

A Critical Review of Methodological Advances, Data Fusion Strategies, and Emerging Challenges

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Abstract

The confluence of big data from Earth observation satellites, ground-based sensor networks, and climate models has created unprecedented opportunities for artificial intelligence to enhance climate change prediction. Yet the rapid proliferation of methodological approaches has outpaced systematic synthesis of best practices, data fusion strategies, and persistent limitations. This paper presents a critical systematic review of 142 peer-reviewed studies published between 2019 and 2025 that employ AI techniques for climate prediction using multi-source geospatial data. We synthesize advances across three analytical domains: temperature and extreme event forecasting, precipitation estimation, and long-term climate trend modeling. The review identifies a decisive shift from conventional machine learning methods toward hybrid architectures that combine deep learning with physical models, with convolutional neural networks and long short-term memory networks demonstrating particular efficacy for spatial and temporal pattern recognition respectively. However, we find that data heterogeneity remains the paramount methodological challenge, with inconsistent preprocessing, scale mismatches, and quality control procedures impeding model generalizability. Furthermore, a critical gap emerges: only 12% of reviewed studies explicitly address model interpretability or uncertainty quantification, limiting operational deployment for high-stakes decision-making. We propose a standardized framework for AI-driven climate prediction that prioritizes reproducible data fusion pipelines, benchmark datasets for model intercomparison, and integration of explainable AI techniques. The paper concludes that while AI has substantially advanced predictive capabilities, realizing its full potential requires shifting from performance maximization to systematic handling of data uncertainty, physical consistency, and actionable interpretability for climate resilience planning.

Keywords: artificial intelligence, climate change prediction, remote sensing, data fusion, deep learning, geospatial analysis

1. Introduction

The accelerating pace of climate change has intensified demands for more accurate, granular, and timely predictions of environmental phenomena. From the frequency of category five cyclones in the Atlantic basin to the duration of drought periods in sub-Saharan Africa, the ability to anticipate climate-related events directly influences disaster preparedness, agricultural planning, infrastructure investment, and human survival. Yet the fundamental challenge confronting climate scientists has shifted in character over the past decade. The problem is no longer insufficient data; it is the overwhelming abundance of heterogeneous, multi-scale, and often inconsistent data streaming from satellites, weather stations, ocean buoys, and climate models. This paradox of plenty—the simultaneous availability of more information than ever before and the persistent difficulty of extracting reliable predictions from it—defines the current moment in climate science.

Remote sensing platforms have revolutionized the observational foundation of climate prediction. The Landsat, Sentinel, and MODIS missions, among others, generate petabytes of imagery annually, capturing land surface temperature, vegetation health, atmospheric composition, and oceanic conditions at spatial resolutions that would have seemed fantastical two decades ago. Concurrently, the Internet of Things has enabled dense ground-based sensor networks that measure localized variables—soil moisture, air quality, precipitation intensity—with high temporal frequency. These data sources are complemented by reanalysis products that blend observations with numerical models to produce spatially and temporally continuous climate fields. Together, these resources constitute what scholars have termed geospatial big data: voluminous, varied, and velocity-driven information that exceeds the analytical capacity of conventional statistical methods.

Artificial intelligence has emerged as the leading response to this analytical challenge. Machine learning and deep learning architectures have demonstrated remarkable aptitude for identifying patterns within high-dimensional geospatial data, learning nonlinear relationships that physics-based models struggle to capture, and generating predictions at computational speeds that

enable near-real-time applications. The literature has documented successful applications across virtually every domain of climate prediction: forecasting extreme precipitation events with lead times that outperform traditional numerical weather prediction, mapping urban heat islands at neighborhood scales, estimating crop yields under drought stress, and modeling sea surface temperature anomalies that drive El Niño-Southern Oscillation forecasts.

However, a closer examination of this rapidly growing literature reveals a troubling pattern. The overwhelming majority of studies prioritize predictive accuracy as the singular metric of success, with model performance reported in terms of R^2 values, root mean square errors, and classification accuracies that often exceed 95%. What these studies typically neglect, or address only in passing, are the foundational decisions that precede model training: how to harmonize data from different sensors with different spatial resolutions, how to handle missing observations and measurement errors, how to ensure that predictions remain physically plausible, and how to communicate uncertainty to end users who must act on those predictions. These are not peripheral concerns but central determinants of whether AI-driven climate prediction will translate from academic demonstration to operational utility.

This paper addresses this gap through a systematic critical review of the literature on AI-based climate change prediction using multi-source geospatial data. We pose three research questions. First, what methodological approaches have been developed for integrating satellite, in situ, and model-derived data for climate prediction, and what are their relative strengths and limitations? Second, what persistent challenges—data-related, computational, or epistemological—constrain the accuracy and generalizability of current approaches? Third, what frameworks or best practices might guide more rigorous, reproducible, and actionable AI-driven climate prediction in the future?

The theoretical framing of this review draws on critical data studies and the emerging field of geo-computational ethics. Rather than treating data as neutral inputs to objective algorithms, we follow scholars who argue that decisions about data selection, preprocessing, fusion, and validation embed value judgments that shape predictive outcomes in consequential ways. The choice to prioritize satellite-derived land surface temperature over ground-based measurements, for example, privileges spatial coverage over localized accuracy. The decision to impute missing data using mean values rather than spatial interpolation propagates assumptions about environmental homogeneity that may be demonstrably false. These choices are not merely technical; they are epistemic, and they warrant the same critical scrutiny that

model architecture and parameter tuning have historically received.

The remainder of the paper proceeds as follows. Section two presents a synthesized review of the literature, organized by data sources, AI methodologies, and application domains, with critical attention to the handling of data fusion and uncertainty. Section three describes our systematic review methodology, including search strategies, inclusion criteria, and analytical framework. Section four presents findings on methodological trends, data challenges, and gaps. Section five discusses implications for practice and proposes a standardized framework. Section six concludes with recommendations for future research.

2. Literature Review

2.1 The Data Landscape: Sources, Characteristics, and Challenges

Contemporary climate prediction draws on an increasingly diverse array of data sources, each with distinctive spatial, temporal, and spectral characteristics. Satellite-based Earth observation constitutes the most voluminous category, encompassing optical sensors that measure reflected solar radiation in visible and near-infrared bands, thermal infrared sensors that estimate land and sea surface temperatures, passive microwave radiometers that penetrate cloud cover to retrieve atmospheric profiles, and active sensors including synthetic aperture radar and LiDAR that capture surface structure and topography.

The spatial resolution of satellite data varies by orders of magnitude, from the 250-meter bands of MODIS to the 10-meter resolution of Sentinel-2 to the sub-meter imagery available from commercial platforms. Temporal resolution exhibits similar variation: geostationary satellites provide observations every 15 to 30 minutes but at coarse spatial resolution, while polar-orbiting platforms offer higher spatial resolution at the cost of revisit intervals ranging from several days to two weeks. Spectral resolution—the number and width of wavelength bands measured—ranges from the panchromatic single band of early Landsat sensors to the 200-plus bands of modern hyperspectral imagers.

This heterogeneity presents a fundamental challenge for AI-driven prediction. Models trained on data from one sensor often fail to generalize to data from another sensor, even when both are ostensibly measuring the same environmental variable. The reasons for this failure are multiple: differences in overpass time affect the diurnal cycle sampled, variations in bandpass characteristics alter the spectral information available, and differences in preprocessing algorithms introduce systematic biases that are difficult to detect and correct.

Ground-based and in situ data offer complementary but differently imperfect information. Weather stations, river gauges, ocean buoys, and soil moisture sensors provide measurements that are generally more accurate than satellite retrievals at point locations. However, these networks are spatially sparse and unevenly distributed: dense in North America and Europe, sparse across much of Africa, South America, and Southeast Asia, and virtually absent from polar and oceanic regions. The disparity between data-rich and data-sparse regions introduces systematic biases into global models and raises questions about the representativeness of training data.

2.2 AI Methodologies for Climate Prediction: From Classical Machine Learning to Hybrid Architectures

The AI techniques applied to climate prediction have evolved substantially over the past decade. Early studies relied on classical machine learning methods including random forests, support vector machines, and gradient boosting, which proved effective for classification and regression tasks with moderate-dimensional input spaces. These methods offer advantages in interpretability: feature importance scores can be extracted, decision boundaries are relatively transparent, and model behavior can be audited more readily than with deep learning alternatives.

However, classical methods encounter limitations when applied to the high-dimensional, spatially structured data that characterize climate prediction. Images, time series, and the combination thereof exceed the capacity of flat vector representations. Consequently, the field has shifted decisively toward deep learning architectures designed for structured data. Convolutional neural networks have become the standard for spatial feature extraction, learning hierarchical representations from raw imagery without manual feature engineering. Researchers have applied CNNs to tasks ranging from cloud detection to land cover classification to estimation of surface variables from satellite radiances.

For temporal prediction tasks, recurrent neural networks and their variant long short-term memory networks have demonstrated substantial skill. LSTMs are specifically designed to capture dependencies across time steps, making them well-suited to forecasting tasks such as precipitation, temperature, and streamflow. A growing number of studies combine CNNs and LSTMs in hybrid architectures that extract spatial features from imagery at each time step then model temporal evolution across the sequence, an approach that has proven particularly

effective for precipitation nowcasting and extreme event prediction.

The most recent methodological innovation involves hybrid physics-AI models that integrate neural networks with numerical climate models. Rather than replacing physical process representations entirely, these approaches use AI to learn sub-grid scale processes, parameterize unresolved dynamics, or correct systematic biases in model output. The rationale is compelling: physics-based models embed fundamental conservation laws and domain knowledge that pure data-driven approaches violate, while AI offers flexibility and computational efficiency that physics-based models lack. Early results suggest that hybrid approaches can outperform both pure physics and pure data-driven methods, particularly for predicting extreme events whose occurrence is rare in training data.

2.3 Data Fusion Strategies: From Simple Stacking to Multi-Scale Integration

The integration of data from multiple sources—data fusion—represents perhaps the most consequential methodological decision in AI-driven climate prediction. The literature reveals a spectrum of fusion strategies, ranging from straightforward concatenation of features to sophisticated architectures designed to handle spatial, temporal, and spectral heterogeneity.

At the simplest level, early fusion involves stacking features from different sources into a single input vector or multi-band image. This approach is computationally efficient and easy to implement, but it implicitly assumes that all data sources are spatially and temporally aligned, that their measurement scales are comparable, and that their information content is complementary rather than redundant. These assumptions frequently fail in practice. Satellite and ground-based data rarely coincide perfectly in space or time, their units and error characteristics differ, and collinearity among predictors can degrade model performance.

Intermediate fusion strategies address some of these limitations by performing feature extraction separately for each data source before combination. For example, a CNN might process satellite imagery to extract spatial features, a separate LSTM might process time series from in situ sensors, and the extracted features could then be concatenated and passed to a final prediction layer. This approach respects the structural differences among data sources and allows for modality-specific preprocessing. However, it still requires that features be extracted independently, potentially missing cross-modal interactions that could improve prediction.

Late fusion, or decision-level fusion, goes further by training separate models on each data source then combining their predictions, typically through averaging or voting. This approach

offers robustness: if one data source is unavailable or degraded, the remaining models can still produce predictions. It also facilitates interpretation by allowing attribution of predictive contributions to specific data sources. However, late fusion cannot exploit correlations across data sources during feature extraction, potentially leaving predictive information on the table. The frontier of fusion research involves learned fusion architectures that dynamically weight data sources based on their estimated reliability, spatial coverage, or relevance to the prediction task. Attention mechanisms, originally developed for natural language processing, have been adapted to learn which parts of the input—which spatial locations, time steps, or data sources—are most informative for a given prediction. These mechanisms can be trained end-to-end alongside the prediction model, optimizing the fusion strategy for the specific task at hand. Preliminary evidence suggests that attention-based fusion outperforms fixed strategies, particularly in heterogeneous environments where data quality and relevance vary spatially.

2.4 Persistent Gaps: Interpretability, Uncertainty, and Physical Consistency

Despite substantial methodological advances, the literature exhibits three persistent gaps that limit the operational utility of AI-driven climate prediction. First, model interpretability remains an afterthought in most studies. The black-box nature of deep learning models, particularly at the scale required for climate prediction, impedes scientific understanding, model debugging, and stakeholder trust. Without understanding why a model made a particular prediction, researchers cannot determine whether it learned a genuine physical relationship or a spurious correlation. They cannot identify failure modes, assess vulnerability to distributional shift, or generate scientific insights about climate processes.

Second, uncertainty quantification is routinely neglected or handled inadequately. Climate predictions are inherently uncertain, and decision-makers require characterizations of that uncertainty to assess risk and plan responses. Yet the vast majority of AI studies report point predictions without confidence intervals, prediction intervals, or probabilistic forecasts. The few studies that address uncertainty typically rely on approximate methods, such as Monte Carlo dropout, whose theoretical guarantees are weak and whose empirical calibration is rarely assessed.

Third, physical consistency is not enforced or evaluated. AI models trained on historical data may learn relationships that violate fundamental physical laws—conservation of mass, energy balance, thermodynamic constraints—and may generate predictions that are internally

inconsistent (e.g., predicting both increasing evapotranspiration and decreasing net radiation). Such violations undermine confidence in predictions, particularly for extrapolation beyond the range of historical conditions. Emerging research on physics-informed neural networks offers one path forward, but these methods remain computationally intensive and have not been widely adopted for operational climate prediction.

The synthesis of this literature reveals a field at an inflection point. The technical capabilities of AI for climate prediction have advanced impressively, yet the methodological foundations remain fragmented and the standards for rigorous evaluation remain underdeveloped. The present paper contributes a systematic analysis that moves beyond cataloging successes to identify structural gaps and propose standardized practices that might accelerate progress.

3. Methodology

3.1 Research Design

This study employs a systematic literature review design following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework. The systematic review is appropriate for research questions that require comprehensive identification, appraisal, and synthesis of existing evidence. Unlike narrative reviews, which risk selective citation and subjective synthesis, systematic reviews follow explicit, reproducible procedures designed to minimize bias.

We augmented the systematic review with critical interpretive synthesis, a methodology that extends traditional systematic review by attending not only to what the literature reports but also to what it assumes, what it overlooks, and how it frames problems. This dual approach allows us to document methodological trends quantitatively while also interrogating the epistemic assumptions that shape those trends.

3.2 Search Strategy

We conducted systematic searches of three electronic databases: Scopus, Web of Science, and the IEEE Xplore Digital Library. The search strategy combined terms related to artificial intelligence or machine learning, terms related to climate prediction or climate modeling, and terms related to remote sensing or geospatial data. The complete search string, developed iteratively through pilot testing, was: (AI OR artificial intelligence OR machine learning OR deep learning OR neural network OR CNN OR LSTM) AND (climate prediction OR climate

forecasting OR extreme event prediction OR precipitation forecast) AND (remote sensing OR satellite data OR geospatial data OR Earth observation).

The search was limited to peer-reviewed journal articles and conference papers published in English between January 2019 and December 2025. This time frame captures the period of most rapid growth in AI applications to climate prediction while maintaining a manageable corpus for analysis. The initial search yielded 1,247 unique records after duplicate removal.

3.3 Screening and Inclusion Criteria

Title and abstract screening excluded records that were not primarily focused on climate prediction (excluding, for example, studies on climate adaptation or mitigation without prediction components) or that did not employ AI methods (including studies using only traditional statistics or process-based modeling). Full-text screening applied the following inclusion criteria: the study must (1) employ one or more AI methods for prediction, (2) use geospatial data from at least one remote sensing source, (3) report quantitative prediction performance metrics, and (4) include sufficient methodological detail to permit replication. Exclusion criteria included studies focused exclusively on atmospheric modeling without geospatial data, studies of climate impacts on non-environmental outcomes, and conference abstracts without full papers.

Full-text screening of the remaining 312 articles resulted in a final analytic sample of 142 studies. The primary reasons for exclusion at this stage were insufficient methodological detail (34% of exclusions), lack of quantitative evaluation (28%), and focus on post-prediction applications rather than prediction itself (22%).

3.4 Data Extraction and Analysis

From each included study, we extracted information across five dimensions: (1) data sources and characteristics (sensor types, spatial and temporal resolution, preprocessing procedures); (2) AI methodology (model architecture, training procedures, hyperparameter optimization); (3) prediction target (variable predicted, spatial and temporal scale, lead time); (4) performance metrics (accuracy measures, validation approach, reported uncertainty); and (5) handling of key methodological issues (data fusion strategy, missing data imputation, interpretability, physical consistency).

Extraction was performed independently by two researchers using a standardized coding form

developed through pilot testing on 20 randomly selected studies. Inter-coder reliability, assessed using Cohen's kappa, was 0.84 for categorical variables and 0.79 for continuous variables. Disagreements were resolved through discussion and, where necessary, consultation with a third researcher.

Quantitative analysis focused on descriptive statistics and trend analysis: the distribution of AI methods over time, the prevalence of different data fusion strategies, and the frequency with which interpretability and uncertainty were addressed. Qualitative analysis employed thematic synthesis to identify recurring challenges, gaps, and recommendations across studies.

3.5 Limitations

Several limitations of this review warrant acknowledgment. First, despite systematic search procedures, we may have missed relevant studies published in non-English languages or in journals not indexed by the selected databases. Second, the review is subject to publication bias: studies reporting positive results or high accuracy are more likely to be published and thus overrepresented in our sample. Third, the rapid pace of methodological development means that some recent advances may not yet have appeared in the peer-reviewed literature. Fourth, our assessment of how studies handle interpretability and uncertainty is necessarily based on what authors choose to report; absence of discussion may reflect either neglect or editorial space constraints rather than actual practice.

4. Findings

4.1 Methodological Trends

Analysis of the 142 included studies reveals clear temporal trends in AI methodology for climate prediction. Between 2019 and 2021, classical machine learning methods—random forests, support vector machines, gradient boosting—dominated the literature, accounting for 58% of studies in 2019. From 2022 onward, deep learning methods increased rapidly, surpassing classical methods in 2023 and accounting for 71% of studies published in 2025.

Among deep learning architectures, CNNs appear most frequently (present in 54% of deep learning studies), followed by LSTMs (41%) and hybrid CNN-LSTM architectures (28%). The preference for CNNs reflects the spatial nature of most climate prediction tasks: land surface temperature, vegetation indices, and precipitation fields are inherently spatial, making convolution a natural inductive bias. LSTMs are preferentially employed for temporal

forecasting tasks, including streamflow prediction and drought forecasting, where sequential dependencies dominate.

Geographically, the literature is heavily concentrated. Studies led by authors from North America (37% of studies), China (28%), and Western Europe (19%) account for 84% of the sample. Africa, South America, and Southeast Asia together account for less than 8%, despite these regions being disproportionately vulnerable to climate impacts and having some of the greatest potential benefit from improved prediction. This geographic disparity raises concerns about the generalizability of methods developed in temperate, data-rich contexts to tropical, data-sparse regions with different climate dynamics and observational infrastructures.

4.2 Data Fusion Practices

Data fusion strategies varied substantially across studies, with early fusion (feature stacking) being most common (47% of studies), followed by intermediate fusion (separate feature extraction then combination) (34%), and late fusion (model ensemble) (15%). Only 4% of studies employed learned or attention-based fusion.

Crucially, the choice of fusion strategy was not consistently justified in relation to the data characteristics or prediction task. In many cases, early fusion appeared to be the default rather than a deliberate choice, adopted because it was straightforward to implement rather than because it was theoretically appropriate. This pattern suggests that data fusion is often treated as a preprocessing step rather than a core modeling decision requiring careful consideration.

Spatial and temporal scale mismatches between data sources were widely acknowledged as challenges (mentioned in 76% of studies) but rarely addressed rigorously (only 23% of studies reported explicit procedures for scale harmonization). The most common approach was resampling all data to the coarsest spatial or temporal resolution among the sources, a method that discards fine-scale information and may introduce artifacts. More sophisticated approaches, including geostatistical fusion and area-to-point kriging, appeared only rarely, likely due to their computational demands and implementation complexity.

4.3 Persistent Gaps: Interpretability and Uncertainty

The most striking finding concerns the neglect of model interpretability and uncertainty quantification. Only 12% of studies explicitly addressed model interpretability, meaning that they attempted to explain why the model made particular predictions or which input features

were most influential. Among these, the dominant approach was permutation feature importance or Shapley additive explanations (SHAP) applied post hoc. Notably, no studies incorporated interpretability as a design criterion during model development; it was always an add-on applied after model training was complete.

Uncertainty quantification fared little better. Only 17% of studies reported any form of prediction interval, confidence interval, or probabilistic forecast. Among these, the most common method was Monte Carlo dropout, an approximate Bayesian technique whose calibration properties are poorly understood for spatial prediction tasks. Ensemble methods, which provide natural uncertainty estimates through prediction variance across ensemble members, were used in only 9% of studies. No studies reported formal evaluation of uncertainty calibration, such as probability-probability plots or reliability diagrams.

Table 1: Prevalence of Methodological Practices in AI Climate Prediction Literature (N=142)*

Practice	Percentage of studies
Reports accuracy metrics	100%
Uses deep learning (2025)	71%
Explicit data fusion strategy	64%
Addresses scale mismatches	23%
Addresses model interpretability	12%
Reports uncertainty quantification	17%
Evaluates uncertainty calibration	0%
Enforces physical consistency	8%
Validates on independent spatiotemporal data	31%
Makes code or data available	22%

Physical consistency constraints were addressed in only 8% of studies. The few studies that did address this issue typically employed physics-informed loss functions, adding terms to the training objective that penalize violations of known physical laws (e.g., conservation of energy, non-negativity of certain variables). While promising, these methods remain challenging to implement and computationally expensive, limiting their adoption.

Perhaps most concerning, only 31% of studies validated their models on independent spatiotemporal data—that is, data from different geographic regions or different time periods than the training data. The remainder relied on random splitting of data, which dramatically overestimates performance for spatial and temporal prediction tasks because nearby points in space and time are not independent. The implications of this widespread practice are substantial: reported accuracies may be systematically inflated relative to what would be achieved in operational deployment.

5. Discussion

The findings of this systematic review reveal a field characterized by rapid methodological innovation and impressive predictive achievements, yet also by systematic neglect of foundational issues that determine real-world utility. The pattern is not one of failure but of incomplete development: researchers have convincingly demonstrated what AI can achieve under idealized conditions but have not yet developed the methodological infrastructure needed to translate those demonstrations into reliable operational tools.

The neglect of model interpretability is particularly consequential. Climate prediction is not a purely predictive enterprise; it is also a scientific enterprise aimed at understanding the mechanisms driving environmental change. A black-box model that predicts precipitation accurately provides no insight into why that precipitation occurs, what physical processes are responsible, or how those processes might change under future warming scenarios. Without interpretability, AI models cannot contribute to the accumulation of scientific knowledge; they can only produce outputs. Furthermore, interpretability is essential for building trust with decision-makers who must act on model predictions.

The absence of uncertainty quantification is equally troubling. Decision-makers rarely need point forecasts; they need risk assessments that characterize the range of possible outcomes and their likelihoods. An early warning system for floods, for example, must trade off false alarms

(which erode trust and incur response costs) against missed events (which cost lives). Optimal decision-making requires probabilistic information that current AI climate models do not typically provide. The lack of uncertainty quantification also impedes model improvement: without characterizing what the model does not know, researchers cannot efficiently target data collection or model refinement efforts.

The geographic concentration of the literature raises questions about generalizability and equity. Models developed and validated in North America, China, and Europe may not perform well in tropical regions with different climate dynamics, different data infrastructures, and different prediction priorities. Yet these are precisely the regions where climate impacts are most severe and where improved prediction could yield the greatest human benefits. The field requires deliberate efforts to develop and validate methods for data-sparse regions, including transfer learning from data-rich regions, semi-supervised learning that leverages unlabeled data, and methods for incorporating expert knowledge when training data are limited.

The reliance on random validation rather than spatiotemporal cross-validation suggests that many reported accuracy metrics are likely inflated relative to operational performance. Spatial autocorrelation means that randomly held-out points are similar to training points; a model that simply memorizes the training data can achieve high accuracy on random holdouts but fail catastrophically when applied to new geographic regions or time periods. Rigorous evaluation requires spatial blocking or time-based splits, yet these practices remain uncommon. The field would benefit from standardized benchmark datasets and evaluation protocols that enable fair comparison across methods and realistic assessment of generalization performance.

These findings have several implications for future research. First, we recommend that researchers adopt a standardized reporting framework that includes explicit description of data fusion strategies, handling of scale mismatches, uncertainty quantification methods, and validation procedures. Such a framework would facilitate replication, meta-analysis, and cumulative progress. Second, we call for development of benchmark datasets spanning diverse geographic regions and time periods, with standardized train-validation-test splits that respect spatial and temporal dependence. Third, we encourage greater attention to methods for uncertainty quantification that are computationally tractable and well-calibrated for spatial prediction tasks. Fourth, we advocate for research on physics-informed and hybrid models that integrate AI with physical constraints, offering a path toward predictions that are both accurate and physically consistent.

6. Conclusion

This systematic review has examined the state of AI-driven climate change prediction using multi-source geospatial data, synthesizing findings from 142 studies across methodological, data-related, and application domains. The central insight is that while AI has substantially advanced predictive capabilities, the field has not yet developed the methodological standards needed to translate these advances into reliable operational tools. The neglect of interpretability, uncertainty quantification, physical consistency, and rigorous validation represents a gap between technical possibility and practical utility that must be addressed if AI is to fulfill its potential for climate resilience.

The scholarly contribution of this paper is twofold. First, we have provided a comprehensive, systematic synthesis of a rapidly growing but fragmented literature, identifying both achievements and persistent gaps. Second, we have proposed a framework for more rigorous, reproducible, and actionable AI-driven climate prediction, centered on standardized reporting, benchmark datasets, uncertainty quantification, and physical consistency.

Climate change is the defining challenge of our era, and improved prediction is an essential tool for meeting that challenge. Artificial intelligence offers genuine promise, but promise is not yet delivery. Realizing that promise requires shifting from performance maximization as the singular goal to a more balanced approach that values interpretability, quantifies uncertainty, respects physical laws, and validates rigorously. The technical capabilities exist; the methodological discipline is still emerging. The task for the coming years is to build that discipline, not study by study but collectively, through shared standards, open data, and a commitment to predictions that are not only accurate but also trustworthy and actionable.

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