International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 04 April 2026
Page No: 2409-2419
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0322

Satellite Imagery Analysis for Climate Monitoring and Space Applications Using Multi-Source Data Fusion and Deep Learning

Gaurav Tiwari[1], Sangam Gupta[2], Anupam Yadav[3], Dipti Ranjan[4]
[1,2,3]UG Scholar, Dept. of CSE, Babu Banarasi Das Institute of Tech. & Manag., Lucknow, UP, India
[4]Assistant professor, Dept. of CSE, Babu Banarasi Das Institute of Tech. & Manag., Lucknow, UP, India
***EmailID:**gt819182@gmail.com[1],sangamg001@gmail.com[2],anupamyadav1614@gmail.com[3]*
diptitiwari777@gmail.com[4]

Abstract

Big climate analysis, space evaluation and space analytics involves an inseparable element of satellite data. The complex of the Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) products has contributed significantly to the improvement of the applications of remote sensing in the context of automation and precision. Convolutional Neural Networks (CNNs), spectral-spatial as well as hybrid deep learning models have been found to be better when it comes to classification and mapping land cover activities in the environment [1], [12]. Transformer-based models and CNN-Transformers hybrids are also used as latest developments and are more efficient at deriving global contextual features in satellite images [21], [22]. The detection of floods, monitoring of glaciers, mapping of wild fires, analyzing the urban heat, and numerous others are only a small number of real-world applications of AI-powered satellite systems [6], [9], [10]. Despite these advances, the problems of computational complexity, multi-sensor data heterogeneity, small scale real-time processing and cross-regional generalization [5], [18], [20] remain present. Research gaps, methodological tendencies, identification of 22 research studies, systematic review, forming the conceptual basis of an integrated climate monitoring system dubbed GeoSpectra is presented.

***Keywords:**The keywords will include Satellite Imagery, Remote Sensing, Climate Monitoring, Deep Learning, CNN, Transformer Models, Environmental analytics, GeoSpectra.*

1. Introduction

Climate change has led to the necessity of conducting extensive environmental-level surveillance on a regular basis. The earth observation systems are holistic in tracking the spatial and time changes and capturing the vegetations health, land-use change, melting and calamities of the glaciers and calamities due to the satellite-based systems [1], [6]. The earliest remote sensing systems were based on classical machine learning models of the Support Vector Machines (SVM) and the Random Forest classifiers [7], [8]. Although useful in a small-scale task, these methods heavily relied on manual feature extraction and could not cope with multispectral and hyperspectral data of high dimensionality [9], [10]. The advent of deep learning made a sweeping change in the work of satellite images analysis. CNN-based structures allowed automatic extraction of features in hierarchical forms and facilitated better classification than the traditional methods [12], [13]. Attention-based and hybrid model further improved spectral-spatial representation learning [14], [15].

Deep models have high benchmark accuracy, but the current state of the art in computing and operations does not allow them to be used in practice to monitor climate [18], [20]. Thus, the systematic review of AI-based satellite analytics is necessary to learn about the current state of research and its limitations.

1.1.The role of Satellite Imagery in Climate Monitoring

The satellite technologies enable the real time and historical monitoring of environmental situation in the whole world. Multi spectral and hyperspectral systems of imaging record spectral information in various wavelengths that assists in the analysis of vegetation, mapping temperatures, urban sprawls, and deforestation [3], [5]. Cyclone damage detection, glaciers retreat analysis, floods and wild fires monitoring and other applications [6], [9], [10] and [11] are just some examples of the practical relevance of satellite-based climate intelligence systems. Nonetheless, this type of interpretation of such massive volumes of data is ineffective and prone to error, which is why the use of AI-based solutions is encouraged.

1.2.Traditional Machine Learning to Deep learning

The original satellite image classification was based on the classical machine learning model of Support Vector Machines (SVM) and Rand Forest classifier [7], [8]. they were operating large hand written feature extraction algorithms, and could not simply work on large high-dimensional data of hyperspectral data [9], [10]. Convolutional Neural Networks (CNNs) became a new epoch in remote sensing as it gave a chance to automatically learn the spatial features and be more efficient in classification [12], [13]. The spectral-spatial deep learning models also became more precise in the complicated terrains [14]. Latest, transformer-based architecture has been proposed so as to embrace long-range dependencies and global contextual dependencies of satellite imagery [21], [22]. These models indicate a paradigm shift towards representation-learning models, rather than feature-engineered models.

1.3.The Issues with AI-based Satellite Analytics

Accuracy of benchmarking is good, and there are various limitations to its operation. Deep learning algorithms require significant processing support and very large fixed data sets [12], [18]. To do so, there is a problem of heterogeneity of data occurring in the integration of multiple sensors such as optical, radar and thermal data [5], [8]. Second, there is high likelihood that the trained and conditioned models might not be applicable to new climatic conditions not related to the specific geographic area where it was first trained [7], [13]. Disaster monitoring must be real time, which is restricted by hardware and latency [9], [18].

1.4.Motivation and Objectives of this Review

Considering the identified challenges, the rationale behind this review is the necessity of having a comprehensive view on AI-driven satellite analytics. The primary objectives are:

- To classify the methodologies into classification, change detection, disaster monitoring and space-based AI systems.
- To compare the weaknesses and advantages of conventional and deep learning methods.
- To find gaps in open research in the processing of the real time, multi-sensor integration and scalability.
- To formulate a conceptual base of a single intelligent platform called GeoSpectra.
- To conduct a systematic review of 22 studies on AI satellite imagery processing studies.

These hybrid systems combine the benefits of both numerical deep learning and sentiment-aware natural language processors, and are always more accurate, stable, and able to predict short-term movement, compared to single-source systems [1][3][5][10][18].

2. Background

2.1.Remote Sensing and Equipment

Remote sensing is considered as the activity of gaining information in the surface of the earth without physically touching the surface, chiefly through the airplane sensors or satellite sensors. New satellites obtain multispectral and hyperspectral images, which allow analysis at various spectral bands in vegetation-monitoring, water-bodies-detection, and land-use classification [1], [2]. Multi spectral imaging records information in a small range of spectral bands whereas hyperspectral imaging records hundreds of continuous bands, enabling identification of materials in a fine way [3]. Nonetheless, the disadvantages associated with hyperspectral data include high dimension and computational complexity [4].Information that compliments each other is provided by satellites systems like optical sensor, thermal sensor, and Synthetic Aperture Radar (SAR) sensor.It has been observed that multi- sensor data integration can be used to improve the performance of classification and environmental monitoring [5], [6].

2.2.Machine Learning in Remote Sensing:

The classical algorithms of Support Vector Machines (SVM), k-Nearest Neighbors (kNN) and Random Forest classifiers mostly on satellite images were used in machine learning [7], [8]. Such models demanded manual feature engineering and knowledge domain in extraction of spectral and texture features.The findings of research have demonstrated that though the classical ML models were moderately classified, these models failed to work with complex spatial patterns and massive data sets [9]. Reduced dimensionality analysis techniques like Principal Component Analysis (PCA) became common in order to save on the cost of computation of the hyperspectral data [10]. The new approaches did not possess the strength of the old ones to work in the non-homogenous and dynamic environment [11].

2.3.Deep Learning Advancements

Hybrid models combining deep learning models such as The introduction of Convolutional Neural Networks (CNNs) can automatically feature hierarchical spatial features of satellite image analysis and can therefore revamp it [12]. The CNNs based architectures performed well compared to SVM and Random Forest models in the classification of land covers [13]. Deep CNN models were proposed in [14] to classify multi-class satellite images, and the authors achieved good levels of accuracy using best benchmarking datasets. The pre-trained models which had been taught to perform remote sensing work had better outcomes after transfer learning techniques were applied to them [15]. The combination of spectral and spatial data with 3D-CNN architectures led to the fact that the accuracy of the hyperspectral image classification of the hybrid models was improved [16]. However, these models are related to the large labeled datasets and enormous computing capabilities.

3. Literature Review

3.1.1. Land Use and Land Cover (LULC) Classification

Land Use and Land cover (LULC) classification has been among the most investigated applications of the satellite image analysis. The first ones were based on the traditional machine learning models, such as Support Vector machines (SVM) and randomly forest to execute a multi-class land mapping task [7], [8]. Despite the moderate rating on the classification accuracy, these models were very sensitive to handcrafted spectral and texture features because they could not extend to complex terrains [9].
Convolutional Neural Networks (CNNs) were developed that came to be of importance in the automated extraction of spatial features of satellite data. The results of the study provided in [1] and [12] indicated that multi-class land cover mapping problem was better solved using CNN-based models compared to traditional classifiers.The deep learning models also proved their correctness when compared with SVM-based systems according to which deep learning models are highly precise and recalling [2], [13]. The spectral-spatial deep learning have been proposed to jointly utilize the spectral and spatial information to improve the prediction capacity of models in heterogeneous landscapes [4], [14]. These kinds of architectures can handle complex terrain variations but are computationally expensive. The transfer learning techniques were also explored with the aim of saving on the training time and enhancing the performance on small data [3]. However, most LULC models are susceptible to large labeled data and less generalization would be achieved when applied to analyze another geographical area [13].
Overall, the research papers on the LULC classification point to a change in the classical versions of ML methods to deep representation-learning models wherein the accuracy has been steadily increasing at an increasing cost in terms of the computational requirements.

3.2.Climate Change and Environmental

Surveillance

The satellites are also applicable in long term time monitoring of environmental and climatic change. Vegetation analysis has largely been used to determine patterns of drought and agricultural stress using index analysis (i.e. NDVI) [5]. Hybridized methods formed by satellite data and machine learning have already demonstrated good performance when it comes to detecting vegetation degradation and other environmental changes.

The analysis of the glacier retreat is the other important sphere of application. In [6], satellite image of multi-temporal type was employed to identify the variations in the edges of glaciers that are indicative of measurable impacts of climatic change. Still on the same point, deep learning through the assistance of thermal imaging has been implemented to identify urban heat islands and temperature variations [7]. The models too are more realistic in the area of temperature mapping and are deficient in adapting to various climatic conditions [13]. The AIs-based classification systems have also been used in forest deforestation detection and environmental degradation monitoring cases [8]. The combination of the monitoring can be made more reliable with the help of multi-source satellites, however, the issue of sensor heterogeneity remains [5], [8]. Although this has been done, most of the environmental monitoring systems entail an offline environment and can not be applied in real-time. Moreover, seasonal variability and atmospheric interference share a similar impact on the regularity of the models in long-term climate analytics [11]. The sum total of all of the climatic related analysis reveals the possibility of the AI-enabled satellite analytics to achieve the aim of the sustainable development provided that the relevant scaled and adaptable monitoring systems exist. Moreover, atmospheric noise and seasonal variations also may become a significant problem related to the regularity in long-term climate analytics designs [11]. Combined with the results of all the deliberations connected with climate, one can arrive at the conclusion that there is the potential of the possibility of achieving the goals of sustainable development of the AI-based satellite analytics, but the demands in relation to the scaleable and widely adjustable monitoring systems are compulsory.

3.3.Hyperspectral Analysis, Disaster Detection, Change Detection

Monitoring of disasters is among the useful real-time satellite images processes. It has been determined that CNN-based segmentation models are highly accurate in detection of floods in Sentinel datasets [9]. The Hybrid CNN-LSTM models are learned with respect to the time variations to improve making predictions on the spread of wildfires [10]. Similarly the semantic segmentation models have also been applied in the cyclone damage assessment in which spatial localization of the damages regions have been enhanced [11]. However, such disaster detection systems are preprocessing and processing intensive hence limits the opportunities of its implementation in real time [9], [18]. The fact that 3D-CNNs are the most suitable in the classification task of hyperspectral images can be seen in the nature of the new possibilities and challenges provided by the hyperspectral imaging since 3D-CNNs can learn spectral-spatial associations [12]. Although PCA and any other form of reduction of features can actually decrease the amount of computing power, it may also lead to the loss of information [13]. It is also possible to develop the strength of classification through fusion strategies but necessitating the use of the spatial-spectral methods which require a lot of memory compared to other methods [14]. The concept of model based change detection has been developed to include pixel based detecting model to deep learning based detecting models. Siamese CNN models are good at identifying bi-temporal change in land cover datasets [15]. The GANs that are applied in change detection enhance the accuracy of boundaries and quality of segmentation although it takes extensive training data [16]. The deep learning method based on the object representation also increases the accuracy of the detection during the analysis of urban transformation [17]. The global world has connected more modern transformer based models and have replaced the older CNN models in the classification and segmentation tests [21], [22]. However, they are extremely costly to calculate, which limits their usage in those satellites that have a resource limit [18]. Overall, the research on disaster detection and hyperspectral analysis demonstrates that the methodology has the high level of development, yet the issues of computational efficiency, scalability, and practicability of the method in the real-time are not yet determined in practice.

4. Proposed Methodology

4.1.Multi- Source Hardware and Software Satellite Data Integration System

The proposed framework controls the satellite data, which is not homogeneous, and integrates it in the following way:

- *Optical (Sentinel-2, Landsat) images.*
- *Images Sun pictures (MODIS, Landsat TIRS).*
- *Radar data (Sentinel-1 SAR)*
- *Soil moisture (SMAP)*
- *Elevation & altimetry (ICESat-2)*

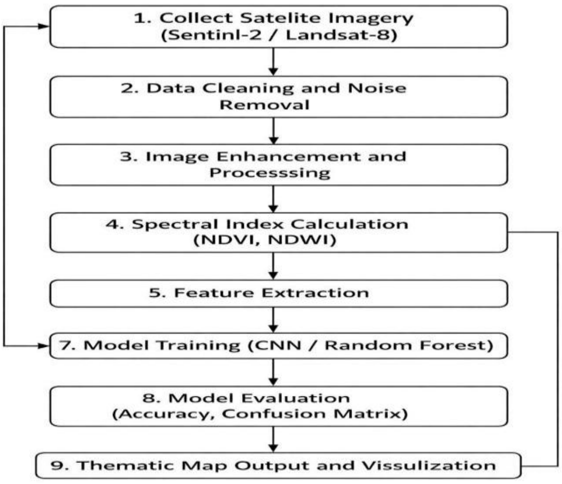

Figure 1 Complete Workflow Of Processing Pipeline

4.2.Data Fusion Model

Let the multi-source dataset be defined as:

$$D = \{D_{opt}, D_{radar}, D_{thermal}, D_{soil}, D_{alt}\}$$

Each dataset contains spatial-temporal observations:

$$X_t = f\left(D_{opt}^t, D_{radar}^t, D_{thermal}^t, D_{soil}^t\right)$$

where:

- $t =$ *time step*
- $X_t =$ *fused climate feature representation*

We apply feature-level fusion using:

$$F = \sum_{i=1}^{n} w_i \phi(D_i)$$

where:

- $\phi(D_i) =$ *feature extraction function (CNN/Transformer encoder)*
- $w_i =$ *adaptive weight learned via attention mechanism*

5. AI-Based Feature Extraction

5.1.Convolutional Neural Network (CNN)

Used for spatial feature extraction:

$$Y = ReLU(W * X + b)$$

where:

- $W =$ *convolution kernel*
- $X =$ *input image*
- $b =$ *bias*

5.2.Transformer-Based Temporal Modeling

To model climate time-series:

$$Attention(Q, K, V) = Softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

This captures:

- *Long-term temperature trends*
- *Seasonal vegetation changes*
- *Extreme weather anomalies*

5.3.Climate Index Computation

NDVI (Vegetation Health)

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

Land Surface Temperature (LST)

$$LST = \frac{BT}{1 + \left(\frac{\lambda BT}{\rho}\right) ln(\epsilon)}$$

where:

- BT= Brightness temperature
- ϵ= surface emissivity

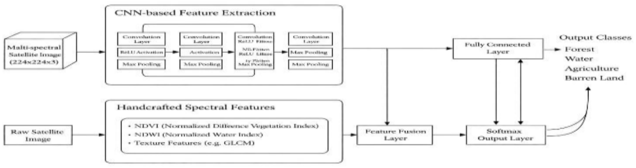

FIGURE 2: Multi-Source Data Fusion Architecture of the Proposed Climate Monitoring Framework.

Table I: Comparative Analysis Of Climate Monitoring Approaches

Approach	**Data Type**	**AI Model**	**Limitation**	**Proposed Advantage**
Single-source optical	Landsat	CNN	Cloud interference	Multi-sensor fusion
Radar-only	Sentinel-1	SVM	Low spectral info	Combined spectral + radar
Thermal-only	MODIS	LSTM	Low spatial resolution	High-res fusion
Proposed Framework	Multi-source	CNN + Transformer + Attention	—	Robust, scalable, predictive

5.4.Comparative Analysis Of Existing Approaches

The comparative evaluation of the selected works of research indicates that the method of the classical machine learning is used on the new deep learning networks to process the satellite images. Most of the Support Vector machines (SVM) and random forest classifier among other supervised learning processes were used in the earlier ones in the classification of land covers tasks [7], [8]. These models had been very effective with structured data and were cruelly susceptible of handcrafted spectral and texture properties and were incapable of explaining the detailed spatial relationship of heterogeneous landscapes [9], [10]. Moreover, the classical models were also known to be weak, in the high dimensional hyperspectral data [13]. The Convolutional Neural Networks (CNNs) were invented, which significantly advanced the possibility to classify data since it enables hierarchical features to be extracted automatically. The studies conducted in [1] and [12] have revealed that multi-class land cover mapping has strong performances as compared to the traditional classifiers. The spectral-spatial deep learning models further enhanced the strength of the classification, by jointly having a shared learning of spatial and spectral information [4], [14]. This was done at the cost of the computational complexity and memory requirements. CNN-based segmentation models were seen to be very accurate in disaster detection application like flood mapping and wildfire monitoring when used in benchmark conditions [9]. Temporal data was implemented on top of hybrid CNN-LSTM models to make wildfire evolution forecasting [10]. Despite higher performance in segmentation as compared to the pixel-based techniques, the models were very costly in terms of preprocessing and their computation needed immense processing power and could not be applied in real-time emergency situations [9], [18]. The models were successfully proposed by Hyperspectral spectroscopy 3D-CNN in extracting spectral-spatial correlation and enhanced classification performance compared to 2D models

[12]. One of the techniques employed to diminish the features to mitigate the curse of dimensionality is Principal Component Analysis (PCA) [13]. In spite of the fact that dimensionality reduction increased the efficiency of computation, it sometimes resulted in loss of part of the information. Spatial-spectral fusion methods were used to further enhance the method and also to raise the memory and processing needs to a significant level [14]. Even the change detection methods have transformed tremendously. Traditional pixel-based models were gradually replaced by deep learning models such as Siamese CNN-based models and GAN-based models [15], [16]. The latter procedures demonstrated higher accuracy of the boundaries and increased the capacity to detect the slight land changes. Nevertheless, their high sensitivity to light and the necessity to use huge annotated datasets remain a viable disadvantage [17]. One of the most recent developments that have occurred in determining the long-range dependencies and global contextual relationships of satellite images is the use of remote sensing systems that are based on transformers [21]. CNN-Transformer hybrids have also shown superior performance in classification and segmentation tests, surpassing the traditional CNN models [22]. The models are very precise but need the power of computational devices equivalent to the graphics cards, and are not easily implemented on a power limited satellite or edge platform [18], [21]. Overall, the comparative analysis indicates that deep learning and hybrid architectures are always more precise and can capture features, however, there are certain problems with computation complexity, scalability, real-time implementation and region generalization. The lack of such a common structure combining multi-sensor fusion and lightweight modeling with scalable processing can be listed among the key limitations of the existing strategies [8], [19], [20].

5.5.Challenges And Research Gaps

However, the success of satellite imagery machine learning has multiple research gaps and issues as breathtaking as the advances in the analysis. Although deep learning-based models have been reported to be highly precise, in regards to classification, segmentation, and change detection capabilities, they cannot be effectively and practically applied to the real environment like to massive climate monitoring systems. Heterogeneity and Multi-Sensor Integration

The sensors are of different types which capture the satellite images and include the following, the optical, thermal, multi-spectral, hyperspectral and the Synthetic Aperture Radar (SAR) sensor. The data that is given by each of the sensors possess different spatial, spectral as well as time resolutions. One of the most difficult issues is the inclusion of these nonhomogenous data in one model [5], [8], [14], [20]. The current literature is largely addressing the individual sensors and does not generalize the capability of making generalizations in other settings of the setting. As an example, experimental findings on applications to model trained on data of optical images have been ineffective with radar based data due to properties of the signal variations [6], [13]. Multi source fusion has been proposed but also a gap in research exists, one of high cross sensor adaptability [3], [21]. The available literature on the subject considers single-sensor datasets, which restricts the ability to generalize the use of the approach in a wide range of environmental conditions. Indicatively, the models used in optical imagery tend to fail when used with radar-based data due to the difference in signal properties [6], [13]. Despite the suggestion of multi-source fusion methods, the strong cross-sensor flexibility is an open research gap [3], [21].

6. Deep Models have High Computational Complexity

Recent system like 3D-CNNs, GAN-driven models of change detections, transformer-based remote sensing networks have remarkably enhanced the performance of classification [12], [16], [21], [22]. These models however require high computing power, use of the GPUs and require a lot of memory. The high dimensional spectral bands of hyperspectral image processing also augment the computational load [4], [12]. This renders the real-time climate monitoring and onboard satellite processing difficult [18]. Thus, there is a high demand of lightweight and energy efficient AI architectures that are more suitable to large-scale satellite systems [10], [19].

6.1.Small Processing Capability in Real-Time

According to many recent disaster detection models, accuracy is high when operating under offline experimental environments [9], [11], but not when deployed in the real-time. Detection systems of floods and wild fires usually involve extensive preprocessing and batch-based inference, interrupting emergency response [9], [10] It has also been suggested that onboard AI processing can be used to conduct analytics faster directly in satellite systems [18]. Nevertheless, onboard memory, energy availability, and restriction on hardware make it impossible to implement computationally intensive deep models [21]. The near real time climate observation is therefore considered a major challenge in research.

6.2.Geographical Regionalization

One of the immense restrictions that have been actualized according to various studies is severe cross-regional flexibility. The benchmark based models also may exhibit a significantly better performance on the same geographic distribution, and a poorer performance on other climatic or environmental conditions [7], [13], [15].The season and atmospheric biases and changes in light are also important factors in as far as the score of the models in land cover issues that involve land cover classification and also the land cover change detection [5],[17]. To some extent, domain adaptation and transfer learning techniques can win over this issue [3] although deep global generalization is an issue that is only yet to solve [22].

6.3.Absence of High-Quality Labeled Data

Deep learning models require huge annotated datasets to train [1], [12]. Nevertheless, satellite imagery labelling is laborious, expensive, and needs professional expertise. Unlabeled samples are particularly influential on hyperspectral data due to the complexity of high dimensions [4], [14]. Algorithms based on semi-supervised and self-supervised learning have been investigated but are not yet popular in climate monitoring systems [16], [21]. Another significant line of research is the development of scalable annotation systems and label-accepting training systems.

6.4. Future Directions

The active development of the Artificial Intelligence which took place recently in the sphere of satellite images analysis has provided the additional opportunities in the sphere of the advancement of climate analysis and space analysis. Although the current body of knowledge proves that classification and segmentation are at high levels, the next step of the study should be devoted to scalability, adaptation, and real-time application to utilize the opportunities of the AI-based Earth observation systems to the full extent.

6.5.Lightweight and Real-Time Architecture Development of AI

One of the most essential fields of future research that we would like to consider is the construction of computationally efficient and lightweight deep learning models that will ultimately be deployed to real-time satellite analytics. Currently, the state of art architecture has 3D- CNNs and Transformer-based networks that are more precise but require massive memory and GPUs [12], [21], [22]. Such computing power restricts its activities in edge computing and onboard satellites [18]. The future research should take into consideration the fact that the techniques of compressing models such as pruning, quantization and knowledge distillation can be applied to reduce the cost of computation without affecting the quality. Edge-AI systems that are capable of reaching inferences into satellite devices can save much time when responding in the process of detecting the disaster at the terminal of the flood and wildfire detecting systems [9] and [10]. The reality that it can be performed virtually in real-time will render it more receptive in responding to the climatic sensitive and emergency cases.

6.6.Multi-Sensor Fusion and Cross-Regional Adaptation

The optical, thermal, hyperspectral as well as radar sensors result in heterogeneous data that were produced by satellite systems. Despite the fact that the reliability of monitoring can be improved by the use of multi-source fusion, the problem of integration remains to be unsolved yet [5], [8], [14]. It is possible to state that the future research can concentrate on the attention-based cross-modal learning and adaptive data fusion algorithms that will be capable of catering to the variability of sensors. And to top it all, most of the existing models have one invariable weakness, namely, intersectional generalization [7], [13]. The domain adaptation and transfer learning models should also be improved to be capable of expanding to other places in the world, yet not retrain a region of a human being. Introduced stable multi-climate adaptation systems will promote uniformity to diverse climatic conditions and seasonal variations [11], [15].

6.7.Self- Supervised Learning, Frameworks and Explainability

The problem of quality labelled satellite information is not accessible yet, thus, it remains the limitation to the deep learning model training [1], [12]. More promising are semi-supervised and self-supervised types of learning, on the basis of the large ones of unlabeled satellite images in representation learning [16], [22]. The methods that should be explored in the future are the unique geospatial intelligent methods of foundation model methods and contrastive learning. Moreover, as an additional step to encourage openness and trust in the climate decision-making framework, the explainable artificial intelligence (XAI) procedures will be introduced in the satellite analytics pipelines [11]. Nevertheless, the policy planning as well as the environmental governance and applications of the disaster management have invaluable models to be interpreted. Lastly, it is also highly sought on structures which are embedded and scalable that can potentially involve multi sensor consolidation, hybrid AI designs, cloud-based distributed computing and real-time notifications [19], [20], [21]. The single platform like the GeoSpectra can be adopted and used in the sustenance of the world as the basis of new generation smart climate monitoring system.

Conclusion

This review article provided a systematic and in-depth study of satellite imagery methods based on Artificial Intelligence_to monitor climate and space uses. Considering 22 up-to-date research papers, it can be stated that deep learning models, specifically Convolutional Neural Networks (CNNs), 3-dimensional spectral-spatial models, GAN-based change detectors, and Transformer-based models have significantly enhanced the performance of land cover classification, disaster detecting, and monitoring in the environment-related tasks [12], [16], [21], [22]. Deep learning models show an increased capacity of automatic feature extraction and learning of the spatial representation compared to the conventional machine learning methods like Support Vector Machines and Random Forest classifiers [7], [13]. Spectral classification has been complemented with spatial classification, particularly in hyperspectral data [4], [14]. hybrid systems combining CNN with a time-dependent system like LSTMs have served to enhance the accuracy of disaster monitoring with the addition of time-dependent information [10]. Even with these methodological improvements, there exist a number of operational limitations. Onboard satellite systems and real time deployment have high computational complexity that inhibits deployment [18], [21]. The still existing issues with large-scale climate analytics are multi-sensor data heterogeneity, low cross-regional generalization, and the absence of an annotated dataset [5], [7], [12]. Besides, the current research focuses on individual applications as opposed to suggest convergent and scalable intelligent systems [19], [20]. Conversely, the underlying comparative analysis and comparison emerged during this review indicates that there is an urgent need to have integrated, lightweight, and adaptive AI that can handle heterogenous satellite data without affecting scalability and real-time responsiveness. These gaps are addressed by the proposed GeoSpectra framework based on the conceptual framework advocating multi-sensor fusion, hybrid deep learning architectures and distributed cloud-edge processing models. To sum up, the use of AI-controlled satellite images is a revolution in the way that we can find a solution to the issue of global climate change. Nevertheless, the creation of effective, scalable and globally adjustable climate monitoring systems demand continuous research in maximising models, elucidation, cross-domain adaptation and combined framework engineering. The findings of this review will provide a properly organized foundation of further improvement of the intelligent Earth observation and space-based climate analytics.

Acknowledgment

The author owes a deep sense of gratitude to Mrs. Dipti Ranjan, Assistant Professor, Department of Computer Science and Engineering, Babu Banarasi Das Institute of Technology and Management, Lucknow, India, whose guidance, constructive feedback, and encouragement, have greatly aided him in the preparation of this review paper. The Department of Computer Science and Engineering is also thanked to the institutional support and academic climate that the institution offers.

References

[1]. X. Lv et al., “Evaluation of GSMaP Version 8 Precipitation Products on an Hourly Timescale over Mainland China,” Remote Sens., 2024.
[2]. Z. Hao et al., “Multitemporal Analysis of Urbanization-Driven Slope and Ecological Impact Using Machine Learning,” IEEE JSTARS, 2024.
[3]. Z. Xiong et al., “EarthNets: Empowering AI in Earth Observation,” IEEE Trans., 2024.
[4]. G. Fodor and M. V. Conde, “Rapid Deforestation and Burned Area Detection Using Deep Multimodal Learning,” 2023.
[5]. G. Choumos et al., “Space-to-Ground Data Availability for Agriculture Monitoring,” 2023.
[6]. E. Dritsas and M. Trigka, “Remote Sensing and Geospatial Analysis in the Big Data Era: A Survey,” 2024.
[7]. H. Gu and Y. Mao, “Multi-Timescale Characteristics of Surface Currents,” 2024.
[8]. H. Bencherif et al., “Ozone Trend Analysis Using Empirical Decomposition,” 2023.
[9]. S. Mao et al., “Aerosol Optical Properties Retrieval Using Polarization Raman Lidar,” 2023.
[10]. W. Qin et al., “ICESat-2 Signal Photon Extraction Using CNN,” 2023.
[11]. R. Lottering, K. Peerbhay, and S. Adelabu, “Remote Sensing Applications in Agricultural, Earth and Environmental Sciences,” Remote Sens., vol. 2024, 2024.
[12]. Y. Wu et al., “Elevation-Dependent Contribution of the Response and Sensitivity of Vegetation Greenness to Hydrothermal Conditions on the Grasslands of Tibet Plateau from 2000 to 2021,” Remote Sens., 2023.
[13]. J. Xu et al., “A Spatial Downscaling Framework for SMAP Soil Moisture Based on Stacking Strategy,” Remote Sens., 2023.
[14]. Y. Wang et al., “Ocean Colour Atmospheric Correction for Optically Complex Waters under High Solar Zenith Angles,” Remote Sens., 2023.
[15]. K. Mu et al., “Coastline Monitoring and Prediction Based on Long-Term Remote Sensing Data—A Case Study of the Eastern Coast of Laizhou Bay, China,” Remote Sens., 2023.
[16]. Z. Li et al., “Intelligent Environment-Adaptive GNSS/INS Integrated Positioning with Factor Graph Optimization,” Remote Sens., 2023.
[17]. L. Song et al., “Attention Network with Outdoor Illumination Variation Prior for Spectral Reconstruction from RGB Images,”

Remote Sens., 2023.
[18]. M. Crivellaro et al., “Characterization of Active Riverbed Spatiotemporal Dynamics through the Definition of a Framework for Remote Sensing Procedures,” Remote Sens., 2023.
[19]. R. Lottering, K. Peerbhay, and S. Adelabu, “Remote Sensing Applications in Agricultural, Earth and Environmental Sciences,” Remote Sens., 2024.
[20]. D. Wang et al., “A Review of Deep Learning in Multiscale Agricultural Sensing,” Remote Sens., 2022.
[21]. S. A. Ahmadi et al., “BD-SKUNet: Selective-Kernel UNets for Building Damage Assessment in High-Resolution Satellite Images,” Remote Sens., 2023.
[22]. M. Gavrouzou et al., “Modification of Temperature Lapse Rates and Cloud Properties during a Spatiotemporally Extended Dust Aerosol Episode over the Mediterranean Basin,” Remote Sens., 2023.
[23]. M.-H. Le et al., “Assimilation of SMAP Products for Improving Streamflow Simulations over Tropical Climate Region,” Remote Sens., 2023.
[24]. B. Nilsson et al., “Consolidating ICESat-2 Ocean Wave Characteristics with CryoSat-2 during the CRYO2ICE Campaign,” Remote Sens., 2023.
[25]. He et al., “Reasoning-Based Scheduling Method for Agile Earth Observation Satellite with Multi-Subsystem Coupling,” Remote Sens., 2023.