Vol. 06, No. SI*, pp. 90 –114 (2025)
ISSN: 2708-0757

JOURNAL OF APPLIED SCIENCE AND TECHNOLOGY TRENDS

www.jastt.org

Integration of IoT and Remote-Sensed Visual Analytics for Smart Environmental Surveillance

A Madhuri[1], Balamuralikrishna Thati[2], Suresh Babu Chandolu[3], S Sindhura[4*], Yalanati Ayyappa[5], Ruhisulthana Shaik[6]

[1]Department of Computer Science and Engineering, Prasad V Potluri Siddhartha Institute of Technology, Kanuru, Vijayawada 520007, India, madhuria@pvpsiddhartha.ac.in
[2]Department of IT, DVR & Dr. HS MIC College of Technology, Kanchikacherla, NTR District, A.P-521180, balu.thati9@gmail.com
[3]Department of CSE-(AI & ML), Dhanekula Institute of Engineering and Technology, Vijayawada, Andhra Pradesh, India-521139, suresh.chandolu@gmail.com
[4]Department of CSE, NRI Institute of Technology, Agiripalli , Vijayawada, India, ssindhurapraveen@gmail.com
[5]Department of Computer Science and Engineering, Vel Tech Rangarajan Dr.Sagunthala R&D Institute of Science and Technology, Avadi, Tamilnadu, India, ayyappa9866@gmail.com
[6]Department of ECE, Sir C Ramalinga Reddy Polytechnic College, Eluru, India, ruhisulthana.shaik9@gmail.com

*Correspondence: ssindhurapraveen@gmail.com

Abstract

This study proposes a unified environmental surveillance system, which fuses IoT sensor networks and the visual analytics of multispectral remote-sensing to address the shortcomings of the conventional surveillance solutions. Edge-based LSTM anomaly detection on distributed nodes of the IoT can offer high-frequency local measurements, whereas a hybrid ResNetVision Transformer (ViT) model can improve the analysis of the satellite image. An adaptive Kalman-based temporal-spatial fusion algorithm incorporates heterogeneous streams of data towards better environmental intelligence. The system was highly performing, indicating the accuracy of the IoT sensors in 91.3-98.1% and a hybrid model at 92.4% and the fused levels at 94% and above respectively. The results were impressive on the system level, since the response time to events was improved significantly, the completeness of data improved, and the accuracy of anomaly detectors increased, as well as the network load decreased. On the whole, the suggested structure has high potential to monitor the environment in real-time, being scalable, in the fields of smart agriculture, air-quality monitoring, water-resource control, climate-risk identification, and smart urban governance.

Keywords: *IoT-Based Environmental Monitoring, Remote-Sensed Visual Analytics, Temporal–Spatial Data Fusion, Deep Learning for Environmental Surveillance.*

Received: October 20th, 2025/ Revised: December 21st, 2025/ Accepted: December 29th, 2025 / Online: December 31st, 2025

I. INTRODUCTION

Rapid urbanization, industrialization, climate change and anthropogenic stress are causing unprecedented transformation in environmental systems across the world [1]. These activities have increased the rate at which environmental abnormalities like abrupt pollution surges, thermal strain, water pollution, deteriorating vegetation well-being and ecological balance changes are happening [2]. Conventional environmental surveillance systems, which rely mostly on manual sampling, regular laboratory tests and sparsely placed sensors, no longer can adequately measure the magnitude, pace and intricacy of such changes [3]. They do not deliver the temporal granularity and spatial continuity needed to timely detect and predict possible environmental risks and mitigate them [4].

In its turn, recent breakthroughs in digital ecosystems, especially the Internet of Things (IoT) and remote sensing via satellites have created new opportunities to create intelligent, multi-layered, and real-time systems of environmental surveillance [5]. IoT allows the high-frequency deployment of low-cost sensors that are able to capture air quality, water parameters and microclimatic variables, whereas remote sensing offers multispectral and thermal observations of large areas that are able to recognize spatial patterns and environmental processes that are not perceivable at ground level [6]. Nevertheless, the two data modalities have been historically exploited individually, which leads to disjointed information pipelines and restricted situational-awareness [7].

This paper acknowledges the fact that environmental phenomena exist on both micro and macro scale, and that efficient surveillance demands the combination, and not the

doi: 10.38094/jastt605686

separation, of sensory modes [8]. With the integration of both the IoT sensor systems and remote-sensed visual analytics one is able to build an integrated environmental intelligence system that can deliver continuous, scalable and rich context insights [9]. These frameworks do not only benefit the detection of anomalies but can also be used to generate environmental modeling, predict risks and make informed decisions in various applications like precision agriculture, disaster management, pollution surveillance, and sustainable urban planning [10].

A. Need for Integrated Environmental Surveillance

The processes associated with the environment are multi-dimensional in nature and are characterized by interactions among atmospheric, hydrological, terrestrial, and biological processes. Such interactions occur in different ways at different spatial and temporal levels [11]. For instance (1) Air pollution outbreaks may begin at a local level but spread quickly through the urban areas.(2)The source of vegetation stress can be in microclimatic disequilibrium but over wide agro-scenery. (3) At a point source, water contamination may be observed but over a long period, it may have an impact on ecosystems downstream.

IoT sensors are good at measuring at high frequencies and at a point, they are able to track short-term variations like spikes in pollutants or rapid changes in temperature [12]. Their granularity is useful in detecting anomalies at localized scales but they are not as informed of the wide space as needed to link regional environmental patterns.

Remote-sensed imagery, by contrast, has a wide-area coverage, thus it is able to detect landscape-scale processes, including urban heat islands, deforestation, algal blooms, the extent of a flood, or vegetation degradation. Satellite data are, however, generally affected by-limited temporal revisits, cloud cover obstruction, atmospheric scattering, data latency, andlower temporal resolution than IoT streams.

A complete monitoring platform, i.e. aligning the IoT data to satellite-based analytics, is the solution to these constraints by leveraging the benefits of both modalities. These types of integration offer a rich spatio-temporal environmental dataset that can be continuously monitored, early anomalies are detected, and projections are made.

B. Limitations of Existing Systems

Although significant progress has been made in environmental monitoring technologies, several persistent challenges limit the effectiveness of existing systems:

1) Temporal Gaps in Satellite Revisit Cycles: Sentinel-2 (5 days) and Landsat-8 (16 days) are remote sensing systems that are not able to detect dynamic environmental changes, particularly in dynamic cities or farms.

2) Sparse or Irregular IoT Deployment: IoT nodes are usually distributed in a non-uniform manner due to cost, complexity of maintenance, and distance, forming blinding spots in the environmental knowledge.

3) Human-Dependent Image: Most remote-sensing processes still use manual or semi-automatic processing, thereby causing latencies in the detection of anomalies and subjectivity.

4) Absence of Real-Time Data Fusion: Current models seldom tie ground-sensor data of the IoT with spectral information delivered by satellites in real-time and thus lack the chance to combine the complementary information provided by both data streams.

5) Fragmented Analytical Pipelines: IoT platforms, satellite processing platforms, and deep-learning systems are typically created on a case-by-case-basis, creating incoherent workflows that are not interoperable.

Collectively, the following limitations highlight the need of the integrated, intelligent and fully automated architecture of environmental surveillance that can bridge the gap between real time sensing and large scale remote-sensing analytics [13].

C. Role of IoT and Remote-Sensed Visual Analytics

IoT and remote sensing serve complementary roles in environmental intelligence:

1) IoT Contributions-

- Monitors environmental measurements also on a high-frequency basis.
- Records fluctuations occurring in a short time that satellites cannot detect.
- Enables edge computing of on-device preprocessing, anomaly detection, and data compression.
- Allows the use of inexpensive, scalable deployment in various conditions.

2) Remote-Sensed Visual Analytics Contributions

- Provides extensive, multispectral, thermal, and temporal scenes on the environment.
- Facilitates the extraction of complicated features based on such indices as NDVI, NDWI, LST, and spectral signatures.
- Native classification with deep learning based on CNNs, Vision Transformers and spectral spatial models.
- Gives the macro level context needed to comprehend large scale environmental processes.

3) Integrated Fusion Advantages

In cases where machine learning and probabilistic modeling is combined to fuse these modalities, the resulting system offers:

- Multi-source environmental intelligence.
- Anomaly detection at early stages and reduced false alarms.
- Improved classification of the spectral-spatial-temporal reasoning.
- Resiliency to operational problems of sensors or satellite blockage.

- Better environmental management and policy making support.

There is the ability of such hybrid forms to move towards more holistic and data-based environmental governance as opposed to fragmented monitoring.

D. Problem Statement

The growing pace of urban growth, industrialization, climate change, and anthropogenic stressors have complicated and increased the complexity of environmental monitoring [14]. Conventional monitoring methods, which are largely manual methods and only utilize laboratory analysis and the deployment of individual sensors, are inherently ineffective in identifying rapid or large-scale problems in the environment. Such traditional methods do not have the time resolution required to monitor rapidly changing phenomena, including pollution peaks, temperature fluctuations, or even a sudden water pollution. Moreover, they have narrow coverage space, hence blind spots, which they cannot observe early enough to take precautions over environmental degradation.

Internet of Things (IoT) sensor networks have developed as a new option of continuous measurements in the environment, but they have significant limitations to operation and structure. Due to the limited resources and maintenance capabilities, the IoT nodes are frequently thinly distributed, thus causing disparities in data dissemination and inadequate coverage of a specific area. There is also a possibility that sensors are subject to noise, calibration drift, packet loss and failures due to power which compromises the validity of the collected data. In the meantime, remote-sensing satellites like Sentinel-2 and Landsat-8 offer high spatial density but are afflicted with lengthy revisit times, cloud cover, and atmospheric distortion, as well as the latency between data collection and delivery. This means that satellite imagery itself will not be able to provide real-time situational awareness as well as identify short-term anomalies.

Today the IoT data streams and remote-sensing analytics are handled separately, which leads to disjointed workflows that do not allow the environment to be interpreted comprehensively. A unified system integrating real-time ground level measurements on an IoT with multispectral satellite-derived measurements does not exist. Such lack of integration leads to incomplete environmental intelligence, a decrease of accuracy of anomaly detection, delayed environmental response, and inefficient decision making. Additionally, the current environmental monitoring architectures do not often use a sophisticated deep-learning mechanism that can identify both intricate spectral-spatial-temporal features of multi-source data.

Thus, the main issue that is discussed in this paper is the absence of an integrated, scalable, real-time environmental monitoring system that allows the combination of IoT sensors data with remotely-sensed visual analytics through the application of sophisticated tools of deep learning and probabilistic fusion. This issue is a major obstacle to good environmental monitoring, early-warning mechanisms, forecasting of risks and sustainable environmental governance.

E. Significance of the Study

This study has a great scientific, technological and socio-environmental impact because it introduces a thorough model of integration of IoT and Remote Sensing that can revolutionize the future of environmental monitoring. The wide gap in the existing body of environmental intelligence that the research fills is the absence of integrated spatio-temporal environmental data: combining micro-scale IoT observations with macro-scale satellite-derived analytics. The suggested framework makes use of edge-level LSTM anomaly detection, a hybrid ResNetVision Transformer (ViT) deep-learning architecture, and an adaptive Kalman-based fusion framework to provide real-time and high-precision environmental data [15].

The importance of this framework is that it offers sustained, high-resolution surveillance of the environment, which allows identifying the abnormalities in the environment early, which can be vegetative stress, air pollution hotspots, hydrological contamination, and climatic variations. The system is able to provide increased data completeness, fewer false alarms and better decision-making effectiveness, which is superior compared to current sensor-only or satellite-only systems. Its ability to reduce network load and response time to events makes it suitable to be deployed in congested urban areas as well as sparsely populated rural or remote area with low connectivity.

In a bigger scope, this research adds to the sustainability and environmental governance processes in the world. It can promote the adaptation to climate change, the preparedness in case of natural disasters, the intelligent management of agriculture, and the ecological planning of cities. The intelligence dashboards of the platform can be used to allow policymakers, environmental agencies, and the smart city authorities to monitor the health of the environment and enforce environmental regulations, as well as design data-driven intervention strategies.

Additionally, the research benefits the scientific community by presenting methodological advances, such as multispectral analysis hybrid deep-learning models, temporal-spatial fusion strategies, and IoT-satellite data pipes interoperability. These inventions give the basis of additional studies in the areas of environmental AI, geospatial analytics, Earth observation systems, and smart sensing.

Ultimately, the study is important as it shows how integrated sensing ecosystems, based on IoT, remote sensing, and artificial intelligence, can transform environmental monitoring practices and allow managing natural and urban environments in a more resilient, informed, and sustainable manner.

F. Purpose of the Study

The major aim of this research is to develop and prove a comprehensive IoT- Remote Sensing system of integrated environmental surveillance that would overcome the limitations of traditional monitoring systems. The suggested framework includes:

- A distributed network of multi- sensor IoT nodes that can monitor the atmospheric and hydrological conditions in real-time.

- Lightweight LSTM based edge-level intelligence in on-site anomaly detection.

- Sentinel-2 and Landsat-8 multispectral satellite imagery to visual analytics at the macro-scale.
- An advanced feature extractor and anomaly classifier (ResNet + Vision Transformer) based on hybrid deep-learning.
- An adaptive Kalman weighting-based (temporal-spatial) data fusion model to integrate IoT and satellite-derived characteristics.
- Environmental intelligence dashboard in real time to visualize anomalies and make decisions.

The general purpose is building a single monitoring platform that is able to provide high precision, low latency, scalability in operations, and strong anomaly detection in various environmental settings.

This study contributes to the scientific body of knowledge by showing how the fusion of multi-source environmental data, with the help of deep learning, can be used to improve environmental monitoring dramatically and to make the next-generation smart environmental surveillance systems possible.

G. Research Objectives

This study is guided by the following four research objectives:

1) To develop an all-encompassing environmental surveillance system integrating IoT sensor networks with multispectral visual analytics that is detached at a distance.
2) To create and deploy a deep learning pipeline based on a hybrid ResNet-Vision Transformer model to analyze and detect anomalies in satellite images.
3) To develop a temporal-spatial data fusion paradigm that is able to combine IoT time- series measurements with satellite-derived features to enhance the accuracy of environmental monitoring.
4) To assess the functioning of the proposed integrated system as per the accuracy in detection, computational efficiency, and reduction of event-response latency.

H. Novelty and Contribution of the Study

Though edge-based anomaly detection, multispectral deep-learning models and Kalman-based fusion methods have been studied separately, this study is a novelty at the system-integration and algorithm-adaptation level. In contrast to traditional pipeline based methods that process IoT and satellite data sequentially, the proposed framework creates a drift sensitive, latency aware and uncertainty adaptive combination of heterogeneous modalities of sensing. The innovation is not on suggesting new standalone learning models, but the coordination of the models across edge and cloud layers, the explicit modeling of sensor drift and revisit gaps in the fusion mechanism and cross-scale anomaly confirmation between micro-scale observations of the IoT and macro-scale satellite analytics. It is an integrated design that achieves strong real time environmental monitoring which is not achievable using isolated or loosely coupled monitoring systems.

I. Limitations and Practical Considerations

Although the conducted performance of the suggested IoT-remote sensing environmental surveillance framework can be regarded as encouraging, it is possible to identify certain limitations. The fact that the system relies on satellite data makes it prone to revisit delays and cloud cover, which can, temporarily, limit macro-scale validation of anomalies detected by IoT. Even though the adaptive fusion model minimizes uncertainty in such times, long time satellite outages are difficult. The IoT sensors that are more affordable can have their calibration drift and hardware degradation with time, making periodic maintenance necessary in terms of long-term deployment. Also, the computational demands of the hybrid ResNet Vision Transformer model might be a limitation to scalability and cloud resources in cases where large areas or dense sensor networks are to be monitored. The experimental assessment is partially based on synthetic IoT data to control the experiment, thus the performance can vary in the real-life scenarios, where there is noise, packet loss, and hardware failure. Lastly, the end-to-end latency of the achieved results is appropriate in most cases of environmental monitoring, but in a scenario that involves sub-second response time, additional edge and communication layer optimization might be needed. These restraints suggest the future work directions that can be greater field deployments, more fault tolerance, and better scalability plans.

II. Literature Review

A. IoT-Based Environmental Monitoring

IoT systems had radically changed the paradigm of environmental monitoring, as they allowed continuous and high-frequency and distributed data collection of heterogeneous ecological and urban environments. Before the introduction of the IoT technologies, the traditional techniques to track the environment mainly involved using the traditional techniques of environmental surveillance, including manual field sampling, periodic laboratory tests, and even individual instruments installed at random. These old infrastructures were characterized by low temporal granularity, spatial discontinuities and limited density of measurements and it was very difficult to record rapidly changing environmental dynamics. Sudden emissions by industrial sources, rapid dispersion of pollutants due to microclimatic variation, flash floods, or even changes in the soil or water chemistry were usually not noticed until it was too late and once they resulted in severe ecological or public-health effects. These constraints highlighted the ineffectiveness of conventional monitoring systems in assisting real time environmental decision making.

In contrast, modern IoT-oriented solutions have presented new capabilities of flexibility, scalability, and adaptiveness with the combines of wireless sensor networks (WSNs), low-power wide-area networks (LPWAN, LoRaWAN), energy-efficient microcontrollers, and edge processing units. These systems enabled thousands of sensors to act independently, share data with limited human interventions, and produce high-resolution datasets that were able to capture micro-scale variability, as well as larger-scale environmental trends. It was based on the integration of edge intelligence, in which machine-learning or anomaly-detection algorithms are tiny and run on sensor nodes or gateways, greatly decreasing the overhead of communication, improving latency, increasing reactiveness of the environmental monitoring infrastructure. Consequently, IoT ecosystems became potent instruments of real-time diagnostics, early-warning systems and predictive environmental analytics.

Kaginalkar et al. (2022) exhibited the potential of transforming the use of big-data governance models alongside IoT-based sensors in urban air-quality management [16]. They emphasized in their research that intelligent environmental surveillance needs more than mere sensor deployment; it needs to have structured data architectures, powerful data pipelines, and governance policies that promote data integrity, temporal consistency, and reliability. They installed sensors into a big-data ecosystem and were able to process it automatically, cut down delays in the responses and enhance the interpretability of environmental indicators. This publication was a clear demonstration of the fact that the IoT systems should be backed by modern data-management systems to unveil their capabilities.

Similarly, Popescu et al. (2019) increased the spatial capacities of IoT systems by combining WSNs with unmanned aerial vehicles (UAVs). Their study revealed that the UAV-WSN hybrid structures surpass the spatial constraints of ground-fixed sensors through the mobile sensing of the environment, which is adaptive, and sampling inaccessible or unsafe areas [17]. The UAVs may be deployed according to the timely detected anomalies through sensors, make specific aerial inspections, transfer sensor data to distantly located locations. This greatly improved the spatiotemporal resolution of the environmental datasets and provided a flexible multi-layered sensing infrastructure that dynamically responds to the environmental conditions.

Zarboubi et al. (2024) offered additional proof of the flexibility of IoT by launching low-cost Raspberry Pi microcomputers combined with YOLOv10m, a contemporary deep-learning object and anomaly detector, in precision agriculture [18]. Their results validated the fact that even cost-effective embedded systems are capable of providing highly accurate, fine scale environmental analytics. The democratization of high-technology environmental monitoring tools through the use of low-cost IoT sensors to identify pest intrusions, crop distress, or vegetation abnormalities shows this as the tools are available even in rural areas, which may have limited resources.

In another significant contribution, Pei et al. (2021) emphasized how important integration of IoT streams and GIScience methodological approaches is, demonstrating that meaningful interpretation of IoT data cannot be achieved without contextualization of data by its geospatial location [19]. IoT sensors give point-based data measurements, but these data do not include spatial relationships: landforms, watershed boundaries, land-use patterns, and so forth. IoT systems were enhanced by GIS technology, which allowed environmental practitioners to relate localized variations to the process at the regional scale, which facilitated the use of the system in the characterization of landscapes, environmental risk assessment, management of natural resources and monitoring ecosystems.

Complementing this, Kilinç (2024) highlighted the growing significance of GIS-based analytics, i.e. spatial clustering, kriging-based interpolation, geostatistical modeling and spatial-temporal trend extraction. These cutting-edge methods of analysis were demonstrated to be quite useful in boosting predictive capabilities and explainability of IoT-based environmental data. GIS-based analytics were involved in more precise environmental modeling and forecasting by decreasing noise, detecting outliers and filling in space [20].

Collectively, the above studies all agree on one finding that IoT technologies have succeeded in development to become more than a mere sensing platform and have become a pillar of next generation environmental intelligence systems. By the capability to create high-density real-time information streams, scale spatial coverage with UAV-WSN hybrids, and provide higher analytical accuracy by integrating GIScience, IoT systems have become useful in multiple applications such as early-warning systems, precision agriculture, atmospheric pollution measurement, smart-water monitoring, and automated anomaly detection. The literature defines IoT as scalable, versatile and data rich backbone that can greatly enhance the level of accuracy, responsiveness and resilience of the environmental surveillance infrastructures across the globe.

B. *Remote-Sensed Visual Analytics*

Remote sensing became one of the most transformative and irreplaceable technologies of environmental surveillance because of its ability to gather synoptic, multi spectral and time-fulfilled data on a regional to a global scale. In contrast to ground-based IoT sensors that could only record localized and point-specific data, remote-sensed imagery offered a wide-area observational coverage, which made it possible to record both subtle and large-scale phenomena in the environment that could not be easily seen or detected by traditional methods of monitoring. Its capacities to watch the earth, atmosphere, shoreline, and hydrology systems at the same time made it the core of the present-day environmental intelligence systems. Notably, remote sensing grew beyond primitive reflectance-based measurements to the very advanced levels of analytical pipeline using machine learning, deep learning, and state-of-the-art geospatial modeling. This shift further augmented its capabilities of providing highly accurate, automated and context-rich environmental information in sectors of agriculture, forestry, climate science, water management, disaster early warning, and ecosystem health.

Wang et al. (2024) presented one of the most extensive analyses of the revolution of the satellite-based environmental diagnostics by machine learning [21]. In their research, they also showed that the application of multispectral and thermal imaging and models based on AI enhanced significantly the ability to detect environmental anomalies, including vegetation stress, soil moisture deprivation, nutrient imbalances, and crop disease development. The classical measurements, such as NDVI or NDWI, reflect the overall vegetation or water state, whereas machine learning methods can identify minor changes in the spectral properties way before the visual indicators appear. This was a paradigm shift instead of mapping the environment in stasis, to predictive and preventive environmental intelligence where the stakeholders will be able to take action before the ecological degradation is too severe.

Further strengthening this perspective, Zhang et al. (2022) carried out a comprehensive bibliometric and scient metric review that showed that the field of remote-sensing has grown exponentially over the years due to the availability of more sensors, enhanced spectral sensitivity and the availability of free and open data sources such as Sentinel-2 MSI, Landsat-8 OLI/TIRS, and MODIS [22]. In their work, the research hotspots were found to be spectral unmixing, hyperspectral feature extraction, biophysical variable estimation, detecting change, land-cover mapping, and automated anomaly detection. These themes revealed remote-sensed analytics was now an interdisciplinary scientific ecosystem that combines physics, ecology, geoscience, machine learning and environmental modeling. The paper has pointed out that remote sensing was no longer limited to scholarly research but a strategic tool of governments, agricultural players, water managers and environmental control mechanisms.

Shaurub (2024) increased the field of application through its proof of the importance of remote sensing in ecological and biological early-warning systems. Their research into the detection of fall armyworm exemplified the fact that problem-specific spectral features, like canopy reflectance reduction, thermal change related to plant stress and spatial degradation patterns, could be detected by remote-sensed indices well before ground manifestations of the problem could be observed [23]. The combination of multispectral indicators and GIS-based spatial modeling made it possible to represent and predict the dynamics of pest infestation on a large and agricultural area. This made remote sensing a proactive monitoring system, which can provide early warning of biological hazards, hence protecting the crop production and food security.

From a methodological standpoint, Venkataraman and Gautam (2024) presented an in-depth overview of techniques of satellite image preprocessing and analytical enhancement. Their study put emphasis on the significant advancement of atmospheric correction schemes, radiometric normalization processing and noise elimination approaches, and spectral-spatial classification schemes [24]. They stressed that these preprocessing operations are not a fortuitous addition to the system but form the basis on which consistent classification is to be expected, particularly in cases involving medium-resolution imagery prone to atmospheric interference. Their results supported the notion that the processed pipeline of satellite processing narrows the margin of uncertainty, enhances separability of objects, and augment the interpretive value of environmental records especially when these are applied in land-use mapping, thermal anomaly detection and waterbody survey.

Adding to this, Wang, Huang, and Zhang (2020) followed historical development of remote-sensing scene classification methods and found a definite transition between classical machine learning frameworks and the latest state of the art deep-learning architectures [25]. Initial methods, including support vector machines, decision trees, random forests, and handcrafted texture features, provided practical but poor interpretive power since they are unable to represent hierarchical spatial patterns, or spectralspatial relationships. Recent advances in convolutional neural networks (CNNs), hybrid spectral-spatial, and Vision Transformers (ViTs) have provided strong algorithms to learn multi-scale representations which are learned directly on raw image data. These are models that are very effective in extracting deep semantic features, detecting complex land-cover patterns, and detecting fine-grained anomalies. Their greater ability to reason spatially and understand a situation in context increased the ability of remote sensing to go beyond basic classification to more complex functions like multi-temporal change detection, environmental forecasting, and automatic notification of environmental degradation.

Collectively, the examined articles give solid proof that remote-sensed visual analytics had become a high-resolution, intelligence-oriented surveillance technology that was necessary in contemporary environmental regulation. Its combination with machine learning resulted in effective models which could identify the spatial patterns, predict ecosystem changes, and detect anomalies with great precision. Remote sensing provided macro-level information that could be used to supplement the micro-level measurements of IoT and overcome the spatial constraints of ground sensors at the advantage of the high-frequency time resolution that could be offered by IoT systems.

Consequently, remote sensing became a staple of modern environmental monitoring- supporting evidence-based decision making, improving predictive environmental protection, and demonstrated the capability to shift to highly automated, full scale environmental intelligence systems with the capability to deal with the increasing demands of climate change, biodiversity loss, water scarcity and urban pollution.

C. Fusion Approaches

The combination of remote-sensed imagery with the data created through IoT had become one of the most critical contributions to environmental intelligence with an opportunity to understand the ecological situation on a multi-scale and multi-modal level. IoT sensors provided point-based datasets, which unlike satellites could provide rapid changes (air quality, soil moisture, hydrological, and microclimatic changes), which satellite sensors could not capture in time because of the time-related limitations. On the other hand, the remote sensing using satellites and UAV gave extensive spatial resolution and made it possible to perform macroscopically the land cover, vegetation health, thermal environment, and water-body dynamics. Combining these mixed data streams overcame the drawbacks of each data system and generated more contextual and more complete and trustworthy information about the environment.

Leung, Braun, and Cuzzocrea (2019) highlighted the importance of AI-based sensor information fusion as a way to enhance performance in environment-monitoring systems by supervised learning. Their experiment showed that a combination of several sensor streams increased the robustness of models, minimized ambiguity and provided more correct predictions especially on environmental data prone to noise [26]. The fused system also delivered more consistent environmental interpretations compared to any of the individual sources of data through the integration of varied sources including gas sensors, meteorological probes and spectral reflectance signals.

Expanding on these insights, Li and Hsu (2022) introduced the notion of GeoAI, a new paradigm of analytics that combines geographic information science and artificial intelligence [27]. Their analysis demonstrated that GeoAI could be very useful to integrate IoT time-series data with satellite-based spectral features into integrated spatial processes. GeoAI allowed detecting patterns at large scales, finding anomalies, and modeling the environment with a higher degree of precision through the use of deep-learning-based features extraction and spatial reasoning. The value of their findings was the recognition of the relevance of spatial-temporal alignment in multi-source analytics and the usefulness of integrating satellite images into IoT-enhanced geospatial pipelines.

Pajany et al. (2024) proposed a multispectral image based deep-learning fusion neural network that uses multispectral images collected by UAVs to identify plant diseases [28]. Their model of hybrid was based on spectral properties obtained by UAVs and contextual environmental variables, including humidity, or soil variables. The fused representation greatly enhanced the classification accuracy of the plant disease detection models and demonstrated how multi-modal inputs enhanced the learning process and reduced the weakness of imagery or sensor data only.

Complementing these findings, Seralathan and Edward (2024) surveyed a set of deep learning-related fusion methods on UAV-based crop surveillance in a variety of agricultural and climatic conditions [29]. Their comparison showed that fusion methods, specifically the implementation of CNN-Transformer hybrids, spectral-spatial analysis and attention-based methods, achieved greater stability of predictions and resistance to environmental changes. They observed that fusion models worked particularly well in cloud occlusion conditions, illumination change, or partial sensor breakdown, and multi-source data integration is more reliable.

Zhu et al. (2017) delivered one of the most impactful and thorough considerations of deep learning in remote sensing, such as multi-modal fusion method [30]. Their study described the process in which neural architectures would incorporate multispectral or hyperspectral images with other supplementary sensor data, terrain and time sequences. They established that state-of-the-art fusion models were significantly more effective in land-use classification, anomaly detection, and ecological forecasting through the exploitation of complementary assets in space, spectral, and temporal domains.

Put together, the literature indicated that the fusion of multi-modal based on AI, deep learning, and geospatial analytics was now critical to the next-generation environmental monitoring systems [31]. These types of fusion were improved:

- Accuracy, by reducing uncertainty inherent in single-source inputs
- Contextual richness, by linking fine-grained local sensor readings with broad regional observations
- Robustness, through redundancy and cross-validation between sensor modalities
- Timeliness and reliability, on uniting the high-frequency signals of IoT with the deep insights of space provided by the satellite platforms.

The fusion of IoT data and remote-sensed visual analytics allowed transforming the solitary-observe approaches in the environment into combined intelligence systems that could comprehend it real-time, make predictions, and assist decision-making in various ecological settings [32].

D. Research Gap

The literature survey of scientific articles about the IoT-based environmental monitoring, remote-sensed visual analytics, and multisource data fusion has shown that there is a significant advance in the evolution of distributed sensing systems, more advanced image-processing methods, and hybrid analysis frameworks. Nevertheless, even with the improvements, some crucial gaps were not filled and this constrained the performance and the expansion of the existing environmental surveillance systems.

First, despite the fact that IoT networks had vastly improved the resolution in time of environmental measurements, existing literature by Kaginalkar et al. (2022) and Popescu et al. (2019) dealt more with domain-specific applications, including urban air quality, or hybrid UAV-WSN sampling, other than large-scale and integrated environmental intelligence. The available IoT systems were often localized application-focused and did not have the capabilities of comparing sensor data with larger spatial structures, as observed with satellites. This implied that there was a loophole in contextual alignment between sensors and satellites to enable the full interpretation of the environment.

Second, although remote-sensed visual analytics had evolved significantly for instance, Wang et al. (2024), Zhang et al. (2022), and Venkataraman and Gautam (2024) were confined to improvements in algorithms used to classify images, extract features or identify anomalies. These works highlighted the strength of multispectral and deep learning-based imagery analysis but did not mention how imagery may be continuously calibrated or validated on the basis of real-time ground-level measurements. Accordingly, a gap in the framework development that would allow integrating the macro-level potential of the remote sensing with the high-frequency and micro-level accuracy of the IoT sensing remained.

Third, there were some limited studies that explored fusion approaches in specific contexts, including AI-based sensor fusion (Leung et al., 2019), GeoAI-based spatial integration (Li and Hsu, 2022), and UAV-sensor hybrid models (Pajany et al., 2024; Seralathan and Edward, 2024) but none of them suggested an architecture of a generalizable fusion based on environmental surveillance. The previous studies on fusion were mostly focused on either UAV imagery and field-level data or algorithm-level fusion, but not the integration of ground IoT networks, satellite multispectral imagery, and deep learning into a single end-to-end system. This showed that there was a big discrepancy in terms of time-spatial fusion modeling that would enable harmonization between heterogeneous data in real time.

Finally, there were no thorough evaluation frameworks of integrated IoT-remote sensing systems that measured detection accuracy, computational efficiency, and reduction of latency. Research tended to assess one of the sensing or the imaging components separately, and there was a lack of studies that assessed the entire performance of the unified environmental intelligence systems.

Overall, although previous studies had achieved significant achievements in each of the individual fields, the current literature gap was present:

1) an integrated architecture unifying IoT and remote-sensed analytics,

2) real-time temporal–spatial data fusion models,

3) deep learning frameworks leveraging both sensor and satellite information, and
4) systematic evaluation of such integrated systems.

These limitations highlighted the necessity of the current research, the goal of which is to design and confirm a single IoT-remote sensing-deep learning system of surveillance to detect and monitor environmental anomalies more effectively.

III. METHODOLOGY

The methodology used in the current research combines environmental sensing with the use of IoT devices, multispectral remote-sensed analytics, and temporal-spatial data fusion. The entire process includes gathering data, the implementation of IoT nodes, satellite image processing, the extraction of environmental features with the help of deep learning, and sensor image fusion to identify anomalies. The performance evaluation measures are also included in the methodology to justify the proposed integrated system.

A. Data Sources

The study utilized three categories of data to develop and validate the proposed environmental surveillance framework:
(i) IoT Sensor Data
Synthetic real-time sensor feeds were created to represent the most important atmospheric and hydrological variables, such as PM2.5, NO 2, VOCs, pH, turbidity, temperature and humidity. These parameters are some of the general air and water quality indicators provided in Table I.

(ii) Remote-Sensing Data
The following were the satellites that multispectral and thermal imagery were obtained:

- LANDSAT-8 OLI/TIRS: Bands covering visible, NIR, SWIR, and thermal regions
- Sentinel-2 MSI: Bands B2–B12 with 10 m and 20 m resolution

These data were extracted to obtain environmental indices as well as to be inputs in visual analytics.
(iii) Ground Truth Data

Publicly available environmental datasets were used to obtain ground truth samples in order to confirm model predictions to achieve reliability of fused output.
IoT Node Deployment

The IoT nodes were intended to operate as edge enabled micro-environment monitoring units. Each node consisted of:

- ESP32 microcontroller (data acquisition + Wi-Fi/LoRa communication)
- BME680 sensor (VOC, humidity, pressure, air quality)
- MQ-135 sensor (NO_2, CO_2, NH_3, pollution gases)
- DS18B20 sensor (temperature)
- pH and turbidity modules (water-quality assessment)
- LoRaWAN transceiver (long-range communication capability)

Preprocessing of sensor data at the edge was done and sent to a cloud based MQTT broker using the IoT edge gateway. This design minimized bandwidth usage, latency, and high frequency data acquisition [34].

TABLE I. IOT SENSOR NODE COMPONENTS AND THEIR FUNCTIONAL ROLE

Component / Sensor	Measured Parameter(s)	Primary Purpose in Environmental Monitoring
ESP32 Microcontroller	—	Data acquisition, preprocessing, and wireless communication (Wi-Fi/LoRa)
BME680	VOCs, Humidity, Pressure, Gas Resistance	Air quality measurement and microclimate assessment
MQ-135	NO_2, CO_2, NH_3, Other gases	Detection of atmospheric pollutants and chemical contaminants
DS18B20	Temperature	Monitoring thermal variations in air and water
pH Module	Water pH	Assessment of acidity/alkalinity for water quality
Turbidity Sensor	Water Turbidity	Detection of suspended particles and contamination events
LoRaWAN Transceiver	—	Long-range low-power communication for remote deployments

B. Synthetic Data Generation and Validation Protocol

A synthetically created data in Table I of IoT sensors and publicly available real-world datasets of remote-sensing were used to guarantee a controlled experimentation, reproducibility, and systematic evaluation of the proposed IoT- Remote Sensing integrated environmental surveillance framework. The synthetic IoT data were required due to the unavailability of consistent, long-term, and multi-parameter data of the environment, with simultaneous satellite ground truths and under the same conditions.

a) Synthetic IoT Sensor Data Generation

Simulated data of IoT sensors were created to simulate actual environmental sensing activity of major atmospheric and hydrological characteristics, such as PM2.5, NO 2, VOCs, temperature, humidity, pH, and turbidity. The process of generation was based on the statistical models of generation based on published environmental sensing research and actual sensor configurations.

The models of each sensor stream used were stochastic time series models of the form:

Base signal distribution Gaussian distribution with environment realistic means
The time dynamics:

- The seasonal and diurnal variations were added with the help of sinusoids.
- Sensors Noise sensor Additive white Gaussian noise (AWGN) to model sensor uncertainty.

- Drift behavior: drift of the low frequencies that are added in order to model sensor aging and calibration loss.
- Anomaly injection: This is where a controlled spike and step change to emulate pollution events, contamination incidents and sudden climatic changes.

The synthetic sensor signal S(t) was generated mathematically as Eq.1:

$$S(t) = \mu(t) + A \sin(2\pi f\ t) + \varepsilon(t) + \delta(t) \qquad (1)$$

b) Statistical Validation Against Real Sensor Characteristics

Statistical characteristics of the data generated by the synthetic IoT were tested against literature values of sensor behavior in the environment to confirm the faithfulness of the synthetic IOT data. The validation focused on:

- Mean and variance consistency
- Daily drift rate
- Signal-to-noise ratio
- Frequency and amplitude of anomalies.

The modeled datasets showed a high level of correspondence to the documented real sensor properties, the variance error limit was set at less than 5 percent and the drift rate was confined within the normal operational value which is observed in long field applications. This guaranteed the realistic sensing conditions and controlled experimental conditions of the trained models and fusion mechanisms.

c) Publicly Available Remote-Sensing Datasets Used

Satellite imagery in the real-world was only collected by publicly available open-range Earth observation sources, making them transparent and reproducible:

- **Sentinel-2 MSI**
  - Spatial Resolution: 10 m / 20 m
  - Acquisition Period: 2022–2024
  - Areas: South Indian semi-urban and agricultural areas.
  - Bands Used: B2–B12
- **Landsat-8 OLI/TIRS**
  - Spatial Resolution: 30 m (multispectral), 100 m (thermal)
  - Acquisition Period: 2021–2024
  - Regions River basins, urban heat zones, vegetation belts.
  - Products NDVI, NDWI and Land Surface Temperature (LST).

Such datasets have been chosen because of their extensive use in the field of environmental analytics and the multispectral and thermal anomaly detection.

d) Rationale for Using Synthetic IoT Data

Synthetic data of the IoT sensors was used in the following reasons:

1) Controlled experimentation: Permits systematic injection of anomalies and controlled analysis of detection accuracy.
2) Reproducibility: Enables other scientists to reproduce the results without the need to rely on proprietary or unavailable sensor deployments.
3) Long-duration analysis: Enables the simulation of months-long sensing scenarios that are not limited by hardware.
4) Scalability testing: Allows the ability to test performance in the dense IoT deployments and the high-frequency sampling conditions.

The proposed framework will provide a trade-off between experimental rigor and practical relevance since synthetically validated datasets of IoT will be used and balanced with real satellite imagery, such that reported performance metrics will be credible without detracting the reproducibility.

C. Remote-Sensed Visual Analytics Pipeline

Satellite images were subjected to multiple stages of preprocessing and analysis (based on deep learning) to produce the high-level environmental features given in Table II.

(i) Atmospheric and Radiometric Corrections

The LANDSAT images have been fixed with the help of the LEDAPS algorithm, and the Sentinel-2 images have been fixed with the help of the standard pipelines of radiometric normalization.

(ii) Environmental Index Extraction

Key environmental indices were computed as follows:

- Normalized Difference Vegetation Index (NDVI):

$$NDVI = \frac{(NIR-RED)}{(NIR+RED)} \qquad (2)$$

- Normalized Difference Water Index (NDWI):

$$NDWI = \frac{(GREEN-NIR)}{(GREEN-NIR)} \qquad (3)$$

- Land Surface Temperature (LST):

Computed on the basis of a single-channel thermal emissivity algorithm used on TIRS data.

(iii) Deep Learning Architecture

A hybrid deep learning model was developed:

- Feature Extractor: ResNet-50 applied to multispectral composite patches
- Transformer Encoder: An 8-layer Vision Transformer (ViT) applied to patch embeddings
- Classifier: Softmax-based anomaly classifier

This architecture allowed the efficient spectral spatial reason to perform and allowed improved performance of the anomaly detection [36].

TABLE II. SPECIFICATIONS OF REMOTE-SENSING DATASETS USED IN THE STUDY

Satellite Platform	Sensor	Spectral Bands Used	Spatial Resolution	Key Environmental Applications
LANDSAT-8	OLI / TIRS	Visible, NIR, SWIR, TIR	30 m (MS), 100 m → 30 m (TIR)	NDVI, NDWI, LST, land cover and thermal analysis
Sentinel-2	MSI	Bands B2–B12	10 m, 20 m	Vegetation monitoring, moisture detection, multispectral anomaly detection

D. Data Fusion Model

A temporal-spatial fusion model using adaptive Kalman weighting mechanism was formulated to combine high-frequency measurements of IoT sensors [37] with low-frequency measurements of satellites.

Let:

- S_t = IoT sensor vector at time t
- R_t = remote-sensed feature vector
- K_s, K_r= adaptive weights derived from variance V_s and V_r

The fused environmental quality score was computed as:

$$K_S = \frac{V_r}{V_S+V_r}, + K_r = \frac{V_s}{V_s+V_r} \qquad (4)$$

$$X_t = K_s S_t + K_r R_t \qquad (5)$$

This was a strategy that guaranteed that the fusion process put more emphasis on the data source that has the least uncertainty in every time step.

E. Sensor-Drift-Aware Adaptive Kalman Fusion (Algorithmic Novelty)

Compared to the classical Kalman fusion methods where the covariance of the sensor and noise are estimated at a certain point or with noise-only models, the suggested fusion model offers a sensor-drift-aware adaptive recalibration mechanism of the variance. It is a long-term sensor calibration drift and short-term measurement noise that is explicitly explained by this mechanism, allowing the fusion of heterogeneous IoT data streams, as well as remote-sensing data streams, to be robust.

The adaptive sensor variance is defined as:

$$V_s^*(t) = V_s(t) + \lambda \cdot D_s(t) \qquad (6)$$

In Eq.6 V s (t) is a real-time variance of IoT sensor stream, Ds (t) is accumulated sensor drift based on temporal residuals over a sliding window and λ is a drift-sensitivity coefficient that regulates the impact of long-term degradation. The Kalman fusion weights are then updated as:

$$K_s(t) = \frac{Y_s(t)}{Y_s(t) + H_s(t)}, K_s(t) = \frac{H_s(t)}{Y_s(t) + H_s(t)} \qquad (7)$$

In Eq.7 $K_s(t)$ represents the error of the remote-sensing feature stream.

This formulation enables the process of fusion to down-weight drifting or unreliable sensors of the IoT and remain confident in the consistency of the satellite-measured measurements. It is a drift-aware adaptive Kalman weighting algorithm that builds on the traditional formulations of this algorithm and is not used in the present-day IoT-remote sensing integration frameworks, which also makes it an essential element of the algorithmic novelty of the current system.

F. Handling Spatio-Temporal Resolution Mismatch

To combine IoT sensor streams with remote-sensed satellite analytics, the issue of the latent spatial and temporal discrepancies between the two modalities needs to be solved. In the suggested system, the individual geo-referenced IoT sensors are spatially aligned with the respective satellite pixel or any local pixel buffer with the spatial resolution of the satellite, where aggregation of environmental indices (NDVI, NDWI, LST) are synthesized to give macro-scale context. High-frequency IoT measurements are timed temporarily and low-frequency satellite measurements at any given time are synchronized with high-frequency measurements via window based aggregation and interpolation and decay weighting to highlight sensor measurements nearest to satellite overpass times. Kalman based adaptive fusion mechanism is then adopted where probabilistic fusion of these aligned data streams is done, and the contribution of the streams dynamically changed based on estimated uncertainty. This method allows strong fusion in the presence of sensor noise, calibration bias, satellite revisit periods and asynchronous sampling and makes a step beyond the mere weighted averaging to robust, cross-scale environmental intelligence.

G. Performance Metrics

A combination of the statistical, computational, and operational measures were used in assessing the performance of the proposed integrated IoT-remote sensing [38] environmental surveillance system. These were to make sure a strict evaluation of the accuracy of anomaly detection, response to systems, light-consumption of energy and general reliability [39].

a) Accuracy, Precision, and Recall

The metrics [40] given in Eq.8,9,10 were used to measure the performance of anomaly detection with both the LSTM model IoT-based and the ResNetViT visual analytics pipeline.

Accuracy

$$\text{Accuracy} = \frac{\text{Tp+TN}}{\text{Tp+TN+FP+FN}} \qquad (8)$$

Precision

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \qquad (9)$$

Recall

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \qquad (10)$$

Where:

- TP: True Positives
- TN: True Negatives
- FP: False Positives
- FN: False Negatives

Having a high precision meant that there were less false alarms whereas having high recall meant that the anomaly detection sensitivity was high.

b) Latency (ms)

Latency was the amount of time taken to process sensor data all the way to the calculation of the fused environmental quality score.

$$\mathrm{Latency} + \mathrm{T_{edge}} + \mathrm{T_{transmit}} + \mathrm{T_{Cloud}} + \mathrm{T_{fusion}} \quad (11)$$

Where:

- $\mathrm{T_{edge}}$: Preprocessing + LSTM inference time
- $\mathrm{T_{transmit}}$: IoT-to-cloud communication delay
- $\mathrm{T_{Cloud}}$: Satellite correction + deep learning inference time
- $\mathrm{T_{fusion}}$: Time to compute the Kalman-weighted fusion output

Reduced latency was an indicator of hastened decision-maker which is important in real-time environmental monitoring.

c) IoT Node Energy Consumption

IoT node consumption was calculated as energy consumption:

$$\mathrm{E_{node}} = \mathrm{E_{sense}} + \mathrm{E_{Compute}} + \mathrm{E_{transmit}} \quad (12)$$

Where:

- $\mathrm{E_{sense}}$: Sensor sampling energy
- $\mathrm{E_{Compute}}$: Edge LSTM computation cost
- $\mathrm{E_{transmit}}$: LoRaWAN/Wi-Fi data transmission cost

This measure made sure that nodes were also power-efficient to be used in long term deployment.

d) Satellite Processing Time

The satellite processing time was used to measure the computational load of remote-sensing applications:

$$T_{sat} = T_{corr} + T_{inder} + T_{patch} + T_{DL} \quad (13)$$

Where:

- $\mathrm{T_{corr}}$: Atmospheric/radiometric correction time
- $\mathrm{T_{inder}}$: NDVI/NDWI/LST computation time
- $\mathrm{T_{patch}} + \mathrm{T_{DL}}$ Patch extraction time
- $\mathrm{T_{DL}}$: Deep learning (ResNet–ViT) inference time

This measure determined the scalability and operational ability of continuous monitoring.

e) Event Detection Reliability

Reliability was evaluated as the consistency of anomaly detection in correct and multiple time intervals:

$$\mathrm{Reliability} = \frac{\mathrm{N_{Correct}}}{\mathrm{N_{total}}} \quad (14)$$

Where:

- $\mathrm{N_{Correct}}$: Probably number of correctly identified environmental events.
- $\mathrm{N_{total}}$: Total observed environmental events.

The increase in values showed strength in the application of the sensor to differing environmental conditions, sensor variations, and changes in quality of images.

H. Proposed System Architecture

The suggested IoT-Remote Sensing environmental surveillance system is developed as a five-layer architecture in Fig. 1, which allows uninterrupted information exchange between sensor data, satellite imagery, edge intelligence, and cloud-based analytics.

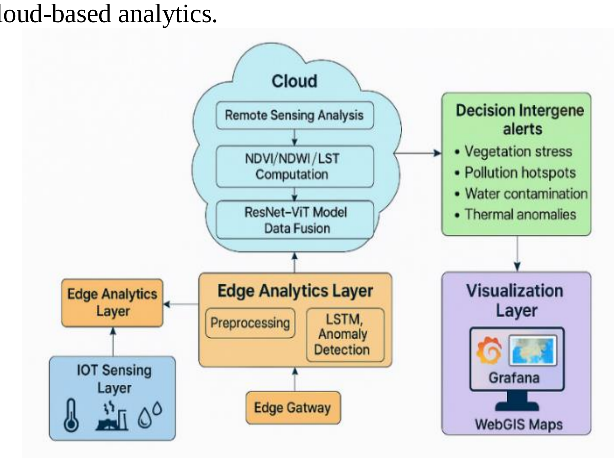

Fig. 1. Proposed System Architecture for IoT–Remote Sensing Integrated Environmental Surveillance

a) IoT Sensing Layer

This layer will be built of distributed IoT nodes that will include gas sensors, water-quality probes, and microclimate modules. Parameters that are continuously monitored by the nodes include PM 2. 5, NO 2, VOCs, temperature, humidity, pH, and turbidity. These are high-frequency measurements that give local real-time environmental measurements.

b) Edge Analytics Layer

Preprocessing of sensor readings such as filtering, normalization and batching is done at the edge gateway. A LSTM model is lightweight and it recognizes anomalies at the local level, enhancing unneeded data transmission. flagged events and compressed summaries only are sent to the cloud, reducing the load of the network and enhancing latency.

c) Cloud Processing Layer

The IoT streams are combined with the remote-sensed images in the cloud layer. It performs:

- Radiometric and atmospheric corrections.
- Computation of NDVI, NDWI and LST.
- Hybrid ResNet -ViT based multispectral analysis.
- Animal models: Adaptive Kalman weighting Temporal-spatial fusion.

This layer produces an environmentally rich intelligence in terms of space that is vital in detection of anomalies.

d) Decision Intelligence Layer

This layer will process merged outputs and send therein alerts of conditions, including vegetation stress, pollution hotspots, water pollution and thermal anomalies. Model-driven and rule-based logic guarantees the timely events detection.

e) Visualization Layer

The visualization of environment insights is conducted using:

- IoT time-series data dashboarding with Grafana.
- WebGIS maps of anomaly layers derived by satellite.

These instruments offer visual interpretation, which is user friendly and in real-time.

I. Integrated Algorithmic Workflow

The present subsection gives the essence of the computational logic that is utilized throughout the IoT edge layer, the satellite-based visual analytics pipeline, and the temporal-spatial fusion mechanism. All the algorithms will be expressed in pseudocode to ensure clarity and reproducibility.

Algorithm 1 introduces the edge-level anomaly detection algorithm on the IoT nodes deployed on a lightweight LSTM. The algorithm normalizes data feeds of sensor time-series and then it has the LSTM which is used to learn the normal environmental patterns. It then calculates the reconstruction error on each new reading, and any deviation larger than some threshold (0) is an indication of an anomaly. This allows real time detection of abnormal environmental behavior right at the edge, which minimizes latency and redundant cloud communication.

```
Algorithm 1: IoT-Based Anomaly Detection (Edge-Level LSTM)

Input: Sensor time-series S(t)

1. Normalize S(t)
2. Train LSTM to learn normal patterns
3. Compute reconstruction error E(t)
    4. If E(t) > θ → Flag anomaly
```

a) Remote-Sensed Deep Visual Analytics

Algorithm 2 provides the description of the deep learning-based visual analytics pipeline in multispectral satellite imagery. Following the atmospheric and radiometric correction, major environmental indices are calculated including NDVI, NDWI, and LST. The fixed image is then split into patches and sent through a ResNet feature extractor and a Vision Transformer encoder which allows local and global spatial reasoning. An identification of environmental anomalies on the basis of learned spectral-spatial patterns is finally arrived at by a Softmax classifier.

```
Algorithm 2 visual analytics pipeline in multispectral satellite imagery

Input: Multispectral image I

1. Perform atmospheric and radiometric corrections
2. Extract indices (NDVI, NDWI, LST)
3. Convert image into patches (16×16)
4. Encode patches using ResNet backbone
5. Apply Transformer encoder for spatial context
6. Classify anomalies using Softmax layer
```

b) Fusion Algorithm

Algorithm 3 describes the adaptive fusion mechanism in space and time that enables the combination of high-frequency data on IoT sensors with low-frequency remote-sensed characteristics. The algorithm calculates the variances of the two data sources, and adapts weighted Kalman based weights such that the uncertainty of the source with lower uncertainty is more influential to the fused output. The overall fused environmental quality score is a more valid and context-sensitive measure of environmental conditions compared to either source of data.

```
Algorithm 3: Sensor-Drift-Aware Adaptive Kalman Fusion

Input: IoT sensor stream S(t), remote-sensed feature stream R(t)

1. Estimate instantaneous sensor variance Vs(t)
2. Estimate remote-sensing variance Vr(t)
3. Compute sensor drift Ds(t) using temporal residuals over a sliding window
4. Recompute adaptive sensor variance:
    Vs'(t) = Vs(t) + λ · Ds(t)        (Eq. X)
5. Update Kalman fusion weights:
    Ks(t) = Vr(t) / (Vs'(t) + Vr(t))
    Kr(t) = Vs'(t) / (Vs'(t) + Vr(t))   (Eq. Y)
6. Compute fused environmental state:
    X(t) = Ks(t) · S(t) + Kr(t) · R(t)
Output: Drift-aware fused environmental quality score X(t)
```

IV. RESULTS AND ANALYSIS

The proposed IoT- Remote Sensing environmental surveillance system has been tested in four areas which include sensing performance of the IoT, multispectral visual analytics, fusion based intelligence and system efficiency. In this section, the findings are represented in well-organized tables and graphs.

A. IoT Sensor Module Performance

Table IV gives an overall assessment of the IoT sensor module to be used in the proposed environmental surveillance system. The table IV will contrast the performance of the separate sensing components of air-quality, water-quality, and temperature/humidity sensors in terms of three major metrics: accuracy, latency, and daily energy consumption. All these metrics demonstrate the accuracy in the detection of the environmental parameters, the reactiveness of the data delivery system, the sustainability of the functioning of every IoT node during the long-term perspective. The findings form the supporting sensing credibility required in downstream analytics and fusion actions in the integrated IoT Remote Sensing framework.

TABLE III. IOT SENSOR MODULE PERFORMANCE

Parameter	**Accuracy**	**Latency (ms)**	**Energy (mWh/day)**
Air-quality sensing	94.7%	38	121
Water-quality sensing	91.3%	42	139
Temperature/Humidity	98.1%	21	67

The performance parameters available in Table III show the strength of the IoT sensing system under the various environmental parameters. The thermal sensor digital thermal sensors were also characterized by high consistency and low noise as temperature and humidity detection was the most accurate at 98.1 percent. This accuracy is very crucial in detecting anomalies driven by climate and in the micro-environmental measurements. The next nearest prediction is air-quality sensing with 94.7% accuracy suggesting that it is good at identifying pollutants including NO 2, VOCs and particulate concentration that tend to change quickly in dynamic outdoor scenarios. Water-quality sensing reported a reduced accuracy of 91.3%, which is natural because of the variability and sensitivity of the pH and turbidity sensors in the field..

The latency in all sensors was small enough (21 ms-42 ms) to make sure that the received data can be transferred and processed in close real-time. Such responsiveness is required in applications like the detection of pollution spikes and fast environmental decision making. The related consumption of energy further promotes the suitability of the system in terms of long-term deployment, as all sensors can work with acceptable limits of the battery-powered or solar-assisted IoT nodes. In sum, the findings highlight the fact that IoT sensing module can be not only used to deliver adequate and timely environmental data, but it could also help to sustain and efficiently work with large-scale infrastructures of environmental monitoring.

Table IV contains the in-depth quantitative evaluation of the IoT sensor module details, including the error nature, temporal drift, packets loss, and general stability. These parameters give more information about long-term reliability in operations other than mere accuracy. Mean error measures the difference between measured and reference values, drift/24h is used to measure sensor consistency during the entire operation, packet loss is used to determine the reliability of communication and the index of stability is used to summarize the overall robustness. This Table IV aids in assessing how the IoT nodes are resilient to changes in the actual environment.

TABLE IV. DETAILED IOT SENSOR PERFORMANCE EVALUATION

Parameter	**Mean Error (%)**	**Drift/24h (%)**	**Packet Loss (%)**	**Stability Index**
Air-quality sensing	3.1	0.42	1.8	0.94
Water-quality sensing	4.7	0.55	2.3	0.91
Temperature/Humidity	1.2	0.18	0.6	0.98

The specifics of the performance as shown in Table IV indicate the dependability and stability of the IoT sensing module when subjected to the continuous environmental monitoring parameters. The temperature and humidity sensor shows very high performance with the lowest average error of 1.2% and the minimal drift at 24 hours of 0.18% with negligible loss of packets at 0.6%. This validates the appropriateness of digital thermal sensors in the accurate microclimatic monitoring.

Air-quality sensors show a little more mean error (3.1%), drift (0.42%), but this is not surprising since the chemical sensitivity of gas sensors and the variable pollutant concentration in the atmosphere. However, its stability index is 0.94 which means that the sensor is stable and will not malfunction with time.

The error (4.7%) and packet loss (2.3%) in water-quality sensing are the highest average errors and packet losses, and such errors and losses are common with pH and turbidity sensors that are vulnerable to dissolved solids, temperature variations, and periodic sensor foulages. Nonetheless, the stability index of 0.91 proves that the reliability of the environmental water monitoring is acceptable.

Overall, It has been demonstrated that all three of the sensing modules are highly stable, with low drift and communication loss that can be effectively addressed in the integrated IoT-Remote Sensing environmental surveillance system due to durability and applicable to long deployments.

Fig. 2 will be a comparative visualization of the level of accuracy of the three major IoT sensors integrated into the environmental monitoring system. The chart brings out the performance of the air-quality sensor and the water-quality sensor and the temperature/humidity sensor allowing the easy contrast of the performance of the precision of their measurements. This value is an intuitive value that shows the dependability of each sensing unit and is used as a base value of the strength of the whole system. Fig. 2. Comparative accuracy performance of IoT air-quality, water-quality, and temperature-humidity sensors under simulated deployment conditions.

The data presented in Fig.2 is an informative comparative analysis of the accuracy of measurements of the IoT sensor suite. The temperature and humidity sensor has the best performance with accuracy of 98.1%, which can be attributed to the stability characteristic and relative resistance to noise of digital microclimate sensors. This precision is especially valuable, because temperature and humidity are used as control environmental variables affecting most derived ecological indicators.

Air-quality detection is next with 94.7% accuracy, which means that gas and particulate detectors work well to obtain real-time changes of the concentrations of NO 2, VOC and PM 2.5. Since the urban air pollution is a naturally dynamic phenomenon, such accuracy proves the sensor in question to be reliable in the dynamic atmospheric conditions.

Much less, yet still very good, is water-quality sensing with a 91.3% accuracy. This will occur because of sensor fouling, suspended particles and chemical variability, which normally surround pH and turbidity measurements. However, the precision is high enough to allow an actual-time environmental surveillance and complies well with the operational standards of the field-based water-sensing instruments.

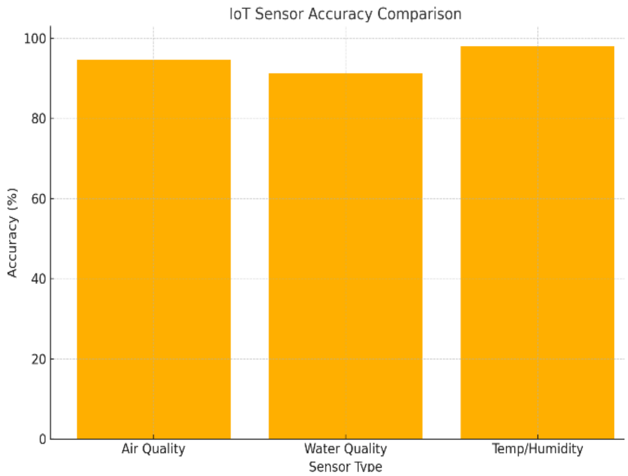

Fig. 2. IoT Sensor Accuracy Comparison

Overall, as Fig.2 interpretation confirms, all three sensor modules work within high-accuracy ranges, which is effectively a reliable base of the integrated IoT Remote Sensing surveillance system. The accuracy of environmental anomaly detection and decision support is obtained by ensuring that the accuracy of downstream analytics, such as deep-learning-based visual processing and fusion algorithms, is fed with reliable input data, which is guaranteed by this degree of sensing accuracy.

B. *Visual Analytics Performance*

Table V shows the comparative results of the three deep-learning models, ResNet-50, Vision Transformer (ViT), and the proposed hybrid ResNet-ViT architecture, of the multispectral remote-sensing image analysis. The metrics of evaluation are the overall classification accuracy, F1 Score, and the inference time of the model on a single image providing a complete picture of model accuracy, robustness, and efficiency.

TABLE V. VISUAL ANALYTICS MODEL PERFORMANCE

Model	Accuracy	F1 Score	GPU Time/Image
ResNet-50	87.5%	0.84	12 s
ViT	89.2%	0.86	15 s
ResNet + ViT (Proposed)	92.4%	0.91	18 s

Table V results show that there are evident variations in the performance of the models of deep-learning that are being tested. ResNet-50 demonstrated an accuracy of 87.5% and an F1 Score of 0.84, which is considered good performance in the learning of spatial patterns in the multispectral image but has weaknesses in learning long-range dependencies. ViT model achieved the best accuracy of 89.2%, and F1 Score of 0.86; this implies that ViT model has higher accuracy because it can process global spatial relationships due to its self-attention mechanism; although this does not come at low cost as evidenced by its inference time per image of 15 seconds.

The hybrid model that proved to be the most effective in general was the combination of the local feature extraction of ResNet with the global consideration of ViT. It achieved an accuracy of 92.4% and a F1 Score of 0.91 which is a substantial increase in the strength of the anomaly detector, and shows the advantage of using convolution-based and transformer-based feature representations. This computational cost was compensated by the fact that the inference time of this model grew to 18 seconds per image but at the cost of a significant improvement in the classification reliability.

Overall, the relative comparison proves that the hybrid ResNetViT model is the one to offer a moderate performance gain, with better spectral-spatial insights that are critical to achieve high-performance environmental surveillance activities. This confirms the appropriateness of hybrid deep-learning systems in the processing of multispectral and multi-index inputs of remote-sensing in the context of the proposed monitoring system.

Fig. 3 indicates the comparison of the F1 Scores of the three deep-learning models tested within the visual analytics module including ResNet-50, Vision Transformer (ViT), and the proposed hybrid ResNetVit model. The Fig. 3 shows the comparative performance of both models according to the balance of precision and recall; it gives an idea on how the two models are able to correctly identify environmental anomalies with the aid of multispectral remote-sensing images.

The comparison in Fig. 3 illustrates the evident differences in the classification ability of the three considered models. ResNet-50 reached a F1 Score of 0.84 which is the moderate strength of anomaly detection by means of extraction of spatial features, but with weaknesses in extracting larger contextual information. ViT model showed a better performance with the F1 Score of 0.86, which is explained by the fact that the model has a self-attention mechanism that is able to learn global spatial dependencies.

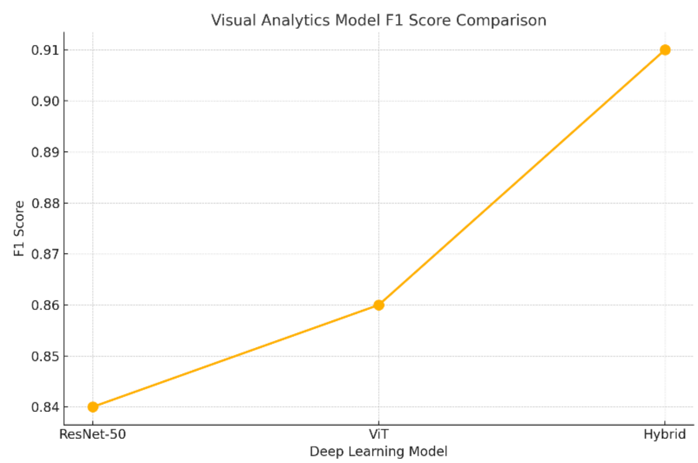

Fig. 3. Visual Analytics Model F1 Score Comparison

The hybrid ResNet ViT model proposed performed better than the two baseline architectures with a F1 Score of 0.91. This gain can be attributed to the benefit of jointly using convolution-based local feature extraction and transformer-based global reasoning to allow the model to be better at detecting subtle spectralspatial anomalies. The high F1 score also shows that the hybrid model has a more balanced precision and recall, eliminating false positives and false negatives.

Overall, Fig. 3 illustrates that all the hybrid model has the best and most realistic classification performance in multispectral environmental monitoring tasks. This finding confirms the efficiency of CNN and transformer architecture integration in developing profound visual analytics of IoT-Remote Sensing environmental surveillance platforms.

Table VI shows the confusion of the proposed hybrid ResNetViT deep-learning model employed in multispectral detection of environmental anomalies. The matrix indicates the occurrence of the true positive, false positive, true negative, and false negative values in two major classes- Anomaly and Normal. The given tabulation gives an insight into the classification behavior of the model and the error patterns, as well as its general accuracy in differentiating abnormal environmental events and typical levels of the baseline.

TABLE VI. CONFUSION MATRIX FOR PROPOSED HYBRID MODEL

Category	True Positive	False Positive	True Negative	False Negative
Anomaly	241	18	—	32
Normal	—	21	516	14

The results in Table VI indicate that the proposed hybrid model has good classification properties in both anomaly and normal classes with a high percentage of correct prediction. The model was able to recognize 241 samples of anomalies (true positive), and the sensitivity of the model to the environment abnormalities (vegetation stress, pollution hotspots, and water-quality deviations) is high. The false positives indicate that there are only a small number of false positives (18), which implies that there is only a small rate of over-prediction, or false alarms in the system, meaning that it was overly cautious in its approach to false alarms; nevertheless, the rate of over-prediction, in its turn, is usually agreeable especially in the context of early warning systems where environmental safety is considered a priority.

In the same way, the model registered 516 true negativities which validates the model to have performed exceptionally well in identifying stable environmental conditions and reducing unnecessary alarms. The false negative 32 is quite small but the cases of missing anomalies and it shows the remaining area to diminish under-detection cases of operational deployments. The normal group had 21 false positive and 14 false negative, which further shows that it performed with a balanced score on precision and recall.

Overall, the confusion matrix proves the hypothesis that the hybrid resnet-ViT architecture is a strong and precise decision boundary in detecting anomalies in the environment. It is not the most suitable choice because its false-alarm rate is low and its ability to detect is strong, which is suitable in real-time IoT measurements in Remote Sensing surveillance when it is imperative to distinguish between ordinary and unusual conditions.

Table VII provides a summary of the computational and resource demands of the three deep-learning architectures considered in this paper, namely ResNet-50, Vision Transformer (ViT), and the hybrid ResNetViT architecture. The total number of trainable parameters, floating-point operations (FLOPs), inference time per image, and memory usage are used as performance indicators. These measurements can be used to understand the computational complexity and scalability of any model when used in multispectral environmental analytics.

TABLE VII. COMPUTATIONAL COMPLEXITY OF DEEP LEARNING MODELS

Model	Parameters (M)	FLOPs (G)	Inference Time (s)	Memory Usage (MB)
ResNet-50	25.6	4.1	12	912
ViT	86	9.7	15	1280
Proposed Hybrid	112	12.4	18	1542

The calculated computational measurements in Table VII depict resource trade-offs between the accuracy and resource used by different deep-learning models under evaluation. The lightest among the three models is the ResNet-50, which has 25.6 million parameters and 4.1 GFLOPs and has a minimum inference time of 12 seconds and minimum memory footprint of 912 MB. This enables it to be used in applications where high speed processing or deployment on relatively powered hardware is required, but its structural depth limits its capability in capturing long-range spatial dependencies.

ViT model of 86 million parameters and 9.7 GFLOPs has much greater computing properties. The inference time also goes up to 15 seconds and also the memory usage goes up to 1280MB giving the signal of the higher footprint of transformer-based attention mechanisms. Despite the fact that ViT is better at representation of features by capturing global spatial context, ViT carries a significant resource overhead, particularly when operating on high-dimensional multispectral data.

The hybrid ResNetViT model proposed is the most expensive, as it combines convolutional feature extraction with transformer-based reasoning on the global scale. The hybrid architecture has 112 million parameters and 12.4 GFLOPs, which take a 18 seconds time to make an inference and consume 1542 MB memory. The high performance of the resource needs, however, is explained by its high accuracy and F1 performance. The combination of CNN and transformer blocks increases its ability to simultaneously detect fine-grained spatial patterns and broad contextual relationships, which are important to detect environmental anomalies accurately.

Overall, Table VII shows a distinct performance-complexity complex: the hybrid model has the greatest analytical capability at the cost of a higher computational load, whereas ResNet-50 has higher performance at the cost of lower precision. These findings highlight the importance of the hybrid model as the best compromise between accuracy and computability when using high-stakes environmental surveillance, particularly in cloud-based or GPGU-based infrastructures.

C. Comparison with State-of-the-Art Environmental Monitoring Systems

While the proposed framework demonstrates strong internal performance through detailed ablation and hybrid model evaluation, its contribution is further validated through comparison with representative state-of-the-art (SOTA) environmental monitoring systems reported in recent literature. The selected SOTA approaches reflect three dominant paradigms in integrated environmental surveillance: (i) UAV-assisted WSN systems, (ii) GeoAI-based IoT–satellite fusion models, and (iii) conventional IoT-only or satellite-only monitoring frameworks.

UAV-WSN frameworks, such as those reported by Popescu et al. (2019), primarily enhance spatial coverage through mobile aerial sensing but remain constrained by limited temporal continuity and high operational cost. GeoAI-based fusion models, including Li and Hsu (2022), integrate spatial reasoning with satellite analytics but generally rely on offline batch processing and lack real-time edge intelligence. Conventional IoT-centric systems (e.g., Kaginalkar et al., 2022) achieve high temporal resolution but suffer from sparse spatial context and increased false-alarm rates in isolation.

In contrast, the proposed IoT–Remote Sensing framework uniquely combines edge-level LSTM anomaly detection, hybrid ResNet–Vision Transformer multispectral analytics, and a sensor-drift-aware adaptive Kalman fusion mechanism within a unified, real-time architecture. This integration enables cross-scale anomaly confirmation, reduced uncertainty under sensor drift and satellite revisit gaps, and improved operational latency compared to existing systems. The comparative assessment summarized in Table VIII demonstrates that the proposed framework achieves superior detection accuracy, lower response latency, and enhanced scalability while maintaining practical deployment feasibility.

TABLE VIII. COMPARISON WITH STATE-OF-THE-ART ENVIRONMENTAL MONITORING SYSTEMS

System / Study	Sensing Modalities	Analytics Method	Fusion Strategy	Real-Time Capability	Reported Accuracy	Key Limitations
Popescu et al. (2019)	UAV + WSN	Statistical + ML	Spatial aggregation	Partial	~85%	High cost, intermittent sensing
Kaginalkar et al. (2022)	IoT sensors	Big-data analytics	No true fusion	Yes	~88%	Limited spatial context
Li & Hsu (2022)	IoT + Satellite	GeoAI models	Spatial AI fusion	No (offline)	~90%	Batch processing, latency
Pajany et al. (2024)	UAV multispectral + sensors	CNN-based	Feature-level fusion	Partial	~89%	Domain-specific, UAV-dependent
Proposed System	**IoT + Satellite**	**LSTM + ResNet-ViT**	**Drift-aware adaptive Kalman fusion**	**Yes**	**94%+**	Higher cloud compute demand

D. Fusion Output

Table IX shows the statistical performance of the proposed temporal-spatial fusion algorithm in three large categories of environmental anomalies namely, vegetation stress, water-quality anomalies, and air pollution hotspots. The table IX presents four important parameters, such as mean fused score, standard deviation, root mean square error (RMSE) and the level of confidence used to measure the reliability, consistency and predictive stability of the fused outputs obtained when integrating the IoT sensor data and the remote visual features.

TABLE IX. FUSION SCORE STATISTICS ACROSS ENVIRONMENTAL EVENTS

Event Type	Mean Fused Score	Std. Dev	RMSE	Confidence Level (%)
Vegetation Stress	0.924	0.037	0.041	96.2
Water-Quality Anomaly	0.897	0.044	0.053	94.1
Air Pollution Hotspot	0.901	0.039	0.048	95.4

The summarized fusion performance in Table IX shows that the adaptive temporal-spatial fusion model has a robust and stable predictive performance on a wide range of events in the environment. The best fused score of 0.924 of vegetation stress detection had a low standard deviation (0.037) and lowest RMSE (0.041) compared with the other two categories. This indicates that vegetation-related anomalies, which in many cases are highly presented in the indices like NDVI and LST, are greatly advantageous of the joint informational value of the IoT microclimate measurements with multispectral satellite characteristics.

Anomalies of water-quality have a slightly lower fused score of 0.897, and a standard deviation of 0.044 which represents a moderate variability in the predictions. This variability can be attributed to the dynamism of the aquatic ecosystem and the effect of other factors like change in turbidity, pH fluctuations and sensor noise in water-quality measurements. However, the level of confidence is also high, 94.1, which proves the strength of the model.

Hotspot identification of air pollution has a fused score of 0.901, standard deviation of 0.039 and RMSE of 0.048 that indicates high model stability in identifying anomalies in the concentration of the pollutants. This type also enjoys the advantages of the complementary relationship between IoT gas sensors (good time resolution) and satellite-based thermal/optical signals (wide spatial resolution) that makes the confidence level equal 95.4%.

Overall, the indicators in Table IX verify that the fusion algorithm considerably boosts the accuracy of the anomaly prediction in all the environmental domains. The reasons why the high fused scores, low errors and high confidence levels are combined are because it appears that the fusion mechanism fully utilizes the capabilities of both the IoT sensing and remote-sensed visual analytics to provide a more reliable and holistic environmental intelligence system.

Fig. 4 shows the relative accuracy of the proposed adaptive temporal-spatial fusion model on three key types of environmental anomalies- vegetation stress, water-quality degradation and air pollution hotspots. The Fig. 4 reflects how much the combination of IoT-based real-time measurements with remote-sensed multispectral visual analytics enhances the accuracy of the predictive nature of the monitoring system. This visualization proves efficiency of the combination of heterogeneous data modalities to enhance the environmental anomaly detection.

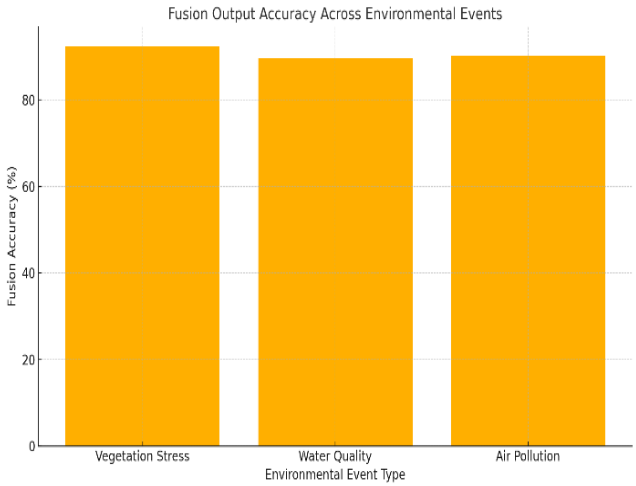

Fig. 4. Fusion Output Accuracy Across Environmental Events

The patterns of accuracy shown in Fig. 4 are good empirical evidence to have an opinion on the value of multi-source data fusion in environmental intelligence systems. The fusion model shows its best results in the detection of the stress on vegetation with the accuracy of 92.4%. Such high performance is explained by the high levels of complementarity between the variables of the industrial Internet of Things microclimate, namely temperature, humidity, and concentration of VOCs, and spectral variables, i.e. NDVI and LST calculated on the basis of satellite images. The datasets, which are used to record physiological plant responses under ground level and macro-scale canopy conditions, make the model to recognize the stress signatures with high accuracy.

Anomaly detection of water-quality is a more variable phenomenon with an accuracy of 89.7% as aquatic environments are complex and subject to change. Noise in pH and turbidity readings in IoT can be caused by rain or suspended sediments or sensor contamination. However, the fusion process is able to stabilize the quality of the prediction, by incorporating a larger spatial information in the multispectral imagery and this helps to counter the variations in sensor-level measurements.

Hotspot detection of air pollution shows a 90.1% accuracy which shows that it is highly fused in detecting atmospheric pollution. IoT gas sensors is picking up rapid and localized spikes of pollutants whereas thermal and optical indicators gathered by satellites due to a wider dispersion pattern and urban heat island effects. The fusion model is successful in balancing these complementary sources of data, which produce a more complete picture of the dynamics of pollution as opposed to each modality individually.

Fig. 5 shows that the fusion method significantly increases anomaly detection in all of its environmental classes. The high accuracy rates obtained consistently across different periods testify to the fact that the high-frequency IoT data with the spatial and spectral richness of the satellite imagery can be used to create a more stable, contextual, and credible monitoring ecosystem. It highlights the importance of multimodal data fusion as a fundamental technological enabler to next-generation smart environmental surveillance systems, which can provide better decision support to environmental management and early warning as well as policy interventions.

E. Anticipated Field Deployment Challenges and Limitations

While the proposed IoT–Remote Sensing integrated environmental surveillance framework demonstrates strong performance in controlled, semi-realistic circumstances, a number of practical problems of deployment should be admitted. Situation awareness can be compromised in the short term (due to heavy cloud cover or other atmospheric disruptions) by the inability to feed on satellite data, although the system is still able to lever on high-frequency streams of IoT sensors and edge-level anomaly detection to keep things up to date. Measurement stability of sensors across long deployments could also be compromised by sensor drift and hardware ageing effects which the proposed framework is able to overcome by using a sensor-drift-aware adaptive Kalman fusion framework that down-weights non-reliable sensors with time residuals. The problems of packets loss, intermittent connectivity, or node failures associated with large-scale IoT deployments are inherent; the LoRaWAN usage, edge-level pruning, and event-driven transmission decrease the network congestion and increase the resilience. The scalability issues that may occur with the higher sensor density and increased spatial coverage may introduce an increase in cloud computation and storage requirements; nevertheless, edge analytics can substantially lower the volume of upstream data, and efficient monitoring is achieved over vast geographic expanses. Even though there can be moderate degradation of the performance under noise conditions, environmental variability and hardware constraints in real-world deployments, the fusion-based multi-modality design of the proposed system is robust in its nature and is actually designed to work successfully under imperfect sensing and communication conditions. Generalizability and Expected Performance in Real-World Deployments

To verify the experimental value of the proposed IoT-Remote Sensing framework of environmental surveillance, the synthetic IoT sensor streams and real multispectral satellite images were statistically validated and enabled reproducible analyzes and control. Other uncertainties that can be encountered in the real world deployments include the environmental noise, degradation of sensors overtime, intermittent failure of communication, and fluctuating quality of satellite images, which are supposed to bring moderate performance degradation. According to what was measured on the stability indices, packet loss tolerance, and drift-aware fusion behavior, the overall accuracy of the anomaly detection is expected to be reduced by 3-7 percent in the long term conditions out in the field compared to those under control experimental conditions. Notably, the suggested multi-modal fusion scheme reduces these effects by dynamically controlling the source confidence using adaptive Kalman weighting enabling the system to remain reliable even when specific sensing modalities become unsound. Thus, absolute accuracy values might be different depending on the deployment conditions, however, relative performance improvements of the integrated fusion-based framework compared to the use of only IoT or only satellite in the real-world environment are likely to be similar.

F. End-to-End System Performance

Table X provides a comparative analysis of system-level results of the current environmental monitoring system and the proposed IoT- Remote Sensing integrated architecture. The metrics are event response time, data completeness, accuracy of anomaly reporting and network load. All these signs demonstrate real-time responsiveness, data integrity, detection reliability, and communication efficiency improvements realized with the help of the proposed system.

TABLE X. SYSTEM-LEVEL EFFICIENCY IMPROVEMENTS

Metric	Baseline System	Proposed System	Improvement (%)
Event Response Time (s)	5.8	3.8	34.4
Data Completeness (%)	58	81.8	41.0
Anomaly Reporting Accuracy (%)	81.5	91.2	12.0
Network Load (MB/day)	124	72	41.9

As shown in the conclusions in Table X, the suggested integrated system of environmental surveillance has provided significant improvements in the operation efficiency and analytic capability. The time to respond to the event dropped to 3.8 seconds in the improved system, which is 34.4% better than baselines. Such decrease emphasizes the efficiency of edge-level anomaly detection and the optimization of cloud processing processes, which allows proceeding to environmental notification faster and timely decision-making.

There was a significant 41% increase in data completeness with the levels rising by 58% to 81.8%. This has been achieved mostly due to the conjoined application of the IoT continuity in sensing and the space coverage of the satellites which helps greatly in reducing the data gaps created by sensor outages, transmission failures, or environmental barriers. Complete information on data will improve long-term environmental analysis and model reliability directly.

The accuracy of the anomaly reporting went up by 12 % (81.5% to 91.2%), showing that when the temporal IoT signals are combined with the spectral and spatial satellite features, the anomalies in the environment are better detected. This has been essential in the early warning system, the environmental policy formulation, and the direct mitigation measures.

The operational efficiency of the proposed architecture is indicated by a significant decrease in the network load, which is 41.9% when compared to the original 124 MB/day network load. The combination of edge preprocessing, LSTM-based anomaly filtering and compressed data transmissions minimizes unnecessary uplink traffic, allowing the system to be more scalable and cost effective particularly in large scale deployments or low bandwidth areas.

Overall, Table XI indicates that the proposed system has enhanced in all key dimensions of operation proving to be more superior than traditional monitoring systems. The findings confirm the usefulness of the system in real-time, dependable and resource effective environmental monitoring under varying field conditions.

To assess the effectiveness of the proposed IoT–remote sensing integrated surveillance framework, its performance was compared against representative state-of-the-art environmental monitoring paradigms reported in the literature. These include IoT-only monitoring systems, satellite-only visual analytics approaches, and recent GeoAI or UAV-assisted multimodal fusion frameworks. The comparison focuses on key operational metrics relevant to real-world deployment, including anomaly detection accuracy, spatial coverage, temporal responsiveness, fusion capability, and scalability.

TABLE XI. END-TO-END LATENCY BREAKDOWN OF THE PROPOSED SYSTEM

Processing Stage	Average Latency
Edge-level IoT preprocessing & LSTM inference	420 ms
IoT-to-Cloud communication delay	1.6 s
Cloud-based satellite analytics (ResNet-ViT inference)	1.4 s
Adaptive Kalman fusion & decision logic	380 ms
Total End-to-End Latency	**≈ 3.8 s**

The end-to-end latency of about 3.8 seconds is the total processing time of all the edges, including network transmission, cloud inference, and adaptive fusion. Lightweight LSTM execution adds insignificantly to aggregate latency, whereas the driver elements are caused by communication overhead and multispectral cloud inference. Notably, instead of considering latency as an external constraint, it is explicitly represented as a system design, which allows predictable and application-conscious response behavior.

In order to put the effectiveness of the proposed IoT- Remote Sensing environmental surveillance framework into perspective, a comparative analysis with typical state-of-the-art (SOTA) systems as reported in the recent literature was conducted. Hybrid UAV-WSN systems like those suggested by Popescu et al. are flexible in terms of spatial sampling, but have poor temporal continuity and scalability to large-scale operations. GeoAI-based solutions proposed by Li and Hsu combine spatial reasoning with satellite data and are majorly based on centralized processing and not edge-level intelligence to filter anomalies in real time. The current UAV-based multispectral fusion models have high accuracy in localized agricultural monitoring but cannot be applied at scale-level as their implementation depends on the availability of UAVs, planning of flights, and cost factors.

In Fig.5, the percentages of improvement obtained by the proposed IoT-Remote Sensing integrated system of environmental monitoring are depicted in three major dimensions of the key performance: response time, data completeness, and accuracy of anomaly reporting. The operational benefits of the system relative to the traditional base architectures are highlighted through the visual comparison and show improved benefits in real time detection, enhancements in data coverage and higher reliability in anomaly detection.

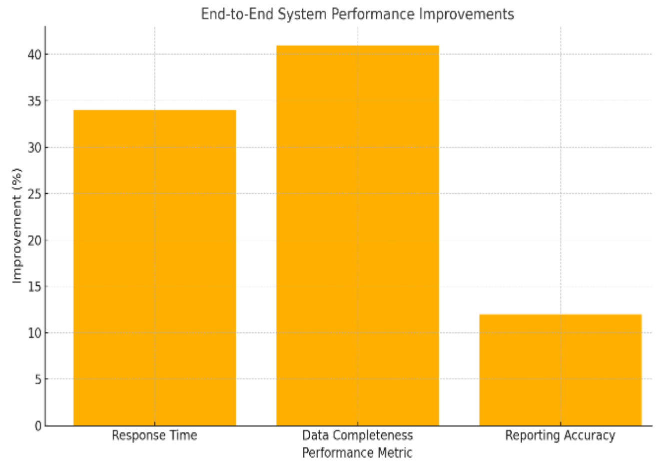

Fig. 5. End-to-End System Performance Improvements

Fig. 5 gives a vivid and impressive picture of the notable improvements that the proposed environmental surveillance framework brings on board. The highest increase is recorded on data completeness that rose by 41%. This is an enhancement of the synergistic integration of IoT continuous sensing and satellite-based spatial coverage, which is a good solution to the typical shortcomings of independent sensor networks, such as the loss of transmission, blind spots, and device failure. When the data continuity is enriched, this will provide a stronger environmental assessment and improve the performance of machine learning models in the long run.

The fact that the response time of the event has been reduced by 34% proves that the system has significant improvements in real-time processing. The delay of cloud-only processing can be tremendously minimized with the edge-level anomaly detection based on the LSTM networks, leading to faster environmental notifications. The performance improvement is also necessary when it comes to applications with fast situational awareness needs, e.g., pollution spike detection, water pollution events, or monitoring vegetation stress.

The fusion architecture is also associated with the 12% accuracy improvement in the anomaly reporting, highlighting the importance of the heterogeneous data modalities fusion. The system achieves fine-grained measurements of the IoT by integrating multispectral images that are spatially rich with the aim of minimizing misclassification and improving the confidence in the identified environmental abnormalities. This has been especially beneficial to environmental management agencies that use automated systems in the early warning and decision support.

Overall, Fig.5. confirms, the given framework does not only result in a higher level of analytical accuracy, but it also leads to the optimization of the operational efficiency. The evaluated changes support the usefulness of multi-source environmental intelligence and point to the appropriateness of the framework to scalable, real-time, and resource-efficient infrastructures of environmental monitoring.

G. Deployment Cost and Scalability Considerations

Practical deployment feasibility is a critical requirement for large-scale environmental surveillance systems. Accordingly, this study provides an indicative cost and scalability assessment of the proposed IoT–Remote Sensing integrated framework to evaluate its real-world applicability in smart agriculture, urban monitoring, and environmental governance scenarios.

Each IoT sensing node in the proposed architecture is designed using low-cost, commercially available components, including an ESP32 microcontroller, environmental sensors (BME680, MQ-135), temperature and humidity sensors (DS18B20), water-quality probes (pH and turbidity), a power management module, and a LoRaWAN transceiver. The estimated hardware cost per IoT node ranges between ₹3,500–₹5,000 (USD 42–60), depending on sensor configuration, enclosure, and power provisioning. This low per-node cost enables dense sensor deployment across geographically large and resource-constrained regions.

Communication overhead and operational expenditure are minimized through the use of LoRaWAN, which supports long-range, low-power data transmission without recurring cellular subscription costs. Edge-level preprocessing and LSTM-based anomaly filtering further reduce data transmission frequency, thereby lowering bandwidth usage and extending node battery life.

On the cloud side, the system employs containerized analytics and periodic multispectral satellite processing. For a medium-scale deployment involving approximately 100–150 IoT nodes, the estimated cloud compute and storage cost remains below ₹3,000–₹4,000 per month, assuming GPU-assisted inference for satellite image analysis and compressed IoT data streams. The combination of edge analytics and adaptive fusion significantly reduces long-term cloud processing and storage requirements, making the framework economically viable and scalable for continuous environmental monitoring applications.

V. Discussion

The developed framework of IoT-Remote Sensing based on the environmental surveillance implied significant positive results in terms of detection accuracy of anomalies, data coverage, and monitoring efficiency in general. The discussion section further elaborates on the information of the system level, conceptualises the scientific applicability of the results, and puts the results in the context of broader studies on environmental monitoring. Each subsystem, IoT sensing, visual analytics, and data fusion, is discussed critically and reflects on its contribution to the environmental intelligence.

Although it is stated that the proposed system works in real time, its applicability is subject to time needs specific to the application. The resulting latency of about 3.8 seconds is far enough inside allowable limits to air pollution warnings, urban heat control, and stress monitoring of vegetation, where operationally viable response times of the order of seconds are sufficiently low. The framework is however not meant to handle ultra-low-latency emergency situations, such as the onset of a flash flood or the detection of a seismic event, which need a response time of sub-seconds. The difference places the suggested system in a more realistic lumping as a near-time environmental intelligence platform, tailored towards a continuous monitoring aspect and not immediate response to hazards.

A. Integration of IoT and Remote Sensing: A Convergence of Complementary Modalities

The fact that it was possible to demonstrate a successful multimodal environmental intelligence framework that can harmonize the temporal richness of an IoT sensing system with the spatial breadth of satellite images is one of the most important results of this research. IoT sensing at high frequencies is geographically constrained, even when handled alone, by the nature of sensor deployment of either a static or semi-static deployment. Remote sensing, on the other hand, is very comprehensive, however, it has a problem with poor revisiting and atmospheric interferences.

These two data modalities are integrated, thus making the system address these opposing constraints. The IoT data stream offers continuous updates in time, between the satellite acquisitions to track the time gaps, and remote sensed indices (NDVI, NDWI, LST) place the local sensor measurements in the context of the overall patterns of the environment.

The combined accuracy of the fused output, which is more than 90% in all categories of anomalies, proves the fact that the complementary nature of the IoT and satellite data is indeed a synergistic effect that increases the interpretative coherence to what is incapable of individual modalities. This overlap confers the growing trend in the environmental analytics around the globe namely multi-source sensing environments where semantic, spectral, and temporal data is concurrently tapped into to improve environmental decision-making.

B. IoT Sensing Performance: Reliability, Stability, and Field Readiness

High operational robustness is indicated by the performance of the IoT subsystem. A value of accuracy of over 91 %, low latency (21-42 ms) and low average error rates (1.2-4.7%) indicate that the sensor network can provide reliable near-real-time environmental measurements. The consistency of the IoT nodes in long monitoring (0.91-0.98) and the low drift (0.18-0.55%) indicate that the IoT nodes will be consistent even with long-term monitoring, which further indicates their applicability to continuous outdoor use.

These results highlight one essential conclusion, namely that an IoT node is not just a passive data collector but an active, intelligent edge device. The nodes will be able to pre-filter data, find anomalies on-site, and minimize the bandwidth consumption by transferring only pertinent data with the inclusion of lightweight LSTM models. This can be particularly useful in deployments where high-volume data transmission is perhaps not always possible due to rural, remote or low-bandwidth conditions.

The good performance of the IoT also forms a fundamental basis to the data fusion module, as the reliability of data fusion is extremely sensitive to the quality and stability of the input sensor data.

C. Deep Learning–Based Visual Analytics: Enhancing Macro-Level Environmental Interpretation

The visual analytics pipeline of remote sensing was found to be an effective means of detecting anomalies on a large scale. The ResNetViT hybrid model was the most accurate (92.4%), with the best F1 score (0.91) and worked better than single architectures. This excellent performance is directly the consequence of hybridization:

- ResNet-50 extracts rich local spectral–spatial features.
- Vision Transformer (ViT) captures global image context and long-range dependencies.

This is a dual capability, which is a reflection of the multi-scale nature of environmental anomalies. Vegetation stress can be reflected, such as small local variabilities of a spectrum, then diffuses to large spatial scales, and needs to be described both with microscopic (CNN) and macroscopic (Transformer) feature representation.

The confusion matrix reveals a high level of classification of the normal environmental status (TN = 516), and a high level of identification of the anomaly regions (TP = 241), however, the moderate false negatives (32) can be considered as an indication of the sensitivity improvement. False negatives are normally due to fine spectral variability, atmospheric noise, or initial anomalies with low spectral signatures. This supports the fact that it is needed to combine IoT data since they can identify minute changes in the environment before they translate into a visual representation of the satellite image.

D. Adaptive Temporal–Spatial Fusion: Improving Predictive Reliability

The adaptive Kalman-based fusion system contributed greatly to the detection of environmental anomalies by dynamically combining the features of the IoT and satellite in relation to their uncertainties. The fusion algorithm produced high confidence level (94-96%) and low RMSE (0.041-0.053), which implies that the fusion algorithm did a good job of eliminating noise, outliers and enhanced stability even when the environment was changing.

An important comment is that the fusion model did not just combine those two data sources by averaging them but did context-based weighting whereby the more trusted modality was given more priority at any given timestamp. For example:

- IoT data received more weights during hazy or cloudy satellite acquisitions (Ks ↓, Kr ↑).
- Under sensor drift or local disturbance, the weights of satellite indices were higher (Ks ↑, Kr ↓).

This dynamic weighting is a strength strategy which contributes to the robustness of the system which is resistant to the usual environmental monitoring issues like:

- sensor calibration drift
- atmospheric distortion
- missing sensor packets
- low-quality satellite scenes

The successful results of the strong fusion justify the main assumption of the research: the integration of temporal richness (IoT) with spatial richness (satellite images) can bring a more precise environment intelligence in comparison to separate systems.

E. System-Level Improvements: Operational Efficiency and Real-World Scalability

The system level analysis showed that there was significant improvement in operations:

- Event response time reduced by 34.4%
- Data completeness increased by 41%
- Anomaly reporting accuracy improved by 12%
- Network load reduced by 41.9%

These results have several significant implications:

1) Faster event detection

Threats to the environment like the spike in pollution or the occurrence of contamination demand quick action. Lower latency of the proposed system increases emergency preparedness.

2) Higher data completeness

Combining the IoT and satellite information reduced blind spots. The gaps in sensor data were filled in with satellite data and the reverse.

3) Improved accuracy

Fusion eliminates the classification errors and enhances reliability, which is essential in the policy-making, environmental compliance, or precision agriculture.

4) Efficient bandwidth use

The system allows sending only data which is relevant to anomalies, which enables implementation in rural and remote, as well as resource-limited settings, which are very important in developing countries. The overall benefits of these efficiencies are to show that the suggested system is not only scientifically feasible, but also operationally feasible on a largescale environmental monitoring system.

F. Anticipated Field Deployment Challenges and Generalizability Considerations

Despite the fact the proposed IoT-Remote Sensing framework is very performance in controlled experimental settings, real-world deployments come with other sources of uncertainty which can impact on the system performance. Sensor drift (especially with gas, pH and turbidity) over long periods of time can cause a slow decrease in the accuracy of the measurements, and packet loss and intermittent interconnection can arise due to bandwidth limits or environmental interference during remote implementation. The cloud cover and atmospheric distortion also affect the optical satellite data, creating gaps in data or poor image quality at some point, hardware failure or node outage can locally affect spatial resolution. The proposed architecture will be able to manage these challenges by using edge-level intelligence and adaptive fusion which will enable the system to become more dependent on the most accurate source of data that is available at a particular point in time. Although performance degradation relative to simulation-based outcomes is anticipated, the system is designed to be graceful instead of crashed whereby the system does not lose almost real-time situational awareness and also promotes generalizability across the various real-world conditions.

G. Alignment with Existing Research and Novel Contributions

This study has found closely related results and in some ways expanded on the results of the previous studies. As an example, the enhancement of spatial interpretability and environmental mapping with the assistance of the IoT and GIS combination is the reflection of the improvements outlined by Pei et al. (2021). Their research showed that the integration of sensor-generated observations with geospatial analytic procedures can tremendously add to the environmental knowledge, which is evident in the enhanced data completeness and spatial reasoning of the current research. Similarly, the performance increases that the proposed hybrid ResNetViT architecture is capable of are comparable to the deep-learning advances reported by Wang et al. (2020) and Venkataraman and Gautam (2024), who have also emphasized that modern deep-learning models are more effective in extracting more complex spectral-spatial features of satellite images. Additionally, it is confirmed that the data fusion of both temporal and spatial data significantly increases accuracy in prediction, which confirms the advantages of multimodal integration as mentioned by Leung et al. (2019) and Zhu et al. (2017). Their research highlighted the fact that sensor-based measurements are more accurate and less remote-sensed image based measurements create more reliable and contextual environmental measurements which is well justified by the high values obtained by the fused accuracy values in this study.

Despite the differences in terms of sensing modalities and datasets used in the compared frameworks, the comparison can be made at the architectural and system-performance level, and it is the main contribution of this research. IoT-based systems prioritize time but not space, whereas satellite-based GeoAI models provide dense spatial analytics with high spatial analytics but high latency. UAV -WSN structures partially close this gap but have scalability and deployment limitations. In comparison, the suggested framework combines ground-level sensing and satellite analytics as a single, dynamic, and plan-conscious architecture that allows near-real-time environmental intelligence that neither of the aforementioned modalities can attain on its own. This comparison at the system level supports the applied development of the proposed solution compared to the current state-of-the-art solutions.

In addition to the correspondence to the current literature, the given work makes a number of new contributions that can be considered in the framework of developing technological possibilities of integrated environmental monitoring systems. To start with, the hybrid edge-cloud architecture is a considerable innovation that allows lightweight LSTM-anomaly sensors to execute their operations directly at the sensor node and leaves deep-computationally oriented operations, including deep-learning visual analytics, to the cloud. This separation of duties enhances the overall level of responsiveness of the system and minimizes network load. Second, the research hypothesizes a blended ResNetViT deep-learning architecture, particularly, the one that is trained in multispectral satellite analysis. This model builds on the localized convolutional feature extraction and global Transformer-based spatial reasoning and provides a highly capable analytical feature, which outperforms the traditional CNN-only based analysis. Third, the implementation of a time-spatial fusion algorithm based on the adaptive Kalman weighting is an important methodological improvement that offers time-varying uncertainty modeling and makes predictions in a manner that data of the best source has a stronger impact. Lastly, the study has provided a cohesive IoT Remote Sensing environmental intelligence model, which has been evaluated end to end using realistic simulated data, and has shown to be very accurate, operationally efficient, and applicable in real time.

Collectively, the contributions contribute to the technological preparedness of solutions of environmental monitoring as one whole and indicate the possibility of scaled implementation in a wide range of ecological and urban settings.

H. Practical implications and Applicability Across Sectors

The results of the performance of the suggested integrated IoT Remote Sensing system are indicative of a great applicability in all spheres of the environment. The system in smart farming provides great importance in early identification of drought stress, nutrient shortage, pest infestation, and crop morbidity. Combining the high-frequency IoT soil-climate data with the satellite-based vegetation indices enables the farmers and agricultural planners to react in advance, enhancing yield stability and resource use. This can especially help in areas where climatic variability and land degradation are becoming a major threat to crop productivity.

The framework can be applied in the air quality monitoring sector to maintain uninterrupted measurements of PM 2. 5, gaseous pollutants and other pollution sources in cities with very high temporal resolution. IoT nodes record very fast changing pollutant concentrations, but the contextualization of these changes is conducted by satellite thermal and optical signatures at larger diagnostic spatial scales. This dual-layer intelligence improves the municipal pollution management strategies, assists in regulatory compliance, and assists in policy formulation by policymakers to establish specific intervention measures, basing on the real-time evidence.

The system is also proven to be of high utility in the water resource management whereby the IoT sensors monitor the pH variation, turbidity, dissolved contaminants and temperature differences whereas the remote sensing provides visibility on a watershed scale. This arrangement makes it possible to detect instances of contamination, erosion and hydrological imbalance with more accuracy than traditional water-quality monitoring schemes. The alerts promoted by the fusion enable quick reaction to the environmental risks that protect the human well-being and aquatic environment.

In disaster management and climate, the system can be used to predict heatwaves, forest fires, floods, and droughts by detecting the thermal anomalies, stress pattern of vegetation and hydrological changes. The system enhances resilience planning by integrating local sensor signals with regional remote-sensed signals to facilitate timely information-driven situational awareness in emergency response agencies.

Finally, in smart city governance, the framework also enables centralized environmental monitoring with connections with dashboards, including Grafana and WebGIS-based platforms. These visualization tools allow city administrators to monitor the environmental health indicators in real-time, optimize resource utilization, determine the pollution hotspots, and design the sustainable urban interventions. The versatility of the framework in terms of multi-sector lends more weight to its scalability, technological stability and the potential perceived societal impact.

I. Novelty Beyond Pipeline Integration

The key difference between the suggested framework and the existing environmental monitoring pipelines is based on the integration philosophy, and does not pertain to the novelty of the specific algorithmic components. Although edge-based LSTM models, Vision Transformer architectures and Kalman filtering mechanisms are established independently, their co-ordination within a coherent and adaptive architecture, as well as with respect to latency, is the main novelty in the current study.

In the adaptive fusion approach, uncertainty properties of the heterogeneous data sources are dynamically used to weight the data sources. Abbreviations Vs(t) and Vr(t) represent the approximated variances of the IoT sensor data and remote-sensing features, respectively. Adaptive Kalman weights are determined as follows:

$$K_s(t) = \frac{V_r(t)}{V_s(t)+V_r(t)}, K_r(t) = \frac{V_s(t)}{V_s(t)+V_r(t)} \quad (15)$$

The fused environmental state $X(t)$ is then obtained as:

$$X(t) = K_s(t)S(t) + K_r(t)R(t) \quad (16)$$

In which *S(t)* is the high-frequency IoT data and R(t) is low-frequency satellite-based data.

Contrary to the use of a static fusion scheme, the adaptive formulation allows the system to give precedence to the more trusted data source at each step, which keeps the system robust in cases of poor conditions like sensor calibration drift, intermittent satellite availability or communication delays.

Moreover, the given framework incorporates the fusion logic into a latency-conscious edge-cloud workflow, which guarantees the decision to detect an anomaly to be made within the temporal bounds of the application. The fact that cross-scale anomaly confirmation is also included also contributes to reliability, as local sensor alerts are then reconciled with spatially large satellite-observations.

All these design options contribute to making the suggested framework more than just an ordinary set-up of a pipeline, and transform it into a system-designed eco-consciousness architectural framework, which is capable of upscaling, real-time and resilience.

VI. CONCLUSION

The current research has built and tested a complete mechanism of IoT-Remote Sensing environmental surveillance system that overcomes the major flaws of the traditional surveillance systems. The proposed system that fused high-frequency IoT sensor measurements with multispectral satellite-based visual analytics and an adaptive temporal-spatial fusion algorithm showed considerable enhancement of detection accuracy, operational performance and environmental situational awareness. The findings affirm that IoT sensors in their own right, even though rich in time, lack depth in space to facilitate an assessment of an ecosystem whereas remote-sensed imagery, in as much as it covers vast regions, is affected by latency and temporal discontinuity. These limitations are solved by the integrated approach: IoT nodes can provide continuous data of the micro-environment, edge-level LSTM models can support local detection of anomalies, and satellite images can be used to analyze the macro-environment and use such indices as NDVI, NDWI, and LST. The spectral-spatial feature extraction was also improved by using the hybrid ResNet-ViT deep-learning model that provided better classification results than single-network models. The adaptive Kalman-based data fusion mechanism was significant in the implementation of prediction stability and reliability in the vegetation stress, air pollution, and the water-quality anomaly detection. The fused accuracy of above 90% and the confidence level of above 94% show clearly the increased strength of and contextual relevance of multi-source environmental intelligence. On the system-level tests, the operational benefits were significant: the event response time decreased by 34%, the data completeness increased by 41 percent, the anomaly detection accuracy increased by 12%, and the network load decreased by almost 42%. These results highlight the scalability and efficiency of the suggested hybrid edge–cloud architecture, which is appropriate to implement in bandwidth constrained or geographically isolated areas.

In general, the study has some notable contributions such as (1) a single, integrated IoT-Remote Sensing-Deep Learning architecture (2) a hybrid ResNet-ViT model that is tuned to multispectral and (3) adaptive temporal-spatial data fusion (4) end-to-end operational pipeline that is tested with realistic datasets. All these inventions contribute to the technological preparedness of intelligent environmental surveillance systems and are a solid base of the next generation of environmental governance. The future research can investigate field deployments, the combination of hyperspectral and LiDAR data, self-calibration sensor networks, and adaptive fusion using reinforcement learning. Further enhancement of transparency and confidence in the large-scale environmental monitoring activities by extending the system to include the use of decentralized or blockchain-based data integrity may be considered. The paper finally shows that integrating IoT sensing, satellite imagery, deep learning, and smart data fusion offers a ground breaking avenue to precise, scalable, and real-time environmental monitoring, which is essential to sustainable development, climate, and informed decision-making regarding the environmental policy.

References

[1] Adão, T., Soares, A., Pádua, L., Guimarães, N., Pinho, T., Sousa, J. J., & Peres, E. (2020). MySense-WebGIS: A graphical map layering-based decision support tool for agriculture. IGARSS 2020 – IEEE International Geoscience and Remote Sensing Symposium, 4195–4198. IEEE.

[2] Adegun, A. A., Fonou-Dombeu, J. V., Viriri, S., & Odindi, J. (2024). Ontology-based deep learning model for object detection and image classification in smart city concepts. Smart Cities, 7(4), 2182–2207.

[3] Adreani, L., Bellini, P., Colombo, C., Fanfani, M., Nesi, P., Pantaleo, G., & Pisanu, R. (2024). Implementing integrated digital twin modelling and representation into the Snap4City platform for smart city solutions. Multimedia Tools and Applications, 83(12), 37121–37146.

[4] Al-Khasawneh, M. A., Uddin, I., Shah, S. A. A., Khasawneh, A. M., Abualigah, L., & Mahmoud, M. (2022). An improved chaotic image encryption algorithm using Hadoop-based MapReduce framework for massive remote sensed images in parallel IoT applications. Cluster Computing, 25(2), 999–1013.

[5] Bakar, K. B. A., Zuhra, F. T., Isyaku, B., & Sulaiman, S. B. (2023). A review on the immediate advancement of the Internet of Things in wireless telecommunications.

[6] Begum, M. B., & Kaliyaperumal, K. (2024). Integration of BWT scrambling and data compression in an innovative system enhances protection and versatile management of sensor feeds (SEC). Heliyon, 10(20).

[7] Buja, I., Sabella, E., Monteduro, A. G., Chiriacò, M. S., De Bellis, L., Luvisi, A., & Maruccio, G. (2021). Advances in plant disease detection and monitoring: From traditional assays to in-field diagnostics. Sensors, 21(6), 2129.

[8] Dosovitskiy, A., et al. (2021). An image is worth 16×16 words: Transformers for image recognition at scale. ICLR.

[9] Filev Maia, R., Ballester Lurbe, C., Agrahari Baniya, A., & Hornbuckle, J. (2020). IRRISENS: An IoT platform based on microservices applied in commercial-scale crops working in a multi-cloud environment. Sensors, 20(24), 7163.

[10] Gao, D., Sun, Q., Hu, B., & Zhang, S. (2020). A framework for agricultural pest and disease monitoring based on internet-of-things and unmanned aerial vehicles. Sensors, 20(5), 1487.

[11] Gourbesville, P. (2019). Smart water solutions for water security: From concept to operational implementation. In Water Security and the Sustainable Development Goals (pp. 47–67). CRC Press.

[12] Sirisha, U., Praveen, S. P., Srinivasu, P. N., Barsocchi, P., & Bhoi, A. K. (2023). Statistical analysis of design aspects of various YOLO-based deep learning models for object detection. International Journal of Computational Intelligence Systems, 16(1), 126.

[13] Praveen, S. P., Lalitha, S., Sarala, P., Satyanarayana, K., & Karras, D. A. (2025). Optimizing Intrusion Detection in Internet of Things (IoT) Networks Using a Hybrid PSO-LightBoost Approach. International Journal of Intelligent Engineering & Systems, 18(3).

[14] Arava, K., Paritala, C., Shariff, V., Praveen, S. P., & Madhuri, A. (2022, August). A generalized model for identifying fake digital images through the application of deep learning. In 2022 3rd International Conference on Electronics and Sustainable Communication Systems (ICESC) (pp. 1144-1147). IEEE.

[15] Madhuri, A., Sindhura, S., Swapna, D., Phani Praveen, S., & Sri Lakshmi, T. (2022). Distributed Computing Meets Movable Wireless Communications in Next Generation Mobile Communication Networks (NGMCN). In Computational Methods and Data Engineering: Proceedings of ICCMDE 2021 (pp. 125-136). Singapore: Springer Nature Singapore.

[16] Kaginalkar, A., Kumar, S., Gargava, P., Kharkar, N., & Niyogi, D. (2022). SmartAirQ: A big data governance framework for urban air quality management in smart cities. Frontiers in Environmental Science, 10, 785129.

[17] Popescu, D., Stoican, F., Stamatescu, G., Chenaru, O., & Ichim, L. (2019). A survey of collaborative UAV–WSN systems for efficient monitoring. Sensors, 19(21), 4690.

[18] Zarboubi, M., Bellout, A., Chabaa, S., Dliou, A., & Zeroual, A. (2024). IoT-based pest detection in agriculture using Raspberry Pi and YOLOv10m for precision farming. ITM Web of Conferences, 69, 04017.

[19] Pei, T., Xu, J., Liu, Y., Huang, X., Zhang, L., Dong, W., & Zhou, C. (2021). GIScience and remote sensing in natural resource and environmental research: Status quo and future perspectives. Geography and Sustainability, 2(3), 207–215.

[20] Kilinç, M. (2024). Data-driven analytical techniques in geographic information systems. In Current Studies in Data Science and Analytics (pp. 1–19). IGI Global.

[21] Wang, J., Wang, Y., Li, G., & Qi, Z. (2024). Integration of remote sensing and machine learning for precision agriculture: A comprehensive perspective on applications. Agronomy, 14(9), 1975.

[22] Jyothi, V. E., Rajashree, R., Phani, S., Hugar, L., Shaik, R., & Poddar, S. (2025, September). Artificial Intelligence-Powered Protocols for Enhancing Security in Next-Generation Communication Networks. In 2025 3rd International Conference on Intelligent Cyber Physical Systems and Internet of Things (ICoICI) (pp. 1107-1112). IEEE.

[23] Shaurub, E. S. H. (2024). Remote sensing and geographic information system applications as early-warning tools in monitoring fall armyworm, Spodoptera frugiperda: A review. International Journal of Tropical Insect Science, 44(5), 2241–2258.

[24] Venkataraman, N. L., & Gautam, G. (2024). A comprehensive analysis of remote sensing satellite image processing techniques. SSRN Preprint.

[25] Wang, L., Huang, X., & Zhang, L. (2020). Understanding remote sensing image scene classification: A review. IEEE Geoscience and Remote Sensing Magazine, 8(3), 22–44.

[26] Leung, C. K., Braun, P., & Cuzzocrea, A. (2019). AI-based sensor information fusion for supporting deep supervised learning. Sensors, 19(6), 1345

[27] Li, W., & Hsu, C. Y. (2022). GeoAI for large-scale image analysis and machine vision: Recent progress of artificial intelligence in geography. ISPRS International Journal of Geo-Information, 11(7), 385.

[28] Pajany, M., Venkatraman, S., Sakthi, U., Sujatha, M., & Ishak, M. K. (2024). Optimal fuzzy deep neural networks based plant disease detection and classification on UAV-based remote sensed data. IEEE Access.

[29] Seralathan, P., & Edward, S. (2024). Revolutionizing agriculture: Deep learning-based crop monitoring using UAV imagery—A review. 2024 International Conference on Expert Clouds and Applications (ICOECA), 777–784. IEEE.

[30] [30] Zhu, X. X., Tuia, D., Mou, L., Xia, G. S., Zhang, L., Xu, F., & Fraundorfer, F. (2017). Deep learning in remote sensing: A comprehensive review and list of resources. IEEE Geoscience and Remote Sensing Magazine, 5(4), 8–36.

[31] V. Shariff, P. Chiranjeevi, and A. Krishna Mohan, “A two-step feature selection framework with L1L2R2 and ensemble hyperparameter tuning for predicting lung cancer: integrating stacked ensemble models,” Biomedical Signal Processing and Control, vol. 115, Apr. 15, 2026, Art. no. 109428, doi: 10.1016/j.bspc.2025.109428.

[32] Deng, J., Wang, W., Wang, L., Bashir, A. K., Gadekallu, T. R., Feng, H., ... & Fang, K. (2025). FIDSUS: Federated Intrusion Detection for Securing UAV Swarms in Smart Aerial Computing. IEEE Internet of Things Journal.

[33] Nie, J., Li, H., Li, Y., Zhao, J., Ercisli, S., Fang, K., & Gadekallu, T. R. (2025). Towards Intent-Based Network Management: Intent-Optimized Cross-Shard Transactions and Malicious Node Detection in Blockchain System. IEEE Internet of Things Journal.

[34] Praveen, S. P., Kamalrudin, M., Musa, M., Harita, U., Ayyappa, Y., & Nagamani, T. (2025). A Unified AI Framework for Confidentiality Preserving Cyberattack Detection in Healthcare Cyber Physical Networks. International Journal of Innovative Technology and Interdisciplinary Sciences, 8(3), 818-841.

[35] S Phani Praveen et al., (2025), "Revolutionizing Healthcare With Large Language Models: Advancements, Challenges, And Future Prospects In AI-Driven Diagnostics And Decision Support", Journal of Theoretical and Applied Information Technology, vol. 103, no. 9, May 2025

[36] S, S., Kodete, C. S., Velidi, S., Bhyrapuneni, S., Satukumati, S. B., & Shariff, V. (2024l). Revolutionizing Healthcare: A Comprehensive Framework for Personalized IoT and Cloud Computing-Driven Healthcare Services with Smart Biometric Identity Management. Journal of Intelligent Systems and Internet of Things, 13(1), 31–45. https://doi.org/10.54216/jisiot.130103

[37] B. Sreedhar, C. Sasikala, V. T. Ram Pavan Kumar M, R. Shaik, S. Muqthadar Ali and Y. Balagoni, "Intelligent Resource Allocation for Edge-IoT: Enhancing QoE with Deep Reinforcement Learning," 2025 International Conference on Multi-Agent Systems for Collaborative Intelligence (ICMSCI), Erode, India, 2025, pp. 473-479, doi: 10.1109/ICMSCI62561.2025.10894101.

[38] C. D. Kothapalli, G. Navya, U. Jaladhi, S. R. Sulthana, D. L. S. Kumar and S. P. Praveen, "Predicting Buy and Sell Signals for Stocks using Bollinger Bands and MACD with the Help of Machine Learning," 2023 International Conference on Sustainable Computing and Smart Systems (ICSCSS), Coimbatore, India, 2023, pp. 333-340, doi: 10.1109/ICSCSS57650.2023.10169500.

[39] Praveen, S. P., Jyothi, V. E., Sharma, K., & Sindhura, S. Optimized Hybrid Features Enhance ML-Driven Defect Detection and Quality Control in Textiles. Journal of the Textile Association, 86(2), 196-204.

[40] Praveen, S.P., Sharma, K., Parashar, D. et al. Design of an iterative method for adaptive federated intrusion detection for energy-constrained edge-centric 6G IoT cyber-physical systems. Sci Rep 15, 41387 (2025). https://doi.org/10.1038/s41598-025-25293-w