

Review

Karst Rocky Desertification in Southwest China: Remote Sensing Progress, Critical Challenges, and Future Pathways

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Abstract

Karst desertification is a major ecological and environmental issue that threatens regional ecological security and sustainable development; its dynamic monitoring is of great significance for evaluating the effectiveness of ecological restoration and promoting regional sustainable development. Based on the Web of Science database, this paper offers a bibliometric-informed narrative review of the evolution of remote sensing monitoring and information extraction technologies for karst desertification from 1987 to 2025. It focuses on analyzing research progress in methods such as multi-source remote sensing data fusion, deep learning models, and integrated GIS analysis, with regard to improving the accuracy of information extraction and the ability to identify spatiotemporal dynamics of karst desertification. This paper also compares the advantages and limitations of different technologies in terms of high-resolution identification and long-term dynamic monitoring. Building on this foundation and drawing on relevant domestic and international research findings, this study examines the development trends and major challenges facing karst desertification monitoring technologies. It further outlines the direction for establishing a long-term, standardized dynamic monitoring system, with the aim of providing a scientific basis for ecological governance and sustainable development in the karst regions of Southwest China.

Keywords: karst rocky desertification; remote sensing monitoring; deep learning; multi-source data fusion; dynamic assessment



Academic Editor:
Nikolaos Koukoulas

Received: 26 April 2026

Revised: 15 June 2026

Accepted: 16 June 2026

Published: 29 June 2026

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1. Introduction

Karst landscapes cover approximately 15% of the world's land area and support about 10% of the global population. Their ecological degradation has become a transcontinental environmental challenge [1]. Karst land degradation is primarily found in regions such as the Mediterranean coast, the Balkan Peninsula, Turkey, Latin America, and southwest China [2]. However, there are significant differences among regions in terms of the intensity of human activity and ecological resilience: the Mediterranean region of Europe is primarily characterized by gradual degradation driven by arid climates, and its ecological restoration systems are relatively well-developed [3]. In Latin America and the Caribbean, soil erosion and localized degradation are predominantly associated with tropical karst

soils [4]. In contrast, the karst region of southwest China—which boasts the world’s largest contiguous area of carbonate rock—is characterized by complex landforms, a fragile ecological environment, and acute land-use conflicts. As such, it is widely regarded as a key representative region for global research on karst land degradation [5]. Particularly in regions such as Guizhou, Guangxi, and Yunnan, karst desertification—as an advanced stage of land degradation—exhibits a feedback loop of “ecological deterioration leading to increased poverty,” posing a serious threat to the construction of regional ecological security barriers and the achievement of the “dual carbon” goals.

Traditional rocky desertification monitoring primarily relies on ground-based plot surveys. Although this method yields high-precision field data, it suffers from limitations including being time-consuming, labor-intensive, costly, highly subjective, and difficult to implement on a large scale in karst mountainous areas with rugged and fragmented terrain. Its inefficiency, akin to that of traditional weeding methods, renders it inadequate to meet the urgent demands of large-scale ecological management [6]. Therefore, developing rapid, objective, and large-scale monitoring methods to enable dynamic observation of the spatiotemporal evolution of rocky desertification is not only crucial for assessing the effectiveness of ecological restoration projects such as converting farmland to forest and closing hillsides for afforestation, but also serves as a core support for providing scientific evidence to inform precise decision-making in rocky desertification control at the national level.

With the rapid development of Earth observation technology, remote sensing has become an important technical tool for monitoring the dynamics of karst desertification [7]. Early studies primarily relied on medium- and low-resolution optical imagery, such as Landsat MSS/TM/OLI and SPOT, to extract information on rock desertification using vegetation indices or traditional classification algorithms [8]. However, the unique surface topography and ecological processes of karst regions make remote sensing monitoring of rock desertification particularly challenging. Karst land surfaces typically exhibit a highly mosaic “rock–soil–vegetation” cover pattern, with significant spatial mixing of different land cover components. This leads to increased heterogeneity within individual pixels, making it prone to the phenomena of “same object, different spectral signatures” and “different objects, same spectral signatures.” Complex terrain and differences between shaded and sunlit slopes can alter the spectral response of land cover and radiation transfer processes, thereby increasing the uncertainty in quantitative remote sensing inversion. The evolution of rock desertification exhibits distinct spatiotemporal dynamics and scale effects; traditional single-temporal, single-source remote sensing data are insufficient to fully characterize its evolutionary process. Consequently, pixel mixing, spectral confusion, topographic effects, and multiscale dynamic changes have become key scientific challenges in the remote sensing monitoring of karst desertification [9], driving the evolution of related research from the analysis of single-source optical imagery toward a multi-source, multiscale, and intelligent approach [10].

To address spectral confusion and topographic interference in complex environments, research has begun to integrate the fine spectral features of hyperspectral imagery, the all-weather observation capabilities of SAR, the three-dimensional structural information of LiDAR, and the ultra-high spatial resolution data from unmanned aerial vehicles (UAVs). Building on this foundation, the introduction of computer vision and artificial intelligence (AI) technologies has further driven a paradigm shift in the remote sensing monitoring of rock desertification. Deep learning models can automatically uncover nonlinear relationships among multidimensional features, effectively enhancing the capabilities for intelligent identification and dynamic monitoring of stone desertification information in complex topographic settings [11].

Current research on rock desertification in the karst regions of Southwest China primarily focuses on the evolution of rock desertification, its driving factors, the extraction of remote sensing data, and ecological restoration [12]. Previous studies have conducted extensive analyses of changes in the extent of rock desertification, the evolution of its severity, and its spatial distribution characteristics at the county or watershed scale [13–15]. However, due to factors such as differences in the temporal and spatial scales of remote sensing data and variations in monitoring methods, existing research still has shortcomings regarding the long-term dynamic evolution patterns of rock desertification, mechanisms for multi-source remote sensing collaborative monitoring, and the accurate extraction of information in complex karst environments. In particular, under the complex “soil-rock-vegetation” cover structure and strong topographic heterogeneity typical of karst regions, traditional remote sensing methods face critical challenges such as spectral confusion, scale effects, and topographic interference, which limit the accuracy and regional applicability of dynamic monitoring of rock desertification.

Based on this, this paper focuses on the dynamic remote sensing monitoring of karst desertification and provides a comprehensive review centered on the following two aspects: (1) Tracing the development of remote sensing monitoring technologies for karst desertification and the evolution of key methods, including the development of optical remote sensing, multi-source data fusion, and artificial intelligence methods; (2) Summarizing the core challenges and typical solutions for remote sensing information extraction in complex karst landscapes, and exploring future development directions for high-precision, intelligent, and multi-scale dynamic monitoring. The aim is to provide a theoretical framework for optimizing remote sensing monitoring systems for karst desertification, as well as for ecological governance and regional sustainable development.

2. Materials and Methods

2.1. Literature Data Acquisition

To ensure the representativeness, systematic nature, and reproducibility of the research findings, this study selected Web of Science as the primary source of literature data. The search was conducted using the Topic Search field, with a cutoff date of 16 October 2025. To achieve the most comprehensive coverage of research on remote sensing monitoring of karst desertification, the following Boolean search query was constructed: (TS = (“karst rocky desertification” OR “rocky desertification” OR “rocky desertification extraction” OR “rocky desertification evolution” OR “karst land degradation”))

The literature search was restricted to the document types “Article” and “Review,” and the language was limited to English. After an initial search yielded relevant literature, the documents were screened and deduplicated according to the PRISMA guidelines. Articles not directly relevant to the research topic, those with no remote sensing monitoring analysis, or duplicate publications were excluded. This process resulted in a valid dataset of relevant literature, which was then used to conduct visualizations of keyword co-occurrence, research hotspots, and knowledge structures using VOSviewer software. The specific search and screening process is shown in Figure 1.

The literature retrieval and screening procedures followed the PRISMA framework to ensure transparency and reproducibility of the review process. All bibliometric and qualitative analyses were conducted using the same dataset derived from the Web of Science Core Collection (WOSCC). Initially, 12,997 records were identified through topic-based retrieval. After excluding non-English publications, early access papers, and records not meeting the document type requirements, 12,154 records remained for screening. Subsequently, studies unrelated to karst rocky desertification remote sensing or lacking substantial monitoring-related content were excluded based on title and abstract assessment, resulting in

9918 records for full-text eligibility evaluation. A total of 8665 publications were initially retrieved from the Web of Science database and used for bibliometric visualization analyses, including keyword co-occurrence, collaboration networks, and publication trend analysis. To further synthesize methodological advances in karst rocky desertification information extraction, studies directly related to remote sensing monitoring and extraction methods were screened, resulting in a subset of 403 publications for detailed review and discussion. The detailed screening process is illustrated in Figure 1.

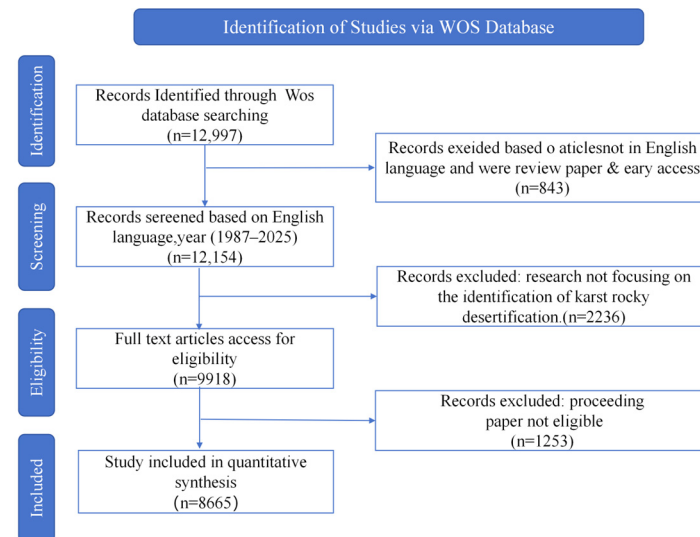


Figure 1. PRISMA flow diagram.

2.2. Analytical Methods

This bibliometric analysis was conducted using VOSviewer (version 1.6.20), a software tool designed for constructing and visualizing bibliometric networks. VOSviewer enables the exploration of knowledge structures and research trends through the analysis of publications, authors, institutions, countries, and keywords. The retrieved records from the Web of Science Core Collection were exported in RefWorks format and subsequently imported into VOSviewer for analysis.

For network construction, the full counting method was applied, assigning equal weight to each occurrence within a publication. Keyword co-occurrence analysis was performed using Author Keywords and Keywords Plus. Prior to analysis, synonymous terms and variant keyword expressions were standardized and merged using a thesaurus file to improve consistency and reduce redundancy in the network. The association strength normalization method was employed to normalize the co-occurrence matrix, thereby enhancing the interpretability of relationships among nodes and minimizing the influence of highly frequent terms.

For the co-authorship analysis, the maximum number of authors per document was set to 25, and the minimum number of documents per author was set to one. Authors without collaboration links were retained in the network. For keyword analysis, the minimum occurrence threshold was set to eight, and keywords without links to other keywords were also included. To improve visualization clarity, small and weakly connected clusters were merged when appropriate. In the resulting network maps, node size represents keyword occurrence frequency, ranging from 8 to 100 occurrences, with the smallest nodes corresponding to keywords appearing eight times. Links between nodes indicate co-occurrence relationships, and link thickness reflects the strength of association. Different colors represent distinct thematic clusters identified by the clustering algorithm.

3. Results

3.1. Visualization Analysis with VOSviewer

3.1.1. Keyword Hotspot Analysis

The results of keyword co-occurrence clustering not only reflect the distribution of research hotspots in the field of karst rocky desertification but also reveal the evolution of the field's knowledge structure and research paradigms (Figure 2). From the perspective of the overall network structure, keywords such as “rocky desertification” and “environmental sciences” occupy central positions in the network and maintain strong connections with multiple cluster sections, including ecological restoration, soil and water erosion, land-use change, and environmental governance. This indicates that research on karst rocky desertification has evolved from early descriptive studies focused primarily on spatial identification and area estimation to a direction emphasizing the analysis of ecological processes, assessment of environmental impacts, and interdisciplinary integration. In particular, the size of keyword nodes related to environmental sciences, ecological restoration, and the carbon cycle has continued to grow, reflecting that current research priorities have gradually shifted from traditional “degradation identification” to studies on “ecological function restoration” and “regional sustainable development.” This demonstrates a clear shift in research paradigms against the backdrop of the “dual carbon” goals and the construction of an ecological civilization.

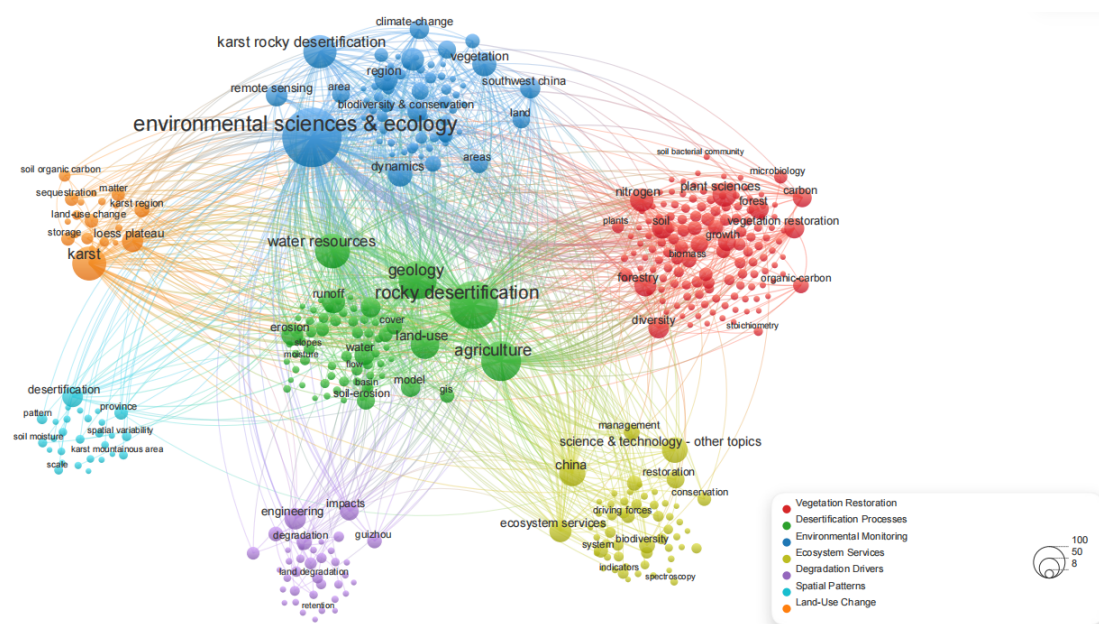


Figure 2. Network Visualization (Keyword co-occurrence network of karst rocky desertification research based on publications retrieved from the Web of Science Core Collection. The network was generated using VOSviewer. Each node represents a keyword, and node size is proportional to keyword occurrence frequency. Links indicate co-occurrence relationships between keywords, with thicker links representing stronger link strength. Different colors denote thematic clusters identified by the clustering algorithm, reflecting major research domains within karst rocky desertification studies).

The high-frequency co-occurrence relationships among different clusters further indicate that research on karst desertification has transcended the scope of traditional landform degradation studies and is gradually evolving into an interdisciplinary research framework that integrates remote sensing science, ecology, hydrology, environmental engineering, and Earth system science. Among these, the yellow cluster, representing research on soil erosion and landform processes, is located at the center of the network and maintains strong connections with multiple themes such as karst desertification monitoring, ecological restoration,

and environmental effects. This indicates that erosion processes and landform evolution mechanisms serve as a crucial scientific link connecting the formation mechanisms of karst desertification with dynamic remote sensing monitoring. The continued growth of research hotspots in ecological restoration and environmental effects, represented by the red and green clusters, indicates that current research is increasingly focused on ecological responses following the remediation of rock desertification, ecosystem stability, and the assessment of carbon sink functions. At the same time, the dense network connections among multiple clusters reflect that remote sensing monitoring technology is evolving from traditional single-source optical remote sensing toward multi-source data fusion, spatiotemporal dynamic analysis, and intelligent recognition.

Figure 3 presents the keyword density visualization generated using VOSviewer. In this map, warmer colors (yellow to red) indicate higher keyword co-occurrence frequencies and stronger research attention, whereas cooler colors (green to blue) represent relatively peripheral topics. The spatial distribution of keyword densities reveals several major research hotspots and thematic concentrations within the field of karst rocky desertification. The most prominent hotspot is centered on ecological restoration, where keywords such as “ecological restoration”, “vegetation restoration”, “ecosystem services”, “biodiversity”, and “soil organic carbon” exhibit high densities and strong interconnections. This pattern suggests that recent studies have increasingly shifted from describing rocky desertification processes toward evaluating ecosystem recovery, ecological functions, and restoration effectiveness. The emergence of ecosystem services and carbon-related terms further indicates growing interest in the ecological benefits generated by restoration programs under the framework of sustainable development.

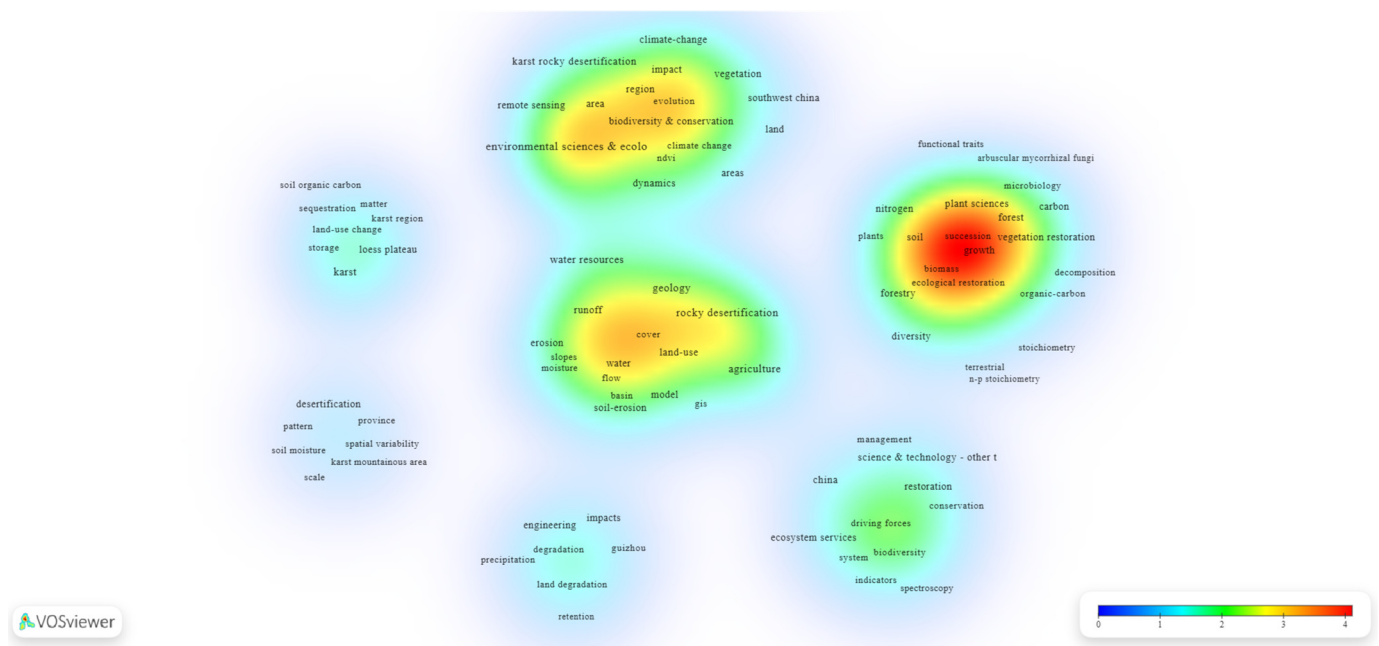


Figure 3. Density Visualization (Density visualization of keyword co-occurrence in karst rocky desertification research generated using VOSviewer. Node labels represent keywords, and colors intensity reflects the density distribution of keywords. Warmer colors (yellow to red) indicate areas with higher keyword density and stronger research attention, whereas cooler colors (green to blue) indicate lower-density and less frequently studied topics. Density values shown in the legend represent relative keyword density calculated by VOSviewer).

A second hotspot focuses on rocky desertification dynamics and driving mechanisms, characterized by keywords including “karst rocky desertification”, “land use”,

“climate change”, “remote sensing”, and “dynamics”. The close association among these terms highlights the widespread application of remote sensing technologies for monitoring spatiotemporal changes in rocky desertification and disentangling the combined effects of land-use change and climate variability on ecosystem degradation. Another notable cluster is associated with environmental degradation processes, where “soil erosion”, “agriculture”, “model”, and “water resources” are strongly linked. This finding reflects continued attention to the interactions between rocky desertification, soil degradation, hydrological processes, and human activities, particularly in ecologically fragile karst landscapes.

Overall, the density distribution suggests that karst rocky desertification research has evolved from early-stage degradation assessment and process identification toward an integrated framework encompassing dynamic monitoring, ecological restoration, ecosystem service enhancement, and climate change adaptation. This transition reflects a broader shift from understanding degradation patterns to promoting ecosystem resilience and sustainable management in karst regions.

3.1.2. Chronological Hotspot Analysis of Karst Rocky Desertification Research

As shown in Figure 4, this figure is an overlay visualization of keywords generated using VOSviewer, which is used to illustrate the temporal evolution of research hotspots. In this visualization, node size represents the frequency of keyword occurrences, while the connections between nodes indicate co-occurrence relationships and association strength. The total link strength reflects the importance of keywords within the research network. Node color indicates the average publication year (APY) of the keywords, with colors transitioning gradually from blue to yellow, corresponding to earlier and more recent research topics, respectively.

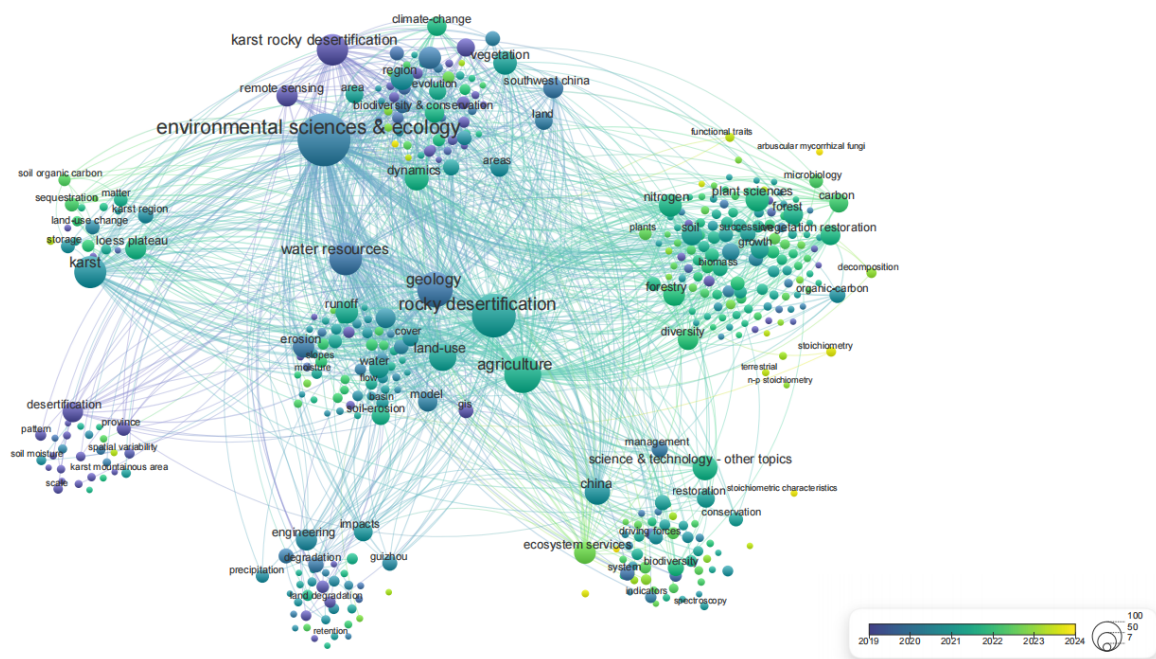


Figure 4. Keyword Timeline Map. Overlay visualization of keyword co-occurrence in karst rocky desertification research generated using VOSviewer. Node size represents keyword occurrence frequency, and links indicate co-occurrence relationships. colors represent the average publication year of keywords, ranging from earlier studies (blue) to more recent research topics (red), illustrating the temporal evolution of research hotspots.

In terms of temporal evolution, earlier studies (blue and blue-green nodes) primarily focused on keywords such as “Karst rocky desertification,” “Land use,” “Soil erosion,” “Agriculture,” and “Guizhou.” These studies focused on the formation mechanisms of karst desertification, the identification of driving factors, and ecological restoration and management practices, laying the foundation for subsequent research.

As research continues to advance, the focus has gradually shifted toward ecological processes and ecological effects. Keywords such as “water resources,” “vegetation,” “ecosystem services,” and “carbon storage” have increasingly become key areas of research, indicating that the focus has gradually shifted from traditional stone desertification control to the assessment of ecosystem functions, ecological and environmental effects, and regional sustainable development issues.

In recent years, emerging research themes represented by yellow and yellow-green nodes have gradually emerged, including keywords such as “Google Earth Engine,” “remote sensing monitoring,” “ecological products,” and “driving mechanisms.” This indicates that cloud-based remote sensing platforms, big data environmental monitoring, the realization of ecological product value, and intelligent dynamic monitoring technologies are becoming important frontier directions in karst desertification research. Overall, research on karst desertification has evolved from “desertification identification and management” to “assessment of ecological processes and effects,” and further to “intelligent dynamic monitoring and realization of ecological value.” The research paradigm has gradually shifted from a focus on single-aspect ecological management to a comprehensive research framework encompassing ecological environments, resource utilization, and regional sustainable development.

3.1.3. Global Number of Publications on Karst Rocky Desertification

Based on statistics on the volume of national publications and the results of collaborative network analysis (Figure 5), research on karst desertification information extraction exhibits a distinct core–periphery structure. China has the largest number of nodes and the highest connectivity within the collaborative network, having established extensive cooperative relationships with Vietnam, the United Kingdom, the United States, Australia, and several European countries, indicating its strong research influence and active international collaboration in this field. Although countries such as the United States and the United Kingdom have relatively small node sizes, they maintain stable connections with multiple nations and play a crucial bridging role in the international collaboration network. At the same time, Southeast Asian countries such as Vietnam have formed relatively dense collaborative ties with China, reflecting a trend toward regional collaborative research driven by similar karst ecological and environmental contexts.

In contrast, although countries such as Brazil and Argentina in South America, as well as Morocco and Senegal in Africa, have participated in relevant research, the scale of their research networks and collaborative connections remains relatively limited, resulting in a smaller sphere of influence within the current international cooperation network. Overall, research on karst desertification information extraction currently remains concentrated primarily in China and the regions of its partner countries, with international collaboration exhibiting distinct regional clustering patterns. In the future, it will be necessary to further strengthen data sharing, methodological exchange, and joint research among different karst distribution areas to enhance the applicability and transferability of research findings across diverse global ecological and environmental conditions.

Cluster analysis diagram of publication output by country/region

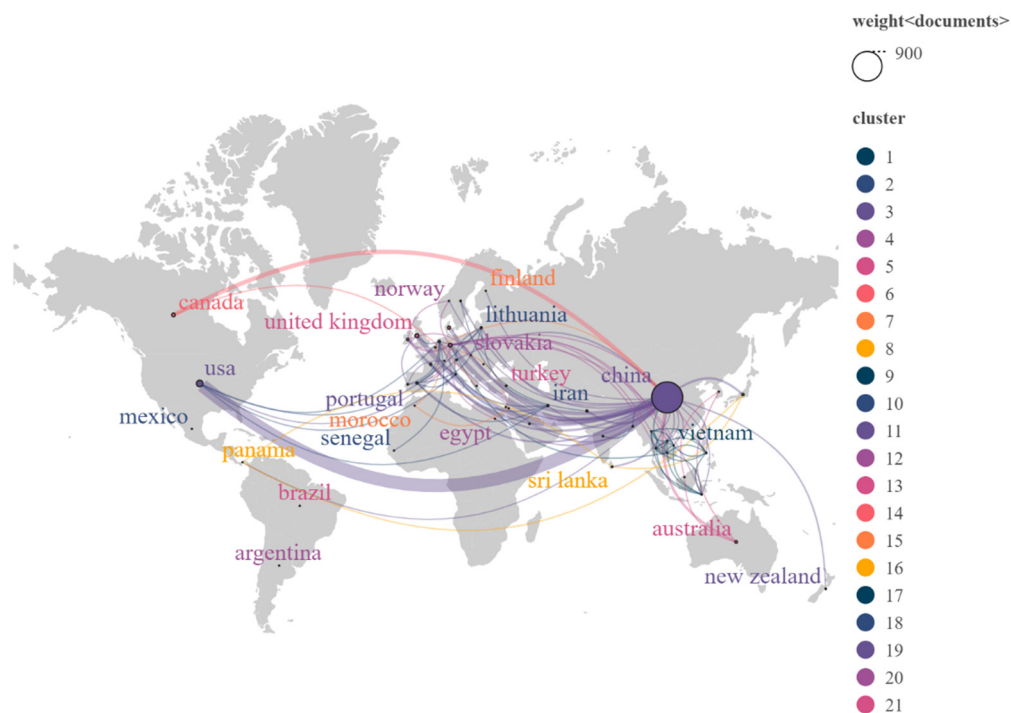


Figure 5. National Cooperation Network. Nodes represent countries, and edges indicate significant co-citation relationships. Colors denote clusters (Cluster 1–21) automatically derived by VOSviewer based on co-citation strength. Countries sharing the same cluster color exhibit highly similar knowledge bases, typically reflecting closely related research themes or disciplines. Node size is proportional to total citation frequency, with larger nodes signifying greater scholarly influence within the dataset. Cluster numbers serve solely as identifiers and carry no ranking or hierarchical meaning.

3.1.4. Publication Trend Analysis

For an in-depth methodological synthesis, we further identified and reviewed studies directly relevant to the extraction of karst rocky desertification information. From an initial pool of 8665 records, we screened for entries containing the keywords “karst rocky desertification extraction” or “rocky desertification extraction”, yielding 403 publications that were subsequently analyzed in detail. Figure 6 illustrates the annual publication trend of 403 studies specifically related to karst rocky desertification information extraction from 1987 to 2025. The publication trajectory reflects the gradual evolution of this research field from an exploratory stage to rapid expansion and increasing methodological sophistication. Between 1987 and 2005, publication output remained relatively low, indicating limited research attention and methodological development. After 2005, publication activity increased steadily and accelerated markedly after 2015. The number of publications reached its highest level in 2022 (167 papers), followed by continued high research activity despite moderate fluctuations during 2023–2025. This trend reflects growing interest in karst rocky desertification monitoring, driven by increasing ecological restoration demands and advances in remote sensing, geospatial analysis, and artificial intelligence technologies. Overall, the sustained growth in publication output highlights the increasing importance of information extraction techniques for understanding and managing karst rocky desertification processes.

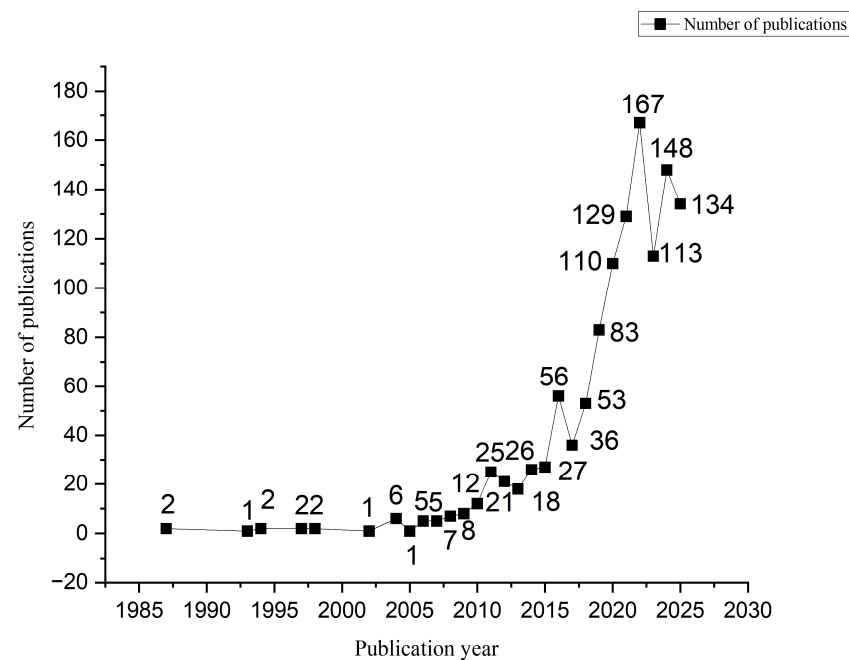


Figure 6. Annual trend of publication output from 1987 to 2025.

3.2. Methods for Karst Rocky Desertification Extraction and Evaluation

3.2.1. Traditional Interpretation and Spectral Index Methods for Extracting Karst Rocky Desertification

Early Karst rocky desertification (KRD) monitoring has evolved from visual interpretation to quantitative spectral-index-based approaches. Early studies mainly relied on manual interpretation of remote sensing imagery. For example, Zhou et al. (2001) [16] identified KRD based on visual characteristics of surface features, whereas Cheng et al. (2015) [5] demonstrated that interpretation consistency remained strongly dependent on expert experience, limiting reproducibility and large-scale application. These limitations stimulated the transition toward quantitative remote sensing methods.

The first generation of quantitative approaches employed general spectral indices to characterize vegetation degradation and surface exposure. Zhang et al. (2010) [17] used the Normalized Difference Vegetation Index (NDVI) and Bare Soil Index (BI) to estimate bare-rock proportions. Such indices provide indirect information on vegetation cover and exposed ground, which are closely associated with KRD severity. Previous studies have shown that fractional vegetation cover and rock-outcrop percentage can serve as key indicators for classifying KRD intensity from mild to severe stages [18]. However, because these indices were not specifically designed for KRD processes, their ability to represent the structural characteristics of rocky desertification remains limited.

To address this issue, several KRD-specific indices were developed. Xia et al. (2006) proposed the Geometric Index of Rock Desertification [19], while Yue et al. (2010, 2011) developed the Karst Rocky Desertification Synthesis Index (KRDSI) [20,21], which integrates vegetation, soil, and exposed-rock information into a unified assessment framework. These indices established a more direct linkage between spectral responses and KRD severity classes. At the sub-pixel scale, Liu et al. (2010) [22], Yang et al. (2014) [23], and Zhang et al. (2014) [24] further applied mixed-pixel decomposition and linear spectral mixture models (LSMMs) to estimate component abundances and improve the quantification of rock exposure and vegetation cover.

Overall, traditional spectral index methods have progressed from generic vegetation and soil indicators to KRD-oriented indices and sub-pixel abundance estimation. This evolution has improved the quantitative assessment of KRD severity and its spatial dis-

tribution [9]. Nevertheless, most approaches rely on linear spectral mixing assumptions and region-specific thresholds, resulting in uncertainties under highly fragmented karst landscapes and limiting cross-regional comparability. Establishing standardized index systems and severity classification criteria, therefore, remains a critical research priority.

3.2.2. Machine Learning Methods for Karst Rocky Desertification Extraction

Machine learning technologies have evolved into a key pillar for extracting remote sensing information on karst desertification, following a clear trajectory from “classical statistical learning—enhanced ensemble learning—multi-model fusion and intelligent modeling.” In the early stages, Support Vector Machines (SVMs), leveraging their advantages in high-dimensional classification with small sample sizes, demonstrated stable nonlinear classification capabilities in the identification of stone desertification grades [25].

Xu et al. achieved an overall accuracy of 84–86% in an evaluation across three counties in Guangxi, with Kappa coefficients all exceeding 0.79 [26]. Building on this foundation, Zhang et al. (2023) systematically tuned SVM hyperparameters using intelligent algorithms such as Cuckoo Search and Particle Swarm Optimization (PSO), improving the accuracy of the PSO-SVM model to 96.2%, with a Kappa coefficient of 0.95 [27]. This strongly confirms that parameter optimization can significantly expand the performance ceiling of such models under complex land surface conditions; however, research at this stage has relied on single-region training, and cross-regional generalization capabilities and spatial stability have yet to be verified.

With the rise in machine learning, Random Forests (RF) have gradually become the mainstream method for regional-scale desertification mapping due to their robustness to high-dimensional features and resistance to overfitting. Zhang et al. (2022) combined the maximum information coefficient with correlation analysis for feature selection and employed a Bagging-based RF ensemble to map desertification in the karst depressions of Guangxi, achieving an overall accuracy of 94.7% and a Kappa coefficient of 0.92 [6]. Pu et al. (2021) systematically compared Random Forests (RF), Bagging decision trees, and Extreme Random Trees and confirmed that RF achieved the highest overall accuracy (85.21%), establishing its consistent advantage in complex karst terrain [28]. Liu et al. (2024), on the other hand, enhanced the model’s adaptability in large-scale, highly heterogeneous regions through optimized feature selection and feature importance analysis [29].

At the same time, multi-factor integration strategies have begun to attract attention: Qian et al. (2021) developed a multi-model framework incorporating vegetation type and seasonal variation factors, finding that the accuracy of the optimized SVM increased to 91.1% after introducing seasonal variables, thereby revealing the contribution of temporal information to the classification of rock desertification [30]. In terms of expanding into ecological risk prediction, Yang et al. (2025) systematically compared the performance of random forests, boosted regression trees, backpropagation neural networks, and SVMs in predicting soil erosion susceptibility [31]. This provided a multi-algorithm benchmark framework for rock desertification risk modeling, shifting the research perspective from accuracy optimization to risk interpretation. However, their modeling still relies primarily on static features, with limited capacity to characterize temporal evolution and spatial continuous processes.

From the perspective of method validation, existing studies generally rely on independent validation via random splitting, with very limited application of spatial cross-validation and temporal transfer validation. Although the issue of class imbalance has been mitigated to some extent through feature selection or ensemble strategies, there is a lack of systematic designs incorporating resampling and cost-sensitive learning. At the same time, the absence of standardized cross-regional benchmark datasets limits the

comparability among different studies (Table 1). Overall, the field has established a division of labor where SVMs handle small-sample nonlinear modeling, RF dominates regional-scale mapping, and multi-model fusion extends to risk prediction. However, three key bottlenecks remain prominent: the absence of spatial cross-validation makes it difficult to assess generalization ability; insufficient research on temporal transfer and inter-seasonal stability limits the potential for dynamic monitoring; and the lack of a unified standardized benchmark constrains rigorous quantitative comparisons. There is an urgent need to establish a comprehensive framework that integrates “spatial generalization learning, temporal transfer modeling, and a standardized data system” to support highly reliable remote sensing-based intelligent monitoring of karst desertification.

Table 1. Comparison of Application Types and Validation Frameworks for Machine Learning Methods in Remote Sensing of Karst Desertification.

Literature	Methodology	Research Focus	Inter-Domain Generalization	Temporal Transfer	Major Contributions
Xu et al. (2015) [26]	SVM	Basic Classification Modeling	Limited	Not Evaluated	Validating SVM Adaptability
Zhang Yali et al. (2023) [27]	Optimization models such as PSO-SVM	Research on Parameter Optimization	Limited	Not Evaluated	Improving the Upper Bound of SVM Performance
Zhang et al. (2022) [6]	RF + Feature Selection	Regional Mapping	Moderate	Not Evaluated	Improve drafting accuracy
Pu et al. (2021) [28]	Comparison of Integrated Models	Comparison of Methods	Moderate	Not Evaluated	Model benchmarking
Liu Zicheng et al. (2024) [29]	RF Optimization Charting	Large-scale applications	Moderate	Not Evaluated	Improve spatial adaptability
Qian et al. (2021) [30]	Multi-model fusion	Spatio-temporal Factor Analysis	Moderate	Limited	Incorporate seasonal information
Yang et al. (2025) [31]	Multi-model Forecasting	Risk Assessment	Moderate	Not Evaluated	Building a Predictive Baseline

3.2.3. Application of Deep Learning Methods in Karst Rocky Desertification Extraction

Deep learning methods overcome the limitations of traditional machine learning by automatically extracting hierarchical features through end-to-end nonlinear transformations, thereby achieving stronger feature representation and higher classification accuracy in KRD extraction. Convolutional neural networks (CNNs), as representative deep learning architectures, extract multi-scale image features via stacked convolutional, pooling, and fully connected layers.

To address large-scale KRD severity mapping, Wang et al. proposed a graph convolutional network segmentation model integrating CNN and graph neural network (GNN), incorporating spectral, topographic, and meteorological variables. This model achieved a mean intersection over union (MIoU) of 84.72%, significantly outperforming mainstream segmentation methods, and enabled efficient monitoring of KRD spatiotemporal dynamics in Guizhou Province from 2015 to 2022 [32]. Similarly, Zhong et al. proposed RAP-Net,

which combines CNN and GNN to classify KRD severity in plateau karst landscapes, effectively correcting omission errors of U-Net and QSD-Transformer [33]. For model lightweighting, Lai et al. (2025). improved DeepLabV3+ with depthwise separable convolutions for bare rock extraction from high-resolution UAV imagery [34], achieving faster inference while maintaining high accuracy [35]. Research has shown that deep CNNs can achieve over 90% overall accuracy in high-resolution multi-source data fusion for complex subtropical karst environments, but model interpretability remains weak; they recommend visualization tools such as SHAP and Grad-CAM [36]. Guan et al. applied a deep belief network (DBN) for soil evaluation in KRD regions, significantly outperforming SVM and BP neural networks [37].

Current challenges include large training sample demands, high computational costs, and insufficient model interpretability. Future research should focus on few-shot learning, interpretable CNN frameworks with physical constraints, and lightweight models for real-time KRD monitoring.

3.2.4. Comparative Evaluation of Methods

In summary, the methods for extracting karst rocky desertification information have formed a technological evolutionary pathway of ‘spectral indices–machine learning–deep learning’, with significant differences among these methods in terms of accuracy, interpretability, and scope of application.

As shown in Table 2, traditional spectral index methods have clear physical meaning, high computational efficiency, and ease of generalization, making them suitable for large-scale rapid assessment, but their accuracy is limited under complex land surface conditions. Machine learning methods significantly improve classification accuracy through multi-source data fusion and are suitable for regional-scale analysis, yet they rely on feature engineering and have limited generalization ability. Deep learning methods possess powerful automatic feature extraction capabilities and perform exceptionally well in high-resolution fine identification and dynamic monitoring, but they suffer from strong sample dependence and insufficient interpretability. The three methods exhibit a progressive and complementary relationship in terms of accuracy, efficiency, and interpretability, collectively forming the technical system for rocky desertification information extraction.

Table 2. Comprehensive comparison of information extraction methods for karst rocky desertification.

References	Method Type	Representative Methods	Advantages	Limitations	Open Access in Representative Literature	Applicable Scale	Development Trends
Zhang et al. [18]	Spectral index method	NDVI, KRDSI, feature space	Clear physical meaning, simple computation, easy generalization	Severe spectral confusion, limited accuracy	moderately	Large scale	Multi-index fusion, hyper-spectral applications
Pu et al. [33]	Machine learning	NDVI, KRDSI, TSFS, Red-NIR-SWIR feature space	High accuracy, strong multi-feature fusion capability	Relies on feature engineering, limited generalization ability	significantly	Medium scale	Transfer learning, explainable AI

Table 2. Cont.

References	Method Type	Representative Methods	Advantages	Limitations	Open Access in Representative Literature	Applicable Scale	Development Trends
Huang et al. [36]	Deep learning	CNN, U-Net, Transformer	Strong automatic feature extraction capability, high accuracy	Large demand for training samples, high computational resource consumption, weak interpretability, and black-box nature of models	significantly	Fine analysis at small to medium scales	Lightweight models, multi-source fusion
Qian, Guan et al. [30,37]	Integrated method	GEE-based monitoring, CA-Markov spatiotemporal simulation	Strong capability in dynamic monitoring and prediction	Complex models, high data requirements	substantially	Multi-scale	Fusion of mechanistic and data-driven approaches

4. Discussion

4.1. Data-Level Challenges in Dynamic Monitoring of Karst Rocky Desertification

The data challenges faced in monitoring karst desertification dynamics stem not only from the general limitations of remote sensing observations but are also significantly influenced by the characteristics of karst landforms. Cloud cover, seasonal variations, and insufficient data continuity are common issues in optical remote sensing monitoring; in subtropical karst regions [38], where cloudy and rainy weather is frequent, these issues further increase the uncertainty associated with long-term monitoring of karst desertification dynamics [39]. In contrast, in karst regions, bare rock, shallow soil, and sparse vegetation are distributed in a highly mosaic pattern. The widespread presence of numerous mixed pixels and complex terrain shading weakens the spectral differences between different levels of rock desertification, making them significant factors affecting the accuracy of information extraction. The complex combinations of slope gradients and aspects formed by peak clusters, depressions, and canyons result in spatial heterogeneity in surface radiative response [40]. This causes the same degree of rock desertification to exhibit varying spectral characteristics under different topographic conditions, thereby increasing the difficulty of model transfer between regions and long-term dynamic monitoring. In terms of observational capabilities, high-resolution imagery can identify small patches of bare rock, but its temporal continuity is limited; medium- and low-resolution data are suitable for long-term sequence analysis, but they struggle to accurately depict fragmented, fossilized desert landscapes [41]. Furthermore, multi-source data from optical, radar, and UAV sources exhibit significant differences in spatial scale, observation mechanisms, and physical responses. Currently, there is still a lack of a unified integration framework for complex karst land surfaces, which limits the continuous monitoring and accurate characterization of the dynamic processes of rock desertification.

4.2. Model-Level Challenges in Dynamic Monitoring of Karst Rocky Desertification

Existing remote sensing models for monitoring rock desertification still face significant challenges in terms of accuracy, generalization, and interpretability. Although deep learning models (such as U-Net and Transformer) can effectively improve the identification of rock desertification boundaries and the extraction of spatial features—with some studies reporting high overall classification accuracy—their performance is highly dependent on large-scale, high-quality labeled datasets. Furthermore, the lack of transparency in the model's decision-making process limits the interpretation of results and their broader application. In contrast, traditional methods based on feature spaces such as NDVI–Albedo have strong physical significance; however, they are prone to classification confusion in transitional areas of stone desertification, particularly under complex surface conditions where vegetation cover and exposed bedrock coexist, which somewhat affects their identification accuracy [18]. Furthermore, the limited ability of these models to generalize across regions remains a significant bottleneck in current research.

Previous studies have shown that when models are applied to different karst regions, their classification performance often declines to varying degrees. This is primarily due to significant differences in lithological composition, topographic conditions, vegetation structure, and land-use patterns across regions, making it difficult for the features learned by the models to adapt to new environmental contexts. These issues indicate that existing models still have shortcomings in terms of characterizing environmental heterogeneity, adaptive feature learning, and cross-regional generalization capabilities, which limit their widespread application in the dynamic monitoring of rock desertification.

4.3. Challenges in System Integration and Real-Time Monitoring

Space-based remote sensing technology has improved the spatiotemporal resolution and data continuity of dynamic monitoring of karst desertification in Southwest China; however, current research still faces several key challenges. First, the monitoring indicator system remains incomplete. Existing studies primarily rely on surface indicators such as vegetation cover and bedrock exposure, with insufficient attention paid to groundwater and soil loss—an erosion process unique to karst regions [42,43]. However, soil migration and water seepage in the subsurface are critical processes linking surface degradation to the evolution of the subsurface karst environment [44,45]; the lack of monitoring of these processes makes it difficult for existing studies to fully elucidate the surface–subsurface coupling mechanisms and three-dimensional evolution characteristics of stone desertification.

In the future, it will be necessary to strengthen the integrated analysis of multi-source remote sensing and subsurface observation data to establish a comprehensive monitoring indicator system that accounts for both changes in surface landscapes and responses of subsurface processes. Second, identifying the nonlinear characteristics of multi-scale succession processes remains challenging. Traditional linear trend analysis struggles to effectively capture the interannual and intra-annual fluctuations in stone desertification succession and the low resilience of ecosystems. In the future, dynamic monitoring and nonlinear analysis methods tailored to complex spatiotemporal processes should be further developed.

At the same time, there remains considerable uncertainty regarding the quantitative analysis of the mechanisms linking climate change to human activities. Further research is urgently needed on the lingering effects of extreme weather events and their interactions with land-use changes [46]. In the future, it will be necessary to rely on the coupled analysis of long-term time series, multi-source remote sensing data, and process models to improve our ability to identify and attribute these mechanisms.

4.4. Conceptual Framework for Karst Rocky Desertification Monitoring

The challenges of karst rocky desertification (KRD) monitoring extend beyond those encountered in general land degradation assessment due to the unique environmental characteristics of karst landscapes. Based on the reviewed literature, a problem-oriented conceptual framework can be established to better connect monitoring objectives with appropriate remote sensing methods and remaining research gaps (Figure 7).

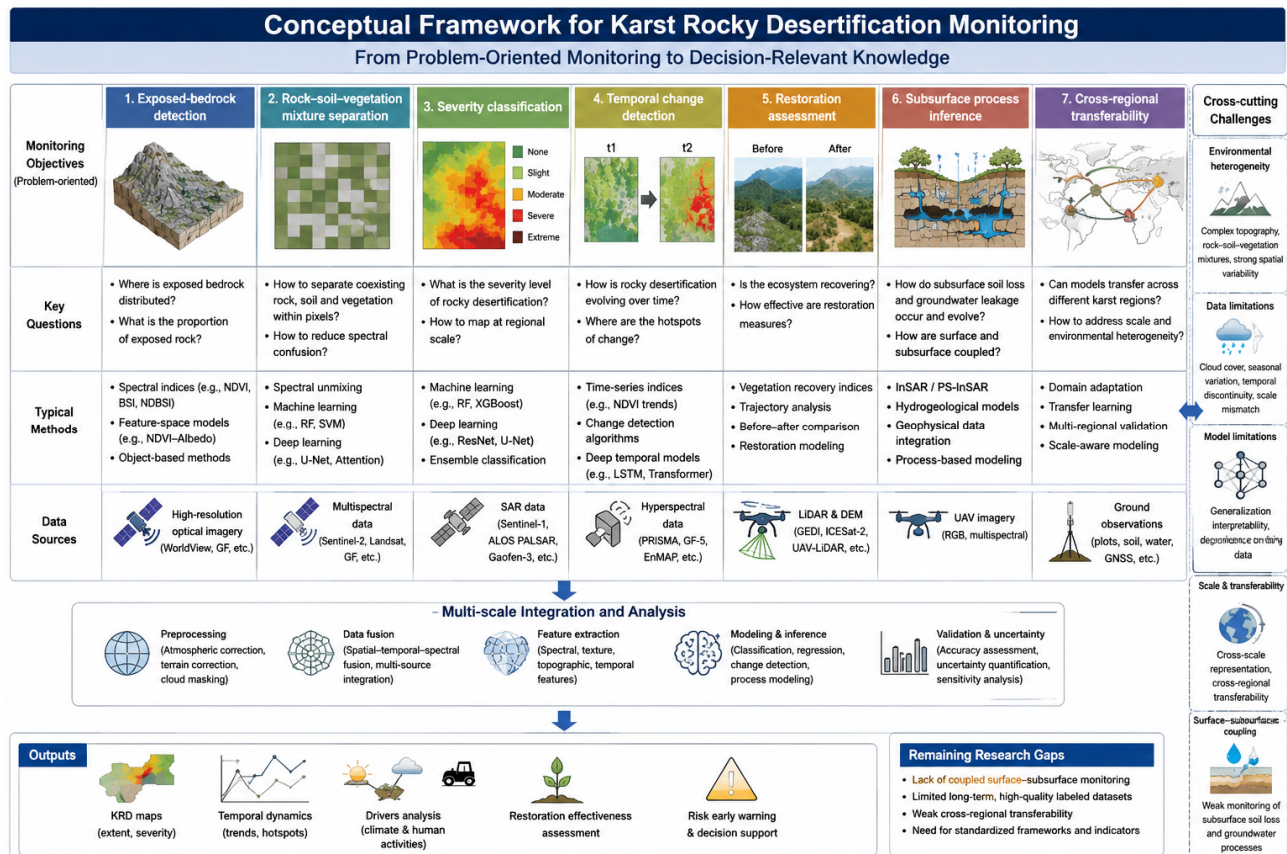


Figure 7. Conceptual framework for monitoring desertification in karst rock formations.

First, exposed-bedrock detection remains the most fundamental monitoring task. Traditional spectral indices and feature-space models are widely used because of their simplicity and physical interpretability. However, their performance is often affected by terrain shadowing and spectral confusion between bare rock, soil, and sparse vegetation.

Second, rock-soil-vegetation mixture separation represents a critical challenge in karst regions, where heterogeneous surface components frequently coexist within individual pixels. Machine learning and deep learning approaches have improved the discrimination of mixed surface features, but their robustness under varying environmental conditions remains uncertain.

Third, severity classification and temporal change detection have become major research directions. Machine learning algorithms currently provide relatively mature solutions for regional-scale classification, whereas deep learning methods offer advantages in extracting complex spatial patterns. Nevertheless, long-term monitoring is still constrained by data continuity, scale mismatch, and model transferability.

Fourth, restoration assessment and subsurface process inference remain among the least developed areas of KRD monitoring. Existing studies mainly focus on surface vegetation recovery and exposed-bedrock dynamics, while underground soil loss, groundwater leakage, and surface-subsurface interactions remain insufficiently monitored. Overall,

future KRD monitoring should move from algorithm-oriented studies toward problem-oriented frameworks that explicitly match monitoring objectives with suitable data sources and analytical methods while addressing scale effects, environmental heterogeneity, and cross-regional transferability.

5. Conclusions and Prospects

5.1. Conclusions

This review traces the development of remote sensing methods for identifying karst desertification in southwest China and analyzes key challenges and future directions. Based on a systematic review of 8665 articles from the Web of Science database, the following three main conclusions were drawn.

- (1) Regarding the maturity of the methods. The spectral index method and the object-oriented method are relatively mature and can reliably map the severity of rock desertification at the regional scale in areas with low cloud cover and gentle terrain. Machine learning methods are also relatively mature but require careful feature engineering and perform robustly when training samples are representative. In contrast, deep learning methods remain largely in the experimental stage: while they achieve higher accuracy under controlled conditions, their high demand for labeled samples, significant computational costs, and poor interpretability hinder their routine operational application.
- (2) There are still three monitoring challenges that current remote sensing technology has not effectively addressed. Subsurface processes (such as soil erosion and groundwater seepage) cannot be reliably monitored using remote sensing alone. Long-term dynamic monitoring is often interrupted by persistent cloud cover and sensor inconsistencies. The ability to transfer models across regions is also problematic, as spectral and topographic heterogeneity can lead to a significant decline in performance when models are applied outside their training areas.
- (3) To improve reproducibility and comparability, future remote sensing studies of karst desertification should adhere to minimum standards. These standards include: clearly reporting cloud masking, topographic correction, and sensor consistency processing steps during preprocessing; using independent test sets and reporting accuracy by category (rather than reporting only overall accuracy); providing uncertainty intervals for key estimates (such as the fraction of exposed bedrock); and, where feasible, sharing code and data to support cross-regional validation.

In summary, spectral index methods and machine learning approaches are now ready for operational application, while deep learning methods still require further standardization. Future efforts should prioritize the development of monitoring frameworks that are scale-aware, robust to cloud cover, and interpretable, in order to directly address challenges such as subsurface processes and cross-regional transferability. Adherence to the aforementioned minimum standards will help advance karst desertification monitoring toward greater reliability and reproducibility.

5.2. Prospects

5.2.1. Innovations in Intelligent Information Extraction Algorithms

Future research should focus on developing intelligent information extraction frameworks that better address the complex spatial heterogeneity of karst rocky desertification [47]. Hybrid deep learning architectures integrating the strengths of convolutional neural networks and Transformer models are expected to improve the representation of multi-scale spatial features and long-term temporal dynamics [48]. In addition, embedding prior ecological and geomorphological knowledge into model architectures may enhance

the interpretability and physical consistency of rocky desertification monitoring results. Given the scarcity of high-quality labeled samples in karst regions, few-shot and weakly supervised learning approaches should be further explored to improve model transferability and reduce dependence on large training datasets.

5.2.2. Multi-Source Data Synergy and the Construction of an Integrated Space–Air–Ground Monitoring System

Future studies should strengthen the integration of optical, hyperspectral, SAR, LiDAR, and ground observation data to improve the monitoring of rocky desertification processes across different spatial and temporal scales [49]. Particular attention should be given to overcoming challenges related to spatial–temporal scale transformation, heterogeneous data fusion, and cross-regional model transferability. Furthermore, establishing integrated space–air–ground monitoring frameworks will facilitate continuous observation of vegetation degradation, exposed bedrock dynamics, soil erosion, and other key indicators, thereby improving the understanding of rocky desertification evolution and supporting more reliable ecological assessment and restoration planning.

Author Contributions: Conceptualization, Y.H. and Z.Z.; methodology, Y.H.; validation, Q.T. and D.H.; formal analysis, B.L. and Y.L.; investigation, Y.H. and Y.L.; resources, Z.Z.; data curation, Y.H.; writing—original draft preparation, Y.H.; writing—review and editing, Y.H.; visualization, Q.T.; supervision, Z.Z.; project administration, Z.Z.; funding acquisition, Z.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Science and Technology Department of Guizhou Province, grant number Qian Ke He Zhong Yin Di [2025] 031 (project: Construction of a Deep-Time Digital Earth Evolution and Cloud-Computing Platform in Karst Mountainous Areas); the Guizhou Provincial Key Laboratory of Remote Sensing Big Data Intelligent Processing and Application, grant number Qian Ke He Ping Tai [2025] 014; and the National Technology Innovation Center for Karst Rocky Desertification Control and Green Development, grant number Qian Ke He Zhong Yin Di [2023] 005. The APC was funded by the Science and Technology Department of Guizhou Province, grant number Qian Ke He Zhong Yin Di [2025] 031 (project: Construction of a Deep-Time Digital Earth Evolution and Cloud-Computing Platform in Karst Mountainous Areas).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: No new data were created or analyzed in this study.

Acknowledgments: The authors sincerely thank the editorial team of Applied Sciences and the anonymous reviewers for their valuable comments and suggestions during the review process, which have significantly improved the academic quality of this paper. The authors gratefully acknowledge the financial support provided by the ‘(210-C426002) Geography Group-based Assistance Program – Provincial Subsidy Fund for Higher Education Development’.

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

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