A SYSTEMATIC REVIEW OF SOIL EROSION SUSCEPTIBILITY: TRENDS AND INSIGHTS FROM 2010 TO 2023

KHOLMURODOVA, M.[1*] – JULIEV, M.[1,2,3] – ABDIKAIROV, B.[4] – DJANPULATOVA, Z.[1] – TURDALIEVA, S.[1] – KHADJIEVA, Z.[1] – KHAMIDULLAEV, SH.[5] – SHAMSIEV, M.[6]

[1]*Institute of Fundamental and Applied Research, "TIIAME" National Research University, Kori Niyoziy 39A, Tashkent 100000, Uzbekistan*
(e-mails: zilolakhondjanpulatova@gmail.com; sojidabonuturdaliyeva58@gmail.com; zuhraxadjiyeva955@gmail.com)

[2]*Turin Polytechnic University in Tashkent, Little Ring Road Street 17, 100095 Tashkent, Uzbekistan*
(e-mail: mukhiddinjuliev@gmail.com)

[3]*Tashkent State Technical University, Universitet 2, Tashkent, 100095, Uzbekistan*

[4]*Institute of Agriculture and Agrotechnologies of Karakalpakstan, Abdametov street, Nukus 230109, Uzbekistan*
(e-mail: abdikairovbekmurat12@gmail.com)

[5]*"TIIAME" National Research University, Kori Niyoziy 39A, Tashkent 100000, Uzbekistan*
(e-mail: shohjahon1208@tiiame.uz)

[6]*Almalyk Branch of Tashkent State Technical University, M. Ulug'bek 45, 110100 Almalyk, Tashkent, Uzbekistan*
(e-mail: shamsiyevmurodjon007@gmail.com)

**Corresponding author*
e-mail: kholmurodovamadinabonu1@gmail.com

(Received 12th Jun 2025; accepted 31st Jul 2025)

Abstract. Soil erosion is a significant threat to soil, a vital natural resource essential for human life. Mapping soil erosion susceptibility is an effective approach to identify vulnerable areas and support soil conservation efforts. This study reviews 339 articles published in English between 2010 and 2023 that focus on soil erosion susceptibility worldwide. The review aims to analyze previous research trends and to determine the most effective models and conditioning factors for future soil erosion susceptibility mapping. The methodology involved systematically collecting and examining published studies, with a focus on the models applied and conditioning factors used for erosion assessment. The results reveal a growing number of publications over the last decade, with India contributing the highest proportion (24%). Among the models, Random Forest emerged as the most widely used method (28.8% of articles), while slope gradient was the predominant conditioning factor (89.2%). The review also highlights the integration of modern technologies, such as Geographic Information Systems (GIS) and Remote Sensing (RS), which enhance the accuracy of erosion susceptibility maps. Overall, the findings suggest that combining advanced machine learning models with key environmental factors significantly improves soil erosion prediction, thereby aiding informed decision-making in land management and soil conservation.
Keywords: *erosion susceptibility, analysis, assessment, conditioning factors, mapping, modeling*

Introduction

Soil is an environment consisting of minerals, organic matter, countless living organisms, liquids, and gases. It is one of the main sources of life on Earth, as it participates in many vital processes through its components (Al-Kaisi et al., 2017). Healthy soil is essential for many processes on Earth, as it plays a key role in ensuring food security, regional self-sufficiency, and development (Arabameri et al., 2020). Soil degradation as a result of erosion is one of the environmental challenges facing almost all countries in the world today, as this problem leads to limitation of human society development (Gafurova and Juliev, 2021; Qiao et al., 2023; Juliev et al., 2024). Unfortunately, large amounts of land globally are being damaged in different ways (Yang et al., 2023). According to Wen (2023) one third of the world's agricultural land has been eroded by varying degrees over the past century. Estimated future soil loss rates have also been provided by some international organizations including Food and Agriculture Organization (FAO) of the United Nations where soil loss predictions in the near future indicates 20-30 billion tons of soil annually (Dissanayake et al., 2019; Karaoğlu, 2023). Consequently, reducing the risk of erosion in agricultural regions is seen as an international priority (Wuepper et al., 2019). Currently, world governments and environmental protection agencies are working together on the problem of soil erosion. One example is the Sustainable Development Goals (SDGs), a set of 17 goals proposed by the United Nations in 2015 to promote a more sustainable future for all. SDG 15 sets out a plan to address issues such as protecting, restoring and sustainably using terrestrial ecosystems, combating desertification, and halting biodiversity loss where neutrality of land degradation is a particular focus of SDG 15.3 (Nasir Ahmad et al., 2020; Panagos et al., 2020; Wen et al., 2023; Juliev et al., 2024).

Soil erosion is the longstanding phenomenon of the degradation of the Earth's upper layer of rock, caused by both natural and anthropogenic forces (Juliev et al., 2022; Veličković et al., 2022). Natural erosion processes include water erosion, glacial erosion, snow erosion, and wind erosion while anthropogenic erosion usually results from deforestation, inadequate agricultural practices, and overgrazing (Jakubínský et al., 2021; Nicu, 2018). In the following years, the emergence of anthropogenic systems as a result of urbanization processes and improper use of natural resources, various structural and functional processes accelerated the process of soil erosion in the units (Abdikairov et al., 2024; Polovina et al., 2021). As mentioned by Arabameri (2018) comparing erosion processes at different country levels, it is obviously seen that human-caused factors are one of the main reasons for erosion. In many African areas, numerous erosion processes are occurring as a result of deforestation, overgrazing and improperly organized agriculture as well as in Asian countries, like as China, Indonesia, and the Philippines, main reasons are deforestation, intensive agriculture, and rapid urbanization (Borrelli et al., 2017). According to Arabameri (2018) intensive farming practices were demonstrated as the main cause of erosion in the United States and Canada. That is why, nowadays world scientific communities are improving methods and models for preventing or evaluating erosion processes in their regions (Evelpidou et al., 2022; Igwe et al., 2020).

A number of approaches and techniques are currently available to evaluate, control and prevent soil erosion (Wen et al., 2023). As stated by Othmani (2023) the first stage to identify optimal erosion control strategies was soil erosion susceptibility prediction and validation the principal erosion sources. An erosion susceptibility map may predict the location of areas of soil which are highly susceptible to erosion (Akgün and Türk, 2011). There are topographical, hydrological, soil characteristics, geological and environmental factors which should be considered to determine the susceptibility of soil to erosion (Bouguerra et al., 2023). Sholagberu (2019) stated that selection of appropriate conditioning factors seems to be difficult as researchers may employ multiply factors. Usually, conditioning factors are selected based on the type of erosion mapping in study area. As stated by Arabameri (2019) factors applied for cropland erosion susceptibility

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2305_999110013

mapping differed from those utilized for watersheds. There are factors usually applied to create erosion susceptibility maps for watersheds including circulation coefficient (Rc), shape coefficient (Rf), elongation coefficient (Re), compactness coefficient (Cc), drainage density (Dd), flow frequency (Fs), texture ratio (T), relief ratio for water bodies (Rh), relative relief (Rr), strength number (RN), bifurcation ratio (Rb), overland flow length (Lo) and hypsometric integral (HI) (Rather et al., 2017; Arabameri et al., 2018; Meshram et al., 2022). Elevation, slope, aspect, precipitation, distance to river, distance to road, distance to stream, soil characteristics, land use/land cover, elevation, vegetation normal index (factors like NDVI), geology and lithology are considered as conditioning factors to develop erosion susceptibility map for cropland or hills (Arabameri et al., 2019; Javidan et al., 2019; Pourghasemi et al., 2020; Ahmadpour et al., 2021). After identifying the factors affecting erosion, the level of influence of each factor was analyzed. Finally, a soil erosion susceptibility map and erosion control measures will be developed. In order to achieve this goal, researchers apply innovative technologies such as GIS, RS, and developed models utilizing similar technologies (Avand et al., 2019; Khosravi et al., 2023).

The models used to develop erosion susceptibility maps can be statistical, heuristic, physical, mathematical or metaheuristic (Mohammady, 2022; Wang et al., 2023, 2022). Physical models may not perform well due to lack of data and poor data quality (Golkarian et al., 2023). According to Reichenbach (2018) since 1980s, over the next three decades, research articles prepared for modeling landslide susceptibility focused on statistical data and applying statistical methods to different geographical regions. Currently, statistical models are effectively used and improved by many researchers to create soil erosion susceptibility maps (Bag et al., 2022). Following models such as Random Forest (RF) (Azedou et al., 2021; Wei et al., 2022), Maximum Entropy Model (MaxEnt) (Cama et al., 2020), Weight of Evidence (WoE) (Gayen and Saha, 2017; Arabameri et al., 2018), Logistic Regression (LR) (Debanshi and Pal, 2020), Boosted Regression Trees (BRT) (Arabameri et al., 2019) and Support Vector Machine (SVM) (Amiri et al., 2019) provided highest results in practice. These models allow to assess the contribution of each susceptibility factor to divide the area into zones characterized by different susceptibility (Meliho et al., 2018). Statistical models generally achieve high predictive performance when applied in a GIS environmental research (Lana et al., 2022). As in recent years, several statistical methods have been applied and further improved in the GIS environmental researches in order to achieve better results with these types of models (Al-Abadi and Al-Ali, 2018). Modern techniques and technologies such as Geographic Information Systems (GIS), Remote Sensing are frequently employed in soil erosion evaluation, modelling, and the generation of erosion susceptibility maps (Borrelli et al., 2021). The combination of RS and GIS can significantly support to effectively solve problems related to different natural hazards, including erosion processes (Arabameri et al., 2021; Khasanov et al., 2021).

To differentiate the current review paper from previously published review articles on soil erosion, many already published review studies on the topic were evaluated. To facilitate comprehension, the findings are shown in *Table 1*.

The present research aimed at investigating and evaluating global soil erosion susceptibility studies from Scopus database for 2010-2023 period which included 339 final published papers in English to figure out key contributions for future study by analyzing publication trend and type, important authors and institutions, major subject areas and keywords, geographical locations, active publishers, most cited papers and co-authorship network, model types and conditioning factors included in researches of soil erosion susceptibility mapping.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
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***Table 1.** Comparison of the present work with prior studies*

Study	Study scope	Data source	Period	No. of articles	Focus/methods	Key findings
Soil erosion modelling (Borrelli et al., 2021)	Global review of soil erosion modeling	Scopus	1994–2017	8471	RUSLE, USLE, WEPP, SWAT	Widely used models identified
Soil erosion control in Asia (Nasir Ahmad et al., 2020)	Asia-focused control practices	Scopus, WoS	2014–2019	Not stated	Agronomic, agrostological, mechanical (11 subtypes)	Three main types identified
Global erosion control techniques (Wen et al., 2023b)	Worldwide control techniques	WoS, Google Scholar	2000–2021	779	Engineering, planting, biological (183 subtypes)	Engineering most prevalent
Soil erosion in Central Asia (Juliev et al., 2024)	Central Asia focus	Scopus	1993–2022	126	General review	60% of agricultural land severely affected
Soil salinity modeling (Abdikairov et al., 2024)	Global salinity modeling	Scopus	1975–2024	177	Regression models	Multiple linear regression and EC most used
Current study	Global erosion susceptibility assessment	Scopus	2010–2023	339	RF, SVM, LR models; key factors: slope, LULC, TWI, aspect	RF most used; slope most frequent factor

Methodology

Scopus online database was selected for the search of materials as it provides extensive coverage and has a global recognition. A total of 339 published papers from this database were obtained applying the following keywords “erosion susceptibility” and “soil erosion susceptibility” on October 3, 2023. There were language and year filters by “English” and “2010-2023”, respectively. Accepted researches containing abovementioned keywords in the title, abstract, and keywords were further analyzed for annual publication trend, important subject areas, active journals, frequent publication type, best authors, top institutions, co-authorship and keyword network, major countries, most cited papers and models developed mapping soil erosion susceptibility with necessary factors. Additionally, 177 research articles from total published papers were selected for further analysis as they devoted to soil erosion susceptibility mapping issues which include model and conditioning factors for the next analysis. Vos viewer software (v 1.6.19, 2023) developed by van Eck and Waltman at Leiden University in the Netherlands applied for analyzing the conceptual framework of titles, abstracts and keywords in publications, correlated them with bibliographic number data, and produced bubble charts to visualize the findings. Additionally, Mapchart online platform was employed to generate countries scientific production activity as well as Microsoft Excel was also utilized to analyze and examine the content presented at this level owing of its flexibility. We performed the research using different formats, such as CSV and RIS files. *Figure 1* visually demonstrates the steps of our research approach and methodologies used in this study.

Results

Scientific production trend

Analyzing the time-series distribution of published research is crucial for understanding the present state and trend of a topic across time. For the period of 2010-2023, a total of 339 articles were published on the topic of susceptibility of soil erosion which illustrated in *Figure 2*. It is possibly to divide the result into 2 sections as initial stage (2010-2019) and developmental period (2020-2023) which contributed 42.5% and 57.5% share, respectively. The highest number of articles belong to 2020 including 17.1% papers. As one of the appropriate reasons for increasing in the number of articles in recent years is a possibility of obtaining information applying new technologies such as Remote Sensing and Geographic Information Systems. In addition, much attention paid to soil erosion problems by international organizations may have also contributed to the development of research topic.

Research period	2010-2023 (339 papers)
Language	English
Subject area	Earth, Environmental and Agricultural sciences
Publication stage	Final
Keyword	"Erosion susceptibility" and "Soil erosion susceptibility"
Statistical analysis	Microsoft Excel 2021 Years, document types, journals, authors, institutions, countries, subject areas, most cited papers, models and factors
	VOS viewer Co-authors, keywords

Figure 1. *Methodological structure for the research*

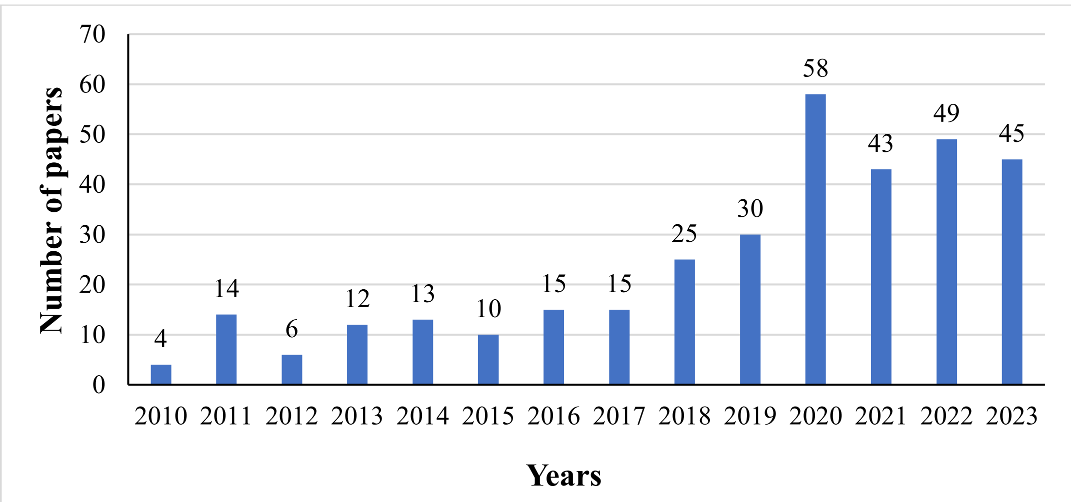

Figure 2. *Annual scientific production*

Most recognized fields of research

There are many subject areas in the Scopus database where each contains scientific papers based on its title and area of coverage. With 190 published articles for the 13 years starting from 2010, the Earth and Planetary Science area ranks first among the remaining

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subject areas and followed by the Environmental Science with 188 papers. Agricultural and Biological Sciences occupied the third position with 69 research articles and Social Sciences are included in the top by 96 published papers. It is obviously seen that research issue on soil erosion susceptibility may belong to some subject areas due to its versatility and resemblance which proved by the results of research. *Figure 3* depicts the most popular subject areas for analyzed research topic.

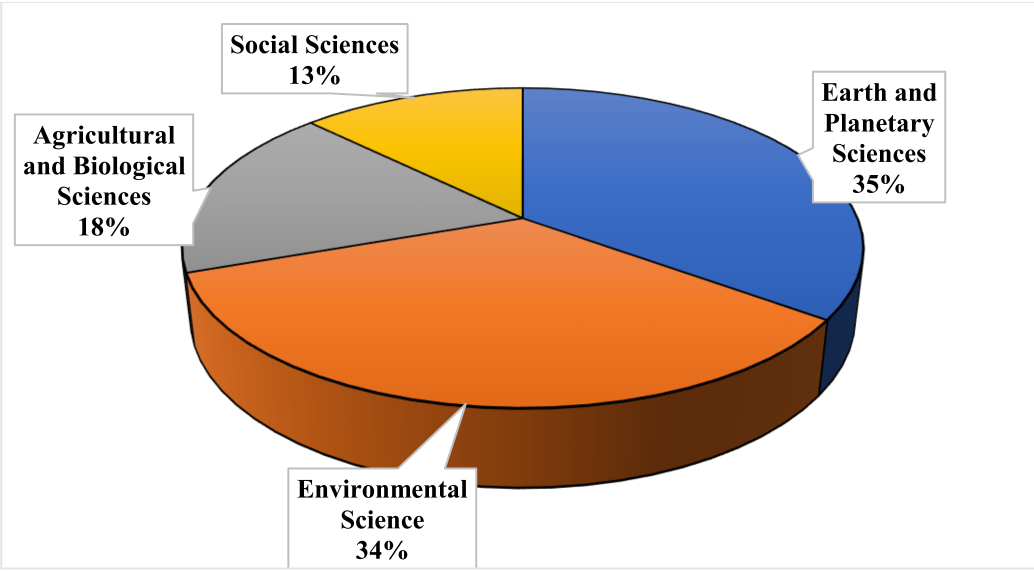

Figure 3. *Top subject areas on soil erosion susceptibility*

Top journals on soil erosion susceptibility

Journals usually receive scores based on the quantity of printed papers. When publishing an article, it is critical for the authors to select an appropriate journal as publication in a prominent international journal allows to expose their research to colleagues in other countries. A total of 339 articles on the subject of soil erosion susceptibility were distributed among 132 journals globally. *Figure 4* demonstrates top 16 journals which produced the most scientific papers on soil erosion susceptibility topic for the last 13 years. It is possible to demonstrate the result by separation into 2 parts: journals with published papers between 6-9 and 10-15. Contribution of selected journals equals 43.4%. Catena with Cite Score of 10.5 and Impact Factor 5.4 was mentioned as a leader with 4.4% contribution and followed by Geomorphology with 4.1% share. Environmental Earth Sciences and Science of The Total Environment are also in the top positions by publishing 13 articles on research topic, individually. These journals are considered with high Impact Factor and Cite Score indicators.

Publication type on soil erosion susceptibility

One of the important moments for researchers to publish their results is to select publication type which allows to demonstrate the research on global scale. For the research period, six different types of publication were demonstrated by Scopus database as shown in *Figure 5*. Among the analyzed publications, 89% belongs to research articles, which occupied the leadership and followed by Conference Papers with 6% contribution. Book Chapter and Letter are also included in shortlist as they covered 5% of publication together. Document types as Erratum and Review were not chosen by the researchers within the considered topic. Scientific research article dominated due to its higher readability and visibility for wide categories of readers.

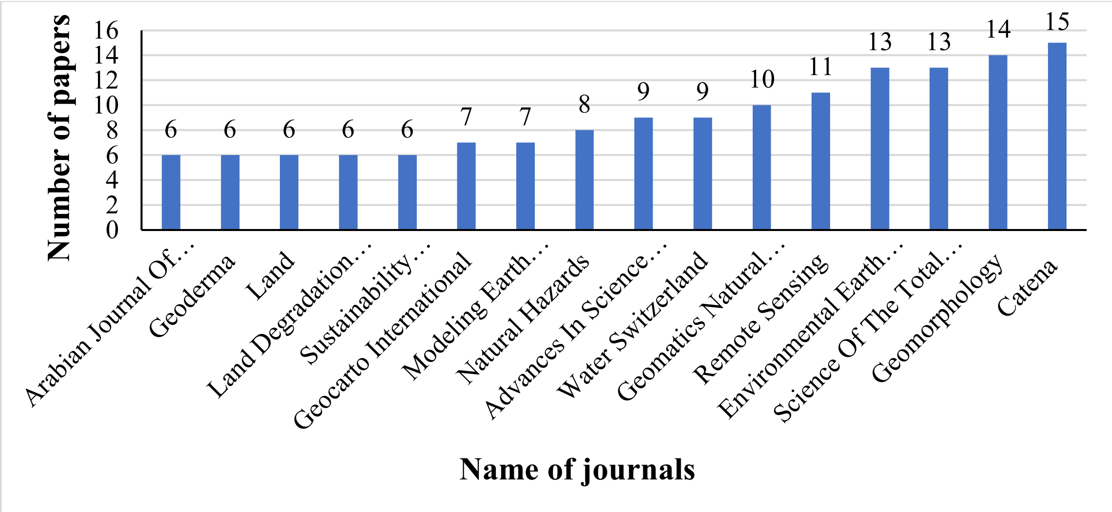

***Figure 4.** Most relevant journals*

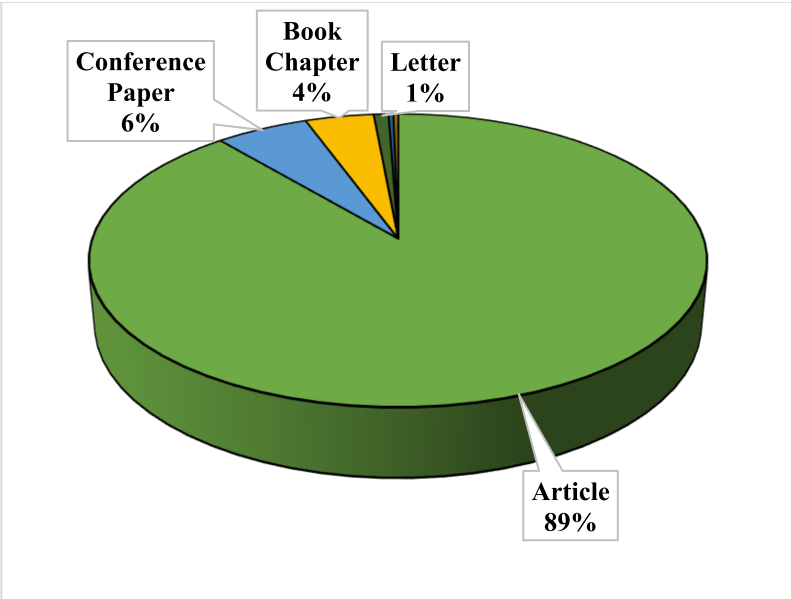

***Figure 5.** Most important document types on soil erosion susceptibility*

The most active authors on soil erosion susceptibility

The authors are researchers who make a significant contribution to the development of soil erosion susceptibility topic. A total of 339 articles found were distributed among 159 authors from 72 countries in the world. We selected 29 the most active authors (*Fig. 6*) with 5 published articles at least which shared 73.5% of total publications. We divided top authors into 4 sections with 5-7, 80-10, 12-14 and 22-24 papers, respectively. H.R Pourghasemi was mentioned as a leader contributing 6.8% to total publications and

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followed by A. Arabameri and B. Pradhan where each produced 6.4%. Other authors promoted 80.4% publications totally.

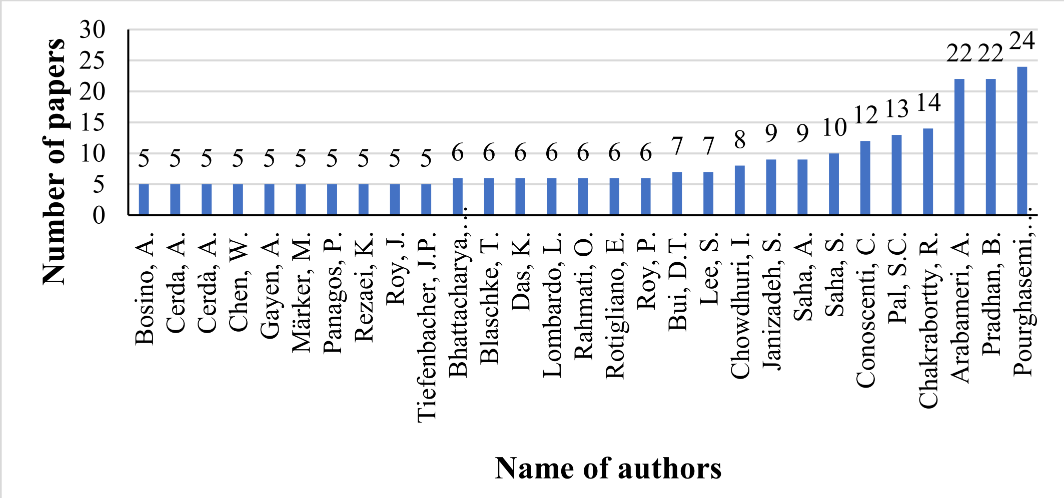

Figure 6. *Top authors on soil erosion susceptibility*

The most important institutions on soil erosion susceptibility

The evaluation ranks major academic institutions based on their contribution to research. Publication of articles in prestigious international journals is one of the criteria for evaluating the rating of institutions. The selection of institutes based on the number of published papers at least 8 and final result included 15 active institutions which illustrated in *Figure 7*. Tarbiat Modares took the top with 10.3% share and followed by Shiraz Universities with 7.3% contribution where both of them located in Iran. The University of Technology Sydney and Sejon Universities each contributed significantly to the development of the topic 6.4% and 6.1%, respectively. We noticed universities and academic institutions from Europe and Asia in the shortlist which means the importance of soil erosion susceptibility issue in the world.

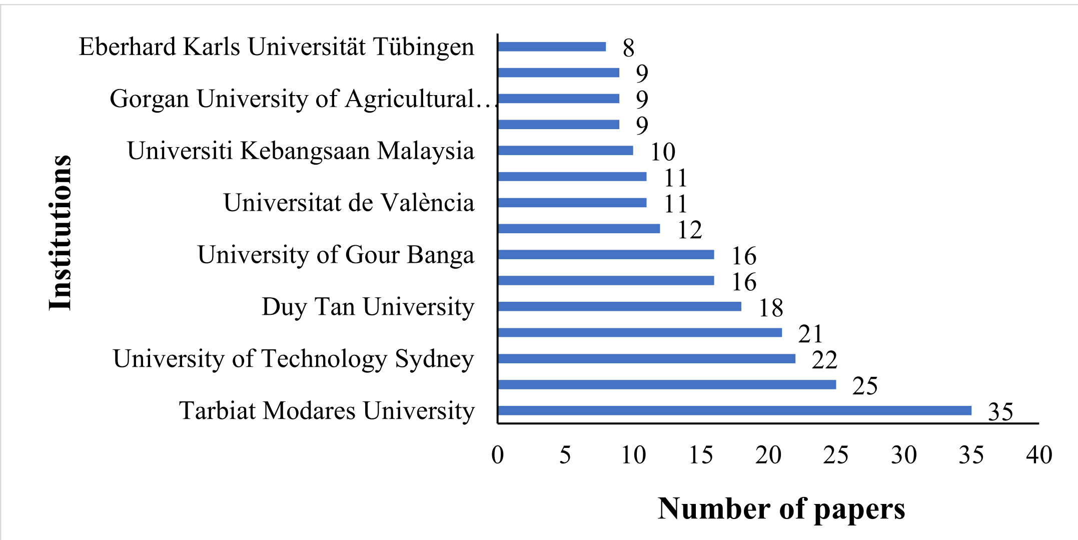

Figure 7. *List of top institutions on soil erosion susceptibility issue in the world*

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Authors collaboration and keyword network analysis

This analysis examines the progression of the thematic area through its categories, reflecting significant research topics in the field. VOSviewer software was used to generate maps of co-authorship and keyword co-occurrences based on the bibliographic data. Maps can be displayed in three different views: Network Visualization, Overlay Visualization, and Density Visualization. The colors, font sizes, and appearance of the maps are freely selected by the user. Maps of top co-authors illustrated in *Figure 8* and keyword co-occurrences demonstrated in *Figure 9* were created using bibliographic data. The co-authorship analysis resulted in a network of 1096 authors. Only authors having a minimum of five publications on research topic were included. There are 26 items distributed over four clusters: cluster 1 (9 items), cluster 2 (7 items), cluster 3 (6 items), cluster 4 (4 items). Arabameri and Pradhan have the most links, showing 82 and 64 total cooperations. A total of 2609 keywords were found for keyword analysis. After excluding low-related and infrequent common keywords (at least fifteen occurrences of a keyword are chosen by default to strengthen co-occurrence results), finally 58 items were identified. Based on the total link strength, each resulting keyword is sketched in a node, creating a network map of all keywords. The size of the node reflects the keyword's degree of importance.

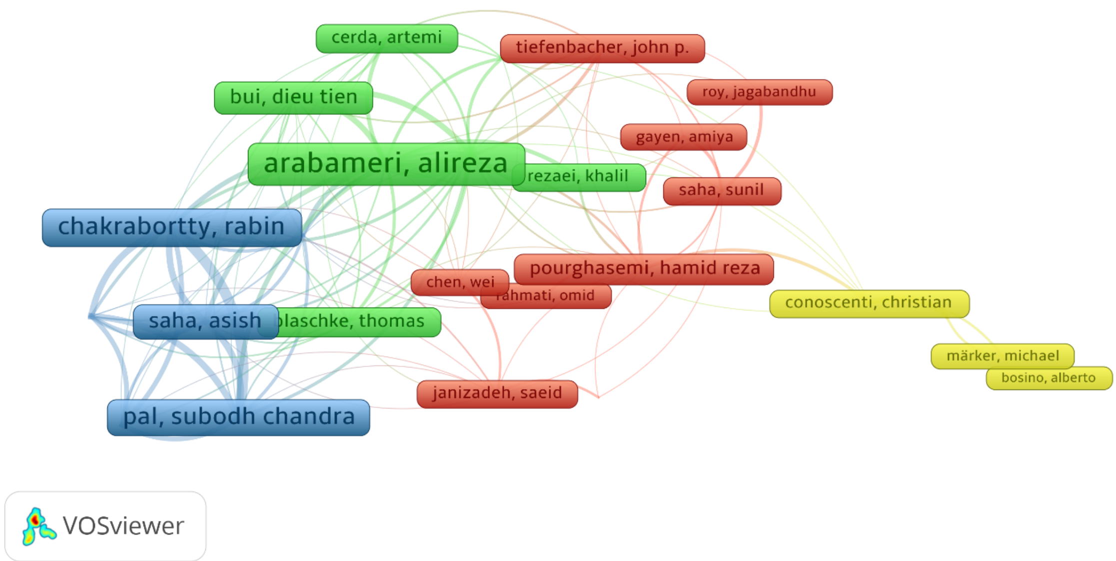

Figure 8. *Network map of top co-authorships based on the total link strength*

Top published countries on soil erosion susceptibility

Countries scientific production activity is an important element devoted to the development of research topic. A total of 72 countries has jointly published 339 different publications on research issue for the period of 2010-2023. The selection of the most active countries based on the number of published papers at least 13 which depicted in *Figure 10*. India occupied the leadership, accounting for almost 23.8% of the total articles and followed by Iran with 22.1% share. It is noticeable that soil erosion susceptibility research topic is actual in the world including states from Europe, South and North America and Australia. African states were not included as there is no countries even with 13 published articles.

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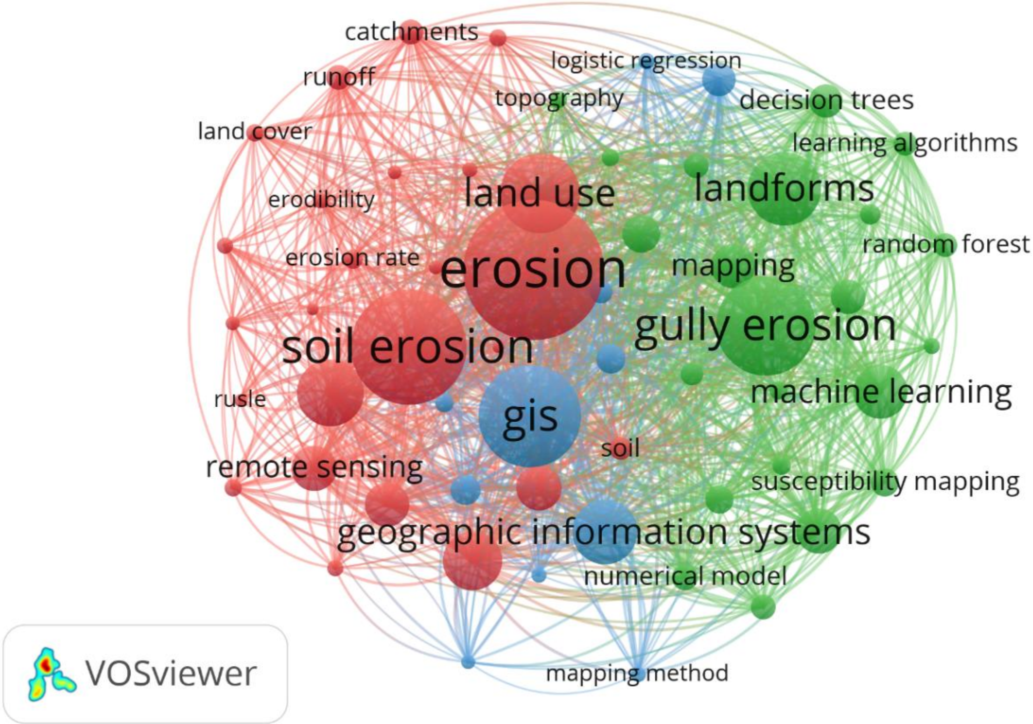

Figure 9. *Network map of top keywords based on the total link strength*

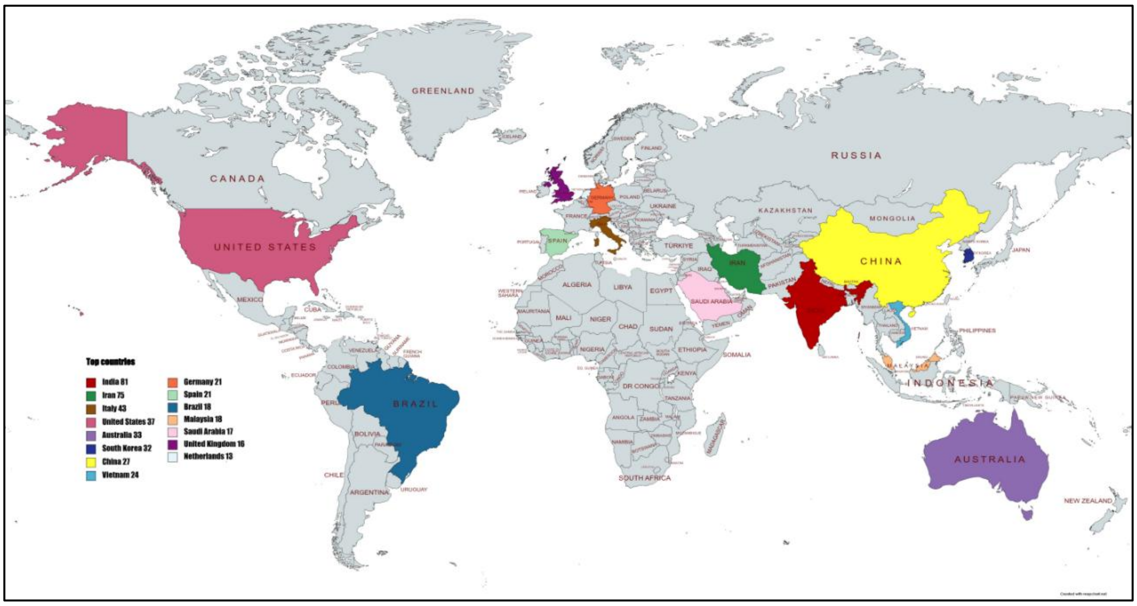

Figure 10. *List of top countries on soil erosion susceptibility issue in the world*

Top cited papers on soil erosion susceptibility

Scientific article citation index promotes it relevance and provides access to researchers. As mentioned by Aksnes (2003) in recent years, highly cited articles had been used as a criteria to evaluate research. As a result, papers with high citations are regarded the first choices for identifying the top articles (Aksnes and Sivertsen, 2004).

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Ten mostly cited papers on soil erosion susceptibility are shown in *Table 2*. A total of 9197 citations were accepted by 305 publications on soil erosion susceptibility. Almost 24% of the citations were given to the selected 10 articles where time framework was 2011-2019. Among the top ten, the most citations (517) were accepted by “Plants as river system engineers” published in the journal Earth Surface Processes and Landforms in 2014 and followed by “Geomorphology and GIS analysis for gully erosion susceptibility mapping in the Turbolo stream catchment (Northern Calabria, Italy)” published in Natural Hazards in 2011 with 258 citations. An article published in Catena scientific journal rounded off the top ten with 140 citations.

Table 2. *List of the top 10 highly cited papers*

Title	Citation	Year	Published journals
Plants as river system engineers	517	2014	Earth Surface Processes and Landforms
Geomorphology and GIS analysis for mapping gully erosion susceptibility in the Turbolo stream catchment (Northern Calabria, Italy)	258	2011	Natural Hazards
Gully erosion susceptibility assessment by means of GIS-based logistic regression: A case of Sicily (Italy)	245	2014	Geomorphology
Performance assessment of individual and ensemble data-mining techniques for gully erosion modeling	225	2017	Science of the Total Environment
Gully erosion susceptibility assessment and management of hazard-prone areas in India using different machine learning algorithms	180	2019	Science of the Total Environment
Evaluation of different machine learning models for predicting and mapping the susceptibility of gully erosion	176	2017	Geomorphology
Gully erosion susceptibility mapping: the role of GIS-based bivariate statistical models and their comparison	169	2016	Natural Hazards
Assessment of the importance of gully erosion effective factors using Boruta algorithm and its spatial modeling and mapping using three machine learning algorithms	146	2019	Geoderma
Modelling gully-erosion susceptibility in a semi-arid region, Iran: Investigation of applicability of certainty factor and maximum entropy models	145	2019	Science of the Total Environment
Spatial modelling of gully erosion in Mazandaran Province, northern Iran	140	2018	Catena

Conditioning factors used in soil erosion susceptibility assessment articles

There is no clearly developed standard for selection of conditioning factors in determination of soil erosion susceptibility (Lei et al., 2020). Therefore, the selection of these factors creates some difficulties for researchers (Wei et al., 2022). The appropriate conditioning factors selection depends on the process and kind of erosion, the characteristics of the examined area, the scale of the research, data availability, and the applied method (Arabameri et al., 2019; Saha et al., 2019; Huang et al., 2022; Boroughani et al., 2023). Conditioning factors such as slope, land use/land cover (LULC), aspect, altitude, TWI, and drainage density are easily derived from widely available sources such

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as Digital Elevation Models (DEMs) and satellite imagery (e.g., Landsat, ALOS), making them practical and accessible for most researchers (Arabameri et al., 2020, 2019; Esmali Ouri et al., 2020). Furthermore, researchers commonly identify and employ a number of topographical, hydrological, and geological aspects (Tehrany et al., 2017). Out of the 339 articles reviewed, 177 studies conducted actual soil erosion susceptibility mapping at the global scale using the conditioning factors listed in *Table 3* (this table summarizes the most frequently used conditioning factors in soil erosion susceptibility mapping, grouped by category. The number of articles indicates how often each factor has been employed in previous studies. The complete list of all identified conditioning factors is provided in *Table A1*. Across these 177 studies, a total of 90 distinct conditioning factors were employed to assess soil erosion susceptibility. Slope has been identified as the most commonly employed factor for soil erosion susceptibility analysis covering 89.2% of researches. Also, land use/land cover, topographic wetness index (TWI), aspect, altitude, drainage density, and distance from rivers are the most frequently used factors for soil erosion susceptibility mapping publications. In addition to the previously described factors, there is another set (plan curvature, stream power index, normalized difference vegetation index, lithology, rainfall, slope length) which has a medium application for more than 40% of the cases. Of course, the utilization of components in soil erosion susceptibility mapping is not just determined by their importance, but also by data availability, scale, and research area.

Table 3. *Frequently used factors by type*

Factor type	Top factors	# Articles
Topographic	Slope, TWI, Aspect, Altitude	158, 113, 110, 109
Land Cover/Use	LULC, NDVI, Geomorphology	134, 75, 33
Hydrological	Drainage Density, Stream Power Index, Flow Acc.	97, 83, 7
Soil-related	Soil Type, Soil Texture, Clay%, Sand%	45, 42, 14, 9
Geological	Lithology, Geology, Lineament Density	74, 28, 10
Climatic	Rainfall, Rainfall Erosivity, Temperature	69, 18, 4
Anthropogenic	Distance from roads, Distance from rivers	53, 91

Models used in soil erosion susceptibility mapping

According to Arabameri (2019), models used for mapping soil erosion susceptibility can be classified into three categories: knowledge-based, bivariate, and multivariate statistical models. Knowledge-based models are multi-criteria and semi-quantitative, where decisions are made based on expert knowledge and experience (Arabameri et al., 2018). Bivariate statistical models are among the simplest approaches to describe complex erosion processes, relying on the relationship between erosion susceptibility factors and erosion hotspots (Igwe et al., 2020; Meliho et al., 2018). Multivariate statistical models, which can handle discrete, continuous, and dichotomous variables simultaneously, offer more flexibility and have shown high predictive capability (Akgün and Türk, 2011). These models are currently widely adopted and yield strong results (Azedou et al., 2021).

This review examined 105 models used for soil erosion susceptibility mapping across 177 papers. The analysis revealed that the Random Forest (RF) model was the most commonly used, appearing in 51 studies (Ahmadpour et al., 2021; Avand et al., 2019;

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Bag et al., 2022; Boroughani et al., 2023; Chakrabortty and Pal, 2023; Ghorbanzadeh et al., 2020; Rahmati et al., 2017; Titti et al., 2022). RF is highly effective for both classification and regression tasks due to its ability to handle both continuous and discrete data, which makes it particularly suitable for developing soil erosion susceptibility maps (Ghorbanzadeh et al., 2020).

Other frequently applied models include Support Vector Machine (SVM), Logistic Regression (LR), Frequency Ratio (FR), and Boosted Regression Tree (BRT), appearing in 33, 23, 22, and 20 studies, respectively (as shown in *Table 4*). Among the 105 models identified, statistical approaches were the most frequently adopted, particularly after 2015, while heuristic methods were mainly used during the earlier stages of research in this field.

The preference for these models is not only due to their predictive power but also their adaptability to diverse environments. For example, RF, SVM, and LR have demonstrated reliable performance particularly in arid, semi-arid, and mountainous regions.

In the reviewed studies, model performance was commonly assessed using the Area Under the Receiver Operating Characteristic Curve (AUC-ROC), which is a widely accepted metric for evaluating classification accuracy in susceptibility mapping (Al-Abadi and Al-Ali, 2018; Arabameri et al., 2021).

To improve clarity, *Table 4* presents an overview of the most frequently employed models, categorized by type and number of appearances. A comprehensive list of all more than 60 models reviewed can be found in *Table A2*.

Table 4. *Summary of models by type and frequency*

Model type	Top models	Number of articles
Statistical	Random Forest (RF), SVM, Logistic Regression (LR), Frequency Ratio (FR), ANN, MaxEnt, BRT	51, 33, 23, 22, 17, 16, 20
Heuristic	AHP, TOPSIS, SAW, COPRAS, VIKOR	14, 7, 2, 3, 2
Physical	SWAT, RUSLE	2, 5

Discussion

Although the soil appears to be a robust and limitless resource at first glance, it is actually a delicate product of thousands of years of evolution (Chakrabortty and Pal, 2023). This valuable element faces several challenges and threats (Nahib et al., 2024) including soil erosion (Yang et al., 2023). Soil erosion poses a serious threat to the environment, society, and the economy. Therefore, assessing soil erosion has become an important research priority (Islam et al., 2022). According to Senanayake (2024) models play a crucial role in monitoring soil erosion, as well as in planning and implementing effective soil erosion management strategies.

The purpose of this work was to evaluate and analyze soil erosion susceptibility studies as well as to select the best model, conditioning factors and inventory types for the development of soil erosion susceptibility maps. The researchers developed the first erosion inventory maps while preparing an erosion susceptibility maps. Inventory mapping is usually created by Google Earth images and field surveys based on points or polygons. As mentioned by researchers (Arabameri et al., 2018; Avand et al., 2019; Ghorbanzadeh et al., 2020; Igwe et al., 2020; Bouguerra et al., 2023; Wang et al., 2023) for the study period, the most point-based inventory maps had been developed and mainly

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for the gully erosion type. According to (Rahmati et al., 2017; Al-Abadi and Al-Ali, 2018; Meshram et al., 2022) polygon-based inventory mapping was rarely performed and had typically been used to map erosion susceptibility in watersheds.

Several studies were reviewed to evaluate the accuracy achieved using the most frequently applied models and conditioning factors. In many cases, high accuracy was obtained with models such as Random Forest, Support Vector Machine, and Logistic Regression which were used by (Ahmadpour et al., 2021; Amiri et al., 2019; Avand et al., 2019; Bag et al., 2022; Band et al., 2020; Barakat et al., 2023; Esmali Ouri et al., 2020; Garosi et al., 2019; Lei et al., 2020; Pourghasemi et al., 2020) where the most commonly utilized factors were slope, land use land cover, aspect, altitude and drainage density. The climate of previously studied regions was mountainous (Aboutaib et al., 2023), arid (Amiri et al., 2019; Avand et al., 2019), semi-arid (Barakat et al., 2023; Esmali Ouri et al., 2020; Garosi et al., 2019), cold arid (Band et al., 2020), and sub-humid (Pourghasemi et al., 2020).

The correctness of information about affecting variables improves the overall accuracy of the task carried out. The factors applied for mapping of soil erosion susceptibility in the analyzed publications were received from different sources. Topographic, Land use, Soil, Geological maps, Landsat images, field surveys and Digital elevation models (DEM) are considered as the main source of information. Most of the factors such as: elevation, slope, aspect, SPI, TWI are obtained by DEM. Advanced Land Observing Satellite (ALOS) digital elevation model with resolutions of 30 m (72), 12.5 m (34), and 10 m (13) are most commonly applied. In the study of Arabameri (2021), the accuracy of the ALOS DEM was tested, and as a result, this DEM was the highest among all predictive models.

The findings of this review, such as the consistent effectiveness of Random Forest and SVM models in arid and mountainous regions (Amiri et al., 2019; Pourghasemi et al., 2020), have clear practical implications for improving erosion prediction accuracy and guiding soil conservation strategies in similar environments. The widespread use of machine learning models particularly Random Forest and SVM demonstrates their reliability and flexibility in analyzing complex terrain and climate settings. Moreover, the consistent use of conditioning factors such as slope, land use/land cover, TWI, and drainage density provides a standardized baseline for decision-makers (Band et al., 2020). These models and conditioning factors have been successfully applied in various restoration and mitigation projects for instance, the integration of RF and DEM-based factors significantly enhanced land-use planning in semi-arid basins (Barakat et al., 2023; Esmali Ouri et al., 2020), demonstrating their practical utility in erosion-prone arid and mountainous regions. Integrating such validated models and factor combinations into regional policies similar to the approach used by Wang (2023) in sub-humid zones can lead to more data-driven planning, improve mitigation effectiveness, and support long-term ecosystem resilience.

Soil erosion control strategies

The application of multiple methods together to protect and prevent soil erosion is more effective compared to using a single method. Silva (2024) provided an example of this by combining soil management, vegetative measures, and structural practices. In western Rwanda, Hishamunda (2024) implemented erosion and landslide control measures using ecosystem-based adaptation over a period of four years. According to the results, practices such as forest restoration and progressive terraces have significantly

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DOI: http://dx.doi.org/10.15666/aeer/2305_999110013

reduced annual soil loss. As noted by Hishamunda (2024), since the research was conducted in a hilly landscape, applying these practices in similar terrains would likely yield effective results.

In recent years, bioremediation methods, unlike the traditional approaches mentioned above, have also been considered effective and promising for preventing soil erosion (Wang et al., 2024). A bio-mediated soil improvement system refers to a network of chemical reactions within the soil controlled by biological activity, which changes soil properties through by-products (DeJong et al., 2010).

Conclusion

This review synthesized 177 studies on soil erosion susceptibility mapping published between 2010 and 2023, selected from 339 Scopus-indexed articles. The analysis revealed that Random Forest was the most frequently used model (among 105 identified), particularly effective in mountainous, arid, and semi-arid environments due to its strong predictive capabilities. SVM and Logistic Regression also showed consistent performance in similar terrains.

Among 90 conditioning factors reported, slope, land use/land cover (LULC), and topographic wetness index (TWI) were the most commonly used and contributed significantly to model accuracy. These findings highlight the importance of selecting models suited to specific terrain-climate contexts and integrating high-influence variables.

Based on the reviewed literature, it is recommended that future studies prioritize robust models such as RF and SVM, and consistently applied conditioning factors such as slope, LULC, and TWI, for improved accuracy and comparability across diverse regions.

Practically, these insights can support regional planning efforts, especially in erosion-prone areas, by improving risk zoning, prioritizing conservation interventions, and guiding data-driven land-use strategies. However, future reviews should include multilingual and non-Scopus literature to reduce publication bias and broaden the geographic scope.

Acknowledgments. The authors express their appreciation to the administration of the Institute of Fundamental and Applied Research “TIIAME” National Research University for their support. In addition, the authors are grateful to the anonymous reviewers of earlier drafts for constructive comments that helped to improve the manuscript.

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DOI: http://dx.doi.org/10.15666/aeer/2305_999110013

APPENDIX

Table A1. *Factors used in soil erosion susceptibility mapping articles*

Factors	No of articles	Factors	No of articles
Slope	158	Sand	9
Land use land cover (LULC)	134	Sediment Transport Index (STI)	9
Topographic wetness index (TWI)	113	Basin Length (Lb)	8
Aspect	110	Distance from lineament	8
Altitude	109	Ferrous minerals	8
Drainage density	97	Stream Length (Lu)	8
Distance from rivers	91	Texture ratio (T)	8
Plan curvature	85	Bulk density	7
Stream power index	83	Flow accumulation	7
Normalized Difference Vegetation Index (NDVI)	75	Hydrological units	7
Lithology	74	Infiltration number	7
Rainfall	69	Iron oxide	7
Slope length	68	Soil Ph	7
Profile curvature	57	Moisture	6
Distance from road	53	Stream density	6
Soil type	45	Stream length	6
Soil texture	42	Bedrock lithology	5
Geomorphology	33	Hypsometric integral	5
Curvature	29	Relative slope position	5
Geology	28	Soil depth	5
Form factor (Rf)	23	Topographic ruggedness index (TRI)	5
Topographic position index-slope (TPI-SLOPE)	23	Basin Perimeter (P)	4
Bifurcation ratio (Rb)	22	Compound topographic index	4
Convergence index	22	Distance from check dams	4
Stream frequency (Fs)	22	Erosivity	4
Elongation ratio	21	Height Above the Nearest Drainage	4
Circulatory ratio (Rc)	21	Runoff	4
Length of overland flow (Lo)	21	Stream order	4
Terrain Ruggedness Index (TRI	20	Temperature	4
Rainfall erosivity	18	Vertical distance to channel network (VDCN)	4
Compactness coefficient (Cc)	17	Bare soil	3
Relief ratio (Rh)	16	Drainage frequency	3
Shape Index	15	Normalized Difference Water Index (NDWI)	3
Clay percent	14	Soil brightness index	3
Ruggedness number (RN)	14	Surface temperature	3
Basin relief	13	Drainage intensity	2
Drainage texture	13	Lineament frequency	2
Catchment area	12	Road density	2
Constant channel maintenance	12	Surface roughness index	2
Soil erodibility	12	Surface water coverage	2
Stream number	12	Vector roughness index (VRM)	2
Silt percent	11	Fault density	1
Lineament density	10	Flow direction	1
Distance to fault	9	Stream link	1
Relative relief (Rr)	9	Stream-gradient index	1

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
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Table A2. *Models used in soil erosion susceptibility mapping*

ID models	Description	Total	Model type	ID models	Description	Total	Model type
RF	Random Forest	51	Statistical	MLP	Multilayer Perception layer	2	Statistical
SVM	Support vector machine	33	Statistical	SAW	Simple additive weighting	2	Heuristic
LR	Logistic regression	23	Statistical	SWAT	Soil and water assessment tool	2	Physical
FR	Frequency ratio	22	Statistical	VIKOR	VlseKriterijumska optimizacija I Kompromisno Resenje	2	Heuristic
BRT	Boosted regression tree	20	Statistical	WSRF	Weighted Subspace Random Forest	1	Statistical
ANN	Artificial neural network	17	Statistical	ANFIS	Adaptive network-based fuzzy inference system	1	Statistical
MaxEnt	Maximum entropy model	16	Statistical	BPNN	Back-propagation neural network	1	Statistical
AHP	Analytical hierarchy process	14	Heuristic	BART	Bayesian additive regression tree	1	Statistical
GLM	Generalized linear model	8	Statistical	Bayesian GL	Bayesian generalized linear mode	1	Statistical
WoE	Weight of evidence	8	Statistical	BFTree	Best-first decision tree	1	Statistical
XGBoost	Extreme gradient-boosting	7	Statistical	BLR	Binary logistic regression	1	Statistical
MARS	Multivariate adaptive regression spline	7	Statistical	BLM	Boosted Linear Model	1	Statistical
TOPSIS	Technique for an order of preference by similarity to ideal solutions	7	Heuristic	BT	Boosted Tree	1	Statistical
CNN	Convolution neural network	6	Statistical	CatBoost	Categorical boosting	1	
MCDM	Multi-Criteria Decision Model	6	Heuristic	CF	Compound Factor	1	Statistical
CART	Classification and regression trees	5	Statistical	GESMCM	Correlation matrix-based gully erosion susceptibility model	1	Statistical
IOE	Index of entropy	5	Statistical	CDTree	Credal decision trees	1	Statistical
KNN	K-Nearest Neighbors	5	Statistical	DB	Deep Boost	1	Statistical
NB	Naïve Baye	5	Statistical	DLNN	Deep learning neural network	1	Statistical
RUSLE model	Revised Universal Soil Loss Equation	5	Statistical	DS	Dempster-Shafer	1	Statistical
EBF	Evidential belief function	4	Statistical	EBO	Eco-biogeography based optimization	1	Statistical
FDA	Flexible discrimination analysis	4		EBO	Ecogeography based optimization	1	Statistical
InfVal	Information value	4	Statistical	ENET	Elastic net	1	Statistical
WIO	Weighted index overlay method	4	Heuristic	ELMNN	Elman neural network	1	Statistical
AdaBoost	Adaptive boosting	3	Statistical	EM	Ensemble model	1	Statistical
CF	Certainty factor	3	Statistical	FC-SAE	Fully connected spare auto encoder	1	Statistical
COPRAS	Complex proportional assessment	3	Heuristic	FDA	Functional discriminant analysis	1	Statistical

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