Forecasting and Social Change*, *174*(December 2020), 121193. https://doi.org/10.1016/j.techfore.2021.121193

Yılmaz Balaban, Ş., & Çalı, S. (2019). A DECISION PROCEDURE FOR SUSTAINABLE ENERGY MANAGEMENT AND PLANNING BASED ON MULTI CRITERIA DECISION MAKING UNDER FUZZY ENVIRONMENT. *Yönetim ve Ekonomi Araştırmaları Dergisi*, *17*(2), 21–41.

Yomralıoğlu, T. (2011). Dünya’da Arazi Yönetimi. *Türkiye’de Sürdürülebilir Arazi Yönetimi Çalıştayı, 26- 27 Mayıs 2011, Okan*, 1–14.

Zaki, J., Nayyar, A., Dalal, S., & Ali, Z. H. (2022). House price prediction using hedonic pricing model and machine learning techniques. *Concurrency and Computation: Practice and Experience*, *34*(27), 1–15. https://doi.org/10.1002/cpe.7342

Zhang, X., Zhu, Y., Gan, W., Zou, Y., & Wu, Z. (2024). Mapping heterogeneity: Spatially explicit machine learning approaches for urban value uplift characterisation and prediction. *Sustainable Cities and Society*, *114*(May), 105742. https://doi.org/10.1016/j.scs.2024.105742