

Analyzing recent trends in deep-learning approaches: a review on urban environmental hazards and disaster studies for monitoring, management, and mitigation toward sustainability

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Abstract

Deep learning has changed the approach of urban environmental risk assessment and management. These methods enable solid models for large data sets, enabling early identification, prediction, and description of environmental risks. The current work analyses the advances in deep learning for urban environmental hazard assessments and disaster studies to provide monitoring, management, and mitigation measures. It reports the improvement in self-supervised learning, transformer architectures, persistent learning, attention mechanisms, adversarial robustness, associated learning, meta-learning, and multimodal learning within the domain of urban environmental hazard analysis. These approaches allow the creation of robust models for handling vast data volumes, facilitating early detection, prediction, and characterisation of diverse environmental threats. This trends analysis for urban applications will bring insights for connecting deep-learning models for effective and proactive approaches to tackle urban environmental hazards and disasters.

Keywords

Deep learning, environment, deep neural network, remote sensing, and geospatial big data analytics

1. Introduction

The rapid expansion of urbanization has intensified the insistence on effective strategies to monitor, manage, and mitigate urban environmental hazards and disasters for sustainability. Deep-learning approaches have emerged as promising tools offering sophisticated solutions to these challenges (Hou et al. 2021; Xiangdong et al. 2021). Assessing recent developments, methodologies, and applications aims to provide a comprehensive overview of how deep-learning techniques are reshaping the landscape of urban resilience. A detailed complete analysis and the synthesis of significant research reveal the potential

contributions of deep learning toward sustainable urban development (Makropoulos et al. 1999). This work enlightens researchers, policymakers, and practitioners about the growing role of deep learning in improving the understanding, response, and management of urban environmental hazards and disasters, for fostering more resilient and sustainable cities.

Urban environments are complex and dynamic and these are characterized by quick changes in land cover, population density, and infrastructure. Monitoring and understanding these variations is pivotal for effective urban planning, resource management, and environmental sustainability (Almeida and Cabral 2024; Lei et al. 2018; Nutkiewicz et al. 2018;

Wijayarathne et al. 2023). Remote-sensing datasets, such as aerial imagery, satellite imagery, and LiDAR data provide valuable information for urban environmental studies (Gibson et al. 2018; Nolan and Lang 2015; Wang et al. 2021). However, the analysis of such datasets poses significant challenges due to their high spatial resolution, data heterogeneity, and the intricate nature of urban features (Deshpande et al. 2019; Ding et al. 2024; Du et al. 2022; Yao et al., 2019). In recent years, deep learning has emerged as a powerful approach for extracting valuable insights from remote-sensing datasets. Deep-learning techniques, based on artificial neural networks, have demonstrated remarkable capabilities in pattern recognition, feature extraction, and predictive modelling (Donnelly et al., 2018; Ma et al. 2021; Rao et al. 2021). These techniques have the potential to overcome the limitations of traditional approaches and unlock new possibilities for urban environmental applications.

The strong environmental concerns along with the spectacular growth of big data have incited the establishment of deep-learning techniques in multiple earth science applications (Dibs et al. 2023; Ren et al. 2019; Zhu et al. 2019). Studies have been carried out to explain the working of these advanced techniques in environmental remote sensing are used to resolve huge environmental challenges. Deep-learning approaches have huge potential in the domain of remote sensing. It is possible to tackle large-scale outstanding challenges with the help of inherent models. Machines have improved processing capabilities when compared to humans (Ajayakumar et al. 2021; Kuhlemann et al. 2020). When compared to current trends in deep learning, deep neural networks help in constructing layers and extracting key characteristics of data (Jain et al. 2021). The best experts are sometimes unable to decide as to which set of transformations best fits the problem. Even though controversial opinions exist in the remote sensing community, but deep learning approach has emerged as a powerful tool to tackle unprecedented large-scale challenges.

Understanding the various types of remote-sensing datasets used in urban environmental studies is crucial for comprehending the applications of deep learning in this context. Aerial imagery provides high-resolution visual data, allowing detailed analysis of land cover and land-use patterns. Satellite imagery offers broader coverage and multispectral information, enabling large-scale monitoring of urban dynamics. LiDAR data, which capture 3D point clouds, facilitate accurate terrain modelling and object detection (Bassuk et al. 2015; Dibs et al. 2023; Han et al. 2020; Qiang et al. 2021). This work emphasizes the concepts, tools,

and methods of deep learning along with its development history. Also, we focus on deep-learning models and technologies, elaborating on the current research status and also its applications in remote sensing (Mellander 2023; Motwake et al. 2024; Onifade et al. 2023). This analyzes the recent trends in deep-learning approaches to urban environmental studies, with a specific focus on the utilization of remote-sensing datasets. The scrutiny of the state of the art in this rapidly evolving field provides a complete overview of the advancements, challenges, and future directions in employing deep learning techniques to address urban environmental issues. The challenges in urban environmental monitoring necessitate innovative solutions that can effectively handle the massive volume of remote-sensing data and extract meaningful information. Deep-learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have demonstrated exceptional capabilities in capturing complex spatial and temporal patterns (Aung and Aung 2019; Khryashchev et al. 2019; Thorp and Drajat 2021; Yang et al. 2024; Zhang et al. 2019). These models can learn hierarchical representations directly from raw input data, eliminating the need for extensive feature engineering. The rich information obtained is embedded within remote-sensing data sets, and deep-learning approaches to facilitate accurate and efficient analysis of urban environmental characteristics (Liu and Weng 2012; Wichansky et al. 2006; Zhang and Fu 2020). The integration of these diverse datasets through deep-learning techniques enables a comprehensive understanding of urban environmental processes (Dacic et al. 2020; Dibs et al. 2023; Lathrop and Hasse 2006; Meerow 2020; Wichansky et al. 2006). Urban environmental hazards involve complete monitoring, effective management, and proactive mitigation strategies and some key aspects of studying, monitoring, managing, and mitigating includes:

(a) **Hazard identification and monitoring:**

- *Data-driven analysis:* Utilize remote sensing, geographic information system (GIS), and Internet of Things (IoT) devices to gather data on various urban hazards such as air and water quality, heat islands, pollution levels, etc. (Klimetzek et al. 2021; Zhang et al. 2021).
- *Early warning systems:* Develop systems that detect and forecast hazards like floods, heat-waves, or pollution spikes, enabling timely alerts to authorities and residents (Doblas et al. 2020; Mutanga and Kumar 2019; Nazarova et al. 2020).

(b) **Risk assessment and analysis:**

- *Vulnerability mapping*: Assess the vulnerability of urban areas to different hazards and identify high-risk zones based on socio-economic, environmental, and infrastructural factors (Das and Pal 2017; Patino and Duque 2013; Prakash et al. 2016).
- *Scenario planning*: Use predictive models and simulations to understand the potential outcomes of various hazard scenarios and their impacts on the urban environment (Alhamwi et al. 2019; Cao et al. 2022).

(c) **Management and preparedness:**

- *Infrastructure resilience*: Strengthen infrastructure to withstand or mitigate the effects of hazards, such as building flood barriers, improving drainage systems, or implementing green spaces to reduce heat islands (Bixler et al. 2019; Vercruysse et al. 2019).
- *Community engagement and education*: Educate residents about risks, preparedness measures, and evacuation plans to increase community resilience and response capabilities (van Manen 2014; Yang et al. 2021).

(d) **Mitigation and response:**

- *Policy implementation*: Enforce regulations and policies that minimize environmental hazards, such as emission controls, waste management, and green building standards (Liu and Song 2024; Subroto and Christianis 2021).
- *Emergency response planning*: Develop and rehearse comprehensive plans for effective responses to disasters, ensuring coordination among emergency services and authorities (Behera et al. 2021; Laborte et al. 2020; Rahman et al. 2021).

(e) **Technology and innovation:**

- *AI and machine learning*: Use AI-powered systems to analyze vast amounts of data for early detection of hazards, dynamic risk assessment, and optimization of response strategies (Chiloane et al. 2021; Dai and Boroomand 2022; Khan et al. 2022; Rajesh and Sairam 2019).
- *Smart infrastructure*: Implement smart city technologies for real-time monitoring and management of urban hazards, integrating data from various sources to make informed decisions (Singh et al. 2020; Sun and Xia 2023).

(f) **Collaboration and global initiatives:**

- *International cooperation*: Collaborate with global organizations and other cities to share

best practices, technologies, and lessons learned in managing urban environmental hazards (Goniewicz et al. 2019; Huang et al. 2020).

- *Research and development*: Invest in research to innovate new technologies and methodologies for better hazard management and mitigation (Adeline et al. 2020; Ala-Juusela et al. 2016; Soares Ito et al. 2021).

Addressing urban environmental hazards requires a multifaceted approach involving technological innovation, community engagement, policy implementation, and continuous research to ensure cities become more sustainable and resilient (Aung and Aung 2019; Qu et al. 2021; Xie et al. 2024). Deep learning has continued to evolve in various domains to make significant steps like as:

(a) *Self-Supervised Learning*: These methods leverage unlabeled data to pre-train models, enabling them to learn representations without requiring explicit annotations to be beneficial in scenarios with limited labelled data.

(b) *Transformer Architectures*: Transformer-based models like generative pre-trained transformer (GPT), bidirectional encoder representations from transformers (BERT), and their variations have gained immense popularity. They have demonstrated remarkable performance across tasks like natural language processing, achieving state-of-the-art results in tasks like language generation, translation, and understanding.

(c) *Continual Learning and Lifelong Learning*: There is an increasing focus on enabling models to continuously learn from new data without forgetting previously learned information. Continual learning techniques address this issue to adapt to new tasks while retaining knowledge from past experiences.

(f) *Federated Learning*: This approach allows training models across decentralized devices while keeping data localized, thus preserving privacy. It is gaining traction in applications where data privacy is crucial, such as healthcare and IoT.

(g) *Meta-Learning*: Meta-learning aims to enable models to learn how to learn, acquire new skills or adapt quickly to new tasks with limited data. This area holds promise in improving the generalization capabilities of models.

(h) *Multimodal Learning*: Combining information from various modalities like text, images, and audio has gained attention. Models capable of

understanding and generating content across multiple modalities have shown great potential in tasks like image captioning, video understanding, and more.

These trends jointly replicate the ongoing efforts to enhance the capabilities, efficiency, and robustness of deep-learning models across diverse application domains (Dai and Boroomand 2022; Liu and Jin 2021). The work offers an overview of the key challenges in urban environmental monitoring explores deep-learning techniques to address these challenges and proposes state-of-the-art deep-learning models for urban environmental applications with their advantages and limitations. It highlights the various types of remote-sensing datasets employed with their specific applications in urban environmental studies. The integration of deep-learning techniques with remote-sensing data holds immense potential to enhance our understanding of urban environments and contribute to sustainable urban development. It identifies the research gaps and future directions to foster the development of deep learning applications. It will provide researchers, practitioners, and policy-makers with valuable insights into the recent trends, challenges, and future directions of deep-learning approaches in urban environmental applications using remote-sensing datasets.

1.1 Deep-learning approaches for remote sensing

Deep learning transforms remote sensing by enhancing image analysis, classification, and pattern recognition. These approaches allow accurate land cover mapping, object detection, and change detection. Deep learning optimizes feature extraction from satellite data, enabling precise environmental monitoring, disaster prediction, and urban development analysis (Loukanov et al. 2020). Remote sensing engages satellites, aircraft, or platforms to gather targeted data. Traditional image processing involves restoration, enhancement, segmentation, transformation, fusion, and feature extraction. Integrating advanced deep-learning techniques into remote sensing enables advanced operations. Machine learning and classifier ensembles, combined with image and data fusion, garner increasing interest (Goldblatt et al. 2018; Jian et al. 2020).

The amalgamation of deep-learning methods with remote-sensing data has facilitated an extensive array of applications. The advantages of deep-learning techniques for remote sensing include the ability to

learn hierarchical representations for the automatic extraction of meaningful features directly from raw data, reducing the need for labour-intensive feature engineering. Deep-learning models exhibit robustness against noise, distortions, and variations in data quality, which are prevalent in remote-sensing datasets. The scalability of deep learning enables the analysis of large-scale datasets, facilitating the monitoring and assessment of extensive regions. Deep-learning techniques can handle the temporal aspect of remote-sensing data, capturing spatiotemporal patterns and facilitating the analysis of dynamic environmental processes.

It will take multidisciplinary teams of researchers in machine learning, environmental domain specialists, and remote sensing to overcome these obstacles and push deep learning for remote sensing forward.

1.2 Deep-learning Approaches for environmental sustainability

Deep-learning approaches have developed as powerful tools for urban environmental sustainability to offer innovative explanations across various fronts. These methods leverage vast amounts of data and complex algorithms to address critical urban environmental challenges, paving the way for smarter, more efficient approaches to sustainability (Brink et al. 2016; Miller 2008). Deep learning plays a crucial role in interpreting satellite imagery and remote-sensing data for urban environmental monitoring and analysis. It enables the automated detection of desertification, land use changes, and habitat degradation for timely intervention and conservation.

These methods empower the assessment of air and water quality by processing sensor data and images for pollution monitoring and early detection of environmental hazards. Climate modelling and prediction significantly benefit from the processing capability of extensive historical data. These models enhance our understanding of climate change patterns for the prediction of extreme weather events and their potential impacts on communities and ecosystems. Deep learning contributes to proactive measures in disaster preparedness and mitigation strategies through more accurate forecasts. Deep-learning methods are used by renewable energy sources to maximise renewable energy efficiency and to optimise the performance of solar panels, wind turbines, and other renewable infrastructure. Recent advancements have proven the techniques of deep learning to be very successful since they can surpass human capability and also solve highly computational

tasks (Alzubaidi et al. 2021; Tereshchuk et al. 2021). However, there are some restrictions on using deep learning and these are explained below:

- (a) Requirement of large training datasets.
- (b) Few of the mathematical calculations and algorithms are complex for a layperson to understand.
- (c) Selecting the ideal architecture and training it optimally are still uncertain and unverified.
- (d) Adapting deep-learning models in remote sensing sometimes becomes challenging.

Deep-learning approaches serve as catalysts in the pursuit of environmental sustainability, offering transformative solutions that enable data-driven decision-making, resource optimization, and proactive measures to safeguard our planet for future generations. There is still a need for deep learning techniques in remote sensing problem management, despite the abundance of data and computing capabilities.

1.3 Deep-learning approaches for urban environmental hazards and disaster studies

Deep-learning methods are revolutionizing the study and management of urban environmental hazards and disasters (Wang et al. 2021). These approaches leverage sophisticated algorithms to analyze vast datasets, offering invaluable insights and solutions to mitigate risks and enhance resilience in urban settings (Bayulken et al. 2021; Biswas et al. 2020). Deep learning enables the early detection of environmental hazards like floods, heatwaves, pollution spikes, and seismic activities. Models trained on historical data can forecast potential disasters, providing valuable time for preparedness and response. These methods facilitate precise risk assessment by analyzing diverse data sources, including satellite imagery, sensor data, and social media feeds. They monitor changes in urban landscapes, detecting vulnerabilities and patterns associated with environmental risks (Barbieri et al. 2020; Ptak-Wojciechowska et al. 2021). By processing real-time data, deep learning aids in optimizing emergency-response strategies. Models can assess damage extent, identify affected areas, and prioritize rescue and recovery operations, contributing to more efficient and targeted assistance. Deep learning assists in designing and reinforcing urban infrastructure to withstand hazards. These methodologies facilitate the development of robust structures, enhanced drainage systems, and adaptable urban

designs by examining structural vulnerabilities and simulating disaster scenarios (Ekici et al. 2021; Powell et al. 2018).

Policymakers can make well-informed decisions with the assistance of deep learning models. They provide comprehensive insights into potential risks and aid in developing strategies that prioritize public safety and environmental preservation (Lacerda et al. 2021; Ranagalage et al. 2019). A significant benefit of deep learning models is their ability for ongoing learning and adaptation. This capability plays a critical role in urban environments which are undergoing constant transition, and it enables continuous improvement as well as updates for risk assessment and disaster response systems..

The increasing rate of urbanisation and the increased severity of environmental hazards underscore the criticality of incorporating deep-learning methodologies in the disciplines of disaster studies and environmental hazard management (Benzougagh et al. 2021). These methodologies provide a proactive and evidence-based strategy for reducing risks, improving readiness, and ultimately aiding in the development of urban environments that are more sustainable and resilient.

1.4 Monitoring, management, and mitigation towards urban environmental sustainability

Urban landscapes are intricate, marked by ever-evolving spatial complexities and numerous environmental elements. Managing these dynamic environmental dynamics within cities is pivotal for adept urban planning, fostering sustainable growth, and ensuring the inhabitant's welfare (Børve 1988; Krentowski et al. 2019). Remote sensing gathers expansive, high-detail data across vast urban expanses and stands as a crucial asset in studying urban environments. However, analyzing and interpreting remote-sensing data in urban contexts pose formidable hurdles owing to the multifaceted complexity and diverse nature of urban characteristics. Monitoring, managing, and mitigating urban environmental sustainability concerns are paramount for fostering liveable, resilient cities (De Luca et al. 2021). Effective monitoring involves comprehensive data collection through various means like satellite imagery, sensors, and IoT devices. Tracking air and water quality, land-use changes, biodiversity, and energy consumption provide crucial insights. Remote-sensing technologies aid in identifying pollution hotspots, understanding climate patterns, and observing urban development. Real-time monitoring

enables swift responses to emerging issues. Urban environmental management necessitates proactive strategies. Green infrastructure initiatives, such as green spaces, permeable pavements, and rooftop gardens, mitigate heat islands and enhance air quality (Kurlovich et al. 2021; Roy et al. 2021). Waste-management practices, like recycling programs and efficient disposal systems, minimize environmental impact. Implementing smart transportation systems reduces congestion and emissions. Effective zoning laws and urban planning promote sustainable development, optimizing land use and resource allocation (Čuček et al. 2012). Mitigating environmental challenges demands a proactive stance. Encouraging community involvement and education fosters sustainable practices, promoting behavioral changes that benefit the environment. Collaboration among governments, city planners, environmental experts, and communities is crucial. Leveraging technology, including Artificial Intelligence (AI), IoT, and remote sensing, augments monitoring capabilities, aiding in predictive analyses and timely interventions (Firouzi et al. 2021). Achieving urban environmental sustainability requires a holistic approach, balancing economic development with ecological conservation. Continuous monitoring, adaptive management strategies, and forward-thinking mitigation efforts are pivotal in creating harmonious, sustainable urban environments, ensuring the well-being of present and future city dwellers while preserving the planet.

1.5 Urban environmental sustainability and deep-learning approaches

Urban environmental sustainability epitomizes the harmonious coexistence of urban development and ecological preservation, fostering resilient, livable cities for present and future generations. Achieving sustainability in urban landscapes necessitates a holistic approach encompassing diverse facets. Efficient resource utilization lies at the core of urban sustainability (Bayulken et al. 2021; Ferrante and Villani 2021). Integrating green spaces, urban forests, and green roofs into city planning mitigates urban heat islands, enhances air quality, and promotes biodiversity (Bartesaghi Koc et al. 2018; Tian et al. 2018). This integration not only beautifies cities but also contributes to climate resilience and ecosystem health.

Implementing effective waste-management strategies, including recycling programs, waste-to-energy initiatives, and circular economy principles, minimizes landfill burden and fosters a more sustainable waste disposal system. Community involvement in urban

planning ensures inclusive decision-making for sustainable development. Building resilient urban infrastructure capable of withstanding environmental hazards like floods, storms, and heat waves is crucial. Designing infrastructure considering climate change projections ensures long-term sustainability and adaptability (Mahanta and Rajput 2019). A suitable environment for sustainable development can be created by the implementation of strong environmental laws, the provision of incentives for sustainable activities, and the incorporation of sustainability standards into frameworks for urban governance (AZMI et al. 2021).

Maintaining healthy urban ecosystems requires juggling three competing priorities: economic development, social justice, and environmental protection. Embracing innovative technologies, fostering community collaboration, and instituting proactive policies can pave the way for resilient, livable cities that thrive in harmony with nature.

An in-depth analysis of the complex relationship between deep learning, urban environmental hazards, and sustainability provides valuable insights and guidance for researchers, policymakers, and practitioners who aim to utilize technology to improve urban environments and communities.

2. Methods and methodology

Validation is an essential stage in the deep-learning process to evaluate the effectiveness of the trained model. The accuracy, precision, or additional relevant metrics of the framework are assessed through a distinct validation or test dataset, contingent upon the specific task at hand. This assessment offers valuable insights regarding the model's capacity for generalization and its performance when applied to unfamiliar data. Regular evaluation facilitates the refinement of the model, the identification of the most effective design, and the optimization of hyperparameters to enhance its overall performance.

Deep-learning models are often considered black boxes due to their complex and nonlinear nature. However, understanding the model's decision-making process and interpreting its predictions are critical for building trust and identifying potential biases or errors. The iterative process of training, evaluation, and refinement allows deep-learning models to continuously improve their performance and adapt to changing environments. The deep-learning process applications in various domains, including computer vision, natural language processing, healthcare, finance, and robotics. Figure 1 presents the



Figure 1: Methodology for analysis through deep-learning approach.

methodological flowchart for visualizing the research workflow and explaining the deep-learning approach.

2.1 Traditional machine-learning methods for remote sensing

Several researchers described machine learning approaches for remote sensing by grouping traditional and recent techniques. These approaches involve the use of various processes relying on statistical and mathematical principles to analyze and interpret the data. Deep-learning approaches have gained prominence in recent years but traditional machine-learning methods continue to be relevant and effective in many remote-sensing applications (Figure 2). The maximum likelihood and K-means clustering are used for remote-sensing imagery as machine-learning approaches. Some modern techniques, including artificial neural networks, genetic algorithms, and support vector machines (SVM) are taken into consideration for analysis as machine-learning methodologies.

One of the primary traditional machine-learning methods used in remote sensing is supervised classification. Supervised classification involves training a model using labeled training data, where each sample is associated with a known class or category. The model learns the statistical relationships between the input features (e.g., spectral bands, texture measures, topographic attributes) and the corresponding classes. Common algorithms used for supervised classification in remote sensing include decision trees, random forests, SVM, and naive Bayes classifiers.

These methods have proven effective in tasks such as land cover classification, land-use mapping, and urban feature extraction. Another traditional machine-learning method applied in remote sensing is unsupervised classification. Unsupervised

classification aims to identify patterns and groupings in the data without prior knowledge of class labels. Clustering algorithms, such as k-means clustering, hierarchical clustering, and self-organizing maps (SOMs), are commonly used for unsupervised classification in remote sensing. These methods are particularly useful for identifying land cover classes or detecting anomalies in the data without the need for labeled training samples.

Traditional machine-learning approaches are utilized not just for classification but also for regression tasks in remote sensing. Regression models predict continuous variables or estimate quantitative values based on input features. For example, models can be developed to predict environmental parameters such as vegetation indices, surface temperature, or pollutant concentrations using remote-sensing data. Linear regression, multiple regression, and support vector regression (SVR) are some of the commonly used algorithms for regression tasks in remote sensing.

Traditional machine-learning approaches for remote sensing also involve feature selection and dimensionality reduction approach. Feature selection identifies the most relevant and informative features from the remote-sensing data, reducing the dimensionality and improving model performance. Methods such as principal component analysis (PCA), linear discriminant analysis (LDA), and feature importance rankings are commonly used for feature selection in remote-sensing applications. Random forests and gradient boosting machines (GBM) are popular ensemble methods used in remote sensing, offering improved generalization and robustness compared to individual models.

While traditional machine-learning methods have proven effective in remote-sensing applications, they do have limitations. These methods often require

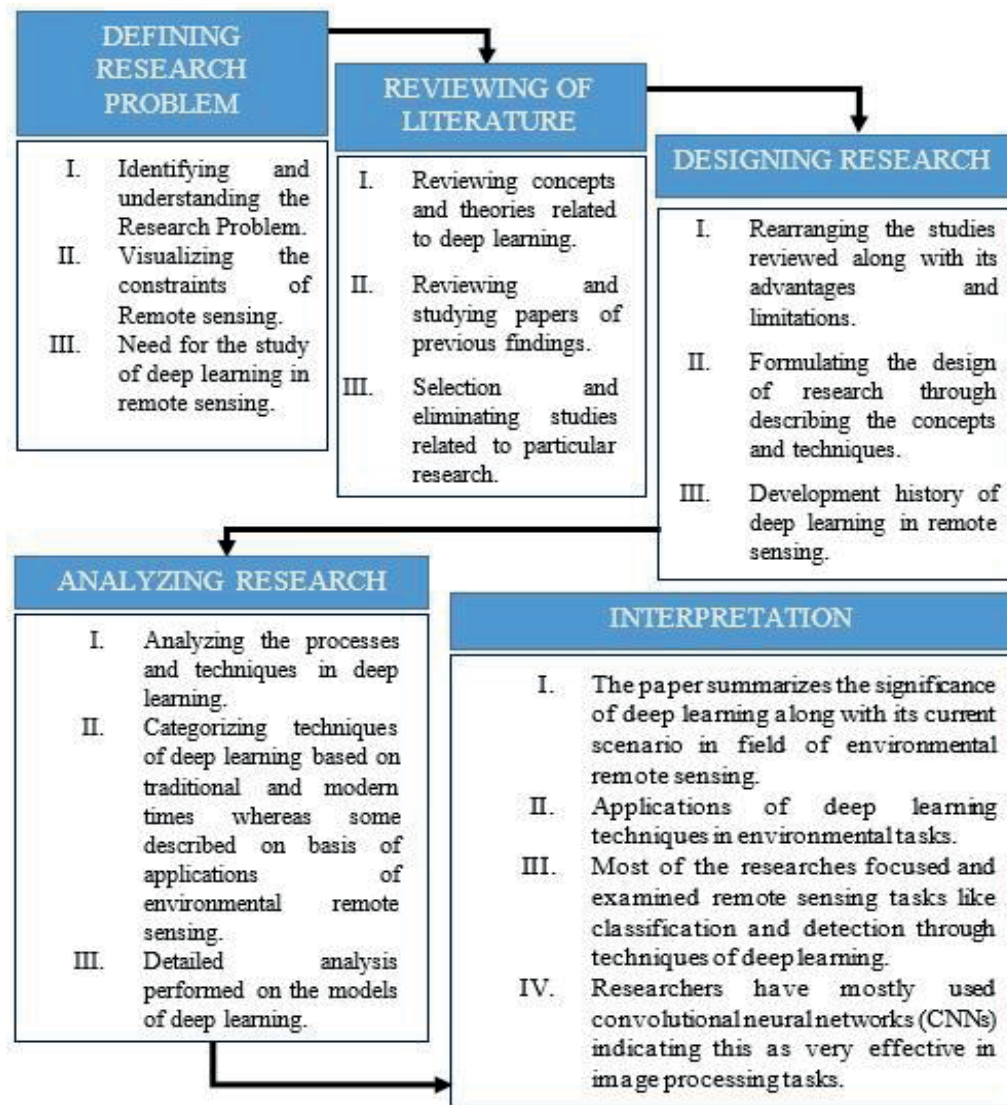


Figure 2: Methodology for augmenting deep-learning approach in remote-sensing applications.

extensive manual feature engineering, which can be time-consuming and subjective. They may struggle with the high dimensionality and complexity of remote-sensing datasets. Traditional machine-learning methods capture intricate spatial patterns or handle temporal dependencies as effectively as deep-learning approaches. These machine-learning methods have been widely applied in remote sensing for tasks such as classification, regression, feature selection, and dimensionality reduction. While they may have limitations compared to deep-learning approaches, traditional machine-learning methods continue to be valuable tools in remote-sensing applications, providing accurate and interpretable results

for a variety of environmental monitoring and analysis tasks.

- Image classification*: It was considered a common and well-known procedure that is non-parametric with good performance. This is sub-categorized into supervised and unsupervised image classification. Supervised involved labeled information by expert users. Unsupervised helped to visualize and monitor similar areas.
- Feature selection and extraction*: Deep-learning techniques helped to extract high-level features automatically. Earlier, linear methods like PCA were quite common. This was surpassed by

genetic algorithms like GBM and SVM. Random forest and other neural networks like CNNs worked well for extracting features.

- (c) *Signal unmixing*: Pixels were a combination of signatures of innumerable objects established within the spatial extent. Several traditional techniques to avoid the unmixing of pixels involved the N-FINDR algorithm, orthogonal subspace projection, vertex component algorithm (VCA) and recently SVM used to select pure pixels.
- (d) *Regression*: This process involved the estimation of response variables built on regular co-variables. One of the most common examples would be forecasting crop yield centered on the images collected from remote-sensing sensors. Simple linear as well as logistic regression methods were more prevalent. Several nonlinear regression techniques have been effectively presented in recent times like neural networks and SVR. Among the neural networks, CNNs were commonly applied to remote-sensing imagery applications.

2.2 Systematic/bibliometric review (SBR)

Literature review holds a pivotal role in any research study, offering insights into prior research and current trends within the domain. It guides the identification of research gaps and the shaping of research questions and objectives. Implementing a Systematic Literature Review (SBR) enhances the review process by including techniques such as keyword analysis, precise selection criteria, and subject categorization. Figure 3 shows the SBR methodology framework employed in this study.

Figure 3 illustrates the proposed methodological framework design toward developing an approach for assessing urban blue-green spaces with certain

resource constraints. In Figure 3, the proposed scientific framework explains the approach starting from data selection to output generation. It explains that preprocessing is a prerequisite for any approach development and implementation. These techniques combined with advanced remote-sensing and deep-learning methods will work as a significant approach to resolve several issues related to functionality, sustainability, and usability of resources. A few of the researchers have begun to investigate the functionality of the proposed approach; yet, overall, very little attention has been paid. This paper examines the prominent methodologies used for examining recent trends in deep-learning approaches for monitoring, management, and mitigation in the context of sustainability management. The focus is on addressing various themes related to sustainability management.

- (a) Evaluation of the existing approaches for urban environmental hazards and disaster studies.
- (b) Review of the advancements made in the approaches for urban environmental hazards and disaster studies.
- (c) Recommendations for urban environmental hazards and disaster studies' analysis approaches.
- (d) Scientific consensus for the management, planning, and presentation of complex decisions to solve real-time issues on urban environmental hazards and disaster studies.

2.2.1 Selection of the relevant database for research

A wide range of academic fields, including Environmental Science, Engineering, Earth and Planetary Sciences, Agricultural and Biological Sciences, Computer Science, and Social Science, are encompassed inside the Scopus collection.

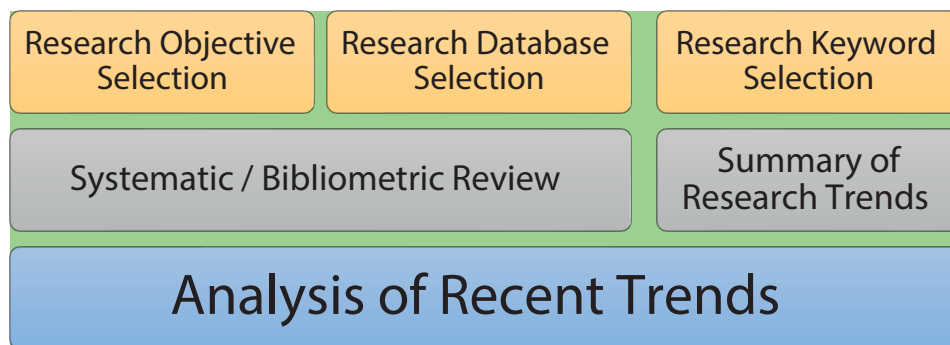


Figure 3: Framework for systematic/bibliometric review.

The systematic literature review is conducted with Scopus and a widely recognized and extensive database. Scopus facilitates thorough evaluation through the use of broad coverage, that allows the use of keywords, publication years, document types, and other search parameters.

2.2.2 Selection of search keywords

Attempts are made to insert the keyword “Urban” into a variety of combinations of chosen search terms. Researchers search the Scopus database for previously published articles in the specified study domain using a variety of keyword combinations. The various combinations being used for the search of documents include *Deep Learning AND “Urban Environment Studies,” Deep Learning AND “Urban Environmental Hazards Studies,” Deep Learning AND “Urban Environmental Disaster Studies,” Deep Learning AND “Urban Environmental Hazards and Disaster Studies,” Machine Learning AND “Urban Environment Studies,” Machine Learning AND “Urban Environmental Hazards Studies,” Machine Learning AND “Urban Environmental Disaster Studies,” Machine Learning AND “Urban Environmental Hazards and Disaster Studies,” Remote Sensing AND “Urban Environment Studies,” Remote Sensing AND “Urban Environmental Hazards Studies,” Remote Sensing AND “Urban*

Environmental Disaster Studies,” Remote Sensing AND “Urban Environmental Hazards and Disaster Studies,” Deep Learning AND “Remote Sensing,” and Machine Learning AND “Remote Sensing.” The database returns a total of 22,677 published records when using the specified combination of search terms. The summary of the search terms is shown in Table 1.

2.2.3 Collection of published articles with selected keywords for search

Table 1 provides an exhaustive summary of the research articles published with the search keywords, and it offers a summary of several search keywords along with the other variants for choosing articles from the Scopus database. The combination of *“Deep Learning” AND “Remote Sensing”* search keyword resulted in 11,381 research documents, the *“Machine Learning” AND “Remote Sensing”* search keyword resulted in 11,289 research documents, the *Remote Sensing AND “Urban Environment Studies”* search keyword resulted in 5 research documents, whereas search keywords like *“Machine Learning” AND “Urban Environment Studies,” “Deep Learning” AND “Urban Environment Studies”* resulted in just one research document. Search keywords like *“Deep Learning” AND “Urban Environmental Hazards Studies,” “Deep Learning” AND “Urban Environmental*

Table 1: Search keywords and significant published articles

Selected keywords for search	Number of published articles
Deep Learning AND “Urban Environment Studies”	1
Deep Learning AND “Urban Environmental Hazards Studies”	0
Deep Learning AND “Urban Environmental Disaster Studies”	0
Deep Learning AND “Urban Environmental Hazards and Disaster Studies”	0
Machine Learning AND “Urban Environment Studies”	1
Machine Learning AND “Urban Environmental Hazards Studies”	0
Machine Learning AND “Urban Environmental Disaster Studies”	0
Machine Learning AND “Urban Environmental Hazards and Disaster Studies”	0
Remote Sensing AND “Urban Environment Studies”	5
Remote Sensing AND “Urban Environmental Hazards Studies”	0
Remote Sensing AND “Urban Environmental Disaster Studies”	0
Remote Sensing AND “Urban Environmental Hazards and Disaster Studies”	0
Deep Learning AND “Remote Sensing”	11,381
Machine Learning AND “Remote Sensing”	11,289
Total	22,677

Disaster Studies,” “Deep Learning” AND “Urban Environmental Hazards and Disaster Studies,” “Machine Learning” AND “Urban Environmental Hazards Studies,” “Machine Learning” AND “Urban Environmental Disaster Studies,” “Machine Learning” AND “Urban Environmental Hazards and Disaster Studies,” “Remote Sensing” AND “Urban Environmental Hazards Studies,” “Remote Sensing” AND “Urban Environmental Disaster Studies,” “Remote Sensing” AND “Urban Environmental Hazards and Disaster Studies” resulted in zero research documents.

There were a total of 22,677 research documents being investigated using various search keyword phrases, but there were an inadequate number of research documents matching the search keywords *Deep Learning AND “Urban Environment.”* These resulted in only zero research documents, which implies that there is an enormous opportunity for exploring this theme.

3. Meta data analysis

The approach discusses the role of secondary datasets, literature review, and preprocessing of datasets for further analyses and visualization. The obtained datasets are prepared for analysis and the generation of the expected results after the preprocessing. Data cleansing, cleaning, classification, anomaly detection, data identification and labelling, trend assessment, geographic distribution analysis, and trend evaluation for analysis. The current trends in deep-learning methods for urban environmental hazard monitoring, management, and mitigation can be better comprehended through the use of such procedures. These proposed operational requirements are laid upon a solid theoretical foundation to enhance the assessment and management of urban resources.

3.1 Trends of yearly contributions to publications

The major research achievements in a certain area can be revealed by analyzing the yearly publication trends in the Scopus database. It outlines the number of documents present worldwide linked to specific keywords relevant to the research theme, such as recent trends in deep-learning approaches for studying urban environmental hazards and disasters. The analyzed data offer insights into the highest and lowest numbers of published documents over the years, providing a snapshot of publication trends. This snapshot aids in understanding the yearly output

within the chosen theme, offering a glimpse into the advancements and evolution of research over time.

3.2 Subject-wise contribution to publications

The investigation of subject-wise contributions to publications delineates the distribution of research output across various fields within a given domain. This analysis showcases the proportional representation of topics or disciplines within the realm of study, offering insights into the emphasis and diversity of research endeavors. The process of classifying publications into specific areas or fields reveals the relative importance and emphasis placed on each area within the broader theme. This investigation enables researchers to discern the predominant areas of interest, highlighting the breadth and depth of scholarship in specific subjects. Subject-wise contributions to publications serve as a compass, providing a comprehensive landscape of research engagement, areas of expertise, and avenues for further exploration within a given field or domain.

3.3. Funding support for publications

It is a well-known fact that to perform good-quality research, it is required to have a good funding source so that the desired research outcome can be achieved. Funding support for publications is a crucial aspect of research dissemination and advancement. It plays a pivotal role in facilitating the publication process, spanning various stages from research inception to manuscript preparation, submission, and eventual publication. Funding sources, including grants, institutional support, or sponsorships, offer financial assistance that aids in covering publication fees, article-processing charges, access fees, or subscription costs associated with scholarly journals or publishing platforms. This support ensures that research findings can reach a wider audience by enabling open-access publications or subscriptions to journals. This funding for publications often signifies endorsement or recognition of the research’s merit and potential impact. This validation assists to enhance the significance of the work, thereby garnering attention from both the academic community and industrial stakeholders. Acquiring financial resources for scholarly publishing is crucial for academics, especially in domains where the expenses associated with publication might be substantial. Securing adequate financial support ensures that valuable research findings are effectively disseminated, contributing to the advancement of

knowledge and fostering collaboration within the scientific community.

3.4 Publications at the global level

Publications on a global scale act as an indicator of a country's research output, influence, and contributions to worldwide knowledge. They provide valuable information on a nation's scientific expertise, partnerships, and progress in several fields. The evaluation of publication outcomes include the analysis of several indicators, such as the quantity of publications, citation counts, collaboration networks, and the distribution throughout diverse fields of study. A high volume of publications signifies a robust research environment within a country, showcasing its commitment to knowledge creation and dissemination. Furthermore, the quantification of citations and the evaluation of the impact of publications serve as indicators of the level of influence and importance that a country's research output holds within the international academic community. Analyzing collaborations and partnerships between countries through co-authorship networks reveals the extent of international collaboration and knowledge exchange. The presence of significant collaborative relationships often signifies that a country is able to capitalize on transnational resources and expertise, resulting in promoting the development of novel ideas and cross-disciplinary investigations. The distribution of publications across diverse fields demonstrates a country's strengths and specialization in specific disciplines. It reflects investments in research areas and provides a roadmap for future development and resource allocation. Understanding publication outcomes at the country level enables policymakers, funding agencies, and researchers to evaluate research performance, identify strengths and weaknesses, and formulate strategies for fostering a thriving research ecosystem. It also contributes to global knowledge sharing, enabling countries to leverage their expertise and contribute to collective advancements in science and technology.

3.5 Document type of published research

Research results are evident as various document types, each serving distinct purposes in disseminating knowledge and findings. Scholarly articles are the bedrock of academic communication, presenting in-depth research and analysis, and contributing significant insights into their respective fields. Conference papers rapidly share novel ideas and preliminary findings, fostering dialog within academic

circles. Theses and dissertations represent extensive research culminations, contributing to the academic canon. Meanwhile, book chapters, monographs, and books offer comprehensive discussions, delving into specific topics or presenting holistic narratives. Patents and technical reports document innovations and advancements, bridging academic research with practical applications. Whitepapers and policy briefs distil research findings for policymakers, facilitating evidence-based decision-making. Moreover, multimedia outputs like videos or infographics supplement traditional formats, enhancing accessibility and understanding. Understanding and valuing diverse document types enriches scholarly discourse, ensuring research reaches various audiences and applications. Each form contributes uniquely to the dissemination and utilization of knowledge, shaping the trajectory of academic and societal progress.

4. Results, and analysis

4.1 Research publications with “Remote Sensing” AND “Urban Environment Studies”

There were five (5) papers found using the search terms “Remote Sensing” and “Urban Environment Studies”. The topic of study is continuously advancing in order to address environmental challenges in urban areas through the utilization of enhanced sensing technologies (Table 2).

The integration of remote sensing with GIS is a prevalent theme in these publications. GIS technology combined with remote-sensing data allows for spatial analysis, mapping, and modeling of urban environments, aiding policymakers and urban planners in making informed decisions for sustainable development. Research articles that focus on the convergence of remote sensing and urban environmental studies demonstrate the crucial significance of sophisticated sensing technologies in understanding, controlling, and guaranteeing the long-term viability of swiftly changing urban environments. Studies often explore the role of remote-sensing technology in comprehending urban landscapes, evaluating environmental alterations, and overseeing urban sustainability. A number of scholarly articles explore on the significance of remote sensing in the surveillance of urban areas. The researchers use satellite imagery, LiDAR (Light Detection and Ranging) data, and several other sensing technologies in order to study the expansion of metropolitan areas, changes in land use, and degradation of the environment. These

Table 2: Summary of exhaustive publications with “Remote Sensing” AND “Urban Environment Studies”

Authors	Publications title	Year	Citations	Funding details	Document type
Barros et al.	“Urban land use pattern identification using variogram on image”	2016	2	Polytechnic School; Conselho Nacional de Desenvolvimento Científico e Tecnológico, CNPq; Universidade de São Paulo, USP	Article
Rau et al.	“Analysis of oblique aerial images for land cover and point cloud classification in an Urban environment”	2015	73	National Science Council Taiwan, (102-2119-M-006-002)	Article
Li et al.	“WRF environment assessment in Guangzhou city with an extracted land-use map from the remote sensing data in 2000 as an example”	2014	2	National Natural Science Foundation of China, (51278262)	Article
He et al.	“Urban local climate zone mapping and apply in urban environment study”	2018	5	Ministry of Science and Technology, MOST; National Natural Science Foundation of China, NSFC, (51508458); Ministry of Science and Technology of the People’s Republic of China, MOST, (SB2013FY112500)	Conference paper
Sun et al.	“Desert heat island study in winter by mobile transect and remote sensing techniques”	2009	47	Architecture and Building Institute; Ministère de l’Intérieur; National Science Council, NSC, (096-2917-I-006-011, NSC94-2211-E-006-069)	Article

studies often highlight the significance of remote sensing in assessing air quality, heat islands, vegetation cover, and water resources within urban settings.

4.2. Research publications with “Machine Learning” AND “Remote Sensing”

The substantial number of publications at this intersection signifies the continuous exploration and innovation within this interdisciplinary domain. It reflects the recognition of machine learning as a powerful tool in unlocking the potential of remote-sensing data across multiple sectors and applications. Trends of publications with “Machine Learning” AND “Remote Sensing” resulted in a total of 11,289 documents. These articles probably include a wide range of studies that investigate the potential synergy between

machine-learning algorithms and remote-sensing technology. The analysis of remote-sensing data can be enhanced by the utilization of machine learning techniques. This approach improves classification accuracy, promotes feature extraction, enables predictive modeling, and enables automated interpretation of satellite imagery or sensor data.

Additionally, Figure 4 illustrates the patterns of annual publications pertaining to the fields of “Machine Learning” and “Remote Sensing.” This extensive compilation of documents is expected to encompass a wide range of application domains, such as environmental monitoring, disaster management, land use classification, agricultural assessment, urban planning, and other related areas. Researchers within these fields likely leverage machine learning to extract actionable insights from remote-sensing data for improved decision-making and problem-solving.

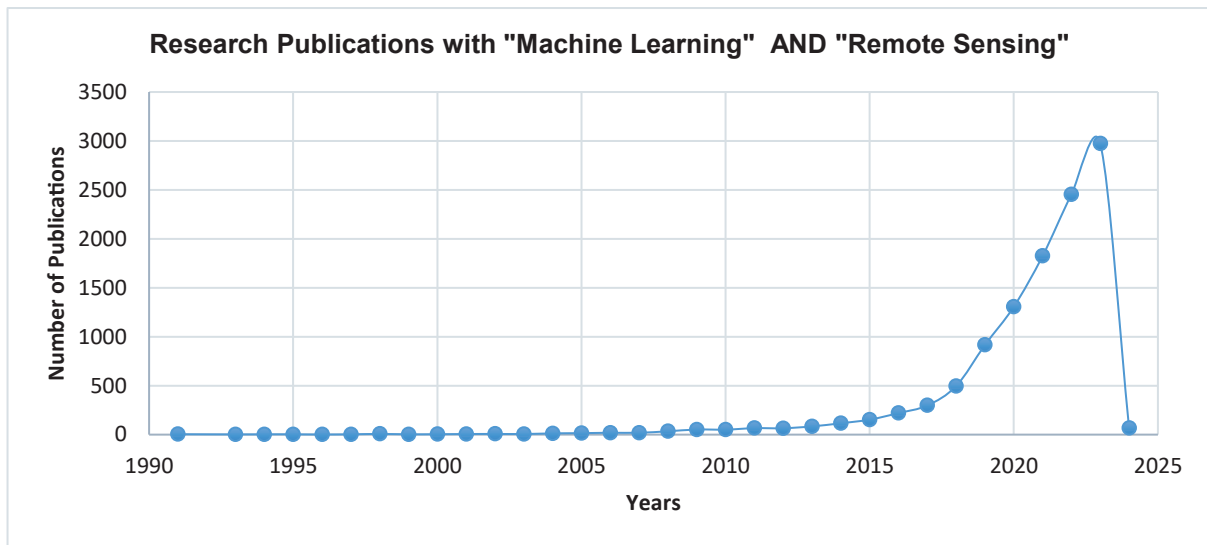


Figure 4: Trends of yearly publications "*Machine Learning*" AND "*Remote Sensing*".

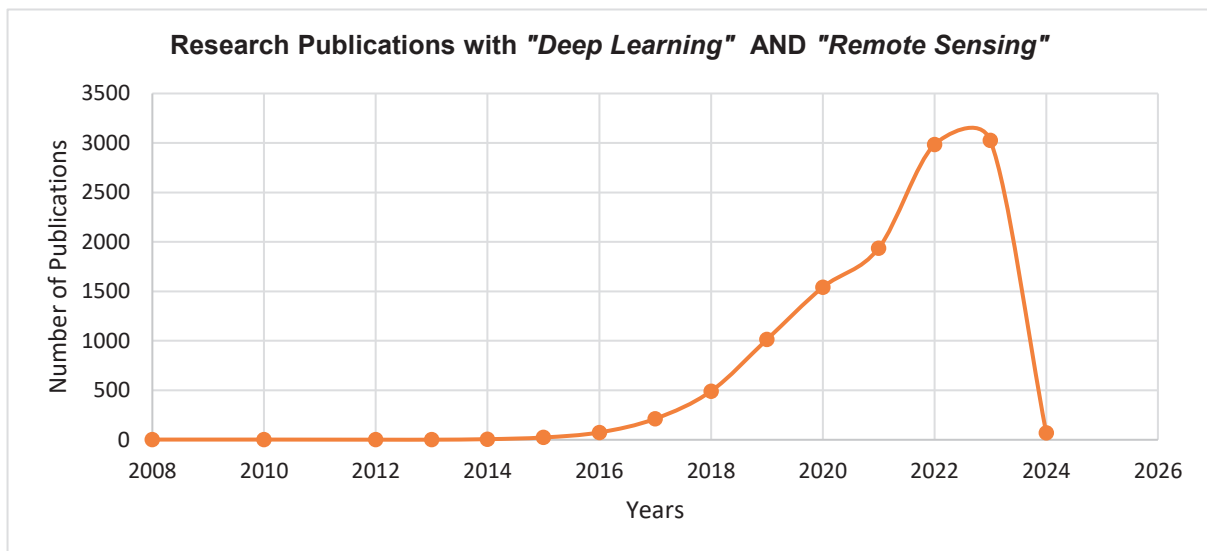


Figure 5: Trends of yearly publications in "*Deep Learning*" AND "*Remote Sensing*".

4.3 Research publications with "Deep Learning" AND "Remote Sensing"

A significant amount of study has been conducted on the integration of "Deep Learning" and "Remote Sensing," resulting in a total of 11,381 documents. This significant volume of publications underscores the burgeoning interest and research activity at the intersection of these two fields.

The observed pattern of annual publications in this field is likely indicative of a steady upward trend, suggesting a persistent interest and investigation into

the intersection of deep-learning approaches with remote-sensing applications.

Figure 5 illustrates the annual publication trends related to the intersection of "Deep Learning" and "Remote Sensing". The integration of deep-learning methods with remote-sensing technologies has attracted significant interest over time, as it has the potential to transform data analysis, pattern identification, and information extraction from remote-sensing datasets. The consistent growth in publications suggests ongoing research endeavors, innovations, and

advancements within this interdisciplinary domain. Researchers continue to explore and harness the capabilities of deep learning in enhancing the analysis, interpretation, and utilization of remote-sensing data across various application domains.

4.4 Research publications in different subjects/disciplines

The research papers encompass a broad range of issues and fields, thereby reflecting the varied interests and investigations present within the academic sphere. These provide specific subject-wise research contributions with selected keywords and more details about the particular keywords or subjects. Specific keywords or subjects related to research contributions explore the outlining subject-wise research contributions or trends associated with those terms. These analyses typically require access to scholarly databases like Scopus, PubMed, IEEE Xplore, or Google Scholar, where one can filter publications based on specific keywords and examine subject-wise research contributions.

Figure 6 shows the composition of research publications with the selected “Deep Learning” AND “Remote Sensing” and “Machine Learning” AND “Remote Sensing”

“Remote Sensing” keywords. It can be observed that there are ample amount of contributions from the fields of Earth and Planetary Sciences, Computer Science, Engineering, Physics and Astronomy, Mathematics, Environmental Sciences, Materials Science, Social Sciences, Agricultural and Biological Sciences, and Decision Sciences with the selected “Deep Learning” AND “Remote Sensing” and “Machine Learning” AND “Remote Sensing” keyword. It signifies that there is good adaptability of the subject compositions across several disciplines over the mentioned year within the given keyword. There is insignificant volume of research contribution in the subjects of Neuroscience, Multidisciplinary, Business, Management and Accounting, Arts and Humanities, Health Professions, Pharmacology, Toxicology and Pharmaceuticals, Economics, Econometrics and Finance, Immunology and Microbiology, Veterinary, Psychology, Dentistry, Nursing with less than 100 publications.

4.5 Funding support for the research contributions

Funding support plays a pivotal role in driving research contributions across various domains,

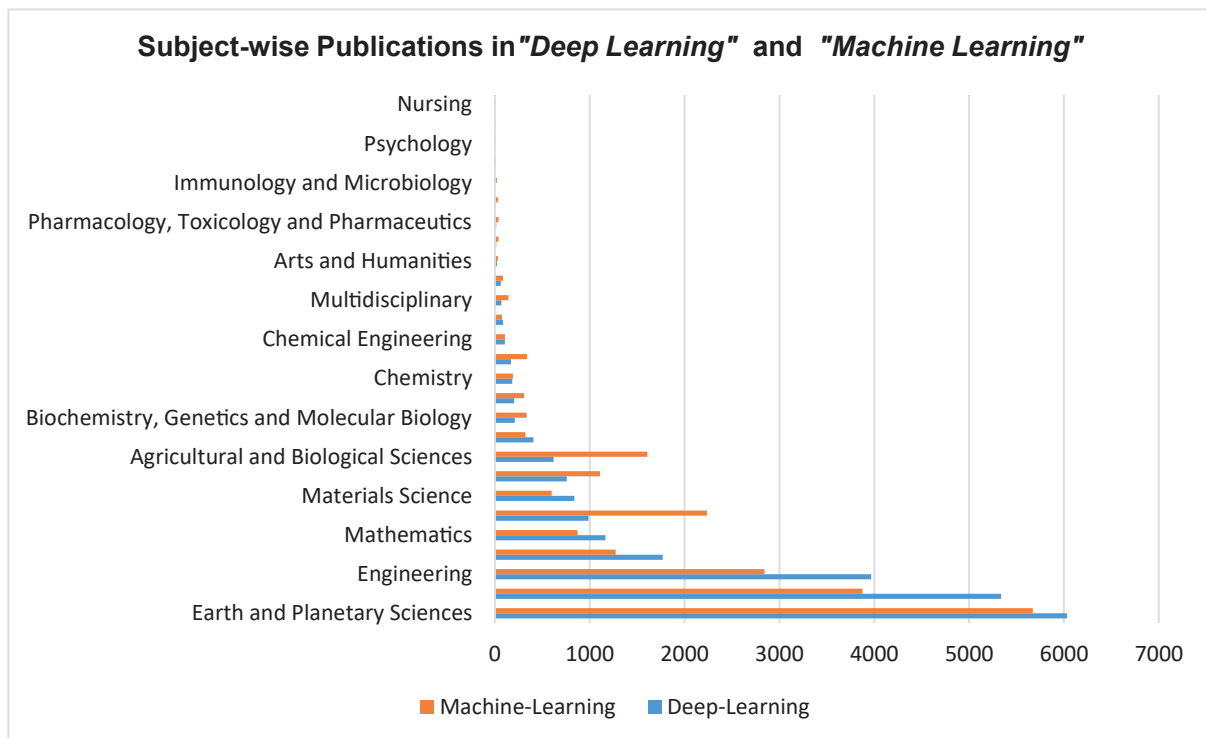


Figure 6: Subject-wise research contributions in “Deep Learning” AND “Remote Sensing.” and “Machine Learning” AND “Remote Sensing”.

including those related to remote sensing, machine learning, and deep learning. Multiple entities offer financial support for research efforts across different fields:

- (a) *Government grants*: Research projects in subjects such as environmental sciences, technology, and innovation are frequently funded by government entities. Organizations like NASA, National Science Foundation (NSF), Department of Energy (DOE), and National Institutes of Health (NIH) offer grants supporting research in remote sensing, machine learning, and related areas.
- (b) *Academic institutions*: Universities and research institutes frequently offer internal financial support in the form of grants, fellowships, or research programs to facilitate the research endeavors of faculty members, postdoctoral researchers, and graduate students within the aforementioned areas.
- (c) *Corporate sponsorship*: Companies working in the fields of technology, aerospace, environmental monitoring, and data analytics have the potential to provide financial support for research initiatives that are in line with their interests towards advancements in remote sensing and machine learning technologies.
- (d) *International organizations*: Entities like the European Space Agency (ESA), United Nations (UN), or World Bank often support research projects related to environmental monitoring, disaster management, and sustainable development, which may involve remote-sensing and machine-learning applications.
- (e) *Nonprofit foundations*: Foundations focused on science, technology, and environmental conservation may provide grants to support research initiatives in these domains.
- (f) *Crowdfunding and philanthropy*: Scientists occasionally acquire financial support through crowdfunding platforms or philanthropic contributions to support particular projects or studies that are in line with public interest or social issues.

Securing funding support is crucial for conducting research, procuring equipment, hiring personnel, and disseminating findings. Researchers often apply for grants, fellowships, or project funding from these various sources to support their investigations and contribute to advancements in remote sensing, machine

learning, and deep-learning applications within the domain. Table 3 indicates the funding available from the various research agencies across the globe to support the mentioned research theme. It can be seen that the majority of the research work is supported by the National Natural Science Foundation of China, National Key Research and Development Program of China, Fundamental Research Funds for the Central Universities, China Postdoctoral Science Foundation, Chinese Academy of Sciences, National Science Foundation, Ministry of Science and Technology of the People's Republic of China, Horizon 2020 Framework Program, Ministry of Education of the People's Republic of China, National Aeronautics and Space Administration, Natural Science Foundation of Shandong Province, European Commission, and China Scholarship Council. Apart from the mentioned funding sources, other sources are only supporting a few research activities in the domain. There were a total of 9525 research publications in the scope of "Deep Learning" AND "Remote Sensing" and 8892 in the area of "Machine Learning" AND "Remote Sensing" sponsored by various funding agencies across the globe. National Natural Science Foundation of China has funded 3121 publications related to "Deep Learning" and "Remote Sensing" and 1903 publications related to "Machine Learning" and "Remote Sensing," National Key Research and Development Program of China has supported 882 publications related to "Deep Learning" and "Remote Sensing" and 603 related to "Machine Learning" and "Remote Sensing", and Other Funding Agencies has contributed 2155 publications for "Deep Learning" and "Remote Sensing" and 2775 for "Machine Learning" and "Remote Sensing". The research publications in the domain of "Deep Learning" and "Remote Sensing" shows a total of 11,381, out of which 9525 were funded by various agencies and 1856 were not funded. Also, in the area of "Machine Learning" and "Remote Sensing," out of a total of 11,289 research publications, 8892 were funded by different agencies, and 2397 have not received funding.

This breakdown demonstrates the substantial support provided by various funding agencies, especially in China, for research endeavors in the domains of "Deep Learning" and "Remote Sensing" as well as "Machine Learning" and "Remote Sensing". Additionally, there is a notable number of research publications that were not funded by these specified agencies, indicating diverse sources of support or self-funded research within these areas.

Table 3: Publications as per the funding sponsor in “Deep Learning” AND “Remote Sensing” and “Machine Learning” AND “Remote Sensing”

Selected funding agency	“Deep Learning” AND “Remote Sensing”	“Machine Learning” AND “Remote Sensing”
National Natural Science Foundation of China	3121	1903
National Key Research and Development Program of China	882	603
Fundamental Research Funds for the Central Universities	424	222
China Postdoctoral Science Foundation	221	113
Chinese Academy of Sciences	210	224
NSF	191	324
Ministry of Science and Technology of the People’s Republic of China	167	126
Horizon 2020 Framework Programme	163	220
Ministry of Education of the People’s Republic of China	135	82
National Aeronautics and Space Administration	128	376
Natural Science Foundation of Shandong Province	108	50
European Commission	105	175
China Scholarship Council	102	86
Conselho Nacional de Desenvolvimento Científico e Tecnológico	95	152
National Basic Research Program of China (973 Program)	93	65
Coordenação de Aperfeiçoamento de Pessoal de Nível Superior	81	138
Natural Science Foundation of Jiangsu Province	79	41
ESA	73	170
Natural Science Foundation of Beijing Municipality	72	35
National Research Foundation of Korea	68	63
European Research Council	67	82
Ministry of Finance	67	36
Natural Sciences and Engineering Research Council of Canada	66	93
Nvidia	66	24
Natural Science Foundation of Hubei Province	62	29
Horizon 2020	58	71
Sichuan Province Science and Technology Support Program	58	26
Deutsche Forschungsgemeinschaft	56	85
European Regional Development Fund	56	106
Japan Society for the Promotion of Science	49	67
Bundesministerium für Bildung und Forschung	46	72
U.S. DOE	44	80
U.S. Geological Survey	42	115

(Continued)

Table 3: Continued.

Selected funding agency	“Deep Learning” AND “Remote Sensing”	“Machine Learning” AND “Remote Sensing”
Natural Science Foundation of Guangdong Province	39	22
Higher Education Discipline Innovation Project	38	26
Key Technology Research and Development Program of Shandong	38	15
	<i>*Sub-Total is 7370</i>	<i>*Sub-Total is 6117</i>
Other Funding Agencies	2155	2775
Total Funded Research Publications	9525	8892
Total Research Publications	11,381	11,289
Total Non-Funded Research Publications	1856	2397

DOE, Department of Energy; ESA, European Space Agency; NSF, National Science Foundation.

4.6 Research outcomes at the global level

Conducting an analysis of the research outcomes of each nation is vital, as it offers a comprehensive understanding of their research capacity and their propensity to foster scientific and technological advancements. Comprehending the study results on a world-wide scale in the convergence of “Deep Learning” and “Remote Sensing”, as well as “Machine Learning” and “Remote Sensing”, and it involves multiple aspects:

- (a) *Advancements in algorithms and models:* Global research outcomes highlight significant advancements in developing sophisticated algorithms and models tailored for remote-sensing applications. These outcomes involve innovations in CNNs, RNNs, generative adversarial networks (GANs), and other deep learning architectures optimized for analyzing remote-sensing data.
- (b) *Enhanced image processing and analysis:* Research outcomes showcase improved techniques in image processing, classification, feature extraction, and object detection from remote-sensing imagery. These outcomes leverage machine learning and deep learning to enhance accuracy and efficiency in extracting meaningful information from complex datasets.
- (c) *Environmental monitoring and change detection:* Globally, research outcomes contribute to better environmental monitoring, land use/land cover classification, change detection, and disaster assessment using remote-sensing data coupled with machine-learning techniques.

These outcomes aid in assessing environmental changes, identifying patterns, and predicting potential hazards.

- (d) *Urban planning and infrastructure management:* Research outcomes focus on utilizing machine learning and deep learning for urban planning, infrastructure monitoring, and smart city development. These outcomes provide insights into optimizing urban spaces, managing resources, and improving infrastructure through remote-sensing data analysis.
- (e) *Cross-disciplinary applications:* Global research outcomes extend beyond traditional remote-sensing domains, integrating machine learning and deep-learning techniques into various fields like agriculture, forestry, climate studies, and healthcare. These outcomes demonstrate the versatility and applicability of remote sensing fused with AI methodologies.
- (f) *Open-source tools and datasets:* Research outcomes often include the development of open-source tools, datasets, and platforms to facilitate the integration of machine learning and deep learning with remote sensing. These resources contribute to the accessibility and advancement of research in these domains.

Overall, research outcomes at the global level signify a continuous evolution, innovation, and application of machine-learning and deep-learning methodologies in harnessing the potential of remote-sensing data for diverse purposes, spanning environmental studies, urban planning, disaster management, and beyond.

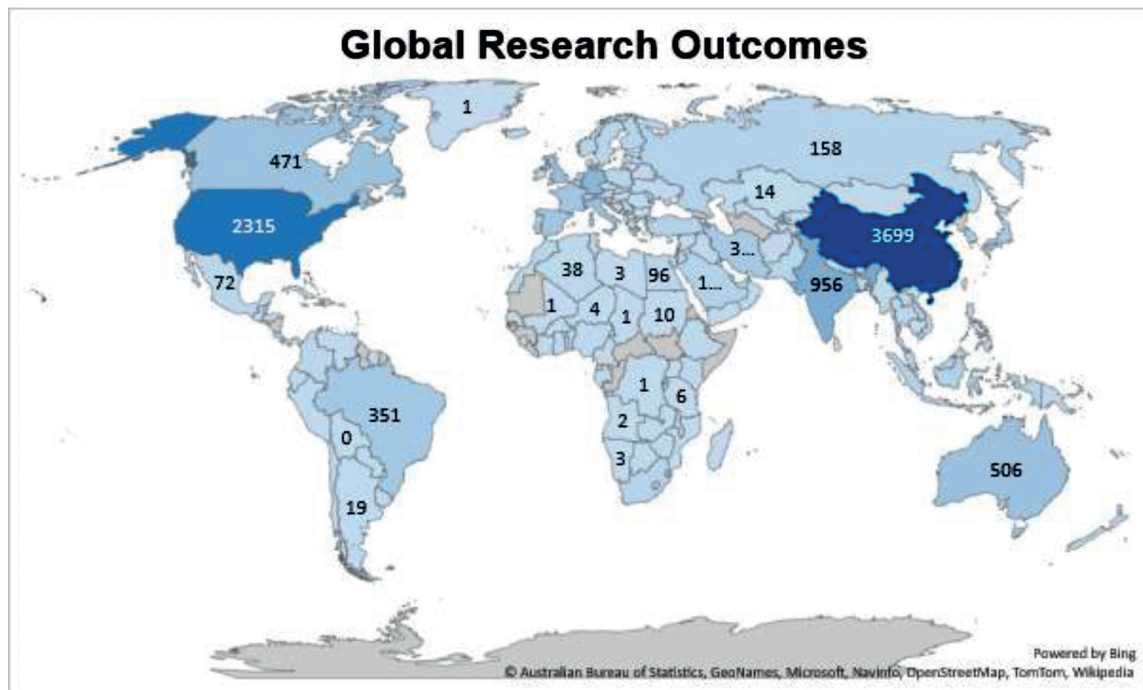


Figure 7: Global research outcomes in the “*Machine Learning*” AND “*Remote Sensing*” domain.



Figure 8: Global research outcomes in the “*Deep Learning*” AND “*Remote Sensing*” domain.

Figures 7 and 8 present the data in a visual way to provide an exhaustive summary of country-wise research contributions. It can be seen that there are insignificant research publications (as per the

Scopus database) from countries like Cambodia, Democratic Republic Congo, Libyan Arab Jamahiriya, Zambia, Namibia, Venezuela, Albania, Nigeria, Kuwait, Mali, Monaco, Montenegro, Palestine,

Suriname, Togo, Trinidad and Tobago, Virgin Islands (British), Barbados, Bhutan, Chad, European Union, Greenland, Guatemala, Guinea-Bissau, Honduras, Afghanistan, Angola, Bolivia, Laos, Madagascar, Malawi, Moldova, Papua New Guinea, Sierra Leone, and Paraguay in the theme of “Deep Learning” AND “Remote Sensing”.

Out of all the research publications, the major research contributions are from China, the United States, India, Germany, France, the United Kingdom, Italy, Canada, South Korea, Australia, Japan, Spain, Brazil, Netherlands, Turkey, Saudi Arabia, Iran, Hong Kong, Greece, Malaysia, Austria, Pakistan, Egypt, Switzerland, Russian Federation, Taiwan, Norway, Morocco, Belgium, Finland, Indonesia, Singapore, Algeria, Poland, United Arab Emirates, Tunisia, Sweden, Viet Nam, South Africa, Portugal in both the research domains, including “Deep Learning” AND “Remote Sensing” and “Deep Learning” AND “Remote Sensing” domains. The research outcomes at each country level can be assessed through the statistical summary of the research publications/documents. This analysis tries to determine the relative research focus of different countries and vice versa, to report on the competitive research contributions made by each nation.

The spatial maps provide a summary of the quantity of research documents produced by each country across several domains. The analysis of research papers is of great importance due to the presence of diverse preferences and privileges within research groups.

In academic and scientific sectors, many document forms, including articles, book chapters, conference proceedings, patents, reviews, and others, are utilized to address diverse research interests and serve specific purposes.

5. Discussions

5.1 Significance of deep learning and applications

Deep learning has emerged as a rapid and powerful method for analyzing large-scale data in remote sensing (Raja and Babu 2019; Sagheer and Yousif 2021). Recent advancements have produced a suite of tools that excel beyond human capabilities, and these are becoming a favored models across multiple application fields. These techniques have been applied to tasks like monitoring green spaces and identifying disaster-prone areas (Konapala et al. 2021; Wang et al. 2021). CNNs have been a primary choice, proving

highly effective in various image-processing tasks. These studies have highlighted the significance of RNNs in analyzing sequential data and recognizing patterns of action. Deep learning exhibits considerable potential and is extensively employed in several applications related to image analysis. Various applications, such as image indexing, object detection, compression, and segmentation, are utilized by prominent Internet businesses like Google, Microsoft, and Facebook (Benz et al., 2004; Joshi et al., 1994). Nevertheless, the need for supplementary datasets that have been annotated remains a primary concern in the enhancement of deep-learning methodologies for remote-sensing applications. Deep learning enhances the understanding of spatial features and aids in various environmental applications, such as land cover mapping, change analysis, evapotranspiration, solar radiation evaluation, and natural hazard prediction, by replacing labor-intensive manual image analysis. These methods are designed for heightened prediction accuracy, heralding a paradigm shift in leveraging datasets for environmental analysis (Gao et al. 2020; Lehnert et al. 2021). Deep-learning techniques in the field of environmental remote sensing undoubtedly proved one of the most important breakthroughs, offering solutions to several problems (Baniya et al. 2018; Tzampoglou and Loupasakis 2017). This would be possible if the fusion of multisensory data and machine-learning technologies were established and arranged in a synchronized way for advanced decision analysis (Li et al. 2021; Saggi and Jain 2018; Syed et al. 2019). These techniques proved to be more accurate and efficient when compared to the traditional methods for the mentioned applications:

- (a) *Imagery-based Land Cover Classification* of networks has been expanded for precise image classification. The fully convolutional network (FCN) is used for classifying multiresolution images. Solving issues in classifying vegetation, especially identifying minute differences in features and loss of features can be performed through FCN. Implementation of CNN along with multi-layer perceptron (MLP) increased the overall classification accuracy (Kelley et al. 2018; Qian et al. 2020).
- (b) *MLP* is a type of neural network comprising one or more layers of perceptron. It mostly comprises three layers of nonlinear activation nodes. Data are introduced into the input layer first, and then in the hidden layers, which comprise one or more layers that help in attaining stages of abstraction. The predictions are achieved

through the output layer also known as the visible layer (Ghaffarian et al. 2020; San Martín et al. 2020).

- (c) *Object Extraction* in deep learning helped in studying water body object detection. The Simple linear iterative clustering (SLIC)-based approach was used at first to segment remote-sensing imagery into super pixels. Then CNN helped to extract features of water bodies (Gehlot et al. 2021; Gulland et al. 2016; Zhao et al. 2021). Another method involved the production of a visual dictionary based on a pretrained deep neural network that is monitored by labeled urban area imagery for distinguishing between areas that are urban and nonurban.
- (d) *Change Detection* algorithms on change vector analysis and the grey level co-occurrence matrix are applied to attain spectral as well as textural variations. Also, a machine model named Gaussian–Bernoulli Deep Boltzmann is used in changed and unchanged areas for extracting deep features (Rengma et al. 2020). Based on features extracted from deep neural networks, a multiresolution profile (MRP) is constructed for detecting changed areas.

5.2 Deep-learning models for remote sensing

Several deep-learning architectures have gained popularity in remote sensing applications, as seen by their extensive coverage in numerous survey publications.

5.2.1 CNNs

This is a network motivated by the human visual cortex, and mainly consisting of three key components: *convolution layers*, *pooling layers*, and *fully connected layers*. After importing the inputs into the model, the following four stages are performed to build the model.

- (a) *Convolution*: Initially, the input maps are convolved via learnable kernels. Then, with the help of the activation function form the output feature maps, in convolution layers.
- (b) *Pooling*: The convolution layers are led by the pooling layer, which helps feature maps in reducing their dimensionality. These are categorized into average and max pooling, which are mostly common. Others like spatial pyramid

pooling, def-pooling, and stochastic pooling have been described by several researchers.

- (c) *Flattening*: The layers generated through the input data are then flattened to analyze the CNN model.
- (d) *Full Connection*: The output maps of the preceding layers act as inputs in fully connected layers when arranged into vectors. The final output is termed a learned feature. By connecting this to the learning classifier, the operation can be easily implemented.

The CNN model is primarily used in image processing, image recognition, and image classification and needs to be explored more to discover its advantages in understanding the information gained through interpreting remote-sensing images.

5.2.2 Stacked autoencoders (SAEs)

The latent representation is generated by the autoencoder, which utilizes the encoder function to map the input data. Next, the decoder converts this information into a reconstruction of the original input. The SAE differs from autoencoders in that it consists of many layers of autoencoders, with the output features of one layer being connected to the input features of the next ones. A single autoencoder was unable to achieve the distinguishing and illustrative characteristics of the raw input data. Therefore, a series of autoencoders are used to progress the learnt code from one to another in order to accomplish the specified goal. In order to carry out the function, the following stages are taken into consideration:

- (a) Input data are used for training the autoencoder and for acquiring learned data.
- (b) The data that are considered as input for the next layer are obtained from its previous layer as learned data. This series continued until the training ended.
- (c) To minimize the cost function, the backpropagation algorithm is implemented after the hidden layers are completely trained.
- (d) Finally, to achieve fine-tuning of data, weights along with the training set are updated.

Autoencoders are one of the most-used deep-learning techniques in the field of remote sensing for feature detection, adding on features to large datasets and thus setting a framework for image processing of big datasets.

5.2.3 Deep belief network

Also termed as a generative graphical model assigned for unsupervised networks including manifold layers of latent variables though connecting in-between layers but no association amid the units within every individual layer, hence following definite direction. This was mainly formed due to a hierarchically arranged series of restricted Boltzmann machines (RBMs).

The RBMs model is generative energy based, comprising of an observable input layer and an unseen layer with connections not within the layers but present in between the layers. Thus, it is considered to be undirected since all the nodes are interconnected, therefore, forming a circular shape. Another advantage of RBMs is that instead of considering only the particular set of input parameters, it can work with all parameters.

5.2.4 RNN

The connections in this network formed directed cycles. In contrast to conventional neural networks, the recurrent neural network (RNN) facilitated the sharing of network parameters throughout all stages, hence enabling the learning of a reduced number of parameters. A finite impulse recurrent network is a directed acyclic graph that can unroll and replace a feedforward neural network, whereas an infinite impulse recurrent network is a directed periodic graph, which cannot be unfolded. Each of them included additional stored states that are controlled by a neural network. If there is a delay of time or feedback loops by another neural network, storage is well substituted. The phenomenon of regulated states was a fundamental aspect of long short-term memory networks (LSTMs) and gated recurrent units, sometimes referred to as gated memory. There was a prevalent occurrence of several functionalities. The following steps show how it functions in analyzing the data:

- (i) The hidden layers help in remembering the sequences of all of the information obtained in the RNN model.
- (ii) The same parameters are used for each input, providing equal weights and biases to all the given layers.
- (iii) The defined layers are then joined together in such a way that all the hidden layers carry the same weight and bias into the single recurrent layer.

This is mostly used for time series analysis, where it customizes the inner state to process a series of inputs of variable lengths. It is also useful in generating semantic image details. It is said to be effective in classification-prediction problems and can be used when merged with convolutional layers to extend the active pixel neighborhood.

5.3 Significance of machine learning and its applications

The application of machine learning in remote sensing has significantly advanced the area, facilitating more precise and effective interpretation of remote-sensing data. The adoption of deep learning, transfer learning, multisource data fusion, graph-based learning, explainability, and scalability has opened new avenues for environmental monitoring, land cover classification, change detection, and various other applications. These advancements hold great potential for addressing critical environmental challenges and advancing our understanding of the Earth's dynamics.

5.3.1 Manifold learning

This is related to dimensionality reduction; the traditional methods of linear dimensionality reduction failed to describe the inherent structures of remote-sensing data. When paralleled with traditional procedures, the nonlinear feature extraction helped in mapping higher into lower dimensional data for better analysis and also preserved the main features of the original data. Some nonlinear transforms are the isomaps, Laplacian methods, and local linear embedding.

5.3.2 Semisupervised learning

Researchers proposed several designs of cluster and bagged kernels. Along with that a semisupervised kernel Fisher discriminant classifier was proposed. However, these methods did not apply to large-scale problems.

5.3.3 Transfer learning

Due to the unavailability of the required training samples, updating the maps by classifying the temporal series of images became challenging. This was tackled by the adoption of methods of transfer learning. Earlier, it involved unsupervised classifiers and then the neural networks, which were extended by the domain adaptation support vector machine (DASVM).

5.3.4 Active learning

This method helped to select the most-relevant training samples. Researchers discussed the SVM for object-oriented classification; for pixel-built classification, the maximum likelihood classifiers were proposed. Studies revealed that active learning is based on information used for detecting targets along with the processing of satellite images of very high resolution.

5.3.5 Structured learning

This term is said to be a recent development of machine learning. Some of the complex output spaces that involved predicting multiple labels, multi-temporal image sequences, and abundance fractions are some of the examples of structured learning. Researchers presented computer vision applications and preliminary results for image processing.

In recent years, there has been a remarkable evolution in machine-learning methods designed specifically for remote-sensing applications. These advancements have revolutionized the field, allowing for more precise and efficient analysis of remote-sensing data. Consequently, a wide array of tasks related to environmental monitoring and analysis has greatly benefited from these innovations. In this section, we delve into the current trends that are shaping the role of machine learning in the realm of remote sensing.

- (a) *Deep learning*: Deep learning has emerged as a dominant trend in machine learning for remote sensing. Deep neural networks, particularly CNNs and RNNs have demonstrated exceptional capabilities in extracting complex spatial and temporal patterns from remote-sensing data. CNNs are widely used for image classification, object detection, and semantic segmentation tasks, while RNNs are employed for tasks involving sequential or time-series data, such as change detection and land cover mapping. Deep-learning models leverage their ability to automatically learn hierarchical representations and features directly from raw data, reducing the need for manual feature engineering and improving accuracy in remote-sensing applications.
- (b) *Transfer learning*: Transfer learning has gained prominence in remote sensing, especially in scenarios where labeled training data are limited. Transfer learning involves leveraging

pretrained models on large-scale datasets, such as ImageNet, and fine-tuning them on remote-sensing data. Transfer learning facilitates efficient training with limited labeled data, enhances generalization, and expedites model convergence by transferring acquired representations and knowledge from one domain to another. This approach has shown remarkable success in tasks such as land cover classification, object detection, and scene understanding in remote sensing.

- (c) *Fusion of multisource data*: With the availability of diverse remote-sensing data sources, there is a growing trend towards fusing data from multiple sensors and modalities to improve the accuracy and richness of the remote-sensing analysis. Machine-learning methods that combine data from sources such as optical imagery, LiDAR point clouds, synthetic aperture radar (SAR) data, and hyperspectral images have gained traction. Fusion techniques, including feature-level fusion, decision-level fusion, and deep fusion networks, enable comprehensive and integrated analysis of multisource data, leading to enhanced land cover classification, 3D modeling, and environmental parameter estimation.
- (d) *Graph-based learning*: Graph-based learning approaches have shown promise in remote sensing, particularly in capturing spatial relationships and contextual information. Graph-based models represent the spatial connections among neighboring pixels or regions as graphs, where nodes represent data samples and edges encode relationships between samples. Graph convolutional networks (GCNs) and graph-based semisupervised learning methods leverage this structure to learn spatial dependencies and perform tasks such as land cover classification, object detection, and change detection. Graph-based approaches enable more accurate and context-aware analysis by considering the spatial context and relationships between features in remote-sensing data.
- (e) *Explain ability and interpretability*: As machine-learning models become more complex, the need for explainability and interpretability in remote-sensing applications has gained importance. Recent trends focus on developing methods to interpret and explain the decisions made by machine-learning models. Techniques such as attention mechanisms, saliency maps, and feature importance rankings provide

insights into the model's decision-making process and highlight the most influential features or regions in the data. Explainable machine learning in remote sensing enhances the trustworthiness of the results, enables domain experts to validate the model's decisions, and facilitates the adoption of machine learning in critical decision-making processes.

- (f) *Scalability and efficiency*: The demand for scalable and effective machine-learning approaches is expanding due to the increasing amount and frequency of remote-sensing data. Recent trends in remote sensing focus on developing algorithms that can handle big data challenges, leverage distributed computing frameworks, and optimize computational resources. Techniques such as mini-batch learning, parallel processing, and model compression aim to accelerate model training and inference, reduce memory requirements, and improve scalability in remote-sensing applications.

6. Conclusions

Recent advancements in high-performance microcomputers, enhanced software, advanced remote-sensing technologies, modern optimization techniques, and high-resolution digital elevation model data have facilitated the development of a sophisticated technological framework for urban analysis. This study offered an overview of deep-learning concepts, models, and their present applications in the field of environmental remote sensing. The remote-sensing community has utilized a variety of techniques including PCA, K-means, artificial neural networks, decision trees, SVMs, and random forests for classification and regression purposes. However, only a few deep-learning approaches have gained significant attention in recent years for mining the required data.

Examining current patterns in deep-learning methods for studying urban environmental hazards and disasters with a focus on sustainability shows a significant shift in using technology to address worldwide issues. The thorough investigation highlights the significant influence of incorporating deep-learning techniques in urban environmental sustainability and disaster management.

The synthesis of these advancements illuminates a substantial shift in our comprehension, analysis, and control of urban environmental hazards. The integration of deep-learning techniques with remote-sensing

data has propelled innovation, delivering exceptional precision and efficacy in the surveillance, mitigation, and regulation of environmental perils. Significant progress has been made in our capacity to comprehend and tackle dynamic urban environmental issues through advancements in spatial analysis, predictive modeling, and real-time monitoring.

Also, the emphasis on sustainability demonstrates a commitment towards developing resilience and protecting the well-being of urban environments. The integration of deep-learning techniques and sustainability frameworks enables proactive measures, facilitating informed decision-making, effective resource allocation, and the creation of resilient urban infrastructures. While these trends exhibit significant potential, they also underscore enduring challenges, such as the need for robust data infrastructure, ethical considerations, and the imperative for interdisciplinary partnerships. Addressing these challenges will be of utmost importance to improve the efficiency and ethical implementation of deep-learning technologies in the development of sustainable urban environments. The application of deep learning techniques in the analysis of urban environmental hazards and disasters is undergoing substantial advancements with a focus on sustainability.

6.1 Future research directions

The prospective path of deep learning in the field of urban environmental hazards and disaster studies offers a captivating terrain abundant with opportunities and pivotal avenues for promoting sustainable urban development.

- (a) *Interdisciplinary collaboration*: Future endeavors will thrive on interdisciplinary collaboration. Integrating expertise from environmental sciences, urban planning, AI, and data science will foster comprehensive solutions. Collaborations will bridge gaps, leveraging diverse knowledge domains to address complex urban challenges.
- (b) *Enhanced data infrastructure*: Investing in robust data infrastructure will be pivotal. Expanding high-quality, diverse datasets accessible to deep-learning models will augment accuracy and reliability in hazard prediction, early warning systems, and risk assessment for urban disasters.
- (c) *Ethical AI and governance*: It is crucial to guarantee the ethical utilization of AI technologies. In the future, there will be a focus on governance frameworks, ethics, and rules in order to

address biases, improve transparency, and promote responsible applications of artificial intelligence in urban settings.

- (d) *Real-time monitoring and prediction:* Advancements in deep learning will enable real-time monitoring and predictive modeling. Dynamic analysis of streaming data models will facilitate prompt disaster response, encouraging proactive measures to minimize the impact on urban ecosystems.
- (e) *Resilience-oriented planning:* Deep-learning applications will play a pivotal role in designing resilient urban spaces. The utilization of predictive modeling and risk-assessment technologies will provide valuable insights for urban planning strategies, facilitating the development of adaptive infrastructure and the establishment of resilient communities in response to environmental threats.
- (f) *AI-driven decision support systems:* The development of AI-driven decision support systems will empower stakeholders. These technologies will assist legislators, urban planners, and disaster-response organizations in making well-informed decisions with practical insights and simulations based on a variety of scenarios.
- (g) *Green infrastructure assessment:* Deep learning will refine assessments of green infrastructure. Cities can achieve an optimal urban planning by accurately identifying and mapping green spaces, thereby allowing for a cohesive balance between development and the preservation of crucial natural areas.

Sustainable urban development is in line with the future of deep learning in disaster studies and urban environmental hazards. Cities must adapt to environmental concerns by becoming more resilient, sustainable, and adaptive.

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