# Preliminary Progress in AI-Driven Data Assimilation

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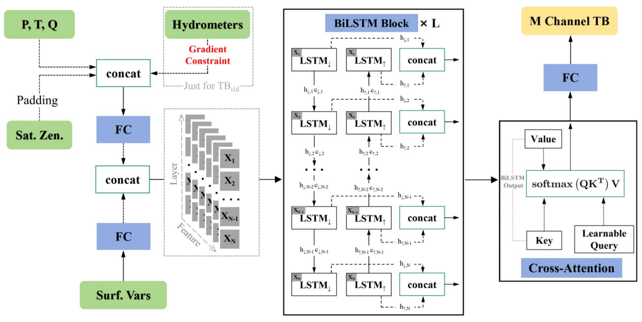
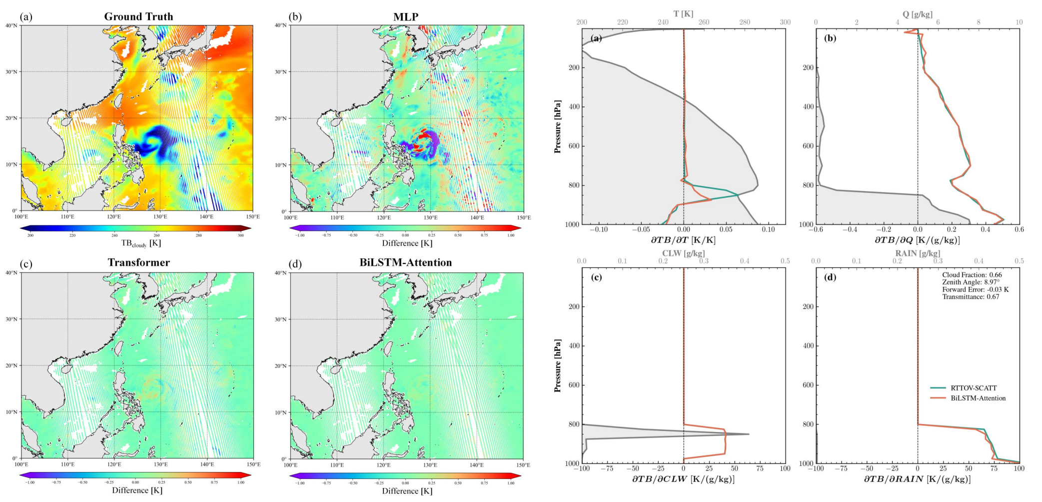
## AI-RTM

**Atmospheric radiative transfer calculations** are computationally expensive, especially for multiple-scattering in cloudy areas. Deep learning models can emulate these processes with **improved efficiency**, while neural networks enable trivial **automatic differentiation for Jacobian calculations.**

- **BiLSTM Structure**: Captures vertical layer dependencies mimicking radiative transfer.
- **Attention Mechanism:** Adaptively weights layer importance for each channel.
- Gradient constraint: Prevents unrealistic hydrometeor Jacobians in clear conditions.




- **Accuracy:** BiLSTM-Attention achieves STD <0.03 K and bias ±0.005 K, vastly outperforming MLP (6 K errors). Typhoon prediction errors <0.4 K.
- **Efficiency:** GPU acceleration: 0.1s forward computation (68× speedup), 2.53s Jacobian calculation (17× speedup vs RTTOV-SCATT).
- **Jacobians:** Physical constraint fine-tuning eliminates humidity oscillations, accurately captures temperature/water vapor/hydrometeor sensitivities for data assimilation.

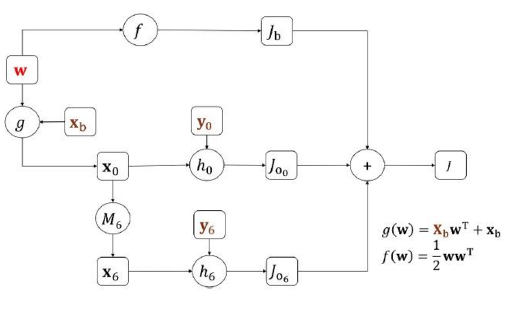



## AI-En4DVar System

Machine learning weather forecasting models achieve comparable accuracy to traditional systems but still depend on conventional data assimilation for initial conditions. Therefore, customized data assimilation systems are urgently needed for ML models to enable independent operation and improve analysis field quality.

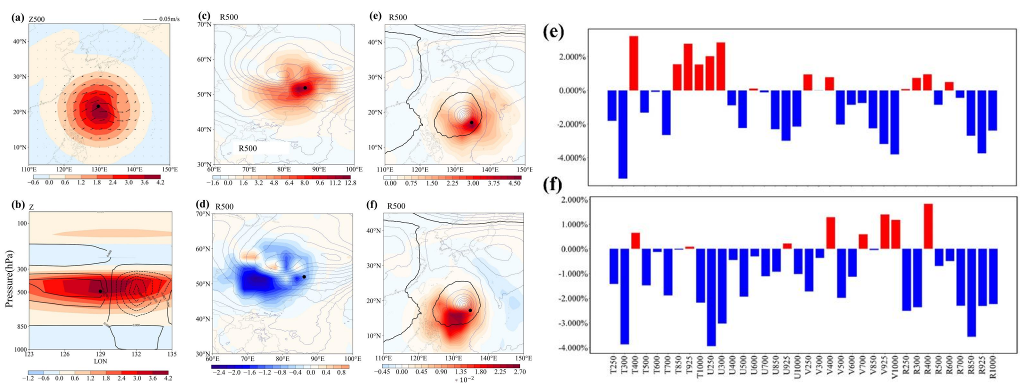
**System Architecture:**

- Ensemble 4D Variational Data Assimilation (**En4DVar**) + **FuXi** forecasting model.
- **Automatic differentiation** for gradient computation, eliminating need for adjoint models.
- 200 ensemble members generated using Perlin noise to construct background error covariance matrix.




**Results:**

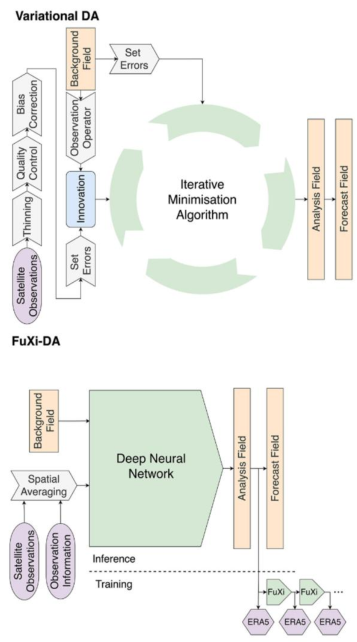
- **Physical Balance:** Maintains geostrophic balance with anticyclonic wind responses to **geopotential increments.**
- **Flow-Dependent Propagation:** Observational information propagates correctly according to background flow dynamics.
- **System Effectiveness:** Significant RMSE reduction across atmospheric variables demonstrates improved analysis quality.



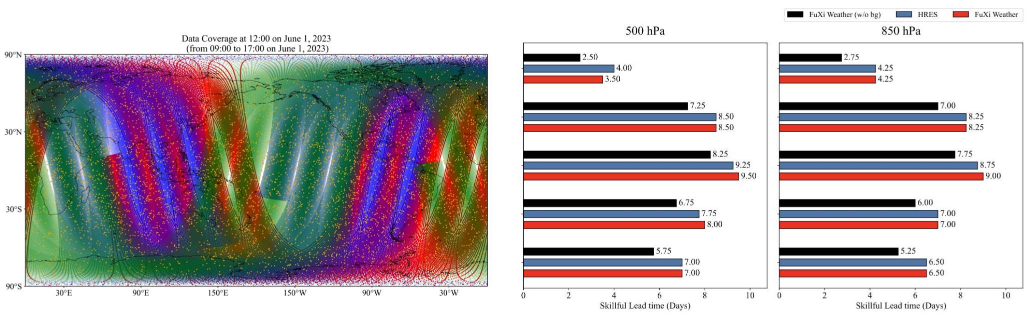
## End-To-End Data Assimilation

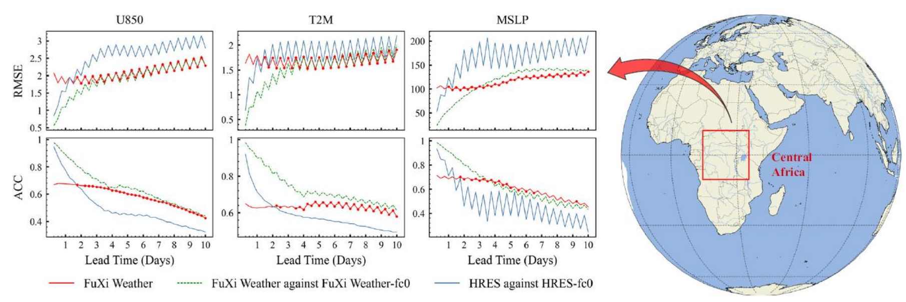
### ML End-to-End Approach vs. Traditional Variational Methods

- **Computational Efficiency:**
The ML End-to-End approach avoids iterative optimization processes, significantly reducing computational cost compared to traditional 4D-Var methods.
- **Enhanced Data Utilization:**
The ML End-to-End approach uses all available satellite observations without sparsification through super-observation processing.
- **Joint Optimization:**
Simultaneously trains analysis and forecasting components using medium-range forecast supervision for improved performance.
- **Operational Simplification:**
Eliminates observation operators and automatically handles cloud detection, bias correction, and multi-source data fusion.




The end-to-end assimilation system **FuXi Weather** directly assimilates passive microwave observations from **three polar-orbiting satellites** (FY-3E, Metop-C, NOAA-20) and GNSS radio occultation data, **achieves global forecast accuracy comparable to ECMWF HRES**. It outperforms ECMWF HRES beyond day 1 in observation-sparse regions such as Central Africa, extending skillful forecast lead times by 0.25-1 days for multiple atmospheric variables while **using considerably fewer observations.**

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