BAMS
Meeting Summary

AI Weather and Climate Prediction and Applications

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Asia Oceania Geosciences Society 2025 Conference Sessions on AI Applications on Weather and Climate Prediction

What: Over 300 participants from Asia, Oceania, North America, and Europe attended a special plenary session and a regular session on artificial intelligence (AI) weather and climate at the Asia Oceania Geosciences Society (AOGS) 2025 Annual Conference. A total of 26 papers were presented by about 60 authors and affiliated with academic, research, and government institutions in mainland China, India, Hong Kong, Korea, Japan, Singapore, Taiwan, and the United States.

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1. Introduction

In 2023, Huawei Corporation in China released the Pangu-Weather model that became the first global artificial intelligence (AI) model to outperform the European Centre for Medium-Range Weather Forecasts' (ECMWF) state-of-the-art numerical weather prediction (NWP) system in medium-range forecasts. It achieved this while being orders of magnitude faster. This breakthrough spurred a surge of research and development efforts of using AI in meteorological research and forecast applications across Asia.

The 2025 Asia Oceania Geosciences Society (AOGS) meeting provided a valuable opportunity for AI researchers and meteorologists from across the region to share progress, exchange ideas, and discuss challenges and future directions. Among several AI-related sessions at the conference, this summary will highlight key takeaways from the special plenary session SS01 (https://www.asiaoceania.org/aogs2025/public.asp?page=special_sessions.asp) and the associated atmospheric sciences session AS58, both of which focused on meteorological applications of AI.

The sessions brought together computer scientists, weather and climate researchers, and forecasters from five Asian operational meteorological services—located in Beijing, Busan, Hong Kong, Singapore, and Taipei—broadening the discussion to span theory, research, implementation, and downstream applications. The rapid pace of AI development in China was reflected in the field of weather forecasting. In a recent national competition, China Meteorological Administration selected 14 models from the submissions of 35 academic, government, and private industry institutions. Developers of three of these selected models—FengWu, FuXi, and TianXing—were among the invited speakers at the special plenary session.

2. Incorporation of physical law constraints

The application of data-driven transformer models to weather forecasting is often limited by their substantial computational requirements during training. Incorporating physical constraints offers a promising path to reduce these demands while improving model interpretability. Addressing this challenge, researchers at Tongji University introduced TianXing (Yuan et al. 2025), a transformer architecture featuring linear complexity and explicit attention decay for efficient and physically consistent global weather forecasting.

TianXing integrates atmospheric physics throughout its framework via three core components: data preprocessing, architectural design, and the loss function. During preprocessing, the model applies mass-conserving remapping to generate uniform cubed-sphere grids. This step rectifies the issue of translational invariance violations common in standard neural architectures when applied to spherical coordinates. The loss function is formulated as a physics-informed objective, combining cross-entropy loss on temporal difference distributions with an energy spectral loss calculated via Fourier transforms. This dual approach reduces forecast blurring and enforces adherence to theoretical energy scaling laws.

Architecturally, TianXing incorporates two specialized mechanisms to embed physical relationships. The Spherical-Distance Attention Decay mechanism prioritizes feature interactions between neighboring grid points before considering more distant ones, thereby emulating the localized nature of atmospheric influence propagation. Complementing this, the Multivariable Coupling Decay mechanism employs a learnable matrix to differentially weight interactions between meteorological variables based on their known physical couplings. For instance, temperature and geopotential height are tightly bound through the hydrostatic equation, while humidity and temperature relationship are significant only under phase changes. This structure guides the model to prioritize physically meaningful connections, mitigating the risk of overfitting and spurious correlations that can arise from purely data-driven, end-to-end training.

In a comprehensive evaluation using 2018 data, TianXing demonstrated state-of-the-art performance. It produced skillful 500-hPa geopotential height (Z500) forecasts with an anomaly correlation coefficient (ACC) greater than 0.6 for up to 10.85 days, matching contemporary benchmarks. The model also exhibited strong performance in tropical cyclone forecasting. It was among the earliest models to predict the landfall of Typhoon In-Fa and successfully captured the precursors to the rapid intensification of Typhoon Vicente. In the latter case, the model identified a reduction in vertical wind shear and an enhancement of mid–upper-tropospheric moisture approximately 12 h before intensification began. This ability to detect dynamically relevant precursors indicates that TianXing's physics-augmented architecture facilitates the learning of genuine atmospheric mechanisms rather than mere statistical artifacts.

3. Machine learning data assimilation

While models like Pangu-Weather demonstrate the power of AI for forecasting, they rely on NWP systems like ECMWF's ERA5 for initial conditions. This not only makes the AI prediction dependent on NWP but can also result in the loss of fine-scale information, particularly when local observation networks are denser than the resolution of the NWP analysis. To overcome these constraints and enable the direct assimilation of vast observational datasets, machine learning (ML) for data assimilation (DA) (ML-DA) has become a major research focus.

The FuXi weather model, developed by researchers at Fudan University and the Earth System and Modeling and Prediction Center of China Meteorological Administration, addresses this challenge through a dual-strategy approach: 1) replacing specific components of conventional DA systems with deep learning alternatives (Y. Li et al. 2024, 2025; Z. Li et al. 2024) and 2) developing end-to-end, data-driven systems (Sun et al. 2025; Xu et al. 2025). For the first strategy, the team created AI ensemble 4D-Var (AI-En4DVar), which utilizes automatic differentiation to replace traditional tangent linear and adjoint models. This framework integrates ML-based satellite observation operators, leading to a significant reduction in computational expense. For the second strategy, they developed FuXi-DA, an encoder–decoder model that learns the complex mappings between observations and background fields directly from data, thereby eliminating the need for explicit, physics-based observation operators.

Built upon this framework, the FuXi Weather system assimilates satellite radiance data from three polar-orbiting meteorological satellites (Fengyun-3E, *MetOp-C*, and *NOAA-20*), and the Global Navigation Satellite System radio occultation data, achieving global 10-day forecast performance comparable to the ECMWF high resolution (HRES) forecast. It also consistently outperforms ECMWF HRES in regions with sparse land-based observations, such as Africa. These promising results motivate plans to incorporate ground-based observations and other data on the Global Telecommunications System (GTS) to conduct full ML DA operations.

At the Rikagaku Kenkyūsho (RIKEN) Center for Computational Science of Japan, NWP output is fed into a convolutional long short-term memory (ConvLSTM) network. This architecture integrates the spatial feature extraction capabilities of convolutional neural networks (CNNs) with the temporal sequence modeling of long short-term memory (LSTM), learning the spatiotemporal evolution of weather patterns to significantly improve precipitation nowcasting. The team has also developed ML-based surrogates for key DA components, such as a purely data-driven satellite observation operator. Such operators can be rapidly developed for new satellite sensors without relying on a traditional radiative transfer model.

A common challenge in traditional DA methods, such as the ensemble Kalman filter, is filter divergence in data-sparse environments, where limited observations fail to constrain the high-dimensional state space. To address this, the RIKEN team is investigating novel frameworks like the Deep Bayesian Filter (DBF), which performs the analysis within a compact, learned latent space. This low-dimensional representation is more effectively constrained by sparse observations, preventing divergence and yielding a more stable and accurate analysis.

4. Climate prediction

While ML models have demonstrated considerable skill in simulating variations within the atmosphere, land, or ocean, respectively, less attention has been paid to developing fully coupled models that explicitly represent their interactions. This coupling is essential for accurate climate prediction, yet a key open question is whether ML approaches can effectively capture the spatially and temporally varying strengths of land–atmosphere and ocean–atmosphere feedbacks. A central challenge lies in representing interactions that evolve over time scales much longer than the model's typical daily time step. Conventional loss functions, which minimize stepwise prediction errors, are ill-suited for capturing slow processes such as the soil moisture–evapotranspiration–precipitation feedback, which operates on subseasonal-to-interannual scales.

Research from Seoul National University demonstrated a promising solution: a multistep training loss function that iteratively feeds model outputs back as inputs over multiple forward passes. This approach forces the model to learn long-term dependencies. In a land–atmosphere coupled model, this method improved Northern Hemisphere heat wave predictions (2018–23) by 5.9%–11.2%, a significant gain over the 1.9%–4.3% improvement achieved with a standard single-step loss. For instance, during the 2018 western European heat wave (Bastos et al. 2020), the coupled model with multistep loss realistically simulated the evolution of soil moisture deficits, surface energy fluxes, and near-surface temperatures, whereas an atmosphere-only model underestimated the drying and produced a cold bias. Similar benefits were observed in ocean modeling, where training with a 30-day multistep loss reproduced realistic climatology and seasonal cycles over decades.

Addition of the loss term with the anomaly fields by rearranging samples for each batch further enabled the model to capture interannual variability, including El Niño–Southern Oscillation (ENSO) and its associated global sea surface temperature (SST) signatures. These results suggest optimized multistep training enables ML models to represent both mean states and variability in coupled climate systems.

Challenges remain in developing AI-based coupled atmosphere–ocean–land–sea ice models. The training of climate models is inherently constrained by the relatively small number of independent samples in observational records, a consequence of high temporal autocorrelation in climate data. Furthermore, using synthetic data from dynamical models for training can introduce and amplify biases. Errors compound across multistep simulations, particularly when models violate fundamental physical constraints like energy conservation. Embedding such physical laws directly into model architecture is a potential pathway to stabilizing long-term simulations. An additional question is whether purely data-driven models can capture climate responses to multidecadal radiative forcing, a time scale that far exceeds their prediction time steps (Raissi et al. 2019).

Models for seasonal and ENSO forecasts were also discussed by researchers at the Chinese Academy of Sciences (CAS) and Nanjing University. Subseasonal to seasonal (S2S) forecasting was addressed by researchers from the Asia–Pacific Economic Cooperation (APEC) Climate Center, Tongji University, University of Tokyo, and CAS.

5. Parameterization of convection

The proper parameterization of convection and clouds presents a significant challenge in NWP and climate models. Deficiencies in these parameterizations are the sources of many persistent biases, such as those affecting the ITCZ, MJO, and the diurnal cycle of precipitation. Traditional physics-based approaches, which often rely on limited observations and empirical relationships, struggle to capture the complexity of convection and lack memory of past atmospheric states. While superparameterized models offer more realistic simulations, their extreme computational cost prohibits their use for long-term or ensemble climate projections. ML, particularly deep neural networks, has emerged as a promising data-driven alternative to overcome these limitations.

Researchers from Scripps Institution of Oceanography and Tsinghua University developed such an alternative: a deep convolutional residual neural network to parameterize moist physics processes (Han et al. 2020). The network was trained on a superparameterized version of the NCAR Community Atmosphere Model (CAM). In both offline tests and multiyear online simulations coupled with NCAR CAM5, the ML-based parameterization accurately reproduced convective diabatic heating and drying, as well as key features of the global precipitation distribution.

Notably, the model demonstrated a striking ability to generalize. In a decadelong simulation forced by +4-K SST—an unseen climate state—the network produced highly encouraging results. It not only replicated global distributions of temperature, moisture, and precipitation but also captured their response to warming, all without exhibiting the instabilities from out-of-distribution extrapolation common in earlier studies. Unique to this work, the neural network incorporated past atmospheric information crucial for convection memory, enabling the hybrid general circulation model (GCM) to achieve stable, decadelong integrations for both present and warmer climates.

Despite this success, significant challenges persist. First, purely data-driven ML relationships are not inherently constrained by physical laws governing the conservation of mass, energy, and momentum. Second, there is no theoretical guarantee for the integration stability of such models or their ability to generalize to different climate regimes. Finally, the atmosphere is an intricately complex system; ML must still prove it can handle interconnected processes like cloud–aerosol interactions and the transport of physical properties, which have not yet been fully attempted. Thus, while promising, a reliable, operational role for machine learning in climate simulation and projection remains a considerable distance away.

6. Downscaling and local special weather

Downscaling converts large-scale model outputs into high-resolution data for weather forecasting. AI provides scalable and efficient methods to generate this detailed information at a low computational cost. However, these AI approaches also present challenges, such as a scarcity of high-resolution training data, difficulties in capturing nonlinear interactions across different scales, and potential poor generalization to unseen regions or conditions.

Researchers at the National Institute for Environmental Studies in Japan used CNNs to downscale coarse-resolution GCM outputs to high-resolution (kilometer-scale, 0.025°) grids derived from station observations. CNN-based models use dynamic and thermodynamic predictors from reanalysis (e.g., temperature, humidity, wind speed, and pressure) across multiple atmospheric levels. They are trained on part of the historical record and validated on the remainder to reproduce observed targets. For snow depth downscaling, predictors also include snow water equivalent to maintain physical consistency. Once validated, the CNN-based model is combined with an ensemble ML framework and bias-corrected Coupled Model Intercomparison Project (CMIP) predictors to generate downscaled projections on the observational grid, following the perfect prognosis approach. This bridges the resolution gap, producing kilometer-scale projections from coarse GCM inputs (Damiani et al. 2025).

After validation, the models were applied to future scenarios. Key snow depth features—altitude-dependent climate change signals, spatial pattern shifts, and latitudinal gradients—closely matched dynamical downscaling results and downscaled fields maintained coherence across CMIP ensemble members. This internal consistency supports scenario-based impact assessments, including winter tourism and water resource management, and aligns with coordinated international initiatives [e.g., Coordinated Regional Climate Downscaling Experiment (CORDEX); Kendon et al. 2025; Giorgi et al. 2009].

The CNN-based approach offers fast training and flexibility across spatial resolutions, but limitations remain in generalizing to unseen regions and in capturing extreme precipitation or snow cover in sparsely observed areas. Incorporating high-resolution regional reanalysis datasets and generative ML models may help address these challenges.

Other downscaling approaches reported at the meeting include the RIKEN Center's exploration of a regional AI model nested within a global AI model and the Indian Institute of Tropical Meteorology's combination of deep learning bias correction, statistical downscaling, and high-resolution value estimation to produce projections at individual local points.

AI applications for localized forecasting and related topics were highlighted by researchers from the following institutions: tropical cyclones—Hong Kong Observatory (HKO), Nanjing University of Information Science and Technology, and Taiwan Central Weather Administration; aviation applications—Agency for Science, Technology and Research, Singapore, and HKO; daily CO estimations—Seoul National University; weather forecasts—National Meteorological Center of China; streamflow predictions—CAS; and satellite-derived rainfall—Kyungpook National University.

7. Agentic AI

Modern Earth science faces mounting challenges from rapidly increasing and fragmented data. This is especially acute in climate research, where massive CMIP datasets generate petabytes of output that overwhelm traditional scientific workflows—still largely manual and fragmented and struggling to keep pace with their scale and complexity. These limitations are most evident in large-scale assessments by the Intergovernmental Panel on Climate Change (IPCC), which require years of labor-intensive analyses and coordination. Diagnostic toolkits [e.g., Earth System Model Evaluation Tool (ESMValTool)] exist, but their predefined design limits flexibility, making adaptation difficult without significant coding expertise. Comparing models with observations or detecting extreme events remains a tedious and resource-intensive task.

To address these issues, Shanghai AI Laboratory developed EarthLink (Guo et al. 2025), an interactive AI multiagent system for geoscientists. It moves beyond traditional tools by allowing researchers to pose questions in natural language. The system then designs multistep experimental plans, generates executable code for data analysis, produces visualizations, and delivers expert-level insights.

EarthLink's core features significantly enhance scientific workflows. Its natural language processing eliminates the need for coding in many tasks, while its autonomous workflow generator designs analysis plans, produces executable code, and interprets results—streamlining complex processes like model–observation comparison. The platform also ensures complete transparency by openly documenting all scripts, results, and reasoning. This transforms scientists into supervisors who can critically evaluate each stage, ensuring rigor and enabling intervention when needed. Finally, EarthLink employs a self-evolving "practice–learn–improve" loop, continuously refining its methods by learning from successful cases to tackle increasingly complex problems with greater accuracy and efficiency.

An experiment using EarthLink to reproduce the study of Geng et al. (2023) on increased occurrences of consecutive La Niña events under global warming was carried out. Similar results in some key signals were obtained that can lead to scientific conclusions consistent with the original research. More detail is available on the EarthLink website (https://earthlink.intern-ai.org.cn/).

Table 1 shows task complexity levels and representative capabilities of the EarthLink in a typical study (Guo et al. 2025).

8. Concluding remarks

AOGS 2025 marked the first time AI was featured as a dedicated topic at the Society's annual meeting, with several sessions presenting a cross section of ongoing work across Asia. This milestone signals the beginning of a new era, where AI is poised to drive transformative advances in weather and climate prediction and research. Looking ahead, many promising directions are emerging—for example, ensemble AI forecasting, which leverages the strengths of generative AI in uncertainty quantification and computational efficiency, as well as domain-specific, self-evolving agentic AI, which may provide new opportunities to enhance research capabilities and accelerate scientific discovery.

Table 1. EarthLink task complexity levels and representative capabilities.

Levels	Description
Level 1: simple statistical analysis	Performs basic climatological tasks, including data retrieval, preprocessing, calculation of annual means, spatial distributions, and interannual variability, with visualizations supporting initial model evaluation
Level 2: mechanistic diagnosis	Solves moderately complex climate problems, such as estimating equilibrium climate sensitivity (ECS) and transient climate response (TCR), by understanding the physical diagnostic framework, invoking common analyses of multiple experiment datasets and applying simple mathematical tools
Level 3: complex scientific reasoning	Decomposes complex climate analyses into clear, logical subtasks. Integrates advanced analytical methods [e.g., empirical orthogonal function (EOF), composite analysis] with specialized knowledge to study complex phenomena such as ENSO diversity, requiring rigorous methodology and an extended reasoning chain
Level 4: semiopen scientific problem	Automatically selects appropriate datasets based on detailed problem descriptions, combining physical understanding with adaptive workflows to address open-ended climate problems. Applies constraint methods (e.g., emergent constraints) to identify the constraint factor and produce constrained forecasts and preliminary decision-oriented recommendations
Level 5: fully open scientific problem	Independently integrates literature based on the given topic or question, generates new ideas, designs experimental plans, and solves problems without requiring predefined guidance

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