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AI in Weather and Climate: Emerging Applications, Methods, and Research Directions

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AI in Weather and Climate: Emerging Applications, Methods, and Research Directions

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Asia Oceania Geosciences Society 2026 Conference Session on Application of AI to Weather and Climate Prediction and Research

What: Over 200 participants from Asia, Oceania, North America, and Europe attended the atmospheric sciences session 27 on AI Weather and Climate at the AOGS 2026 Annual Conference. A total of 39 papers were presented by about 150 authors and co-authors affiliated with academic, research, and government institutions in Belgium, Canada, mainland China, India, Hong Kong, Korea, Italy, Japan, Singapore, Taiwan, Thailand, U.K., and the U.S.

When: 4-5 August 2026

Where: Fukuoka, Japan

1. Introduction

The 2026 Asia Oceania Geosciences Society (AOGS) Annual Meeting featured several sessions dedicated to artificial intelligence (AI) in the atmospheric, oceanic, and hydrological sciences. Session AS-27, titled “Application of AI to Weather and Climate Prediction and Research,” served as a direct follow-up to the special session on AI in weather and climate prediction at the

2025 AOGS meeting (Chang et al. 2025). While the 2025 session highlighted the rapid development of large global AI weather models, the field has evolved considerably in a single year. The focus of this year's session shifted toward a broader spectrum of weather and climate applications. The following sections synthesize the key scientific findings and methodologies presented during the session.

2. Local and Regional AI Weather Prediction

The first generation of AI weather models demonstrated global forecast skill; the next challenge is to make that skill useful at the regional and local scale.

To improve forecasting over complex terrain at the meso-γ scale (<20 km), a team from National Taiwan University and UCLA proposed a knowledge-guided framework. Using physically consistent training data from a scenario-based TaiwanVVM ensemble, they applied a Variational Autoencoder (VAE) to compress local flow fields into a low-dimensional, interpretable latent space aligned with synoptic regimes. A sequence-to-image transformer then emulates kilometer-scale atmospheric circulation, enabling efficient downscaling when coupled with future climate projections.

Addressing urban microclimates, investigators at City University of Hong Kong developed a Multi-Input Super-Resolution Neural Operator (MISRNO) to downscale coarse meteorological data. Trained on multi-level nested Weather Research and Forecasting (WRF) simulations incorporating meteorological variables and static geophysical parameters—such as terrain height, land use, and building morphology—the model utilizes a Galerkin-type self-attention mechanism as a kernel integral operator. This allows the model to continuously downscale variables to arbitrary, unseen resolutions.

To tackle local-scale forecasting within complex urban settings, researchers at Hong Kong University of Science and Technology introduced the Multi-Modal Local-scale Weather Prediction (MMLWP) framework. By combining local ground-based observations with a graph neural network-based AI foundation model, MMLWP resolves subkilometer heterogeneity that conventional methods fail to capture, significantly reducing errors in temperature, relative humidity, and wind speed over 24-hour lead times in Hong Kong.

To address systematic errors in AI-based radiation parameterizations, scientists at Tongji University developed WRF-iRad (intelligent Radiation), an observation-constrained parameterization coupled online into the WRF model. Using a two-stage training strategy, they performed physics-guided pretraining with simulation data followed by fine-tuning constrained by CERES satellite observations. A soft-constraint optimization combines observation flux loss with physics-consistency loss, reducing shortwave flux RMSE by 53.1% and heating rate RMSE by 21.6% offline. Online coupling exhibited strong numerical stability and a 11- to 321-fold GPU-driven speedup, showing substantial improvements in 2-meter temperature forecasts during extreme heat waves.

Tropical cyclone track forecasting was addressed by two groups: one from Jeju National University and Korea Hydrographic and Oceanographic Agency, and another from Central Weather Administration Taiwan and National Taiwan University. Additionally, high-resolution regional forecasting models were presented by researchers at Japan Weather Association, as well as a team from Central Weather Administration and National Tsing Hua University in Taiwan.

3. AI for Precipitation and High-Impact Weather

High-impact precipitation events are intermittent, highly non-linear, and notoriously difficult to forecast. Conventional models struggle with spatial blurring, systematic biases, and the "double-penalty" problem of spatial displacement in convective cells. To address these limitations, researchers are developing standardized benchmarks, generative models, and advanced downscaling techniques to capture both general precipitation patterns and localized extremes.

For global precipitation nowcasting, researchers at RIKEN Center for Computational Science developed the experimental GSMaP RIKEN AI Nowcast (GSMaP_RAIN) system. They trained a multi-scale convolutional long short-term memory (ConvLSTM) model on 24-hour satellite sequences from JAXA's GSMaP product to predict the subsequent 12 hours. The model utilizes five downsampling levels to capture multi-scale atmospheric features and incorporates adversarial training along with nonlocal statistical constraints to mitigate the blurring common in deep-learning nowcasting.

Addressing systematic model biases and spatial refinement, a team at Tongji University designed DecGAN, a multi-step generative adversarial network. Trained on Community Earth System

Model (CESM) simulations and validated against HadISST and ERA5 data, DecGAN performs end-to-end bias correction and spatial downscaling for Asian precipitation and Pacific sea surface temperature. The model preserves structural fidelity while significantly reducing systematic and accumulated prediction errors, supporting regional impact assessments.

To resolve extreme events missed by global models, a team from University of Tokyo, Japan Meteorological Agency, and Japan Agency for Marine-Earth Science and Technology designed a high-resolution regional machine-learning model. Trained on the 5-km RRJ-ClimCORE regional reanalysis over Japan's complex terrain, the model employs variable-specific loss functions tailored to the physical characteristics of individual fields. This physics-aligned loss formulation avoids the spatial smoothing of standard mean-squared-error objectives, improving predictions of cyclone-associated winds and convective precipitation structures.

Other contributions to high-impact weather forecasting were presented by researchers at Hong Kong University of Science and Technology on tropical cyclone rainfall trends, University of Toyama on efficient heavy rainfall prediction, and Meteorological Research Institute, Japan on ensemble precipitation forecasting. Additionally, a team from Seoul National University, Korea Advanced Institute of Science and Technology, and National Institute of Meteorological Sciences discussed East Asian extreme rainfall, while researchers from Kyungpook National University, University of St. Thomas, and Ulsan National Institute of Science and Technology focused on predicting heat waves and extreme tropical night temperatures.

4. AI–Physics Integration and Intelligent Numerical Models

A major limitation of purely data-driven weather models is their susceptibility to violating fundamental conservation laws. Integrating AI with dynamical models offers a hybrid paradigm, combining the physical consistency and long-term stability of physics-based cores with the computational speed of deep learning.

Highlighting the potential of hybrid models for climate experiments, researchers from National Taiwan University, University of California, San Diego and Woods Hole Oceanographic Institution evaluated atmospheric responses to Arctic sea-ice loss. Using Google's NeuralGCM, which couples a dynamical core with machine learning parameterizations, they conducted simulations forced by pre-industrial and future sea-ice concentrations. The model successfully reproduced near-surface warming, weakened mid-latitude zonal winds, and realistic North Atlantic blocking, though it revealed stratospheric discrepancies compared to conventional models.

To investigate whether deep-learning models capture genuine physical dynamics, investigators at Fudan University conducted controlled tropical heating experiments within Huawei's Pangu-Weather model. Under an austral winter background state, the model successfully reproduced the classic Matsuno–Gill tropical response and planetary Rossby wave propagation to polar regions. It correctly simulated how convective heating in the Atlantic and Indian Oceans deepens the Amundsen Sea Low, while Pacific heating weakens it. However, the model overestimated the relative influence of Pacific heating, highlighting biases learned from reanalysis data that could affect extended-range predictions.

To standardize precipitation postprocessing and support hybrid model verification, researchers at Royal Meteorological Institute of Belgium and Nanyang Technological University introduced EUPreciPBench. This public dataset pairs Central European COSMO ensemble forecasts with EURADCLIM gauge-adjusted radar composites as a verification reference. By linking physical numerical ensembles with observational data, the benchmark facilitates standardized intercomparisons of methods addressing intermittency and double-penalty errors, while providing a rigorous framework to assess whether postprocessing AI models preserve physical consistency.

Additionally, researchers at Seoul National University developed a deep learning-based recursive prediction system for tropical upper-ocean temperature using a stochastically-driven large ensemble. Another team from Union College and University of Chicago demonstrated that online learning offers a robust pathway for adaptive turbulence modeling in atmospheric and oceanic simulations, successfully bridging physics-based closures and data-driven methods within a unified framework.

5. AI with Observations, Remote Sensing, and Data Assimilation

Weather forecasting is heavily dependent on the quality of initial conditions, which are determined by data assimilation (DA) systems. Conventional DA faces severe challenges in representing non-Gaussian errors, managing dense satellite observations, and mitigating rank deficiency in small ensembles. AI offers new opportunities to enhance DA components and accelerate geostationary retrievals.

An airport visibility forecasting model, VisBiLSTM, developed by researchers from Indian Institute of Information Technology and University of Oxford, demonstrates how data-driven architectures can bypass traditional thermodynamic modeling limits. Trained on METAR observations from 2015 to 2025 across three Indian airports, this attention-based bidirectional LSTM identifies relative humidity and temperature as the primary drivers of visibility through mutual information analysis. The model achieves highly satisfactory multi-step forecast skills, yielding a six-hour mean absolute error of 288 meters at Kolkata and providing a robust, site-specific solution to operational winter fog challenges.

To address fundamental hurdles in conventional data assimilation, investigators at Meteorological Research Institute, Japan and Environment and Climate Change Canada are developing targeted AI solutions. Rather than attempting to replace the entire assimilation pipeline, they utilize deep learning to improve specific components of the system. These include AI-based approaches for data quality control, non-Gaussian data assimilation, error-covariance generation, super-resolution of meteorological fields, and machine learning weather prediction, making high-resolution, observation-rich forecasting computationally feasible.

On the remote sensing front, researchers at Tohoku University developed HimCld Version 2, an advanced deep-learning retrieval system for the Himawari geostationary satellite. Trained on extensive infrared observations paired with active remote sensing from CloudSat/CALIPSO, the model retrieves 14 cloud properties for the entire disk in approximately 40 seconds. It provides built-in, pixel-level uncertainty estimates and achieves remarkable accuracy, retrieving cloud top heights within 2 km and characterizing deep convection optical thicknesses up to 200, which is highly valuable for real-time nowcasting. In addition, a team from Navamindradhiraj University and Tohoku University developed a convolutional neural network algorithm for geostationary sounding to derive temperature and relative humidity profiles over Southeast Asia using Himawari-8 multispectral observations.

Using data from a new balloon-borne particle imaging radiosonde named Rainscope, researchers from Yamaguchi University, Railway Technical Research Institute, Japan, and Kyushu

University studied the microphysical behavior of melting particles. They successfully reconstructed the vertical profile of hydrometeor density within the cloud melting layer and tracked how particle falling angles shift as melting progresses.

AI was also used by researchers at National Center for High-Performance Computing, Taiwan to develop an interactive benchmark and visualization platform based on Weatherbench 2 and Streamlit. The visual interface displays discrepancies between model forecasts and observations through interactive heatmaps, reducing data interpretation difficulties and helping identify strengths and weaknesses in AI weather models under specific conditions.

6. Explainable and Physically Interpretable AI

As deep-learning models match or exceed numerical models in weather forecasting skill, understanding *why* these models make their predictions is paramount. Explainable AI and physically interpretable frameworks are critical to build scientific trust, diagnose model biases, identify physical precursors of extreme weather, and extend classical diagnostic frameworks to future climates.

The controlled tropical heating perturbation experiments conducted in the Pangu-Weather model by investigators at Fudan University also demonstrated how physical sensitivity testing can serve as a powerful form of explainable AI. By systematically analyzing how the neural network propagates tropical heating anomalies as planetary Rossby waves, the researchers were able to diagnose the model's internal representations. This diagnostics-oriented approach revealed that while the model successfully learned linear regulation mechanisms and wave-guide dynamics, its over-reliance on Pacific heating signals exposes systematic biases in the relationships learned from reanalysis datasets, offering a clear path for targeting future model improvements.

The knowledge-guided regional forecasting framework developed by a team at National Taiwan University and UCLA discussed in Section 2 also represents a significant advancement in physical interpretability. Instead of treating the deep-learning model as a black box, the researchers utilized the Variational Autoencoder (VAE) specifically to compress complex, high-dimensional local flow fields from the Taiwan Vector Vorticity Model ensemble into a two-dimensional latent space. Because this latent space is explicitly aligned with upstream synoptic regimes, the sequence-to-image transformer emulator remains causally linked to well-understood physical drivers, providing scientists with a robust and interpretable tool for assessing downscaled future climate scenarios.

To extend physically interpretable climatological frameworks to future projections, investigators at Pukyong National University addressed the limitations of the Spatial Synoptic Classification (SSC). While SSC relies on sub-daily observations, climate models typically project data at daily resolution. The team developed a deep-learning model to map daily atmospheric variables to global SSC air-mass categories, successfully learning the underlying synoptic relationships. This framework removes sub-daily data dependence, enabling researchers to investigate shifts in air-mass distributions under future climate change scenarios.

Other contributions to explainable AI were presented by scientists from National Institute of Advanced Industrial Science and Technology on the post-processing correction of lidar-derived turbulence intensity, from Yokohama National University and Fujitsu Limited on the relationship between typhoon intensity changes and lightning activity, and from Korea University on NOz interference in urban NO2 monitoring.

7. Subseasonal-to-Decadal Climate Variability

Subseasonal forecasting overlaps with extended-range forecasting. Researchers at University of Tokyo and Yokohama National University developed an uncertainty-aware deep-learning framework for one-month predictions of the Western North Pacific Subtropical High (WNPSH). Pretrained on a millennial-scale climate ensemble dataset (d4PDF) and fine-tuned on ERA5, their self-attention 3D convolutional neural network achieved an anomaly correlation coefficient of 0.6 at a 10-day lead time. Combining SHAP explainable AI with the concept of "windows of opportunity," the team identified specific physical precursor signals in initial conditions—such as intraseasonal oscillations and mid-latitude wave trains—showing that WNPSH predictability can extend to 15 days during favorable events.

Two studies from Central Weather Administration, Taiwan and National Central University proposed solutions for stabilizing extended-range forecasts. One introduced a scale-aware recentering technique that stabilizes ensemble predictions in Shanghai AI Lab’s FengWu Model by focusing on highly predictable large-scale waves, thereby maintaining spatial forecast correlations. The second study evaluated ECMWF's AIFS-ENS and NVIDIA's FourCastNet 3

(FCN3) models, demonstrating that FCN3's stochastic formulation yields superior physical consistency and stability over multi-week integrations.

On seasonal timescales, a team from Pukyong National University and Seoul National University demonstrated that a seasonal forecasting framework utilizing Neural Ordinary Differential Equations significantly reduces computational costs and mitigates cumulative errors, thereby enhancing long-term prediction. They also employed multifractal detrended fluctuation analysis to quantify climate memory characteristics, revealing the intrinsic limits of predictability. In parallel, investigators at National Taiwan University showed that WNPSH variability on interannual scales can be captured by a recurrent neural network, although low-frequency ENSO modulations and historical data uncertainties prior to the 1970s impose a hard ceiling on long-term predictability.

On multi-decadal timescales, a team from University of Washington, Lawrence Livermore National Laboratory, Pacific Northwest National Laboratory, and NOAA Pacific Marine Environmental Laboratory employed a machine learning algorithm to decode the drivers of historical Arctic Amplification (AA) from 1980 to 2022. While climate models consistently simulate AA as a warming response, they rarely match observed rates. By training an algorithm to isolate and remove the signature of natural internal variability, the team demonstrated that natural fluctuations have simultaneously dampened global warming and accelerated Arctic warming, bringing adjusted observations (AA of 3.02) into alignment with model ensemble ranges (2.13 to 3.58). The analysis decoded a robust spatial fingerprint of internal variability—characterized by global cooling and Arctic warming (i-GCAW) since 1980—featuring enhanced warming in the Barents and Kara Seas alongside cooling in the tropical Eastern Pacific and Southern Ocean, proving that internal climate variability is a key driver of model-observation warming discrepancies.

8. Concluding Remarks

In the year since the special AI session of the 2025 AOGS Annual Meeting, AI applications in weather and climate research and prediction have advanced dramatically. In addition to global modeling, atmospheric and computer scientists are increasingly applying AI and machine learning (AI/ML) techniques to solve highly specialized local and regional weather challenges, improve data analysis and assimilation, study long-term climate variability and changes, and explore novel frontiers in physical interpretability and remote sensing retrievals. These multi-dimensional advancements indicate that the integration of AI into all aspects of meteorological research, development, and prediction has entered a new phase.

Figure 1 is a photo of the conveners and co-chairs of the session.

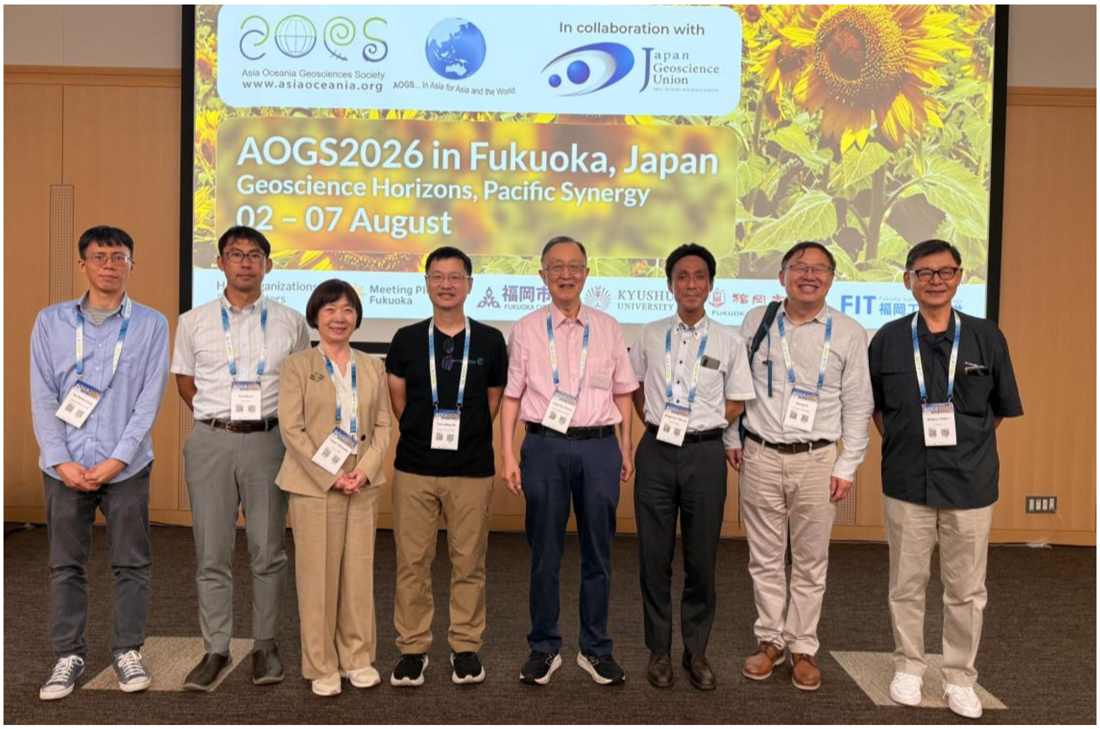

Figure 1: Convenors and co-chairs of AOGS 2026 Session AS-27: Applications of AI to Weather Prediction and Research, from left: Yu-Chiao Liang (National Taiwan University), Takuya Kawabata (Meteorological Research Institute), Yukari Takayabu (University of Tokyo), Chien-Ming Wu (National Taiwan University), Chih-Pei Chang (National Taiwan University), Shigenori Otsuka (RIKEN Center for Computational Science), Qiang Fu (University of Washington), Shigeo Yoden (Kyoto University). Not in the photo: Hao Li (Fudan University and Shanghai Academy of AI for Science) and Bin Wang (University of Hawaii).

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Reference

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