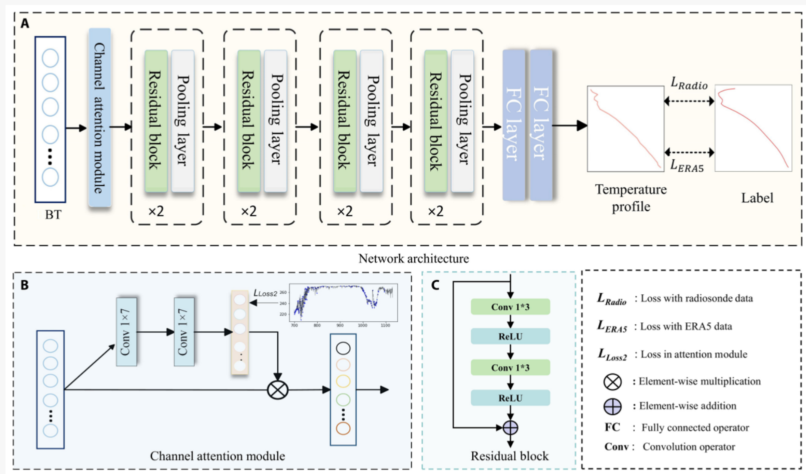
Physics-constrained AI boosts satellite weather accuracy

FAYETTEVILLE, GA, UNITED STATES, January 29, 2026 /EINPresswire.com/ -- Accurate atmospheric temperature profiles are vital for weather forecasting and climate monitoring, yet existing methods face trade-offs between physical consistency and computational efficiency.



Physics-Constrained CNN Architecture for Atmospheric Temperature Retrieval. (A) Overall framework of our proposed retrieval model. (B) Detailed architecture of the attention module. (C) Detailed architecture of the residual block.

Atmospheric temperature profiles describe how temperature changes with altitude and are essential for understanding weather systems, climate dynamics, and extreme events. Traditional measurements based on radiosonde balloons are accurate but limited by sparse coverage and low temporal resolution. Satellite hyperspectral instruments provide continuous, wide-area observations, but retrieving temperature profiles from these data remains challenging. Physical retrieval methods are computationally demanding and sensitive to initial assumptions, while purely data-driven deep learning models can produce physically unrealistic results. Based on these challenges, there is a strong need to develop retrieval approaches that combine the efficiency of artificial intelligence (AI) with the reliability of physical principles, requiring in-depth research into physics-aware learning strategies.

The new study was conducted by researchers from Nanjing University of Information Science and Technology in collaboration with national meteorological institutions in China. It was published (DOI: 10.34133/remotesensing.0841) on December 23, 2025, in the Journal of Remote Sensing. The research addresses a long-standing challenge in atmospheric science: how to retrieve accurate temperature profiles from hyperspectral satellite observations without violating fundamental physical laws. By embedding physical knowledge directly into a deep learning framework, the proposed technique offers a practical solution to improve the reliability of satellite-based temperature retrievals.

The study introduces a physics-constrained convolutional neural network designed specifically for atmospheric temperature profile retrieval. Unlike conventional deep learning models that rely solely on data correlations, this approach incorporates physical knowledge into both feature extraction and model optimization. A key innovation is a channel attention mechanism guided by radiative weight functions, which allows the model to focus on temperature-sensitive spectral channels. In addition, physically based reanalysis data are used as training constraints, encouraging outputs that align with known atmospheric behavior. As a result, the model outperforms existing neural network methods and current operational satellite products, achieving lower errors and reduced bias, particularly in the middle and upper troposphere where accurate temperature information is most critical.

To evaluate the new method, the researchers applied it to hyperspectral infrared observations collected by the FY-4A satellite's Geostationary Interferometric Infrared Sounder (GIIRS). The model was trained and tested using matched satellite data, radiosonde measurements, and ERA5 atmospheric reanalysis data over 89 stations across China during two summer seasons. Performance was assessed using standard error metrics, including root mean square error and mean bias.

The physics-constrained model achieved an overall temperature retrieval error of approximately 2 K, outperforming two state-of-the-art neural network models and the operational GIIRS Level-2 product. Improvements were most pronounced between 150 and 550 hPa, a key region for weather forecasting. Additional experiments showed that removing the physics-guided attention module or the physical reanalysis constraint led to noticeable performance degradation. These results demonstrate that embedding physical knowledge not only improves accuracy but also enhances the robustness and interpretability of deep learning-based retrievals.

"AI is powerful, but it must respect physical reality," said a member of the research team. "By teaching the model how the atmosphere behaves, we can significantly improve both accuracy and reliability." The researchers emphasize that this work shows how physics and data-driven learning can complement each other, paving the way for more trustworthy AI applications in meteorology and climate science.

The study employed a deep convolutional neural network enhanced with a physics-guided channel attention module. Hyperspectral brightness temperature data served as the primary input, while radiosonde observations and ERA5 reanalysis data were used as training references. The model was optimized using a combined loss function that balances observational accuracy with physical consistency. Extensive experiments, including ablation tests and multi-time validation, were conducted to assess the contribution of each model component.

The proposed physics-constrained AI framework has broad potential beyond temperature retrieval. It could be extended to humidity profiling, air quality monitoring, and other satellite-based atmospheric products. As climate change intensifies extreme weather events, more reliable and physically consistent satellite data will be critical for early warning systems and decision-making. By bridging the gap between physical modeling and AI, this research points toward a new generation of Earth observation technologies that are both fast and scientifically trustworthy.

References
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