ISSN: 2456-8503

International Journal for Development of Science and Technology (IJDST)

REVIEW

Climate insight 360: AI and remote sensing for advanced climate change modeling

Srikumaran[1*]

Abstract

Climate change poses a critical threat to global ecosystems, human health, and economic stability. Addressing these challenges requires innovative approaches that provide accurate, real-time insights into Earth's dynamic environment. This paper presents Climate Insight 360, a comprehensive framework that integrates Artificial Intelligence (AI) and Remote Sensing technologies for advanced climate change modeling. By leveraging high-resolution satellite imagery from platforms such as Land sat, MODIS, and Sentinel and state-of-the-art AI algorithms, Climate Insight 360 enables precise climate prediction, continuous monitoring, and informed decision support. The framework facilitates early warning systems, supports climate adaptation strategies and provides actionable insights for policymakers and researchers. Through this integration of AI and remote sensing, Climate Insight 360 represents a transformative approach for understanding and mitigating the impacts of climate change.

Keywords: Climate change modeling, artificial intelligence, remote sensing, machine learning, environmental monitoring, decision support systems.

1. Introduction

Climate change is no longer a distant or theoretical concern; it is a pressing global challenge that significantly affects ecosystems, human societies, and economic systems worldwide [1]. The growing frequency of extreme weather events, rising sea levels, rapid glacial melting, and accelerating biodiversity loss emphasize the urgent requirement for accurate and timely climate prediction systems [2]. Conventional climate modeling techniques, although scientifically reliable, depend largely on historical data and statistical assumptions, which often limit their adaptability and predictive performance under rapidly evolving environmental conditions [3].

[1]*Assistant Professor, Department of Computer Science, Sri Krishnasamy Arts and Science College, Sattur.*

**Corresponding Author: srikumaran1996@gmail.com*

Recent developments in Artificial Intelligence (AI) and machine learning have opened new possibilities for overcoming these limitations by enabling the discovery of complex and nonlinear patterns within large-scale environmental datasets [4], [5]. In response to these challenges, the proposed Climate Insight 360 framework integrates advanced remote sensing technologies with AI-based modeling approaches. This unified system delivers real-time, high-resolution, and actionable climate intelligence by combining satellite observations with intelligent data analytics [6], [7]. The framework supports proactive planning, climate mitigation strategies, and evidence-based decision-making for policymakers, scientists, and disaster management authorities.

2. Remote sensing: Gateway to global environmental data

Remote sensing refers to the acquisition of information about the Earth's surface and atmosphere without direct physical contact, primarily through satellites, unmanned aerial vehicles (drones), and airborne sensors. It plays a crucial role in climate science due to several distinctive characteristics:

1. Global coverage, including remote and inaccessible regions [8].
2. High temporal resolution enabling continuous environmental monitoring [9].
3. Multispectral and hyper spectral imaging capabilities [10], [11].
4. Long-term environmental data archives from Land sat, MODIS, and Sentinel missions [12], [13].

2.1. Applications in climate modeling

1. Remote sensing data support a wide range of climate-related applications, including:
2. Monitoring land-use and land-cover changes [14].
3. Measuring sea surface temperatures and ocean dynamics [15].
4. Assessing vegetation health and biomass [16].
5. Detecting atmospheric greenhouse gas concentrations [17].
6. Tracking glacial retreat and snow cover [18].

These applications provide a strong foundation for climate modeling, environmental assessment, and disaster risk management.

3. Climate insight 360: Framework and methodology

Climate Insight 360 is an integrated framework that combines AI algorithms, remote sensing datasets, and cloud-based computing infrastructure to offer a comprehensive understanding of the Earth's climate system [19].

3.1. Key components

Data Collection High-resolution satellite data from Sentinel, MODIS, and Land sat missions [20]. Data Processing AI-driven preprocessing techniques for noise reduction, cloud masking, and feature extraction [21], [22]. Modeling and Prediction Machine learning and deep learning models for climate trend analysis and forecasting [23]. Visualization Interactive geospatial dashboards for real-time monitoring and analysis [24]. Decision Support Actionable insights for scientists, policymakers, and government agencies [25], [26].

3.2. Workflow

Satellite data collected from Earth observation missions such as Land sat, MODIS, and Sentinel are initially ingested into cloud-based platforms for large-scale storage and processing [27]. The raw data are subsequently preprocessed using AI-based algorithms for noise suppression, cloud detection, and feature extraction. Machine learning and deep learning models then analyze the processed data to identify spatiotemporal patterns and predict climate trends and extreme events [28].

The resulting predictions are visualized through interactive dashboards and geospatial mapping tools to facilitate real-time monitoring and interpretation. Finally, the extracted information is translated into policy-relevant insights and decision-support outputs for scientists, policymakers, and environmental agencies. (Insert a figure1). Here illustrating the workflow: Satellites → AI Processing → Prediction → Visualization → Decision Support).

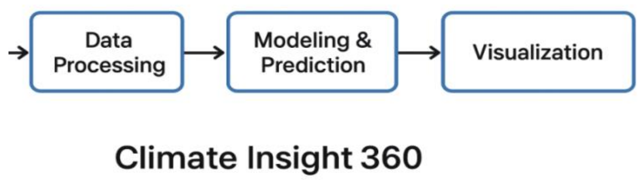

Figure 1: Climate insight 360

4. Advantages of the framework

The Climate Insight 360 framework offers several advantages

1. Real-time climate monitoring and early warning systems for extreme events.
2. Support for climate adaptation and mitigation planning.
3. Improved policy formulation through data-driven risk assessment.
4. A scalable and adaptive platform for interdisciplinary climate research.

5. Applications and case studies

- *Disaster Early Warning Systems:* AI-based flood, cyclone, and drought prediction using satellite data.
- *Agricultural Planning:* Crop health monitoring and yield prediction under changing climate conditions.
- *Urban Climate Analysis:* Assessment of urban heat islands and land-use dynamics.
- *Carbon Monitoring:* Tracking greenhouse gas emissions and their environmental impact.

6. Challenges and future scope

Processing large volumes of high-resolution, multi-spectral satellite data requires advanced cloud infrastructure. AI model uncertainty due to environmental noise and data gaps must be addressed Integrating heterogeneous data sources from multiple sensors is complex.

7. Future scope

- Integration of IoT-based ground sensors for hyper-local climate observations.
- Development of autonomous climate decision-support systems using reinforcement learning.
- Enhanced predictive accuracy through hybrid AI and physics-informed models.

8. Conclusion

Climate Insight 360 represents a next-generation approach to climate change modeling by effectively integrating AI and remote sensing technologies. The framework enables real-time, accurate, and actionable climate intelligence that supports sustainable development, disaster resilience, and informed policy decisions. As climate risks continue to intensify globally, the adoption of intelligent, data-driven systems such as Climate Insight 360 is essential for effective climate action.

Conflict of interest statement: No conflict.

Funding: This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Data availability statement: The data used in this study were obtained from publicly available remote sensing sources, including Land sat, MODIS, and Sentinel satellite missions. The processed datasets generated during the current study are available from the corresponding author upon reasonable request.

Ethical approval: This research does not involve human participants or animals. Therefore, ethical approval was not required for this study.

Acknowledgement: I gratefully acknowledge Sri Krishnasamy Arts and Science College, Sattur, for providing the necessary facilities and academic support to carry out this research. The author also thanks the providers of open-access satellite data, including NASA and ESA, for making their datasets publicly available.

References

1. Reichstein M, Deep learning and process understanding for data-driven earth system science, Nature. 2019, 566(1):195-204. doi.org/10.1038/s4158 6019-0912.1
2. Ma Y, Artificial intelligence for climate change mitigation and adaptation, IEEE Access. 2020, 8(2):211976-211989. doi.org/10.1109/access.2020.3 030728
3. Rolnick D, Tackling climate change with machine learning, communications of the ACM. 2022, 65(7):66-77. doi.org/10.1145/3485128
4. Zhang L, Zhang L, Du B, Deep learning for remote sensing data: A technical tutorial, IEEE Geoscience and Remote Sensing Magazine. 2016, 4(2):22-40. doi.org/10.1109/mgrs.2016. 2540798
5. Li X, Deep learning in earth observation: A review IEEE transactions on neural networks and learning systems. 2018, 29(8):3843-3859. doi.org/10.1109/tnn ls.2017.2778922
6. Le Cun Y, Hinton G, Bengio Y, Deep learning, Nature. 2015, 521(1):436-444. doi.org/10.1038 /nature14539
7. Reichstein M, Data-driven earth system science. 2019, 366(1):63-64. doi.org/10.1126/science.aay2724
8. Gomez-Chova L, Cloud screening algorithms for remote sensing data, remote sensing of environment. 2017, 203(3):1-14. doi.org/10.1016/j.rse.2017.03.014
9. Wu Z, Spatiotemporal deep learning for climate prediction, artificial intelligence review. 2021, 54(2):563–592. doi.org/10.1007/s10462-020-09879-7
10. Schultz MG, Can AI boost earth system science, earth system dynamic. 2021, 12(1):1031-1047. doi.org/10.5 194/esd-12-1031-2021
11. Guo H, Big earth data: A new frontier in earth science, bulletin of the American meteorological society. 2020, 101(10):e1910-e1922. doi.org/10.1175/bams-d-19-030 1.1
12. Aschbacher A, Milagro-Perez MP, The european earth observation programme copernicus, remote sensing of environment. 2012, 120(3):70-85. doi.org/10.1016/j.rse.2011.12.008
13. Justice CO, MODIS: An overview, IEEE transactions on geoscience and remote sensing. 2002, 40(8):1673-1696. doi.org/10.1109/tgrs.200 2.803582
14. Wulder MA, Landsat continuity: Issues and opportunities, remote sensing of environment. 2019, 225(1):127-147. doi.org/10.1016/j.rse.201 9.02.001
15. Hastie T, Tibshirani R, Friedman J, The elements of statistical learning, 2nd ed., Springer. 2009, 978(1):300-387. doi.org/10.1007/978-0-387-8485 8-7
16. Quinlan JR, Induction of decision trees, machine learning. 1986, 1(2):81-106. doi.org/10.1007/bf00 116251
17. Breiman L, Random forests, machine learning. 2001, 45(3):5-32. doi.org/10.1023/a:101093340432 4
18. Schmidhuber J, Deep learning in neural networks: An overview, neural networks. 2015, 61(7):85-117. doi.org/10.1016/j.neunet.2014.09.0 03
19. Liu Y, Climate change detection using deep neural networks, proceedings of the national academy of science. 2016, 113(1):4863-4868. doi.org/10.1073/ pnas.1506123113
20. Kumar L, Mutanga O, Remote sensing of above-ground biomass, ISPRS Journal of Photogrammetry and Remote Sensing. 2017, 129(1):85–100. doi.org/10.1016/j.isprsjprs.2017.04. 11
21. Bonan GB, Ecological climatology, 3rd Cambridge University Press. 2016
22. Trenberth KE, Global warming and changes in drought, nature climate change. 2014, 4(1):17–22. doi.org/10.1038/nclimate2067
23. Foley JA, Global consequences of land use, science. 309(5734):570-574. doi.org/10.1126/science.1111772

24. Li W, Fu H, Yu L, Cracknell A, Deep learning based oil palm tree detection, Remote Sensing. 2017, 9(1):39-90. doi.org/10.3390/rs9010014
25. Mohan S, AI-based flood prediction using satellite data, Journal of Hydrology. 2021, 603(1):126901. doi.org/10.1016/j.jhydrol.2021.126901
26. National Research Council, Earth Science and Applications from Space, National Academies Press, 2007. doi.org/10.17226/11820
27. Chen Y, Hyperspectral image classification using convolutional neural networks, IEEE transactions on geoscience and Remote Sensing. 2016, 54(10):6232 6251. doi.org/10.1109/tgrs.2016.2582165
28. Kussul N, Crop yield forecasting using satellite data and machine learning, Remote Sensing. 2017, 9(7):1-50. doi.org/10.3390/rs9070745