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Spatiotemporal Modeling and Environmental Prediction in Earth System Observation: A Review

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ABSTRACT

The continuous monitoring and precise prediction of Earth system dynamics are fundamental to understanding global environmental changes, managing natural resources, and mitigating the impacts of climate change and natural disasters. Over the past few decades, the proliferation of remote sensing technologies, terrestrial sensor networks, and advanced satellite constellations has led to an exponential increase in Earth observation data. This data is inherently characterized by complex spatial dependencies and temporal dynamics, necessitating the development of robust spatiotemporal modeling frameworks. This comprehensive review paper synthesizes the current state of spatiotemporal modeling and environmental prediction within the domain of Earth system observation. We systematically trace the evolution of modeling paradigms from traditional geostatistical approaches and classical time-series analysis to contemporary deep learning architectures and hybrid physics-informed neural networks. By examining critical preprocessing methodologies, data assimilation techniques, and predictive architectures, this paper highlights how modern computational frameworks handle the high dimensionality, nonlinearity, and multi-scale nature of environmental data. Furthermore, we evaluate the empirical performance of these models across diverse applications, including climate modeling, extreme weather forecasting, ecological monitoring, and urban air quality assessment. The review concludes by identifying persistent challenges, such as model interpretability, computational demands, and data sparsity in remote regions, while charting future directions toward the development of highly accurate, real-time digital twins of the Earth system.

KEYWORDS

Earth System Observation, Spatiotemporal Modeling, Environmental Prediction, Deep Learning, Remote Sensing .

INTRODUCTION

The Earth system is a highly complex, interconnected network of physical, chemical, and biological processes that operate across a vast range of spatial and temporal scales. From the localized transpiration of a single forest canopy to the global circulation of oceanic currents, understanding these phenomena requires continuous and comprehensive observation. The advent of modern Earth system observation has revolutionized our capacity to monitor these processes, providing a continuous stream of data that forms the empirical foundation for environmental science. However, the transition from mere observation to accurate environmental prediction remains one of the most formidable scientific challenges of our time. This challenge is primarily driven by the intricate spatiotemporal dependencies inherent in environmental data, where events at one location are inextricably linked to conditions at neighboring locations, and present states are heavily influenced by historical trajectories. As the impacts of anthropogenic climate change accelerate, manifesting in more frequent extreme weather events, accelerated biodiversity loss, and shifting agricultural zones, the imperative to develop accurate predictive models has never been more urgent. The concept of spatiotemporal modeling addresses the core requirement of analyzing data that is distributed across both space and time. Historically, analytical approaches often treated the spatial and temporal dimensions in isolation. Spatial analysts utilized geostatistical tools to map static phenomena, while time-series analysts forecasted future states based on localized historical data without considering broader geographic influences. This bifurcated approach proved inadequate for modeling the dynamic, fluid nature of the Earth system, where variables such as temperature, precipitation, aerosol concentration, and soil moisture exhibit strong autocorrelation in both dimensions simultaneously. The recognition of this limitation catalyzed the development of integrated spatiotemporal frameworks designed to capture the complex, non-linear interactions that define environmental processes [1]. Early integrations relied heavily on stochastic mathematical models, which, while theoretically rigorous, struggled to scale with the rapidly increasing volume and dimensionality of Earth observation data. Today, we are operating in the era of big data in Earth observation. Satellite constellations managed by international space agencies, alongside thousands of commercial microsatellites, generate petabytes of data daily. This data encompasses a wide array of modalities, including optical imagery, thermal infrared readings, microwave radiometry, and active radar measurements. When combined with localized data from terrestrial internet-of-things sensor networks, autonomous ocean gliders, and atmospheric weather balloons, the resulting datasets present unprecedented opportunities for high-resolution environmental prediction [2]. Yet, this deluge of information introduces significant computational and methodological hurdles. The data is frequently noisy, inconsistently sampled, obstructed by cloud cover, and characterized by high levels of redundancy. Consequently, the field has witnessed a paradigm shift toward advanced machine learning and artificial intelligence techniques, which excel at extracting latent patterns from massive, unstructured datasets. Despite the widespread adoption of data-driven methodologies, relying solely on empirical data without incorporating the governing laws of physics often leads to models that are brittle, uninterpretable, and prone to violating fundamental conservation principles, such as the conservation of mass and energy. Therefore, the contemporary frontier of spatiotemporal modeling involves the synthesis of domain-specific physical knowledge with flexible machine learning architectures. These hybrid models aim to leverage the predictive power and computational efficiency of neural networks while remaining tethered to the physical realities of the Earth system [3]. This synthesis is particularly crucial when projecting conditions into future climate scenarios that fall outside the historical distribution of the training data.

This comprehensive review paper aims to provide a critical evaluation of spatiotemporal modeling and environmental prediction within the context of Earth system observation. The primary objectives are to trace the historical and theoretical development of these models, detail the dominant methodological frameworks currently employed in the field, and assess their practical efficacy across various

environmental domains. By synthesizing literature from remote sensing, computer science, atmospheric physics, and ecology, this paper seeks to establish a holistic understanding of how multi-dimensional data is transformed into actionable environmental intelligence. The subsequent sections will delve into the foundational concepts of Earth observation, explore the architectural nuances of state-of-the-art predictive models, present comprehensive results from empirical applications, and discuss the trajectory of future research in establishing predictive digital representations of the planetary system.

2. Background and Literature Review

2.1 Evolution of Earth Observation Systems

The capacity to model and predict environmental phenomena is fundamentally constrained by the quality, resolution, and availability of observational data. The history of Earth system observation is characterized by a continuous quest to expand the spatial coverage and temporal frequency of measurements. Early environmental monitoring was entirely reliant on localized, ground-based stations. While these stations provided highly accurate and continuous time-series data for specific points, their sparse geographic distribution left vast regions of the planet, particularly oceans, deserts, and polar regions, virtually unmonitored. This spatial data sparsity severely limited the development of global environmental models and localized the scope of ecological forecasting. The launch of the first meteorological satellites in the mid-twentieth century marked a watershed moment in Earth observation, inaugurating the era of systematic remote sensing. Programs such as the Television Infrared Observation Satellite provided the first continuous synoptic views of global cloud patterns, revolutionizing weather forecasting. Subsequently, the initiation of the Landsat program introduced the capability to monitor the terrestrial surface systematically using multispectral sensors. This allowed scientists to track changes in land cover, vegetation health, and urban expansion over decades [4]. Concurrently, the deployment of geostationary operational environmental satellites enabled continuous monitoring of atmospheric dynamics over fixed planetary hemispheres, providing the high-frequency temporal data necessary for tracking rapidly evolving phenomena such as severe storms and hurricanes. Over the decades, sensor technology has evolved dramatically, moving beyond simple optical imaging to encompass a broad spectrum of electromagnetic wavelengths. Passive sensors, such as those found on the Moderate Resolution Imaging Spectroradiometer, capture naturally reflected or emitted energy, providing critical data on sea surface temperature, ocean phytoplankton levels, and global vegetation indices. However, passive optical sensors are inherently limited by their inability to penetrate cloud cover or operate during the night. To overcome these limitations, active remote sensing technologies were developed [5]. Synthetic Aperture Radar systems emit their own microwave pulses and measure the backscattered signal, enabling continuous observation of the Earth surface regardless of atmospheric conditions or solar illumination. This technology has proven indispensable for monitoring sea ice extent, measuring ground deformation through interferometry, and estimating forest biomass. Similarly, Light Detection and Ranging systems utilize laser pulses to create highly precise three-dimensional structural models of forest canopies and topographical features. The current landscape of Earth observation is defined by the integration of multiple data streams. International collaborative efforts, such as the Copernicus program, provide an unprecedented operational framework by deploying a constellation of Sentinel satellites tailored for specific environmental monitoring tasks, including atmospheric composition, marine environment tracking, and emergency management [6]. Furthermore, the miniaturization of satellite technology has led to the proliferation of CubeSats deployed by commercial entities. These mega-constellations offer daily global coverage at high spatial resolutions, significantly reducing the temporal revisit time and enabling the capture of highly dynamic environmental processes. This massive influx of multi-modal, high-frequency data forms the essential substrate upon which modern spatiotemporal predictive models are built.

2.2 Development of Spatiotemporal Modeling Techniques

The theoretical foundations of analyzing geographic and temporal data originate from the disciplines of geostatistics and time-series analysis. Early spatial modeling was heavily influenced by the fundamental

principle that near things are more related than distant things. This concept of spatial autocorrelation drove the development of interpolation techniques such as Kriging. Originally developed for the mining industry to estimate ore grades, Kriging provides a statistically optimal method for interpolating values at unobserved locations based on the spatial covariance of sampled points. Concurrently, temporal analysis relied on autoregressive integrated moving average models, which excel at forecasting future values in a stationary time series by leveraging lagged historical observations [7]. As the need to model phenomena that vary simultaneously across space and time grew, researchers sought to integrate these distinct methodologies. This led to the formulation of spatiotemporal autoregressive moving average models, which extended temporal forecasting techniques by incorporating a spatial weight matrix to account for neighborhood effects. While these stochastic models provided rigorous frameworks for understanding uncertainty and variance, they exhibited significant limitations when applied to the complex realities of Earth system observation. These traditional models predominantly assume linearity and stationarity, meaning they presume that the underlying physical processes remain constant over time and space. However, environmental variables, such as precipitation patterns or pollutant dispersion, are notoriously non-linear, non-stationary, and heavily influenced by external forcing mechanisms like topography and meteorological shifts. Furthermore, classical statistical models suffer from the curse of dimensionality; their computational complexity scales exponentially with the number of observation points, rendering them impractical for processing modern high-resolution satellite imagery or global climate grids [8]. To address these limitations, the scientific community increasingly turned to machine learning algorithms. Early adoption involved shallow algorithms such as Support Vector Machines and Random Forests. These data-driven models demonstrated superior capability in capturing non-linear relationships without requiring strict assumptions about data distribution. Random Forests, for instance, became widely used for classifying land cover types from multispectral satellite data and for estimating continuous environmental variables like soil moisture and forest biomass through regression techniques [9]. Despite their success, these traditional machine learning models generally treat data points as independent and identically distributed, fundamentally failing to explicitly model the intrinsic spatiotemporal autocorrelation present in Earth observation data. Analysts had to rely on manual feature engineering, crafting complex input variables that encapsulated spatial coordinates and temporal lags, a process that is both labor-intensive and prone to overlooking complex, multi-scale dependencies. The critical breakthrough in spatiotemporal modeling occurred with the advent of deep learning architectures. Deep neural networks, with their hierarchical structures and vast number of parameters, possess the inherent capacity to automatically learn complex feature representations directly from raw data. This paradigm shift eliminated the bottleneck of manual feature extraction and provided architectures specifically designed to handle sequential and grid-like data structures [10]. The application of these advanced architectures to Earth observation data marked the beginning of a new era in environmental prediction, enabling models to ingest vast multidimensional arrays of atmospheric, oceanic, and terrestrial data and produce highly accurate forecasts of future environmental states.

Table 1: Comparison of Methodological Approaches in Environmental Modeling

Model Category	Primary Techniques	Strengths	Limitations
Classical Statistical	Kriging, Spatial Autoregression	Theoretical rigor, uncertainty quantification	Cannot handle high-dimensional data, assumes linearity
Traditional Machine Learning	Random Forests, Support Vector Regression	Captures non-linear relationships, robust to outliers	Ignores inherent spatiotemporal dependencies, requires manual features
Deep	Convolutional	Automatic feature	Black-box nature,

Learning	Networks, Recurrent Networks	extraction, handles massive datasets	requires large training data, high computational cost
Physics-Informed ML	Hybrid Neural Networks, Differentiable Physics	Obeys physical laws, better generalization, highly interpretable	Complex to formulate loss functions, difficult to balance gradients

3. Methodological Frameworks and Analysis

3.1 Data Acquisition and Preprocessing Strategies

The process of transforming raw Earth observation measurements into a format suitable for complex spatiotemporal predictive modeling requires extensive preprocessing and data assimilation. Observational data collected from satellite sensors, often referred to as Level 0 data, consists of raw, unprocessed instrument telemetry. Before this data can be utilized for scientific analysis or ingested into machine learning models, it must undergo a rigorous pipeline of radiometric calibration and geometric correction [11]. Radiometric calibration converts the raw digital numbers recorded by the sensor into physically meaningful units, such as top-of-atmosphere reflectance or spectral radiance, accounting for sensor degradation over time. Geometric correction is equally critical, as it maps the image pixels to precise geographic coordinates on the Earth surface, compensating for the distortions caused by satellite altitude variations, sensor viewing angles, and the curvature and topography of the planet. One of the most persistent challenges in utilizing optical remote sensing data for spatiotemporal analysis is the ubiquitous presence of clouds and atmospheric aerosols. Clouds can obscure significant portions of the Earth surface, resulting in datasets that are spatially incomplete and temporally irregular. To mitigate this, researchers employ sophisticated cloud masking algorithms that utilize multiple spectral bands, particularly thermal and shortwave infrared, to distinguish between clouds, snow, and the underlying surface. Once the contaminated pixels are masked, the resulting data gaps must be addressed to create the continuous data cubes required by predictive models. Gap-filling techniques range from simple temporal interpolation and spatial smoothing to advanced deep learning methods, such as generative adversarial networks, which reconstruct missing areas by learning the contextual spatial patterns and temporal trajectories of the surrounding unclouded data [12].

Beyond individual satellite datasets, modern spatiotemporal modeling relies heavily on data assimilation techniques. Data assimilation is the science of combining diverse, often disparate observations with a dynamic physical model to produce a coherent, statistically optimal estimate of the evolving state of the Earth system. This is particularly relevant in atmospheric and oceanic sciences, where satellite observations are merged with data from weather balloons, buoys, and commercial aircraft. Algorithms such as the Ensemble Kalman Filter and variational data assimilation techniques mathematically balance the uncertainties inherent in the observational instruments with the uncertainties of the physical models. The output of these assimilation systems, known as reanalysis datasets, provide globally gridded, continuous, and physically consistent records of essential climate variables over decades. These reanalysis products are frequently employed as both the training ground truth and the input features for modern spatiotemporal predictive neural networks.

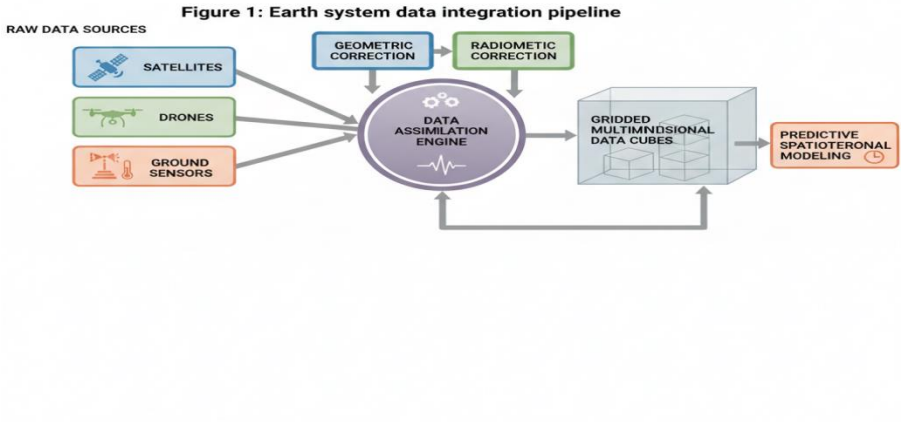


Figure 1: Earth system data integration pipeline

3.2 Advanced Predictive Architectures

The architectural design of deep learning models for spatiotemporal prediction is primarily dictated by the need to capture spatial hierarchies and temporal dynamics simultaneously. For modeling spatial context, Convolutional Neural Networks have become the foundational building block. Originally designed for computer vision tasks, these networks utilize localized filters that slide across two-dimensional spatial grids, automatically learning features ranging from simple edges to complex spatial textures. In the context of Earth observation, these grids typically represent maps of environmental variables such as land surface temperature or precipitation estimates. By stacking multiple convolutional layers, the network can capture broad spatial dependencies, recognizing how atmospheric pressure anomalies in one region might influence weather patterns thousands of kilometers away [13]. To address the temporal dimension, Recurrent Neural Networks, particularly Long Short-Term Memory networks and Gated Recurrent Units, are widely utilized. These architectures possess internal memory mechanisms that allow them to maintain a hidden state representing the historical context of the data sequence. This is essential for environmental prediction, where the current state of a variable, such as soil moisture, is highly dependent on cumulative previous rainfall and evaporation rates. However, traditional recurrent networks process sequences as flat vectors, inherently losing the spatial structure of the data. To bridge this gap, researchers developed the Convolutional Long Short-Term Memory network, an architecture that replaces the dense matrix multiplications within the recurrent cells with convolution operations. This structural innovation allows the network to process sequences of spatial grids, explicitly learning how spatial patterns evolve over time. These networks have become a standard baseline for a wide variety of predictive tasks in Earth science, including precipitation nowcasting, sea ice movement prediction, and urban air pollution forecasting [14].

Despite their utility, convolutional approaches are optimized for data structured on regular Euclidean grids, which poses significant challenges for global Earth system observation. Representing the spherical Earth on a flat grid inevitably introduces severe spatial distortions, particularly near the poles, violating the assumptions of standard convolution operations. Furthermore, many critical environmental observation networks, such as ground-based air quality monitoring stations or river gauge networks, are irregularly distributed across the landscape, forming complex topologies rather than neat grids. To analyze this non-Euclidean data, Graph Neural Networks have emerged as a powerful spatiotemporal tool. In a graph-based representation, monitoring stations or geographic regions are treated as nodes, and the physical distances, wind trajectories, or hydrological connections between them are modeled as weighted edges. Graph Convolutional Networks can propagate information across this network

structure, capturing complex spatial relationships that are constrained by physical geography rather than simple grid proximity. By integrating graph convolutions with recurrent temporal units, researchers can accurately predict localized environmental phenomena across dispersed sensor networks. Most recently, the field has been revolutionized by the adaptation of Transformer architectures and attention mechanisms. Unlike recurrent networks, which process data sequentially and struggle with very long-term dependencies, Transformers evaluate the entire temporal sequence simultaneously. The core innovation, the self-attention mechanism, allows the model to dynamically weigh the importance of different spatial locations and past time steps relative to the prediction target. For instance, when forecasting a drought, an attention-based model can automatically learn to focus heavily on precipitation deficits from several months prior, while disregarding less relevant interim fluctuations. Vision Transformers have also been adapted to process satellite imagery, splitting data cubes into patches and utilizing attention to model global dependencies across the entire field of view much more efficiently than deep convolutional networks [15]. The ultimate evolution of these predictive architectures involves the integration of physics-informed constraints. Purely data-driven deep learning models are often described as black boxes; they can achieve high predictive accuracy on the test dataset but may produce physically impossible results when deployed in novel scenarios. Physics-Informed Neural Networks address this by embedding partial differential equations representing established physical laws directly into the model training process. During optimization, the network calculates a loss function that penalizes not only the prediction error relative to the observational data but also any violations of the governing physical equations, such as the Navier-Stokes equations for fluid dynamics or conservation of mass principles. This hybrid approach ensures that the model respects the fundamental constraints of the Earth system, significantly improving its reliability, interpretability, and ability to extrapolate predictions into unprecedented future climate states.

4. Results and Discussion

4.1 Climate Modeling and Weather Forecasting

The application of advanced spatiotemporal modeling has yielded transformative results in the realm of climate and weather prediction. Historically, weather forecasting has relied almost exclusively on Numerical Weather Prediction models. These physical models divide the atmosphere into a three-dimensional grid and utilize massive supercomputers to step forward in time by solving complex thermodynamic and fluid dynamic equations. While highly accurate, these models are extraordinarily computationally expensive and often struggle to capture localized, rapid-onset events with high precision due to necessary parameterization of sub-grid scale processes like cloud formation [16]. Recent literature demonstrates that spatiotemporal deep learning models are rapidly approaching, and in specific contexts exceeding, the performance of traditional numerical models. For ultra-short-term forecasting, known as nowcasting, data-driven spatiotemporal networks have shown remarkable success. By treating precipitation prediction as a video prediction task, where sequential radar reflectivity images are fed into Convolutional Long Short-Term Memory networks or advanced Generative Adversarial Networks, researchers have generated highly accurate, high-resolution precipitation forecasts up to six hours in advance. These neural networks operate in a fraction of the time required by physical models, allowing for near-instantaneous updates as new radar observations are ingested. This rapid predictive capability is critical for issuing timely flash flood warnings and managing aviation routing during severe weather events. On a global scale, artificial intelligence models designed to predict medium-range weather phenomena, such as global geopotential height and temperature fields, have demonstrated the ability to produce operational forecasts that rival leading physical systems. By training deep spatiotemporal architectures on decades of global reanalysis data, these models learn the complex, multi-scale atmospheric dynamics governing global circulation. The results show that data-driven models can accurately predict the trajectory of extreme events, such as the track and intensity of tropical cyclones, several days in advance with reduced computational overhead. Furthermore, spatiotemporal modeling has been effectively utilized in statistical downscaling, a critical process in climate science.

Global Climate Models project long-term climate trends at very coarse spatial resolutions. Using super-resolution convolutional networks, researchers successfully map these low-resolution global projections to high-resolution local impacts, accurately predicting regional temperature and precipitation shifts necessary for local adaptation planning.

Table 2: Typical Earth Observation Data Sources and Spatiotemporal Characteristics

Data Source Type	Common Sensors / Instruments	Typical Spatial Resolution	Typical Temporal Frequency
Geostationary Satellites	Advanced Baseline Imager	1 km to 4 km	5 minutes to 15 minutes
Polar Orbiting Optical	Landsat OLI, Sentinel-2 MSI	10 m to 30 m	5 days to 16 days
Active Microwave (SAR)	Sentinel-1 C-Band SAR	5 m to 20 m	6 days to 12 days
Terrestrial Sensor Networks	Air Quality Monitors, Stream Gauges	Point-based (Irregular)	Continuous / Hourly

4.2 Ecological and Hazard Monitoring

Beyond atmospheric predictions, spatiotemporal frameworks are extensively applied to terrestrial ecology and natural hazard management. A primary area of success is the monitoring and prediction of agricultural conditions. Crop yield estimation is a highly complex problem that depends on the interplay of dynamic meteorological variables, static soil properties, and specific crop phenology over the growing season. By utilizing Recurrent Neural Networks integrated with attention mechanisms, researchers have effectively analyzed time-series stacks of multispectral satellite vegetation indices combined with weather data to predict end-of-season crop yields with high fidelity months before the actual harvest. This capability provides essential foresight for global food security analysis and agricultural commodities markets. Forest ecology and wildfire management have also benefited immensely from these advancements. Wildfires are profoundly influenced by spatiotemporal variables including historical drought severity, fuel load accumulation derived from optical imagery, topography, and real-time wind vectors. Graph Neural Networks and convolutional models have been deployed to assess daily wildfire susceptibility across vast forested regions. These models continuously ingest satellite-derived land surface temperature and moisture indices to identify areas at imminent risk of ignition and to predict the rapid spatial expansion of active fire fronts. The results indicate that incorporating the temporal memory of vegetation dryness significantly improves the true positive rate of fire prediction compared to relying solely on current-day meteorological metrics. In urban environments, the spatiotemporal prediction of air quality, specifically the concentration of fine particulate matter and nitrogen dioxide, remains a critical public health application. Urban air pollution is characterized by high spatial variability due to the complex canyon effects of city architecture and dynamic temporal patterns driven by traffic emissions and planetary boundary layer fluctuations. Traditional dispersion models require exhaustive emissions inventories and computational fluid dynamic simulations. Conversely, spatiotemporal graph convolutional networks have demonstrated exceptional capability in forecasting urban air quality by modeling the urban sensor network as a graph. These models successfully capture the complex dispersion patterns by weighting the graph edges using historical wind direction data and proximity metrics. Empirical results consistently show that hybrid networks, which combine spatial graph convolutions with temporal recurrent units, significantly outperform traditional time-series forecasting algorithms, providing highly localized and accurate pollution forecasts that enable city administrations to issue targeted health advisories.

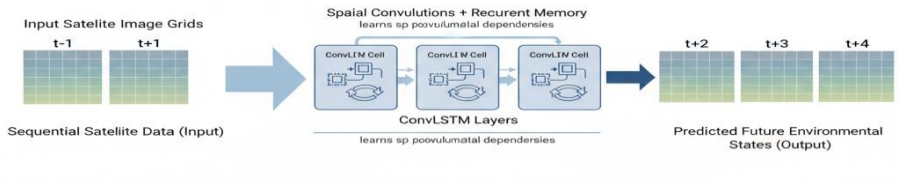


Figure 2: Spatiotemporal prediction architecture

5. Conclusion

The comprehensive observation of the Earth system and the subsequent modeling of its intricate spatiotemporal dynamics are essential endeavors for understanding and managing our rapidly changing global environment. This review has synthesized the critical advancements in the field, highlighting the transition from classical, independent spatial and temporal statistical methods to sophisticated, integrated deep learning architectures. The proliferation of remote sensing data, characterized by increasing spectral, spatial, and temporal resolutions, provides an unprecedented observational foundation. However, it is the evolution of advanced methodological frameworks, particularly Convolutional Neural Networks, Graph Neural Networks, and attention-based Transformers, that has unlocked the predictive potential of this massive data volume. The empirical results across diverse applications demonstrate the remarkable efficacy of these spatiotemporal models. In climate and weather prediction, deep learning architectures are achieving forecasting accuracies that challenge established numerical weather prediction systems while requiring orders of magnitude less computational time during the inference phase. In ecological and hazard monitoring, the ability to continuously analyze multidimensional data streams has facilitated proactive management strategies, from predicting crop yields to forecasting urban air pollution dispersion and wildfire expansion. These successes underscore the transformative impact of artificial intelligence in environmental science. Nevertheless, significant challenges persist that must guide future research. The prevailing black-box nature of purely data-driven models raises critical concerns regarding their interpretability and their reliability under novel, unprecedented climate conditions. The scientific community is currently addressing this through the development of physics-informed neural networks, which represent a crucial step toward harmonizing empirical machine learning with fundamental thermodynamic and fluid dynamic laws. Furthermore, managing the computational demands of processing global, high-resolution, long-term spatiotemporal datasets requires continued innovation in efficient algorithmic design and distributed computing infrastructure. Ultimately, the synthesis of comprehensive Earth observation networks with robust, physics-constrained spatiotemporal modeling frameworks is paving the way toward the realization of highly accurate Digital Twins of the Earth. These advanced digital replicas will provide unparalleled capabilities for simulating environmental scenarios, optimizing resource management, and developing robust strategies to navigate the profound environmental challenges of the future [17].

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