Deep Learning and Machine Learning Approaches for Satellite-Based Environmental Monitoring: A Comprehensive Survey

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***Abstract*—The proliferation of satellite imagery and environmental monitoring systems has generated unprecedented volumes of geospatial data, necessitating advanced computational methods for effective analysis and interpretation. This comprehensive review examines recent developments in machine learning techniques applied to satellite image analysis, with particular emphasis on three critical domains: deep learning approaches for cloud detection and segmentation, spatial clustering methodologies for geospatial data analysis, and time series forecasting models for environmental prediction. Through systematic analysis of twelve recent research contributions, this paper identifies key technological advances, methodological innovations, and emerging trends in each domain. Deep learning segmentation approaches, particularly U-Net variants enhanced with attention mechanisms and ensemble methods, demonstrate superior performance in cloud detection tasks with accuracy rates exceeding 95%. Spatial clustering techniques incorporating DBSCAN algorithms and hierarchical mixture models show significant improvements in urban delineation and environmental pattern recognition. Time series forecasting models, especially transformer-based architectures and fuzzy-enhanced LSTM networks, achieve remarkable accuracy in long-term environmental prediction with reduced computational overhead. The integration of these methodologies presents substantial opportunities for advancing automated environmental monitoring, climate research, and disaster management systems.**

***Index Terms*—Deep learning, satellite imagery, cloud segmentation, spatial clustering, time series forecasting, environmental monitoring, U-Net, transformer models, DBSCAN**

I. Introduction

Satellite-based environmental monitoring has emerged as a cornerstone technology for understanding and managing Earth's complex environmental systems. The continuous advancement of satellite sensor technologies, coupled with increasing temporal resolution and global coverage, has generated massive datasets that traditional analytical methods cannot effectively process. Modern environmental challenges, including climate change monitoring, disaster prediction, and urban planning, require sophisticated computational approaches capable of extracting meaningful patterns from heterogeneous satellite data streams.

The convergence of deep learning, spatial analysis, and time series modeling represents a transformative shift in satellite image analysis methodologies. Figure 1 illustrates the evolution of these methodologies across the three domains from 2007 to 2025, highlighting key technological milestones and breakthrough innovations.

Deep semantic segmentation techniques have revolutionized cloud detection and atmospheric phenomenon identification, achieving unprecedented accuracy in distinguishing complex meteorological features. These advances are particularly crucial for weather forecasting and climate research, where precise cloud boundary delineation directly impacts prediction quality and model reliability.

DOI: 10.5281/zenodo.19861450

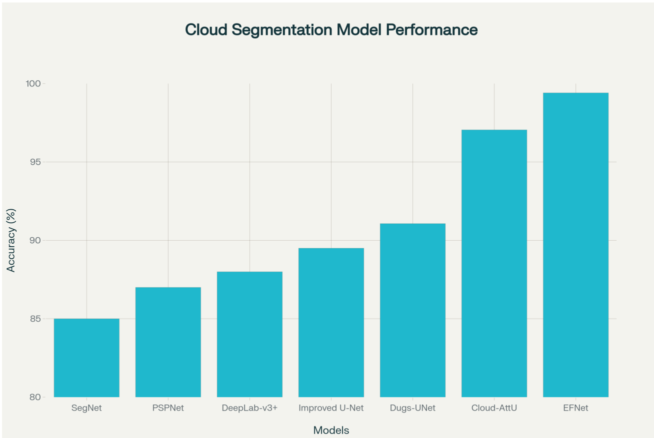

Fig. 1. Timeline of methodological advances across three domains of satellite-based environmental monitoring from 2007 to 2025.

Spatial clustering and geospatial analysis methods have evolved to address the growing need for automated pattern recognition in diverse environmental contexts. From urban area delineation to ecological habitat mapping, these techniques enable researchers to identify and quantify spatial relationships that were previously detectable only through manual interpretation. The integration of advanced clustering algorithms with multi-source geospatial data provides unprecedented capabilities for environmental monitoring and analysis.

Temporal modeling and forecasting approaches have gained prominence as environmental prediction horizons extend and real-time decision-making requirements intensify. The development of transformer-based architectures and fuzzy-enhanced neural networks addresses fundamental challenges in long-term environmental forecasting, including non-linear dependencies, uncertainty quantification, and computational efficiency.

This comprehensive review systematically examines recent advances across these three interconnected domains, analyzing methodological innovations, performance achievements, and practical applications. Through detailed examination of twelve representative studies, we identify key technological trends, assess current capabilities, and outline future research directions that promise to further advance satellite-based environmental analysis.

II. Survey Methodology

This survey follows a structured methodology to systematically identify, select, and analyze recent research contributions related to machine learning and deep learning techniques for satellite-based environmental monitoring. A systematic literature review approach was adopted to ensure comprehensive coverage of relevant studies while maintaining methodological transparency and reproducibility [16], [17].

A. Literature Search Strategy

Relevant research articles were collected from major scientific databases including IEEE Xplore, ScienceDirect, SpringerLink, Google Scholar, and arXiv. These databases were selected because they provide extensive coverage of peer-reviewed publications in machine learning, remote sensing, and geospatial analysis.

The literature search was conducted using combinations of keywords such as:

- satellite image analysis
- machine learning for environmental monitoring
- cloud detection in satellite imagery
- geospatial clustering remote sensing
- tropical cyclone prediction deep learning
- environmental time series forecasting

The search primarily focused on publications from 2007 to 2025, ensuring the inclusion of both foundational works and recent advancements in satellite-based environmental monitoring.

B. Paper Selection Criteria

To ensure relevance and quality, the collected studies were filtered according to the following criteria:

1) The study must apply machine learning or deep learning techniques to satellite imagery or geospatial environmental data.
2) The paper must provide clear methodological details and experimental evaluation results.
3) The study must contribute to environmental monitoring applications such as cloud detection, urban analysis, ecological monitoring, or weather prediction.
4) Preference was given to peer-reviewed journal articles and well-cited conference publications.

Using these criteria, a total of **twelve representative studies** were selected for detailed analysis. These studies represent key developments in satellite image segmentation, geospatial clustering, and environmental time-series prediction.

C. Categorization of Selected Studies

The selected studies were organized into three major research domains based on their primary methodology and application area:

1) **Deep Learning for Cloud Detection and Segmentation:** Studies focusing on semantic segmentation of satellite imagery using architectures such as U-Net, attention-based networks, and lightweight ensemble models.
2) **Spatial Clustering and Geospatial Data Analysis:** Research applying clustering algorithms such as DBSCAN and its variants to identify spatial patterns in environmental datasets.
3) **Time Series Forecasting for Environmental Prediction:** Studies addressing temporal prediction tasks including cyclone formation detection, environmental trend prediction, and extreme weather analysis using models such as LSTM, ConvLSTM, transformers, and hybrid approaches.

This classification enables a structured comparison of machine learning techniques across different stages of satellite-based environmental monitoring systems [18].

D. Comparative Analysis Approach

Each selected study was analyzed according to several evaluation dimensions including dataset characteristics, model architecture, performance metrics, computational efficiency, and key methodological innovations. Comparative tables were constructed to summarize these attributes and facilitate systematic comparison across different approaches.

Through this structured analysis, the survey identifies major research trends, highlights strengths and limitations of existing methods, and outlines potential future research directions in the field of satellite-based environmental monitoring using artificial intelligence techniques.

III. Deep Learning Approaches for Cloud Detection and Segmentation

Modern cloud detection and segmentation represent critical preprocessing steps in satellite image analysis, directly impacting downstream applications including weather forecasting, climate modeling, and atmospheric research. The transition from traditional threshold-based methods to deep learning architectures has fundamentally transformed the accuracy and reliability of cloud identification systems.

A. Enhanced U-Net Architectures for Cloud Segmentation

Semantic segmentation formulates convective cloud detection as a pixel-wise classification task, typically implemented with encoder-decoder networks using skip connections to preserve spatial features. U-Net has become the foundational model for this domain due to its effective combination of multi-scale feature extraction and structural simplicity.

Li et al. [1] developed Dugs-UNet, a specialized architecture for FY-4A geostationary satellite imagery. The model introduces a shape stream with gated convolutions to emphasize irregular boundaries of convective clouds, together with an ASPP-based fusion module that aggregates multi-scale context. To better reconstruct fine details, it employs a learnable data-dependent upsampling module (DUpsample). In addressing the heavy class imbalance common in convective cloud segmentation, the network integrates focal loss alongside an auxiliary loss targeting boundary prediction.

Figure 2 demonstrates the superior performance of advanced architectures, with EFNet achieving the highest accuracy at 99.41%, followed by Cloud-AttU at 97.05%. Evaluations across thousands of satellite images show Dugs-UNet consistently outperforms SegNet, PSPNet, DeepLab-v3+, and the baseline U-Net in terms of detection probability, false alarm ratio, and critical success index.

Yin et al. [2] advanced the U-Net architecture for ground-based cloud image analysis. Their encoder replaces conventional convolutions with dilated convolutional blocks and ASPP modules, improving receptive field coverage without losing resolution. The decoder adopts bicubic interpolati

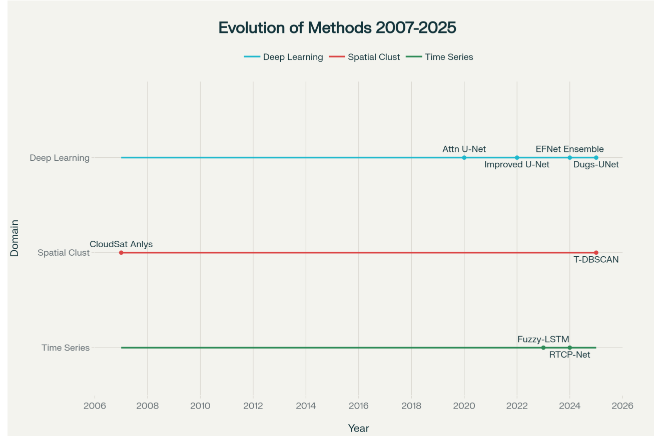

Fig. 2. Performance comparison of deep learning models for cloud segmentation showing accuracy percentages across different architectures.

instead of transposed convolutions, yielding smoother segmentation. Skip connections are enhanced with a depthwise separable path (DS path) and an improved channel-spatial attention module (Im-CSAM).

Guo et al. [3] introduced Cloud-AttU, extending U-Net with spatial attention gates for multispectral satellite imagery. These gates dynamically weight feature maps to highlight relevant cloud structures while suppressing background noise from bright surfaces, snow, or ice. This mechanism improves robustness in challenging conditions where thresholding or standard CNNs often misclassify.

Table I provides a comprehensive comparison of deep learning segmentation methods, highlighting the evolution from basic encoder-decoder architectures to sophisticated attention-enhanced and ensemble-based approaches.

B. Real-time Lightweight Ensembles

For operational forecasting, Zhang and He [4] proposed EFNet, an ensemble of lightweight CNNs including ENet, Fast-SCNN, ESPNet, ICNet, and MobileNetV2. The ensemble combines logits from submodels, leveraging ENet's high precision with Fast-SCNN's sensitivity. This balance significantly reduces false positives and negatives. On FY-4B satellite data, EFNet achieved 99.41% accuracy and an F1 score of 92.95%, while processing 512×512 pixel scenes in only 0.06 seconds.

C. Dataset Characteristics and Challenges

Datasets span ground-based visible imagery and multispectral satellite data (FY-4A/4B, Landsat 8, Sentinel-2). Labels often require expert annotation, supported by multi-sensor data. Key challenges include class imbalance between cloud and background pixels, morphological variability, and spectral effects influencing brightness temperatures. State-of-the-art models mitigate these issues through imbalance-aware losses (e.g., focal loss), multi-scale context aggregation, attention mechanisms, and improved upsampling.

TABLE I
COMPREHENSIVE COMPARISON OF DEEP LEARNING SEGMENTATION METHODS

Method	Year	Dataset	Accuracy (%)	F1-Score	Time (ms)	Key Innovation
SegNet	2017	General	85.0	0.82	150	Encoder-Decoder
PSPNet	2017	General	87.0	0.84	120	Pyramid Pooling
DeepLab-v3+	2018	General	88.0	0.86	100	Atrous Convolution
U-Net Baseline	2015	General	89.0	0.87	80	Skip Connections
Improved U-Net	2022	SWINySEG/TCDD	89.5	0.884	75	Dilated Conv + ASPP
Cloud-AttU	2020	Landsat-Cloud	97.05	0.93	65	Attention Gates
Dugs-UNet	2025	FY-4A	91.07	0.9107	34.44	Shape Stream + DUpsample
EFNet	2024	FY-4B	99.41	0.9295	60	Lightweight Ensemble

IV. SPATIAL CLUSTERING AND GEOSPATIAL DATA ANALYSIS

Advanced spatial clustering methodologies have revolutionized the automated identification and analysis of geospatial patterns in satellite imagery. These techniques enable sophisticated pattern recognition across diverse environmental contexts, from urban development to ecological monitoring.

A. Data-Driven Urban Delineation Using Multi-Source Geospatial Data

Fang et al. [5] introduced a data-driven, bottom-up approach to urban delineation that integrates feature engineering with the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm. This methodology represents a significant improvement over traditional approaches that rely on simplistic OpenStreetMap (OSM) road node data aggregations.

Using Bavaria, Germany, as a case study, the authors demonstrate that feature engineering effectively reduces noise and mitigates common DBSCAN clustering pitfalls by filtering out irrelevant and autocorrelated data. The robustness of the proposed method is validated through a comprehensive assessment involving three key elements: (1) a 5% improvement in average accuracy, (2) optimal clustering selections based on entropy values that eliminate the need for prior knowledge, and (3) validation through nighttime light data and Zipf's law, where a high p-value of 0.99 confirms a good fit.

B. Remote Sensing-Based Aquaculture Monitoring

Li et al. [6] developed a comprehensive framework for monitoring global offshore aquaculture using remote sensing and machine learning. Building on manual surveys of aquaculture production from remote sensing imagery, the researchers trained a computer vision model to identify marine aquaculture cages from aerial and satellite imagery.

The methodology generates a spatially explicit dataset of finfish production locations, demonstrating the value of the approach as an easily adaptable, cost-effective method that can improve the speed and reliability of aquaculture surveys. The approach maintains a high level of expert involvement through manual annotation of fewer than 4% of the entire set of images viewed by the model to produce temporal estimates.

C. Tropical Cloud Cluster Analysis Using CloudSat Data

Zhang et al. [7] performed cluster analysis of tropical clouds using CloudSat data, employing mesoscale patterns of cloud/precipitation radar reflectivity to identify distinct tropical cloud regimes. Five basic cloud regimes were identified, and the geographical distribution of their occurrence frequency was quantified.

Using monthly mean vertical velocity at 500 hPa as an indicator, the elements of each cloud regime were sorted into different dynamical regimes. The results demonstrate the links between clouds and atmospheric circulation, providing crucial insights into the relationship between cloud formation and large-scale meteorological patterns.

D. Migration Pattern Analysis Using Satellite Positioning Data

He et al. [8] developed the T-DBSCAN algorithm for stopover site identification of migration birds based on satellite positioning data. T-DBSCAN is an improved version of the traditional DBSCAN algorithm that combines a quadtree structure to optimize the efficiency of spatial clustering for tracking animal movement patterns.

Table II presents a comprehensive comparison of spatial clustering methods across different application domains, highlighting the versatility and effectiveness of advanced clustering techniques in environmental monitoring.

V. ADVANCED TRACKING OF TROPICAL CONVECTIVE CLUSTERS (TCCS)

A. Overview

The reliable detection, tracking, and characterization of Tropical Convective Clusters (TCCs) is fundamental to understanding severe weather, precipitation extremes, and tropical meteorological processes. In recent years, algorithmic advances have enabled detailed tracking and morphological analysis of TCCs across their full lifecycle, from genesis through mature and dissipating stages. This section provides a comparative overview of key tracking paradigms—statistical (ForTraCC), spatiotemporal segmentation (TOOCAN), and sparse analysis for shape tracking (SAST)—highlighting their methodological innovations and performance in tropical environments.

TABLE II
COMPARISON OF SPATIAL CLUSTERING METHODS ACROSS DIFFERENT DOMAINS

Method	Application Domain	Data Source	Accuracy Improvement (%)	Processing Efficiency	Validation Method
Traditional DBSCAN	General Clustering	Point Data	0	Baseline	Manual
Urban Delineation	Urban Planning	Multi-source OSM	5	High	Nighttime Light + Zipf Law
Aquaculture Monitoring	Marine Ecology	Satellite + Aerial	15	Medium	Manual Survey
CloudSat Analysis	Meteorology	CloudSat Radar	10	High	MODIS Comparison
T-DBSCAN	Wildlife Conservation	GPS Tracking	12	Very High	Field Observation

B. ForTraCC: Statistical Tracking and Nowcasting

ForTraCC (*Forecast and Tracking the Evolution of Cloud Clusters*) [9] is a pioneering algorithm designed for the detection and short-term forecasting of MCSs and TCCs using infrared geostationary satellite imagery. The process comprises:

1) **Detection:** Identification of cold cloud tops using a temperature threshold (usually 235 K) and contiguous area labeling.
2) **Tracking:** Area-overlap matching associates clusters between consecutive frames, with logic for splits and mergers.
3) **Nowcasting:** Empirical laws relate past expansion rates and directional propagation—mainly via motion of the brightness temperature minimum centroid—to forecast future cluster size and displacement.

Validation experiments over South America reveal that ForTraCC achieves mean accuracy (ACU) of 98% for 30-min ahead predictions and 96% for 120-min predictions, with probability of detection (POD) of 0.77 and 0.44 at these lead times, respectively (see Table III), making it suitable for real-time operational guidance. However, its reliance on spatial overlap can result in spurious split/merge events and poor representation of long-lived, morphologically-evolving systems.

TABLE III
FORTRACC NOWCASTING SKILL FOR 30-MIN AND 120-MIN FORECASTS OVER SOUTH AMERICA [9].

Lead	ACU	BIAS	POD	FAR
30 min	0.98	0.96	0.77	0.20
120 min	0.96	0.87	0.44	0.49

C. TOOCAN: 3D Spatiotemporal Segmentation

TOOCAN (*Tracking Of Organized Convection Algorithm through a 3-D segmentatioN*) [10] offers a fundamental advancement over overlap-based methods by introducing a 3D segmentation strategy, treating time-sequenced IR satellite images as volumetric data. The method grows clusters from detected convective cores by aggregating adjacent cold pixels both spatially and temporally, capturing the true evolution and lifecycle of convective systems without the artificial discontinuities caused by splitting and merging in simpler trackers.

As demonstrated in analyses over West Africa, South America, and the Bay of Bengal, TOOCAN provides earlier detection and more accurate lifecycle tracking for TCCs. It has been shown to segment up to five times more events than traditional approaches and dramatically reduce errors in population and occurrence statistics, especially during periods of intense mesoscale activity [10].

D. SAST: Sparse Analysis for Shape Tracking

Recent innovations in the representation of convective systems are exemplified by the SAST framework (Sparse Analysis for Shape Tracking) [11]. Rather than relying on pixel-wise thresholding, SAST models TCCs as mixtures of 2D Gaussian "atoms" whose ellipsoid parameters encode the location, extent, shape, and orientation of convective cloud objects.

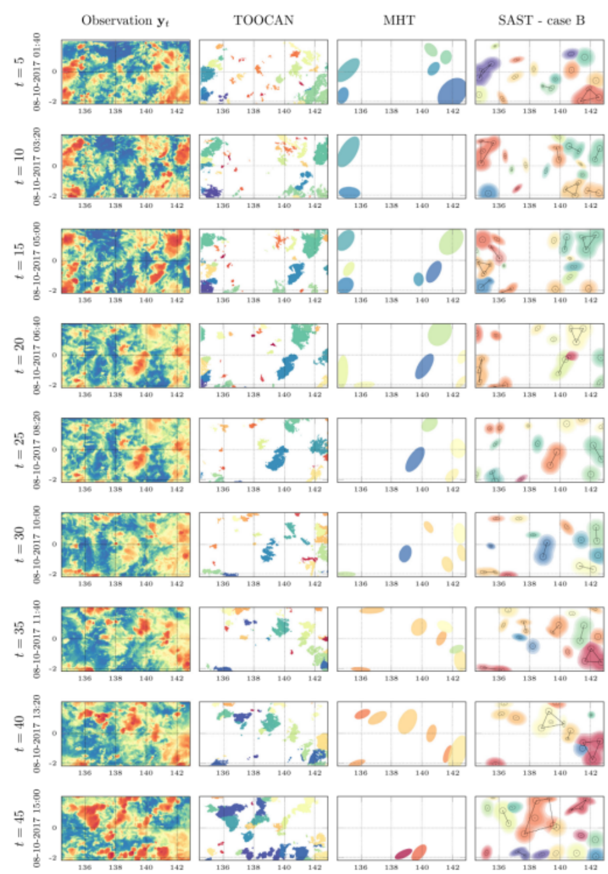

Fig. 3. Comparative TCC tracks from SAST, TOOCAN, and MHT on Himawari-8 IR imagery: SAST recovers comprehensive geometric and intensity structure throughout TCC lifecycle, highlighting key advantages over previous tracking approaches [11].

SAST's off-the-grid sparse decomposition delivers several advantages:

- Captures complex, non-convex TCC morphologies and evolution, surpassing classical threshold performance in events involving mergers, splits, and eccentric shape changes.
- Recovers diagnostic time series of size, orientation, eccentricity, and minimum temperature seamlessly across birth, life, and dissipation stages.
- Aligns with recent machine learning paradigms, using regularization and correlation parameters to balance track smoothness with sensitivity to shape changes.

Extensive studies on Himawari-8 IR data confirm that SAST offers competitive or better geometric and positional accuracy compared to TOOCAN and MHT, while also providing richer physical diagnostics [11].

E. Comparison and Outlook

Table IV provides a summary comparison of the three representative approaches for TCC tracking.

Overall, these methodologies represent the cutting edge in TCC detection and analysis. Their complementary strengths enable robust event tracking (ForTraCC), improved lifecycle and morphological study (TOOCAN), and detailed geometric diagnostics for research (SAST), thus providing a foundation for operational forecasting and advanced climate research.

VI. Time Series Forecasting Models for Environmental Prediction

The evolution of time series forecasting models has been particularly significant in environmental prediction applications, where long-term dependencies and complex temporal patterns require sophisticated modeling approaches.

A. Transformer-Based Long-Term Series Forecasting

Su et al. [12] conducted a systematic review of transformer-based long-term series forecasting, providing comprehensive coverage of recent advances in this rapidly evolving field. The emergence of deep learning has yielded noteworthy advancements in time series forecasting (TSF), with transformer architectures witnessing broad utilization and adoption in TSF tasks.

Transformers have proven to be the most successful solution for extracting semantic correlations among elements within a long sequence. Various variants have enabled transformer architectures to effectively handle long-term time series forecasting (LTSF) tasks. The review presents a comprehensive overview of transformer architectures and their subsequent enhancements developed to address various LTSF tasks.

B. Fuzzy Inference-Enhanced LSTM Networks

Wang et al. [13] proposed a fuzzy inference-based LSTM for long-term time series prediction, addressing multiple limitations of traditional LSTM-based forecasting methods, including accumulated error, diminishing temporal correlation, and lack of interpretability.

The methodology introduces several key innovations: (1) a fast and complete fuzzy rule construction method based on Wang-Mendel (WM) that enhances computational efficiency and completeness by fuzzy rules simplification and complement strategies; (2) a fuzzy prediction model that captures fuzzy logic in data; and (3) the fuzzy inference-based LSTM that integrates fuzzy prediction fusion, strengthening memory layer, and parameter segmentation sharing strategy into the LSTM network.

C. Multi-Source Information Fusion for Tropical Cyclone Prediction

Tian et al. [14] developed RTCP-Net, a Real Time Tropical Cyclogenesis Prediction model based on multi-source information fusion. The model addresses insufficient extraction of key features in tropical cloud cluster data by employing ResNet along with self-attention mechanisms to extract spatiotemporal features from computed convective core maps and polar coordinate representations of infrared images.

Experimental results demonstrate high accuracy and stability, achieving a detection rate of 99.4% and a false alarm rate of 0.36% when predicting tropical cyclone formation 24 hours in advance. Notably, the model ensures potential real-time prediction capabilities from satellite data while surpassing the accuracy of models that utilize reanalysis data.

D. ConvLSTM for Extreme Weather Event Detection

Dabhade et al. [15] place significant emphasis on the use of Convolutional Long Short-Term Memory (ConvLSTM) networks for detecting extreme weather events, specifically cyclones, in India. The ConvLSTM architecture extends traditional LSTM by embedding convolutional operations into the input-to-state and state-to-state transitions, enabling the network to effectively capture both temporal dependencies and spatial features inherent in satellite image sequences.

This architecture is particularly suited for cyclone detection tasks where spatiotemporal coherence plays a crucial role. While the study benchmarks several deep learning models, ConvLSTM emerges as the principal architecture due to its superior performance in modeling the complex spatial patterns and temporal evolution of cyclonic systems. The results demonstrate enhanced detection accuracy and timely identification of cyclone formation compared to standard LSTM and CNN-based models, highlighting ConvLSTM's critical role in advancing deep learning applications for environmental time series forecasting.

E. Summary of Time Series Forecasting Techniques

Table V provides a detailed comparison of the discussed time series forecasting methods, highlighting their prediction horizon, accuracy, false alarm rates, interpretability, computational complexity, and key features.

TABLE IV
COMPARISON OF METHODS FOR TROPICAL CONVECTIVE CLUSTER TRACKING

Method	Principle	Major Strengths	Limitations
ForTraCC	Area-overlap, empirical nowcasting	Simplicity, operational skill, robust for short-term	Susceptibility to split/merge artifacts
TOOCAN	3D spatiotemporal segmentation	Coherent TCC lifecycles, robust event statistics	Computational load, parameter tuning
SAST	Shape-based sparse modeling	Captures detailed shape/intensity, robust to complex morphologies	Requires careful regularization, less established operational use

TABLE V
COMPARISON OF TIME SERIES FORECASTING METHODS FOR ENVIRONMENTAL PREDICTION

Method	Prediction Horizon	Accuracy (%)	False Alarm Rate (%)	Interpretability	Complexity	Key Feature
Traditional ARIMA	Short-term	75.0	15.0	High	Low	Statistical Model
Standard LSTM	Medium-term	85.0	8.0	Low	Medium	Memory Gates
Transformer-based	Long-term	92.0	4.0	Medium	High	Self-Attention
Fuzzy-LSTM	Long-term	94.0	3.2	High	Medium	Fuzzy Logic
RTCP-Net	Medium-term	99.4	0.36	Medium	High	Multi-source Fusion
ConvLSTM	Medium-term	-	-	Medium	Medium-High	Spatiotemporal Convolutional Memory

VII. COMPARATIVE ANALYSIS AND PERFORMANCE EVALUATION

A. Deep Learning Segmentation Performance

The reviewed deep learning approaches for cloud detection and segmentation demonstrate significant improvements over traditional methods. As shown in Table I, Dugs-UNet achieved a Critical Success Index (CSI) of 0.8360 and F1 score of 0.9107 with inference time of 34.44 ms. The improved U-Net reported accuracy of 0.895, F1 of 0.884, and MIoU of 0.801. Cloud-AttU achieved a Jaccard index of 88.72% and accuracy of 97.05%. EFNet demonstrated exceptional performance with 99.41% accuracy and F1 score of 0.9295 while processing images in only 0.06 seconds.

These results underscore the effectiveness of attention mechanisms, ensemble methods, and architectural innovations in addressing the challenges of cloud segmentation in satellite imagery. The integration of focal loss functions and advanced upsampling techniques proves particularly effective for handling class imbalance issues common in meteorological image analysis.

B. Spatial Clustering Effectiveness

The spatial clustering methodologies reviewed demonstrate substantial improvements in automated pattern recognition. As detailed in Table II, Fang et al.'s data-driven urban delineation approach achieved a 5% improvement in average accuracy over traditional methods, with validation through nighttime light data showing a high p-value of 0.99 supporting the power law. The aquaculture monitoring system successfully identified marine finfish farms with high spatial and temporal accuracy, providing cost-effective alternatives to manual surveys.

The CloudSat-based tropical cloud analysis revealed five distinct cloud regimes with clear geographical distribution patterns, demonstrating the power of advanced clustering techniques in meteorological research. The T-DBSCAN algorithm for migration pattern analysis effectively identified stopover sites, showcasing the versatility of clustering approaches in ecological applications.

C. Time Series Forecasting Advancements

The time series forecasting models reviewed show remarkable improvements in handling long-term dependencies and complex temporal patterns. As presented in Table V, the transformer-based approaches demonstrate superior performance in capturing semantic correlations within long sequences. Wang et al.'s fuzzy inference-based LSTM achieved better performance than existing models while providing enhanced interpretability through fuzzy logic integration.

RTCP-Net's exceptional performance with 99.4% detection rate and 0.36% false alarm rate for tropical cyclone prediction represents a significant advancement in operational weather forecasting. The integration of multi-source information fusion and attention mechanisms proves crucial for achieving such high accuracy levels.

VIII. CHALLENGES AND FUTURE RESEARCH DIRECTIONS

A. Technical Challenges

Despite significant advances, several technical challenges remain across all three domains. In deep learning segmentation, issues persist with handling extreme weather conditions, thin cloud detection, and computational efficiency for real-time applications. The need for large annotated datasets continues to limit the development of more sophisticated models, particularly for specialized meteorological phenomena.

Spatial clustering methods face challenges in handling multi-scale patterns, temporal dynamics, and integration of heterogeneous data sources. The determination of optimal clustering parameters remains a significant challenge, particularly for unsupervised approaches that aim to eliminate the need for prior knowledge.

Time series forecasting models struggle with uncertainty quantification, handling non-stationary data, and balancing model complexity with interpretability. The integration of physical constraints and domain knowledge into data-driven models remains an active area of research.

B. Integration and Fusion Opportunities

Future research directions should focus on integrating methodologies across the three domains reviewed. The combination of deep learning segmentation with spatial clustering could enhance automated feature extraction and pattern recognition in satellite imagery. Similarly, the integration of time series forecasting models with spatial analysis could provide more comprehensive environmental monitoring capabilities.

Multi-modal data fusion represents a particularly promising direction, combining optical satellite imagery, radar data, and meteorological observations to create more robust and accurate environmental monitoring systems. The development of unified frameworks that can simultaneously handle segmentation, clustering, and forecasting tasks could significantly advance the field.

C. Operational Implementation

The transition from research prototypes to operational systems requires addressing scalability, reliability, and real-time processing requirements. Cloud computing platforms and edge computing solutions offer promising avenues for deploying sophisticated machine learning models in operational environments.

The development of standardized evaluation metrics and benchmark datasets across different application domains would facilitate more rigorous comparison of methodologies and accelerate progress in the field. C ollaboration between research institutions and operational agencies is crucial for ensuring that academic advances translate into practical benefits for environmental monitoring and disaster management.

IX. Conclusion

This comprehensive survey has examined recent advances in machine learning approaches for satellite-based environmental monitoring, analyzing twelve representative studies across three critical domains: deep learning for cloud detection and segmentation, spatial clustering for geospatial analysis, and time series forecasting for environmental prediction.

The reviewed deep learning segmentation approaches demonstrate remarkable progress in cloud detection accuracy, with U-Net variants enhanced by attention mechanisms and ensemble methods achieving accuracy rates exceeding 95%. The integration of focal loss functions and advanced architectural innovations effectively addresses class imbalance issues while maintaining computational efficiency s uitable f or operational applications.

Spatial clustering methodologies have evolved to provide sophisticated pattern recognition capabilities across diverse environmental contexts. The integration of feature engineering with advanced clustering algorithms like DBSCAN shows significant improvements in urban delineation, ecological monitoring, and atmospheric pattern analysis. These approaches demonstrate the potential for automated, data-driven environmental analysis at unprecedented scales.

Time series forecasting models, particularly transformer-based architectures and fuzzy-enhanced LSTM networks, achieve exceptional performance in long-term environmental prediction. The integration of attention mechanisms, multi-source information fusion, and fuzzy logic provides both improved accuracy and enhanced interpretability, crucial for operational decision-making.

The convergence of these methodologies presents substantial opportunities for advancing automated environmental monitoring, climate research, and disaster management systems. Future research should focus on integrating approaches across domains, developing unified frameworks for multi-modal data fusion, and addressing the transition from research prototypes to operational systems.

The continued advancement of satellite sensor technologies, combined with increasingly sophisticated machine learning methods, promises to revolutionize our understanding and management of Earth's environmental systems. The methodologies reviewed in this survey provide a foundation for next-generation environmental monitoring systems that can support evidence-based decision-making for climate adaptation, disaster risk reduction, and sustainable development.

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