# Pangu-DART: Enabling Ensemble Kalman Filter Data Assimilation for ML-Based Numerical Weather Prediction Models

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## Background and Motivation

- ❑ Machine-Learning (ML)-based numerical weather prediction (NWP), once trained, performs faster and is computationally more efficient than traditional physics-based NWP. For example, the Pangu-Weather model can generate a single 0.25° x 0.25° resolution global forecast in 10 seconds;
- ❑ Ensemble data assimilation, such as the Ensemble Kalman Filter (EnKF), is a statistical approach to improve the accuracy of weather forecasts by integrating real-time observations. The EnKF requires a sufficient number of ensemble members (30-100) to adequately represent the time-evolving forecast background error covariance and forecast uncertainty. However, the computational cost of traditional NWP remains very high;
- ❑ Combining ML-based models with ensemble data assimilation offers a cost-effective alternative to traditional NWP systems;
- ❑ An interface between Pangu-Weather and National Center for Atmospheric Research (NCAR) Data Assimilation Research Testbed (DART) has been developed.

## Pangu-DART Interface

- ❑ Supports vertical interpolation in pressure coordinate
- ❑ Update upper-level model variables:
  - U V T Q
- ❑ 0.25° x 0.25° global topographical data created with Weather Research & Forecasting Pre-Processing System (WPS)

## Computing Platform and Data

- Hardware requirement for Pangu-Weather forecast fulfilled through Google Colab:
  - An A100 GPU
  - 34 GB GPU RAM & 8 GB CPU RAM
- DART DA performed on NCAR's Casper HPC
- ERA5 10-member initial condition at 0000 UTC October 6th 2024
- Observations from NCAR Research Data Archive (RDA) Dataset:
  - Radiosondes, aircraft observation, satellite wind from NCEP PREPBUFR (RDA ds337.0)
  - Global satellite winds from SATWND (RDA ds351.0)

## Test Case: Hurricane Milton (2024)

- ❑ Hurricane Milton formed on October 5th 2024 in western Caribbean Sea and became extratropical on October 10th. It rapidly deepened by more than 100 hPa in 2 days over the Gulf of Mexico, becoming the second-most intense Atlantic hurricane with a peak minimum sea level pressure of 897 hPa, second only to Hurricane Rita (2005).
- ❑ Here we perform a 4-day forecast with Pangu-Weather and 4-day DA cycles with Pangu-DART to compare their performance.

## Results

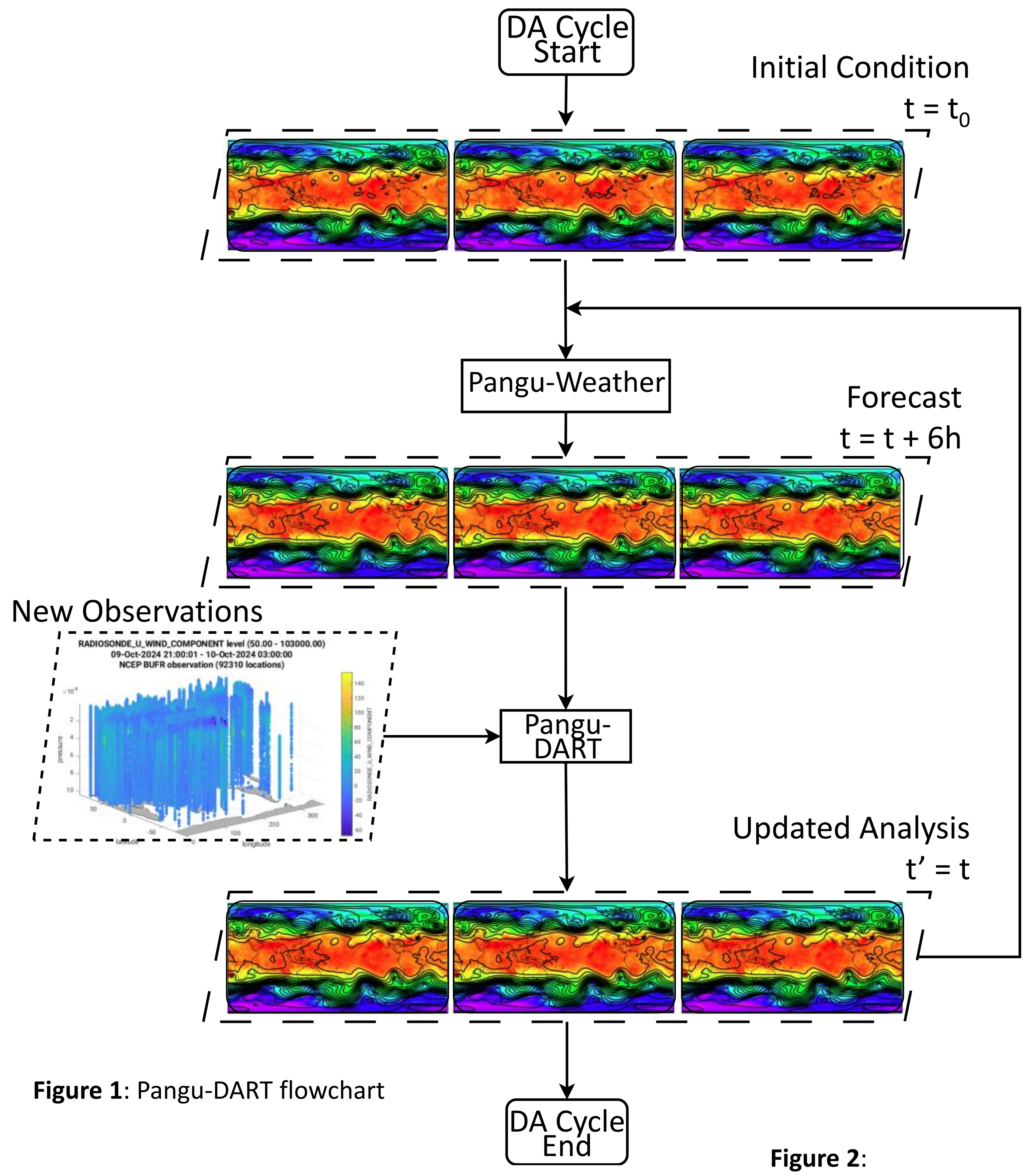


**Figure 1**: Pangu-DART flowchart

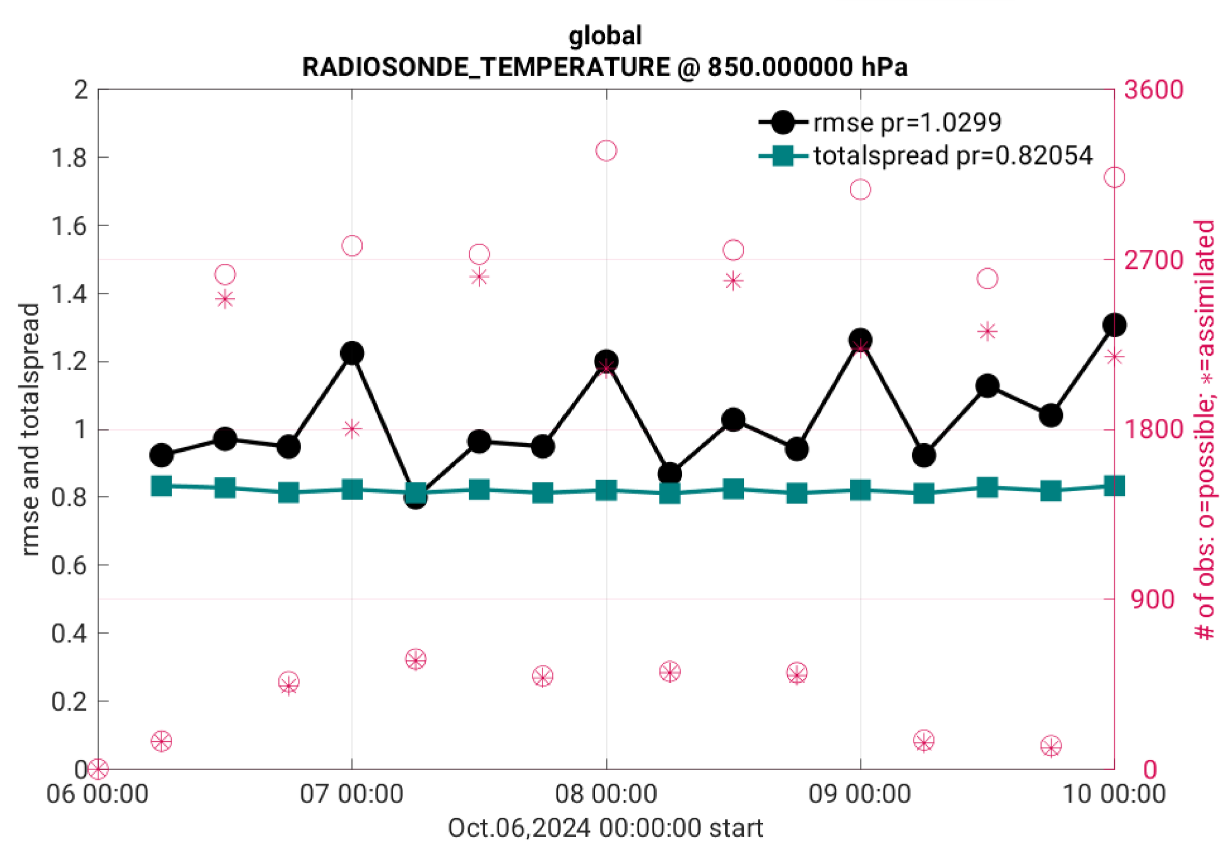


**Figure 2**: Pangu-DART observation space global diagnosis from approximately 990-775hP. The red circles and stars mark the number of observation available and assimilated at each time (right axis). The black line is the root mean square error of the prior model estimates of the temperature (K) relative to the temperature observed by RADIOSONDE (left axis). The green line is the total spread.

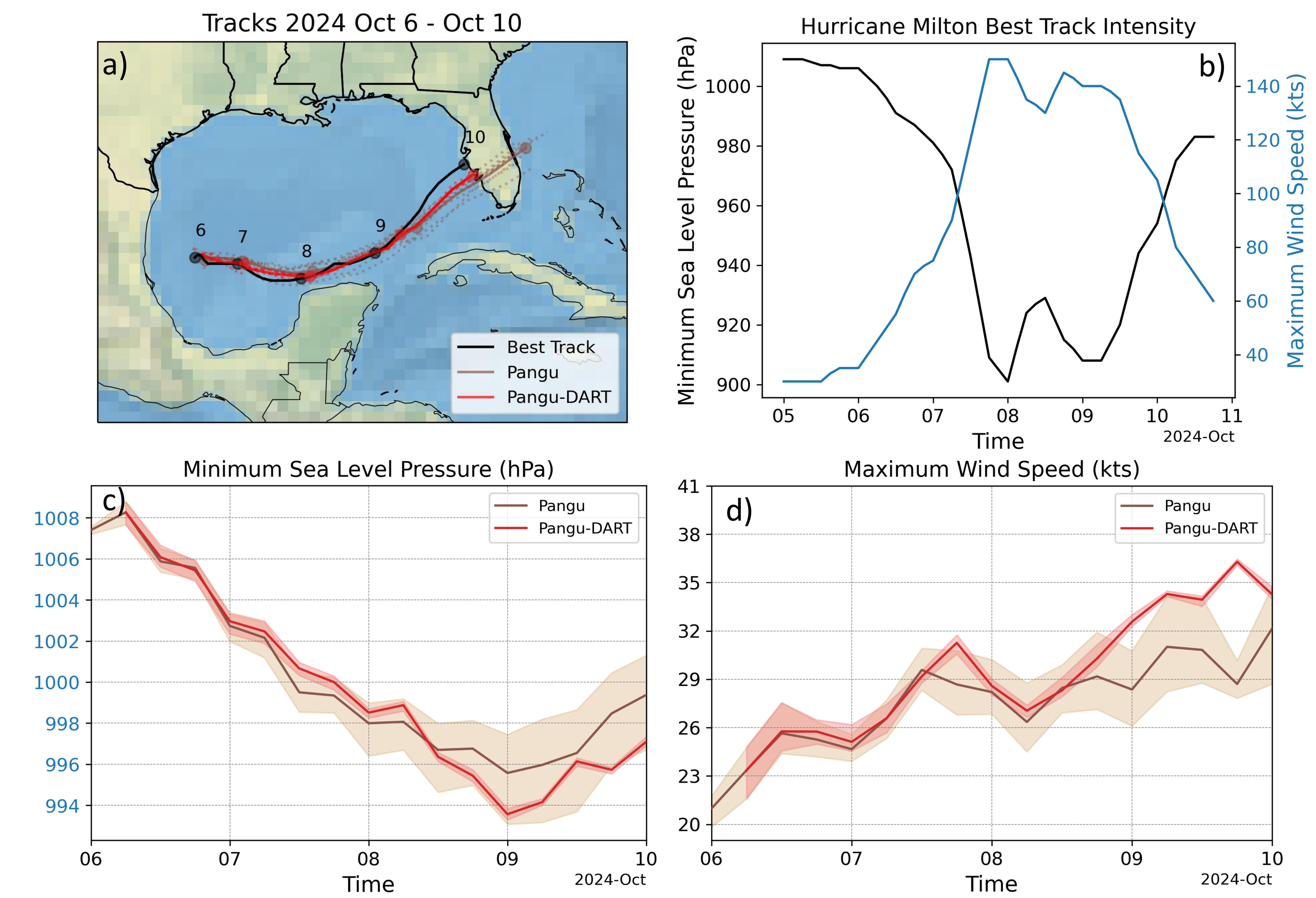


**Figure 3**: a) Tracks of Hurricane Milton (0000 UTC 6 Oct 2024 to 0000 UTC 10 Oct 2024) from IBTrACS (International Best Track Archive for Climate Stewardship, black), Pangu-Weather forecast ensemble mean (brown), and Pangu-DART analysis ensemble mean (red). Individual ensemble members are shown with dotted lines; b) Milton's minimum sea level pressure (black) and maximum wind speed (blue) from IBTrACs; c) Milton's minimum sea level pressure from Pangu-Weather forecast ensemble mean (brown), and Pangu-DART analysis ensemble mean (red). Shading area shows range from 10th to 90th ensemble percentiles; d) Same as c) but for maximum wind speed.

## Conclusions

1. The analysis track of Hurricane Milton improves after data assimilation.
2. Neither the Pangu-Weather forecast nor the Pangu-DART analysis captures Hurricane Milton's intensity, measured by minimum sea level pressure and maximum wind speed criteria (e.g., Bonavita 2024).
3. The ensemble spread is constrained with Pangu-DART.
4. No significant improvement in the global forecast error within the observation space.

## Limitations and Future Work

1. Machine Learning models tend to regress toward the mean, resulting in a lack of ensemble spread needed for effective data assimilation
2. Observation usage is limited due to the insufficient vertical resolution in the Pangu-Weather model.
3. Further development for other vertical interpolation options and surface observation assimilation.
4. We aim to design the interface to be compatible with other ML weather models.

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