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Utilising land use scenario modeling and machine learning for mitigating drought risks in degraded landscapes

Aditya Nugraha Putra[1,2*], Sephia Dewi Meila Chrisaputri[3], Cindy Monica Manurung[3], Michelle Talisia Sugiarto[4], Novandi Rizky Prasetya[4], Irma Ardi Kusumawati[5], Istika Nita[2], Mohd Hasmadi Ismail[6], Silvia Kohnová[1], Kamila Hlavčová[1]

[1] Department of Land and Water Resources Management, Faculty of Civil Engineering, Slovak University of Technology in Bratislava, Bratislava 81005, Slovakia.
[2] Soil Science Department, Faculty of Agriculture, Brawijaya University, Veteran Street, Malang 65145, Indonesia.
[3] Agroecotechnology Study Program, Faculty of Agriculture, Brawijaya University, Veteran Street, Malang 65145, Indonesia.
[4] Soil and Water Management Study Program, Faculty of Agriculture, Brawijaya University, Veteran Street, Malang 65145, Indonesia.
[5] Yayasan Bumi Hijau Lestari, Telaga Bodas Raya, Semarang 50235, Indonesia.
[6] Faculty of Forestry and Environment, Universiti Putra Malaysia, Serdang, Selangor 43400, Malaysia.
[*] Corresponding author. E-mail: aditya.putra@stuba.sk

Abstract: Land-use change is a key driver of environmental degradation and increasing drought risk. This study assesses drought dynamics in the South Malang Plateau, East Java, by integrating remote sensing data with the Random Forest (RF) algorithm. Three land use scenarios were developed: Business-as-Usual (BAU) for 2030 (predicted using the CA-ANN method in QGIS), participatory mapping (PM), and land capability classification (LCC). Using 175 stratified random field points (70% for training, 30% for validation), the analysis integrated 25 predictor variables across climatic, anthropogenic, topographic, and vegetation index factors. The RF model used for drought classification achieved an overall accuracy of 92.57%. Based on unsupervised classification of historical satellite imagery, between 2017 and 2023 multistrata agroforestry declined by nearly 50%, natural forest cover decreased by 27.6%, and settlements more than doubled. Under the 2030 BAU scenario, forest cover is projected to decline further to 9,195.16 ha. Drought analysis shows a peak in 'Severe Drought' at 18.1% in 2019, dropping to 3.1% by 2030, while 'Extreme Drought' steadily rises from 6.2% to 7.0%, particularly in deforested areas. Among the scenarios, the integrated LCCPM approach demonstrated higher potential to reduce drought vulnerability and land degradation. The integrated land capability classification- participatory mapping (LCCPM scenario) is recommended to strengthen landscape resilience and promote sustainable land management.

Keywords: Remote sensing; Land cover; Machine learning; Geographic information system; Water management.

1 INTRODUCTION

Land-use change is increasingly recognized as a primary driver of environmental degradation and hydro-meteorological disasters (Chanie, 2024; Gáspár and Škrinár, 2023). The rapid decline of vegetative cover is estimated to have reached a 45% reduction in 2023, leaving approximately 8.8 million hectares of land barren. It has significantly disrupted ecosystem functions and exacerbated drought risks. The consequence there of this situation is a low level of interception, low infiltration, and low water retention, while at the same time the surface runoff and drought increased (Khadka et al., 2020). This phenomenon is exacerbated by another driving factor such as climate change, demographic pressures, infrastructure expansion, escalating demands for food and energy, and the strategic economic importance of certain regions (Esengulova et al., 2024).

Addressing these challenges calls for advanced methods capable of detecting, simulating, and evaluating land-use dynamics to support sustainable regional development. In this context, remote sensing (RS) and model–based prediction tools have become increasingly valuable. RS offers consistent, high-resolution spatiotemporal data on land cover changes and vegetation health, making it a powerful tool for monitoring landscape transformations. At the same time, predictive modeling allows for scenario–based simulations, helping forecast future land-use patterns and assess environmental risks under varying policy frameworks or land management strategies (Sedighi et al., 2024).

Since 2000, there has been a 29% increase in the frequency and duration of drought events globally compared to the previous two decades, impacting over 1.4 billion people (Mera, 2018). By 2050, around 75% of the global population is projected to live in areas highly vulnerable to severe drought. In Indonesia, the Meteorology, Climatology, and Geophysics Agency (BMKG) forecasts that 317 seasonal zones (45.61%) will experience peak dryness in August 2024, with 217 seasonal zones (31.22%) in July and 68 seasonal zones (9.78%) in September, signaling widespread dry conditions. The South Malang Plateau, with its complex geology, is particularly vulnerable. The South Malang Plateau, shaped by a long history of tectonic activity, is underlain by a complex geological structure consisting of both fractured volcanic rocks and sedimentary formations (Irwan, 2020), including extensive karst landscapes. These lithological conditions contribute to shallow soil depth, limited water-holding capacity, and deep aquifers that are difficult to access, collectively intensifying the region's vulnerability to severe droughts, especially during prolonged dry seasons (Putra et al., 2025b).

The South Malang Plateau, characterized by its complex geological formations, including karst, volcanic, tectonic, and alluvial landscapes, which are particularly susceptible to land degradation and desertification (Prasetya et al., 2025). The area naturally has shallow soil layers, widespread rock outcrops, soil erosion and underground water systems (Putra et al., 2025). On the other hand, these areas serve vital functions for life within them such as hydrological regulation and carbon storage, biodiversity and buffer zone functions, agriculture, animal habitat, and water use and spring conservation (Figure 1).

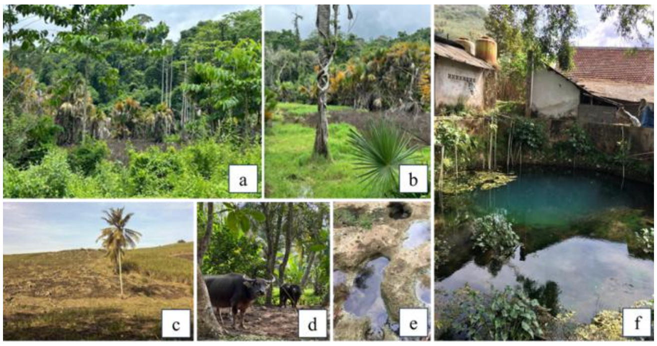

Fig. 1. Ecosystem functions carried out by the South Malang Plateau to meet the needs of living things in it include (a) Hydrology regulation and carbon stock, (b) Biodiversity function and buffer zone, (c) Agriculture land, (d) Animal's habitat, (e) Springs conservation and (f) Water usage.

This vulnerability manifests in reduced soil fertility, declining crop yields, increased water scarcity, and habitat fragmentation, all of which threaten agricultural productivity, freshwater availability, and regional ecological stability (Danáčová et al., 2024; van der Esch et al., 2022). Environmental stressors in the South Malang Plateau, such as deforestation, unsustainable agricultural expansion, urban encroachment, recurrent droughts, topsoil erosion, and increasing climatic aridity (manifested through rising temperatures and declining precipitation), have collectively accelerated the degradation of natural resources and landscape resilience (Olofintoye et al., 2022; Purwanto et al., 2023). Without coordinated, science-based, and context–sensitive management interventions, the region is projected to experience compounding degradation (Ke et al., 2024). These environmental stressors, if left unchecked, not only accelerate ecological deterioration but also generate cascading socio–economic impacts, disproportionately affecting local communities that rely on natural resources for their livelihoods (Belal et al., 2014; Kogo et al., 2021; Webb et al., 2017). In this context, model–based land use prediction combined with RS provides a vital foundation for spatially explicit planning and targeted intervention. RS offers consistent, repeatable, and large-scale data, making it especially valuable for capturing landscape dynamics in near–real time, particularly in data-scarce or environmentally sensitive regions.

Additionally, scenario modeling has become an essential tool in regional planning and landscape management, particularly as climate variability intensifies (Putra et al. 2025a). By developing future land use scenarios, such as business–as–usual (BAU), participatory mapping (PM), and land capability classification (LCC)-based approaches, planners can explore potential environmental trajectories and make more informed, resilient policy decisions. These methods support efforts to balance development goals with conservation priorities, which is especially crucial in degraded and vulnerable ecosystems.

By integrating land use scenario modeling with machine learning, this study offers a strategic pathway to anticipate and mitigate drought risks in the South Malang Plateau, an increasingly vulnerable landscape where land degradation, poverty, and water scarcity converge, threatening both ecological resilience and the survival of local communities. The use of land use scenarios in this study, BAU, PM, and LCC offers an evidence–based framework to assess how different land management strategies may affect drought vulnerability. Scenario planning plays a crucial role in regional landscape governance, enabling stakeholders to explore plausible future conditions, evaluate trade-offs, and identify sustainable land allocation strategies amid uncertainty (Jahanishakib et al., 2018; Ren et al., 2019).

Given these challenges, there is an urgent need for an integrated and scientifically robust approach to mitigate drought risks through proactive land-use planning and early warning systems. Although various technologies have been deployed globally, efforts in Indonesia remain fragmented. Despite regulatory frameworks like Malang Regency Regional Regulation No. 3 of 2010, limited attention has been given to systematic monitoring of land-use change and its drought implications in the South Malang Plateau (Samsi et al., 2022). Current methodologies lack spatially explicit, high-resolution data to inform targeted strategies. This study addresses this gap by integrating Sentinel–2A imagery with machine learning approaches, Random Forest (RF), for drought classification and Cellular Automata–Artificial Neural Network (CA–ANN) for land–use projection. Sentinel–2A, with its 10–20 m spatial resolution and frequent revisit time, enables detailed monitoring of land use/land cover (LULC) dynamics over time. Sentinel-2A data (2017–2023) were processed using K-means clustering to map 14 land cover classes. RF leveraged 25 biophysical and anthropogenic predictors, while CA–ANN simulated 2030 land-use under different scenarios. Unlike conventional scoring-based methods, RF excels in processing multivariate datasets (Fan et al., 2022), refining scenario modeling and supporting more effective land management policies.

The CA–ANN–Markov approach is a hybrid, pattern-based modeling method that integrates artificial neural networks (ANN) with cellular automata (CA) to simulate land use change, while a Markov chain component estimates the probability of land conversion over time. This method was chosen for its strong ability to capture nonlinear spatial relationships and temporal dynamics in land use patterns (Jahanishakib et al., 2018). Unlike traditional models that depend solely on historical trends or fixed empirical rules, the CA–ANN–Markov approach is better suited to account for the complex interactions between land uses and adapt to changing socio–environmental conditions. This makes it particularly valuable for predicting landscape changes in rapidly evolving or environmentally sensitive regions.

Remote sensing is a powerful tool for observing land use changes over time. When combined with machine learning methods such as CA–ANN and RF, it becomes more effective for analyzing and predicting land use. CA–ANN simulates future land use based on spatial and temporal patterns, while RF accurately classifies land types using satellite data. The novelty of using both lies in CA–ANN's ability to model land expansion and RF's capacity to identify key features in change. This combined approach is useful for studying drought, as land conversion can reduce soil moisture and vegetation. In addition to RF, this research integrates participatory mapping and land capability assessments to ensure contextually relevant and socially inclusive strategies. The South Malang Plateau's diverse topography requires a nuanced, community-engaged modeling approach. This study generates high-resolution risk maps to guide policymakers and stakeholders in designing sustainable, drought-mitigating interventions.

By embedding stakeholder knowledge into a geospatial modeling framework, this study illustrates how hybrid models can play a critical role in supporting climate adaptation, land restoration, and enhanced governance, particularly in regions that are data-scarce and ecologically fragile. This integration ensures that local insights inform spatial decision-making, leading to more context-sensitive and sustainable outcomes. This study aims to: (1) analyze the historical trend of land use change in the South Malang Plateau using multitemporal Sentinel–2A remote sensing data from 2017 to 2023; (2) simulate and compare future land use patterns under three scenarios: BAU, PM, and LCC; and (3) assess spatiotemporal drought dynamics and evaluate how each scenario influences future drought risk. We hypothesize that there has been deforestation and an increase in agricultural land and settlements with a consequent increase in drought. Land use interventions by looking at aspects of LCC and PM can reduce the level of drought hazard in the South Malang Plateau.

2. MATERIAL AND METHODS

2.1. Research location

The research was conducted in the South Malang Plateau, Malang Regency, East Java with a total area of 99642.01 ha. The research area is located at 112˚17'–112˚57' E and 7˚44'–8˚26' S (Figure 2).

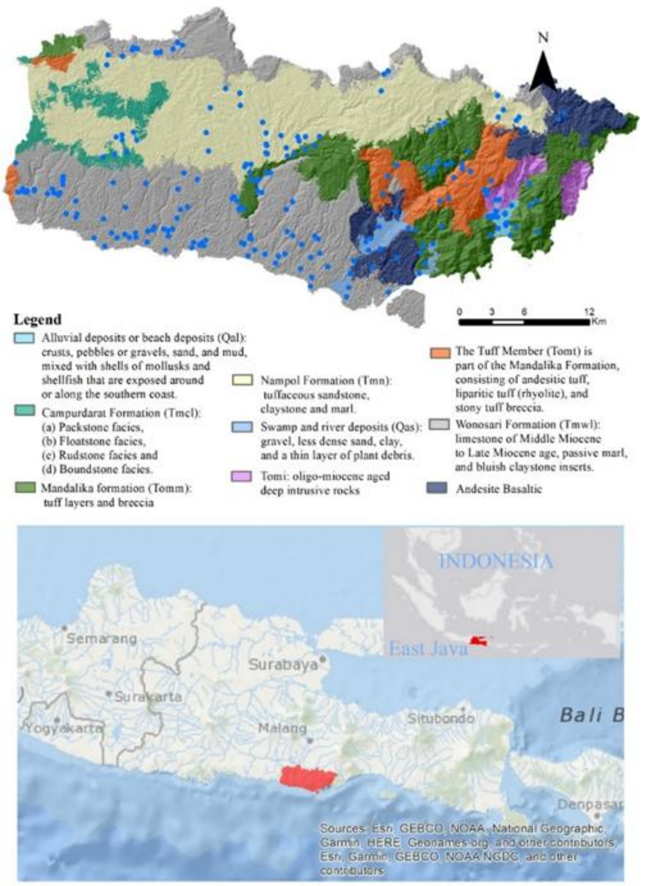

Fig 2. Map of research location and training area (blue points).

This area has an elevation of up to 590 meters above sea level. The average air temperature ranges from 18.2℃ to 26.5℃, with an average humidity of 58% to 97% (Statistic of Malang Regency, 2023). The study area receives an average annual rainfall of 1688 mm, predominantly between November and March, while experiencing a distinct dry season from June to September. The soil moisture follows an ustic regime, indicating periodic dryness that limits water availability for plants during certain months (Naorem et al., 2023). These climatic and soil conditions significantly impact agricultural practices by influencing plant development, irrigation requirements, and nutrient dynamics in the soil (Silva et al., 2023). Moreover, rainfall distribution and evapotranspiration patterns play a critical role in shaping farming strategies (Zhou et al., 2022). Based on the Schmidt–Ferguson climate classification (Schmidt and Ferguson, 1951), the region falls under the "D" category, which denotes a monsoonal climate characterized by a short dry season of 3–4 months and high rainfall intensity during the wet season. Annual precipitation in this climate type typically exceeds 2,000 mm, with rainfall concentrated in fewer than eight wet months per year and a dry season that does not extend beyond four months.

2.2 Image acquisition and classification

To analyze land use-land cover (LULC) in 2017, 2019, 2021, and 2023, Sentinel–2A images were downloaded from the European Space Agency (https://browser.dataspace.copernicus.eu/) (Sujarwo et al., 2022). The LULC classification was conducted using an unsupervised classification method approach (Aggarwal et al., 2023). The image analysis was performed in ArcMap 10.8 (Phuong and Thien, 2023), utilizing the K-means clustering method with 50 classification classes. The identified LULC categories included forest, production forest, simple agroforestry, multistrata agroforestry, shrubs and bushes, paddy fields, orchards, agricultural dryland, Rock Out Crop (ROC), agricultural land in government forest area, government built-up area, settlements, and river. The accuracy of the classified LULC maps was assessed using the Kappa coefficient(Srivastava et al., 2022), based on 100 georeferenced validation points selected through purposive sampling (Mariye et al., 2022). Of these, 70% (70 points) were used for training and 30% (30 points) for validation. A Kappa value of ≥ 0.70 was considered acceptable to ensure the reliability of classification results (Phinzi et al., 2021).

2.3 Land use scenarios

Three land use scenarios were developed: Business-as-Usual (BAU) for 2030, participatory mapping (PM), and land capability classification (LCC). The BAU scenario, aligned with regional spatial planning, was predicted using the CA-ANN method in QGIS (Değermenci, 2023), based on 2019–2021 land use data and driving factors like roads and built-up areas. The model was validated using 2023 land use derived from unsupervised classification, achieving a Kappa coefficient >80%, and was then used for 2030 projection (Mäyrä et al., 2023).

ANN is a computational model inspired by biological neural networks. It consists of interconnected nodes (neurons) that process input data to recognize patterns and make predictions. ANN is widely used for classification and regression tasks, including LULC prediction.

$$Y = f\sum_{i=1}^{n} Ш_i X_i + b \tag{1}$$

In a neural network, Y represents the output of a single neuron in the neural network which computed by applying an activation function f to the weighted sum of the input features X_i, each multiplied by its corresponding weight $Ш_i$, and added to a bias term b.

CA is a discrete dynamic model where space is divided into a grid of cells. Each cell changes its state over time based on its previous state and the states of neighboring cells, following predefined transition rules. CA helps in spatial modeling by simulating urban growth and LULC dynamics. The state of a cell at time $t + 1$ is determined by:

$$S_{i,j}^{t+1} = f(S_{i,j}^{t}, N_{i,j}^{t}, R) \quad (2)$$

The new state $S_{i,j}^{t+1}$ of a cell at position (i,j) is determined by its current state $S_{i,j}^{t}$, the states of its neighboring $N_{i,j}^{t}$ cells, and a set of transition rules R. Participatory Mapping (PM) combines scientific analysis with stakeholder input to ensure environmentally and socially relevant outcomes (Poku-Boansi, 2021). This study involved 36 stakeholders, including farmers, officials, and NGOs, through five stages: data collection, stakeholder profiling, consistency analysis, conflict analysis, and proposal assessment using land capability evaluation (I. Brown et al., 2011).

The analysis of LCC based on limiting factors of classes I to VIII follows the approach developed by (Rayes, 2007), categorizing land into classes I–VIII based on physical limitations. Biophysical data, such as soil texture, depth, drainage, slope, erosion, and climate, were scored to assess constraints. GIS-based weighted overlay analysis identified key limiting factors to produce the LCC map. Validation involved field surveys and historical comparisons. The results informed sustainable land use recommendations aligned with land suitability levels.

2.4 Random Forest algorithm

Random Forest (RF) is a supervised ensemble learning algorithm that constructs a large number of decision trees during training and outputs the mode of the classes (for classification) or mean prediction (for regression) from all trees. In this study, RF was implemented to classify drought severity using 25 predictor variables, including landform, elevation, temperature, SPI, rainfall, slope, and population density. The model utilized the Bagging technique (Bootstrap Aggregating), whereby each tree was trained on a bootstrapped subset of the data to reduce variance and prevent overfitting. A total of 100 decision trees were generated, and Gini impurity was used as the splitting criterion. Hyperparameters such as the number of variables randomly selected at each node (mtry), tree depth, and minimum leaf size were optimized through grid search and cross-validation.

$$\hat{Y} = \frac{1}{T}\sum_{t=1}^{T} h_t(X) \quad (3)$$

The final prediction $(\widehat{Y})$ was computed by majority voting across the ensemble of decision trees, where each individual tree $h_t(X)$ contributes to the final classification based on the input feature vector X. Accuracy assessment was conducted using a confusion matrix, yielding an overall accuracy of 92.57%, with F1-scores between 0.97 and 1.00 across five drought categories. These results confirm the model's robustness and suitability for handling high-dimensional, multi-source environmental data in heterogeneous landscapes.

2.5 Drought analysis

The drought map was generated using the RF algorithm, which integrates multiple environmental and climatic variables as predictive indicators (Figure 3). The RF model utilizes an ensemble of decision trees to classify drought severity, ensuring high predictive accuracy and robustness (Schonlau and Zou, 2020). In the RF framework, variable importance (VI) is quantified to evaluate the relative contribution of each predictor in the classification process. In this study, VI was computed using the mean decrease in Gini impurity, which measures the average gain in purity (homogeneity) achieved when a particular variable is used to split decision nodes across all trees in the ensemble. A higher Gini reduction indicates that the variable plays a more significant role in improving model accuracy. This approach is particularly useful in high-dimensional environmental data where multicollinearity is common and variable selection is nontrivial (Breiman, 2001).

In our model, 25 predictor variables were used, including landform, slope, elevation, temperature, rainfall, SPI (Standardized Precipitation Index), plan curvature, and population density. The variable importance results showed that landform, temperature, and SPI were the top contributors to drought classification, indicating their dominant role in shaping drought spatial dynamics across the South Malang Plateau. The use of VI in RF allows for transparent interpretation of feature influence, and has proven effective in geospatial drought modeling and land use impact assessments (Aldrich, 2020; Lovatti et al., 2019).

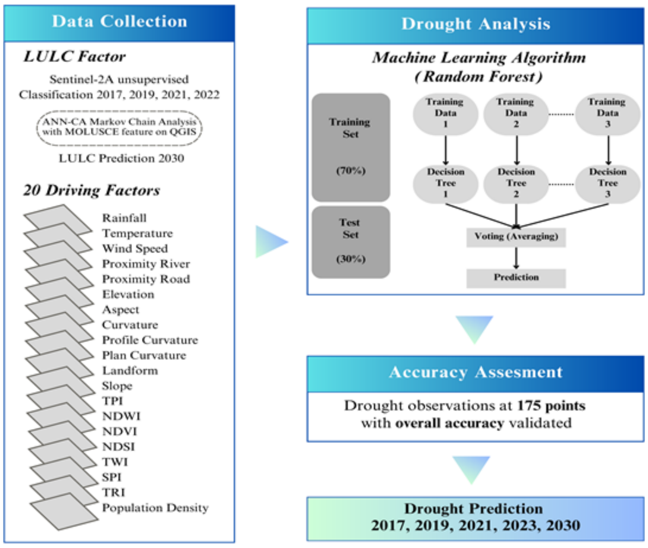

Fig 3. Framework of the research.

2.6 Drought training set data

A total of 175 observation points were selected across the 99,000-hectare study area using purposive sampling, with stratification based on distinct landform units previously delineated using a land mapping unit (LMU) approach following Putra et al. (2024). Unlike studies employing large numbers of random points, this study prioritized ecological representativeness over quantity by ensuring that each major landform type (e.g., uplands, depressions, karst hills, volcanic ridges) was proportionally represented. This targeted approach allowed for efficient ground validation while preserving spatial coverage and supporting robust landscape-level analysis. Drought classification was conducted based on standardized criteria from the Natural Resources Conservation Service (USDA, 2025), which categorizes drought intensity into six levels: Normal, Abnormally Dry, Moderate Drought, Severe Drought, and Extreme Drought (Table 1).

Table 1. Drought categories and possible consequences.

Description	Possible Impacts	Example Percentile Range for Most Indicators	Values for Standard Precipitation Index and Standardized Precipitation-Evapotranspiration Index
Normal	Normal condition	30.01 or Above	–0.49 or above
Abnormally Dry	Short-term dryness slowing planting and crop/pasture growth; Lingering water deficits after drought; Pastures or crops not fully recovered.	20.01 to 30.00	–0.5 to –0.79
Moderate Drought	Some damage to crops and pastures; Streams, reservoirs, or wells are low; water shortages developing or imminent; Voluntary water-use restrictions requested.	10.01 to 20.00	–0.8 to –1.29
Severe Drought	Likely crop or pasture losses; Common water shortages; Water restrictions imposed.	5.01 to 10.00	–1.3 to –1.59
Extreme Drought	Major crop and pasture losses; Widespread water shortages or restrictions.	2.01 to 5.00	–1.6 to –1.99

Table 2. Sources of factors contributing to the drought risk map.

Parameters	Factors	Method/Sources
Climatic	Rainfall; Temperature and Wind Speed (Masroor et al., 2020)	https://dataonline.bmkg.go.id
Anthropogenic	Population density (Putri et al., 2020)	https://malangkab.bps.go.id
	Distance to road and river (Pham et al., 2020)	https://tanahair.indonesia.go.id/ (DEMNAS)
Topographic	Aspect; Slope; Elevation; Topographic Position Index; Topographic Wetness Index; Topographic Ruggedness Index; Stream Power Index; Curvature; Landform (Rana et al., 2025)	https://tanahair.indonesia.go.id/ (DEMNAS)
Vegetation	Normalized Difference Vegetation Index (NDVI) (Dang et al., 2011)	$\frac{(NIR - RED)}{(NIR + RED)}$
	Normalized Difference Soil Index (NDSI) (Rogers and Kearney, 2004)	$\frac{(Red\ Edge - RED)}{(Red\ Edge + RED)}$
	Normalized Difference Soil Index (NDWI) (Zahari and Raja Ariffin, 2018)	$\frac{(NIR - SWIR)}{(NIR + SWIR)}$

2.7 Data collection on drought contributing factors

Drought-driving factors were analyzed using ArcGIS 10.8 and selected based on a review of prior studies and expert input, grouped into four main categories (Table 1). The Random Forest (RF) model was chosen for its strong predictive performance and non-parametric nature, allowing for high classification accuracy without statistical assumptions (Antoniadis et al., 2021). RF, as an ensemble of decision trees, reduces error rates and enhances accuracy. In each tree, the most influential variable serves as the primary splitter, ensuring consistent feature importance across the model (Chen et al., 2022), thus improving model stability and interpretability for drought assessment.

2.8 Drought monitoring

Drought severity maps were generated using the RF algorithm and environmental–climatic predictors (Figure 2). The model assessed drought vulnerability based on land use and environmental variables (Table 2), with input classified into five drought categories: normal, abnormally dry, moderate, severe, and extreme. The assessment followed Kukartseva et al. (2024), which evaluates actual drought impacts by observing river conditions and vegetation or crop health.

2.9 Accuracy assessment

Field observations for drought assessment were conducted at 175 points strategically distributed across various regions. Of these, 100 points were located in diverse landforms, including karst, volcanic, tectonic, and alluvial formations, while the remaining 75 points were situated near springs, rivers, and areas adjacent to water sources. The accuracy of the resulting drought map was validated using overall accuracy analysis, ensuring its precision and applicability for addressing drought risk management and mitigation strategies. The overall accuracy was calculated using the formula as confirmed and used by Kolachian and Saghafian (2021).

$$Overall\ Accuracy = \frac{\Sigma Field\ Observation\ Match\ Points}{Total\ Points}$$

3 RESULTS

3.1 LULC classification and changes

Over the six–year period, notable land use transformations occurred (Table 3). Multistrata agroforestry declined by 49.7%, from 21493.54 ha (19.8%) in 2017 to 10809.41 ha (10.0%) in 2023, indicating intense land conversion. In contrast, simple agroforestry remained relatively stable at around 32000 ha (29.5% to 29.9%) with minor fluctuations. Natural forest cover decreased by 27.6%, from 12795.58 ha (11.8%) to 9255.74 ha (8.6%), consistent with global deforestation trends linked to agriculture, settlements, and resource extraction. Production forest declined modestly by 3.7%, from 11797.05 ha (10.8%) to 11355.64 ha (10.4%), raising concerns about forest policy effectiveness. Settlement areas more than doubled, increasing by 185.5% from 3096.78 ha (2.9%) to 8842.68 ha (8.1%), reflecting rapid urbanization. Finally, agricultural land within Perhutani-managed forests rose significantly by 133.2%, from 2367.26 ha (2.2%) to 5520.41 ha (5.2%), indicatingintensified agricultural activity in forest zones.

3.2 Projected LULC change in 2030 under business-as-usual scenario

The BAU projection for 2030, generated through CA-ANN modeling, reveals that existing trends are likely to persist in the absence of intervention. Multistrata agroforestry is projected to decline by 46.8%, from 20210.19 ha in 2023 to 10755.35 ha in 2030, while simple agroforestry shows a modest decrease of 3.5%, stabilizing at 32638.87 ha. Natural forest cover is expected to drop by 27.6%, reaching a critical threshold of 9195.16 ha These projections underscore the urgency of implementing targeted conservation measures to mitigate environmental risks. Production forest is projected to increase slightly by 4.8%, reaching 11927.11 ha, suggesting that some regulatory frameworks may be effective in stabilizing this land class. However, settlement areas are anticipated to expand by 114.9%, growing from 4206.92 ha to 9041.96 ha, reinforcing concerns over land-use conflicts and the potential encroachment of built-up areas into ecologically sensitive zones.

3.3 Comparative analysis of LCC, PM, and LCCPM approaches

A comparative evaluation of the three classification methodologies highlights notable differences in land use estimations. The LCC-based approach appears to underestimate certain land categories, particularly natural forests (7329.89 ha under LCC versus 11702.11 ha under LCCPM). This discrepancy suggests that land-use-based classification alone may not capture the full complexity of landscape dynamics. The PM approach, although more inclusive, seems to yield conservative estimates in certain categories, such as multistrata agroforestry (11083.30 ha) and settlement areas (8842.68 ha). The LCCPM hybrid method offers a more balanced perspective, capturing a wider range of landscape interactions and providing a more comprehensive representation of land-use dynamics.

3.4 Driving factors of the risk of drought

Understanding the relative importance of predictor variables is essential for identifying key environmental and geographical factors that influence model outcomes. By evaluating the contribution of each variable, researchers can gain critical insights into the primary drivers shaping spatial and ecological patterns. As shown in Figure 3 and 4, the bar chart ranks predictor importance scores (%) in descending order. The analysis reveals that "Landform" is the most influential predictor, followed by "Air Temperature", "Plan Curvature" and the "Stream Power Index (SPI)". These dominant variables highlight the critical roles of terrain features and climatic conditions in shaping spatial dynamics (Xiao et al., 2024). Mid-tier contributors, such as "Distance from River", "Rainfall", and "Distance from Road" also exert notable influence, underscoring the importance of hydrological proximity and precipitation patterns (Van Loon and Laaha, 2015).

Socio-economic and topographic factors, including "Population" and "Elevation" exhibit moderate importance (Saha et al., 2023), while variables such as "Slope", "Topographic Position Index (TPI)", "Terrain Ruggedness Index (TRI)", "Topographic Wetness Index (TWI)", and "Aspect" demonstrate relatively lower significance. Although these variables individually contribute less to the model, they still provide valuable context for interpreting spatial dynamics (Rana et al., 2025). The prominence of landform and temperature-related factors underscores their pivotal roles in predicting spatial variability and ecological processes (Zhang et al., 2023). These findings provide critical insights for researchers and policymakers, highlighting the need to prioritize terrain characteristics and climatic factors in spatial modeling, environmental management, and policy development (Dhawale et al., 2024).

Table 3. LULC changes in Malang District from 2017 to 2030.

Type of LULC	2017	2019	2021	2023	2030	LCC	PM	LCCPM
			Ha					
Multistrata Agroforestry	21493.54	13229.74	12376.26	10809.41	10755.35	12185.39	11083.30	10770.18
Simple Agroforestry	31704.95	33083.57	33194,99	30852.79	32638.87	30815.87	36373.20	36512.65
Natural Forest	12795.58	11462.78	10063,39	9255.74	9195.16	19183.97	8981.79	11702.11
Production Forest	11355.64	11624.31	11846,83	11797.05	11927.11	7329.89	7618.67	9509.24
Perhutani Built-up Area	509.98	752.93	975,45	1132.04	1252.05	1129.40	1132.04	934.24
Orchards	4246.29	4285.52	4548,26	4819.23	5005.96	4524.19	4819.23	4818.57
Meadow	93.95	129.55	152,63	188.23	166.15	186.26	172.41	186.91
Settlement	3096.78	6195.22	7727,79	8842.68	9041.96	8829.49	8842.68	8838.06
ROC and Agricultural Land in Perhutani Area	2367.26	3209.20	4302,99	5520.41	5966.52	0	0	0
Rice Field	111.75	242.96	161,20	164.50	146.04	137.13	164.50	144.72
Shrubs and Bushes	1516.75	1465.98	1314.34	753.92	1444.22	752.93	743.37	752.93
Non-irrigated Dry Field	10336.02	13946.74	12964.36	15492.49	12089.13	14395.07	19697.20	15345.13
River	13.52	13.52	13.52	13.52	13.52	13.52	13.52	13.52
Total			99642.01					

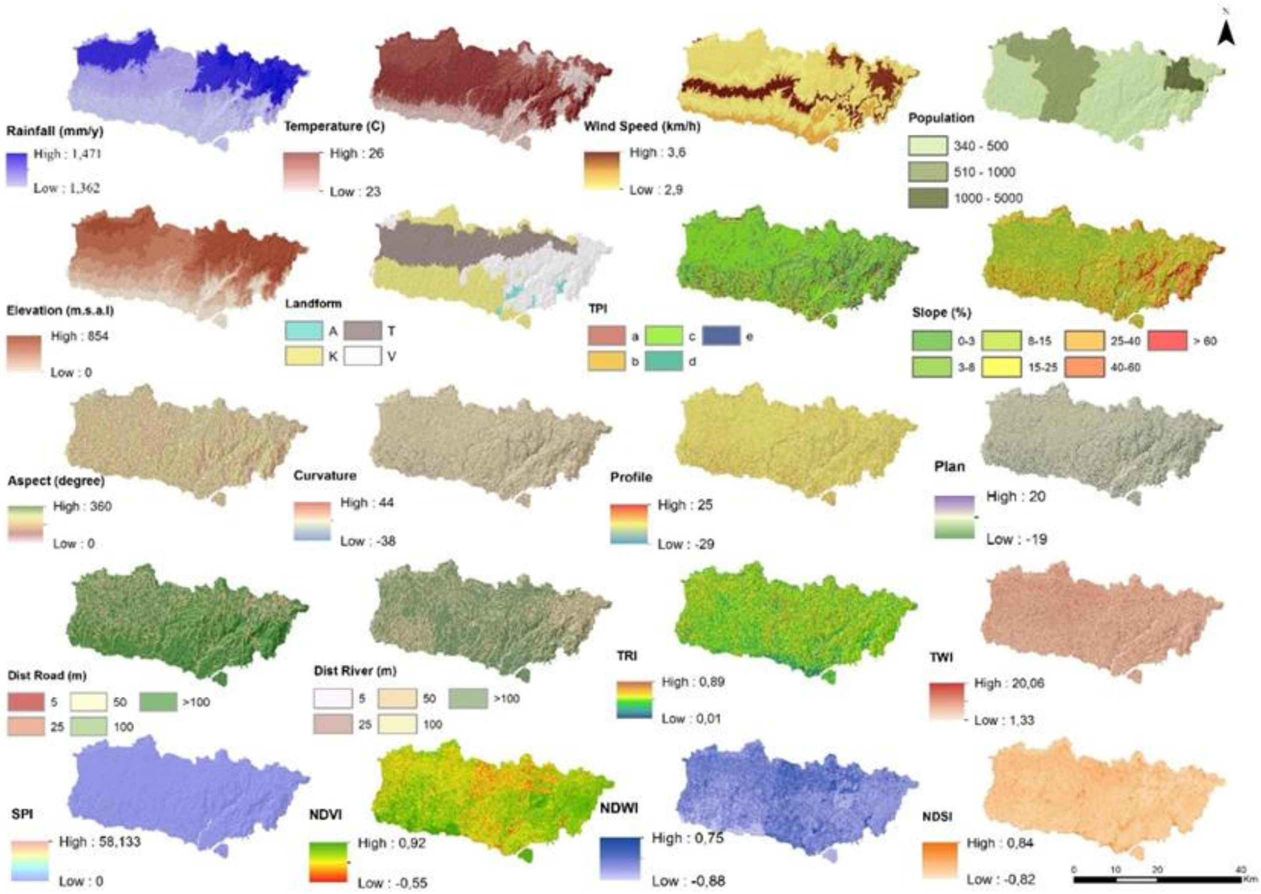

Fig. 3. Drought Indicators in Each Visualization (a) rainfall, (b) air temperature, (c) wind speed, (d) population, (e) elevation, (f) landform, (g) topographic position index, (h) slope, (i) aspect, (j) curvature, (k) profile curvature, (l) plan curvature, (m) distance from road, (n) distance from river, (o)TRI, (p) TWI, (q) SPI, (r), (s) and (t), (o) NDVI, (p) NDSI, (q) NDWI.

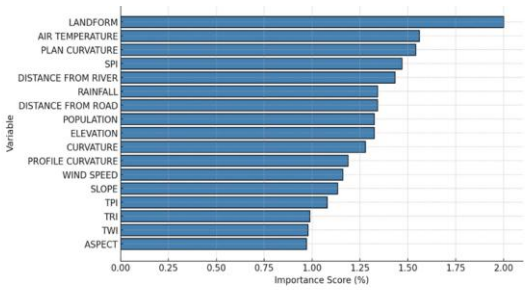

Fig 4. Variable importance visualization.

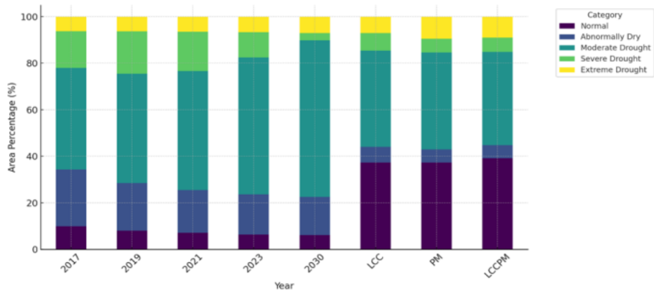

Fig 5. Historical data, prediction and scenarios drought analysis result.

3.5 Drought risk of south Malang plateau

The temporal analysis of drought severity, as shown in Figure 5, reveals critical shifts in drought intensity across the South Malang Plateau, with particular concern over the increasing prevalence of high–risk categories. "Extreme Drought" steadily rose from 6.2% in 2017 to 7.0% by 2030, highlighting a long-term intensification of aridity, especially in areas affected by forest loss, declining soil moisture retention, and reduced vegetative resilience. In contrast, "Severe Drought" reached a peak of 18.1% in 2019 but dropped sharply to 3.1% by 2030. This decline may reflect a complex redistribution—either toward more extreme conditions or temporary improvements linked to short-term climatic variability or localized management efforts. These trends suggest a shifting drought dynamic where mid-level stress may give way to chronic desiccation or brief recovery phases under continued environmental pressure.

Meanwhile, "Moderate Drought" areas expanded dramatically from 43.7% to 67.2% over the same period, indicating increasing susceptibility of diverse land cover types, particularly agroforestry systems and natural forests, to prolonged dry conditions (Gao et al., 2018). Conversely, "Normal" conditions shrank from 10.0% to 6.1%, underscoring a declining environmental baseline and reduced resilience against hydrological stress. The persistent expansion of drought-affected zones aligns with theoretical frameworks of land degradation under climate extremes (Staal et al., 2020) (Rattayová et al., 2024) , where water scarcity threatens both ecosystem productivity and local livelihoods.

These trends carry important implications for sustainable land management and climate adaptation efforts. The growing drought footprint emphasizes the urgent need for proactive interventions, including strategies to enhance water resource efficiency, mitigate hydrological stress, and protect the ecological functions of vulnerable landscapes (Davis et al., 2015). Additionally, integrating land-use planning with climate-resilient agricultural and conservation practices will be vital for preserving environmental stability and supporting agricultural sustainability amid mounting drought risks (Granata and Di Nunno, 2025).

Although the LCC, PM, and LCCPM land use scenarios demonstrate potential to shift drought severity toward milder categories, they still lack integration of key feedback mechanisms such as vegetation resilience, soil degradation loops, and adaptive land management. Moreover, the model does not fully distinguish between localized anthropogenic pressures and broader climatic influences (Roy et al., 2022). These findings reinforce the need to differentiate between temporary recovery and long-term vulnerability, while recognizing spatial thresholds for persistent drought. Future research should incorporate higher-resolution climate data with land system modeling to capture these interactions more precisely. Above all, building policies that enhance both ecological and hydrological resilience, such as through integrated water resource strategies and conservation-focused land use planning, remains imperative to prevent irreversible degradation (Granata and Di Nunno, 2025s).

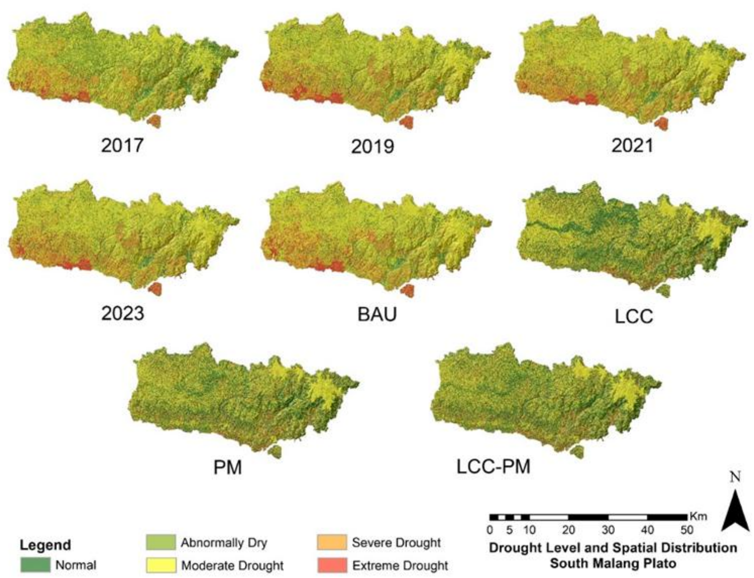

Fig 6. Drought risk distribution of the South Malang Plateau.

3.6 Accuracy assessment of drought map

The accuracy test was conducted to determine the level of accuracy of the map in representing the actual conditions in the field (Wiggers et al., 2020). The method used is overall accuracy which calculates the percentage of correctly classified pixels from the total pixels observed (Shao et al., 2019). This test is important because the level of map accuracy affects the validity of information for decision–making (Nkomeje, 2017). The accuracy test on 175 validation points showed an overall accuracy value of 92.57% which is categorized as good and acceptable (Wulansari, 2017). The most misclassification occurred in the extreme drought category, where 3 points were misclassified as normal. In contrast, the category with the best accuracy, was severe drought with no misclassification. This result shows that the classification method has high accuracy, especially in distinguishing drought categories from moderate to extreme.

4 DISCUSSION

4.1 Impact of land use change on drought risk

From 2017 to 2023, multistrata agroforestry experienced a sharp decline from 21493.54 ha to 10809.41 ha, while natural forest cover dropped from 12795.58 ha to 9255.74 ha. Simultaneously, areas under moderate drought expanded from 43.7% to over 63.5% (Figure 7), indicating a strong spatial correlation between vegetation loss and increased drought exposure. Built-up zones more than doubled in size, and settlement areas grew from 3096.78 ha to 8842.68 ha, replacing deep-rooted vegetation with impervious surfaces and simplified land cover. This transformation reduces evapotranspiration buffering, soil moisture retention, and microclimatic stability, key mechanisms linking land use to drought vulnerability (Wassie, 2020; Zhou et al., 2022). Our Random Forest model reinforces this connection, assigning high variable importance to landform, air temperature, SPI, and plan curvature, factors affected by vegetation cover and land management practices.

Fig. 7. Land use change and drought-related conditions: a) threats to springs (left), b) river drought (center), and c) decreasing water volume (right).

A statistical comparison across scenarios further confirms this relationship. The LCCPM scenario, which restores multistrata agroforestry to 19,770.18 ha and natural forest to 11702.71 ha, results in the highest share of "Normal" and "Abnormally Dry" categories (~40%) among all projections (Figure 7). This aligns with findings that vegetation complexity enhances ecosystem resistance to drought by improving infiltration, regulating surface energy balance, and sustaining groundwater recharge (Pan et al., 2011; Owuor et al., 2016). Conversely, the BAU trajectory demonstrates continued degradation, with reduced canopy structure linked to rising exposure to moderate and extreme drought. As highlighted by Slavíková and Milman (2023), without mitigation, recurrent land conversion can push vulnerable areas across irreversible ecological thresholds. These model–supported trends underscore that land cover change is not only associated with but causally linked to drought intensity patterns–requiring integrated land-water-climate policy responses.

Model-based projections indicate that agricultural expansion into areas previously dominated by multistrata vegetation and mixed land cover types significantly increases drought susceptibility, particularly in zones already identified as moderately to severely dry. This shift reduces the land's capacity for moisture retention and ecological buffering, thereby accelerating land degradation. As (Pitman, 2022) emphasizes, multifunctional landscapes play a crucial role in sustaining both ecological resilience and agricultural productivity, which are compromised when land is simplified into monocultures. Furthermore, (Gabriele et al., 2023) demonstrated that land use intensification without adequate conservation measures in climate-sensitive zones leads to persistent degradation detectable via remote sensing, reinforcing the importance of spatial planning tools informed by model outputs. This would also jeopardize agricultural productivity and water availability, impacting local socio–economic resilience (Sharannya et al., 2021).

Alternative land use scenarios, LCC, PM, and LCCPM, offer varying mitigation potentials against drought. The LCC scenario, focused on conserving forest and agroforestry cover, helps slow aridification by maintaining the land's water retention capacity (Siriri et al., 2013). While not eliminating drought risk, it reduces its pace. The PM scenario, integrating planning with mitigation, balances development and sustainability through afforestation, better farming, and controlled urban growth (Azadi et al., 2018). The most effective is the LCCPM scenario, which unifies conservation, planning, and mitigation to enhance soil moisture, reduce runoff, and stabilize local climates (Lei et al., 2016). However, actual impact depends on policy enforcement, funding, and local participation; without these, even well-designed strategies may remain aspirational.

4.2 Reliability and limitation of multilocation model use

Random Forest (RF) achieved a high classification accuracy of 92.57% in mapping drought severity across the South Malang Plateau, using 25 biophysical and climatic variables such as landform, surface temperature, SPI, rainfall, elevation, slope, and population density. The model classified five drought categories (0–4) with excellent performance metrics, including F1-scores ranging from 0.97 to 1.00 and sensitivity values above 0.95. Validation against 45 field-surveyed ground-truth points confirmed a strong spatial agreement between predicted and observed drought conditions (Indaryono et al., 2024). Its strengths lie in handling small sample sizes, tolerating missing or noisy input data, and producing robust multi-class classifications (Abdelaziz et al., 2025). These capabilities make RF especially suitable for diverse, multi-site environmental analyses involving complex topography, climate variability, and mixed land use.

However, the reliability of RF models in multilocation applications remains context–dependent. Models trained on spatially homogeneous areas may underperform when applied to heterogeneous or distant regions with different environmental drivers (Park et al., 2024). Furthermore, RF can be biased toward majority classes in imbalanced datasets and may produce slightly inconsistent results due to its inherent randomness in feature selection and sample bootstrapping (Zhu, 2020). Therefore, while RF offers high accuracy within the study region, caution is advised when extrapolating its use across dissimilar locations without local calibration and validation. The Random Forest model demonstrated strong scalability by accurately classifying drought severity across a heterogeneous landscape of approximately 99000 hectares in the South Malang Plateau. This indicates that RF can effectively handle large-scale, multi-variable environmental datasets, and with the application of spatial cross-validation and local data calibration, the method is extendable to even broader regional assessments.

4.3 Implications for drought mitigation and land use planning

The variable importance analysis (Figure 4) revealed that landform, air temperature, plan curvature, and SPI are the most influential drivers of drought in the South Malang Plateau. These findings suggest that drought in the region is controlled by both climatic (e.g., elevated temperature, rainfall deficit) and physiographic (e.g., terrain shape, elevation) factors. From a mitigation standpoint, this necessitates a landscape-based approach, aligning land management with the biophysical susceptibility of the terrain. For example, agroforestry or climate-adaptive farming should be prioritized on undulating and convex landforms prone to water loss, while reforestation and soil moisture conservation practices can be directed at high SPI-variability zones. This is in line with integrated drought risk frameworks (Pulwarty and Sivakumar, 2014), which emphasize the coupling of land characteristics and climate indicators for location-specific resilience.

Furthermore, the temporal and scenario-based drought severity analysis (Figure 5) underscores the necessity of aligning land use change with drought mitigation. Under business-as-usual (BAU) projections, the share of moderate-to-extreme drought remains persistently high. However, simulated land use scenarios such as Land Capability Class (LCC), Participatory Management PM, and especially LCCPM demonstrate marked improvements in normal and abnormally dry areas. This indicates that future drought resilience is not solely dependent on climate, but also on how land is used and governed. Effective mitigation, therefore, should include zoning regulations that restrict high-risk agricultural expansion in vulnerable landforms, incentive mechanisms for sustainable land cover retention, and local empowerment for adaptive land stewardship. As noted by (Sivakumar et al., 2014), multilocation drought models are reliable only when supported by spatially-tailored policies and institutional coordination at the ground level.

4.4 Methodological advances and comparison with previous studies

This study presents a significant methodological advancement by integrating pattern-based land-use simulation through the CA–ANN–Markov model with process-based approaches, including participatory mapping (PM) and land capability classification (LCC), all supported by Random Forest (RF) machine learning for drought risk assessment. The CA–ANN–Markov model was selected for its strength in capturing nonlinear spatial dynamics by learning from historical land-use patterns and transition probabilities (Gharaibeh et al., 2020; Nwaogu et al., 2018). Compared to other pattern-based models like CLUE–S or DINAMICA EGO, CA–ANN–Markov is more adaptable in heterogeneous and fragmented landscapes, where spatial dependencies strongly influence land transformation (Rahman et al., 2017). It has also demonstrated superior performance over traditional CA–Markov and rule-based approaches, particularly in capturing complex spatial patterns and improving prediction accuracy in land use change simulations (Gharaibeh et al., 2020). Its ability to simulate temporal trajectories under a Business-as-Usual (BAU) scenario also provided a useful contrast to stakeholder-informed alternatives (Frifra et al., 2024).

To overcome the limitations of conventional top-down modeling, this study incorporates participatory mapping and LCC, allowing land-use scenarios to reflect both biophysical constraints and community–driven preferences. Local knowledge was gathered through semi–structured interviews, Participatory Rural Appraisal (PRA) tools, and stakeholder validation, ensuring that resulting spatial recommendations are not only technically sound but also socially acceptable (Mondal and Paul, 2022). While prior research has highlighted the value of community participation in land–use governance (Basupi et al., 2017; Brown et al., 2018a, 2018b; Hewitt et al., 2014; Karimi and Brown, 2017), few have successfully integrated it into a predictive modeling framework, making this study a noteworthy contribution to both methodology and practice.

Furthermore, the application of the RF algorithm for drought classification, using 25 predictor variables spanning climatic, vegetative, topographic, and anthropogenic dimensions, significantly enhances both accuracy and interpretability. With an overall classification accuracy of 92.57%, RF outperforms traditional regression-based or threshold methods, offering deeper insight into how land-use dynamics relate to hydrological stress. The spatial outputs produced by RF enrich scenario comparisons by linking each land–use pathway to its corresponding drought vulnerability outcome.

Taken together, this integrated modeling framework supports the development of adaptive, stakeholder-informed land-use strategies. By combining predictive modeling, participatory processes, and ecological suitability, the approach advances current thinking in land degradation modeling and delivers actionable insights for drought mitigation. While earlier studies often treated spatial modeling and stakeholder engagement as distinct efforts, this research demonstrates how their integration can enhance both predictive accuracy and policy relevance. Future research could further expand this framework by incorporating socio-economic modeling, feedback mechanisms, and dynamic climate projections to support more comprehensive and resilient land management strategies in data-limited yet ecologically vulnerable regions.

5 CONCLUSION

This study provides valuable insights into the impact of land-use changes on drought risk dynamics in the South Malang Plateau. Between 2017 and 2023, a decline in multistrata agroforestry and natural forest cover occurred alongside a sharp increase in settlement areas and intensified agricultural activities. These changes disrupted hydrological functions, reducing water retention and exacerbating drought conditions. The findings reveal a shift in drought severity, with a reduction in "Normal" areas and an expansion of "Moderate Drought" zones. Projections for 2030 under the BAU scenario indicate further deterioration. The evaluation of land classification methods highlights the benefits of integrating PM with LCC. The LCCPM approach captures complex land-use interactions and offers a more accurate representation of landscape dynamics. Random

Forest modeling showed 92.57% accuracy, identifying key drought-driving factors such as landform, air temperature, plan curvature, and SPI. These findings emphasize the need for tailored mitigation strategies. Scenarios suggest that forest conservation, sustainable agriculture, and controlled urban expansion can improve hydrological resilience. This study underscores the need for integrated land–use policies prioritizing ecological stability alongside socio–economic development.

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