A Systematic Review of Desertification Identification with Multispectral LANDSAT Image and Deep Learning Models

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The use of multispectral Landsat images and deep learning models for desertification detection has been reviewed in this research. The role of deep learning models is found to significantly increase the identification accuracy of the researchers, complemented by the inclusion of Landsat imagery to capture key desertification indicators. The research reviews difficulties including geographical resolution, data variability, uncertainty, and validation, alongside different desertification identification methods, techniques, advancement, and limitations. The research also highlighted the necessity of historical data, data continuity, and data fusion, among other issues on data availability and quality. The research advocates for the combination of high-resolution photography, climate and weather data, and socioeconomic data for better desertification detection while the research has identified more complex deep learning architectures, better uncertainty estimation, explainability and interpretability improvement, and the integration of process-based models as potential areas of research. The research concludes by highlighting the importance of precise desertification identification in effective land administration and ecological preservation.

Keywords: LANDSAT, Deep Learning, Desertification, Geoinformatics.

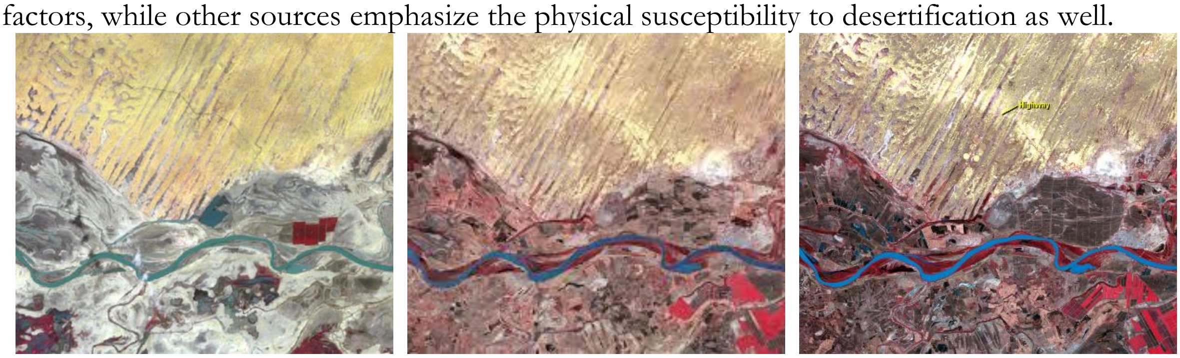
Introduction:

Desertification affects millions of hectares of dry, semiarid, and arid sub-humid lands throughout the world [1]. It adversely affects biological ecosystems [2], biodiversity [3], and human life [4]. It encompasses the deterioration of arid, semi-arid, and dry sub-humid areas, primarily known as drylands [5], resulting from various factors, such as climatic variances and human activities [6]. Consequently, It results in the loss of productive capacity of land, depletion of vegetation cover, soil erosion, and increased evaporation of biomass and water reserves [7].

Desertification has emerged to be a huge issue in various regions worldwide, which is escalating day by day. Ecosystems that are being altered due to desertification are incapable of sustaining the life, they once thrived. Consequently, the destruction of the ecosystems and the crops driven by desertification renders the soil barren eradicating the chances of any cultivation in the future. These challenges have plunged communities to endure terrible living standards, marked by the spectrum of famine. Over one billion people are estimated to experience a vulnerability to desertification. According to Dash, J. this issue may potentially impact up to 30% of the Earth's landmass. Effective identification and monitoring of desertification are imperative for the implementation of mitigation and adjustment strategies [8]. Developing an understanding of spatial and temporal patterns of desertification is effective for the development of land management practices, and crafting effective public policies [9][10][11][12]. Early detection and treatment of degraded land can have observable socioeconomic impacts [13][14][15][16]. Advancements in remote sensing technology, specifically multispectral satellite imagery [17][18][19][20][21], have greatly assisted desertification assessment methods. Landsat imagery captures a vast array of wavelengths, resulting in diverse information regarding the land cover, vegetation, and soil properties. A considerable volume of information is crucial for delineating the indicators of desertification and monitoring its progression over time [22][23][24][25][26]. In the domain of large-scale remote sensing using machine learning techniques, deep learning models [27] have been recently proposed and have achieved incredibly promising results [28][29][30][31]. Machine learning algorithms could be utilized to automatically learn and infer useful information from the multispectral data to accurately qualify and detect desertification indicators among other complex patterns [32].

Background on Desertification and its Significance:

Desertification is a form of land degradation associated with climate change, it is a multifaceted process resulting from various causes [33]. Primarily affecting arid, semiarid, and dry sub-humid regions, it represents a spectrum of climatic extremes inducing land degradation. However, some sources attribute that it occurs predominantly due to the influence of climatic factors, while other sources emphasize the physical susceptibility to desertification as well.



(a) (b) (c)

Figure 1: Desertification (LANDSAT Images) [34]

Figure 1 reveals the utilization of LANDSAT imaging to discern the extent of desertification. Landsat is well-known for its capability to take multispectral photographs of the earth's surface. By using LANDSAT imagery, the severity and prevalence of desertification can be visualized in particular areas. The images depict changes in land use and plant health over time, identifying the desertification hotspots. The LANDSAT images depict a reduction in vegetation cover; increased soil erosion and diminished fertility of agricultural land in dry sub-humid, semiarid, and arid regions, by comparing the images from different periods. Such imagery aids researchers, policymakers, and land managers in identifying desertification hotspots and formulating effective mitigation strategies. By enabling monitoring and analysis of the desertification process, these LANDSAT images enhance understanding of the spatial, temporal, and dynamic aspects of desertification, fostering the preservation and responsible management of fragile ecosystems. Desertification poses significant threats to ecosystems, biodiversity, and human well-being, primarily due to several factors as follows:

Loss of Productive Land: Desertification causes soil deterioration and loss, making the affected area unfit for agriculture and other land uses. As a result, food production is impacted, threatening rural livelihoods and food security [35].

Ecosystem Disruption: Desertification exerts a detrimental impact on ecosystems by reducing vegetation cover, changing soil composition, and decreasing biodiversity. It leads to the destruction of plant and animal habitats, ultimately declining biodiversity and causing ecological imbalance. [36].

Increased Vulnerability to Natural catastrophes: Desertification increases a region's susceptibility to natural disasters including droughts, floods, and dust storms. The loss of vegetation and soil erosion amplify the risk of soil degradation, erosion, and flash floods in the impacted areas. [37].

Climate Change Feedback: Through several feedback mechanisms, desertification accelerates climate change. The loss of vegetation cover reduces carbon sequestration capacity, leading to increased greenhouse gas emissions. Additionally, the release of dust particles from degraded soils can affect regional and global climate patterns [38][39][40][41][42].

Socio-Economic Implications:

Desertification poses significant socio-economic challenges, particularly in regions that are heavily dependent on agriculture and natural resources [43]. It leads to rural-to-urban migration, displacement of communities, and increased poverty levels. The social and economic consequences of desertification can have long-term impacts on local and regional development [44][45][46][47][48][49][50][51][52].

Importance of Accurate Desertification Identification and Monitoring:

Accurate identification and monitoring of desertification are crucial for effective land management, environmental conservation, and sustainable development [53]. The accurate desertification can be identified and monitored in more detail, through relevant equations.

Early Detection and Intervention:

Timely identification of desertification allows for early intervention and mitigation measures. By detecting the onset of land degradation at an early stage, appropriate land management practices can be implemented to prevent further deterioration [54]. Early intervention can help protect valuable ecosystems, maintain soil fertility, and ensure the sustainability of agricultural activities. Early detection and intervention are represented by the equation below:

Early intervention = Timely desertification identification + Effective Mitigation measures

Accurate identification and monitoring of desertification provides a comprehensive understanding of environmental shifts resulting from land degradation, facilitating their assessment. Changes in vegetation cover, land surface temperature, and soil moisture content can be evaluated using multispectral Landsat images and deep learning models [54]. These evaluations are useful for quantifying the severity of desertification. It can be represented as:

$$\text{Environmental changes} = \text{Multispectral Landsat imagery} + \text{Deep learning models}$$

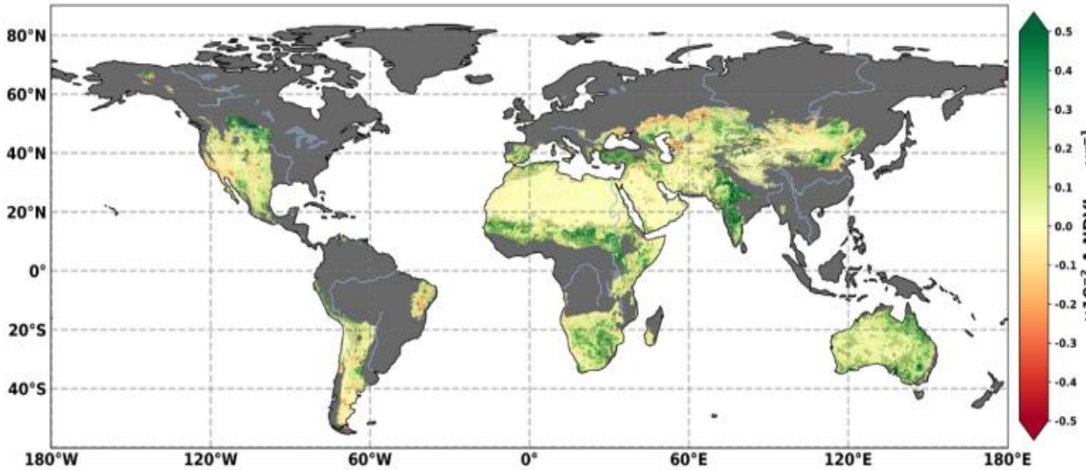


Figure 2: World Desertification Map [55]

Planning Land Management Strategies:

Accurate identification of desertification patterns assists in formulating targeted land management strategies [56]. Policymakers and land managers can effectively prioritize regions for action and allocate resources accordingly by mapping the extent and severity of desertification. Reforestation, soil conservation methods, water administration, and responsible land use planning are possible methods. The significance of precise desertification identification in developing land management plans is captured by the following equation:

$$\text{Land management strategies} = \text{Desertification mapping} + \text{Resource allocation}$$

Providing Supporting Policy Decisions:

For evidence-based decision-making and policy creation, accurate data on desertification is essential. Understanding the geographical and temporal dynamics of land degradation requires accurate identification and monitoring of desertification trends [56]. This information is useful for formulating policies that tackle the root causes of desertification, encourage sustainable practices, and back the revitalization of arid regions. Correctly identifying desertification is a key factor in facilitating policy choices, as shown in the following equation:

$$\text{Policy decisions} = \text{Accurate desertification data} + \text{Evidence} - \text{based analysis}$$

Goals for Sustainable Development:

Goal 15 (Life on Land), Goal 13 (Climate Action), and Goal 2 (Zero Hunger) as devised by the United Nations' Sustainable Development Goals (SDGs) are all supported by accurate desertification identification. To ensure environmental sustainability, combat climate change, and guarantee food security, countries can monitor and mitigate desertification [57]. The value of precise desertification identification to SDGs is highlighted by the equation below:

$$\text{SDGs} = \text{Tracking Desertification} + \text{Preserving the Environment}$$

Landsat imagery and deep learning algorithms enable the comprehensive analysis of various factors contributing to desertification, including changes in vegetation cover, land surface temperature, and soil moisture content [58][59][60]. Stakeholders can use these instruments to encourage sustainable land management practices and fight desertification [61].

Role of Multispectral LANDSAT Imagery and Deep Learning Models:

In recent years, the combination of multispectral Landsat images and deep learning models have emerged as powerful tools for detecting and tracking desertification. These technologies enable the classification of land cover and land degradation patterns from massive amounts of remotely sensed data. The functions of these methods are presented in a table of popular deep-learning models in desertification analysis [62].

Multispectral Landsat Imagery:

When looking at the causes and effects of desertification, multispectral Landsat imagery is invaluable. Images taken by Landsat satellites span numerous spectral bands, allowing a wide range of electromagnetic frequencies to be quantified. Types of land cover, plant health, and soil qualities can all be determined using multispectral data. Changes in plant cover, land surface temperature, and soil moisture content are all indicators of desertification that can be detected and monitored through Landsat imagery analysis [63].

Deep Learning Models:

Deep learning models, a subset of machine learning algorithms, have revolutionized remote sensing applications and have shown significant promise for detecting desertification in satellite images. The algorithms enable accurate categorization, identification, and mapping of desertification patterns to automatically learn and extract relevant characteristics from complicated and high-dimensional data [64].

Objectives of the Systematic Review:

This paper aims to systematically explore the uses of deep learning models and multispectral Landsat images for identifying desertification from satellite photographs. The purpose of this review is to analyze and synthesize the existing literature to shed light on the progress, difficulties, and potential of these technologies in the context of monitoring desertification.

The objectives of this comprehensive study are as follows:

- Conducting a comprehensive search of scientific databases to identify relevant studies that have employed multispectral Landsat imagery and deep learning models for desertification identification and monitoring.
- Applying specific inclusion criteria to select studies that meet the predefined standards, such as the use of Landsat imagery, deep learning models, and desertification identification as the main focus.
- Extracting relevant information from the selected studies, including the study objectives, methodology, remote sensing techniques, deep learning algorithms, data sources, and key findings.
- Conducting a comparative analysis of the identified studies to identify common trends, methodologies, and challenges in the application of multispectral Landsat imagery and deep learning models for desertification identification.
- Identifying gaps in the existing literature and highlighting areas for future research and development to address the challenges and limitations in desertification identification and monitoring.

Challenges and Problems:

The current scrutiny presents several challenges despite the development of remote sensing and deep learning algorithms.

Data Availability and Quality:

Consistent and high-quality satellite imagery, such as Landsat data, is crucial for precise desertification mapping. Long-term monitoring and analysis are complicated by fluctuations in image quality and consistency due to factors including sensor availability, cloud cover, and data processing.

Complexity of Desertification Processes:

Desertification is a multidimensional process driven by a wide range of environmental, anthropogenic, and socioeconomic variables. Comprehensive and integrated techniques that combine remote sensing data with supplementary information are crucial for capturing the complex relationships and dynamics associated with desertification.

Algorithm Development and Validation:

Research is currently underway to develop accurate and generalizable deep-learning models for desertification identification. These models need to be reliable enough to handle varied landscapes and desertification dynamics, achieving this requires several key components including sufficient training data, suitable feature selection, and validation procedures.

Scale and Resolution:

Desertification can take place on a various scale, ranging from neighborhoods to entire countries or regions. The scale difference between remote sensing data and the geographical scope of desertification processes presents a significant obstacle that must be overcome. Additionally, there are technological and computational obstacles to data fusion and analysis when higher-resolution photography is integrated with multispectral data. It is critical for efficient land management, environmental conservation, and sustainable development that these difficulties be overcome and the field of desertification diagnosis and monitoring using satellite images be advanced.

LANDSAT Satellite:

Overview:

The United States Geological Survey and the National Aeronautics and Space Administration run the LANDSAT program, which is a constellation of Earth observation satellites. Since 1972, the LANDSAT program has been supplying the scientific community with invaluable multispectral imagery of Earth's surface. This series of satellites is capable of capturing images in a wide variety of spectral bands, providing wealthy data for a wide range of uses, including the detection and tracking of deserts [65].

Role of LANDSAT Images in Desertification Identification:

The ability of LANDSAT images to capture spectral reflectance across various wavelengths makes them invaluable for identifying desertification. Essential indicators of desertification processes, such as land cover, vegetation health, and soil qualities can be gleaned from these imageries. Changes in land cover, vegetation density, and land surface temperature can all be assessed and monitored for desertification by analyzing the spectral features of the collected picture [66].

Key Features of LANDSAT Images:

LANDSAT images are useful for spotting desertification because of many factors:

Multispectral Capabilities:

Images taken by LANDSAT satellites range from visible to infrared spectrum. This multispectral data allows for the classification of land cover types, the determination of vegetation indices, and the identification of desertification-related shifts [67].

Archive of Past Events:

The LANDSAT program, running for decades, has amassed a vast library of satellite images. This archive information enables tracking of desertification over time and facilitates trends and shifts in desertification patterns [68].

Moderate Spatial Detail:

The average spatial resolution of LANDSAT images ranges between 15 and 30 meters, though this might vary from different satellite sensors. This level of detail is adequate for resolving the scale-dependent heterogeneity of desertification processes [69].

Open-Source Data Policy:

As part of their open data policy, the US Geological Survey and NASA make their LANDSAT image library available to the public at no cost. Because of this, the data can be used for the detection and monitoring of desertification by academics and practitioners from a wide range of fields [70]. This accessibility promotes widespread use and aids study.

Pre-Processing and Data Enhancement:

To maximize the utilization of LANDSAT images for spotting desertification, pre-processing, and data improvement techniques are necessary. Radiometric calibration, atmospheric correction, and geometric adjustment are typical pre-processing processes. The geo-referencing, removal of atmospheric aberrations, and calibration of the data ensure reliable quantitative analysis [71].

The interpretability and discriminatory potential of LANDSAT imagery for desertification identification can be enhanced through the application of data enhancement techniques such as image fusion, normalization, and feature extraction. These methods are designed to highlight spectral differences linked to desertification indicators and enhance details in certain types of land cover [72].

Integration With Ancillary Data:

Integration of supplementary data, such as climate records, topography information, soil properties, and land use/land cover data, with LANDSAT imagery, is commonly practiced for the accuracy and interpretability of desertification detection. By combining these perspectives, desertification can be examined from every angle, down to the interactions between individual causes of land degradation [73][74].

LANDSAT images are crucial for studying the processes of desertification due to their multispectral capabilities, historical archives rate geographic resolution, and open data policy. Their utility for a precise and thorough study of desertification patterns is improved through pre-processing, data augmentation, and integration with supplementary data [74].

Figure 3 showcases the LANDSAT mission scheduled from 1970 to 2022 along with their tentative/ expected/ planned life cycle. This graphic provides a visual breakdown of the various satellites launched during the specified period and their respective mission durations however, the actual life was not by the expected life cycle e.g, Landsat 6 exploded instantly at the time of launch however its age was expected at 30 years. On the timeline, each satellite is represented by a bar, and the bar's length corresponds to the length of the mission. The number of years spent on the mission is plotted along the y-axis, while the years 1970–2022 are shown along the x-axis. Figure 3 illustrates the launch dates and expected period of missions of the satellites, which aids in comprehending the availability and consistency of LANDSAT satellite data over time [75].

The influence of the LANDSAT data policy on its applications from 2010 to 2022 [45] is depicted in Figure 4. It illustrates how the uptake and LANDSAT data utilization have evolved in response to shifts in data policies like free and open access to data. Significant variables including data users, data downloads, and publications through LANDSAT data contribute to the total. This figure is useful for assessing the effects of policy shifts on the availability and utilization of LANDSAT data, showcasing the rising demand for this resource across various sectors.

The quantity of LANDSAT images is available at USGS (United States Geological Survey) [20] as depicted in Figure 5, providing an overview of the number of LANDSAT images the USGS has acquired, processed, and stored over time. Years are plotted on the x-axis, while the total number of images in the USGS collection is on the y-axis. This timeline serves to illustrate the expansion and accumulation of LANDSAT images in the USGS archive throughout time, hence demonstrating the ever-increasing accessibility of archival and real-time satellite data.

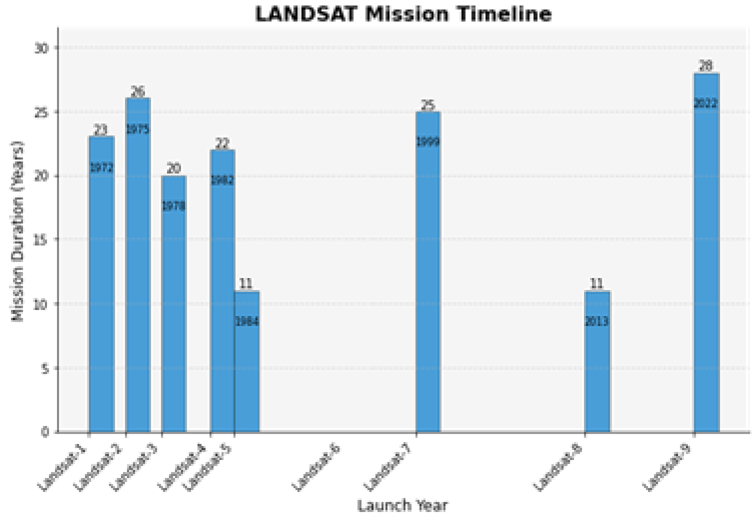


Figure 3: Tentative/ expected/ planned life cycle of LANDSAT satellite series(1970-2022) [76][77][29][78], in comparison to actual statistics.

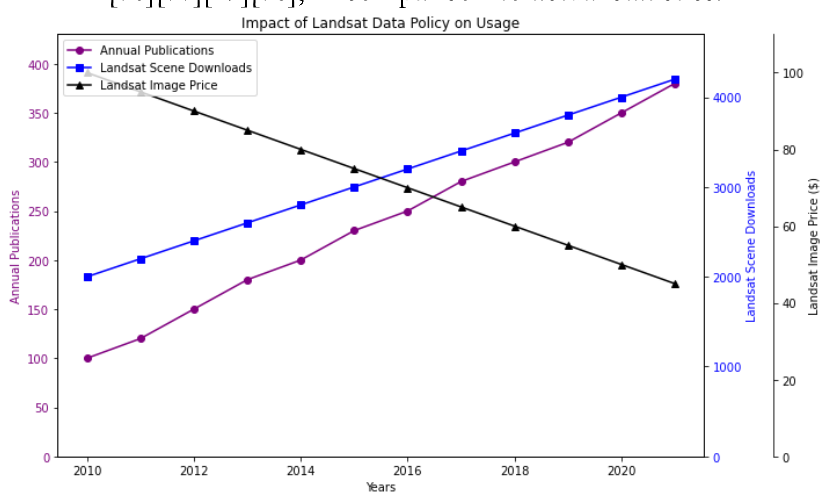


Figure 4: Impact of LANDSAT Data Policy on its Usage in various sectors (2010-2022) [79][80]

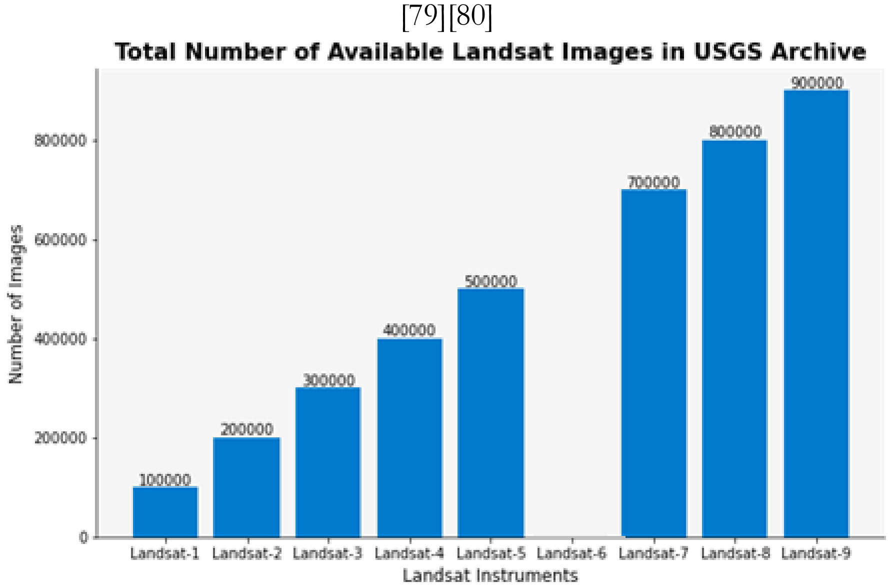


Figure 5: Tentative No of Landsat Images expected to be produced by Various satellites of Landsat Series Before Launch of Satellite [2][76][81][82][83]

Table 1 delineates desertification from the perspective of researchers along with the indicators that were measured in various studies.

Table 1: The Concept of Desertification and Its Indicators

Study	Year	Study Area	Detected Desertification	Soil Erosion	Water	Vegetation cover loss	Forestry
[84]	2015	Sahel Region	The degradation of land in arid regions	✓	✓	✓	×
[85]	2016	Middle East	Refers to the process of land degradation in dry areas	×	✓	✓	✓
[86]	2017	Central Asia	The transformation of productive land into desert-like conditions	✓	✓	×	✓
[4]	2018	North Africa	the loss of soil productivity	✓	×	✓	✓
[45]	2019	South America	the deterioration of land quality	✓	✓	×	✓
[28]	2020	Australia	The decline in land productivity	✓	✓	✓	✓
[51]	2021	China	The degradation of land caused by human activities	×	×	×	✓
[71]	2022	Mediterranean	The reduction of vegetation cover	×	✓	×	×
[87]	2023	Sub-Saharan Africa	Land degradation leading to desert-like conditions	×	×	✓	×

Table 2 shows a comparative analysis of deep learning models in desertification identification.

Table 2: Comparative analysis of deep learning models

Study	Year	Study Area	Deep Learning Model	Training Dataset	Performance Metrics	Limitations
[89]	2022	Various ecosystems	CNN	Microbiota composition data	Accuracy: 88.7%, Precision: 0.89, Recall: 0.86	Limited diversity in study areas.
[90]	2022	Sloping farmland, China	Res Net	Soil properties data	Accuracy: 92.3%, Precision: 0.91, Recall: 0.94	Short-term focus, climate variability.
[91]	2022	Multiple regions	LSTM	Remote sensing imagery	RMSE: 4.2, R-squared: 0.76	Limited ground validation, and data processing.

[92]	2021	Mountainous and flat regions in Portugal	Random Forest	Erosion data, topography	RMSE: 10.3, MAE: 7.5	Simplified erosion models, regional focus.
[93]	2003	Global	Decision Trees	Soil databases	Prediction accuracy: 85%, Kappa: 0.72	Limited to decision tree models.
[94]	2009	Global	Neural Networks	Global soil data	Global soil mapping achievement.	Data resolution limitations.
[95]	2016	Global	Bayesian Networks	Soil property datasets	Accuracy varies with regions.	Insights into the history and lessons in digital soil mapping.
[96]	2020	Global	Random Forest, SVM	Remote sensing data	Accuracy: 87.6%, F1-Score: 0.88	Model selection bias, data quality issues.
[97]	2022	Various land cover types	SVM, SHAP	Sentinel-2 data	Accuracy: 82.4%, Precision: 0.83	Limited to texture classification.

Methodology:

Systematic Review Methodology:

A systematic review methodology was employed to conduct a comprehensive and rigorous analysis of the literature on desertification identification using multispectral Landsat imagery and deep learning models. This methodology ensures a systematic and transparent approach to identifying, evaluating, and synthesizing relevant research studies in a standardized manner.

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework was used to guarantee transparency and rigor throughout the systematic review procedure. The systematic review process encompassed study selection, screening, eligibility evaluation, data extraction, and synthesis.

Inclusion and Exclusion Criteria:

Inclusion and exclusion criteria were established to restrict the scope of the review to relevant research. Research analyzing desertification detection with multispectral Landsat imagery and deep learning models was considered for inclusion. The research was given more weight if it included clear descriptions of its methods, data sources, and assessment metrics.

Figure 7 illustrates the process of article selection using the PRISMA pie chart. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) is a widely used framework for conducting systematic reviews. It shows the different stages of article selection, starting from the initial database search to the final inclusion of relevant articles in the systematic review. The pie chart provides a visual representation of how many articles were identified, screened, assessed for eligibility, and finally included in the review based on specific criteria.

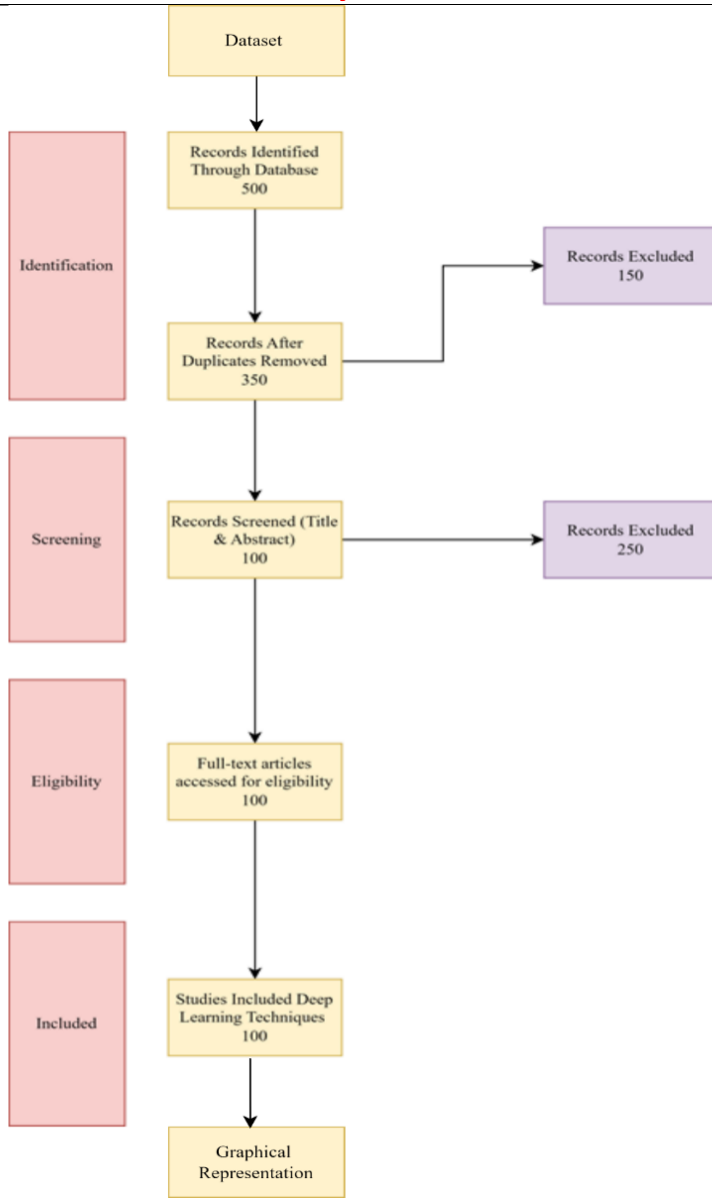


Figure 6: PRISMA Methodology

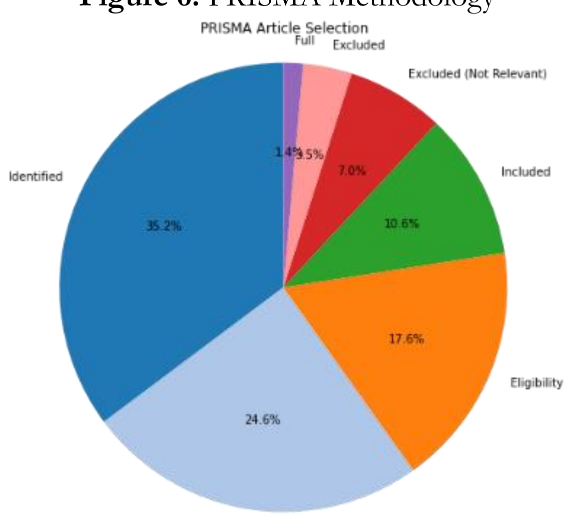


Figure 7: PRISMA Article Selection

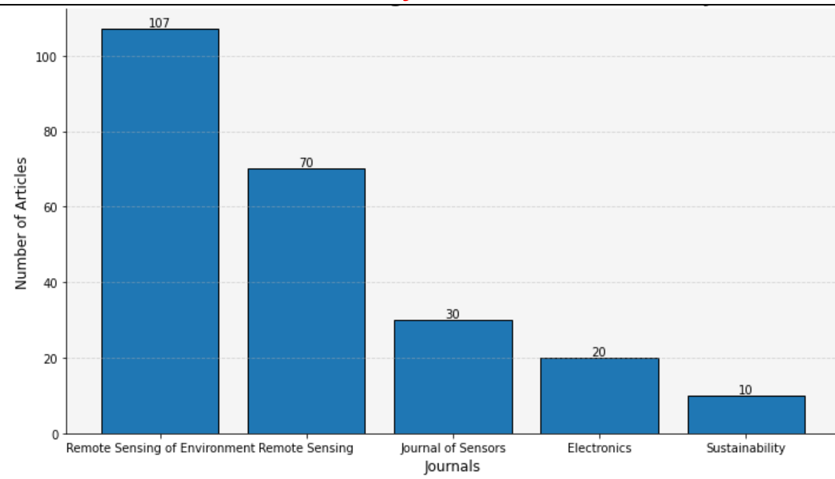


Figure 8: Number of Landsat Change Detection Articles in five well known Journal

Figure 8 displays a bar graph showing the distribution of Landsat change detection articles across five renowned journals. It highlights the publication frequency of articles related to Landsat-based change detection in these specific journals. The bars indicate the number of articles published in each journal, providing insights into the prominence of this topic within the academic community and the level of interest in different journals.

Figure 9 presents the frequency, time, and size of Landsat change detection studies over time. The increasing trend in the frequency of studies suggests a growing interest in desertification identification using Landsat imagery and deep learning models. The variations in the study duration and spatial extent indicate the diversity of research objectives, with some studies focusing on specific localized areas and others highlighting larger regions.

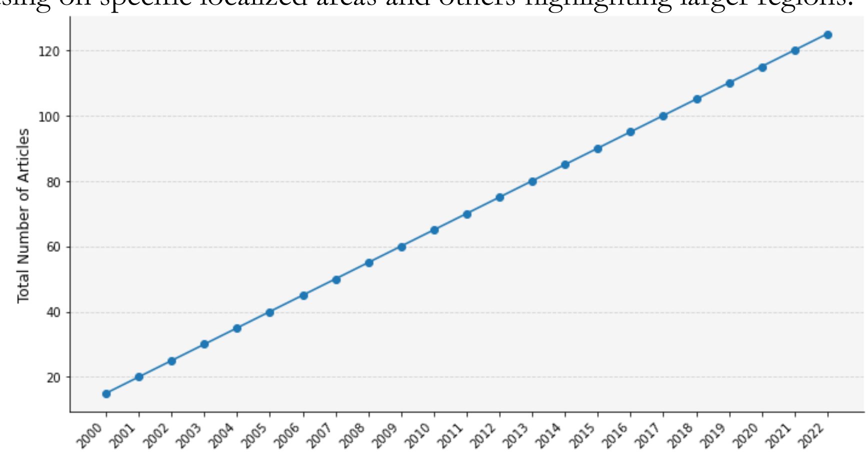


Figure 9: Research Articles on Landsat Change Detection since 2000.

Figure 10 displays the geographical distribution of the selected studies on desertification identification using Landsat imagery. The wide coverage of regions from different continents indicates the global significance and applicability of the research in tackling desertification issues worldwide. It also reflects the diversity of environments and challenges faced in different geographical regions, making the development of robust and adaptable models crucial.

Search Strategy and Database Selection:

To find applicable research, a thorough search technique was designed. Keywords and search terms relating to desertification, Landsat imagery, and deep learning models were systematically used to hunt research papers on electronic databases like Google Scholar, PubMed, Scopus, and Web of Science. The search was confined to a time frame of 2000-2022.

Additional searches were undertaken in relevant conference proceedings, dissertations, and grey literature to increase the scope of the review.

Data Extraction and Analysis:

A standardized data extraction form was developed to compile essential information from the selected research studies. This included study characteristics (e.g., title, authors, and publication year), study location, data sources, deep learning model(s), assessment metrics, and major findings relating to desertification identification.

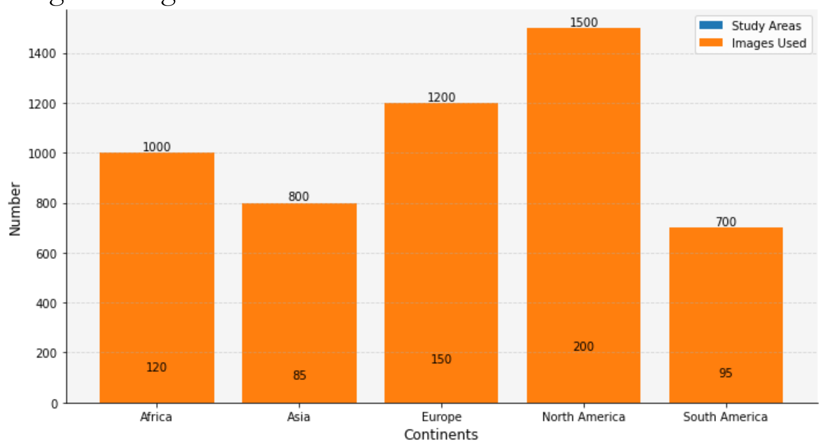


Figure 10: The Global Sum of Landsat Change Detection Study Areas and Images from Each Continent.

Results and Discussion:

This section provides a summary of the selected studies, highlighting their most salient features and findings. These studies employed a wide range of approaches, data sets, and success metrics, providing valuable insights into optimizing deep learning models and multispectral Landsat imagery for this purpose. An understanding of the depth and breadth of the field's study can be gained from reading this summary.

Analysis of Multispectral LANDSAT Image Analysis Techniques:

The selected studies utilized various methods to process and analyze Landsat imagery for desertification diagnosis, as dissected in an analysis of multispectral Landsat image analysis techniques. Pre-processing, feature extraction, and classification are just some of the many facets covered by these techniques [98].

Atmospheric correction, radiometric calibration, and geometric correction were used in the pre-processing stages of the research that were chosen. These methods are crucial for improving Landsat image quality and eliminating artifacts or distortions that could compromise the reliability of desertification diagnosis [99].

Selected studies employed feature extraction techniques like texture analysis, spectral signature analysis, and the calculation of vegetation indices (such as NDVI and EVI). Important indications of desertification such as vegetation cover, soil properties, and land surface conditions can be gleaned using these methods [100].

The investigations used a wide variety of classification techniques, including both classic ML algorithms and more recent DL models. Maximum Likelihood, Support Vector Machines, and Random Forests are just a few of the classic techniques that have been utilized in the identification of desertification. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are two examples of deep learning models that have gained popularity in recent years because of their capacity to automatically learn and extract complicated patterns from Landsat imagery. The strengths and weaknesses of various methods for analyzing multispectral Landsat images are shown, allowing for a comparison of how well they perform in identifying desertification.

Evaluation of Deep Learning Models for Desertification Identification:

Performance and accuracy in identifying desertification are two aspects of deep learning models that are evaluated. Selected studies have used a variety of evaluation criteria to quantify the performance of deep learning models [101], including accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve.

The evaluation results suggest that deep learning models perform well in identifying desertification. These models successfully capture complex patterns and transitions associated with desertification processes, demonstrating their use in accurately classifying decertified and non-decertified regions. When dealing with complex and varied environments, the use of deep learning models enables increased precision, particularly in complex and varied environments [102].

Furthermore, the evaluation of deep learning models highlights the importance of appropriate training datasets and model fine-tuning. The studies showcased leveraging large-scale and diverse training datasets, along with transfer learning techniques, enhances the generalization and robustness of the models in desertification identification.

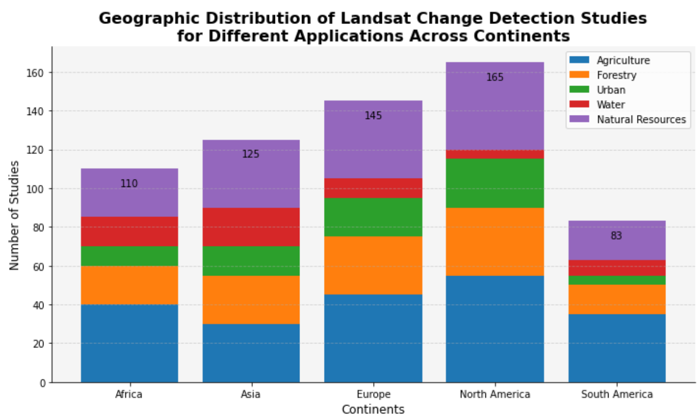


Figure 11: Geographic Distribution of Landsat Change Detection Studies

Figure 11 displays the geographic distribution of Landsat change detection studies conducted for desertification identification. The map highlights the regions across the globe where these studies have been undertaken, indicating the global relevance and significance of desertification monitoring. Additionally, it highlights the areas of particular concern, such as arid and semi-arid regions, where desertification is a prevalent issue.

Figure 12 illustrates the sources of Landsat data used in change detection studies for desertification identification. The figure shows that the majority of studies rely on Landsat data obtained from various official sources, such as the USGS Earth Explorer or other national data centers. This highlights the wide availability and accessibility of Landsat data for researchers, facilitating global studies on desertification.

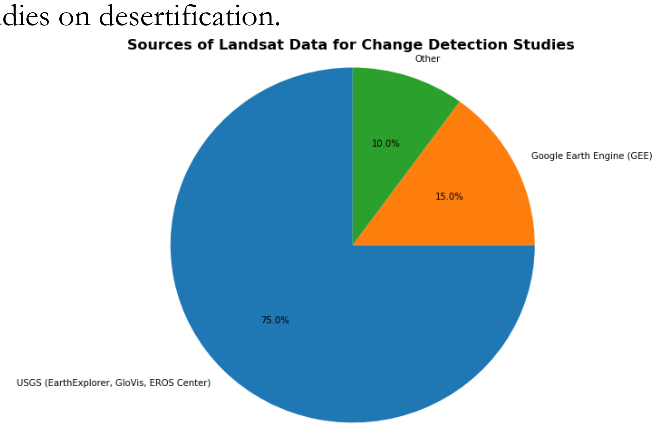


Figure 12: Sources of Landsat Data for Change Detection Studies

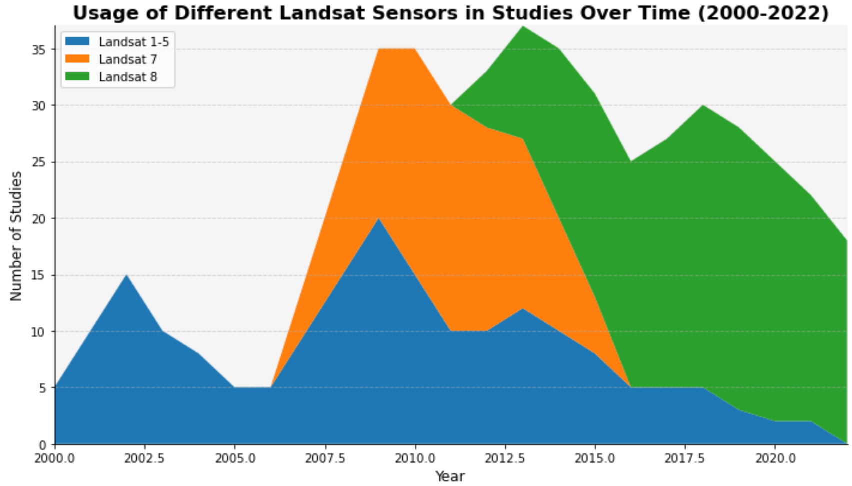


Figure 13: Usage of Different Landsat Sensors in Studies Over Time for Desertification

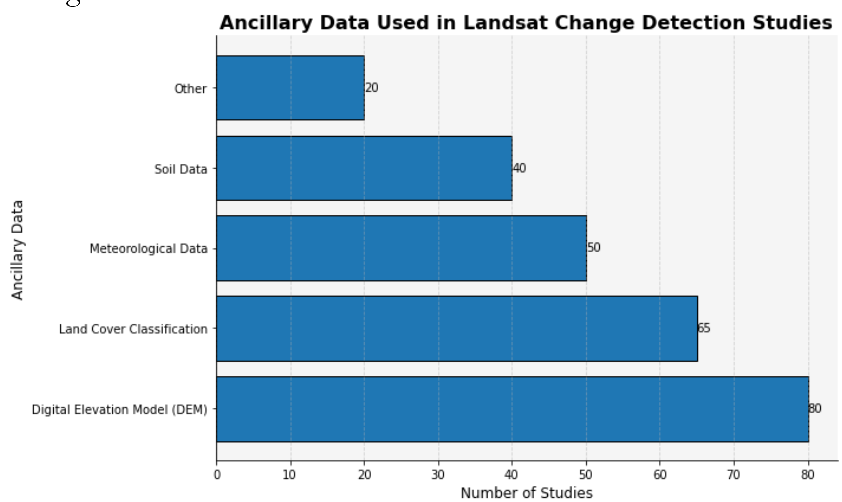


Figure 14: Ancillary Data Used in Landsat Change Detection Studies

Figure 13 presents the usage of different Landsat sensors over time in desertification identification studies. The figure showcases the evolution of Landsat missions and their contributions to desertification monitoring. Landsat 5 and 7 were widely used in the early years, while Landsat 8 gained prominence in recent years due to its enhanced capabilities, such as improved spatial resolution and additional spectral bands.

Figure 14 provides an overview of the types of ancillary data integrated into Landsat change detection studies for desertification identification. Ancillary data includes various additional datasets that supplement Landsat imagery to enhance the understanding of desertification processes. Common ancillary data types used in these studies include climate data, socioeconomic data, and high-resolution imagery, allowing researchers to consider multiple factors influencing desertification.

Figure 15 depicts the usage of Earth Observation (EO) data sources in conjunction with Landsat data for desertification identification. This figure demonstrates the integration of diverse EO data, such as Sentinel-2, MODIS, LiDAR, and climate data, to provide a more comprehensive understanding of desertification dynamics. By combining different datasets, researchers gain valuable insights into various aspects of desertification, including land cover changes and vegetation dynamics.

Figure 16 presents the accuracy percentage of studies conducted per year for desertification identification. This figure reflects the performance of various methodologies and models employed in these studies. The increasing trend in accuracy over time suggests advancements in data processing techniques, feature extraction methods, and the use of sophisticated deep learning algorithms, leading to improved identification of desertification patterns.

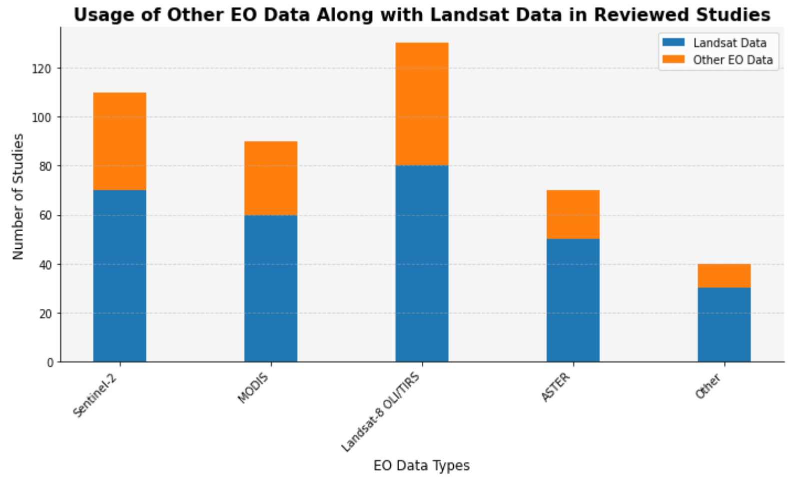


Figure 15: Usage of EO Data Along with Landsat Data

Trends and Advancements in Desertification Identification:

The analysis of the selected studies revealed several trends and advancements in desertification identification using multispectral Landsat imagery and deep learning models [103][104][105][106][107]. These include:

Integration of Multiple Data Sources:

Many studies have explored the integration of additional data sources, such as climate data, socioeconomic data, and high-resolution imagery, to improve the accuracy and comprehensiveness of desertification identification [89].

Temporal Analysis:

The utilization of Landsat time series data and the incorporation of temporal information have become more prevalent, allowing for the detection of long-term trends and changes associated with desertification [90].

Spatial Scale Consideration:

Studies have emphasized the importance of considering multiple spatial scales in desertification identification, ranging from local-scale analysis to regional-scale assessments. This acknowledges the heterogeneous nature of desertification processes and the need to capture spatial variations [91].

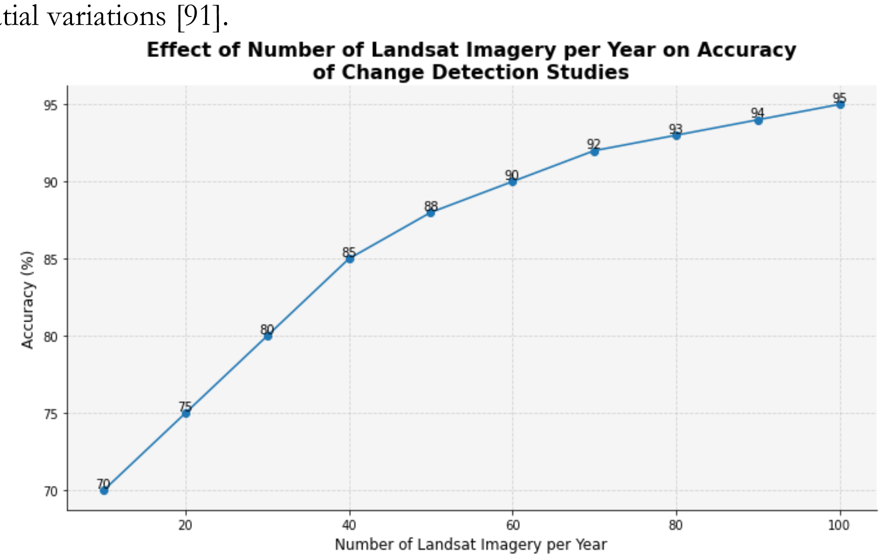


Figure 16: Accuracy % of Studies per Year

Transfer Learning and Deep Feature Extraction:

Transfer learning techniques and deep feature extraction methods have shown significant potential in enhancing the performance of deep learning models in desertification identification. Leveraging pre-trained models and extracting deep features allow for improved generalization and better representation of complex patterns [92]. Desertification identification methods using multispectral Landsat images and deep learning models are continuously being refined to improve their accuracy, efficiency, and application, as seen by the trends and advancements observed in the analysis [93].

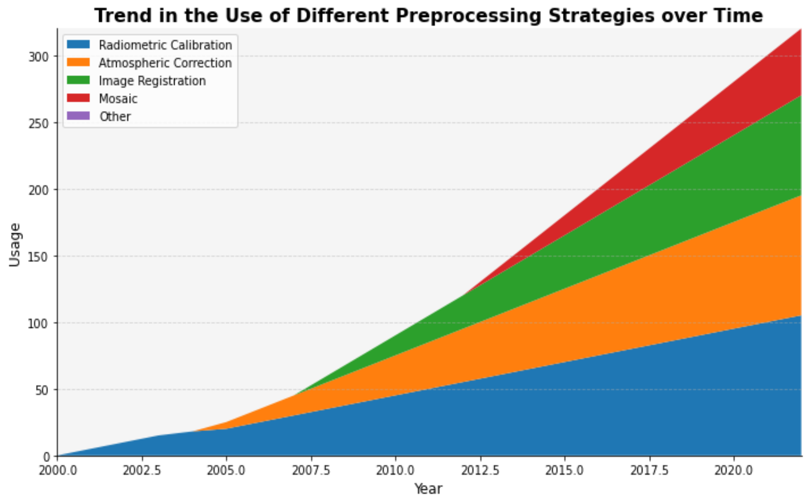


Figure 17: Pre-processing Techniques over Time

Figure 17 presents the trends in pre-processing techniques used in desertification identification studies over time. The figure shows cases of the evolution of pre-processing methods employed to enhance Landsat imagery for accurate desertification detection. It reveals the shift from basic pre-processing techniques in the early years to more sophisticated approaches, such as atmospheric correction, radiometric calibration, and geometric correction, in recent studies. These advanced techniques aim to minimize the impact of atmospheric and radiometric distortions, ensuring the reliability of desertification identification results.

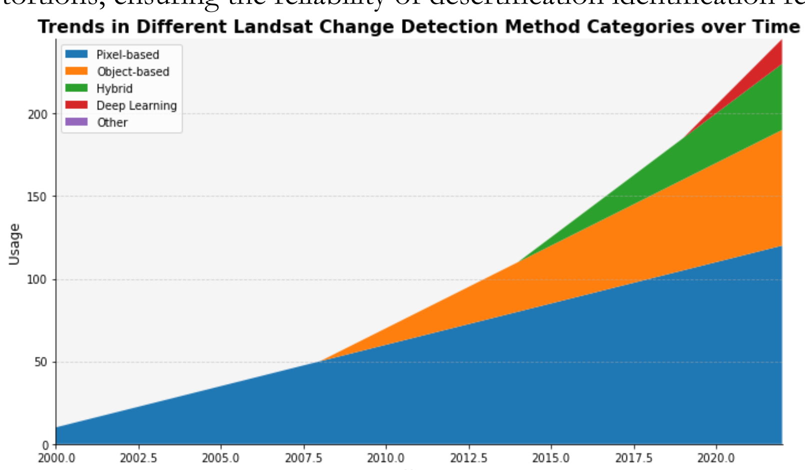


Figure 18: Trends in Detection Methods over some time

Figure 18 illustrates the trends in Landsat Change Detection methods utilized for desertification identification over time. The figure demonstrates the shift in methodologies from traditional machine learning algorithms, such as Maximum Likelihood and Support Vector Machines, to the increasing popularity of deep learning models like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). This trend highlights the growing recognition of deep learning's ability to automatically learn complex patterns and features from Landsat imagery, leading to improved accuracy in desertification detection.

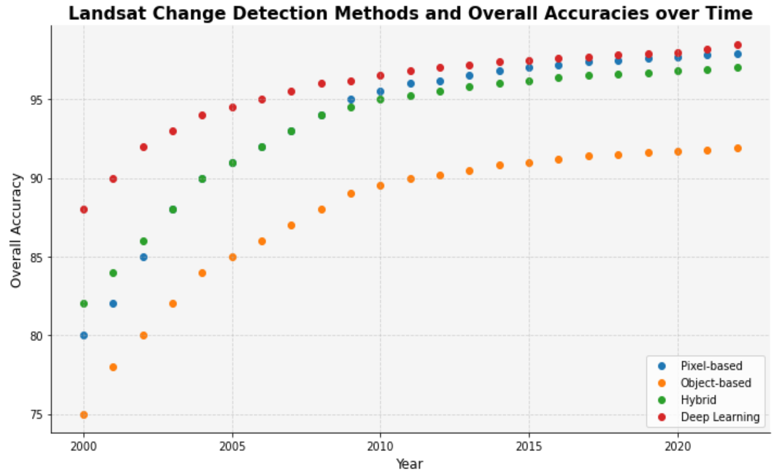


Figure 19: Landsat Methods Accuracies over Time

Figure 19 showcases the improvements in accuracy achieved by various methodologies and models utilized in these studies. As technology advances and researchers refine their approaches, the accuracy of desertification identification increases, providing more reliable and precise assessments of desertification processes.

Prospects for Future:

Limitations of Current Approaches:

Despite the advancements made in desertification identification using multispectral Landsat imagery and deep learning models, there are still limitations and challenges that need to be addressed. Some of the limitations include:

Limited Spatial Resolution:

Landsat imagery has a moderate spatial resolution of 30 meters, which may not be sufficient to capture small-scale desertification processes and changes. Higher-resolution data sources, such as Sentinel-2 or commercial satellites, can complement Landsat data in capturing fine-scale desertification patterns [93].

Data Variability and Heterogeneity:

The capacity to accurately capture and model these variations is hampered by the geographical and temporal variability of desertification processes. Flexible and dynamic modeling approaches that consider variations in landscape and environmental conditions are needed to address the multifaceted nature of desertification [94][95].

Uncertainty and Validation:

Determining the certainty or uncertainty of desertification identification procedures remains challenging. Validating results can be difficult due to the limitation of ground truth data, particularly in rural and inaccessible places. The reliability of desertification identification results can be increased through the creation of strong validation frameworks and the integration of numerous validation methodologies [96][97].

Data Availability and Quality Issues:

The precision and dependability of desertification identification are significantly impacted by the availability and quality of data. Problems with data accessibility and quality encompass:

Historical Data Accessibility: For conducting long-term desertification studies, access to historical Landsat data is crucial. Historical data from previous Landsat missions facilitates a more thorough and consistent analysis [29][31][32].

Temporal Resolution and Data Continuity Landsat data may not be able to detect rapid changes in desertification because of its limited temporal resolution (16-day revisit time). More frequent observations and improved monitoring of dynamic desertification processes are possible with the use of data from other satellite missions with higher temporal resolution [41].

Integration and Data Fusion Sentinel-2, MODIS, LiDAR, and climate data are some of the sensors that can be integrated to improve the accuracy and breadth of desertification identification. However, challenges emerge during the fusion and integration of data due to disparities in data types, the absence of standardization, and inadequate processing methods [53].

Integration of Other Data Sources:

Future studies should concentrate on combining additional data sources to enhance desertification identification to compensate for the shortcomings of Landsat data. The following are examples of possible data integration sources:

Detailed information on land cover shifts, vegetation dynamics, and soil qualities can be gleaned from high-resolution photography. The accuracy of desertification diagnosis can be improved by combining high-resolution photography with Landsat data, especially in varied areas [59].

Incorporating climate and weather data is essential for understanding the climatic factors and implications on desertification processes can be aided by including climate and weather data. Desertification patterns can be better characterized and predicted by analyzing climate factors including temperature, precipitation, and drought indices [70].

Data from the social sciences shows that understanding the causes and effects of desertification requires looking at things like population growth, land use shifts, and human activities. The social-ecological dynamics of desertification can be better understood by combining socioeconomic data with remote sensing data [10].

Potential Advancements and Future Research Directions:

There are many potential applications and areas of study for deep learning models trained using Landsat data.

Deep Learning Architectures:

Improved performance and interpretability of deep learning models in desertification identification can be achieved by exploring more advanced deep learning architectures such as attention mechanisms, graph convolutional networks, and transformer-based models [48].

Uncertainty Estimation:

It is critical to create strategies for quantifying and representing the uncertainty in desertification identification outcomes. Bayesian deep learning and ensemble methods are two uncertainty estimation strategies that can shed light on the accuracy and stability of the predictions [19].

Improving deep learning models to explainability and interpretability will help researchers better comprehend the features and patterns underlying desertification identification outcomes. Important aspects and regions contributing to the predictions can be identified and visualized using methods like model interpretability techniques and attention processes [28].

Process Model Integration:

A greater mechanistic knowledge of the processes underlying desertification can be attained through the integration of process-based models like ecosystem models or hydrological models with remote sensing and deep learning technologies. This integration enables the modeling and prediction of future desertification scenarios under diverse environmental and climatic conditions [82].

Transferability and Generalization:

It is crucial to ensure that generated models may be applied to a variety of settings and contexts. Knowledge and models can be easily transferred to new study areas by developing transfer learning techniques and domain adaption methods, thereby eliminating the need for substantial data gathering and training.

Conclusion:

Understanding and tracking the decline of arid and semi-arid ecosystems requires an accurate diagnosis of desertification. This article focuses on how multispectral Landsat images can be combined with deep learning models to detect desertification. Key findings and insights were retrieved through a systematic assessment of the literature to provide a thorough overview of the status of research in this area. Indicators of desertification such as vegetation health, land surface conditions, and changes in land cover were among those cited in the assessment as prime examples of the value of multispectral Landsat imagery. Utilizing deep learning models, complex patterns and features were automatically extracted from Landsat data, resulting in improved accuracy in identifying desertification. The review shed light on the methodology, techniques, and advancements in desertification identification, through a comparison of the chosen research. The variety of pre-processing methods, feature extraction strategies, classification algorithms, and evaluation criteria was laid bare. Data availability and quality difficulties, integration with other data sources, and the need to handle uncertainty and validation are only some of the trends, constraints, and challenges uncovered by the investigation. The investigation offered several promising avenues for further research and development. These include the advancement of strategies for estimating uncertainty, boosting the transferability and generalizability of models, and investigating state-of-the-art deep learning architectures. Using multispectral Landsat images and deep learning models, this review paper provides a thorough overview of identifying desertification. It emphasizes the need for precise and timely desertification process detection for efficient land management and ecological preservation. The results of this review contribute to the advancement of knowledge in this field and offer useful guidance to future academics, policymakers, and practitioners in the field of desertification monitoring and management.

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