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REVIEW

Earth Observation for Environmental Security: Emerging Multi-Sensor Fusion Techniques

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ABSTRACT

Climate change, natural disasters, pollution, and fast urbanization have made environmental security a more serious international issue. Timely, accurate, and multi-dimensional information is essential in the effective monitoring and management of such complex challenges in the environment. The Earth Observation (EO) systems, including optical sensors, radar sensors, Light Detection and Ranging (LiDAR) sensors, thermal sensors, Unmanned Aerial Vehicle (UAV) sensors, and in-situ sensors, offer a good coverage of space and time, as well as provide useful information on land, water, and atmospheric processes. But the shortcomings or weaknesses of individual sensors, such as their vulnerability to weather conditions, spectral or spatial resolution, and gaps in time, can tend to limit their ability to provide a complete picture of the environment. One of the solutions has been multi-sensor fusion, which combines heterogeneous data and makes it more accurate, robust, and interpretable. This systematic review analyzes the latest methods of multi-sensor fusion, which are machine learning, deep learning, probabilistic models, and hybrid approaches, in terms of methodological principles, preprocessing needs, and computational frameworks. Applications in environmental security are highlighted, which include monitoring natural disasters, monitoring of climate and ecosystem, pollution monitoring, monitoring of land use change, and early warning systems. The review also covers evaluation measures, validation plans, and uncertainty

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measures, where a strict measure of evaluation is vital to making actionable decisions. Lastly, emerging issues, e.g., data heterogeneity, computational needs, sensor interoperability, and prospects in the future, e.g., AI-based adaptive fusion, UAVs and Internet of Things (IoT) integration, and scalable cloud-based systems, are discussed. The synthesis has highlighted the transformational capability of multi-sensor EO in terms of improving the environment in the context of environmental security and sustainable management.

Keywords: Earth Observation; Environmental Security; Multi-Sensor Fusion; Remote Sensing; Data Integration

1. Introduction

Natural hazards and environmental changes are becoming increasingly prominent as fundamental determinants of the world's sustainability, ecosystem stability, and human health. The rate and intensity of environmental hazards like floods, wildfires, droughts, land degradation, and coastal erosion are compounded by rapid urbanization, climate change, deforestation, and environmental degradation [1–6]. These difficulties have increased the significance of environmental monitoring systems that can deliver a timely, reliable, and vast amount of information to facilitate environmental management and the reduction of risks. In this regard, the term environmental security has increasingly been taken seriously in environmental science as well as in the policy discourse. Environmental security is the general idea of safeguarding the environment, the natural resources, and human communities against any environmental hazards that can jeopardize the ecological stability, economic practices, and social strength. It includes ecological security, which aims at preserving the integrity and sustainability of natural ecosystems, and human and infrastructure security, which deals with the environmental hazards that have a direct impact on human settlements, agriculture, and essential infrastructure. **Figure 1** illustrates the conceptual model of the multi-platform Earth Observation systems, data fusion processes, and environmental security applications, highlighting that multi-sensor fusion acts as the conduit through which different Earth Observation datasets interface with operational environment security processes, converting their heterogeneous raw measurements into environmental intelligence [5,7].

Another important tool in the evaluation of environmental security has become the Earth Observation (EO) technologies, which have become one of the most important in monitoring the environmental processes. The satellites, through remote sensing, provide repeatable, large-scale, and constant measurements of the surface, atmosphere, and oceans of the Earth. Sensor technologies have been worked out greatly in the past two decades, and this has magnified the EO systems on a large scale. New satellite missions such as optical multispectral sensors, Synthetic Aperture Radar (SAR), Light Detection and Ranging (LiDAR), and thermal infrared sensors are complementary to one another to provide information about the environmental conditions. Vegetation health, land cover, and water quality. Spectral reflectance sensors and SAR sensors of structural and moisture-related information can be acquired under any weather conditions or in inaccessible areas during daylight. LiDAR sensors will provide additional three-dimensional structural data of vegetation and terrain, and thermal sensors can monitor temperature changes caused by other processes, such as wildfires or urban heat islands [8].

Despite these developments, individual sensors are attributed to drawbacks that restrict their applicability in tracking activities that are multifaceted in the setting. Optical imagery is most often affected by cloud cover and atmospheric conditions, SAR data is often hard to read due to both speckle noise and geometric distortions, and LiDAR data is often limited either spatially or temporally. As such, a single form of sensor may provide a partial/imprecise environmental analysis. It has therefore been made possible through multi-sensor data fusion as a viable means of supplementing such shortcomings through the merging of complementary data in multiple observation systems. Fusion methods can enhance the spatial resolution, temporal coverage, and accuracy of classification and provide stronger environmental monitoring by enhancing the capability to integrate heterogeneous data [5,9].

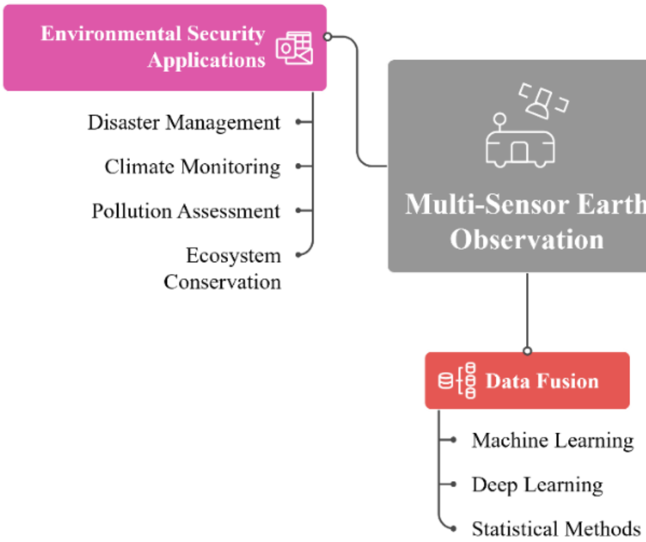

Figure 1. Conceptual framework of multi-sensor Earth Observation for environmental security, illustrating data flows from diverse sensing platforms to fusion processes and decision-support applications.

Geospatial data processing and machine learning, including artificial intelligence, have improved over the past few years and allowed the potential of the multi-sensor EO fusion to grow significantly. Massive multi-source datasets can now be integrated and analyzed with the help of deep learning models, cloud computing platforms, and infrastructures with massive geospatial data. Such developments have simplified many uses of the device in environmental monitoring, including: determining flood, mapping wildfires, monitoring deforestation, monitoring the coastal region, and monitoring pollution. Multi-Sensor fusion has also been handy in the improvement of early warning systems and decision-making in the course of disaster management and evaluation of environmental hazards[5,10].

Although there is a large amount of literature review of remote sensing technologies and algorithms fusion strategies, the majority of the existing surveys are general remote sensing strategies or algorithm-specific algorithmic development with no distinction given on their relevance to the environmental security problem. Environmental monitoring is emerging as more complex and interdisciplinary, leading to an increase in the demand to develop more general synthesis in connecting the advancements in the EO sensor technologies, data fusion strategies, and environmental security applications. In particular, the issue concerning the role of the different combinations of sensors and fusion strategies in supporting or contributing to the environmental monitoring assignments is required to inform future studies and implementations[11–15].

This paper aims at addressing this gap and hence provides a review of the prevailing developing approaches in the application of multi-sensor fusion to Earth Observation with special focus on environmental security. The review also gives an overview of the latest trends in the EO sensor technologies, data fusion algorithm and environmental monitoring systems. Conceptual taxonomy is proposed, which creates a definition of fusion techniques and approaches in relation to sensor modalities, fusion levels, and the purpose of environmental monitoring. Additionally, representative studies are analyzed in terms of a comparative-based framework with sensor combinations, combination strategies, data sets, and measures utilized in evaluations being determined in the context of environment implementation. By systematically analyzing the strengths and weaknesses of existing approaches, this review identifies important methodological challenges and new directions of research in the multi-sensor EO fusion in determining environmental security[16,17].

Such a synthesis will assist the article in providing a systemic perspective of the existing state of multi-sensor fusion technologies and their role for the researchers and practitioners in environmental security issues. The findings show that the role of complex EO systems and emerging data analytics is becoming increasingly important in supporting sustainable environmental management and increasing resiliency to environmental risks in an ever-more-dynamic world.

2. Earth Observation Systems for Environmental Security

Modern environmental monitoring and management depend heavily on Earth Observation systems that give important information about complex and dynamic natural processes. A wide range of platforms encompasses these systems, including satellites, airborne vehicles, unmanned aerial vehicles, and ground-based in-situ sensors[18]. The advantages of each platform are different due to their spatial, spectral, and temporal coverage of the environment, allowing for carrying out detailed studies of environmental conditions at the local to the global level. As the number of extreme weather events and urban sprawls continue to rise, as well as environmental degradation, EO systems are now becoming imperative in providing environmental security, supporting disaster management, and informing policy and planning. The constant development of sensor technologies, data collection platforms, and processing algorithms has made a great contribution to the ability to track, measure, and cause changes in the environment, with high precision and timeliness[19,20].

2.1. Optical Sensors

Some of the most widely employed EO instruments are still optical sensors, which can record fine spectral and spatial data. Multispectral sensors are typically mounted on satellites like the Landsat, Sentinel-2, and Satellite Pour l'Observation de la Terre (SPOT, Satellite for Earth Observation), where they capture data in multiple broad spectral bands that can be used to monitor vegetation health, soil moisture, water quality, as well as land cover dynamics. Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) are vegetation indices that have been extensively used to measure the productivity of an ecosystem and monitor environmental stress. Hyperspectral sensors on satellites, such as Hyperion and PRecursore IperSpettrale della Missione Applicativa (PRISMA), have hundreds of narrow spectral bands and can discriminate surface materials/with a high level of fine resolution of surface materials, species-level consideration of vegetation, and can detect very small chemical/structural anomalies. These sensors have been used in precision agriculture, habitat surveillance, and pollution/contamination detection. In spite of their flexibility, optical sensors are limited by the atmospheric conditions; the cloud cover, aerosol presence, or even low light can seriously deteriorate data quality. However, recent increases in high-resolution optical satellites, small-satellite constellations, onboard calibration methods, and techniques have alleviated these drawbacks in part and allowed near-daily revisit, as well as provided better data reliability[21,22].

2.2. Radar Sensors

Radar systems, especially the Synthetic Aperture Radar (SAR) and Interferometric SAR (InSAR), offer an alternative view of the optical image, because by exploiting the microwave frequencies, the radar system can penetrate the clouds and can work during the dark. The SAR sensors, which are installed on platforms like Sentinel-1, RADARSAT, and TerraSAR-X, can measure the structure of the surface, identify alterations in the water level, and trace the city's progress. The capabilities are enhanced by the InSAR techniques that reveal even the slightest deformations of the ground, which allows early prediction of the landslides, subsidence, glacier processes, and instability of the infrastructure. Recent advances in polarimetric SAR (PolSAR) enable surface features to be differentiated by the scattering mechanisms, which can improve the accuracy of the classification of forests, wetlands, and urban areas. Radar imagery, however, necessitates very intricate processing, such as speckle filtering, terrain correction, and coherence analysis in order to extract significant information. It has been demonstrated that combining SAR with optical data has a promising future in offering better devastation, flood, and land-cover data, especially in adverse weather situations when optical sensors cannot work[23].

2.3. LiDAR and Altimetry Systems

LiDAR and altimetry sensors offer the most important three-dimensional information to supplement spectral and radiometric information. LiDAR systems in the air and ground send laser pulses and record the time to get back the laser pulse and create dense point clouds of the surface features, making fine-scale topography, canopy configuration, and built environment. LiDAR has found applications in the estimation of forest biomass, mapping of cities, flood risk, and erosion at the coast. LiDAR can be collected by a satellite, including the ICESat-2 mission, which allows measuring ice sheets' elevation and the height of vegetation at a large scale. The altimetry sensor, found on many satellites, is used to measure the height of the surface of the land or water, which helps to monitor the rise of sea levels, the discharge of rivers, and the melting of glaciers. LiDAR has unmatched structural detail but is expensive to operate, has a large volume of data, and has a small spatial coverage. The integration of LiDAR with multispectral data or SAR data has seen a growing ability to give the environment a multi-dimensional analysis that improves the knowledge of the surface structure and composition [9,24].

2.4. Thermal and Microwave Sensor

Thermal and microwave sensors provide the necessary knowledge on earth energy and moisture processes. The thermal infrared sensors capture the radiation emitted on the surface, and they offer details on land surface temperature, urban heat islands, water temperature, and volcanic activity. Microwave radiometers, such as passive and active instruments, are utilized in estimating the soil moisture, the snow depth, and the precipitation, and this plays a role in hydrological research, drought surveillance, and climate research. The sensors are also extremely useful in environmental uses where the temperature and moisture variations are very important. Developments in sensor design have enhanced spatial and temporal resolution, which allows mapping of thermal anomalies and hydrological differences at a finer scale. The combination with other EO data allows the improvement of the capability to connect surface temperature and moisture fields with vegetation stress, flood hazards, and climate impacts [25].

2.5. In-Situ Sensing Platforms and UAV

In-situ sensors and Unmanned Aerial Vehicles (UAVs) are used to complement satellite observations through their ability to collect high-resolution, flexible, and fast data. The multispectral, hyperspectral, thermal, and LiDAR payloads can be deployed on UAVs to enable the intimate tracking of small-scale environmental events, e.g., local flooding, wildfire propagation, or agronomical stress. UAV-based EO makes it possible to conduct a quick evaluation of the post-disaster zone, and timeliness and accessibility are essential [8]. The in-situ sensors are automated weather stations, water quality probes, soil moisture sensors, etc., which serve as key ground-truth data to verify and calibrate the remotely sensed data. A combination of UAV and in-situ data with satellite images has the benefits of ensuring high spatial, temporal, and spectral resolution that allows strong environmental monitoring and analysis. In addition, sensor networks can be used to enable high-frequency monitoring of the environment that is continuous and enhances the detection of dynamism in the environment [26]. Diversity of sensors and platforms deployed in environmental security monitoring. The variety of sensors and platforms deployed in environmental security monitoring, as well as their spatial, spectral, and temporal properties, are summarized in **Table 1**.

Table 1. Overview of major Earth Observation sensor types, platforms, spatial and temporal resolutions, and representative environmental security applications.

Sensor Type	Platform	Spatial Resolution	Spectral/Measurement Range	Temporal Resolution	Applications
Optical (Multispectral)	Landsat, Sentinel-2	10–30 m	Visible, Near-Infrared (NIR), Shortwave Infrared (SWIR)	5–16 days	Vegetation health, water quality, land cover
Hyperspectral	Hyperion, PRISMA	5–30 m	100–400 bands	16 days	Species identification, pollution, mineral mapping
SAR	Sentinel-1, RADARSAT	5–20 m	C, X, L bands	6–12 days	Flood mapping, surface deformation, soil moisture
LiDAR	Airborne/Terrestrial/UAV	<1 m	N/A (structural)	Event-based	Canopy structure, topography, urban mapping
Thermal Infrared (Thermal IR)	Landsat, Moderate Resolution Imaging Spectroradiometer (MODIS)	30–1,000 m	8–14 μm	Daily–16 days	Heat islands, water/soil temperature

Table 1. *Cont.*

Sensor Type	Platform	Spatial Resolution	Spectral/Measurement Range	Temporal Resolution	Applications
Microwave Radiometers	Soil Moisture Active Passive (SMAP), Advanced Microwave Scanning Radiometer 2 (AMSR2)	1–50 km	1–10 GHz	1–3 days	Soil moisture, snow depth, precipitation
UAV-Mounted Sensors	Multispectral/LiDAR/Thermal	0.1–5 m	Varies	Event-based	Localized monitoring, post-disaster assessment
In-Situ Sensors	Ground stations, probes	Point-scale	Various	Continuous	Soil, water, air quality measurements

2.6. Methodology

This study has employed the structured literature review method, which fulfills the task of synthesizing the literature on the application of multi-sensor Earth Observation (EO) fusion techniques in environmental security applications. The review process was undertaken with a clear statement of the search strategies, selection criteria, and analysis procedures.

Several large scientific databases were consulted, including Web of Science, Scopus, ScienceDirect, and IEEE Xplore, and they are reputed to be exhaustive in regard to the number of journals and conference proceedings in the domain of remote sensors, environmental science, and geospatial analytics. The search was confined predominantly to the past five to twenty years, 2005–2025, as it is the period when the technologies of satellite sensors, machine learning methods, multi-source data integration forms, etc., have been evolving at a very high rate.

Search queries were constructed using a combination of both relevant search keywords and Boolean operators. Search terms were further reduced to core search terms, which included the following: Earth observation, remote sensing, multi-sensor fusion, data fusion, environmental monitoring, and environmental security. Other names were also used, such as SAR optical fusion, multimodal remote sensing, and machine learning remote sensing, to capture the new trends of data-based fusion techniques.

A sequence of selection processes was done after searching the database, which selected the records. First, titles and abstracts were filtered to exclude duplicate records and evidently irrelevant publications. All the remaining articles were then filtered based on full-text evaluation with the aim of determining their applicability in the multi-sensor fusion techniques based on EO, which will be applied in environmental monitoring and environmental risk assessment[27,28].

To be sure that the nature of chosen studies was relevant and of high quality, some inclusion criteria were applied during the review. The criteria of inclusion were that the articles should be talking about multi- sensor or multi- source EO data integration, must have methodological or applications contribution, and must be published in English-language peer-reviewed journals or conference proceedings. Research that concentrated on individual sensors, remote sensing, or imaging applications that were not contingent on each other was left out.

Each of the chosen articles revealed the most important data, and the information discussed the types of sensors employed, the extent of fusion, data analysis techniques, data presented, and the areas where it applies to the environment. The literature was then summarized using a thematic analysis, whereby the literature was divided into sensor types, fusion methods, uses in monitoring, and methods of evaluating the environment. This synthesis is what provides the foundation on which this is discussed and compared below[29,30].

3. Emerging Multi-Sensor Fusion Techniques

Multi-sensor fusion in Earth Observation is an effort to synthesize the heterogeneous data streams with the aim of improving the accuracy, reliability, and completeness of the environmental monitoring systems. As individual sensors measure different physical quantities of the surface of the Earth and atmosphere, a combination of measurements made by individuals can give a more detailed description of the processes on the planet. The optical sensors offer the information with the rich spectral data, which can be applied in the vegetation analysis and land cover classification, as well as the Synthetic Aperture Radar (SAR) sensors, which provide the structural and moisture-related information and can be operated irrespective of weather and illumination, hence the sensors can be used even when there is no sunlight. LiDAR sensors can be employed to give finer-grained three-dimensional structural information, and the thermal sensors are employed to identify the surface temperature changes of phenomena that impact the environment, such as wildfires or heat stress [12].

Good multi-sensor fusion requires good preprocessing and alignment of the datasets to have good multi-sensor fusion. Since EO data are offered on multiple platforms and geometries of acquisition, a lot of preparations must be made before fusion. These steps tend to include geometric correction and spatial co-registration, which ensures that pixels in different sensors are associated with a single geographical location. Radiometric normalization tends to prevent sensor calibration differences and atmospheric variations. There is also time matching of data gathered at varying times, particularly in high-frequency changes like a flood or a wildfire outbreak. It is a common practice of resampling to equalize the differences in the spatial resolution of sensors in order to allow them to form homogenous multi-channel data.

In the case of preprocessing, one can use fusion techniques using different forms of data representation depending on the level of integration. In pixel-based fusion, spectral bands, radar backscatter, or thermal measurements are directly added to a common multi-dimensional dataset. It is not a very noisy method and does not lose much space detail, although it can be excessively noisy and redundant when sensor properties differ significantly. At the feature level, the descriptors are fused at a higher level of the specific datasets and combined. These could be vegetation indices implemented on the basis of optical data, texture data implemented on the basis of SAR data, or canopy height data implemented on the basis of LiDAR data. These attributes can then be compiled to form a complete environmental situational picture [12].

Decision-level fusion is a higher level where independent models are implemented to each sensor data, and the obtained results are paired together. Other popular methods of combining model predictions are methods of ensemble learning, probabilistic inference, and voting. The approach may be used to increase strength in situations of sensors with opposite error characteristics or noncongruent data sets.

New trends in machine learning and deep learning have further enhanced the multi-sensor fusion capabilities. Segmentation is usually performed with convolutional neural networks (CNNs) and encoder-decoder networks, e.g., U-Net, for applications such as flood mapping and burned-area detection. The algorithms that are typically applied in tasks related to classification are the Random Forest, Support Vector Machine, and deep neural networks, which are applied to identify the kind of land cover or an environmental anomaly. Algorithms such as autoencoders and clustering algorithms are frequently unsupervised or semi-supervised and are used in settings that involve detecting anomalies (e.g., the identification of oil spills or stress patterns on unusual vegetation).

Multi-sensor EO fusion systems have numerous practical problems with implementation despite all these advances. The scarcity of training data is among the largest challenges that restrict the functionality of the supervised learning models. Another common impact on optical datasets is cloud contamination, which can diminish the supply of data when the critical monitoring occurs. The other issues include sensor noise, variation in spatial resolution, and domain shift, with the models being trained on one geographic region and applied in a different region, which is defined by different environmental factors [31,32].

The resolutions to these problems would consist of the construction of effective preprocessing chains, a transferable model of machine learning, and adaptive fusion strategies capable of integrating the heterogeneous datasets. Additionally, there are advancements in artificial intelligence, cloud computing, and high-performance Geospatial processing platforms that will most probably be further enhanced and raise the degree of scalability and workability of the feature of Multi-Sensor fusion methods in environmental security monitoring.

3.1. Concepts and Levels of Multi-Sensor Fusion

Multi-sensor fusion is a conceptual process that incorporates data provided by multiple sources of data in order to produce better information that is more useful than any of the datasets used separately. There are a number of levels at which fusion may be done, with its unique benefits and methodological conditions. Pixel-level fusion is a process that takes in the raw sensor data and integrates trade-off spectral, spatial, or temporal information to produce a representation of the observed phenomena using a high-resolution representation. At the feature level, in contrast, the method works directly on extracted features or attributes, e.g., vegetation indices, texture measures, topographic features, and can provide a more adaptable combination of heterogeneous data sources. Decision-level fusion is the last step in analysis, which is an amalgamation of independent models or classifier outputs to enhance overall decision-making. The level of fusion has its own computational and methodological problems, such as the necessity of proper co-registration, normalization, and sensor-to-sensor matching [33,34]. **Figure 2** shows the workflow and hierarchical structure of the pixel-level, feature-level, and decision-level fusion. The level of multi-sensor integration can be made at various points of the data processing pipeline, and the fusion level is an important factor that determines the impact of environmental monitoring systems on their effectiveness and complexity.

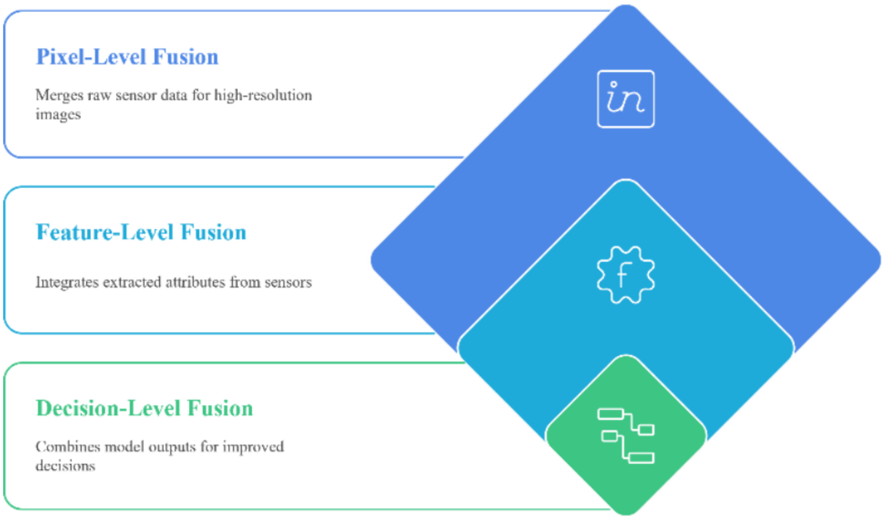

Figure 2. Schematic representation of multi-sensor fusion levels and workflows, including preprocessing, harmonization, and integration using machine learning and deep learning methods.

3.2. Data Preprocessing and Harmonization

Successful multi-sensor fusion depends on the successful preprocessing and harmonization of data. Preprocessing helps to counter sensor-specific artifacts, radiometric variations, geometric distortions, and atmospheric interference to make them compatible. Co-registration brings information from multiple sensors into spatial and time coordinates, whereas normalization and resampling processes balance the disparity of resolution and dynamic range. These measures play an important role in reducing the errors that may spread during the fusion process. Also, sophisticated filtering and noise-reduction functions are usually used to improve the signal quality and minimize sensor noise or other environmental disturbances. The preprocessed and harmonized datasets are the basis of the further fusion methods that allow the significant incorporation of multiple EO sources [5,16,35,36]. **Table 2** describes the key multi-sensor fusion levels and the methods associated with them, their benefits, and the applications.

Table 2. Classification of multi-sensor fusion levels, associated methodologies, advantages, and typical environmental security applications.

Fusion Level	Description	Typical Methods	Advantages	Applications
Pixel-Level	Raw data integration at the pixel scale	Pan-sharpening, weighted averaging	High spatial and spectral detail	Flood mapping, urban monitoring
Feature-Level	Integration of extracted features	Vegetation indices, texture analysis	Reduces data dimensionality, robust to noise	Land cover classification, biomass estimation
Decision-Level	Fusion of independent model outputs	Majority voting, Bayesian fusion, ensemble machine learning (ML)	Flexible, handles heterogeneous data	Disaster early warning, risk assessment

3.3. Machine Learning-Based Fusion

The use of machine learning (ML) methods has gained increased attention within the domain of multi-sensor EO fusion, with nonlinear relationships between heterogeneous datasets as such being complex and therefore modellable by machine learning methods. Random forests, support vector machines, and gradient boosting are classical algorithms that have found broad application in feature-level and decision-level fusion. The methods are especially useful in land cover classification, vegetation detection, and the detection of changes, as they can use the supporting information of the optical, radar, LiDAR, and thermal sensors. Fusion models based on ML can operate with high-dimensional data and identify the patterns of interest, and minimize the impact of noise and redundant features. The quality and representativeness of training data are, however, a key aspect of their performance, and overfitting must be avoided by careful cross-validation[37,38].

3.4. Deep Learning Approaches

Deep learning has also changed the concept of multi-sensor fusion, wherein it provides automated feature extraction and hierarchical representation learning using complex EO data. Convolutional neural networks (CNNs) are popular in spatial feature detection of optical and SAR images, whereas recurrent neural networks (RNNs) and long short-term memory (LSTM) networks are effective in detecting temporal features in multi-temporal images. Research in the past couple of years has been exciting with the introduction of transformer-based models, attention systems, introduction of the capabilities of dynamically moving the attention within the multi-modal multi-sensors within a multi-modal fusion approach. The fusion that is based on deep learning may be done on a pixel and feature level, which will contribute a lot to the accuracy of classification, detection of anomalies, and predictive modeling. Although they appear to have their benefits, these methods require a lot of computational power and labeled data to be available, making them expensive to use in the real-time setting or location with limited resources[39,40].

3.5. Probabilistic and Statistical Fusion Models

Probabilistic and statistical methods provide a mathematically sound means to integrate data provided by multiple sensors, to measure the amount of uncertainties, and to propagate the error measures throughout the fusion. By such means as Bayesian inference, prior knowledge can be combined with observational data to produce probability-based predictions, and Dempster-Shafer's theory offers a methodology by which evidence of heterogeneous sources may be aggregated in terms of their relative reliability. The models can also be especially useful in environmental security applications, where sensors with different types of data can possess dissimilar accuracy, reliability, or temporal coverage. Machine learning approaches can also be employed in statistical fusion to create hybrid models that take advantage of both information and knowledge[41].

3.6. Hybrid and Adaptive Fusion Techniques

The hybrid fusion methods take a mixture of several techniques, including machine learning, deep learning, and probabilistic modeling, in order to leverage the advantages of both approaches. As an example, CNNs can be used to extract features, and then these can be probabilistically combined with radar-derived data to produce high-quality flood maps. Adaptive fusion methods dynamically change the contribution of each sensor depending on the situation, quality of the sensor, or environmental conditions, so that the most reliable and informative data dominates the output. Multi-temporal monitoring, disaster response, and complex or rapidly changing environments are also examples of the applications of such techniques[5,32,42].

Table 3 gives a comparative overview of emerging multi-sensor fusion methods, such as machine learning, deep learning, probabilistic, and hybrid methods.

Table 3. Comparison of emerging multi-sensor fusion techniques, their methodological characteristics, strengths, limitations, and environmental security applications.

Technique	Description	Advantages	Limitations	Environmental Applications
Machine Learning (Random Forest—RF, Support Vector Machine—SVM)	Feature/decision-level integration	Handles high-dimensional data, interpretable	Requires training data	Land cover, vegetation stress, pollution mapping

Table 3. *Cont.*

Technique	Description	Advantages	Limitations	Environmental Applications
Deep Learning (CNN, RNN, Transformer)	Automated feature extraction	Captures complex patterns, multi-temporal analysis	Computationally intensive, needs large datasets	Flood, wildfire, deforestation monitoring
Probabilistic Models (Bayesian, Dempster-Shafer)	Integrates data with uncertainty quantification	Robust to sensor errors, provides confidence estimates	Requires prior knowledge, complex modeling	Flood risk, drought assessment, hazard mapping
Hybrid Approaches	Combines ML/Deep Learning and probabilistic methods	Flexible, adaptive, improves accuracy	Complexity, high computational cost	Multi-hazard monitoring, ecosystem assessment

3.7. Computational Platforms and Big Data Integration

The volume, speed, and diversity of EO data that continue to grow require high-end computing infrastructure to accomplish multi-sensor fusion. Cloud computing, high-performance computing clusters, and distributed processing structures can be used to scale to large volumes of data to enable analysis and visualization on a near-real-time basis. The value of fused products can be further improved with the integration of EO data with auxiliary data like geographic information systems (GIS), in situ measurements, and socio-economic data. This is due to the ability of big data analytics to be combined with automated preprocessing and machine learning pipelines to enable continuous monitoring, early warning, and decision support in environmental security. New platforms also support collaborative data sharing and open access to EO data and resources, increasing the possibility of multi-sensor fusion among research and operational communities [17,43].

4. Applications in Environmental Security

Multi-sensor Earth Observation (EO) data has been integrated to significantly increase the potential of monitoring, evaluating, and controlling environmental threats. Environmental security covers environmental protection of ecosystems, natural resources, and human communities against environmental threats, such as natural disasters, pollution, global warming, and soil erosion. Multi-sensor fusion can provide the whole, timely, and dependable information to facilitate decision-making to reduce risks, manage resources, and develop policies. Using the mutually reinforcing data of optical, radar, LiDAR, thermal, and in-situ sensors, the researchers and practitioners can eliminate the shortcomings of single sensors and retrieve actionable information in a broad application domain [5,12,44].

4.1. Natural Disaster Monitoring and Response

Natural disasters such as floods, wildfires, hurricanes, landslides, and earthquakes are direct threats to human lives, infrastructure, and ecosystems. There is vital situational awareness during, before, and after such events, which is given by EO-based monitoring. An example is the utilization of optical sensors to provide high-resolution images in the analysis of fire scars, damaged infrastructure, and the extent of flooding, and radar sensors to look through cloud cover and smoke to allow near-real-time mapping during unfavorable weather conditions [45]. The methods of InSAR identify ground deformation that is so subtle in the case of an earthquake, landslides, or volcanic eruption, which contributes to the advancement of early warning and risk evaluation. It has been demonstrated that the integration of optical and radar data has enhanced the accuracy of flood mapping through the integration of fine spatial information with coverage at all seasons. The use of UAV-based EO in conjunction with satellite imagery makes it possible to conduct prompt evaluation of the disaster and rescue operations, and resource assignment becomes more focused and effective. Disaster monitoring by multi-sensor fusion not only improves the accuracy of detection, but it also minimizes the response time, which is very important in ensuring that the losses are minimal both in terms of casualties and economic damages [46,47].

4.2. Climate Change and Ecosystem Monitoring

Climate change has a strong impact on the ecology, as it affects vegetation dynamics, glacial retreat, rising sea level, desertification, and the reduction of biodiversity. With multi-sensor EO, the overall monitoring of these phenomena is possible at both spatial and temporal scales[48]. The vegetation health, species composition, and phenological changes are measured with the help of optical and hyperspectral sensors, whereas LiDAR can offer more specific data about the forest canopy, biomass estimation, and carbon stock measurement. The radars and altimeter devices monitor the adherence of ice sheets, ice mass, and changes in sea levels, providing a significant understanding of the climate patterns over a long period. The thermal and microwave sensors are useful in the measurement of energy flux, soil moisture, and hydrological cycles. Integrating information from these complementary sensors will enable researchers to come up with combined models to measure the ecosystem responses to climate variability, create sensitive areas, and assist in adaptive management efforts. As an example, multi-sensor fusion has been used to track the loss of mangrove forests, the amount of carbon released into the atmosphere due to deforestation, and the receding polar glaciers, which is important data to mitigate and preserve climate policies[49].

4.3. Pollution and Environmental Quality Assessment

Environmental security must be tracked through monitoring the air, water, and soil abundance, as environmental pollution has a direct effect on human health and ecosystems. Surface water contamination, algal blooms, and hotspots of urban pollution can be detected by optical sensors, whereas heat emission of industrial facilities can be detected by thermal sensors. These observations are complemented with microwave and hyperspectral sensors that identify chemical signatures as well as suspended sediments and nutrient concentration of water bodies. Multi-sensor fusion improves the capacity to map pollution at a greater spatial and temporal resolution level and also distinguishes anthropogenic pollution and natural variations. As an illustration, aerosols' optical depth derived by satellite and aerosol products can be used to estimate the concentration of particulate matter accurately in both urban and rural regions when combined with ground-based measurements of air quality. Equally, combined optical and radar data enhance surveillance over oil spills, sediment movement, and eutrophication of rivers and coastal areas. These facilities assist in the enforcement of regulations, early warning mechanisms, and sustainable environmental management[50,51].

4.4. Land Use and Land Cover Change Detection

The changes in land use and land cover (LULC) are crucial in the management of sustainable resources, planning of urban areas, and environmental security. Multi-sensor EO is an accurate, frequent, and detailed mapping of the LULC dynamics, revealing processes like deforestation, urbanization, agricultural conversion, and wetland degradation. Spectral data on vegetation and soil classification is offered by optical sensors, whereas radar sensors identify structural alterations in the landscape, such as the canopy density of the forest and the growth of buildings. LiDAR also improves the detection as it is able to give data on the terrain and vegetation structure in three dimensions. Incorporating the datasets in such a way as a multi-sensor fusion, the analyst can detect minor variations in land cover that could be a sign of environmental stress, illegal logging, or urban encroachment onto the conserved lands. Multi-temporal fusion methods can be used to observe changes over years or decades, so that trends can be analyzed and predictive models of the land degradation or urban sprawl can be made[52].

4.5. Early Warning Systems and Risk Assessment

The creation of early warning systems of environmental hazards is one of the most effective uses of multisensory EO fusion. Through integration of various datasets, these systems can identify precursors of disasters, vulnerability, and issue warnings to the authorities and communities in time. As an illustration, unified optical, radar, and meteorological information has been applied to project flooding danger, wildfire ignition areas, and track landslide liable slopes. Equally, the concept of multi-sensor fusion can be used in drought monitoring by combining vegetation indices, soil moisture, precipitation, and thermal aberrations. They are based on sophisticated modeling systems, which may include machine learning and statistical methods in order to integrate data across multiple sources and deliver probabilistic risk estimates. The capability of providing timely hazard warnings within near-real-time and with a spatial resolution can greatly contribute to preparedness, minimize economic damages, and increase the resilience of nature [5,53].

4.6. Case Studies and Applications of Multi-Sensor Fusion for Environmental Security

Fusion of Multi-sensor Earth Observation (EO) has been a common application used in environmental monitoring and analysis of environmental security, as a result of its capability to combine complementary information using heterogeneous sensors [5]. Single remote sensing systems are usually limited by factors like cloud pollution, low temporal frequency, narrow spectral coverage, or low spatial resolution. Multi-sensor fusion is a solution to such shortcomings, as it incorporates data provided by optical sensors, radar, LiDAR, thermal sensors, and UAV-based sensors and, therefore, increases the detection accuracy, spatial completeness, and temporal consistency. An increasing body of literature shows that hybrid datasets are more dependable in environmental intelligence in managing disasters and ecological security, and in the study of land-use [5,54,55]. The application of multi- sensor fusion methods in environmental security research is summarized as representative in **Table 4** [36].

Table 4. Representative Studies on Multi-Sensor Fusion for Environmental Security Applications.

Year & Region	Sensors Used	Fusion Level	Method	Dataset	Evaluation Metrics	Performance Improvement	Limitations
2018, Southeast Asia	Sentinel-1 SAR + Landsat-8 optical	Feature-level	Random Forest classification	Flood event imagery	Overall Accuracy, Kappa	Flood detection accuracy increased from 82% to 91%	Temporal mismatch between sensors
2019, Amazon Basin	LiDAR + Landsat optical	Feature-level	Regression modeling	Forest biomass datasets	Root Mean Square Error (RMSE), R²	Biomass estimation error reduced by ~25%	Limited LiDAR coverage
2020, Australia	MODIS thermal + Sentinel-2 optical	Decision-level	CNN-based fire detection	Wildfire monitoring datasets	Precision, Recall, F1-score	Detection accuracy improved by 12% compared to thermal-only approach	Training data imbalance
2021, Europe	Sentinel-1 SAR + Sentinel-2 optical	Pixel-level	Deep learning semantic segmentation	Land-use classification dataset	IoU, Accuracy	Urban classification accuracy increased from 85% to 93%	High computational cost
2022, Coastal China	SAR + Optical + UAV imagery	Feature-level	Multi-source feature integration with SVM	Coastal monitoring dataset	Accuracy, F1-score	Oil spill detection improved by ~15%	Data preprocessing complexity
2023, Global Case Studies	Optical + SAR + LiDAR	Hybrid fusion	Transformer-based deep learning	Multi-source EO dataset	Precision, Recall, Intersection over Union (IoU)	Improved detection consistency across environments	Large data requirements

One of the most popular areas where multi-sensor fusion is used is flood monitoring and mapping. Optical images are capable of giving fine spectral data, which can be utilized to demarcate water bodies and flooded vegetation, although in extreme weather conditions, the optical sensors are likely to be distorted by the existence of clouds. Synthetic Aperture Radar (SAR) sensors, such as Sentinel-1 sensors, can operate in all weather conditions and despite the condition of illumination, and can peer through clouds. SAR and optical images have therefore been combined in many studies in order to improve the effectiveness and extent of floods. It has been demonstrated that machine learning classifier-based feature-level fusion methods, e.g., Random Forest or Support Vector, significantly surpass single-sensor-based methods in detecting the extent of a flood. A radar backscatter and optical spectral index combination can be employed in such applications to differentiate more in a flood situation on water, vegetation, and urban surfaces.

The application of multi-sensor fusion is also common in wildfire detection and assessment of burnt territories. The thermal infrared sensors provide first-hand information on unusual surface temperature conditions created by active fires, as opposed to optical sensors, where it is possible to map out the area that is under fire and recover vegetation. Fusion techniques may be used to complement small or partially obscured fire events when they are used with radar data and high-resolution optical data. The models of deep learning have been used more recently in conjunction with a multi-sensor data to automatically identify the hotspots and the edges of a burned region by a wildfire. It has been found that convolutional neural networks trained on both the optical and thermal datasets are more successful in classification and can detect faster than the conventional threshold-based ones[12].

Other important areas of application are forest monitoring and deforestation detection, which are important in environmental security and climate control. The optical images of sensors such as the Landsat and Sentinel-2 have been utilized in determining the changes in vegetation through spectral indices such as NDVI. However, biomass distribution or forest structure cannot be entirely captured using optical imagery alone. LiDAR sensors provide three-dimensional structural data, including canopy height and vertical vegetation profiles, unlike the SAR sensors, which do not have this feature but can penetrate vegetation layers and provide structural and moisture data. The study outcome of works that have incorporated the canopy measures established by the use of LiDAR on optical vegetation indices have revealed tremendous improvements in the measurement of biomass of forests and forest deforestation, which has a high probability of detection. These two approaches may be particularly effective in tropical forest surveillance, where the optical surveillance is limited by the constant cloud cover[56].

The other field where the multi-sensor fusion has been somewhat useful is urban expansion and land-use change monitoring. High-resolution optical imaging provides spatial information of infrastructures in urban areas in a comprehensive fashion, and SAR imaging provides surface roughness and structural properties of built environments. These complementary features have been applied in feature-level fusion in order to classify the urban land-use categories better. Compared to a single-sensor model, classification accuracy and detection of the patterns of informal settlements and urban growth of deep learning models using fused optical and SAR-based input have increased.

Cosmological multi-sensor EO integration can also be applied to monitor the coastal and marine environment. The coastal ecosystems are highly dynamic and prone to environmental threats such as the increase in sea level, the erosion of the beaches, and pollution. Data concerning the surface roughness, as well as ocean dynamics, can be provided with the help of radar sensors, whereas the data related to the color of water, turbidity, chlorophyll levels, and so on, can be obtained with the help of optical sensors. The combination of these data sets allows the researchers to trace the coastal processes with a higher approach and time scale. Oil slick monitoring and marine pollution incidents have also been monitored with the use of multi-sensors, i.e., a combination of SAR-based observation of oil slick and optical spectral techniques to determine the occurrence and size of the contamination[57].

Despite these advancements, the performance of the multi-sensor fusion systems is also dependent on the quality, compatibility, and preprocessing of the input datasets. The differences in the spatial resolution and acquisition time, and the sensor characteristics, can introduce uncertainty in the fusion results. But numerous studies have determined that multi-sensor techniques have large improvements in classification, detection, and monitoring of the environment

5. Evaluation Metrics and Validation Methods

The value and use of multi-sensor Earth Observation (EO) products are highly reliant on stringent evaluation and validation processes. Sound evaluation of fused datasets is a guarantee that the information on the environment is credible yet useful in decision-making concerning security, disaster management, and policy-making. Multi-sensor data is very complex and heterogeneous, as it can be optical, radar, LiDAR, thermal, or in-situ measurements, and hence, the validation mechanisms need to deal with the dissimilarity of spatial, spectral, and temporal aspects and the inherent uncertainties of any sensor system. The metrics of evaluation and validation methodologies give the framework to measure the performance, robustness, and reliability of fusion techniques, and make improvements as well as consistency across applications[12].

5.1. Quantitative Evaluation

The initial phase of assessing multi-sensor fusion outputs is the choice of suitable quantitative measures. To construct classification and land cover maps, some commonly used measures are overall accuracy, producer accuracy, user accuracy, and the Kappa coefficient, which is the measure of agreement between the predicted and reference data sets. Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and correlation coefficients are some of the metrics that are typically used when dealing with continuous variables in an environmental monitoring setting, e.g., surface temperature, soil moisture, and vegetation indices. These measures give quantitative results of deviation and bias as well as accuracy, and allow objective comparison between fused data and ground truth data or high-quality reference data. In addition, spatial agreement measures, like Structural Similarity Index (SSIM) and Intersection over Union (IoU), are also commonly used to determine the faithfulness of spatial patterns, especially with high-resolution EO products; both the geometric and thematic accuracy are paramount[58,59].

5.2. Cross-Sensor and Multi-Temporal Validation

Fused EO datasets need strong reference or ground-truth data in order to be validated. In situ measurements such as meteorological stations, soil moisture probes, water quality sensors, and UAV-collected high-resolution imagery can be used as a critical measure of fused product accuracy. Ground-truth information can be used to both calibrate and validate data and assist in determining systematic errors, sensor biases, and misalignments across datasets. Nevertheless, it might not be straightforward to get detailed ground-truth data, especially on remote, inaccessible, or dynamically changing spatially controlled environments. In order to overcome these limitations, cross-sensor validation strategies have become the norm. With the aid of benchmarking of fused outputs with either independent EO data or other sensor measurements, the researcher is able to conduct consistency and reliability tests without only using in-situ benchmarks. As an illustration, SAR-derived flood map results can be checked with high-resolution optical imagery, or LiDAR-derived canopy height models could be variously compared with UAV survey-derived stereophotogrammetric data[60,61].

The multi-temporal and dynamic monitoring applications that are especially sensitive to temporal validation include catastrophe assessment, monitoring, land use change, and ecosystem monitoring. The time-series analysis can be used to identify how consistent and sensitive fused datasets are to changes in the environment, so that any observed trends are not the result of data integration artifacts or sensor noise. Change detection measures, time correlation analysis, and trend consistency measures are the common techniques that are used to ensure the consistency of fused products with time[44].

5.3. Uncertainty Quantification

The other important aspect of evaluation in multi-sensor fusion is uncertainty quantification. There are also errors that exist in the environmental datasets due to sensor noise, atmospheric interference, time misalignments, and spatial resolution variations. Increasingly probabilistic methods are being used to provide estimates and propagate these uncertainties in the fusion process, including Bayesian modeling, Monte Carlo simulations, and ensemble techniques. Fused products can deliver predictions and confidence intervals by accounting for uncertainty explicitly, and this alone can be invaluable to risk assessment, decision-making, and prioritization in environmental security applications[62].

5.4. Field-Based Ground Truthing

Along with quantitative indicators, visual inspection and expert knowledge are also required in the process of validating multidimensional EO products. The spatial inconsistencies, spatial registration errors, and abnormalities that might not have been picked by numerical measures can all be observed in the visual analysis of fused imagery. Specialized knowledge, especially ecological, hydrological, and geophysical knowledge, can offer contextual knowledge that will supplement the interpretation of validation results so that the resulting fused outputs are useful and sensible[63].

5.5. Comparative Studies and Benchmarking

The multi-sensor fusion has been proven to be effective through case studies that show that rigorous evaluation and validation are effective in multi-sensor fusion. An example is the flood mapping based on fused SAR with optical imagery that has been compared with UAV imagery and in situ water level measurements and has shown improvements in both the spatial and temporal coverage. Equally, fused LiDAR and Hyperspectral methods have been used to monitor deforestation with measurements being downed to field surveys and cross-sensor analysis whereby the biomass and canopy or times have been confirmed as robust. These papers confirm that there should be combined validation methods that incorporate quantitative measurements, ground truth, sensor-to-sensor comparisons, and human interpretation to provide a holistic overview of the quality of fused EO products [16,42,64].

5.6. Practical Considerations in Validation

In order to ascertain the accuracy, reliability, and usefulness of a multi-sensor fused dataset in the environmental security application, evaluation measures and validation procedures are important. Through employing rigorous quantitative methods, in situ and cross-sensor validation, quantification of uncertainties, and expert interpretation, researchers and practitioners can produce high-confidence information on the environment. These validated datasets play an important role in aiding disaster management, climate surveillance, pollution evaluation, ecosystem administration, and policy development, which ultimately positions the effectiveness of environmental safety measures [5].

6. Challenges and Future Directions

Regardless of the major improvements in the methods of multi-sensor Earth Observation (EO), there are still several challenges that restrict the full potential of these methods as they apply to environmental security. Complex technical, computational, and methodological challenges are emerging as a result of the integration of heterogeneous data sets provided by optical, radar, LiDAR, thermal, and in-situ sensors, which will need to be resolved in order to obtain robust, scalable, and operationally relevant solutions. Simultaneously, new opportunities are emerging with new technologies and methodological innovations that can be utilized to improve the system of environmental monitoring, early warning systems, and decision support frameworks. Knowledge of these issues, coupled with future orientations, allows for the environmental security area to direct research, operational implementation, and policy formulation [5,12]. The challenges and future directions of research on multi-sensor Earth Observation fusion are presented in **Figure 3**. Despite its significant advantages for environmental monitoring, key challenges remain, including data integration, scalability, and model generalization, which are critical for developing working environmental security monitoring systems.

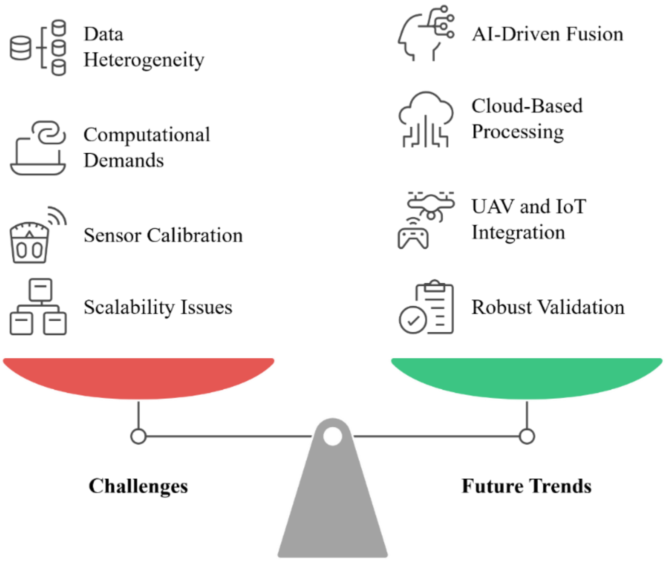

Figure 3. Overview of major challenges and future research directions in multi-sensor Earth Observation fusion, including data heterogeneity, computational demands, AI-driven adaptive fusion, and IoT integration.

6.1. Data Heterogeneity and Integration Challenges

Data heterogeneity is one of the leading issues. The EO datasets are diverse, with respect to spatial resolutions, spectral attributes, temporal frequency, sensor modalities, and noise attributes. Optical sensors can give rich spectral data with high spatial resolution, but the cloud cover and atmospheric conditions can lead to effects. Radar sensors operate in all weather conditions and during both day and night, but with short spectral information, and themselves need special processing to decode the backscatter information. LiDAR data and altimetry data can give structural and elevation data, but also tend to be poorly covered and expensive to operate. Surface fluid dynamics are captured by thermal and microwave sensors, which are often simpler to use. To be able to integrate such a disparate set of data, advanced preprocessing, co-registration, normalization, and harmonization techniques are needed. All minor mismatches or inconsistencies might spread in the fusion workflows and result in classification and change detection as well as predictive modeling errors. These problems will require the creation of strong multi-resolution fusion algorithms, adaptive weight techniques that consider sensor-based uncertainties and reliabilities [65–67].

6.2. Computational and Big Data Limitations

The other major difficulty is the computational and storage requirements of multi-sensor EO data. The growing size, type, and speed of EO data, especially of high-resolution satellites, UAVs, and LiDAR systems, impose titanic demands on data management, processing, and storage systems. The fusion methods based on machine learning and deep learning, though effective, are highly intensive in terms of computing, as they may demand high-performance GPUs, distributed processing systems, and cloud-based storage systems. The critical constraint of real-time or near real-time disaster response processing, flood mapping, wildfire monitoring, and other dynamic environmental processes is an area of active need, that is, efficient algorithms, parallel computing architecture, and automatic processing pipelines [9].

6.3. Sensor Interoperability and Standardization

Other constraints include sensor calibration, quality control, and interoperability. The Units of Bias and Software Station. A variance in sensor design, calibration processes, and data collection times will result in biases and variances in the fused datasets. Environmental monitoring should be done through a high-quality assessment and standardization, and metadata management to provide comparability between sensors and time. In addition, there are interoperability issues associated with combining EO data with other types of data, like in-situ measurements, socio-economic data, and meteorological models. Strategic creation of standardized common data, open-source repositories, and automation under validation is essential to ensure integration and reproducibility [68].

There are additional challenges of scalability to regional and global environmental monitoring. The grading of data gathered by UAVs and on the ground, networks is limited to limited areas, but when scaling down and up, UAV images or in-situ networks are receptive to large spatial areas, which necessitates efficient data fusion models and powerful extrapolation methods. Equally, worldwide monitoring software, like forest cover, climate change, and water management, requires bypassing of multi-temporal examination of vast EO information, and so requires not only more rapidness but methodological quality [69].

6.4. Emerging Directions in Multi-Sensor Fusion

In the future, there are a number of new directions that will address these challenges and increase the usefulness of multi-sensor EO to environmental security. The next-generation satellite missions, small satellite constellations, and high-resolution UAV platforms are likely to expand the space, time, and spectral coverage, which offers new possibilities to integrate multiple sensors. Adaptive fusion frameworks, which will be powered by artificial intelligence, machine learning, and deep learning, will allow the extraction of features, detect anomalies, and predictive models automatically, increasing the capabilities of real-time monitoring. Attention-based models, transformers, and hybrid

AI-probability solutions present opportunities to provide context-aware sensor weighting and to quantify the level of uncertainty to enhance the resilience of fused products [5,12].

Another potential direction is integration with the Internet of Things (IoT), sensor networks, and citizen-science platforms. With the integration of EO data and ground-based, high-frequency environmental data, it can be created to have dynamic, high-resolution surveillance systems that give early warning of the occurrence of floods, wildfires, droughts, and pollution incidents. Scalable multi-sensor data stream processing using cloud computing, edge processing, and distributed analytics further allows near-time decision support and deployment into operations [12,70].

Lastly, policy and societal issues have to be touched upon in order to translate technological advances into environmental safety results. EO fusion, which uses multiple sensors, can be used in the regulation enforcement, urban planning, disaster readiness, and climate change adaptation policies. The creation of standard frameworks of data sharing, data validation, and interoperability, as well as capacity-building efforts, would facilitate the fused EO products to be actionable, equitable, and accessible to the stakeholders, such as governments, non-governmental organizations, and local communities.

6.5. Implications for Environmental Security

Even though there are some challenges of multi-sensor EO fusion, such as data heterogeneity, computational requirements, sensor calibration, and scalability, there are more opportunities with the current technological development and improvement in methods. With adaptive fusion based on AI, combined with UAV and IoT networks, and a firm foundation of validation and interoperability standards, the future of EO systems is set to offer high accuracy, prompt, and actionable insights on environmental security. Such developments will not only improve the response to disasters and ecosystem monitoring but also assist in managing the resources and adapting to climate sustainability at the regional and global levels [71–73].

7. Conclusion

Multi-sensor Earth Observation (EO) has become a revolutionary method of dealing with intricate environmental security issues. Multi-sensor fusion, which integrates information on different platforms, such as optical, radar, LiDAR, thermal, and in-situ sensors, addresses all of the weaknesses of individual data, giving a complete, high-resolution, and temporally robust view of the environmental processes. It is especially important in the context of applications to natural disaster monitoring, climate and ecosystem evaluation, pollution monitoring, land use change detection, and early warning applications, when the quality and timeliness of information can be directly used to focus a threat mitigation policy decision and sustainable management policies.

The review has observed that emerging fusion methods, such as machine learning, deep learning, probabilistic models, and hybrid methods, play a critically important role in the operation of improving the accuracy, reliability, and interpretability of fused EO products. The methods, together with sophisticated preprocessing, harmonization, and computational models, allow obtaining significant insights out of data heterogeneity. Strict evaluation and validation measures, such as quantitative measures, quantifying uncertainty, cross-sensor and expert interpretations, were also noted in the discussion as assuring that fused products are both plausible and practical.

Although the improvements are significant, a number of issues are present, such as heterogeneity of data, computational and storage requirements, sensor calibration and compatibility problems, and the necessity to rely on scalable solutions to monitor the region and the globe. Nevertheless, new tendencies in high-resolution satellite missions, the integration of UAV and IoT, cloud-based computing, and adaptive fusion based on AI can provide some interesting ways out of these restrictions. EO systems have the potential to offer real-time multi-dimensional environmental intelligence through these innovations to facilitate more successful disaster preparedness, resource management, and climate change adaptation efforts.

To sum up, it is important to highlight that multi-sensor fusion is one of the most important frontiers in Earth Observation, which can be used to revolutionize environmental security monitoring and decision-making. The future success of ensuring that EO technologies can benefit society and the ecology will require further advancement of advanced tools of fusion, effective validation tools, and developed computational platforms. Multi-sensor EO is essential in improving resilience, ecosystem protection, and sustainable development at local, regional, and global levels as the environmental pressures of the world intensify.

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Conflicts of Interest

The authors declare no conflict of interest.

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