water

Article

Utilizing Hybrid Machine Learning and Soft Computing Techniques for Landslide Susceptibility Mapping in a Drainage Basin

Yimin Mao [1], Yican Li [2], Fei Teng [2], Arkan K. S. Sabonchi [3], Mohammad Azarafza [4] and Maosheng Zhang [5,*]

[1] School of Information and Engineering, Shaoguan University, Shaoguan 512005, China; mymlyc@163.com
[2] Xi'an Center of Mineral Resources Survey, China Geological Survey, Xi'an 710105, China; canmermer@126.com (Y.L.); xatwenchuan@163.com (F.T.)
[3] Department of Computer Techniques Engineering, Imam Ja'far Al-Sadiq University, Baghdad 10011, Iraq; arkan.khalil@sadiq.edu.iq
[4] Geotechnical Unit, Faculty of Civil Engineering, University of Tabriz, Tabriz 5166616471, Iran; m.azarafza.geotech@gmail.com
[5] School of Human Settlement Environment and Civil Engineering, Xi'an Jiaotong University, Xi'an 712000, China
* Correspondence: xjtzms@xjtu.edu.cn

Abstract: The hydrological system of thebasin of Lake Urmia is complex, deriving its supply from a network comprising 13 perennial rivers, along withnumerous small springs and direct precipitation onto the lake's surface. Among these contributors, approximately half of the inflow is attributed to the Zarrineh River and the Simineh River. Remarkably, Lake Urmia lacks a natural outlet, with its water loss occurring solely through evaporation processes. This study employed a comprehensive methodology integrating ground surveys, remote sensing analyses, and meticulous documentation of historical landslides within the basin as primary information sources. Through this investigative approach, we preciselyidentified and geolocated a total of 512 historical landslide occurrences across the Urmia Lake drainage basin, leveraging GPS technology for precision. Thisarticle introduces a suite of hybrid machine learning predictive models, such as support-vector machine (SVM), random forest (RF), decision trees (DT), logistic regression (LR), fuzzy logic (FL), and the technique for order of preference by similarity to the ideal solution (TOPSIS). These models were strategically deployed to assess landslide susceptibility within the region. The outcomes of the landslide susceptibility assessment reveal that the main high susceptible zones for landslide occurrence are concentrated in the northwestern, northern, northeastern, and some southern and southeastern areas of the region. Moreover, when considering the implementation of predictions using different algorithms, it became evident that SVM exhibited superior performance regardingboth accuracy (0.89) and precision (0.89), followed by RF, with and accuracy of 0.83 and a precision of 0.83. However, it is noteworthy that TOPSIS yielded the lowest accuracy value among the algorithms assessed.

Keywords: landslide susceptibility; hybrid artificial intelligence models; soft computing; Urmia Lake drainage basin; geographic information systems; machine learning algorithms

Citation: Mao, Y.; Li, Y.; Teng, F.; Sabonchi, A.K.S.; Azarafza, M.; Zhang, M. Utilizing Hybrid Machine Learning and Soft Computing Techniques for Landslide Susceptibility Mapping in a Drainage Basin. *Water* **2024**, *16*, 380. https://doi.org/10.3390/w16030380

Academic Editor: Long Ho

Received: 9 December 2023
Revised: 6 January 2024
Accepted: 11 January 2024
Published: 24 January 2024

1. Introduction

Landslides are a common and serious geological hazard, posing a significant threat to both life and finances [1–3]. A landslide is a geological phenomenon characterized by the downhill movement of rock, soil, or debris along a slope. The mechanism underlying a landslide involves a delicate balance between gravitational forces and the stability of the materials on the slope. When the gravitational force acting on a slope becomes greater than the resisting forces holding the materials in place, a landslide can occur. This imbalance is often triggered or exacerbated by various factors such as heavy rainfall, snowmelt, earthquakes, or human activities that weaken the materials or increase their vulnerability [4].

Several critical parameters interact to influence the likelihood and severity of landslides. First, the slope angle plays a significant role, as steeper slopes are more susceptible to landslides due to stronger gravitational forces. Geological and soil properties are also essential; loose, unconsolidated materials are more prone to sliding than cohesive, well-consolidated soils or rocks. Water content is a critical factor, as excess water reduces friction and increases pore water pressure within the materials, making them more likely to move downslope [5–8]. Vegetation can either stabilize or weaken slopes, depending on its presence or absence. Earthquakes can trigger landslides by weakening materials, while human activities such as construction, mining, and deforestation can alter landscapes and increase risk. The underlying geology, previous landslide history, and the degree of saturation in the soil or rock also influence landslide susceptibility [9,10]. Additionally, fault zone activity and seismic vibrations can disrupt the geological and soil structure, reducing the normal gravitational force on potential landslide surfaces, while increasing the shear force, ultimately resulting in landslides [11]. Recognizing the complex interplay of these parameters is crucial for landslide prediction, mitigation, and prevention. Scientists and engineers use various methods, such as slope stability analysis and monitoring systems, to assess and manage landslide risk. Mitigation strategies may include implementing effective drainage systems, reinforcing slopes, planting vegetation for stabilization, and regulating construction in landslide-prone areas. Public awareness and early warning systems also play a vital role in reducing the risks associated with landslides, helping communities effectively prepare for and respond to these hazardous events [12].

The study of landslides and susceptibility analysis is of paramount importance due to the inherent risks they pose [6]. Landslides can result in tragic loss of human lives and endanger public safety [11]. Through rigorous analysis, we can identify areas susceptible to landslides and implement preventive measures, including engineered slope stabilization and early warning systems [13,14]. Landslides can have far-reaching environmental impacts, including habitat destruction and soil erosion. The process of susceptibility analysis aids in pinpointing regions at risk and informs land-use planning and the development of zoning regulations [15,16]. Research on landslide susceptibility mapping (LSM) is undertaken with the goal of predicting the spatial distribution and likelihood of landslide occurrences [16]. LSM identifies areas prone to landslides, and this information can be used by policymakers, scientists, engineers, and the general public to prevent catastrophic landslides [17]. This represents a fundamental step towards evaluating landslide hazards and developing reduction strategies [18,19]. Therefore, conducting landslide susceptibility modeling and mapping research is imperative.

The assessment of landslide risk methods can be broadly categorized into three primary approaches, i.e., qualitative, quantitative, and semi-quantitative. Qualitative approaches often rely on aerial imagery, field interpretation, and expert/engineering judgment [20–23].Despite the logical outcomes and high performance of various models, geologists always seek new methods for more precise identification of landslide-prone areas and the creation of reliable maps required for environmental planning. Therefore, introducing a novel approach based on artificial intelligence algorithms, deep learning, and remote sensing (RS) and geographic information systems (GIS) techniques for landslide modeling is of paramount importance in landslide risk management [24]. In recent decades, with the rapid development of RS, GIS, and the enhancement of computational power in artificial intelligence algorithms, machine learning has played a pivotal role in improving the accuracy and reliability of landslide prediction [23]. Machine learning methods rely on field observations and statistical computations [24]. Additionally, machine learning employs computer algorithms to analyze and predict information by learning from a training dataset [25]. These methods exhibit a high capability for detecting landslide occurrence behavior using estimation distribution algorithms, are data-centric in nature, and often involve extensive modeling process iterations. In several studies, these methods have demonstrated a relative advantage over two-variable and multivariable statistical models [26,27]. Various machine learning-based hybrid methods, such as logistic regression

(LR), naïve Bayes (NB), fuzzy logic (FL), support-vector machines (SVM), k-nearest neighbors (k-NN), kernel logistic regression (KLR), Bayesian logistic regression (BLR), random forest (RF), rotational forest, random subspace, adaptive neuro-fuzzy inference system (ANFIS), decision tree (DT), classification and regression trees (CART), and many other methods [28–32], have been employed in landslide susceptibility assessment.

The presented study objective is the use of combined machine learning and soft computing techniques to analysis landslide susceptibility mapping for the Urmia Lake drainage basin. Combining machine learning and soft computing techniques in landslide susceptibility mapping offers several compelling advantages: (1) it significantly enhances the accuracy of susceptibility models. Machine learning algorithms excel at capturing intricate relationships within data, while soft computing techniques, like fuzzy logic and neural networks, adeptly handle uncertainties and vague input parameters, resulting in more reliable predictions; (2) the hybrid approach ensures model robustness by accommodating a wide range of input data, including geological, topographical, and environmental factors. This versatility is vital in addressing the multifaceted nature of landslide susceptibility within drainage basins. Moreover, the hybrid model's ability to adapt to changing environmental conditions and data availability makes it versatile for different regions and drainage basins, where climate patterns and terrain characteristics may vary significantly. However, adopting a hybrid approach comes with its share of challenges. First and foremost, it can introduce complexity. Integrating multiple techniques may necessitate advanced computational resources, both in terms of processing power and data availability. Managing the intricacies of such models can be demanding in terms of implementation and maintenance. Second, data requirements can be substantial. Constructing an effective hybrid model demands a substantial volume of high-quality data, encompassing historical landslide records, geological information, topographic data, and environmental variables. Collecting and maintaining these datasets can be resource-intensive. Third, expertise is crucial. Developing and fine-tuning a hybrid model requires proficiency in both machine learning and soft computing techniques, which may not be readily accessible in all research or application contexts. Additionally, while hybrid models provide high accuracy, they may sacrifice interpretability, potentially complicating communication with stakeholders or decisionmakers. Finally, there is a risk of overfitting due to the complexity of hybrid models, necessitating careful regularization and validation procedures to ensure generalizability beyond the training data.

The novel concept of employing a hybrid approach that merges machine learning and soft computing techniques for landslide susceptibility mapping in drainage basins underscores the innovative and distinct qualities of this methodology as compared to traditional practices. Novelty, in this context, can be delineated through several key factors. First, the methodology's novelty resides in its seamless integration of machine learning and soft computing techniques, effectively uniting two distinct computational paradigms. This synthesis capitalizes on the capabilities of machine learning to handle intricate data relationships and soft computing technique's prowess in modeling the inherent uncertainties and vagueness present in geological and environmental data. This amalgamation represents a pioneering aspect of the methodology, as it combines the strengths of both disciplines to yield susceptibility maps that are not only more precise but also more reliable. Second, the methodology's novelty is underscored by its remarkable ability to significantly enhance the performance of susceptibility mapping models. By synergizing machine learning algorithms, known for their proficiency in processing large and complex datasets, with soft computing techniques that adeptly capture the nuanced uncertainties prevalent in geological and environmental information, the hybrid model achieves a marked improvement over conventional methods. This heightened performance sets it apart as a pioneering approach in landslide susceptibility assessments, promising more accurate and dependable results for landslide susceptibility mapping in drainage basins.

2. Studied Drainage Basin

2.1. Geological Setting

Urmia Lake is located in northwestern Iran and is one of the largest saltwater lakes in the world. Lake Urmia receives its water supply from a network of 13 perennial rivers and numerous small springs, along with direct rainfall over the lake's surface.A substantial portion of this inflow, nearly half, originates from the Zarrineh River and the Simineh River. In recent years, the region surrounding Lake Urmia has prompted ecological and environmental concern due to decreasing water levels and environmental degradation. Efforts have been made to address these issues and restore the health of the lake and its drainage basin [33]. Figure 1 shows the Urmia Lake drainage basin in Iran. During its peak size, Lake Urmia held the distinction of being the most expansive lake in the Middle East and ranked as the sixth-largest saltwater lake globally, boasting a surface area spanning approximately 5200 km^2 [34]. Notably, Lake Urmia does not have any natural outflow, meaning that water loss occurs solely through the process of evaporation.

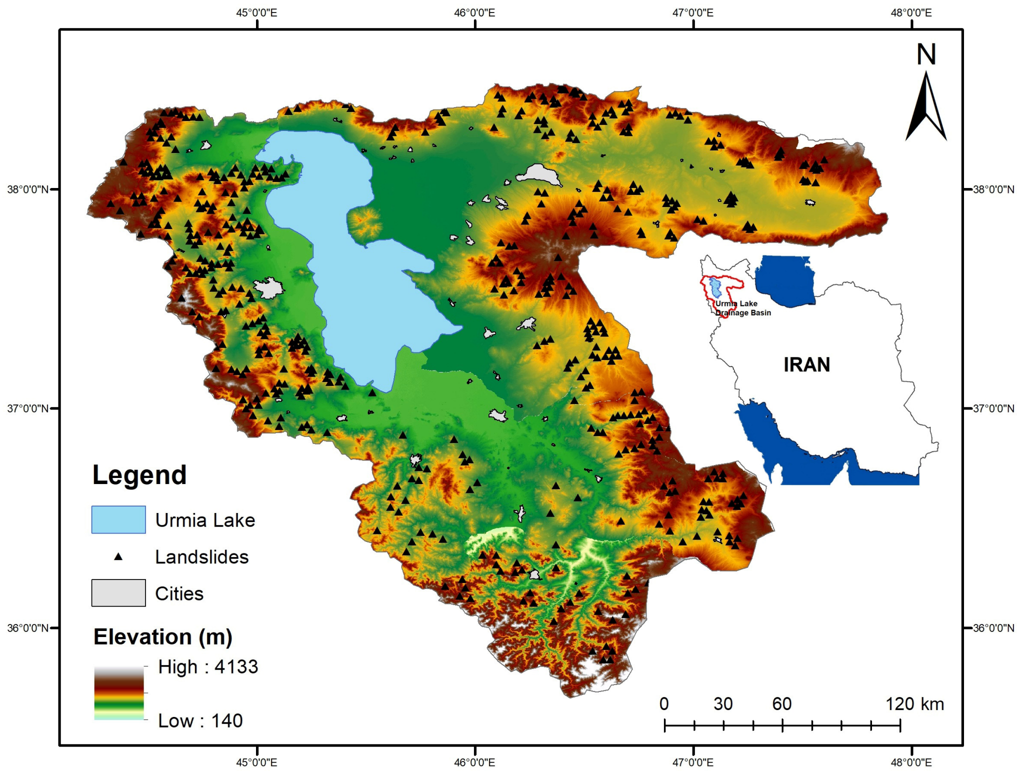

Figure 1. Iran'sUrmia Lake drainage basin.

The climate within the Urmia Lake drainage basin exhibits notable seasonal variations. Summers are typically warm to hot, with temperatures frequently soaring above 30 °C (86 °F). Figure 2 provides information regarding climate changes that occurred in the Urmia Lake drainage basin, displaying data collected from different stations of the Iran Meteorological Organization (IMO) database [35]. During this season, rainfall is relatively scarce [36]. Conversely, winters in the region are marked by cold temperatures, often dropping below freezing, leading to substantial snowfall, especially in higher elevations. Spring and autumn serve as transitional periods, offering milder temperatures and sporadic rainfall. Spring is of particular significance as it plays a crucial role in replenishing Lake Urmia's water levels. Rainfall is unevenly distributed across the basin, with more substantial amounts observed in the northwestern and western sectors, while the southern and eastern regions receive comparatively less precipitation, contributing to arid conditions [34]. The geological landscape of the Urmia Lake drainage basin is intricate and shaped by various natural processes. Tectonic activity is a prominent factor, given the region's proximity to the convergence of tectonic plates. This activity has led to the formation of geological features such as fault lines, folded rock structures, and uplifted mountain ranges. A geological map of the studied area, which is adapted from a geological survey of Iran [37], is provided in Figure 3. Additionally, volcanic activity has left its mark on the basin, resulting in the presence of volcanic rocks and expansive basalt plateaus in certain areas [33]. Sedimentary deposits are also prevalent, including alluvial plains and terraces formed as rivers and streams have transported and deposited materials over time [35]. Notably, salt deposits are a significant geological feature, both within and around Lake Urmia. These vast salt flats contribute to the high salinity of the lake and play a central role in the region's geology. Lastly, karst topography is found in select locations, characterized by limestone formations featuring sinkholes and caves [36]. In summary, the climate within the Urmia Lake drainage basin exhibits distinct seasons, and the region's geology reflects a complex interplay of tectonic forces, volcanic history, sedimentary processes, salt deposits, and karst landscapes. Together, these factors shape the hydrology, environmental dynamics, and geological diversity of this remarkable region.

2.2. Triggering Factors Selection

Landslides manifest under specific triggering conditions, often referred to as ”conditioning” or “triggering” factors [14–17]. These factors initiate or expedite the landslide process. Gaining a comprehensive understanding of the influence and varieties of these triggering factors is crucial for crafting precise and detailed susceptibility maps [19]. Triggering factors are pivotal elements in landslide susceptibility analysis, representing the specific conditions or events that have the potential to initiate or hasten landslide occurrences [24,25]. These factors hold paramount importance in landslide assessment for several compelling reasons [27]. They serve as the linchpin for identifying areas that are at heightened risk of landslides. By meticulously evaluating these triggering factors, experts and researchers can precisely pinpoint geographic locations in which conditions are inherently conducive to landslide events [14,16]. This targeted assessment enables the development of susceptibility maps that offer a clear visualization of vulnerability across a given region. The identification of triggering factors significantly enhances the assessment of landslide risk [3]. It empowers experts to gauge the likelihood of landslides transpiring in a particular locale and to assess the potential consequences of such events, including their impact on communities, infrastructure, and the environment [5–11]. Furthermore, the awareness of these factors plays a pivotal role in the establishment of early warning systems. By continuously monitoring conditions known to trigger landslides, authorities can proactively issue warnings to communities, thus mitigating the risk of casualties and damage. Moreover, triggering factors inform land use planning and zoning regulations, ensuring that areas prone to landslides are designated for less critical purposes, thereby diminishing exposure to risk. Finally, they inform the development of tailored mitigation strategies, such as enhanced drainage systems or slope stabilization, based on the specific triggering factors prevalent in an area [20]. In essence, triggering factors are the foundation upon which informed decision making, risk mitigation, and community safety in landslide-prone regions are built.

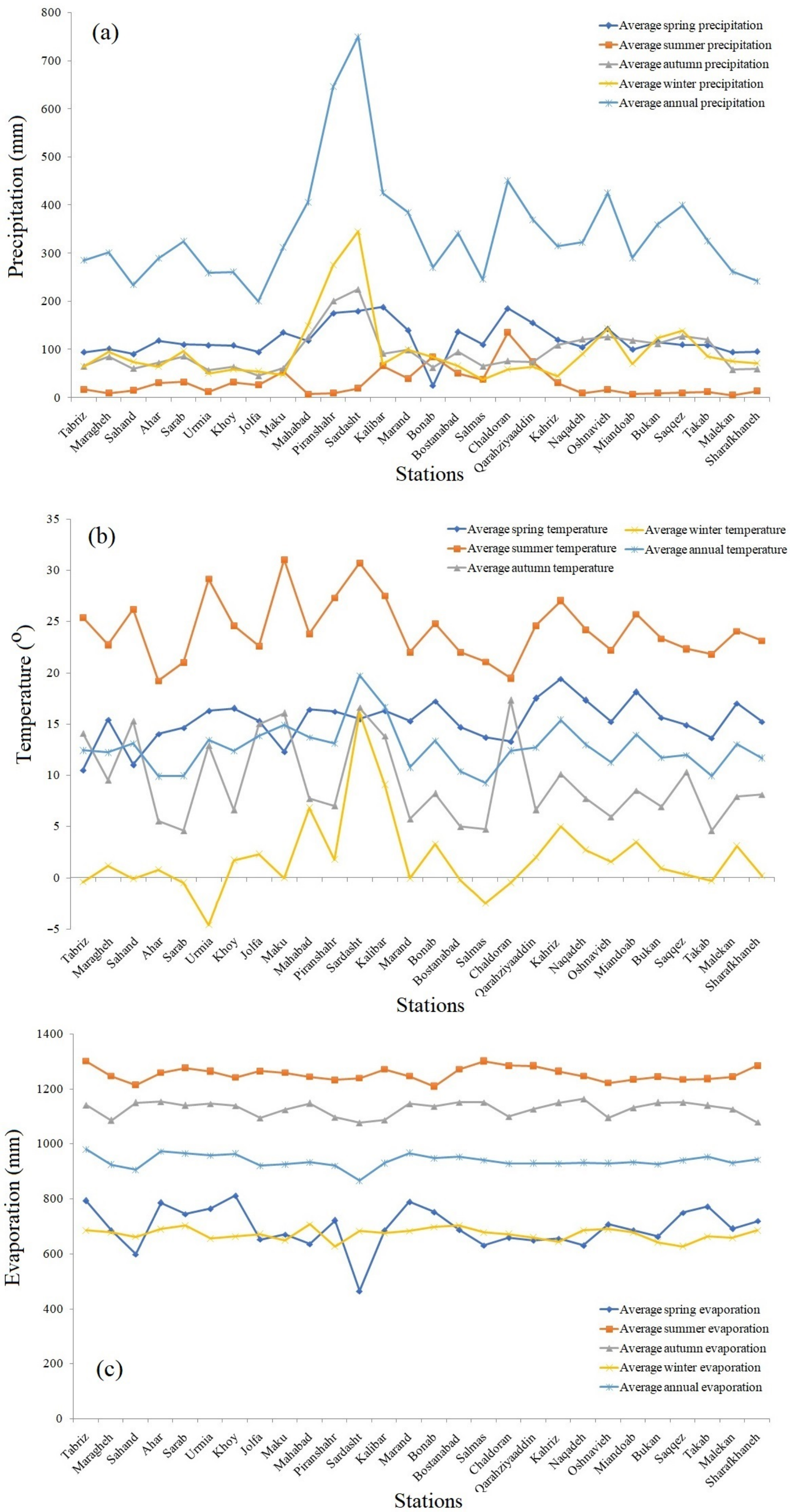

Figure 2. The climatologic variations for the Urmia Lake drainage basin (note: all data reflects the average value): (**a**) rainfall; (**b**) evaporation; (**c**) temperature (adapted from Ref. [35]).

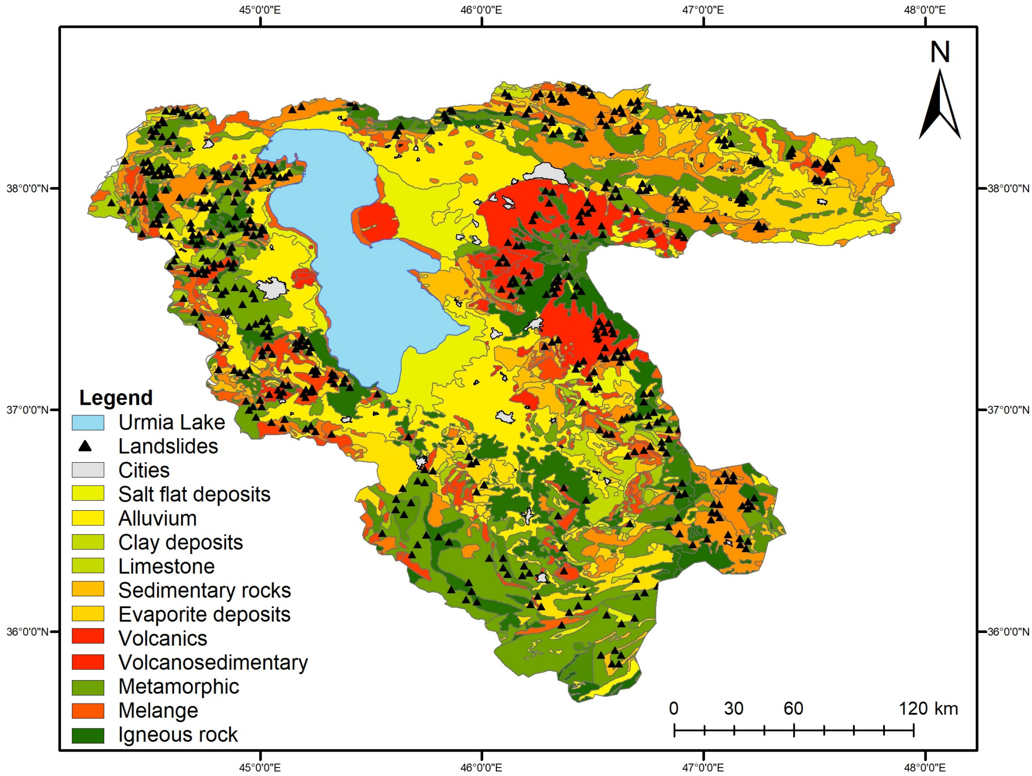

Figure 3. Geological map of the Urmia Lake basin (adapted from Ref. [37]).

In the extensive analysis of factors influencing landslide occurrence within the studied region, a comprehensive framework has been established, delineating five distinct groups of triggering factors. These factors have been meticulously identified through a combination of remote-sensing techniques and exhaustive field survey studies. The resultant parameters within these groups include geomorphological characteristics, geological attributes, climatic conditions, seismic activity, and human-induced activities. These triggering factors can be further categorized into specific variables that play pivotal roles in landslide susceptibility. Within the morphological group, variables such as slope aspect, slope angle, and slope elevation have been scrutinized. The geological category encompasses parameters like lithology, drainage density, landuse/landcover, and weathering conditions. Climatic considerations revolve around precipitation, temperature, and evaporation patterns. Seismicity is assessed through the analysis of factors like the unsafe radius of faults and seismic activity earthquake dispersion. Lastly, human activities are evaluated based on variables including the proximity to roads and the distance to urban centers. Figure 4 provides the GIS-based information maps showing the triggering factors used to analyze the susceptibility for landslides in the studied area. In totality, there are a total of eleven distinct triggering factors identified, each contributing uniquely to the occurrence of landslides within the Urmia Lake drainage basin, and these factors can be categorized into the five overarching groups previously outlined.

It should be noted that in this analysis, the selection of triggering factors involves a thorough assessment of various criteria to ensure the accuracy and dependability of the analysis. These criteria typically focus on factors that play a role in initiating landslides. Key considerations include the relevance of factors to landslide occurrences, the availability and quality of the data, the need for correlations without interdependence between factors, the determination of spatial and temporal variations, validation through expert knowledge and field observations, enhancement of model performance, and ensuring reproducibility and consistency across different studies or areas. By carefully evaluating these criteria, this article aim to identify triggering factors that significantly impact LSM, thereby enhancing the precision and reliability of landslide susceptibility analyses.

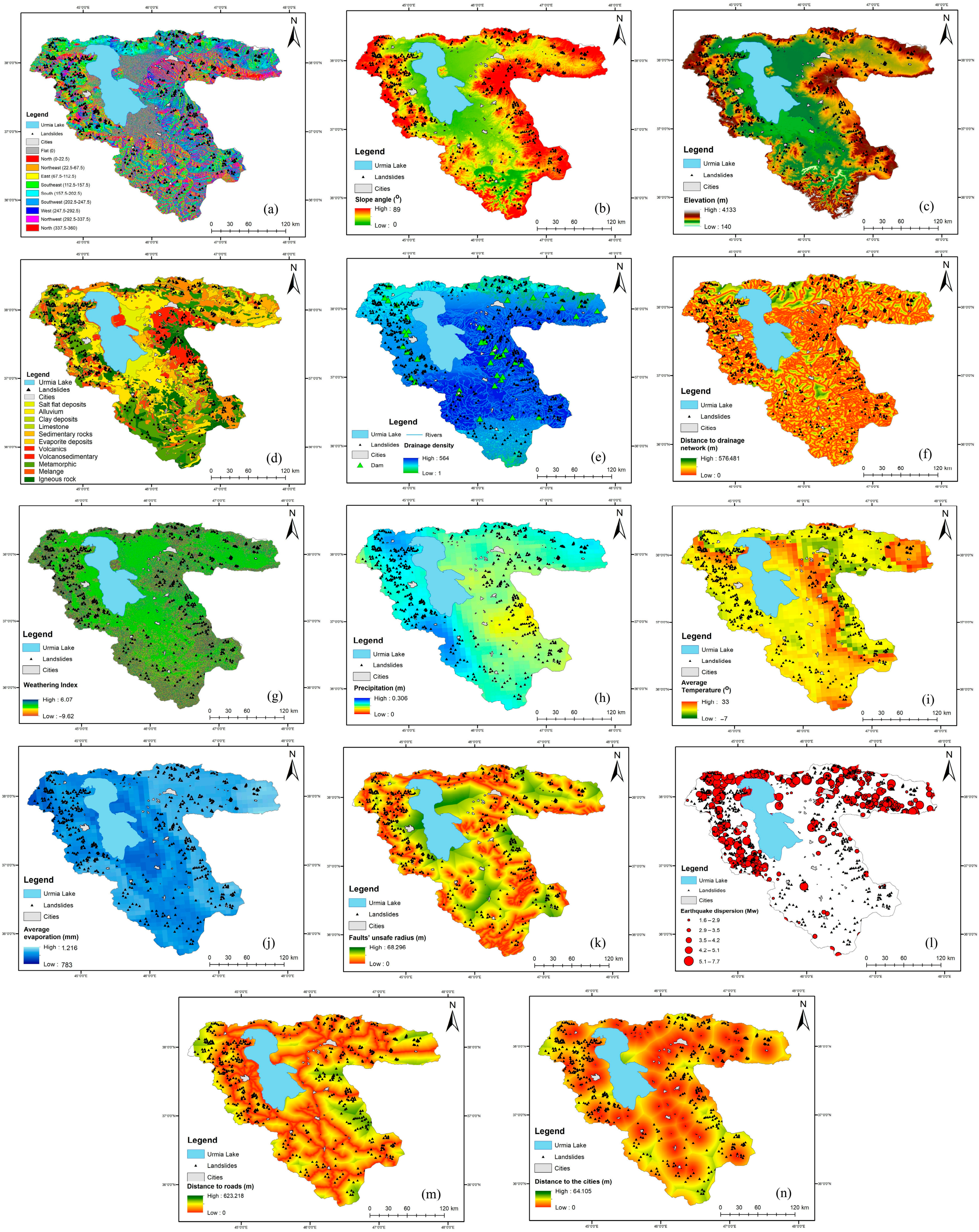

Figure 4. The map of landslide triggering factors prepared for this study: (**a**) slope aspect; (**b**) slope angle; (**c**) elevation; (**d**) lithology; (**e**) drainage density; (**f**) distance to drainage network; (**g**) weathering; (**h**) precipitation; (**i**) temperature; (**j**) evaporation; (**k**) unsafe fault radius; (**l**) seismic activities; (**m**) distance to roads; (**n**) distance to the cities.

2.3. Adjustment of Triggering Factors

Adjusting triggering factors in landslide susceptibility analysis is a critical step to ensure that the assessment aligns with the specific conditions and nuances of the study area. These adjustments are imperative for enhancing the accuracy and applicability of landslide susceptibility assessments. Here, we provide a detailed breakdown of how these adjustments are carried out. (i) Parameterization is a key adjustment process. It involves fine-tuning the parameters within each triggering factor category to accurately reflect the unique geological, topographical, and climatic characteristics of the study area. For instance, if the region exhibits distinct lithological variations, the parameters related to geology must be tailored to effectively capture these specific lithological attributes. Parameterization ensures that the factors considered in the analysis are customized to the region's geological and environmental intricacies. (ii) Weighting is another essential adjustment mechanism. Not all triggering factors exert the same level of influence across different regions. Adjusting the weights assigned to each factor based on their relative importance in the study area allows for a more nuanced susceptibility assessment. For example, in regions where heavy rainfall is a predominant factor contributing to landslides, it may be assigned a higher weight in the analysis, thereby giving it more significance in the susceptibility assessment. Lastly, data resolution and temporal considerations play a crucial role in the adjustment of triggering factors. By adapting the resolution of the data used for triggering factors, such as utilizing higher-resolution topographic or rainfall data, the analysis becomes more precise. Additionally, accounting for temporal changes in susceptibility due to factors like land-use alterations, climate variations, or seismic activity ensures that the assessment reflects the current conditions and provides a dynamic understanding of landslide susceptibility over time. Table 1 provides information regarding data adjustments made for landslide susceptibility analysis in this study. In summary, triggering factor adjustments are indispensable for tailoring landslide susceptibility assessments to the specific attributes of the study area. These adjustments include parameterization, weighting, data resolution, temporal considerations, and the incorporation of local knowledge, all of which collectively enhance the accuracy and contextual relevance of the analysis. The goal is to provide a highly accurate and region-specific assessment of landslide susceptibility, contributing to effective risk management and mitigation strategies in areas prone to landslides.

Table 1. The triggering factor adjustments used in this study.

Triggering Factors	Adjustment	Target Point of Adjustment	Advantages	Limitations
Elevation	Data Resolution	Fine-tuning elevation data	More accurate slope assessment, better representation of local terrain.	Limited to the resolution of available data.
Slope aspect	Weighting	Relative importance	Reflects regional topographical influences; nuanced susceptibility mapping.	Assumes uniform importance if not adjusted.
Slope angle	Parameterization	Slope categories	Captures slope variations; customized susceptibility assessment.	May oversimplify slope variability.
Lithology	Parameterization	Lithological attributes	Accounts for local geological diversity; precise susceptibility assessment.	May require extensive geological data.
Drainage density	Data Resolution	Fine-tuning density data	Accurate representation of local drainage patterns; better assessment.	Limited by resolution of available data.
Landuse/ Landcover	Data Resolution	Fine-tuning land-use data	Improved representation of land use; precise susceptibility mapping.	Limited by the resolution of land-use datasets.

Table 1. *Cont.*

Triggering Factors	Adjustment	Target Point of Adjustment	Advantages	Limitations
Weathering	Parameterization	Weathering conditions	Reflects local weathering characteristics; customized assessment.	Requires detailed weathering data.
Precipitation	Temporal Adjustment	Update historical records	Reflects changing rainfall patterns, dynamic susceptibility assessment	Assumes stationary precipitation patterns
Temperature	Parameterization	Temperature ranges	Considers local temperature variations; tailored assessment.	Requires historical temperature data.
Evaporation	Parameterization	Evaporation rates	Accounts for regional evaporation dynamics; precise assessment.	Requires historical evaporation data.
Distance to faults	Data Resolution	Fine-tuning density data	Accurate representation of fault proximity; better assessment.	Limited by the resolution of fault datasets.
Seismic activities	Data Resolution	Fine-tuning land-use data	Improved representation of seismic activity; precise mapping.	Limited by the resolution of earthquake data.
Distance to roads	Data Resolution	Fine-tuning land-use data	Enhanced representation of road proximity; nuanced assessment.	Limited by the resolution of road datasets.
Distance to cities	Data Resolution	Fine-tuning land-use data	Better representation of urban proximity; refined susceptibility mapping.	Limited by the resolution of city datasets.

3. Materials and Methods

3.1. Data Preparations

Data preparation is of immense importance in the context of landslide susceptibility mapping for the Urmia Lake drainage basin due to its pivotal role in ensuring the accuracy and reliability of the modeling process. This significance can be illuminated through various key facets: (i) data quality assurance is paramount, as it involves meticulous cleaning, validation, and rectification of input data to eliminate inaccuracies and inconsistencies. Given the intricate and diverse nature of the Urmia Lake drainage basin, even minor errors can lead to misleading susceptibility assessments. Therefore, rigorous data quality measures are imperative. (ii) The comprehensive integration of diverse datasets from various sources and formats is crucial to capture the multifaceted nature of landslide triggers and predisposing factors within the basin. This integration spans geological, topographical, environmental, and hydrological variables, ensuring a holistic understanding of the susceptibility landscape. Spatial data, facilitated by GIS tools, must be adeptly prepared, ensuring georeferencing and standardization for seamless compatibility and consistency in spatial analysis and modeling. Moreover, the consideration of temporal data, such as rainfall records and historical landslide events, accommodates the dynamic nature of the basin, permitting the identification of temporal patterns regarding susceptibility. In essence, data preparation is the cornerstone that enables the modeling process to yield accurate, actionable, and reliable landslide susceptibility assessments for the Urmia Lake drainage basin.

The study was meticulously executed in several distinct stages, which can be categorized as follows. The initial stage involved a comprehensive ground survey, remote-sensing analysis, and the meticulous documentation of historical landslide occurrences within the study area. Subsequently, we assembled the primary dataset, which was rooted in both landslide-triggering factors and the precise geolocation of historical landslide incidents. This dataset served as the foundation for our supervised learning approaches. To facilitate the implementation of our predictive model, we meticulously prepared training and testing datasets. These datasets were utilized in the development of a hybrid machine learning and soft computing predictive model, which in turn enabled the generation of susceptibility maps for the study region. The predictive model was then deployed and subjected to rigorous verification procedures to ensure its accuracy and reliability in assessing landslide susceptibility. Lastly, the culmination of our efforts resulted in the production of landslide susceptibility assessments for the entirety of the Urmia Lake drainage basin. A visual representation of the data preparation flow for this landslide susceptibility assessment can be found in the flowchart presented in Figure 5.

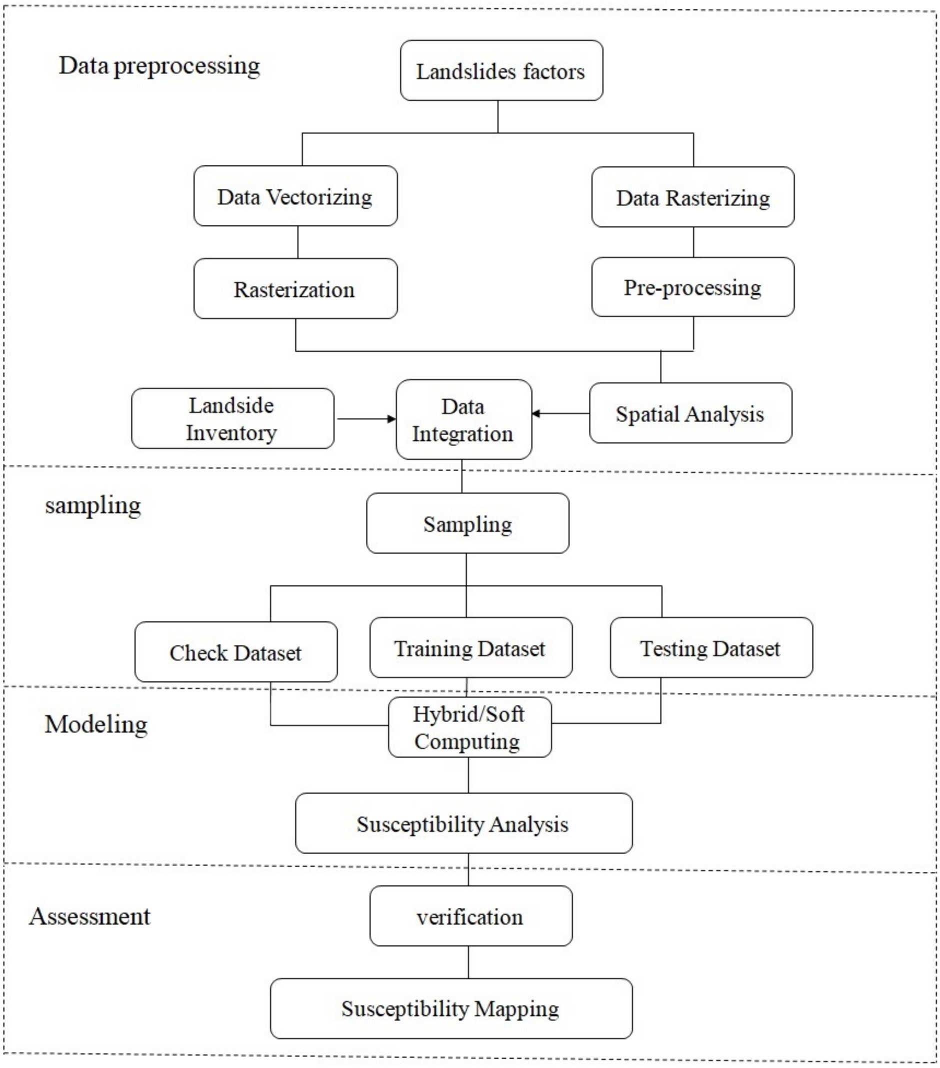

Figure 5. The flowchart showing the data preparation regarding the landslide susceptibility assessment for the studied area.

The primary source of information for this study was a thorough and all-encompassing approach that encompassed a ground survey, a remote-sensing analysis, and the meticulous documentation of historical landslides that have transpired within the basin. These are all provided in Table 2. The historical is records of landslides within the studied region or in close proximity to it offer invaluable insights into the spatial distribution of these events. This historical data serves as a critical resource for susceptibility assessments when identifying areas prone to landslides. Furthermore, these past landslide occurrences act as milestones in understanding the behavior of landslides, essentially allowing us to witness how history repeats itself. By studying these events, we gain essential knowledge about landslide dynamics and can more effectively detect areas at risk. Moreover, establishing a clear link between the triggering factors, such as geological, topographical, and environmental conditions, and the historical landslides is of paramount importance. This linkage provides a foundation for identifying well-founded connections that significantly influence susceptibility assessments.

Table 2. The main triggering factors and data resources.

Main Origin	Triggering Factors	Data Sources	Resolution
Geomorphologic	Elevation	DEM	±30 m
	Slope aspect	DEM	±30 m
	Slope angle	DEM	±30 m
Geologic	Lithology	Geological data	±30 m
	Drainage density	DEM, Google Map, IWRM *	±30 m
	Landuse/landcover	Geological data, Google Map,	±30 m
	Weathering	Geological data	±30 m
Climatologic	Precipitation	IMO †	±30 m
	Temperature	IMO	±30 m
	Evaporation	IMO	±30 m
Seismic	Distance to faults	Geological data, Google Map	±30 m
	Seismic activities	IIEES ** data	±30 m
Human works	Distance to roads	DEM, Google Map	±30 m
	Distance to cities	DEM, Google Map	±30 m

Notes: * Iran Water Resources Management Company (IWRM); † Iran Meteorological Organization (IMO); ** International Institute of Earthquake Engineering and Seismology (IIEES).

In our study, we meticulously selected and geolocated a total of 512 historical landslide events across the Urmia Lake drainage basin, employing GPS technology. These precise locations were then incorporated into GIS, serving as benchmark sites for our comprehensive analysis. This rich historical dataset is instrumental in enhancing the accuracy and reliability of our susceptibility assessments, offering a deeper understanding of the complex interplay between environmental factors and landslide occurrences in the region. To provide the susceptibility map for the Urmia Lake drainage basin, a landslide inventory database was prepared. This database was obtained from field surveys and remote-sensing observations. In this regard, the data were collected based on selected triggering factors from various resources, including satellite images, spatial photogrammetry, variability maps, geological and meteorological data, etc. Table 2 provides the resources for the LSM used data in this study.

It should be noted that to achieve an accurate LSM, it is imperative to uphold the independence of each triggering factor used in the model calculation. By maintaining the independence of these factors, the reliability and accuracy of the evaluation model are ensured. This approach allow for a more comprehensive assessment, preventing potential biases or confounding effects that could compromise the integrity of the susceptibility mapping. Therefore, ensuring the autonomy and distinctiveness of each triggering factor contributes significantly to the robustness and precision of the LSM model. Under such conditions, all data provided is gathered independently, ensuring that it remains uninfluenced by, nor reliant upon, other factors. Statistical checks for control and domain-specific expertise assist in identifying variables that contribute uniquely to LSM, without including redundant information. The evaluation of multicollinearity among the triggering factors is essential. Assessing correlation levels helps to eliminate highly correlated variables, thereby maintaining independence and averting redundancy within the model.

3.2. Data Normalization and Modifications

Normalization serves a pivotal role in achieving feature uniformity, facilitating smoother convergence during model training, and ultimately enhancing the overall performance of the model. It entails the adjustment of feature scales to a standardized range, thereby mitigating any disparities that may hinder effective model learning. A suite of common normalization techniques, including min–max scaling, z-score standardization, log transformation, and others, are at the disposal of researchers. The selection of a specific normalization approach hinges upon the inherent characteristics of the database under consideration [38]. In the context of the presented study, min–max scaling and z-score standardization were judiciously employed as the normalization techniques of choice for harmonizing the database prior to model implementation. It is important to underscore that irrespective of the chosen normalization method, the key to success lies in the consistent application of these normalization transformations to both the training and testing datasets. This harmonious treatment ensures data coherence and fosters improved outcomes when employing techniques in the context of the analysis [39].

Min–max scaling, a technique frequently employed for feature scaling, achieves the transformation of feature values within a dataset to a predefined range, commonly spanning from 0 to 1. The methodology is grounded in a twofold process: first, subtracting the minimum value observed within the feature from each individual data point; and second, dividing this result by the range, which corresponds to the numerical span between the maximum and minimum feature values. The salient objective of min–max scaling revolves around the preservation of the intrinsic disparities between data points, while enforcing a standardized scale for all. Its pertinence is particularly relevant when confronted with datasets harboring features of diverse units or magnitude ranges, thereby obviating the risk of certain features overshadowing the learning process due to their more substantial numerical magnitudes [38]. In essence, min–max scaling serves as an invaluable tool in homogenizing the feature values, enabling equitable comparisons across features that may otherwise exhibit vastly dissimilar numerical characteristics. This is presented in Equation (1). Through this transformation, the relative distinctions among data points remain intact, fostering an unbiased learning environment wherein all features are afforded equal prominence, regardless of their initial units or magnitudes.

$$Y_{norm} = \frac{Y - Y_{\min}}{Y_{\max} - Y_{\min}} \quad (1)$$

where Y_{norm} is the normalized value of the feature, Y is the original value of the feature, $Y_{\min}$ is the minimum value of the feature across the dataset, and $Y_{\max}$ is the maximum value of the feature across the dataset. This formula rescales each data point (Y) by subtracting the minimum value and dividing by the range ($Y_{\max} - Y_{\min}$). Normalization techniques serve the paramount purpose of rendering data amenable to machine learning algorithms that exhibit sensitivity to the scale of input features. Min–max scaling, for instance, orchestrates a transformation wherein values are painstakingly constrained within the [0, 1] range. This meticulous process caters to the idiosyncrasies of algorithms by homogenizing feature scales [39]. Conversely, z-score standardization, with its distinctive approach, transmutes data such that it possesses a mean (average) value of precisely 0 and a standard deviation of 1. This procedure occurs through the subtraction of the feature's mean from each individual data point, followed by division by the standard deviation [40], as illustrated in Equation (2).

$$Z_{norm} = \frac{Z - \mu}{\sigma} \quad (2)$$

where Z_{norm} is the standardized value of the feature, Z is the original value of the feature, μ is the mean (average) of the feature across the dataset, and σ is the standard deviation of the feature across the dataset. This computational formula serves as a means to ascertain the extent to which a given data point (Z) diverges from the mean (μ) of the corresponding feature in terms of standard deviations. When Z_{norm} yields a positive value, it signifies that Z surpasses the mean, whereas a negative Z_{norm} denotes that Z falls below the mean. This transformation imparts a pivotal attribute to the data's distribution, relocating its center to zero, while conferring a consistent dispersion factor of 1. This pivotal adjustment streamlines the comparative analysis of data across distinct features and datasets, particularly when grappling with the intricacies of machine learning algorithms [39]. It is imperative to underscore that both min–max scaling and z-score standardization have their unique utility, with each tailored to specific scenarios contingent upon the attributes of the database and the requisite considerations of the machine learning and soft computing models. The selection of these normalization techniques hinges upon a judicious assessment of the database's idiosyncrasies and the compatibility of the chosen method with the specific algorithmic requirements, fostering a balanced and contextually apt approach to data preparation. Effective data normalization plays a pivotal role in establishing equitable contributions from all features during the model's training process. This proactive measure effectively mitigates complications stemming from disparities in feature scales, thus enhancing the overall performance and convergence dynamics of the proposed predictive model. Figure 6 shows the estimated impact coefficients for data normalization achieved by these two approaches.

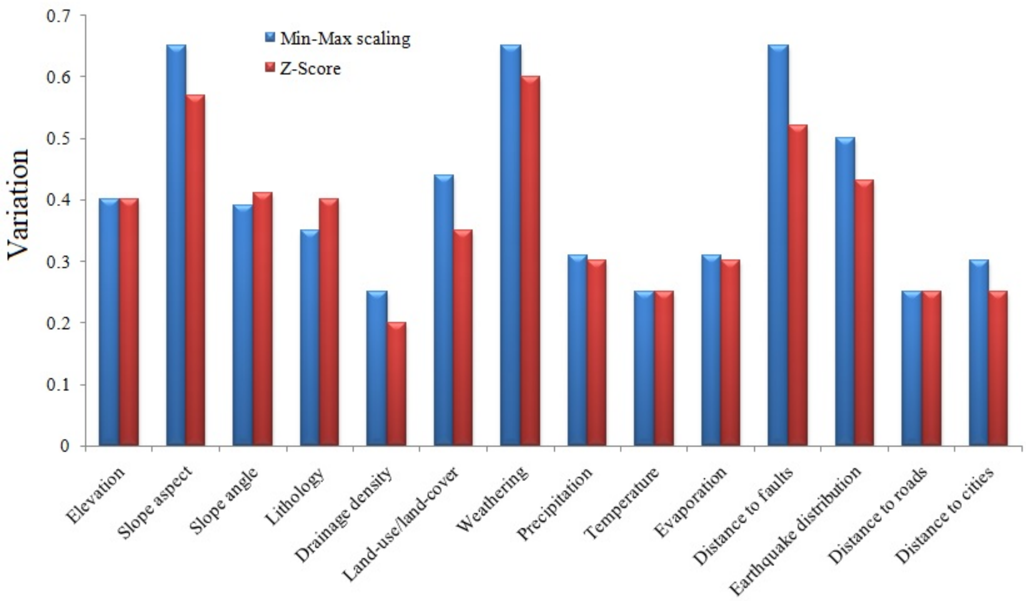

Figure 6. The obtained impact factor for min–max scaling and z-score methods.

3.3. Predictive Modeling Principles

As mentioned previously, the presented study used hybrid machine learning classifiers and soft computing to identify the risk of landslide occurrence in the Urmia Lake drainage basin. Machine learning is a vast field that has found applications in various domains, including information technology, statistics, probability, artificial intelligence, psychology, neuroscience, and many other disciplines. Through machine learning, problems can be easily solved by creating a model that accurately represents a selected dataset [40]. Machine learning is all about devising algorithms that enable computers to learn. It is a process of discovering regular statistical patterns or other data-related insights. Machine learning algorithms are designed to mimic a human approach to learning certain tasks. These algorithms can also provide insights into the relative complexity of learning in different environments.

The hybrid machine learning predictive models considered in this article can be categorized as support-vector machine (SVM), random forest (RF), decision trees (DT), logistic regression (LR), fuzzy logic (FL) and the technique for order of preference by similarity to the ideal solution (TOPSIS), implemented for landslide susceptibility assessment. SVM serves as a non-parametric supervised classification method extensively used in satellite image classification for various mapping tasks. Operating based on mathematical functions called kernels, SVM is designed to categorize multiple classes by determining the optimal hyperplane that best separates data points, known as support vectors [41]. This hyperplane aims to maximize the margin between different classes, maintaining a safety margin between the hyperplane and the nearest data points, termed "support vectors". The orientation of this hyperplane is defined by a weight vector "w" and a bias term "b" within a feature space. SVM poses this task as an optimization problem, aiming to minimize "w", while ensuring the correct classification and adherence to specific constraints for all data points. In cases of non-separable data, slack variables ("ξ_i") allow for controlled misclassification. The outcome of this optimization problem yields the optimal hyperplane, win which support vectors contribute to the margin width, and "w" and "b" define the effective decision boundary that distinguishes between classes. This decision boundary is expressed through specific equations within the feature space in Equations (3)–(6).

$$W \times x + b = 0 \tag{3}$$

$$y_i(w \times x_i + b) \geq 1 \qquad \text{(for support vectors)} \tag{4}$$

$$y_i(w \times x_i + b) \geq 1 - \xi_i \qquad \text{(for non-support vectors)} \tag{5}$$

$$\xi_i \geq 0 \qquad \text{(slack variables for handling non-separable data)} \tag{6}$$

Here, "$\|w\|$" represents the Euclidean norm of the weight vector, "w" is the weight vector, "x" is the feature vector, "b" is the bias term, and "ξ_i" represents a measure of how far a data point is from being correctly classified. Table 3 provides the advantages and limitations of the applied predictive hybrid models.

Table 3. Advantages and limitations of the applied predictive hybrid models.

Model	Advantages	Limitations
SVM	- Effective for both classification and regression tasks - High accuracy, especially in high-dimensional spaces - Works well with small to moderate-sized datasets - Good at handling non-linear separability through kernel tricks - Strong generalization capability, reducing overfitting	- Can be sensitive to the choice of kernel function - Can be computationally intensive for large datasets - May require careful parameter tuning for optimal performance - Interpretability can be limited, especially with complex kernels - Performance may degrade when data is noisy or has overlapping classes
RF	- High accuracy and robustness - Handles both classification and regression - Reduces overfitting through ensemble	- Can be computationally expensive - Less interpretable compared to decision trees
DT	- Simple to understand and interpret - Handles both categorical and numerical data - Useful for feature selection	- Prone to overfitting without pruning - Sensitive to small variations in data - Limited expressiveness for complex data
LR	- Interpretable and provides insights - Suitable for binary and multi-class problems - Requires relatively few computational resources	- Assumes linearity in relationships - May not perform well with non-linear data - Sensitive to multicollinearity
FL	- Handles uncertainty and vagueness in data - Useful in expert systems and control - Allows gradual degrees of truth - Represents ambiguous or imprecise data	- Complexity in defining membership functions - Lacks a clear mathematical foundation - May require domain-specific tuning
TOPSIS	- Provides a structured approach for multi-criteria decision making - Offers a systematic way to analyze complex decisions - Balances positive and negative aspects in decision making - Suitable for applications in various fields, including business and engineering - Helps select the most balanced and appropriate solution	- Highly dependent on the accurate definition of criteria, weights, and ideal solutions - May not work well with a large number of alternatives or criteria - Results can be sensitive to variations in data or criteria - The method does not inherently consider interactions between criteria - Assumes that the criteria are independent and equally weighted, which might not be realistic, in some cases

RF is an ensemble learning method combining multiple decision trees for improved accuracy and robust predictions in both classification and regression tasks. DT a is fundamental model for classification and regression, recursively dividing data based on informative features, forming tree structures, and providing interpretability, but it is susceptible to overfitting [39,40]. LR is linear model used for binary and multi-class classification, employing a logistic function to transform features into probability scores between 0 and 1, offering enhanced interpretability. FL addresses uncertainty by allowing gradual truth degrees (0 to 1) for handling vague or ambiguous data; it is utilized in artificial intelligence and decision-making processes. The technique for order of preference by similarity to ideal solution (TOPSIS) assists in ranking alternatives by comparing them to ideal and worst-case scenarios, aiding systematic decision making, but requiring careful criterion definition and weight assignment for reliable outcomes [42,43].

Landslide susceptibility assessments often involve multiple criteria or attributes, known as triggering factors. Machine learning models allow for the integration of these diverse factors, facilitating a comprehensive analysis. They adopt a data-driven approach, learning from historical landslide occurrences to uncover hidden patterns and trends, which are often elusive using traditional methods. Models like SVM, DT, RF, and LR are esteemed for their accuracy and robustness, ensuring dependable predictions and the ability to generalized to new and unseen areas (see Figure 7). Furthermore, ensemble methods like RF mitigate overfitting, elevating the overall accuracy of susceptibility assessments. DT and LR models offer transparency, enabling geologists and decisionmakers to understand the underlying factors that contribute to landslide susceptibility. FL adeptly handles uncertainty and vagueness in the data, commonly encountered in such assessments. TOPSIS, designed for multi-criteria decision making, proves invaluable in prioritizing various attributes in landslide susceptibility assessment. These models can seamlessly integrate remote sensing and GIS data, yielding a holistic view of the landscape and enhancing the accuracy of susceptibility models.

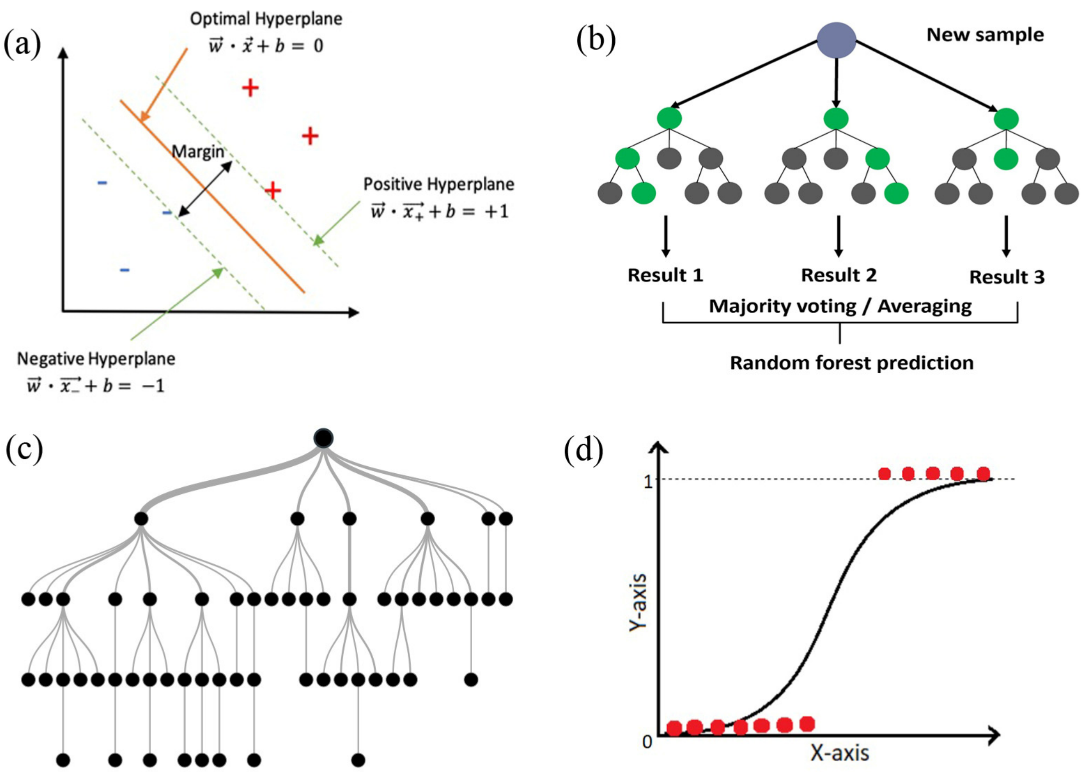

Figure 7. A visual representation of the basics of the hybrid machine learning models: (**a**) SVM; (**b**) RF; (**c**) DT; (**d**) LR.

3.4. Hybrid Model Implementation

In the realm of landslide susceptibility assessment, a highly effective hybrid strategy involves the integration of SVM with ensemble methods, specifically DT, RF, and LR. To validate the hybrid model, we conducted training on a meticulously curated database comprising 14 distinct triggering factors and a repository of 512 historical landslide records. This comprehensive database encapsulates a wealth of geological and environmental data. To ensure the model's robustness, the dataset was thoughtfully partitioned into training and testing subsets, comprising 70% and 30% of the primary database, respectively. This partitioning strategy guarantees that the model is both trained and rigorously evaluated on diverse datasets, enhancing its reliability and predictive accuracy. In the context of the depicted process flowchart, the subsequent steps are employed to execute hybrid machine learning algorithms using a meticulously prepared database. These delineated stages serve to elucidate the process of creating a prognostic model based on various predictive models. The following breakdown provides a comprehensive overview of the implementation methodology for predictive modeling:

Step 1 (Data Collection and Preparation): To initiate the process, compile an extensive dataset that encompasses essential details related to triggering factors and historical landslide records. These data sources are acquired through a combination of historical records, on-site field surveys, and remote sensing observations. Next, undertake data preprocessing procedures, which encompass tasks such as addressing missing data points, encoding categorical variables, and standardizing the feature scales. This pivotal stage plays a fundamental role in the data preparation process, ensuring that the dataset is appropriately structured and ready for subsequent model training activities.

Step 2 (Dataset Splitting): Partition the meticulously preprocessed dataset into distinct training and testing subsets. A conventional and widely adopted division practice involves allocating 70% of the data for training purposes, while the remaining 30% is reserved for testing. This strategic separation is integral in the machine learning process, as it enables the model to glean insights and patterns from the training subset, subsequently evaluating its performance on unseen and distinct data within the testing subset. This approach verifies the model's ability to generalize and make accurate predictions beyond the confines of the training dataset, a critical aspect of robust model assessment.

Step 3 (Feature Selection): Determine the pertinent features or variables within the dataset that are anticipated to exert the most substantial influence on landslide susceptibility and the identification of suitable locations within the studied Urmia Lake drainage basin. The process of feature selection assumes a pivotal role in enhancing model performance and curbing computational complexity. By pinpointing and incorporating only the most relevant features, the model becomes more effective in its predictive capabilities, while streamlining the computational burden. This tailored selection process is integral to the accurate assessment of landslide susceptibility and the suitability of the model in the Urmia Lake drainage basin.

Step 4 (Model Building): Execute the hybrid machine learning models, tailoring their implementation to meet distinct requirements set for each model. This implementation phase leverages the carefully prepared main database, and during the training process, the model endeavors to identify intricate connections between triggering factors and vulnerable regions which have previously experienced landslides. This determination extends to the mapping of susceptible areas within the studied landscape. By accommodating unique prerequisites for each model, the hybrid approach aims to capture and model complex relationships with precision, contributing to a more robust and accurate landslide susceptibility assessment.

Step 5 (Hyperparameter Tuning): Conduct hyperparameter tuning to enhance the overall performance of the predictive model. Engage in systematic experimentation with a range of hyperparameter configurations, including parameters like the number of trees, the tree depth, and the learning rate. These pivotal hyperparameters are precisely documented in Table 4 and were meticulously selected for utilization in this study.

Table 4. The hyperparameters for the comparative machine learning models (adapted from Ref. [42]).

Classifier	Hyperparameters
SVM	- Kernel type (kernel) - Regularization parameter (C) - Kernel coefficient (gamma)
RF	- Number of trees (n_estimators) - Maximum depth of trees (max_depth) - Minimum samples per leaf (min_samples_leaf) - Maximum features to consider (max_features)
DT	- Maximum depth of the tree (max_depth) - Minimum samples per leaf (min_samples_leaf) - Maximum features to consider (max_features)
LR	- Inverse of regularization strength (C) - Maximum number of iterations for convergence (max_iter) - Handling of multi-class classification (multi_class) - Regularization parameter (L1, L2, or none) - Weighting for handling class imbalance (class_weight) - Tolerance for stopping criteria (tol) - Scaling factor for the intercept term (intercept_scaling) - Reusing previous solution as the initial guess (warm_start)

Step 6 (Model Evaluation): Assess the performance of the trained predictive models by applying them to the testing dataset.

Step 7 (Interpretation and Insights): Examine the model's output to extract valuable insights regarding the connections between triggering factors and their influence on landslide susceptibility. This analysis aims to shed light on the mapping of areas at potential risk for landslides.

Step 8 (Model Deployment): If needed, deploy the trained models for real-time predictions or further analysis.

These steps outline a general framework for implementing hybrid machine learning and soft computing predictive modeling to analyze the landslide susceptibility for the Urmia Lake drainage basin (see Figure 8). Adjustments may be necessary, based on the specific details of the dataset and research objectives.

FL and TOPSIS models was implemented asparallel analyses with the mentioned machine learning models to justify and extended our understanding regarding the studied drainage basin. The ensuing steps were executed on the meticulously curated database to generate a susceptibility map for the Urmia Lake drainage basin. The input data and triggering factors correspond to those utilized in the previously described machine learning models.

Step 1 (Data Collection and Preparation): Gather comprehensive data related to triggering factors, historical landslide occurrences, and other relevant geospatial information within the study area. This step is the same as the step 1 used in the other machine learning-based models.

Step 2 (Preprocessing and Data normalization): Clean and preprocess the data, i.e., handle the missing values, encode the categorical variables, and normalize the features. Also, normalize the data to bring all the attributes to a common scale. This ensures that no single attribute dominates the analysis due to its scale.

Step 3 (Feature Selection): Identify and select the most influential features (variables) that have a significant impact on landslide susceptibility within the region. This step is the same as the step 3 used for the other machine learning-based models.

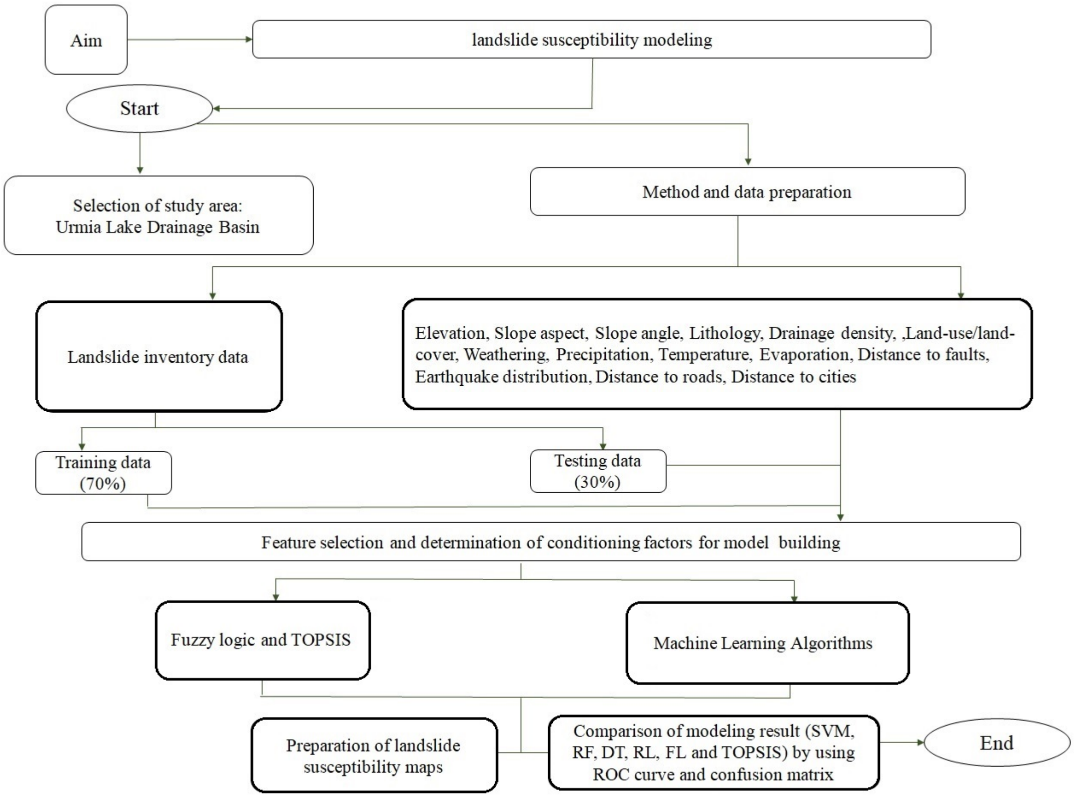

Figure 8. A general framework for implementing hybrid modeling.

Step 4 (Rules and Assignments): In this stage, for the FL model, a set of fuzzy logic rules describing the relationships between the selected features and landslide susceptibility is developed. In the TOPSIS model, weights are assigned to each attribute based on its importance to landslide susceptibility. Weights and rules are typically assigned based on expert knowledge or through statistical techniques.

Step 5 (Fuzzy Modeling for FL): Convert the crisp (numerical) data into fuzzy sets using membership functions (known as fuzzification). Define linguistic variables and their associated membership functions to represent data uncertainty. Build a fuzzy inference system that combines the fuzzy rules and fuzzified input data to make decisions about landslide susceptibility. This system should use fuzzy logic operators (e.g., AND, OR) to perform rule inference. Transform the fuzzy output from the inference system into a crisp value that represents the degree of landslide susceptibility for each location (known as defuzzification).

Step 5 (Ideal and Negative-Ideal Solutions for TOPSIS): Determine the ideal solution (representing the best conditions for landslide susceptibility) and the negative-ideal solution (representing the worst conditions) for each attribute. These solutions are based on the weighted and normalized data. Then, calculate the similarity of each location to both the ideal and negative-ideal solutions using a chosen distance or similarity measure, such as Euclidean distance. After that, compute the TOPSIS score for each location by comparing its similarity to the ideal and negative-ideal solutions. This score quantifies the degree of landslide susceptibility. Finally, rank the locations based on their TOPSIS scores, with higher scores indicating higher susceptibility.

Step 6 (Mapping): Create a susceptibility map that visualizes the ranking and provides insights into areas at greater risk for landslides. This stage was implemented for all modeling, as well as for FL and TOPSIS.

Both fuzzy logic and TOPSIS are valuable techniques for landslide susceptibility assessment, offering different approaches to handle uncertainty and multi-criteria decision making. The specific implementation steps may vary, based on the dataset and the characteristics of the study area.

3.5. Model Verification

The performance of the proposed method was assessed based on both the confusion matrix and the receiver operating characteristic (ROC) curve [41]. A confusion matrix serves as a fundamental tool in the realm of machine learning and statistical classification tasks. It plays a pivotal role in evaluating the performance of the classification models. This matrix provides a comprehensive breakdown of how well a model's predictions align with the actual class labels. In the context of binary classification problems, which involve two classes, a typical confusion matrix is structured as a 2×2 table. Within this matrix, four key elements take center stage: True positives (TP) represent correct positive predictions, true negatives (TN) signify accurate negative predictions, false positives (FP) indicate erroneous positive predictions (type I errors), and false negatives (FN) point to missed positive instances (type II errors). This binary confusion matrix enables the quantification of model accuracy, precision, recall, F1 score, and specificity, all of which provide vital insights into the model's performance [40]. Figure 9 illustrates the confusion matrix principle [41]. The utility of the confusion matrix lies in its ability to offer a comprehensive overview of a model's strengths and limitations, particularly regarding its capacity to accurately classify instances from both positive and negative classes. By exploring these metrics and the confusion matrix, practitioners can make informed assessments of a model's predictive power and identify areas for improvement, ultimately enhancing the model's suitability for classification tasks.

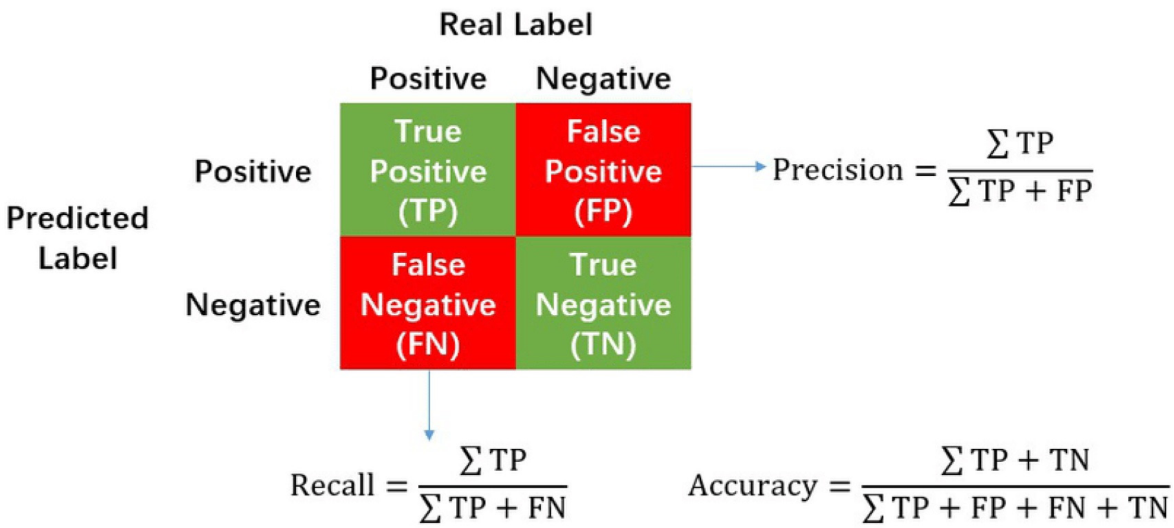

Figure 9. A general overview of the confusion matrix principle(adapted from Ref. [41]).

The ROC curve is a graphical tool extensively employed to assess the performance of binary classification models. This curve portrays the dynamic relationship between the true positive rate (sensitivity, Se), which quantifies the model's ability to correctly identify positive instances, and the false positive rate (1-specificity, 1-Sp), which measures the model's tendency to mistakenly classify negative instances as positive across varying discrimination thresholds. By systematically altering the threshold, a set of data points is generated, forming the ROC curve. A higher curve on the ROC plot indicates a model's ability to make more accurate positive predictions, while limiting false alarms. The area under the ROC curve (AUC-ROC) serves as a concise summary metric, quantifying the model's overall discriminatory capacity, with a perfect model achieving an AUC-ROC of 1.0 (See Figure 10). The ROC curve is a valuable tool for identifying a model's performance in distinguishing between positive and negative cases, particularly as the discrimination threshold varies. It is widely employed in applications where the balance between minimizing false positives and maximizing true positives is critical, including medical diagnoses, credit risk assessment, and fraud detection. The AUC-ROC simplifies model comparison, making it a versatile tool for selecting the best-performing model among alternatives, ultimately enhancing decision making in binary classification tasks.

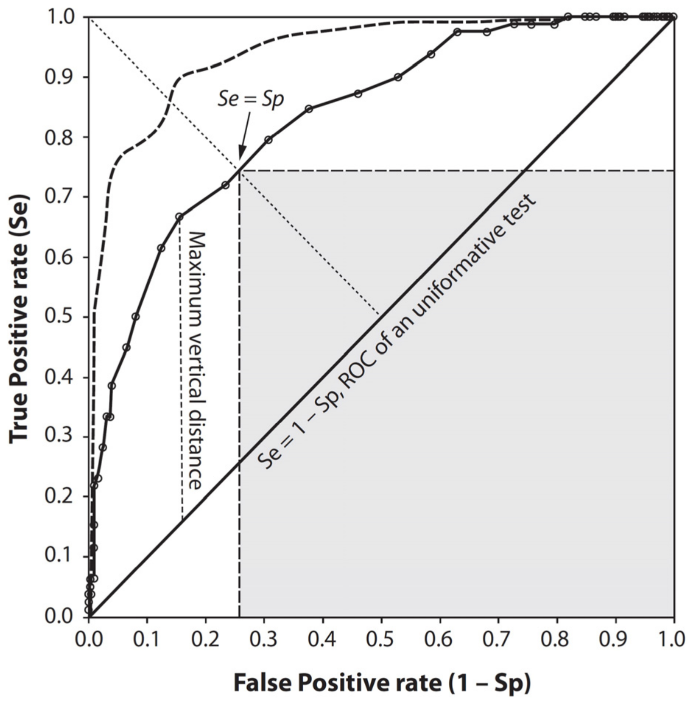

Figure 10. ROC curve analysis (adapted from Ref. [40]).

4. Results

This study harnessed a diverse array of methodologies, including SVM, DL, RF, and LR, juxtaposed against the outcomes derived by employing fuzzy logic and TOPSIS. Following an analysis of the resultant maps, it was evident that SVM and fuzzy logic outperformed other methods in assessing landslide susceptibility within the Urmia Lake basin. The core objective of this research was to scrutinize landslide susceptibility and forecast occurrences within the Urmia Lake basin, utilizing a spectrum of machine learning and soft computing methods, as previously enumerated. These models were crafted based on identified triggering factors and were bolstered by historical landslide data. The preparation of maps was conducted within a GIS framework, meticulously cross-checked by experts to ensure accuracy in the findings. Furthermore, the models underwent a performance evaluation via the scrutiny of confusion matrices and ROC curve analysis. Figures 11 and 12 show the susceptibility maps of the studied basin using various hybrid predictive models. In Figure 11, the SVM, DL, RF, and LR-based maps are presented, and in Figure 12, the fuzzy logic and TOPSIS models are illustrated. Based on these findings, it is evident that various algorithms and techniques within machine learning and soft computing have demonstrated competency in conducting landslide analysis, to varying degrees. However, when comparing their performance, SVM and fuzzy logic stand out by showcasing the highest accuracy in pinpointing vulnerable or susceptible areas prone to landslides.

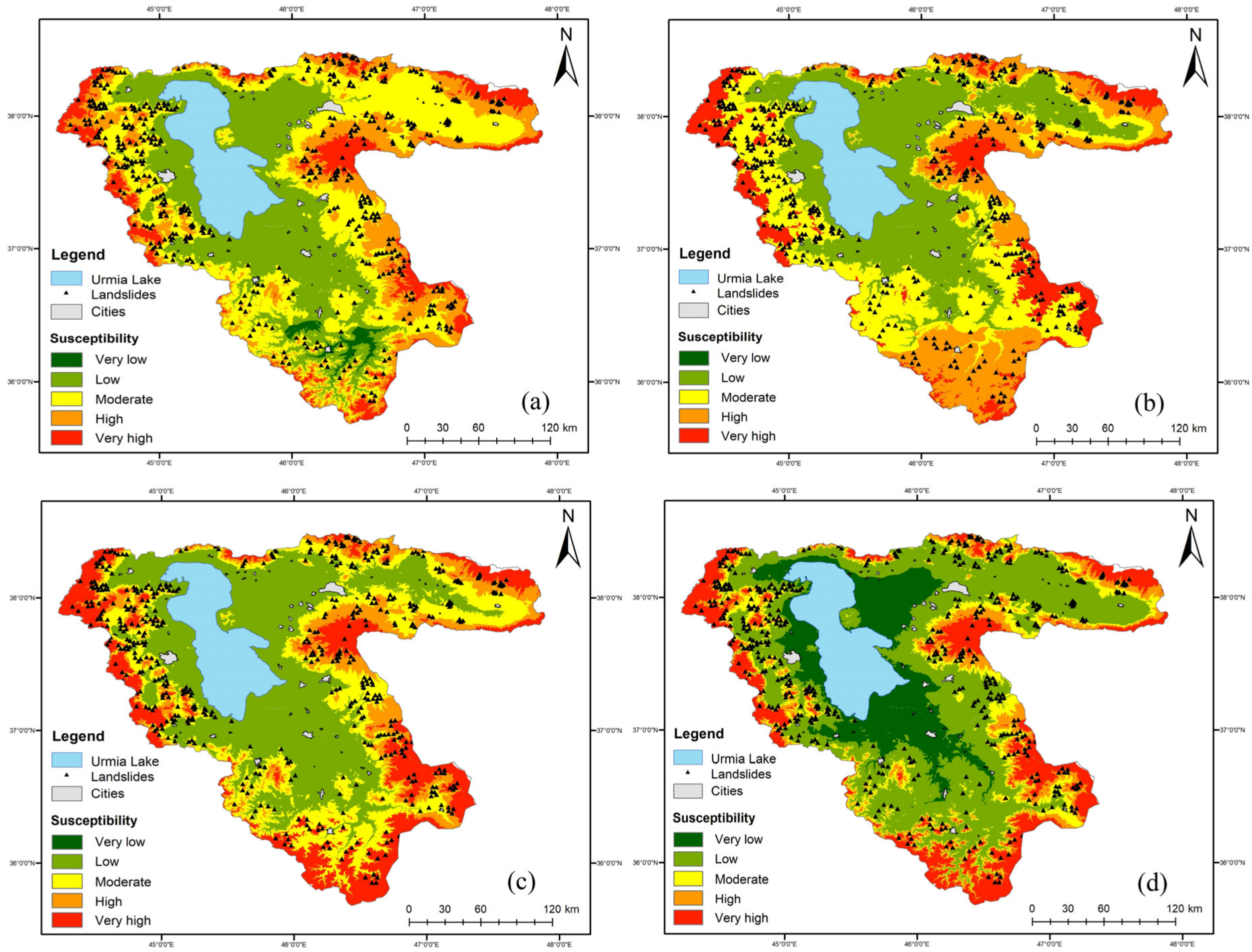

Figure 11. Landslide susceptibility maps for the Urmia Lake basin evaluated via the following machine learning techniques: (**a**) SVM; (**b**) DT; (**c**) RF; (**d**) LR.

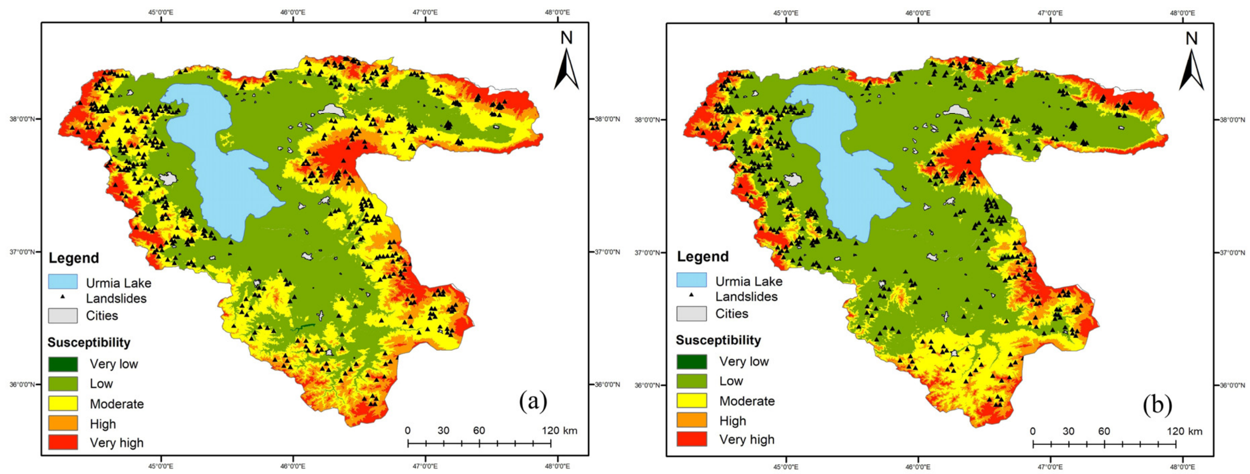

Figure 12. Landslide susceptibility maps for Urmia Lake basin evaluated via the following verification techniques: (**a**) fuzzy logic; (**b**) TOPSIS.

As depicted in Figures 11 and 12, regions susceptible to landslides have been identified in the northwestern, northern, northeastern, and some southern and southeastern areas, emphasizing a primary focus on these zones. These identified areas (as illustrated in Figure 1) coincide with mountainous regions and elevations, notably overlapping with the Urmia Dokhtar mountain range in the northwest, Marmisho and Aun-ben-Ali heights in the north, the Sahand mountain range in the northeast, and Kurdistan heights in the south. The vicinity surrounding Urmia Lake comprises plains and is not prone to landslide occurrences. Hence, it can be concluded that morphological changes emerged as one of the pivotal factors significantly contributing to these landslide occurrences. The information presented in these maps could assist citizens, planners, and engineers in mitigating, reducing, and preventing damages caused by existing and potential landslides. By considering factors related to construction activities, building vulnerabilities, and other properties, a risk and hazard analysis can be conducted. The outcomes of this research can serve as a means to explain current landslide occurrences, make emergency decisions, and streamline efforts to prevent and reduce landslide risks in the future, particularly in cities such as Tabriz, Maragheh, and Urmia. These cities are located within regions prone to landslide occurrences.

Figure 13 presents the ROC curve outcomes, while Table 5 illustrates the values of the confusion matrix in regards to the performance of the predictive models. Obtaining a confusion matrix for all hybrid machine learning and soft-computing models utilized in landslide susceptibility analysis holds pivotal significance for several reasons. Primarily, it serves as a crucial tool for assessing the performance of these models by comparing their predicted outcomes against actual data. This matrix provides a comprehensive breakdown of the correct classifications of landslides and non-landslides, shedding light on areas in which the model succeeds or fails. Matrices such as accuracy, precision, recall, specificity, and F1-scoreoffer a nuanced evaluation, allowing us to gauge the model's effectiveness in identifying areas prone to landslides. Moreover, comparing these matrices among different models aids in selecting the most suitable method based on its capacity to minimize errors and provide accurate predictions. Notably, analyzing the confusion matrix aids in fine-tuning the model parameters to enhance the predictive capabilities and informs decision-making processes for stakeholders and planners. This comprehensive evaluation supports the prioritization of areas for mitigation efforts, emergency planning, and optimal resource allocation to minimize the adverse impact of landslides on communities and infrastructure. Ultimately, the confusion matrix plays a fundamental role in guiding strategic decisions and optimizing the effectiveness of landslide risk management strategies. On the other hand, ROC analysis for all predictive models utilized in landslide susceptibility assessment holds significant importance, for several key reasons: the ROC curve showcases how a model's sensitivity and false positive rate vary across different thresholds, providing a comprehensive view of its performance at various decision points. This graphical representation allows for direct model-to-model comparisons, aiding in visualization and determining which model exhibits superior performance. The AUC values derived from the ROC curve serve as a singular metric, simplifying the assessment of each model's ability to discern between landslide-prone and non-prone areas. A higher AUC suggests better discriminatory power. Moreover, ROC analysis assists in selecting the optimal threshold aligning with specific project objectives, balancing sensitivity and specificity as needed. The insights derived from ROC analysis not only guide decisionmakers in selecting models, but also inform strategic planning, resource allocation, and risk mitigation strategies, ensuring the effective management of landslide-prone regions. Ultimately, ROC analysis is instrumental in comprehensively evaluating and comparing model performances, aiding in informed decision making for landslide risk management.

Table 5 displays the performance of different machine learning models in predicting landslide susceptibility across training and testing datasets. SVM demonstrates superior performance in regards to accuracy, precision, recall, and F1-score for both datasets. This consistency suggests SVM's robustness in generalizing to new data, making it a reliable choice for landslide prediction. The DT model reveals a slightly lower performance compared to SVM, with a particularly notable decline in the metrics between the training and testing phases. This discrepancy may indicate a potential overfitting on the training data, resulting in decreased predictive power for the unseen datasets. Additionally, the RF model performs reasonably well, although it exhibits a slight drop in precision and recall on the testing data compared to the performance of SVM. LR trails behind the other models, displaying lower predictive capabilities for both datasets. It is important to note that the performance metrics for the TOPSIS model are limited, with only the accuracy (binary) available, indicating moderate performance. However, a comprehensive evaluation should consider factors beyond these metrics, such as computational efficiency and interpretability, to select the most suitable model for landslide susceptibility analysis. Overall, while SVM emerges as the most consistent and robust performer, a holistic assessment of various model aspects is essential in making a well-informed selection for practical application in predicting landslide susceptibility.

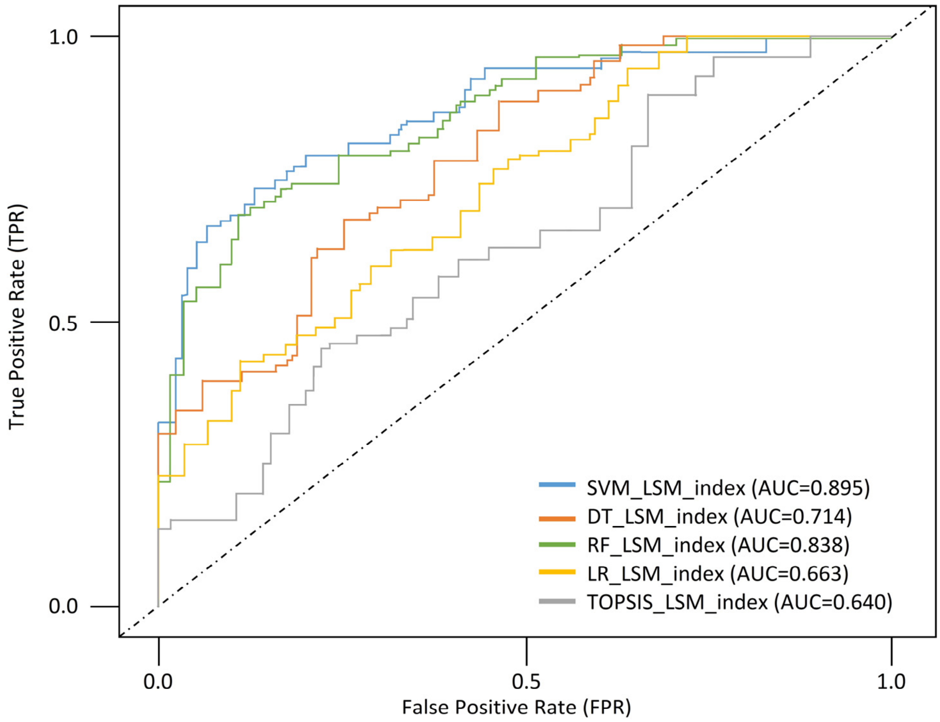

Figure 13. Estimated ROC curve for machine learning–based models.

Table 5. The obtained performance criteria for the predictive models.

Methods	Dataset	Performance Criteria			Accuracy
		Precision	Recall	F1-Score	
SVM	Train Test	0.89 0.85	0.85 0.85	0.85 0.85	0.89
DT	Train Test	0.75 0.72	0.75 0.70	0.72 0.70	0.72
RF	Train Test	0.83 0.80	0.80 0.83	0.83 0.80	0.83
LR	Train Test	0.69 0.64	0.67 0.60	0.67 0.60	0.67
TOPSIS	Entire data	-	-	-	0.64

5. Discussion

This study employed an extensive range of methodologies, including SVM, DL, RF, and LR, in conjunction with fuzzy logic and TOPSIS, to evaluate landslide susceptibility within the Urmia Lake basin. Analyses of the resulting maps highlighted the superior performance of SVM and fuzzy logic in this assessment. The primary aim was to scrutinize landslide susceptibility and to forecast occurrences in the region, utilizing diverse machine learning and soft computing methods, based on identified triggering factors and historical landslide data. The preparation of susceptibility maps was meticulous, conducted within a GIS framework and validated by experts to ensure accuracy. These models underwent performance evaluation via confusion matrices and ROC curve analysis. The maps identified high susceptibility zones primarily in the northwestern, northern, northeastern, southern, and southeastern areas, coinciding with mountainous regions and higher elevations, indicating morphological changes as crucial factors contributing significantly to landslide occurrences. The data presented in Figures 11 and 12 illustrate the susceptibility maps for different models, emphasizing the efficacy of SVM and fuzzy logic in pinpointing vulnerable areas prone to landslides. These findings can aid citizens, planners, and engineers in mitigating damage caused by landslides. They can also be used for risk and hazard analyses related to construction activities and building vulnerabilities, particularly in landslide-prone cities such as Tabriz, Maragheh, and Urmia. The evaluation involved analyzing confusion matrices for all hybrid machine learning and soft-computing models used in landslide susceptibility analysis. This comprehensive assessment provides insights into the models' performance, enabling the selection of suitable models and the fine-tuning of parameters to enhance predictive capabilities. Additionally, ROC analysis aids in determining each model's discriminatory power and assists in selecting optimal thresholds aligning with specific project objectives.

Table 5 depicts the performance of different machine learning models in predicting landslide susceptibility across training and testing datasets. SVM exhibited superior performance in regards to accuracy, precision, recall, and F1-score consistently across both datasets, suggesting its reliability in generalizing to new data. DT showed slightly lower performance, potentially indicating overfitting on the training data. RF displayed reasonable performance, but with a decline in some metrics for the testing data. LR demonstrated lower predictive capabilities for both datasets. While TOPSIS showed moderate performance in regards to accuracy (binary), a comprehensive evaluation should consider factors beyond these metrics, including computational efficiency and interpretability, to select the most suitable model for practical application in predicting landslide susceptibility. Thus, while SVM emerged as the most consistent and robust performer, a holistic evaluation of various aspects of the method is crucial for selecting an appropriate model for landslide susceptibility analysis in practical scenarios.

6. Conclusions

This study incorporated a diverse range of methodologies, including SVM, DL, RF, and LR, along with the utilization of fuzzy logic and TOPSIS, to assess landslide susceptibility within the Urmia Lake basin. The comparative analysis of the resultant maps indicated that SVM and fuzzy logic outperformed the other methods used in this assessment. Our primary objective was to scrutinize landslide susceptibility and forecast occurrences in the Urmia Lake basin using various machine learning and soft computing methods constructed based on identified triggering factors and historical landslide data. The study's methodology involved meticulous ground surveys, remote sensing analyses, and comprehensive documentation of 512 historical landslide occurrences across the Urmia Lake drainage basin, facilitated by GPS technology. Furthermore, the investigation delved into the complex water sources sustaining the Lake Urmia basin, which primarily relies on a network of 13 perennial rivers, small springs, and direct precipitation. Notably, a significant portion of this inflow is provided by the Zarrineh River and the Simineh River, as the lake lacks a natural outlet and experiences water loss solely through evaporation. Employing a variety of hybrid machine learning predictive models like SVM, RF, DT, LR, FL, and TOPSIS, the research strategically applied these models to assess landslide susceptibility. The objective was to precisely evaluate landslide occurrences within the region, with the results highlighting specific areas, including the northwestern, northern, northeastern, and some southern and southeastern regions, as the main high susceptibility zones for landslides. In analyzing the predictive performance of different algorithms, it became evident that SVM exhibited superior accuracy (0.89) and precision (0.89), followed by RF, with an accuracy of 0.83 and a precision of 0.83. Notably, TOPSIS yielded the lowest accuracy among the evaluated algorithms. These findings provide valuable insights into landslide susceptibility in the Lake Urmia basin, aiding in the development of proactive mitigation strategies for high-risk zones.

Author Contributions: Y.L., F.T., A.K.S.S. and M.A.: conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, visualization, and writing—original draft preparation; Y.M. and M.Z.: writing—review and editing and supervision. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Key Improvement Projects of Guangdong Province (grant No. 2022ZDJS048), the Shaoguan Science and Technology Plan Projects (grant No. SZ2022KJ06 and 220607154531533); and the Science and technology projects of education government in Jiangxi province (GJJ209406, GJJ218505, and GJJ218504).

Data Availability Statement: All required data and information were included in this published article.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

LSM	landslide susceptibility mapping
RS	remote sensing
GIS	geographic information systems
LR	logistic regression
NB	naïve Bayes
FL	fuzzy logic
SVM	support vector machines
KLR	kernel logistic regression
BLR	Bayesian logistic regression
RF	random forest
ANFIS	adaptive neuro-fuzzy inference system
DT	decision tree
IMO	Iran Meteorological Organization
TOPSIS	technique for order of preference by similarity to ideal solution
PIS	positive-ideal solution
NIS	negative-ideal solution
GPS	Global Positioning System

References

1. Nanehkaran, Y.A.; Chen, B.; Cemiloglu, A.; Chen, J.; Anwar, S.; Azarafza, M.; Derakhshani, R. Riverside Landslide Susceptibility Overview: Leveraging Artificial Neural Networks and Machine Learning in Accordance with the United Nations (UN) Sustainable Development Goals. *Water* **2023**, *15*, 2707. [CrossRef]
2. Huang, Y.; Zhao, L. Review on landslide susceptibility mapping using support vector machines. *Catena* **2018**, *165*, 520–529. [CrossRef]
3. Kavzoglu, T.; Colkesen, I.; Sahin, E.K. Machine learning techniques in landslide susceptibility mapping: A survey and a case study. In *Landslides: Theory, Practice Modelling*; Springer: Heidelberg, Germany, 2019; pp. 283–301.
4. Azarafza, M.; Azarafz, M.; Akgün, H.; Atkinson, P.M.; Derakhshani, R. Deep learning-based landslide susceptibility mapping. *Sci. Rep.* **2021**, *11*, 24112. [CrossRef] [PubMed]
5. Broeckx, J.; Vanmaercke, M.; Duchateau, R.; Poesen, J. A data-based landslide susceptibility map of Africa. *Earth-Sci. Rev.* **2018**, *185*, 102–121. [CrossRef]
6. Yeon, Y.K.; Han, J.G.; Ryu, K.H. Landslide susceptibility mapping in Injae, Korea, using a decision tree. *Eng. Geol.* **2010**, *116*, 274–283. [CrossRef]
7. Zhu, C.; He, M.C.; Jiang, B.; Qin, X.Z.; Yin, Q.; Zhou, Y. Numerical investigation on the fatigue failure characteristics of water-bearing sandstone under cyclic loading. *J. Mount. Sci.* **2021**, *18*, 3348–3365. [CrossRef]
8. Zhu, C.; He, M.; Karakus, M.; Cui, X.; Tao, Z. Investigating toppling failure mechanism of anti-dip layered slope due to excavation by physical modelling. *Rock Mech. Rock Eng.* **2020**, *53*, 5029–5050. [CrossRef]

9. Lee, S.; Ryu, J.H.; Won, J.S.; Park, H.J. Determination and application of the weights for landslide susceptibility mapping using an artificial neural network. *Eng. Geol.* **2004**, *71*, 289–302. [CrossRef]
10. Azarafza, M.; Ghazifard, A.; Akgün, H.; Asghari-Kaljahi, E. Landslide susceptibility assessment of South Pars Special Zone, southwest Iran. *Environ. Earth Sci.* **2018**, *77*, 805. [CrossRef]
11. Lee, S.A.R.O. Application of logistic regression model and its validation for landslide susceptibility mapping using GIS and remote sensing data. *Int. J. Remote Sens.* **2005**, *26*, 1477–1491. [CrossRef]
12. Liu, S.; Wang, L.; Zhang, W.; He, Y.; Pijush, S. A comprehensive review of machine learning-based methods in landslide susceptibility mapping. *Geol. J.* **2023**, *58*, 2283–2301. [CrossRef]
13. Ado, M.; Amitab, K.; Maji, A.K.; Jasińska, E.; Gono, R.; Leonowicz, Z.; Jasiński, M. Landslide susceptibility mapping using machine learning: A literature survey. *Remote Sens.* **2022**, *14*, 3029. [CrossRef]
14. Nanehkaran, Y.A.; Mao, Y.; Azarafza, M.; Kockar, M.K.; Zhu, H.H. Fuzzy-based multiple decision method for landslide susceptibility and hazard assessment: A case study of Tabriz, Iran. *Geomech. Eng.* **2021**, *24*, 407–418.
15. Nohani, E.; Moharrami, M.; Sharafi, S.; Khosravi, K.; Pradhan, B.; Pham, B.T.; Melesse, A. Landslide susceptibility mapping using different GIS-based bivariate models. *Water* **2019**, *11*, 1402. [CrossRef]
16. Wang, Y.; Fang, Z.; Wang, M.; Peng, L.; Hong, H. Comparative study of landslide susceptibility mapping with different recurrent neural networks. *Comput. Geosci.* **2020**, *138*, 104445. [CrossRef]
17. Youssef, A.M.; Pourghasemi, H.R. Landslide susceptibility mapping using machine learning algorithms and comparison of their performance at Abha Basin, Asir Region, Saudi Arabia. *Geosci. Front.* **2021**, *12*, 639–655. [CrossRef]
18. Nikoobakht, S.; Azarafza, M.; Akgün, H.; Derakhshani, R. Landslide susceptibility assessment by using convolutional neural network. *Appl. Sci.* **2022**, *12*, 5992. [CrossRef]
19. Achour, Y.; Pourghasemi, H.R. How do machine learning techniques help in increasing accuracy of landslide susceptibility maps? *Geosci. Front.* **2020**, *11*, 871–883. [CrossRef]
20. Cemiloglu, A.; Zhu, L.; Mohammednour, A.B.; Azarafza, M.; Nanehkaran, Y.A. Landslide Susceptibility Assessment for Maragheh County, Iran, Using the Logistic Regression Algorithm. *Land* **2023**, *12*, 1397. [CrossRef]
21. Pourghasemi, H.R.; Pradhan, B.; Gokceoglu, C. Application of fuzzy logic and analytical hierarchy process (AHP) to landslide susceptibility mapping at Haraz watershed, Iran. *Nat. Hazards* **2012**, *63*, 965–996. [CrossRef]
22. Nanehkaran, Y.A.; Licai, Z.; Chen, J.; Azarafza, M.; Yimin, M. Application of artificial neural networks and geographic information system to provide hazard susceptibility maps for rockfall failures. *Environ. Earth Sci.* **2022**, *81*, 475. [CrossRef]
23. Di Napoli, M.; Carotenuto, F.; Cevasco, A.; Confuorto, P.; Di Martire, D.; Firpo, M.; Calcaterra, D. Machine learning ensemble modelling as a tool to improve landslide susceptibility mapping reliability. *Landslides* **2020**, *17*, 1897–1914. [CrossRef]
24. Fang, Z.; Wang, Y.; Peng, L.; Hong, H. A comparative study of heterogeneous ensemble-learning techniques for landslide susceptibility mapping. *Int. J. Geograph. Inform. Sci.* **2021**, *35*, 321–347. [CrossRef]
25. Mersha, T.; Meten, M. GIS-based landslide susceptibility mapping and assessment using bivariate statistical methods in Simada area, northwestern Ethiopia. *Geoenviron. Disasters* **2020**, *7*, 20. [CrossRef]
26. Małka, A. Landslide susceptibility mapping of Gdynia using geographic information system-based statistical models. *Nat. Hazards* **2021**, *107*, 639–674. [CrossRef]
27. Bourenane, H.; Meziani, A.A.; Benamar, D.A. Application of GIS-based statistical modeling for landslide susceptibility mapping in the city of Azazga, Northern Algeria. *Bull. Eng. Geol. Environ.* **2021**, *80*, 7333–7359. [CrossRef]
28. Ali, S.A.; Parvin, F.; Vojteková, J.; Costache, R.; Linh, N.T.T.; Pham, Q.B.; Ghorbani, M.A. GIS-based landslide susceptibility modeling: A comparison between fuzzy multi-criteria and machine learning algorithms. *Geosci. Front.* **2021**, *12*, 857–876. [CrossRef]
29. Mehrabi, M. Landslide susceptibility zonation using statistical and machine learning approaches in Northern Lecco, Italy. *Nat. Hazards* **2022**, *111*, 901–937. [CrossRef]
30. Pham, Q.B.; Achour, Y.; Ali, S.A.; Parvin, F.; Vojtek, M.; Vojteková, J.; Anh, D.T. A comparison among fuzzy multi-criteria decision making, bivariate, multivariate and machine learning models in landslide susceptibility mapping. *Geomat. Nat. Hazards Risk* **2021**, *12*, 1741–1777. [CrossRef]
31. Sadighi, M.; Motamedvaziri, B.; Ahmadi, H.; Moeini, A. Assessing landslide susceptibility using machine learning models: A comparison between ANN, ANFIS, and ANFIS-ICA. *Environ. Earth Sci.* **2020**, *79*, 536. [CrossRef]
32. Abdollahizad, S.; Balafar, M.A.; Feizizadeh, B.; Babazadeh Sangar, A.; Samadzamini, K. Using hybrid artificial intelligence approach based on a neuro-fuzzy system and evolutionary algorithms for modeling landslide susceptibility in East Azerbaijan Province, Iran. *Earth Sci. Inform.* **2021**, *14*, 1861–1882. [CrossRef]
33. Javadzadeh, H.; Ataie-Ashtiani, B.; Hosseini, S.M.; Simmons, C.T. Interaction of lake-groundwater levels using cross-correlation analysis: A case study of Lake Urmia Basin, Iran. *Sci. Total Environ.* **2020**, *729*, 138822. [CrossRef] [PubMed]
34. Tudryn, A.; Motavalli-Anbaran, S.H.; Tucholka, P.; Gibert-Brunet, E.; Lankarani, M.; Ahmady-Birgani, H.; Dufaure, O. Late Quaternary environmental changes of Lake Urmia basin (NW Iran) inferred from sedimentological and magnetic records. *Quat. Int.* **2021**, *589*, 83–94. [CrossRef]
35. Iran Meteorological Organization, IMO. Meteorological Data for Urmia Lake, Tabriz, Urmia, Bonab, Maragheh Stations. 2023. Available online: https://www.irimo.ir (accessed on 3 April 2023).

36. Lak, R.; Mirzapour, B.; Aleali, M.; Djamali, M.; Shahbazi, R. Mineralogical reconstruction of Late Pleistocene-Holocene climate and environmental changes in southern wetlands of Lake Urmia. *Geopersia* **2021**, *11*, 205–218.
37. Geological survey of Iran, GSI. *Geological Map of Urmia Lake Basin*; Geological Survey and Mineral Exploration of Iran Press: Tehran, Iran, 2009.
38. Suarez-Alvarez, M.M.; Pham, D.T.; Prostov, M.Y.; Prostov, Y.I. Statistical approach to normalization of feature vectors and clustering of mixed datasets. *Proc. R. Soc. A Math. Phys. Eng. Sci.* **2012**, *468*, 2630–2651. [CrossRef]
39. Yaman, O.; Ertam, F.; Tuncer, T. Automated Parkinson's disease recognition based on statistical pooling method using acoustic features. *Med. Hypotheses* **2020**, *135*, 109483. [CrossRef]
40. Chollet, F. *Deep Learning with Python*; Manning Publications Company: New York, NY, USA, 2017.
41. Aggrawal, C. *Neural Networks and Deep Learning: A Textbook*; Springer: Berlin/Heidelberg, Germany, 2018.
42. Mittal, K.; Jain, A.; Vaisla, K.S.; Castillo, O.; Kacprzyk, J. A comprehensive review on type 2 fuzzy logic applications: Past, present and future. *Engineering Appl. Artif. Intell.* **2020**, *95*, 103916. [CrossRef]
43. Pandey, V.; Komal, A.; Dincer, H. A review on TOPSIS method and its extensions for different applications with recent development. *Soft Comput.* **2023**, *27*, 18011–18039. [CrossRef]