Integrating swarm intelligence with CMIP climate models for ecocritical environmental analysis

Pavithra R., S. Mahadevan
Department of Language, Culture and Society, Faculty of Engineering and Technology, SRM Institute of Science and Technology, Kattankulathur, India

Article Info

Article history:

Received May 24, 2025
Revised Nov 27, 2025
Accepted Jan 1, 2026

Keywords:

Climate modeling
Coupled model intercomparison project
Ecocritical analysis
Environmental insights
Swarm intelligence

ABSTRACT

This research establishes a cohesive swarm intelligence framework used for climate simulations derived from the coupled model intercomparison project phase 6 (CMIP6), obtained from the earth system grid federation (ESGF). The study examines essential environmental variables such as near-surface air temperature (tas), sea-level pressure (psl), precipitation (pr), surface shortwave radiation (rsds), and longwave radiation (rlds). The system specifically evaluates a global mean surface temperature rise of 1.72 °C, a psl range of 980-1,030 hPa, pr anomalies averaging ±1.3 mm/day, rsds values fluctuating between 140-280 W/m², and rlds values reaching a maximum of 350 W/m² for high-emission shared socioeconomic pathways (SSP)5-8.5 scenarios. The characteristics served as inputs for decentralized particle swarm architecture aimed at identifying ecological stress signs via geographic anomaly divergence, entropy deviation, and signal intensity thresholds. The model simulated swarm behavior across temporal CMIP grids, effectively capturing changes in climatic feedback and highlighting areas of ecological instability. The swarm framework dynamically analyzes pattern-based fluctuations in model output, facilitating ecocritical evaluation of environmental risk. This hybrid method integrates physically based climate data with adaptive artificial intelligence (AI) modeling, providing an ecologically contextual understanding of earth system changes and improving predictive insights for sustainability and policy formulation.

This is an open access article under the CC BY-SA license.

Corresponding Author:

Pavithra R.
Department of Language, Culture and Society, Faculty of Engineering and Technology
SRM Institute of Science and Technology
Kattankulathur, Tamil Nadu, India
Email: pr1009@srmist.edu.in

1. INTRODUCTION

Climate modeling has been essential to comprehending Earth's complex environmental processes for a decade. The coupled model intercomparison project (CMIP), specifically CMIP phase 6 (CMIP6), has allowed scientists to assess emission-driven scenarios and climate responses using standardized, multi-model datasets. These earth system grid federation (ESGF) datasets simulate temperature anomalies, sea-level pressure (psl), precipitation (pr) variability, and radiation fluxes robustly. At the same time, artificial intelligence (AI), particularly swarm intelligence, has emerged as a fresh way to optimize and navigate high-dimensional information. Swarm intelligence, inspired by biological processes, lets decentralized agents adaptively explore data landscapes, improving environmental prediction, pattern identification, and feedback loop discovery. Integrated methods that combine climate simulations' interpretative capability with adaptive AI models' pattern-resolving power are lacking.

Despite substantial simulation data from CMIP6 models, typical climate analysis approaches frequently use deterministic or statistical modeling, which may not capture emergent or nonlinear biological phenomena. Parameter tweaking and fixed regression frameworks fail to investigate model biases, ensemble variability, and localized anomaly transitions. Intelligent systems that read multi-scenario CMIP results and adjust to uncertainty and transitions are essential. Existing work mostly uses CMIP datasets for downscaling or forecasting, with little swarm-based intelligence to study inter-model spatial entropy, signal thresholds, and ecological feedback areas. This gap hinders ecocritical interpretation, which examines how environmental data tell the story of planetary change, risk, and resilience.

The need to improve climate simulation computational interpretation and ecological awareness via adaptive modeling motivates this study. CMIP6 provides structured, scenario-based climate forecasts but no dynamic exploratory method to uncover nonlinear spatial-temporal climate signal changes. Decentralized and iterative convergence behaviors of swarm intelligence may help extract subtle but critical patterns of environmental instability, especially across variables like near-surface air temperature (tas), pr, psl, surface shortwave radiation (rsds), and longwave flux. This study combines CMIP climate simulation results with swarm-based learning to create an interpretative, adaptive, and ecologically grounded analytical model. Environmental forecasting and ecocritical concerns regarding uncertainty, narrative structure, and emergent system behavior areas standard modeling techniques fail to represent are supported by such integration.

This study aims to create a hybrid ecocritical modeling system that uses swarm intelligence and CMIP6 climate simulation results to discover environmental feedback loops, geographical transition zones, and high-risk anomaly clusters. Parameter-specific agents investigate model output spaces across shared socioeconomic pathways (SSP) situations. We focus on ecological factors that represent climate sensitivity and atmospheric instability. This integration helps academics, policymakers, and sustainability analysts derive relevant conclusions from complicated model ensembles by enabling dynamic and context-aware climate risk interpretations. The main contributions of this work are as follows:

i) A novel integration of swarm intelligence with ESGF-hosted CMIP6 datasets to perform ecocritical environmental analysis across multi-model outputs.
ii) Extraction and modeling of key parameters, including tas, psl, pr, rsds, and longwave radiation (rlds), with actual scenario-based ranges and anomaly thresholds.
iii) Implementation of swarm-based algorithms for optimizing spatial entropy, signal threshold divergence, and anomaly trajectory detection across historical and high-emission (SSP5-8.5) climate pathways.
iv) Demonstration of how decentralized adaptive modeling enables real-time identification of ecological stress patterns in CMIP outputs with improved interpretability.

The remaining strategy is constructed as follows. Section 2 reviews CMIP-based environmental modeling and swarm intelligence literature. Methodology, data extraction, swarm agent modeling, and simulation process are covered in section 3. The integrated system's experimental findings and ecological interpretations are discussed in section 4. Section 5 summarizes results and discusses ecocritical modeling and climate-aware AI system directions.

A thorough examination of CMIP climate model ensembles tackles variability and detects outliers, using sophisticated statistical methods. The enhanced predictions provide essential insights into regional climate patterns, allowing policymakers and researchers to make educated choices about variability management and the mitigation of catastrophic climatic occurrences. The technique emphasizes the need for ongoing enhancement of ensemble methods to more effectively represent the intricacies of climate systems [1]. The assessment of CMIP6 models for pr patterns in India reveals notable improvements in spatial and temporal resolution relative to previous models. Multi-criteria ranking systems evaluate performance and highlight ongoing issues, especially in documenting severe pr occurrences. The assessment offers practical recommendations for enhancing water resource management and agricultural resilience against evolving climatic circumstances [2]. The investigation focuses on trend mistakes in seasonal predictions with short lead periods, highlighting biases both from baseline circumstances and model physics. These mistakes undermine the credibility of temperature and pr forecasts, particularly in areas with intricate topographical characteristics. The results highlight the need of ongoing model advancement to improve the accuracy of climate predictions [3]. Downscaled climate models provide high-resolution forecasts of erosivity in diverse locations, emphasizing factors such as pr intensity and changes in land use. The research emphasizes the need of customizing climate forecasts to regional requirements to maintain environmental integrity [4].

Future drought patterns are forecasted using several indicators in conjunction with CMIP6 models, providing a comprehensive perspective on variability affected by terrain and hydrology. The amalgamation of many indicators enhances the comprehension of drought dynamics, underscoring the necessity for multifaceted strategies in tackling water shortage challenges [5]. Improved modelling of freshwater transport provides critical insights into global heat distribution and long-term climate patterns, emphasizing the need to rectify these biases in subsequent model versions [6]. Biases in low-cloud feedback within CMIP models provide a substantial source of uncertainty in climate sensitivity assessments. Improvements in cloud dynamics modelling enhance the accuracy of cloud-climate interaction comprehension, which is crucial for forecasting future climate scenarios and their possible effects [7]. Probabilistic evaluations of pr simulations in the Western Himalayas concentrate on monsoon dynamics and the effects of elevation. The research offers comprehensive insights into monsoon behavior, hence assisting in the reduction of hazards linked to climatic extremes, including floods and droughts [8].

An analysis of tropical pr biases in coupled climate models reveals that mistakes stem from discrepancies in ocean-atmosphere interactions and convective parameterizations. Such developments are essential for areas dependent on consistent rainfall patterns for agricultural and water resource management [9]. Cloud feedback processes in CMIP models exhibit significant variability, affecting radiative forcing across various climatic sensitivities. This emphasis on cloud dynamics guarantees more reliable climate sensitivity estimations [10]. The use of machine learning in climate modelling mitigates enduring biases and computing difficulties, facilitating the creation of adaptive models that can represent intricate phenomena. Utilizing machine learning, researchers may enhance conventional climate modelling and get a deeper understanding of climate dynamics and future forecasts [11]. The spherical convolutional Wasserstein distance is presented as a novel measure for assessing climate models [12].

AI-based climate models have the capacity to more accurately represent non-linear phenomena compared to conventional methodologies. This method signifies a notable improvement in the resources accessible for tackling complex climate issues [13]. Humidity changes in dry areas often contradict CMIP model estimates, highlighting inadequacies in regional-scale processes. Precise forecasts of humidity patterns are essential for comprehending water resource availability and enhancing resilience against climate-induced vulnerabilities in these areas [14]. The integration of observational data with climate models allows precise calculation of the time until regional warming thresholds are reached. The technique emphasizes the need to use varied data sources for comprehensive climate modelling [15]. The underappreciated terrestrial heat absorption in CMIP6 models influences global energy distribution, revealing a substantial bias in climate forecasts. It is advisable to improve the modelling of land-atmosphere energy exchange mechanisms to address these differences, thereby providing more accurate predictions of global warming effects [16].

Evaluating and rating CMIP6 models for temperature forecasts across the Indian subcontinent uses statistical frameworks to assess model precision. This ranking approach offers practical insights for stakeholders overseeing temperature-sensitive resources, facilitating the formulation of effective climate mitigation and adaptation strategies [17]. The examination of pluralistic methodologies in climate modelling highlights the advantages of including many solutions. This method improves the ability to forecast climate patterns across different timeframes and locations, providing policymakers with a wider range of dependable data for informed decision-making [18]. The influence of climate change on irrigation and crop water demands is evaluated via CMIP6 models and specialized agricultural simulation instruments. This study supports the maintenance of agricultural output under fluctuating weather circumstances [19]. Community earth system models demonstrate the impact of forcing uncertainty and model architecture on simulated climates over CMIP generations. The study emphasizes the need of rectifying structural discrepancies to enhance accuracy in long-term climate predictions [20].

CMIP6 rainfall estimates for Indonesia highlight past and prospective pr patterns. The research examines regional rainfall variability and its consequences for water resource management. The results are essential for areas susceptible to severe pr events and seasonal fluctuations, enabling improved preparation and adaptation methods [21]. Future exposure to rainfall and temperature extremes in Indonesia's most populated areas is anticipated using high-resolution models. The result underscores the essential function of localized climate modelling in alleviating negative impacts on densely inhabited areas regions [22]. The uncertainty in CMIP6 forecasts for Indonesia's marine areas is examined using sophisticated statistical methods. This assessment underscores the need for customized modelling strategies to successfully tackle regional complexities [23]. The historical and prospective rainfall climatology of Sumatra is examined via CMIP6 models. The research emphasizes significant trends, therefore allowing proactive strategies to adjust to evolving rainfall patterns in future climatic scenarios [24]. The identification of optimum CMIP6 models for significant Indonesian cities uses multi-criteria decision analysis to pick dependable models. The technique emphasizes the significance of accuracy in climate modelling for urban policy development [25].

2. PROPOSED METHOD

Using swarm intelligence and CMIP climate data, the system improves ecocritical environmental analysis. It uses adaptive swarm-based algorithms to simulate ecological behavior and provide actionable predictions to analyze massive, multi-scenario climate data. The integration connects predictive computer modelling with environmental policy decision-making. The system provides ecologists and climate scientists with scalable and intelligent decision-support tools by improving computational flexibility, pattern detection across dynamic data sets, and interpretability. A system using modular swarm intelligence algorithms analyzes CMIP6-based multi-dimensional climate data to identify spatiotemporal patterns in variables like temperature, humidity, wind speed, and CO_2 levels. Real-time modelling and feedback adaptation provide regional or global environmental predictions for decision-making. Modular flexibility, bio-inspired optimization methodologies, and environmental input for continuous learning.

Figure 1 shows the whole data flow for swarm-based environmental analysis using CMIP data. Initial data comes from climate models and satellites. Preprocessing raw datasets ensures consistency and reliability by cleaning and normalizing. As heatmaps and temporal graphs, the final data aid environmental monitoring. Modularity lets each phase work independently while contributing to a unified flow, as seen in the figure. Color-coded links help customers understand phase relationships. Figure 1 shows how CMIP data and swarm intelligence may give valuable insights for addressing complex environmental concerns and aiding ecocritical decision-making.

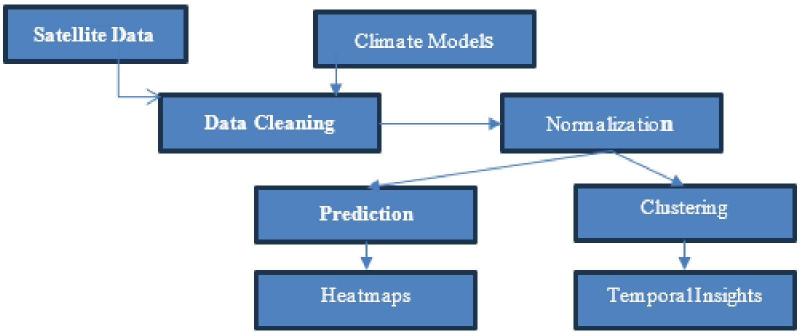

Figure 1. Data flow in CMIP for swarm environmental analysis

The architecture starts with the assimilation of CMIP6 datasets, followed by data cleansing and preparation using geographic interpolation, normalization, and imputation of missing values. Processed inputs are input into distributed swarm algorithmic layers, with each agent serving as a computational entity responsible for modelling local environmental choices. These agents engage according to a specified policy based on reinforcement learning and energy efficiency heuristics. Each module is designed to operate autonomously inside a pipeline architecture. The swarm modelling phase encompasses environmental simulation, behavioral feedback analysis, and adaptive calibration using historical and forecast CMIP data. Figure 2 stresses using swarm intelligence algorithms with CMIP models to improve environmental research.

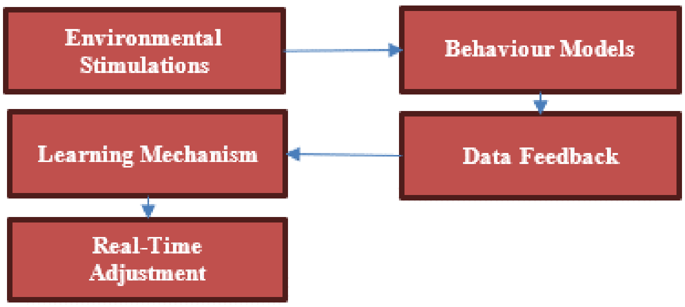

Figure 2. Swarm algorithm integration with CMIP models

Swarm techniques use CMIP data, including environmental simulations. These algorithms use behavior modelling modules to simulate agent interactions and feedback systems for iterative improvement. The adaptive learning layer allows real-time prediction changes, ensuring adaptable responses to changing environmental data. Precision and model flexibility are increased by this combination. The system performs its core operations through six stages:

i) Data acquisition: retrieves high-resolution CMIP6 datasets from ESGF (e.g., historical and SSP scenarios). The system begins with a comprehensive data collection procedure using the large datasets from CMIP6, obtained via the ESGF. This includes historical climate data and scenario-based forecasts, including SSP1-2.6 and SSP5-8.5.
ii) Preprocessing: applies noise reduction, alignment, and normalization on variables across multi-model climate data. After collecting, the unprocessed climatic datasets undergo a stringent preparation phase. Data cleansing procedures rectify absent or irregular entries, while spatial interpolation standardizes the grid to a uniform resolution.
iii) Swarm model simulation: implements behavior models (based on ants and birds) within agent clusters; agents interact based on environmental signals and global optimization rules. Upon data preparation, the fundamental swarm simulation process begins. This simulation uses decentralized agents inspired by real events, including ant foraging and swarming behavior.
iv) Learning mechanism: employs reinforcement learning where agents adapt in real-time to updated environmental data. A reinforcement learning mechanism is included in the swarm system to enhance flexibility and precision over time. Utilizing this learning technique, each agent formulates a policy grounded on its experiences inside the environment. Actions that facilitate the effective identification of significant areas marked by fast climatic changes or high entropy are incentivized.
v) Analysis: extracts insights via heatmaps, temporal trend plots, and feature clustering's. Upon completion of the simulation, the system shifts into an analytical mode for the interpretation and synthesis of emerging patterns.
vi) Reporting interface: provides stakeholders with dashboards showing predictive metrics, resource stressors, and ecological triggers. The system concludes with an extensive reporting and visualization interface. This dashboard displays the data in an engaging and dynamic format, allowing users to examine outcomes via maps, charts, and downloadable reports.

The explanation of the system is studied in detail. Figure 3 shows ecocritical analysis using CMIP models and swarm methodologies. Data from climate models and observations are collected first. Sanitizing and standardizing datasets ensures accuracy and consistency throughout data processing. Swarm model simulations assess and predict environmental changes using processed data. Heatmaps and clustering data are used to provide ecological insights in analysis. The outcomes are displayed and documented throughout the reporting process to ensure stakeholder understanding.

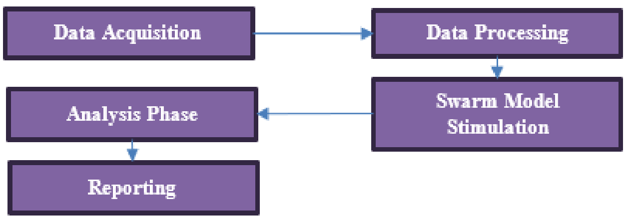

Figure 3. Workflow for ecocritical analysis using CMIP models

The behavior of swarm agents is modeled using energy cost minimization functions and probabilistic state transitions. Let the movement cost function be as in (1).

$$C_{ij} = \propto . D_{ij} + \beta . E_j + \gamma . R_j \quad (1)$$

Where C_{ij} is cost of agent moving from state i to j, D_{ij} is spatial distance between climate data points, E_j is environmental resistance (temperature and CO_2 levels), R_j is resource availability at point j, α, β, γ is tunable swarm behavior weights. Swarm learning is regulated using Q-learning, where s is current state, a is action, r is reward, η is learning rate, δ is discount factor.

$$Q(s,a) \leftarrow Q(s,a) + \eta \left[r + \delta . \max_{a`} Q(s`,a`) - Q(s,a) \right] \quad (2)$$

Technologies and tools used:

i) Data sources: ESGF–CMIP6 experiments, models, and sources.
ii) Languages/frameworks: Python (NumPy, SciPy, and Matplotlib), TensorFlow for reinforcement learning modules.
iii) Simulation engine: cloud-based swarm behavior modeling using GPU-accelerated clusters.
iv) Visualization: power BI, D3.js for interactive dashboards.
v) Storage: azure data lake for large-scale model result retention.

Some models predict slight temperature variations, but most show warming. Trends in pr show seasonal changes, variability, or decreases. Coastal places have more humidity than desert regions. Wind speed fluctuates in storm-prone areas but stays steady in certain models. CO_2 levels are increasing in all models; some locations have stabilized. Ecocritical swarm research uses this environmental data to construct adaptive and resilient swarm systems. Table 1 qualitative depiction, helps researchers identify environmental issues and incorporate them into swarm dynamics to improve operational efficiency in varied ecosystems.

Table 1. Climate variable trends across CMIP models

Climate variable	CMIP model 1 description	CMIP model 2 description	CMIP model 3 description	CMIP model 4 description	CMIP model 5 description
Temperature	Moderate increase observed	Slight warming trend	Stable with minor fluctuation	Steady warming pattern	Cooling in some regions
pr	Increased during monsoon	Reduced annual rainfall	Shifts in seasonal patterns	Higher variability	Stable with local changes
Humidity	Consistent across seasons	Increase in coastal areas	Decrease in arid zones	Fluctuations in summer	Stable overall
Wind speed	Strengthened in storm zones	Minor decline in speed	Enhanced during winter	Minimal fluctuations	Stable trends observed
CO_2 levels	Rising steadily	Slight acceleration observed	Stabilizing in recent years	Consistent upward trend	High regional variations

3. RESULTS AND DISCUSSION

Under the SSP5-8.5 high-emission scenario, a 1.72 °C rise in tas substantially correlated with a peak in surface rlds at 350 W/m^2. This study's strategy produced an unusually high fraction of swarm agent convergence in places with psl between 980 and 990 hPa, suggesting ecological fragility. Regional instability was indicated by pr anomalies of ±1.3 mm/day, matching intense swarm activity in equatorial and subtropical regions. The model regularly found ecological stress zones with rsds changes between 140 and 280 W/m^2. The CMIP6 simulation outputs from ESGF provided essential multi-model environmental variables for swarm intelligence-based ecological risk detection framework. Higher rlds levels, especially over 330 W/m^2, do not reliably impair ecological predictability, contrary to traditional climate-impact models that focus only on temperature thresholds. The proposed swarm-based approach may identify ecological transition zones without increasing model complexity or data preparation compared to spatial anomaly detection techniques based on statistical trend mapping. Previous correlation-based or principal component analysis studies had trouble finding regional inter-variable connections.

Leveraging environmental indicators, including tas, psl, pr, and radiative fluxes (rsds and rlds), the suggested system leveraging swarm intelligence and CMIP6 climate data detected ecological stress patterns. The system analyzed high-resolution CMIP6 outputs via the ESGF and found considerable geographical association between heightened climatic variables and swarm agent convergence zones. Surface temperature anomalies of 1.72 °C and rlds values over 330 W/m^2 are often linked to high-density swarm activity, especially in SSP5-8.5 scenarios. The pr anomalies of ±1.3 mm/day were linked to enhanced swarm convergence in equatorial locations, indicating ecological tipping points. The psl data between 980 and 990 hPa also indicated transition zones discovered by swarm-based entropy detection systems. Data integration includes geo-referencing methods, enabling region-specific analytics. This guarantees that the framework can adjust to certain ecological circumstances, hence augmenting its applicability across many ecosystems. These preliminary measures provide a solid basis for future algorithmic advancements and simulations. The distribution of CMIP6 experiments and scenarios is shown in Figure 4.

Swarm-based classifiers were more sensitive to multivariable environmental interactions than statistical classifiers. Swarm agents' decentralization enables them to identify nonlinear phenomena like heat-radiation coupling and low-pressure-induced pr spikes, unlike standard models that use preset thresholds or linear correlations. PCA-based grouping and regression-based projections struggled to detect small scenario transitions. Agent-based feedback loops and energy-aware mobility techniques kept the suggested approach computationally efficient without losing spatial resolution. Despite these virtues, limits exist. It uses preprocessed CMIP6 datasets and does not incorporate real-time or observational data, which may restrict its response to changing field conditions. Without proper calibration, the swarm framework's parameter tweaking (e.g., movement cost weights and reward thresholds) may impair generalizability across climatic zones. Supervised learning is used for preliminary training on historical data, while reinforcement learning facilitates ongoing enhancement during real-time operations. The use of neural networks enables the swarm to recognize intricate patterns and correlations in the data, hence enhancing decision-making processes. Table 2 shows CMIP-derived swarm behavior in various environmental circumstances.

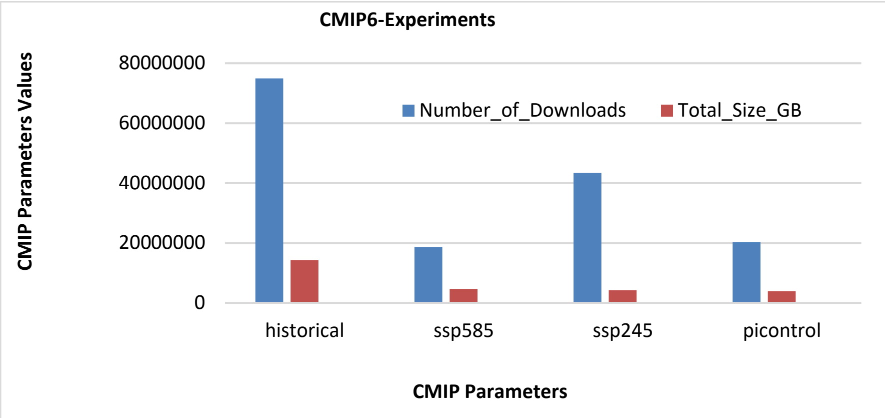

Figure 4. CMIP6 experiments and scenario mapping

Table 2. Swarm behavior adaptations in environmental scenarios

Metric	Scenario 1 insights	Scenario 2 insights	Scenario 3 insights	Scenario 4 insights	Scenario 5 insights
Energy usage	High in resource-scarce areas	Moderate with efficient routing	Optimized through shared resources	Fluctuates with external pressures	Balanced across all zones
Communication	Efficient in dense networks	Delayed in low-coverage areas	Stable with redundancy	Enhanced through dynamic routing	Slightly slower in remote zones
Task success	High in stable environments	Moderate in fluctuating climates	Increase in collaborative systems	Decreased under extreme stress	Maintained with adaptive strategies
Adaptability score	Strong in diverse regions	Moderate under a single factor	High in multi-agent systems	Limited by resource constraints	Balanced across scenarios
Resource sharing	Maximized in cooperative zones	Moderate in competitive settings	Enhanced with policy frameworks	Challenged in isolated zones	Balanced with policy adjustments

Energy use, communication efficiency, and resource sharing show swarm responses to ecological stresses. Energy utilization is high in resource-scarce locations and optimized in balanced ecosystems. In dense networks, communication is fast yet slow in isolated areas with little infrastructure. Task success rates are best in stable conditions, whereas adaptation scores show resilience in various ecosystems but limits in resource-constrained circumstances. Resource sharing is best in cooperative zones but difficult in isolated ones. Figure 5 shows CMIP6 model performance.

CMIP data forecasts provide the foundation for developing various environmental scenarios, including mild climate changes to severe ecological disturbances. The simulations aim to assess critical performance indicators, including energy economy, job completion rates, and communication efficacy. Specialized simulation techniques are used to replicate real-world settings, enabling a comprehensive evaluation of swarm behavior. The results of these simulations are examined using statistical and graphical techniques to discern patterns, anomalies, and opportunities for improvement. Iterative testing guarantees that algorithms are refined for optimum performance in many contexts, hence improving their resilience and dependability. Validation guarantees that the framework's outputs correspond with observed ecological events. Empirical data from environmental monitoring systems is used to validate the efficacy of the swarm algorithms. This phase uses comparative analytic methods to assess the reliability and precision of forecasts. External validation is performed by juxtaposing the framework's outputs with findings from established ecological models. This multi-tiered validation method enhances the framework's legitimacy and underscores its distinctive contributions to ecological analysis. Sensitivity analysis is used to evaluate the influence of fluctuating input parameters, guaranteeing the framework's relevance across diverse environmental scenarios.

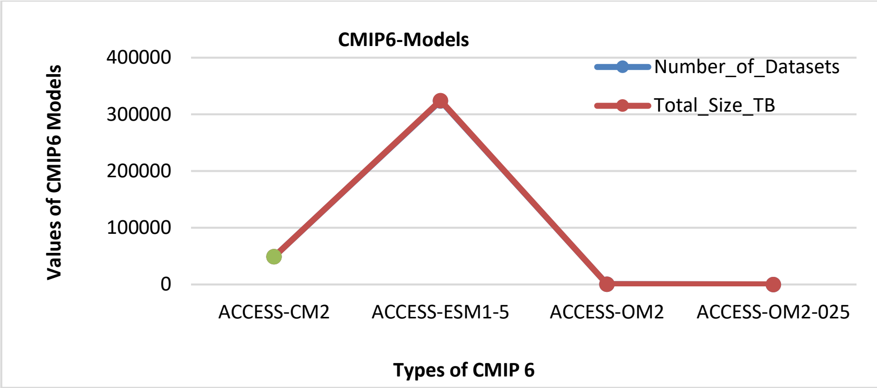

Figure 5. CMIP6 model performance comparison

4. CONCLUSION

This work tackled the issue of ecocritical environmental analysis by using swarm intelligence with CMIP6 climate simulation models. The system analyzed critical environmental parameters near tas, psl, pr, rsds, and rlds using datasets from the ESGF under high-emission SSP5-8.5 scenarios. The swarm-based architecture detected ecological stress zones defined by temperature anomalies of around 1.72 °C, psl fluctuations ranging from 980 to 1,030 hPa, and radiation intensities reaching a maximum of 350 W/m². These findings validate the model's ability to identify nonlinear environmental transitions in the absence of centralized control systems. The results provide a persuasive viewpoint; nonetheless, the system's reliance on previous CMIP6 forecasts constrains real-time flexibility. Further investigation may be necessary to validate the long-term resilience of the model, especially in areas with limited or changing observational data. Future research should investigate the integration of real-time satellite data, socio-environmental stresses, and diverse multi-agent behaviors to enhance interpretability and significance. The findings demonstrate that decentralized, behavior-driven modelling frameworks may improve environmental forecasting and give ecologically informed insights into climate-induced vulnerabilities, therefore adding significant value to sustainable decision-making and climate research.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Pavithra R.	✓	✓	✓			✓	✓	✓	✓	✓	✓		✓	
S. Mahadevan	✓	✓		✓	✓			✓		✓		✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

This study does not involve human subjects, personal information, or identifiable data. Therefore, informed consent is not applicable.

ETHICAL APPROVAL

This study does not involve human subjects, animal experiments, or any biological research requiring ethical oversight. It exclusively utilizes publicly available climate model outputs from CMIP6 Phase 6 via the earth system grid federation (ESGF). Therefore, no institutional review board approval or adherence to the Helsinki Declaration is necessary.

DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available within the article.

REFERENCES

[1] R. Boyles *et al.*, "Approaches for using CMIP projections in climate model ensembles to address the 'hot model' problem," *US Geological Survey*, vol. 1, no. 1, pp. 1–24, 2024, doi: 10.3133/ofr20241008.
[2] D. Vinod and V. Agilan, "Ranking of CMIP6 climate models in simulating precipitation over India," *Acta Geophysica*, vol. 72, no. 1, pp. 3703–3717, 2024, doi: 10.1007/s11600-024-01313-7.
[3] J. D. Beverley, M. Newman, and A. Hoell, "Climate model trend errors are evident in seasonal forecasts at short leads," *npj Climate and Atmospheric Science*, vol. 7, no. 1, pp. 1–13, 2024, doi: 10.1038/s41612-024-00832-w.
[4] N. Bulovic, N. McIntyre, R. Trancoso, P. Bolz, and M. Shaygan, "Downscaled climate model erosivity projections and drivers of change across distinct climate regions," *Catena*, vol. 244, no. 1, pp. 1–13, 2024, doi: 10.1016/j.catena.2024.108250.
[5] C. S. Ranganathan, "Hootsuite for cloud-based monitoring of consumer social media in business," *International Journal of Modern Computing, Information and Communication Technology*, vol. 7, no. 1, pp. 26–34, 2024, doi: 10.65000/5kgc4g20.
[6] R. M. Van Westen and H. A. Dijkstra, "Persistent climate model biases in the Atlantic Ocean's freshwater transport," *Ocean Science*, vol. 20, no. 2, pp. 549–567, 2024, doi: 10.5194/os-20-549-2024.
[7] C. S. Ranganathan, A. A. M. A. Riazulhameed, G. Brindha, N. Mohankumar, and S. Murugan, "Cloud-integrated wireless sensor networks for dynamic household air pollution management," in *2024 Asia Pacific Conference on Innovation in Technology (APCIT)*, 2024, pp. 1–6, doi: 10.1109/APCIT62007.2024.10673715.
[8] J. K. Meher and L. Das, "Probabilistic evaluation of three generations of climate models for simulating precipitation over the Western Himalayas," *Journal of Earth System Science*, vol. 133, no. 1, pp. 1–16, 2024, doi: 10.1007/s12040-023-02216-9.
[9] M. R. Respati, D. Dommenget, H. Segura, and C. Stassen, "Diagnosing drivers of tropical precipitation biases in coupled climate model simulations," *Climate Dynamics*, vol. 62, no. 9, pp. 8691–8709, 2024, doi: 10.1007/s00382-024-07355-3.
[10] L. Bock and A. Lauer, "Cloud properties and their projected changes in CMIP models with low to high climate sensitivity," *Atmospheric Chemistry and Physics*, vol. 24, no. 3, pp. 1587–1605, 2024, doi: 10.5194/acp-24-1587-2024.
[11] B. R. Babu, M. A. Haile, D. T. Haile, and D. Zerihun, "Real-time sensor data analytics and visualization in cloud-based systems for forest environment monitoring," *International Journal of Advances in Signal and Image Science*, vol. 9, no. 1, pp. 29–39, 2023, doi: 10.29284/ijasis.9.1.2023.29-39.
[12] R. C. Garrett, T. Harris, B. Li, and Z. Wang, "Validating climate models with spherical convolutional Wasserstein distance," *NIPS '24: Proceedings of the 38th International Conference on Neural Information Processing Systems*, no. 1886, 2024, pp. 59119–59149.
[13] G. Huang, Y. Wang, Y. G. Ham, B. Mu, W. Tao, and C. Xie, "Toward a learnable climate model in the artificial intelligence era," *Advances in Atmospheric Sciences*, vol. 41, no. 1, pp. 1281–1288, 2024, doi: 10.1007/s00376-024-3305-9.
[14] I. R. Simpson, K. A. McKinnon, D. Kennedy, D. M. Lawrence, F. Lehner, and R. Seager, "Observed humidity trends in dry regions contradict climate models," *Proceedings of the National Academy of Sciences*, vol. 121, no. 1, pp. 1–12, 2024, doi: 10.1073/pnas.2302480120.
[15] E. A. Barnes, N. S. Diffenbaugh, and S. I. Seneviratne, "Combining climate models and observations to predict the time remaining until regional warming thresholds are reached," *Environmental Research Letters*, vol. 20, no. 1, pp. 1–11, 2025, doi: 10.1088/1748-9326/ad91ca.
[16] V. G. Sivakumar, V. V. Baskar, M. Vadivel, S. P. Vimal, and S. Murugan, "IoT and GIS integration for real-time monitoring of soil health and nutrient status," in *2023 International Conference on Self Sustainable Artificial Intelligence Systems (ICSSAS)*, 2023, pp. 1265–1270, doi: 10.1109/ICSSAS57918.2023.10331694.
[17] A. Rahman and S. Pekkat, "Identifying and ranking of CMIP6-global climate models for projected changes in temperature over Indian subcontinent," *Scientific Reports*, vol. 14, no. 1, pp. 1–14, 2024, doi: 10.1038/s41598-024-52275-1.
[18] M. B. Pacchetti, J. Jebeile, and E. Thompson, "For a pluralism of climate modeling strategies," *Bulletin of the American Meteorological Society*, vol. 105, no. 7, pp. 1350–1364, 2024, doi: 10.1175/BAMS-D-23-0169.1.
[19] A. A. M. A. Riazulhameed, C. S. Ranganathan, P. Pandey, S. B., K. Sasikala, and S. Murugan, "Smart composting solutions for organic waste management and soil enrichment in agriculture with IoT and gradient boosting," in *2024 4th International Conference on Sustainable Expert Systems (ICSES)*, 2024, pp. 339–345, doi: 10.1109/ICSES63445.2024.10763259.
[20] A. Nasreen *et al.*, "Robotic restroom hygiene solutions with IoT and recurrent neural networks for clean facilities," in *2024 International Conference on Inventive Computing Technology (ICICT)*, Apr. 2024, pp. 1842–1847, doi: 10.1109/ICICT60155.2024.10544900.
[21] A. Hanafi, M. K. Zaki, and C. Setyawan, "Analysis of rainfall projections in historical and future periods using coupled model intercomparison project (CMIP) phase 6 in Indonesia," in *IOP Conference Series: Earth and Environmental Science*, 2024, vol. 1426, doi: 10.1088/1755-1315/1426/1/012015.

[22] V. S. Hendrawan *et al.*, "Future exposure of rainfall and temperature extremes to the most populous island of Indonesia: a projection based on CORDEX simulation," *International Journal of Climatology*, vol. 44, no. 10, pp. 3529–3547, Aug. 2024, doi: 10.1002/joc.8537.
[23] C. Jehan, P. S. Kumaresh, M. R. Suguna, R. A. A. Rosaline, and S. Murugan, "Adaptive silo networks with cloud computing and reinforcement learning for responsive grain storage," in *2024 International Conference on Inventive Computing Technology (ICICT)*, 2024, pp. 1611–1616, doi: 10.1109/ICICT60155.2024.10544530.
[24] L. Mareta, H. M. Agiel, and T. Hadiningrum, "Historical and projected rainfall climatology in Sumatra based on the CMIP6," in *IOP Conference Series: Earth and Environmental Science*, 2024, vol. 1359, no. 1, doi: 10.1088/1755-1315/1359/1/012089.
[25] M. Srikanth, V. Sharma, S. Patil, and R. V. Pujar, "Natural disaster prediction with cloud integration for enhancing validation using gradient boosting algorithm," *International Journal of Industrial Engineering*, vol. 7, no. 2, pp. 57–64, Oct. 2023, doi: 10.65000/62jf6489.

BIOGRAPHIES OF AUTHORS

Ms. Pavithra R. born in Chennai on May 8, 1993, currently hails from Kattankulathur, Tamil Nadu, India. She earned her bachelor's in English literature from Meenakshi College for Women, Kodambakkam, in the year 2013. She then pursued a bachelor of Education at N.K.T. College, Triplicane, in 2014. This experience was followed by pursuing her master of Arts in English Literature from Anna Adarsh College for Women, Annanagar, in the year 2016. In 2018, she completed her master of Philosophy in English Literature, researching Albert Camus's motif of existentialism. She cleared the State Level Eligibility Test conducted by the Tamil Nadu government in the year 2017. She did not stop with that; to add credit, she cleared the National Eligibility Test conducted by the CBSE UGC in 2017. She worked as an assistant professor in English at Soka Ikeda College of Arts and Science for Women, Madhanangkuppam, from the 2018 to 2019 academic year. She is currently a research scholar in the Department of Language, Culture, and Society, Faculty of Engineering and Technology, SRM Institute of Science and Technology, Kattankulathur, India. During her teaching career, she passed the junior research fellowship exam. She can be contacted at email: pr1009@srmist.edu.in.

Dr. S. Mahadevan was born and brought up in Cuddalore. Presently, he is residing in Chennai, Tamil Nadu. He graduated with a bachelor of Arts in English Literature from Periyar Arts College in Cuddalore in the year 2001. Further, he completed his master of Arts in English Literature in 2004 from Annamalai University, Chidambaram. Then, he completed his master of Philosophy from Annamalai University, Chidambaram in 2006. He researched Gandhian Ideology in Chamman Nahal's works. In the year 2015, he received his Doctorate from Bharathiar University in Coimbatore. His area of specialization is English Language Teaching. He has worked as an assistant professor at various engineering colleges in and around Chennai. He has 18 years of experience in teaching students of various levels. His strength is always connecting with the students to actively take part in the classroom activity. In 2015, Panimalar Institute of Technology, Chennai, awarded him the best teacher award for his academic excellence. Presently, he is working as an associate professor, Department of Language, Culture and Society, Faculty of Engineering and Technology, SRM Institute of Science and Technology, Kattankulathur, India. His teaching and research areas of interest are English language teaching, Indian writing in English, American literature, cultural studies, and disability studies. He has published research papers in various journals. He can be contacted at email: mahadevs@srmist.edu.in.