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ORIGINAL

AI-Driven Climate Modeling: Validation and Uncertainty Mapping – Methodologies and Challenges

Modelización Climática Impulsada por IA: Validación y Cartografía de Incertidumbre - Metodologías y Desafíos

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ABSTRACT

Climate models are fundamental for predicting future climate conditions and guiding mitigation and adaptation strategies. This study aims to enhance the accuracy and reliability of climate modeling by integrating artificial intelligence (AI) techniques for validation and uncertainty mapping. AI-driven approaches, including machine learning-based parameterization, ensemble simulations, and probabilistic modeling, offer improvements in model precision, quality assurance, and uncertainty quantification. A systematic review methodology was applied, selecting peer-reviewed studies from 2000 to 2023 that focused on climate modeling, validation, and uncertainty estimation. Data sources included observational records, satellite measurements, and global reanalysis datasets. The study analyzed key AI-driven methodologies used for improving model accuracy, including statistical downscaling techniques and deep learning-based uncertainty prediction frameworks. Findings indicate that AI-enhanced models significantly improve climate projections by refining parameterization, enhancing bias correction, and optimizing uncertainty quantification. Machine learning applications facilitate more accurate predictions of meteorological phenomena, including temperature and precipitation variability. However, challenges remain in addressing observational biases, inter-model inconsistencies, and computational limitations. The study concludes that AI-driven advancements provide critical improvements in climate model reliability, yet ongoing refinements are necessary to address persistent uncertainties. Enhancing observational datasets, refining computational techniques, and strengthening model validation frameworks will be essential for reducing uncertainty. Effective communication of climate model outputs, including uncertainty mapping, is crucial for supporting informed policy decisions. AI-driven climate modeling is a rapidly evolving field, and continuous innovation will be key to improving predictive accuracy and resilience in climate adaptation strategies.

Keywords: Climate Modeling; Validation Methodologies; Uncertainties Methodologies; Challenges; Climate Systems.

RESUMEN

Los modelos climáticos son fundamentales para predecir las condiciones climáticas futuras y orientar estrategias de mitigación y adaptación. Este estudio tiene como objetivo mejorar la precisión y confiabilidad de la modelización climática mediante la integración de técnicas de inteligencia artificial (IA) para la validación y el mapeo de incertidumbre. Los enfoques impulsados por IA, como la parametrización basada en aprendizaje automático, las simulaciones en conjunto y la modelización probabilística, ofrecen mejoras en la precisión de los modelos, el control de calidad y la cuantificación de la incertidumbre. Se aplicó una metodología de revisión sistemática, seleccionando estudios revisados por pares entre 2000 y 2023 que se centraron en la modelización climática, la validación y la estimación de incertidumbre. Las fuentes de datos incluyeron registros observacionales, mediciones satelitales y conjuntos de datos globales de reanálisis. Se analizaron metodologías clave basadas en IA para mejorar la precisión de los modelos, incluidas técnicas de reducción de escala estadística y marcos de predicción de incertidumbre basados en aprendizaje profundo. Los resultados indican que los modelos mejorados con IA optimizan las proyecciones climáticas al refinar la parametrización, mejorar la corrección de sesgos y optimizar la cuantificación de incertidumbre. Las aplicaciones de aprendizaje automático permiten predicciones más precisas de fenómenos meteorológicos, como la variabilidad de temperatura y precipitación. Sin embargo, persisten desafíos relacionados con sesgos observacionales, inconsistencias entre modelos y limitaciones computacionales. Se concluye que los avances impulsados por IA mejoran significativamente la confiabilidad de los modelos climáticos, pero se requieren refinamientos continuos para abordar incertidumbres persistentes. La mejora de los conjuntos de datos observacionales, el perfeccionamiento de las técnicas computacionales y el fortalecimiento de los marcos de validación serán esenciales para reducir la incertidumbre. La comunicación efectiva de los resultados de los modelos climáticos, incluido el mapeo de incertidumbre, es crucial para respaldar decisiones políticas informadas. La modelización climática impulsada por IA es un campo en rápida evolución, y la innovación continua será clave para mejorar la precisión predictiva y la resiliencia en las estrategias de adaptación climática.

Palabras clave: Modelización del Clima; Metodologías de Validación; Metodologías de Incertidumbre; Desafíos; Sistemas Climáticos.

INTRODUCTION

Climate models, including General Circulation Models (GCMs), Regional Climate Models (RCMs), and Earth System Models (ESMs), play a critical role in estimating long-term climate patterns, distinct from Numerical Weather Prediction (NWP) models that focus on short-term forecasting.(1,2) The World Meteorological Organization (WMO) defines climate over 30-year periods, historically using 1960–1990 as a benchmark and more recently adopting 1980–2010 to incorporate satellite-era data. Climate models generate “simulations” for past and present conditions and “projections” for future scenarios based on assumed forcings.(3) These models provide insights into present climatologies and paleoclimates, though their ability to predict future climate change is inherently uncertain.(4,5)

The integration of artificial intelligence (AI) into climate modeling is improving accuracy and uncertainty quantification. AI-driven techniques, including machine learning-based parameterization and deep learning-assisted downscaling, enhance model performance and validation efforts. However, challenges remain in ensuring model reliability. Climate model validation primarily compares historical simulations with meteorological observations, while paleoclimate validation relies on proxy data. Future climate projections, based on emission scenarios, are subject to model uncertainties.(6,7)

True model validation requires independent assessment beyond developer-led evaluations. While iterative model refinement improves consistency, external scientific review is necessary for credibility.(8) Adherence to international standards, such as ISO 9000, is increasingly recommended to ensure transparency and reproducibility.(9,10,11) AI is also advancing quality control (QC) and quality assurance (QA) in climate modeling, using automated anomaly detection and bias correction to enhance model robustness. Techniques such as double-blind evaluations, sanity checks, and traceable workflows further minimize errors.(12) Comprehensive documentation, including Algorithm Theoretical Basis Documents (ATBDs), ensures reproducibility in climate modeling.(13,14,15)

Validating prognostic variables like temperature is relatively straightforward, but diagnostic variables such as precipitation pose greater challenges. Precipitation validation is complicated by high spatial and temporal variability, as well as limited observational coverage over oceans.(1,2,4,16) The Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report highlights the difficulty of attributing regional precipitation changes due to observational gaps and high uncertainties. AI-based ensemble learning and probabilistic modeling are emerging as tools to address these validation challenges.

This study examines the role of AI in enhancing climate modeling, focusing on uncertainty quantification and validation. It distinguishes climate models from Numerical Weather Prediction (NWP) models and evaluates AI-driven techniques like machine learning in improving projections.(5,8,17,18) The study assesses validation methodologies, emphasizing independent review and adherence to international standards. It also addresses challenges in validating diagnostic variables like precipitation and explores AI-enhanced Quality Assurance (QA) and Quality Control (QC) protocols. By advancing these areas, this research aims to improve climate model reliability and support effective climate change mitigation and adaptation strategies.

METHOD

To ensure a systematic and comprehensive review of the literature on climate modelling, validation, and uncertainty mapping, specific inclusion and exclusion criteria were applied. These criteria were used in combination with Boolean operators to refine the search process, capturing relevant studies while filtering out irrelevant or low-quality sources.

Inclusion Criteria

Studies must be directly related to climate modelling and validation. This includes research focused on climate modelling methodologies such as General Circulation Models (GCMs), Regional Climate Models (RCMs), and Earth System Models (ESMs). Additionally, studies addressing validation techniques—such as comparisons with observational data, the use of proxies for paleoclimates, or the application of Quality Assurance (QA) and Quality Control (QC) protocols—were included. Research discussing uncertainty quantification, mapping, and reduction in climate models was also considered.

The review included studies published between 2000 and 2023 to ensure relevance to current methodologies and challenges. Studies with a global, regional, or local focus were included as long as they addressed climate modelling and validation. Research that utilizes observational data, satellite data, reanalysis data, or proxy data for validation purposes was considered.

Only peer-reviewed journal articles, conference proceedings, and technical reports from reputable sources, such as the Intergovernmental Panel on Climate Change (IPCC) reports, are included. Furthermore, studies must demonstrate clear methodological approaches, incorporating standardized validation protocols, uncertainty quantification techniques, or QA/QC frameworks.

Exclusion Criteria

Studies that focus solely on weather forecasting, non-climate-related modelling, or non-scientific perspectives are excluded. Research published before 2000 was not considered unless it is foundational or highly cited in the field. Non-peer-reviewed articles, opinion pieces, and studies lacking methodological rigour were also excluded. Additionally, studies not published in English were excluded due to potential translation challenges. Research with a narrow focus that does not contribute to the understanding of climate modelling, validation, or uncertainty mapping was not be included in the review.

Search Strategy

The search was conducted using academic databases such as Scopus, Web of Science, PubMed, and Google Scholar. Boolean search strings were applied to refine search results, ensuring the inclusion of only relevant studies. Titles and abstracts were first screened for relevance, followed by a full-text review of selected studies. Key information, including methodologies, validation techniques, uncertainty quantification approaches, and challenges, was extracted from the included studies.

Table 1. Summary of Studies Included in the Systematic Review

Authors	Year	Focus Area	Study/Key Findings
Elsawah et al.	2020	Climate modeling and socio-environmental systems	Identifies key challenges in climate system modeling and highlights the role of AI in improving accuracy.
Shen et al.	2018	Uncertainty quantification in hydrological impacts	Demonstrates how AI can enhance uncertainty estimation in climate models through probabilistic techniques.
Callaghan et al.	2021	AI-driven climate impact mapping	Highlights how machine learning improves the attribution and validation of climate change impacts.
Cannon	2018	Bias correction in climate models	Discusses the use of multivariate quantile mapping for improving climate model predictions.
Meyer & Pebesma	2021	Model spatial applicability	Explores AI applications in spatial prediction and uncertainty analysis.
Beven	2018	Uncertainty in environmental modeling	Emphasizes the challenges of reducing uncertainty in climate modeling and suggests AI-driven solutions.

Duncanson et al.	2019	AI in biomass and environmental model validation	Demonstrates how AI improves climate data accuracy through automated validation methods.
Srivastava et al.	2019	AI and species distribution models	Evaluates AI-based environmental modeling approaches and their reliability.
Chabrillat et al.	2019	Remote sensing and AI for climate analysis	Examines the use of AI and imaging spectroscopy in climate studies.
Merz et al.	2020	Impact forecasting for natural hazards	Discusses AI-driven risk assessment and prediction of climate-related disasters.
Salcedo-Sanz et al.	2020	Machine learning for climate information fusion	Reviews various AI techniques used in climate modeling and forecasting.
Hassani et al.	2021	AI and soil-climate interaction modeling	Explores AI-based approaches in assessing climate-induced soil salinization.
Turyasingura et al.	2022	Climate change and water resources	Provides a meta-analysis of AI applications in climate-driven hydrological studies.
Vermeulen et al.	2010	Climate modeling and food security	Examines AI-assisted climate modeling for agricultural risk assessment.

Expected Outcomes

By applying these criteria, this methodology aims to identify and synthesize high-quality studies on climate modelling, validation, and uncertainty mapping. The goal is to provide a comprehensive understanding of current methodologies, challenges, and best practices in the field. The use of Boolean operators ensures a focused and efficient search process, minimizing the inclusion of irrelevant or low-quality sources.

RESULTS

Rain gauges measure precipitation at specific points, which may not accurately represent larger areas, especially vast regions with few observation points, such as the Amazon Basin. Additionally, rain gauges are subject to technological flaws and spatial biases, with variations in instrument length distribution.

Ground-based radar measurements face multiple sources of uncertainty, including beam obstruction, attenuation, and abnormal propagation. Precipitation occurs in solid, liquid, and mixed forms, with significant temporal variability.[19,20] Indirect satellite estimations suffer from poor temporal sampling, while satellite-based measurements over land, coastal, and oceanic regions rely on different methodologies and assumptions.

Merged precipitation records are unsuitable for trend analysis due to sensor drift and their limited durations. Many Level-2 product methods are based on Bayesian estimations, which require prior estimates. The quality of Level-3 precipitation products is influenced by microwave observations, making them dependent on the availability and accuracy of such data. Estimates based on satellite and ground-based observations vary significantly across latitudes due to biases and uncertainties.[21]

The error characteristics resulting from the combination of multiple datasets are not well understood. Diabatic heating field estimations contain known errors that impact models of precipitation processes. Statistical methods used to correct biases or interpret model output remain unvalidated. GCM-driven regional climate model (RCM) simulations cannot be directly compared to observational time series.[22]

High-resolution global cloud-resolving models (G-CRM) show greater promise than RCMs for decision-making and improving the understanding of precipitation physics. However, the end-to-end characteristics of satellite-based retrievals remain poorly understood. Satellite products exhibit greater disagreement when assessing global trends and variability compared to their consistency in regional-scale variations.

Analysis of Data in Precipitation Validation

When analyzing data, it is crucial to account for ground radar uncertainty in precipitation validation. Due to spatiotemporal variability, precipitation datasets should be used cautiously in models.[23-25] The indirect nature of satellite estimations and their limited temporal sampling must be carefully compared. To ensure independent verification, model adjustments using relevant datasets are necessary. Parameterizations should be validated using data that were not involved in model development or tuning. To prevent overfitting, global microphysics observations should be utilized alongside empirical parameters. Ground validation initiatives play a vital role in improving the representation of simulated precipitation.

According to the “scope principle,” a model cannot claim superior performance at higher resolutions than those used for its validation. The blending of global precipitation products involves complex subtleties that must be carefully considered during validation. Additionally, satellite-derived and rain gauge-based estimation methods may not always be applicable across different spatial and temporal scales. The accurate measurement of shallow and very light precipitation remains a significant challenge, requiring further investigation. Although

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precipitation is a critical component of model validation, there is no universal reference for comparison.(26) Further research and targeted observations are needed to address this gap.

For models intended for policymaking and broader societal applications beyond pure research, their code and precipitation database techniques must be publicly audited. Quality control should be applied at every stage of model and database development, ensuring transparency, auditability, and traceability. Independent scientists, unaffiliated with model development or specific research networks, should be responsible for validating these models. Additionally, users should be informed about the confidence levels of observational databases and model results.(27)

Validation efforts should prioritize underrepresented regions and processes to ensure accurate precipitation representation in models, particularly in tropical woodlands. A key challenge is identifying the correct microphysical processes required for precipitation estimation techniques before substantial validation can occur. Recent projects have significantly contributed to the understanding of precipitation processes. For example, cloud-resolving modeling and global precipitation measurement efforts in Brazil have advanced significantly.(28,29) Other studies have focused on the relationship between mid-latitude frontal precipitation processes and terrain-induced rainfall uncertainty. Research on satellite-based precipitation measurements in the northeastern Pacific, particularly along the coastline, has also provided valuable insights. Similarly, investigations into warm-season orographic precipitation regimes and their hydrologic impacts in complex terrain have been instrumental in advancing knowledge.

Before using satellite precipitation datasets for model validation, several factors must be considered. Validation can be conducted using precipitation model means, commonly applied in various studies, or other first-order statistical metrics. These include assessments of climate phenomena such as ENSO, representations of the diurnal rainfall cycle, and analyses of high- and low-intensity rainfall frequency. Additionally, validation can focus on physical parameters such as latent heat and the microphysics of precipitation within models.

Latent Heat Release in Precipitation Modeling

Current observational tools cannot fully monitor or identify phase shifts between water's vapour, liquid, and frozen states. The vertical distribution of latent heat significantly influences the atmosphere, impacting tropical circulations, cyclone intensity, and midlatitude weather systems.(30,31,32,33) The launch of satellite-based precipitation measurement missions has provided much-needed rainfall data and the ability to predict the four-dimensional structure of latent heat on a global scale. The success of these missions has led to further advancements in global precipitation measurement.

Cloud-resolving models (CRMs) have become essential tools for algorithm development and ground validation efforts. These models play a crucial role in quantifying the relationships between diabatic rain and atmospheric warming.(30,31,32,33) Extensive simulations have been used to develop rainfall and heating retrieval techniques. Several latent heat algorithms have been created, tested, and applied for satellite-estimated surface rain rate and precipitation profile inputs over the past two decades.(34) Each algorithm has its strengths and limitations. Comparisons between different thermal data sets have shown regional differences in heating intensities, with some models producing stronger heating patterns than others. Differences in low-level heating between the eastern Pacific and other regions may be attributed to variations in convection processes. While these heating datasets provide valuable insights, uncertainties remain, requiring careful interpretation.

Precipitation Microphysics in Climate Modeling

The precipitation microphysics paradigm explains the interactions between water vapour, aerosol, cloud formation, and precipitation processes. To prevent overfitting, microphysics observations must be global rather than limited to specific conditions. Advanced cloud-resolving models are used to explore aerosol-cloud-precipitation interactions at high resolutions. These processes are critical to the global water and energy cycle, and their validation with observational databases helps ensure model accuracy. However, microphysical schemes contain uncertainties, as many processes cannot be directly observed or quantified.

Spectrum bin microphysical (SBM) methods provide the most detailed representations of microphysical processes and typically outperform bulk microphysical schemes in modeling cloud and surface precipitation.(12,35) While SBM schemes improve traditional bulk parameterizations, they remain complex and introduce additional uncertainties. The challenge lies in balancing the realism of microphysics schemes with the computational efficiency required for climate modeling.

Key Considerations for Validating Climate Models with Precipitation Data

Several key factors must be addressed to improve the validation of climate models using recent precipitation datasets:

1. Precipitation Retrieval Methods: Space-based precipitation retrievals depend on radiative and microphysical modeling techniques. Identifying a cloud as precipitating is inherently difficult, which

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can lead to significant errors. Continuous improvements in passive and active sensor technology are necessary to refine precipitation retrievals.

2. Precipitation Phase Identification: The precipitation phase (rain, snow, or mixed) plays a crucial role in climate model validation. However, accurately distinguishing between precipitation types remains a challenge due to the limitations of moderate-resolution data. Some validation efforts use satellite-based observations to compare against climate model outputs.

3. Reliability of Precipitation Predictions: Inaccurate precipitation predictions, particularly for snowfall, significantly impact climate modeling. Recent studies have begun integrating observational data with climate models to identify validation challenges. Some researchers have emphasized the importance of analyzing cloud optical characteristics and the top-of-atmosphere radiation budget alongside precipitation data to refine global simulations. Other studies have highlighted discrepancies between satellite and model-based precipitation estimates, which require further explanation. The effects of rising temperatures on the precipitation phase and intensity must also be considered, as changes in the melting level height can influence surface precipitation characteristics.

4. Temporal and Spatial Considerations: Ground-based precipitation intensity measurements alone cannot capture long-term climate changes. Validating statistical moments such as precipitation timing, duration, and intensity is essential. Understanding and modeling precipitation patterns require innovative approaches, including assessments of the diurnal rainfall cycle and global datasets from satellite observations.

5. Observational Uncertainty in Climate Studies: Climate models require robust observational uncertainty quantification and statistical assessments. Some research has demonstrated varying performance levels of precipitation datasets when compared to global reanalysis products. Additionally, discrepancies between global precipitation datasets and regional climate models highlight the need for improved validation techniques.

6. Integration with Other Climate Variables: Precipitation is a fundamental component of the water cycle, but it must be analyzed in conjunction with other variables such as soil moisture, sea surface temperature, evapotranspiration, and wind fields. Comprehensive climate model evaluations require the integration of precipitation data with these additional datasets to ensure more accurate and reliable simulations.

By addressing these considerations, climate modeling efforts can achieve greater accuracy and improve the representation of precipitation processes in simulations.(36,37) Further advancements in observational technologies and data assimilation techniques will be essential to overcoming the remaining challenges in precipitation validation.

The Coordinated Regional Climate Downscaling Experiment (CORDEX) and the Coupled Model Intercomparison Project (CMIP) have integrated satellite precipitation data into regional climate models (RCMs), with a strong focus on Africa and Asia. Earlier projects assessed uncertainties in defining European climate risks by comparing RCM outputs with satellite data. CORDEX identified regional and seasonal variations in simulating the West African summer monsoon, with biases from individual models affecting results.(16) Multimodel averages generally outperformed individual simulations, though common issues persist, such as the premature onset of precipitation in the diurnal cycle.(38,39) While recent improvements have enhanced the replication of African precipitation patterns, higher resolution does not always guarantee better performance. Model formulation remains key to achieving reliable results.

Satellite precipitation datasets have also exposed limitations in CMIP5 simulations. Comparing multiple models against reference datasets has improved the understanding of strengths and weaknesses in water cycle predictions. Rainfall distribution over the Congo Basin remains inconsistent across datasets, particularly in some seasons. High-resolution satellite data has helped clarify these discrepancies. Observations also indicate that CMIP5 models frequently overestimate oceanic precipitation. Addressing biases like the double ITCZ and cold tongue effect requires a better representation of deep convection sensitivity to humidity and improved ocean model resolution.

In climate model research, it is essential to validate improvements across multiple models and ensembles. Studies have shown that satellite precipitation datasets have a limited impact on altering central tendencies, variability, uncertainty, or consensus in historical skill assessments of CMIP3 and CMIP5 models.(1,4,5,8) However, the influence of these datasets varies by region and season, highlighting both performance improvements and potential skill degradation. This underscores the global and regional significance of satellite-derived datasets in climate modeling. In South Asia, certain CMIP5 models exhibit shared biases in convective and large-scale precipitation, suggesting that while global bias patterns may be informative, regionally clustering models may not always be appropriate.

Further research is needed to assess the accuracy of satellite observations and climate models in detecting

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extreme events such as droughts and floods. High-resolution and long-term observational data pose challenges for leveraging global resources, particularly in representing convective processes within models. Improved convection representation is critical, as it can influence projections of wet and dry extremes.[22] For example, dry extremes in Africa may be more severe than previously forecasted. Studies utilizing percentile-based indices have demonstrated that different base periods can yield significantly varied results, emphasizing the importance of methodological consistency in climate analysis. The integration of satellite precipitation data is crucial for addressing disparities in data products, understanding estimation limitations, and overcoming scaling challenges. Considerable progress has been made in developing global databases for extreme events, which play a vital role in climate change research and precipitation analysis. These databases provide valuable insights into all climate-related events, particularly the most severe ones linked to climate change.

Beyond extreme event studies, a growing area of research focuses on short-duration rainfall extremes. Accurately capturing these events is challenging due to data inconsistencies and insufficient quantification in climate change projections. Short-duration rainfall processes remain less understood compared to longer timescales. To address this gap, sub-daily gauge datasets have been proposed as a means to enhance temporal resolution, with satellite data serving as a valuable tool for improving the accuracy and reliability of precipitation measurements.

Uncertainties in Climate Modeling

Climatic models aid in understanding and predicting climatic patterns over many timescales, including seasons, years, decades, and centuries. Climate change models assess the extent of observable changes may be caused by natural changes, human activity, or both. By deliberately understanding climate projection uncertainty, we can make stronger, more informed decisions. Additionally, this method lets us recognize and manage climate change risks. However, failing to Consider that uncertainties might hide hazards and undermine risk management measures. It can also increase maladaptation, worsening the situation instead than enhancing it. Well established physics models underpin climate models' sciences, but cloud representation affects them. As an example, when Hurricane paths and climates are forecast as cones, not lines scenarios.

Various categories of Climate Models

A climate model is a computer simulation that replicates the Earth's climatic system, including the atmosphere, ocean, land, and ice. These models have the capability to accurately simulate past climate conditions or even predict the future climate. Scientists employ climate models to evaluate their findings. Comprehend the climate and evaluate their hypotheses. For example, they have the ability to replicate the analyze the atmospheric conditions in a specific area and thereafter compare the findings with actual observations in the real world. This comparison enables scientists to assess the precision of their model and pinpoint specific areas.[40] Identify areas that require enhancement. Furthermore, climate models are employed to forecast the forthcoming climate. Scientists can predict the probable consequences of global warming by inputting various scenarios regarding our climate. This allows us to predict the probable effects of global warming. Climate models are crucial for comprehending the intricate systems that constitute the climate of our world. Climatic models assist in forecasting future climatic patterns and comprehending historical ones. Each model type possesses unique characteristics and serves distinct objectives, however collectively they enhance our comprehension. Regarding Earth's climatic system, various climate models exist, including the Global Climate model.[41,42] There are three types of models used in climate science: Global Climate Models (GCMs), Regional Climate Models (RCMs), and Earth System Models (ESMs).

1. Global Climate Models (GCMs): These models employ mathematical equations to replicate the interactions of energy and matter in various regions of the ocean, atmosphere, and land. They divide the Earth's surface into a three-dimensional grid of cells, with each cell representing a distinct area of the Earth's crust. The outcomes of the activities simulated in each cell are transmitted to adjacent cells are used to simulate the transfer of matter and energy over a period of time. Global Climate Models (GCMs) are predominantly designed to replicate the intricate workings of Earth's climate system.
2. Regional Climate Models (RCMs): These models concentrate on certain regions and possess a higher level of specificity, higher levels of precision than General Circulation Models (GCMs). They replicate the climatic conditions of specific geographic locations expanding over several thousand square kilometers to form a continent. The Regional Core Model Evaluation System (RCMES) offers a fundamental capacity for evaluating regional models and Climate community.
3. Earth System Models (ESMs): These models are integrated systems that simulate the interactions between the land, ocean, and atmosphere components that interact with one another in the biogeochemical processes. They utilize interactive biogeochemistry. This encompasses the carbon cycle. ESMs quantify a wide range of emissions and land variables. Surface albedo is influenced by both natural vegetation changes and land use histories, including agricultural activities and the fields of forestry and

aerosol chemistry.

Uncertainty Sources

Several factors cause climate modeling uncertainty. One important source is approximated processes like turbulence that cannot be directly resolved the atmosphere, oceans, and cloud convection. Insufficient comprehension of Earth's systems and interactions, climatic variability, constraints bias and measurement mistakes from imprecise observational sensors and climate models contribute to ambiguity. A few major uncertainties are listed below.

Physical Process Parameterization and Representation: Climate models are mathematical. show physical processes. Some processes are too small or complex to physically measure. In the model, a streamlined process substitutes them.[43,44,45] This is called parameterization. The creation of clouds is typically parameterized because it happens less than 1 kilometer.

Initial and boundary conditions: The climate model affect due to the conditions including wind, temperature, pressure, and moisture. Even minor modifications in these circumstances can affect results. Boundary conditions, or values set by the modeler, are also important.

Computational Limitations: To make accurate forecasts, climate models demand tremendous computational resources due to their complexity and high resolution. While parameterization and spatial resolution have improved throughout time, computing abilities remain limited. Still, limits pause a challenge.

Future Emission Scenarios: Climate models utilize scenarios to predict future greenhouse gas levels. These scenarios assume social, political, and economic issues affecting emissions and land use. However, there is intrinsic ambiguity in assumptions.

Feedback Mechanisms: Feedback mechanisms can increase or decrease pressures, begin warming. Cloud feedback mechanisms can greatly impact global warming. Warming can improve cloud cover or characteristics or reduce warming.

Uncertainty Types: Climate modeling involves uncertainty owing to the complexity of the climate system. Uncertainties originate from numerous aspects of the process of modeling. This uncertainty may result from model constraints future uncertainty or climate variability. There are two sorts of uncertainty: epistemic and aleatory.

1. Epistemic Uncertainty: It arises from a lack of knowledge about a phenomenon, hindering proper modeling. Limited understanding of Earth's processes and climatic interconnections typically contributes to this issue. observational instrument models, bias, and measurement mistakes. For instance, some climate modeling parameters are based on few empirical investigations. If we have lack of understanding about these criteria, it can cause epistemic issues uncertainty.
2. Aleatory Uncertainty: Natural processes are unpredictable. This phenomenon is modelled using a probabilistic model and cannot be lessened by acquiring more data or knowledge. Example: future concentrations of greenhouse gasses from humans are unpredictable by physical physics and must be estimated from social, political, and economic analyses.

Three Components of Uncertainty

Model, scenario, and internal variability can all induce uncertainty. Inter-model variability and model setups cause model uncertainty. Scenario uncertainty is linked to greenhouse gas emissions uncertainties, aerosols and gasses. Internal variability is climate's natural fluctuations system that normally lasts a decade or two.[46,47] The above figure displays the uncertainty range of each component. Above figure depicts us, uncertainty from multiple outcomes is modest, but it grows with time until 2100. Internal variability causes the most uncertainty and it nearly diminishes in the remote future. Model uncertainty dominates or less during future estimates. These uncertainties can greatly affect climate model results and projections. For uncertainties in climate model parameters or architecture can affect climate projections. Like climate projections, it can decrease their accuracy due to the inherent unpredictability of nature. Understanding and managing these uncertainties is crucial essential for climate science adaption and decision-making.

Impacts of Uncertainty

Uncertainty in climate modeling can significantly affect our understanding and forecast of climate change. This uncertainty might have many outcomes making precise climate predictions difficult. Understanding these uncertainties is critical for determining the amount of adaptation necessary and evaluating the consequences of various climate mitigation strategies.[44,48] Some prominent uncertainty effects as follows:

- Impact on Climate Projections: Uncertainty in climate modeling can dramatically impact results and projections. Uncertainties in model parameters or architecture can affect climate projections. Aleatory uncertainty—the unpredictability of natural processes can impair climate projections.
- Effects on Policy and Decision-Making: Climate modelling uncertainty can also have major policy

and decision-making ramifications. An example, assigning a single set of probabilities for all emissions scenarios could mislead decision makers confidence, which can lead to costly changes if the world changes unexpectedly. Thus, robust adaptation requires understanding and addressing these uncertainties climate science decision-making.

- Climate science is gaining public trust: This has nearly doubled in certain areas. Despite rising climate science credibility, optimism is scarce. Most participants felt deeply responsible as corporations and governments could do more to help the environment.

Measure and Reduce Uncertainty

Climatic models offer crucial data for policymakers to anticipate probable climatic scenarios. This data can help mitigate and adapt to climatic change.[49-51] It is crucial to identify and reduce underlying uncertainty in policymaking and other major choices are affected by model results. In such context, quantifying and minimizing ambiguity is crucial. Reduce uncertainty by model ensembles, better observational networks, computing, sensitivity more analysis, model validation, etc.

Ensemble Modeling: The ensemble Modeling method involves running numerous climate models or versions of a single model with slightly variable initial conditions. The ensemble of model results will represent several future climates, enabling quantification uncertainty. However, not all models are equally good at modelling the entire climate system.

Improvements to data collecting and observational networks: Sharing, accessing, and using observational data can improve our knowledge for the climatic system. The challenge is controlling the massive data volume and quality.

Improved Computing Capabilities: Increased computational capacity enables more precise climate modeling. High-resolution models enhance the simulation of small-scale characteristics like violent thunderstorms. Physics better captures cloud and rain development. Even with better computing, model complexity and climatic chaos remain issues system.

Sensitivity Analysis: This strategy identifies characteristics that strongly affect model results. It helps analyze parameter interactions and their optimal values. range and geographical variation. However, our sensitivity analysis is restricted, knowing intricate climate processes and relationships.

Comparing and Validating Models: This compares outputs from different measure model performance by comparing outputs to observational data. For this, model Intercomparison projects provide community-based infrastructure. These comparisons are difficult due to model structure discrepancies parameterizations.

These methods can measure and minimize climate modeling uncertainty, but they also challenge and limit. These mostly derive from our poor grasp of climatic system complexity and chaos, and practical issues data management and calculation. The use of uncertainty Quantifying climate models is still new, and high-resolution models are used to reducing uncertainty takes huge processing power.

Model for Analysis

Climate models' uncertainty can be evaluated by comparing several models for a certain scenario. Data distribution range represents uncertainty for those models. Averaging and weighted averaging are ensemble modeling methods make predictions more accurate and reliable. Comparing model and observed data can help us determine how reliable such forecasts are and if the actual scenario falls within the model's uncertainty range forecasting backward (table 1). For this paper, we examined the uncertainty range for a few selected Model ensemble and observed data were compared.

Table 1. List of Selected Models for Analysis

Model Name	Modelling Centre	Horizontal Resolution
ACCESS-CM2	Commonwealth Scientific and Industrial Research Organization, Australia	1,25°×1,875°
ACCESS-ESM1-5	Commonwealth Scientific and Industrial Research Organization, Australia	1,25°×1,875°
BCC-CSM2-MR	Beijing Climate Center China Meteorological Administration, China	1,125°×1,125°
INM-CM4-8	Institute for Numerical Mathematics, Russian Academy of Science, Russia	1,5°×2°
MPI-ESM1-2-HR	Max Planck Institute for Meteorology, Germany	0,9375°×0,9375°

Source: Adopted from Duncanson et al.[8] and Meyer, and Pebesma[10]

Model simulation data from 1985-2014 was compared to observed data. Historical data was analyzed from the year 2013. The data of the selected 5 models was averaged to create model ensemble. Data output from dotted lines showed the 5 climate models. Figure 1 shows that the 5 model's simulated outcomes follow a pattern. similar pattern, but different values. To compare results to observed data, the 5 model's average (blue solid line) was taken. The models missed the peak in observed data, but temperature variation was captured similar throughout the plot. From April 2013 to August 2013, the observed temperature is between model ranges. For the rest of the year, the observed data does not fall into these 5 model's uncertainty ranges. Using the problem can be solved by having additional models, which can yield better accuracy than one model.

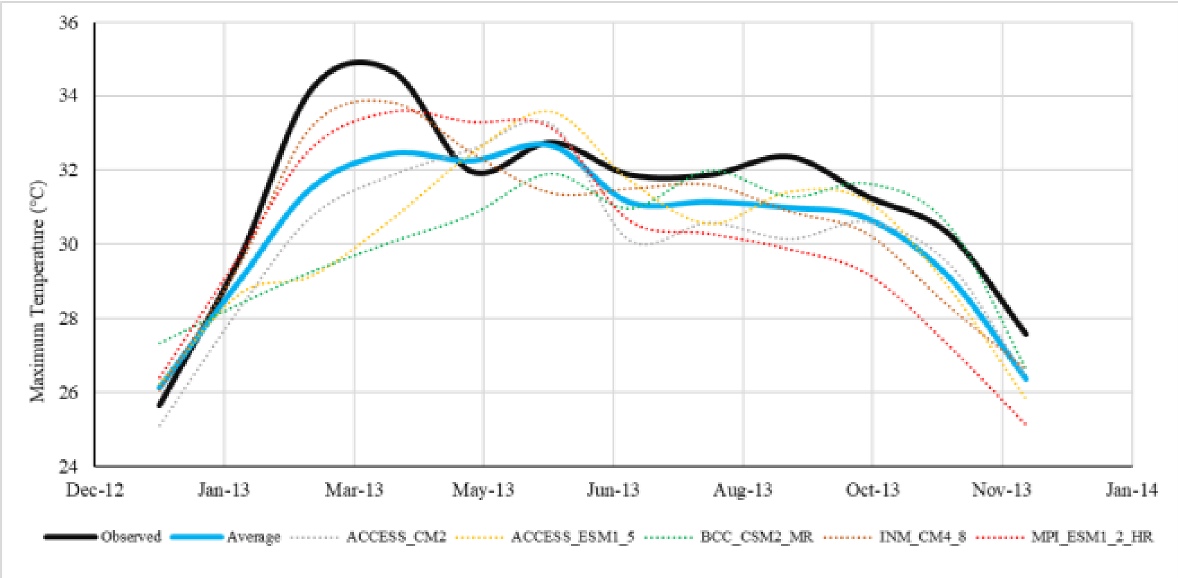

Figure 1. Variation in Monthly Maximum Temperature

Average Monthly Maximum Temperature Plotted

Figure 2 displays the outputs from five models for predicting the average monthly maximum temperature in 2024. These numbers, like past outputs, showed significant variation. INM-CM4-8 overestimated heat between February 2024 and April 2024, while ACCESS-CM2 overestimated May 2024 temperatures till July 2024. November's BCC-CSM2-MR model differs most. Other than these with minimal notable deviations, the models define a temperature range where future temperature may remain in the range. This shows how hot it can become upcoming year, despite not having specific values (figure 2).

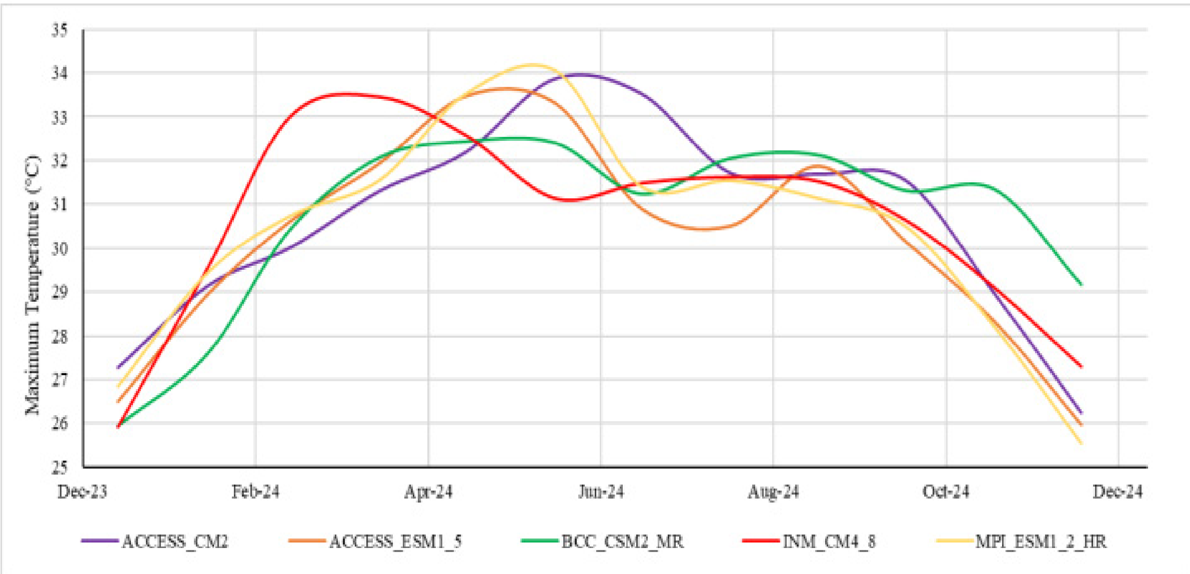

Figure 2. Variation in Monthly Maximum Temperature plot from 5 models

Average Monthly Maximum Temperature Plot from 5 Models

The graph represents the maximum temperature (˚C) over a year, from December 2023 to December 2024, using multiple climate models. The models include ACCESS_CM2 (purple), ACCESS_ESM1_5 (orange), BCC_

CSM2_MR (green), INM_CM4_8 (red), and MPI_ESM1_2_HR (yellow). The general trend shows a steady increase in temperature from December 2023, with peaks occurring between March and June 2024, followed by a gradual decline towards December 2024. Among the models, INM_CM4_8 (red) exhibits an early temperature rise, reaching its peak around March 2024. In contrast, MPI_ESM1_2_HR (yellow) and ACCESS_ESM1_5 (orange) display fluctuations with their highest temperatures occurring slightly later, around May to June 2024. The BCC_CSM2_MR (green) model predicts a relatively lower temperature peak compared to the others, maintaining lower values throughout most of the year. ACCESS_CM2 (purple) and MPI_ESM1_2_HR (yellow) follow similar trends but with varying temperature magnitudes. Overall, the temperature variations across models follow a seasonal pattern, with increasing temperatures in the first half of the year and a decline in the latter half. These differences highlight the variability among climate models in predicting temperature trends, though they all indicate a consistent seasonal cycle.

CONCLUSION

AI-driven climate modeling enhances predictive accuracy, validation, and uncertainty quantification, making it a crucial tool for climate research. This study highlights the role of AI in improving model reliability through machine learning-based parameterization, probabilistic modeling, and ensemble simulations. By integrating AI-enhanced Quality Assurance (QA) and Quality Control (QC) techniques, climate projections become more transparent and actionable.

Despite advancements, challenges persist in capturing complex meteorological phenomena and quantifying inter-model variability. Addressing these uncertainties requires continuous improvements in observational data, model parameterizations, and computational methods. Effective communication of uncertainty remains vital for informed decision-making in climate adaptation and mitigation strategies.

As AI-driven innovations continue to evolve, climate models will play an indispensable role in shaping climate policies and resource management. Strengthening model accuracy and uncertainty mapping will enhance their credibility, ensuring resilience against climate change impacts.

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