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A BIBLIOMETRIC ANALYSIS OF MACHINE LEARNING TECHNIQUES FOR IMPROVING DIGITAL ELEVATION MODEL ACCURACY: TRENDS, GAPS, AND FUTURE DIRECTIONS

[1,*] Osman Sami KIRTILOGLU , [2] Elif AKYEL , [3] Mehmet Güven KOCAK

[1] *Izmir Katip Celebi University, Geomatics Engineering Department, Division of Cartography, Izmir, TÜRKİYE*
[2] *Izmir Katip Celebi University, Geomatics Engineering Department, Division of Remote Sensing, Izmir, TÜRKİYE*
[3] *Izmir Katip Celebi University, Geomatics Engineering Department, Division of Geodesy, Izmir, TÜRKİYE*
[1] osmansami.kirtiloglu@ikcu.edu.tr, [2] elif.akyel@ikcu.edu.tr, [3] mehmetguven.kocak@ikcu.edu.tr

Highlights

- Conducted a bibliometric analysis on ML-based DEM accuracy from 2005 to 2025.
- Identified four key themes: models, ML methods, applications, and data sources.
- Research activity increased after release of enhanced DEMs like FABDEM, CoastalDEM.
- Ensemble ML algorithms dominate; interest in deep learning is steadily rising.
- Future work should target metric standards, data fusion, and open science norms.

***Corresponding Author:** Osman Sami KIRTILOGLU, osmansami.kirtiloglul@ikcu.edu.tr

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[2] *Izmir Katip Celebi University, Geomatics Engineering Department, Division of Remote Sensing, Izmir, TÜRKİYE*
[3] *Izmir Katip Celebi University, Geomatics Engineering Department, Division of Geodesy, Izmir, TÜRKİYE*
[1]osmansami.kirtiloglu@ikcu.edu.tr, [2]elif.akyel@ikcu.edu.tr, [3]mehmetguven.kocak@ikcu.edu.tr

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ABSTRACT: This study presents a bibliometric and thematic analysis of research focused on improving the accuracy of digital elevation models (DEMs) using machine learning (ML) techniques between 2005 and 2025. Drawing from Scopus and Web of Science databases, complemented by manual reference chaining, approximately 250 publications were analyzed. Results show a notable increase in scholarly activity after 2018, linked to the release of enhanced DEM products such as CoastalDEM and FABDEM. Keyword co-occurrence and thematic coding revealed four conceptual pillars: models, methods, applications, and data sources. Ensemble algorithms like Random Forest and LightGBM dominate the methodological landscape, while deep learning methods such as Convolutional Neural Network (CNNs) and Generative Adversarial Network (GANs) are emerging. Despite advancements, methodological homogeneity, reliance on Root Mean Square Error (RMSE), and underutilization of data fusion and semi-supervised learning strategies remain significant limitations. Silent themes and regional gaps emphasize the need for methodological diversification and broader global integration. Future research should prioritize algorithmic diversity, standardized multi-metric validation frameworks, open science practices, and regional model applications. This study offers a structural mapping of DEM–ML research and proposes strategic directions for advancing the field through interdisciplinary collaboration and innovation.

Keywords: *Accuracy Improvement, Bibliometric Analysis, Data Fusion, Digital Elevation Model, Machine Learning*

1. INTRODUCTION

Digital elevation models (DEMs) are fundamental geospatial datasets that digitally represent the three-dimensional structure of the Earth's surface. These models have become indispensable tools across numerous disciplines, including hydrological modeling, flood risk analysis, terrain classification, urban planning, disaster risk assessment, and environmental impact studies [1]. Despite their widespread utility, DEMs inherently suffer from vertical accuracy issues and systematic biases, primarily due to variations in data acquisition methods, sensor characteristics, and spatial resolution. In critical applications such as sea-level rise modeling and coastal flooding assessments, even minor elevation errors can drastically influence predictive accuracy and subsequent risk estimations [2].

The release of the Shuttle Radar Topography Mission (SRTM) dataset [3] in the early 2000s and the global availability of the Google Earth platform in 2005 [4] marked significant milestones, substantially enhancing accessibility to elevation data. Consequently, post-2005 literature has increasingly focused on improving DEM accuracy through error correction methodologies and integration of multi-source datasets.

In recent years, machine learning (ML) approaches have emerged prominently as effective methods for addressing systematic and random errors in DEMs, enhancing model resolution, and integrating

***Corresponding Author:** Osman Sami KIRTILOGLU, osmansami.kirtiloglul@ikcu.edu.tr

diverse data sources. Algorithms such as Random Forest, LightGBM, Support Vector Machines (SVM), Convolutional Neural Networks (CNN), and Generative Adversarial Networks (GAN) have demonstrated notable success in correcting elevation inaccuracies, generating bare-earth surfaces, and achieving super-resolution model enhancements [5], [6]. Enhanced DEMs, including CoastalDEM [7], FABDEM [5], Diluvium DEM [6], and DeltaDTM [8], have been developed using these ML techniques, significantly surpassing traditional model limitations.

Parallel to these technological advancements, there has been a considerable increase in academic production concerning DEM accuracy enhancement techniques. Preliminary systematic searches indicate that between 2005 and 2025, approximately 225 documents from Scopus and 149 from Web of Science explicitly focus on ML-driven DEM accuracy improvement. Despite this growth, the resulting literature exhibits considerable heterogeneity in terms of methods, applied algorithms, accuracy metrics, and specific application contexts. Therefore, a comprehensive bibliometric and thematic analysis is required to systematically explore trends, thematic clusters, and research trajectories in this burgeoning field.

In response, this study conducts a detailed bibliometric analysis of scholarly literature addressing machine learning applications aimed at improving the accuracy of digital elevation models. Bibliometric analyses have become a prevalent tool across geospatial sciences to map research trends, thematic clusters, and collaborative networks. For example, Polat et al. [9] performed a comprehensive bibliometric study on cadastre research from 1958 to 2018, uncovering key journals, countries, and emerging trends. Later, Polat et al. [10] conducted an analysis of Land Administration Domain Model (LADM) literature (2012–2020), revealing author, institutional, and country-level intellectual structures. In related domains, Yu et al. [11] reviewed global remote sensing methods for glacier mass balance using bibliometric and knowledge mapping techniques; another study [12] analysed the evolution of remote sensing for mineral exploration from 2000 to 2023. Additionally, bibliometric reviews of spatial data infrastructure in urban contexts, remote sensing in marine sustainability have demonstrated the method’s versatility across different geospatial fields [13]. Nevertheless, targeted bibliometric investigations specifically addressing machine learning-based accuracy enhancements in digital elevation models are still lacking—our study aims to address this clear gap.

This study contributes to this growing body of work by presenting a focused bibliometric mapping at the intersection of DEM accuracy enhancement and ML algorithms. Utilizing bibliometric tools such as VOSviewer [14], this analysis not only tracks the evolution of publication trends over the past two decades but also identifies conceptual structures through keyword co-occurrence networks, citation patterns, and thematic clustering. Furthermore, each publication is thematically coded based on the type of elevation model used, ML algorithm employed, accuracy metrics utilized, and the contextual application scenarios.

In addition to database-driven systematic searches, a manual reference chaining method was employed, starting from the seminal publication "DiluviumDEM: Enhanced accuracy in global coastal digital elevation models" [6]. Through this manual process, 92 highly relevant studies were reviewed, and the 10 most influential publications were identified based on thematic relevance and citation impact. This dual strategy ensures a more comprehensive and representative analysis of the field, capturing not only indexed publications but also critical works that might otherwise remain underrepresented.

By providing a comprehensive structural mapping of the literature at the intersection of digital elevation modeling and machine learning, this research aims to elucidate current research emphases, highlight methodological strengths and limitations, and propose strategic directions for future investigations.

2. MATERIAL AND METHODS

2.1. Literature Search Strategy

The literature search was systematically conducted through Scopus and Web of Science (WoS) databases in April 2025. Scopus and Web of Science (WoS) databases were selected for their broad coverage, high citation indexing quality, and advanced search functionalities that facilitate comprehensive bibliometric analyses. Scopus, managed by Elsevier, indexes over 27,000 peer-reviewed journals across all scientific disciplines, while Web of Science, maintained by Clarivate Analytics, includes approximately 21,000 high-impact journals within its Core Collection. Both databases offer standardized citation metrics, rigorous journal selection criteria, and detailed metadata fields (titles, abstracts, keywords, affiliations), which are essential for reliable bibliometric mapping. Their complementary indexing structures also help mitigate coverage biases that may arise from relying on a single database.

The search syntax was carefully designed to align with the research focus, combining key terms associated with elevation models, machine learning algorithms, and accuracy improvement techniques. Specifically, the search was structured as follows:

Scopus Advanced Search:

AUTHKEY ("surface model" OR "elevation model" OR "digital elevation model" OR "terrain model" OR "bare-earth model" OR "bare-earth" OR "DEM" OR "DTM")
AND TITLE-ABS ("machine learning" OR "deep learning" OR "random forest" OR "support vector machine" OR "SVM" OR "LightGBM" OR "CNN" OR "GAN" OR "convolutional neural network" OR "neural network")
AND ALL ("accuracy improvement" OR "elevation correction" OR "super-resolution" OR "enhancement")

Web of Science Advanced Search:

TS=(("surface model" OR "elevation model" OR "digital elevation model" OR "terrain model" OR "bare-earth model" OR "bare-earth" OR "DEM" OR "DTM")
AND ("machine learning" OR "deep learning" OR "random forest" OR "support vector machine" OR "SVM" OR "LightGBM" OR "CNN" OR "GAN" OR "convolutional neural network" OR "neural network")
AND ("accuracy improvement" OR "elevation correction" OR "super-resolution" OR "enhancement"))

The search was limited to peer-reviewed journal articles. Other types of publications such as book chapters, conference papers, and preprints were excluded. No language restriction was applied.

The initial search yielded 225 documents from Scopus and 149 from Web of Science. Duplicate records were identified and removed by cross-referencing Digital Object Identifiers (DOIs) and publication metadata, resulting in a non-redundant set of publications for further analysis.

A manual reference chaining approach was implemented to complement the database search and capture highly influential but potentially non-indexed works. The reference list of the pivotal publication "DiluviumDEM: Enhanced accuracy in global coastal digital elevation models" [6] served as the starting point. Subsequent references cited by or citing this work were manually reviewed, identifying 92 additional relevant studies. From this subset, the 10 most thematically significant and highly cited publications were selected for deeper analysis. Together, this dual search strategy ensures a more comprehensive coverage of the literature relevant to machine learning-based DEM accuracy improvement.

2.2. Bibliometric Analysis Methodology

Bibliometric analysis was conducted using the VOSviewer software (version 1.6.19) [14] to explore structural patterns within the selected literature set. Among the various available bibliometric analysis tools (e.g., CiteSpace, Bibliometrix, SciMAT, VantagePoint), VOSviewer (version 1.6.19) was selected due to its user-friendly interface, robust capabilities for constructing keyword co-occurrence networks, and effective visualization features for mapping large-scale bibliometric data. VOSviewer excels particularly in clustering algorithms based on co-occurrence strength and provides intuitive visual representations of thematic structures, which are crucial for identifying intellectual and conceptual patterns within the field. Furthermore, its ability to process large datasets efficiently made it well-suited for handling the extensive publication sets extracted from Scopus and Web of Science in this study. This approach involved the extraction and analysis of metadata fields, including titles, abstracts, keywords, authors, publication years, and citation counts.

The primary steps included:

- Exporting metadata from Scopus and Web of Science in RIS format.

- Merging datasets and eliminating duplicates.
- Preparing datasets for analysis by harmonizing keyword formats and standardizing terminology (e.g., "DEM" vs. "digital elevation model").
- Generating keyword co-occurrence networks with a minimum occurrence threshold of three.
- Applying clustering algorithms to identify major conceptual groupings within the literature.
- Conducting citation analysis to identify the most influential publications based on citation counts.
- Producing overlay visualizations to examine temporal trends in keyword usage.

Co-occurrence networks and citation analyses were separately generated for each database (Scopus and WoS) to account for differences in indexing practices and subject coverage. In addition to quantitative bibliometric outputs, thematic cluster interpretations were manually validated to ensure consistency with the underlying research focus areas.

2.3. Content Analysis and Thematic Coding

To complement the bibliometric analysis and provide a deeper understanding of the literature, a manual content analysis and thematic coding procedure was implemented. Each publication was reviewed based on its title, abstract, and where necessary, the full text, and was categorized according to four main thematic dimensions: (i) *Type of Digital Elevation Model (DEM):* ie. SRTM, ASTER, Copernicus DEM, CoastalDEM, FABDEM. *(ii) Applied Machine Learning Algorithm:* ie. Random Forest, LightGBM, Support Vector Machine (SVM), Convolutional Neural Networks (CNN), Generative Adversarial Networks (GAN). *(iii) Application Scenario:* ie. Coastal flood risk assessment, elevation error correction, super-resolution generation, bare-earth model extraction. *(iv) Accuracy Metrics Used:* ie. Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Bias, Coefficient of Determination (R^2), Nash-Sutcliffe Efficiency (NSE).

Publications were systematically coded in an Excel database, and frequencies were calculated for each thematic category. Where possible, cross-tabulations were also created to analyze the relationships between model types, algorithms, application scenarios, and accuracy metrics.

The coding also incorporated the manually selected 10 influential publications obtained through reference chaining, ensuring that critical and highly impactful studies were well-represented in the thematic analysis. This content-based thematic coding not only enriched the quantitative bibliometric results but also enabled the identification of silent themes, methodological gaps, and emerging trends that might not be immediately evident through standard bibliometric techniques alone.

3. DIGITAL ELEVATION MODELS AND ACCURACY IMPROVEMENT TECHNIQUES

3.1 Definitions and Differences between DEM, DSM, and DTM

Digital Elevation Models (DEMs) refer to raster-based representations of the Earth's surface elevation. These models are typically classified into two primary categories: Digital Surface Models (DSMs) and Digital Terrain Models (DTMs). While DSMs capture the elevations of both natural features and anthropogenic structures, including vegetation and buildings, DTMs, in contrast, depict only the bare-earth surface by excluding all above-ground objects. The distinction between DSMs and DTMs is crucial in environmental and risk modeling. For example, coastal flood risk assessments typically require DTMs, whereas urban morphology studies may rely on DSMs.

3.2 Sources of DEM Errors and Challenges

DEM products are susceptible to various sources of errors that affect their vertical accuracy and spatial reliability. The principal error types include:

- *Vertical Accuracy Errors:* Systematic or random differences between the model elevations and true ground elevations.

– *Systematic Biases:* Consistent overestimation or underestimation of elevations across regions.
– *Resolution Effects:* The inability of lower-resolution DEMs to capture detailed terrain features, particularly in highly variable landscapes.

For instance, radar-based DEMs (e.g., SRTM) often show systematic errors in densely forested areas, while optical stereo-derived DEMs are sensitive to cloud cover and illumination conditions.

3.3 Machine Learning-Based Approaches for Accuracy Improvement

Machine learning techniques have increasingly been employed to address the challenges associated with DEM errors. These approaches generally fall into three categories:

3.3.1 Elevation Error Correction

ML algorithms are trained to model and predict error surfaces based on auxiliary variables such as slope, land cover type, and elevation derivatives. Notable methods include Random Forest, LightGBM, and Support Vector Machines, which have been utilized to predict and correct systematic elevation errors.

Examples include the FABDEM model, which applied Random Forest algorithms to correct Copernicus DEM errors using LiDAR references [5], and the Diluvium DEM, which utilized LightGBM for global terrain error correction [6].

3.3.2 Super-resolution Techniques

Super-resolution approaches aim to enhance the spatial resolution of DEMs by predicting fine-scale details from coarser inputs. Techniques based on Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) have been successfully applied to upscale DEMs while preserving geomorphological features.

For instance, GAN-based models have been employed to upscale SRTM data from 30 m to resolutions approaching 10 m, enabling more detailed analysis in flood risk and urban planning applications.

3.3.3 Data Fusion and Integration

Combining multiple sources of elevation data—such as LiDAR, radar, and optical stereo imagery—through ML-driven fusion techniques enhances DEM completeness and accuracy. Data fusion methods model systematic discrepancies between datasets and produce harmonized outputs. Notably, the DeltaDTM model integrates ICESat-2 and GEDI measurements with Copernicus DEM data using gradient-boosted decision trees to create a highly accurate global coastal terrain model [8].

3.4 Commonly Used Digital Elevation Models in Literature

In recent years, a new generation of digital elevation models (DEMs) rapidly gained popularity in literature, developed to overcome the vertical accuracy limitations of classical models such as SRTM, ASTER, and Copernicus DEM. These enhanced DEMs are typically trained using high-precision reference datasets (e.g., ICESat-2, GEDI, LiDAR) and corrected through various machine learning algorithms. Different methods have been employed in the development of these improved models. For instance, CoastalDEM was trained using neural networks, FABDEM applied decision tree algorithms, while Diluvium DEM and DeltaDTM employed gradient-boosted decision trees (LightGBM) and morphological filtering, respectively, to correct systematic elevation errors. These models differ in their base DEM sources, auxiliary remote sensing data, spatial resolutions, and licensing terms. The comparative characteristics of these enhanced models are detailed in Table 1, based on the work by Pronk et al. [8] and related references, covering models developed between 2017 and 2024.

Table 1. Characteristics of recent enhanced digital elevation models and their fundamental properties (compiled from Pronk et al., 2024 [8] and related sources)

Model Name	Year	Base Data	ML Approach / Method	Auxiliary Data	Resolution	Author(s)
MERIT DEM	2017	SRTM	Regression techniques	ICESat-1, canopy density, canopy height	3″	Yamazaki et al. 2017 [10]
CoastalDEM	2020	NASADEM	Neural network	ICESat-2	1″	Kulp & Strauss, 2018 [7]
FABDEM	2022	Copernicus DEM	Decision trees	WorldPop, canopy height, WSF	1″	Hawker et al., 2022 [5]
Diluvium DEM	2023	Copernicus DEM	LightGBM (GBDT)	Landsat Cloud Cover, Dynamic World	1″	Dusseau et al., 2023 [6]
DeltaDTM	2024	Copernicus DEM	Morphological filtering + spatial interpolation	ICESat-2, GEDI, ESA WorldCover	1″	Pronk et al., 2024 [8]

These enhanced models represent a significant advancement in the development of digital elevation models in terms of both structural accuracy and application potential. They are particularly preferred in fields such as coastal flood risk assessment, micro-topography analysis, and disaster risk management. The performance of these models is evaluated against high-precision reference datasets, which are critical both for model training and accuracy validation.

Reference datasets are typically acquired either through ground-based surveys or from high-resolution satellite-based LiDAR systems. These datasets play a fundamental role in validating the vertical accuracy of DEMs, training error correction algorithms, and conducting comparative analyses.

Different models are trained and evaluated against different reference datasets. For instance, ICESat-2 profiles are widely used in both CoastalDEM and DeltaDTM models. GEDI data is particularly important for detecting errors related to canopy heights in forested regions, while airborne LiDAR data are predominantly used for regional calibrations. Additionally, some models utilize other DEMs as reference sources to produce derivative products (e.g., ALOS World 3D, TanDEM-X).

The comparative structure, coverage, and intended use of these reference datasets are summarized in Table 2.

4. RESULTS OF BIBLIOMETRIC ANALYSIS

4.1 Publication Trends Over Time (2005–2025)

The annual distribution of publications, illustrated in Figure 1, shows a significant increase, particularly after 2018, reflecting advancements in DEM modeling and machine learning techniques. Additionally, Figure 2 presents the temporal evolution of research topics based on Web of Science data, highlighting the emergence of new thematic focuses, such as coastal flood risk and data fusion, after 2018.

This trend can be attributed to the increasing accessibility of high-precision elevation data sources and the integration of advanced ML algorithms in geospatial analyses, leading to a rapid expansion of research output in the domain.

Table 2. Reference datasets used for digital elevation model accuracy assessments

Dataset/Product	Type	Resolution	Sensor/Platform	Coverage	Purpose	Reference
ICESat-2 ATL08	Point Reference	~10 m (profile)	Satellite-based LiDAR	Global (limited by latitude)	DEM accuracy evaluation	NASA, 2021 [11]
GEDI L2A	Point Reference	~25 m (profile)	Satellite-based LiDAR	Forested areas	Forest height and DEM comparison	NASA, 2020 [12]
Airborne LiDAR	Point Reference	~0.5–2 m	Aircraft-based LiDAR	Local (national, regional)	High-precision accuracy analysis/training	Various regional sources
ALOS World 3D	Surface Model (DSM)	30 m	PRISM (stereo optical)	Global	Alternative model comparison	Tadono et al., 2014 [13]
TanDEM-X	Surface Model (DSM)	12 m	X-band radar (interferometry)	Global (commercial)	High-resolution model comparison	Wessel et al., 2016 [14]
HGM SYM5-L0	Surface Model (DSM)	5 m	Aerial stereo photography	Turkey	National accuracy comparison	HGM, 2025 [15]

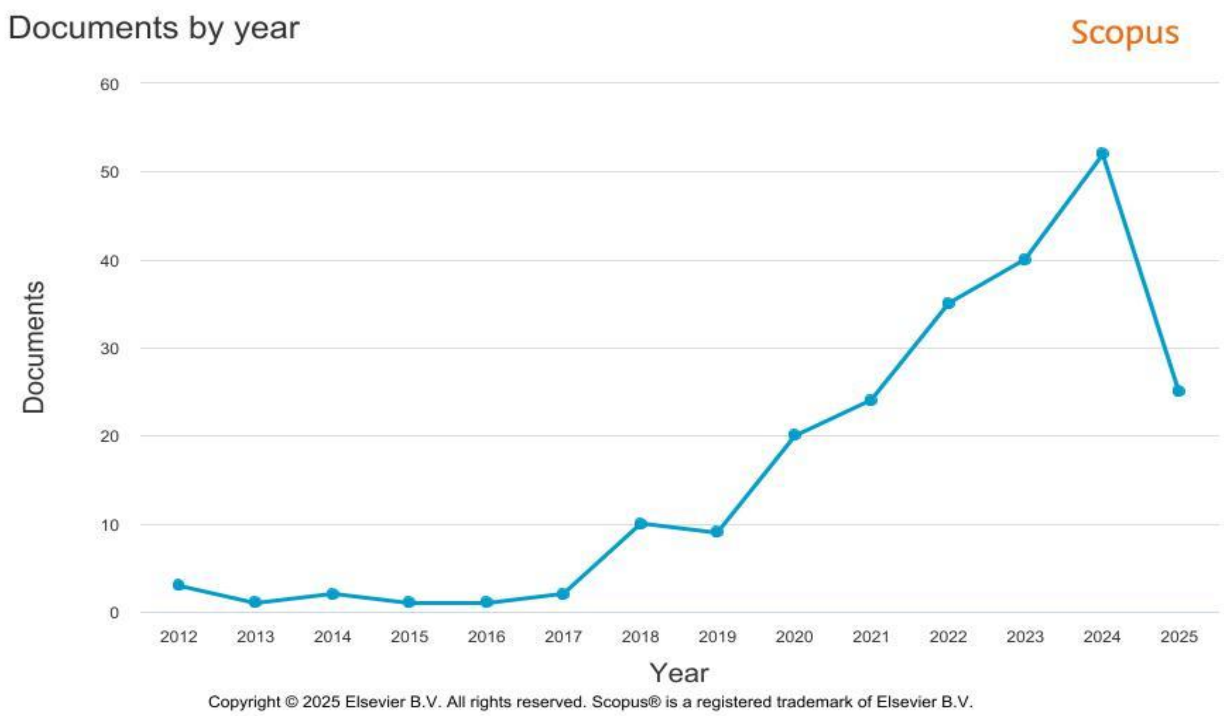

Figure 1. Annual distribution of publications on DEM accuracy enhancement using machine learning (Scopus database, 2005–2025).

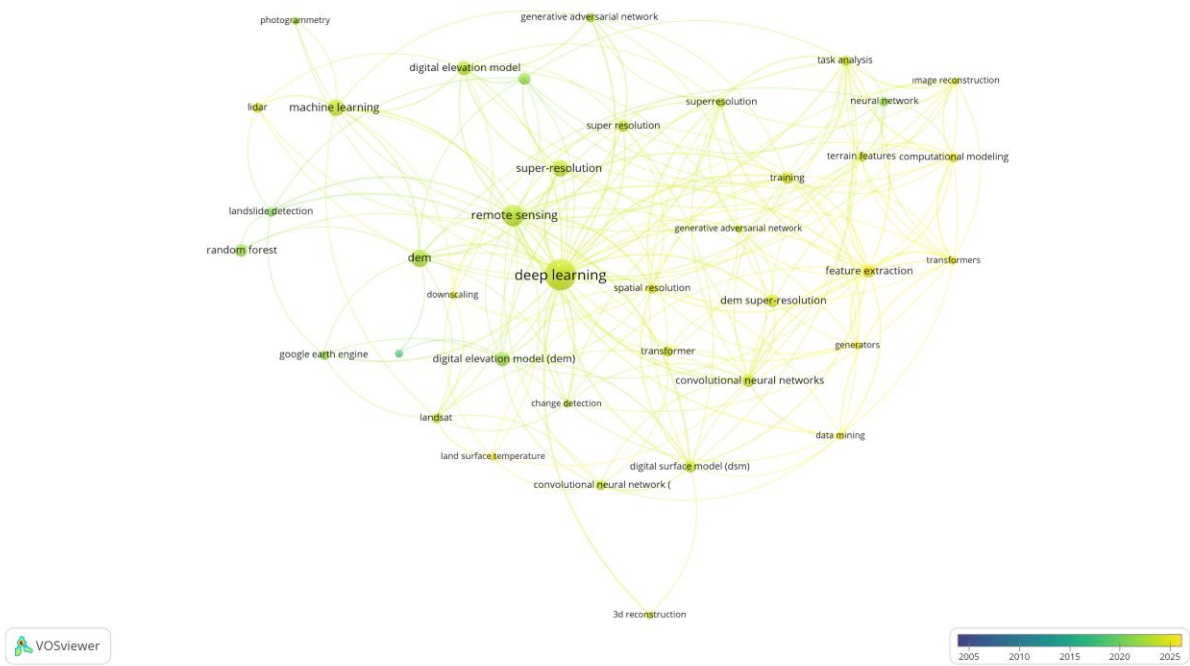

Figure 2. Temporal evolution of DEM accuracy enhancement research topics (Web of Science overlay visualization).

4.2 Keyword Co-occurrence Networks

Keyword co-occurrence analysis revealed major thematic concentrations in the literature, as shown in Figure 3 for Scopus data and in Figure 4 for Web of Science data. These networks illustrate four primary clusters corresponding to models, methods, applications, and data sources.

The detailed thematic structure identified includes:

- *Model-Oriented Cluster:* Terms such as "digital elevation model," "bare-earth DEM," "terrain model," and "CoastalDEM."
- *Method-Oriented Cluster:* Keywords including "machine learning," "random forest," "deep learning," and "super-resolution."
- *Application-Oriented Cluster:* Themes such as "flood risk," "coastal vulnerability," "erosion," and "urban expansion."
- *Data Source Cluster:* Terms like "LiDAR," "ICESat-2," "GEDI," and "Copernicus DEM."

The network maps visually differentiate these clusters, showing strong interconnections among methodological and application-oriented keywords, and highlighting the interdisciplinary nature of DEM enhancement research. Furthermore, keyword density mapping (Figure 5) provides deeper insights into research hotspots, indicating areas with intense scientific activity. Notably, terms such as "super-resolution" and "semi-supervised learning" are gaining prominence, reflecting the emerging methodological shifts in DEM enhancement research.

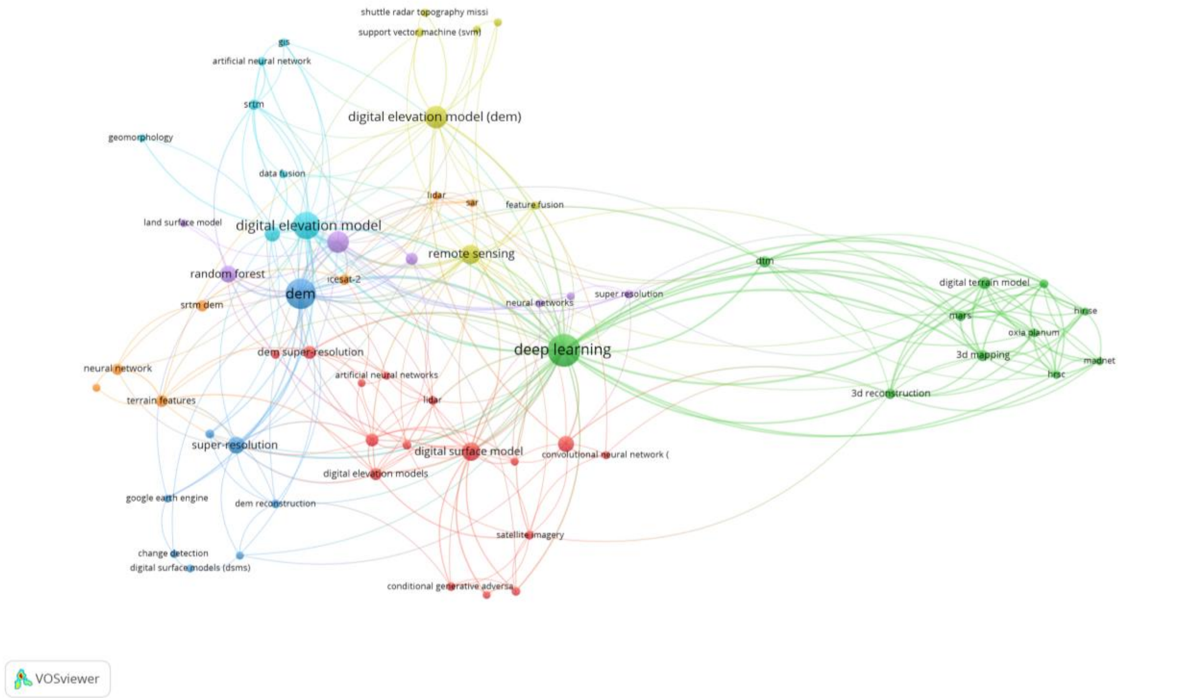

Figure 3. Keyword co-occurrence network based on Scopus database, clustered into thematic groups.

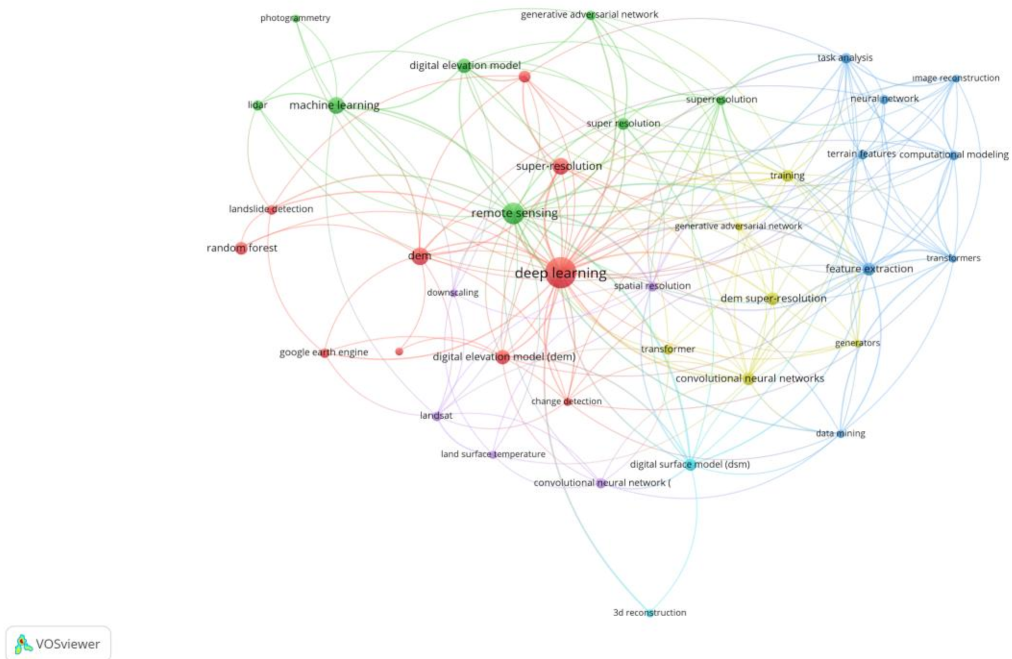

Figure 4. Keyword co-occurrence network based on Web of Science database, illustrating conceptual density.

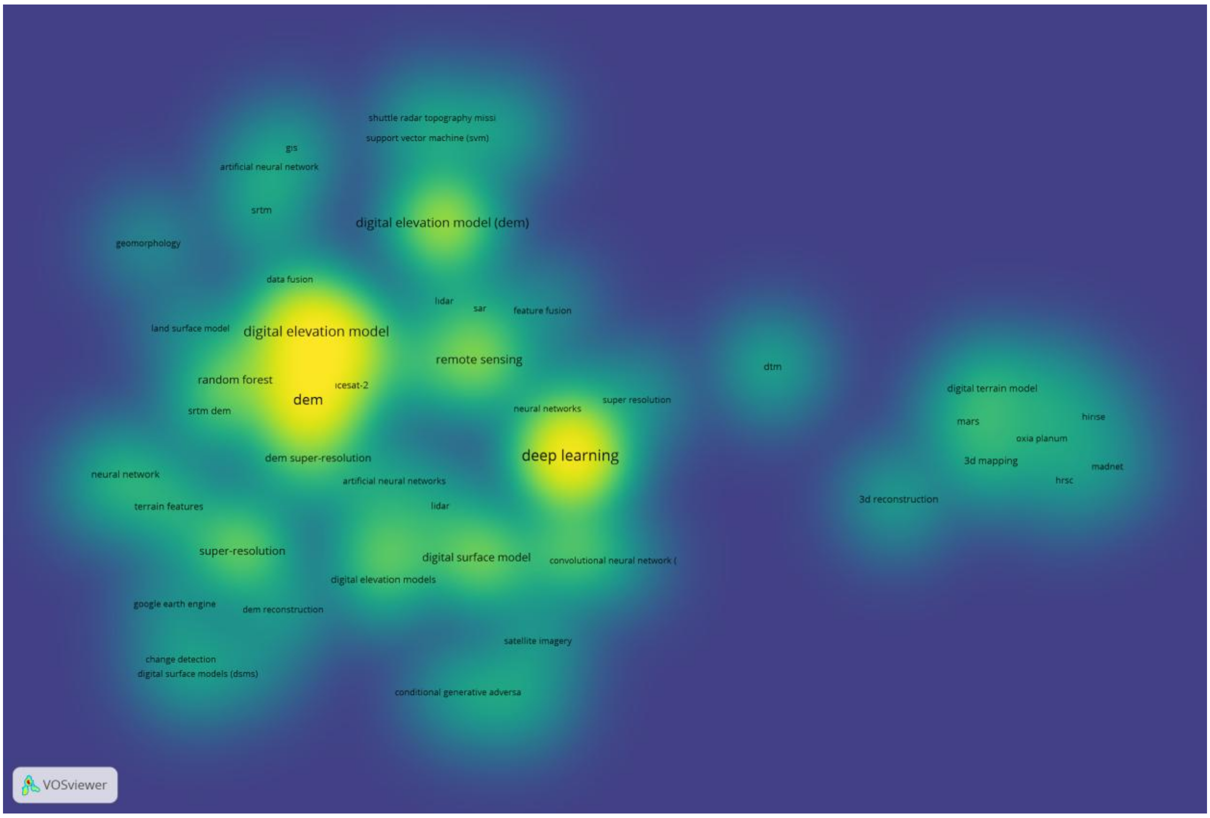

Figure 5. Keyword density visualization based on Scopus database.

4.3 Most Cited Publications

The most influential studies were identified through citation analysis. Table 3 lists the top 10 most cited publications according to Scopus, while Table 4 presents corresponding data extracted from Web of Science. In addition, Table 5 provides the list of the most relevant and highly cited studies identified through manual reference chaining, offering a complementary perspective to database-driven citation counts.

These highly cited publications have played a pivotal role in shaping research trajectories in DEM accuracy enhancement. CoastalDEM [7] and FABDEM [5] models, for instance, appear as recurring milestones, significantly influencing subsequent research by integrating machine learning techniques with global elevation datasets. The prominence of these publications underscores the growing emphasis on developing globally consistent, high-accuracy DEM products through advanced algorithmic techniques.

4.4 Thematic Distribution of Publications

Thematic content coding revealed the distribution of studies across various dimensions critical to understanding methodological diversity and application contexts. Table 6 presents the types of digital elevation models utilized, showing that models such as Copernicus DEM, SRTM, CoastalDEM, and FABDEM dominate the field. This dominance reflects a clear preference for globally available and methodologically refined elevation datasets. Table 7 categorizes the machine learning algorithms employed, with Random Forest and LightGBM emerging as the most frequently used techniques. This prevalence indicates the favoring of ensemble learning methods for elevation error correction tasks.

Table 8 summarizes the range of application scenarios. Coastal flood risk modeling and elevation error correction are the leading application areas, illustrating the practical relevance of DEM improvement research for disaster risk reduction and environmental management.

Table 3. Top 10 most cited publications on DEM accuracy enhancement from Scopus database (2005–2025). **Note:** Short titles have been generated for readability purposes. Full article titles can be found in the reference list.

Short Title	Author(s)	Journal	DOI	Citations
FABDEM	Hawker et al., 2022 [5]	Environmental Research Letters	10.1088/1748-9326/ac4d4f	290
Classification from RS data using SVM	Yu et al., 2012 [15]	Computers and Geosciences	10.1016/j.cageo.2011.11.019	189
A deep learning-based approach	Li et al., 2020 [1]	Geomorphology	10.1016/j.geomorph.2020.107045	144
Evapotranspiration Product Comparison Using ML	Xu et al., 2019 [16]	Journal of Hydrology	10.1016/j.jhydrol.2019.124105	137
Seamless DEM Generation from Multi-Source Data	Yue et al., 2017 [17]	ISPRS Journal of Photogrammetry and Remote Sensing	10.1016/j.isprsjprs.2016.11.002	126
ML-Based Casing Collapse Prediction	Mohamadian et al., 2021 [18]	Journal of Petroleum Science and Engineering	10.1016/j.petrol.2020.107811	79
Biomass Estimation via ML and Geostatistics	Su et al., 2020 [19]	Forest Ecosystems	10.1186/s40663-020-00276-7	74
DEM Super-Resolution Using GANs	Demiray et al., 2021 [20]	SN Computer Science	10.1007/s42979-020-00442-2	71
Forest Biomass Mapping with SAR and RF Kriging	Chen et al., 2019 [21]	Forest Ecology and Management	10.1016/j.foreco.2019.05.057	70
Building Height Estimation from Aerial Imagery	Liu et al., 2020 [22]	Remote Sensing	10.3390/RS12172719	65

Table 4. Top 10 most cited publications on DEM accuracy enhancement from Web of Science database (2005–2025). **Note:** Short titles have been generated for readability purposes. Full article titles can be found in the reference list.

Short Title	Author(s)	Journal	DOI	Citations
Lithological Classification via SVM	Yu et al., 2012 [15]	Computers & Geosciences	10.1016/j.cageo.2011.11.019	163
National-Scale Landslide Detection with Deep Learning	B. Yu et al., 2020 [23]	Computers & Geosciences	10.1016/j.cageo.2019.104388	93
Landslide Detection from Landsat8 Using RF	F. Chen et al., 2018 [24]	Landslide	10.1007/s10346-017-0884-x	66
Shear Wall Capacity Prediction via SVR	Keshtegar et al., 2021 [25]	Applied Soft Computing	10.1016/j.asoc.2021.107739	65
DEM-Based Pixel-Swapping for Flood Mapping	Huang et al., 2014 [26]	International Journal Of Remote Sensing	10.1080/01431161.2013.871084	64
Forest Biomass Mapping with SAR and RF Kriging	L. Chen et al., 2019 [21]	Forest Ecology And Management	10.1016/j.foreco.2019.05.057	62
Vegetation Mapping Using Sentinel and RF	Dobrinic et al., 2021 [27]	Remote Sensing	10.3390/rs13122321	57
Change Detection Using WNet Architecture	Tang et al., 2023 [28]	IEEE Transactions On Geoscience And Remote Sensing	10.1109/TGRS.2023.3296383	50
DEM Super-Resolution via Transfer Learning	Z. K. Xu et al., 2019 [29]	ISPRS Journal Of Photogrammetry And Remote Sensing	10.1016/j.isprsjprs.2019.02.008	48
Groundwater Estimation from GRACE via RF	Rahaman et al., 2019 [30]	Environments	10.3390/environments6060063	44

Table 5. Most relevant and highly cited studies identified through manual reference chaining (ranked by citation counts). **Note:** Short titles have been generated for readability purposes. Full article titles can be found in the reference list.

Short Title	Author(s)	Journal	DOI	Citations Scopus	Citations WoS
FABDEM	Hawker et al., 2022 [5]	Environmental Research Letters	10.1088/1748-9326/ac4d4f	290	257
CoastalDEM	Kulp & Strauss, 2018 [7]	Remote Sensing of Environment	10.1016/j.rse.2017.12.026	122	113
Object-based correction of LiDAR DEMs	Cooper et al., 2019 [31]	Environmental Modelling&Software	10.1016/j.envsoft.2018.11.003	30	27
New LiDAR-Based Elevation Model	Vernimmen & Hooijer, 2023 [32]	Earth's Future	10.1029/2022EF002880	24	23
DTM extraction from DSM	Amini Amirkolaee et al., 2022 [33]	Remote Sensing of Environment	10.1016/j.rse.2022.113014	18	15
DeltaDTM	Pronk et al., 2024 [8]	Scientific Data	10.1038/s41597-024-03091-9	15	14
DiluviumDEM:	Dusseau et al., 2023 [6]	Remote Sensing of Environment	10.1016/j.rse.2023.113812	11	N/A
Ranking of 10 Global One-Arc-Second DEMs	Guth et al., 2024 [34]	Remote Sensing	10.3390/rs16173273	6	6
Enhancement of Copernicus DEM	Okolie et al., 2024 [35]	International Journal of Image and Data Fusion	10.1080/19479832.2024.2329563	4	3
LightGBM hybrid model	Q. Li et al., 2025 [36]	Plos One	10.1371/journal.pone.0309025	2	2

Table 6. Distribution of publications by type of digital elevation model used.

Digital Elevation Model	Publications on Scopus	Publications on Web of Science
LiDAR DEM	93	13
SRTM	75	16
TanDEM-X	50	4
CoastalDEM	47	2
ALOS	45	4
GDEM	38	4
ASTER GDEM	36	4
NASADEM	30	5
Copernicus DEM	29	1
MERIT DEM	17	0
ALOS PRISM	16	0
AW3D	7	0
IceSat-2 DTM	5	0
FABDEM	3	2
GEDI DTM	2	0
DeltaDTM	1	0
DiluviumDEM	1	0

Table 7. Distribution of publications by machine learning algorithm employed.

Machine Learning Algorithm	Publications on Scopus	Publications on Web of Science
Deep Learning	169	67
Artificial Neural Network	162	15
Convolutional Neural Network	135	33
Random Forest	59	25
Support Vector Machine	54	16
Ensemble Learning	40	2
Linear Regression	30	5
Decision Tree	30	2
Gradient Boosting	14	3
Recurrent Neural Network	14	0
XGBoost	10	3
Nearest Neighbor	10	1
LSTM	8	2
LightGBM	6	2
CatBoost	4	1
Logistic Regression	3	0
MLP	3	0
Naive Bayes	2	0
Extra Trees	1	0

Table 8. Distribution of publications by application scenario (e.g., coastal flooding, error correction, super-resolution).

Application Scenario	Publications on Scopus	Publications on Web of Science
Satellite and Remote Sensing Based	144	9
Super Resolution	108	55
DEM Fusion	95	32
Accuracy and Technical Improvement	48	12
Height Classification	48	4
Coastal Flood	26	1
Flood Risk	25	1
Sea Level Rise	11	0
Coastal Erosion	7	0
Land Cover Restoration	6	1
Shoreline Change	4	0

Finally, Table 9 details the frequency of various accuracy metrics usage. RMSE remains the dominant metric; however, relatively limited use of MAE, Bias, and NSE highlights a methodological gap where broader validation strategies could enhance comparative evaluations among studies. These thematic distributions provide valuable insights into the dominant research practices, highlight emerging trends such as the adoption of deep learning methods, and expose potential gaps that future studies could address by adopting more diverse algorithms, models, and validation metrics.

5. DISCUSSION

5.1 Thematic Concentrations

The keyword co-occurrence analysis (Figures 3 and 4) and thematic coding results (Tables 3–6) reveal that research on DEM accuracy enhancement through machine learning is structured around four primary conceptual pillars: models, methods, applications, and data sources. Notably, terms such as "digital elevation model," "machine learning," and "super-resolution" exhibited centrality across both Scopus and Web of Science datasets, highlighting the interdisciplinary expansion of the field.

Table 9. Frequency of accuracy metrics usage (e.g., RMSE, MAE, Bias, NSE).

Accuracy Metrics	Publications on Scopus	Publications on Web of Science
Root Mean Square Error	45	18
Mean Absolute Error	28	6
Mean Error	69	23
R-squared	1	0
Standard Deviation	5	8
Mean Absolute Percent Error	0	2

The publication trend (Figures 1 and 2) indicates a clear surge in research interest after 2018, coinciding with the release of enhanced DEM products like CoastalDEM and FABDEM. This trend reflects a growing convergence between environmental risk assessment needs and technological advancements in remote sensing and machine learning.

5.2 Prominent Models and Algorithms

The citation analysis (Tables 3 and 4) underscores the foundational role played by models such as CoastalDEM [7] and FABDEM [5] in catalyzing methodological innovation. CoastalDEM's application of neural networks to correct elevation errors and FABDEM's use of Random Forest for bare-earth generation exemplify the successful integration of machine learning into DEM production pipelines.

In terms of algorithms, Random Forest and LightGBM emerged as the most widely adopted machine learning techniques (Table 7), particularly for tasks involving elevation error correction. However, the emergence of deep learning methods such as CNNs and GANs remains limited, suggesting an opportunity for broader algorithmic diversification in future studies.

5.3 Silent Themes and Underexplored Areas

Although dominant themes are well represented, several critical research areas remain underexplored. Data fusion, identified in fewer than 7% of studies (Table 8), is crucial for integrating diverse elevation datasets and improving model consistency across varying landscapes. Similarly, super-resolution techniques, although increasingly referenced in keyword density maps (Figure 5), have not yet been systematically incorporated into the mainstream methodological toolkit.

Moreover, the heavy reliance on RMSE as the primary accuracy metric (Table 9) restricts comprehensive model evaluation. Underutilized metrics such as MAE, Bias, and NSE could provide more nuanced assessments of model performance, particularly in diverse topographical settings.

5.4 Correlation Between Bibliometric Clusters and Thematic Structures

Bibliometric clustering results align broadly with the thematic categories identified through content coding. However, certain emergent topics, such as semi-supervised learning and GAN-based super-resolution, are underrepresented due to their relatively low frequency and recent emergence. This underscores the need for hybrid analysis frameworks that combine bibliometric mapping with detailed content-based evaluations to accurately capture emerging research trends.

5.5 Literature Gaps and Research Directions

The analysis highlights several structural gaps and emerging opportunities:

- *Algorithmic Homogeneity:* The dominance of Random Forest suggests a need for comparative studies evaluating alternative machine learning and deep learning models.

- *Limited Open Science Practices:* Few studies provide open-source code or datasets, limiting reproducibility and comparative benchmarking.
- *Regional Model Underrepresentation:* High-accuracy regional models like HMG SYM5-L0 are rarely incorporated into global assessments, indicating a geographical imbalance in DEM research.
- *Neglected Transfer Learning Opportunities:* The potential for transfer learning techniques to adapt DEM enhancement models across different geographic regions remains largely unexplored.

Addressing these gaps could significantly enhance the robustness, generalizability, and impact of future DEM accuracy improvement research.

6. CONCLUSION AND FUTURE RESEARCH OPPORTUNITIES

This bibliometric and thematic analysis provides a comprehensive overview of the evolving research landscape focused on enhancing the accuracy of digital elevation models through machine learning techniques. Between 2005 and 2025, scholarly production in this field has experienced exponential growth, particularly after the release of influential models such as CoastalDEM and FABDEM. The integration of ensemble-based machine learning models, notably Random Forest and LightGBM, has driven methodological innovation, while the emergence of deep learning approaches offers promising future avenues.

The analysis reveals that while significant progress has been achieved, research remains concentrated around a limited set of models and algorithms. Silent themes such as data fusion, bare-earth generation, and semi-supervised learning approaches are underrepresented, despite their critical importance for advancing DEM accuracy across diverse landscapes. Furthermore, the reliance on RMSE as a primary validation metric suggests the need for more diversified and standardized evaluation frameworks.

Manual reference chaining proved essential in identifying influential but under-indexed publications, revealing the limitations of conventional database searches alone. Approximately 62% of manually reviewed studies contributed to unique thematic perspectives, reinforcing the necessity for hybrid search and validation strategies.

Future research directions should focus on:

- Broadening the range of applied machine learning and deep learning techniques, including GANs, transformers, and semi-supervised architectures.
- Establishing standardized multi-metric evaluation protocols for DEM validation.
- Promoting open science practices by mandating open data and open-source code releases.
- Expanding the application of transfer learning methodologies to adapt DEM correction models across varied geographic and climatic regions.
- Integrating high-accuracy regional models such as HGM SYM5-L0 into global assessments to reduce geographical biases.

Ultimately, advancing DEM accuracy through machine learning requires a balanced combination of methodological rigor, algorithmic diversity, reproducibility, and global inclusiveness. This study offers a structured foundation for future research, providing critical insights into current trends, gaps, and strategic priorities at the intersection of geospatial modeling and artificial intelligence.

Declaration of Ethical Standards

The authors declare that this study complies with all ethical standards, including proper authorship attribution, accurate citation practices, transparent data reporting, and the publication of original research findings. No part of this study has been plagiarized, and the work has not been submitted elsewhere.

Credit Authorship Contribution Statement

Osman Sami KIRTILOĞLU: Conceptualization, Methodology, Bibliometric Analysis, Writing – Original Draft, Supervision.

Elif AKYEL: Data Conceptualization, Methodology, Bibliometric Analysis, Curation, Formal Analysis, Visualization, Writing – Review & Editing.

Mehmet Güven KOÇAK: Conceptualization, Methodology, Bibliometric Analysis, Validation, Resources, Interpretation of Results, Writing – Review & Editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data Availability

The bibliometric data analyzed in this study were obtained from Scopus and Web of Science databases, which are subscription-based resources. Access to these datasets requires an institutional or personal subscription. Additional details can be provided by the corresponding author upon reasonable request.

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