Enhancing quantitative precipitation estimation in the NWP using a deep learning model

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Abstract

Precise quantification of precipitation is crucial for effective planning and minimizing property damage or loss of human life caused by extreme weather events, especially under the rapidly changing climate. Currently, quantitative precipitation forecasting (QPF) in numerical weather prediction (NWP) models rely heavily on parameterization schemes for microphysics, boundary layers, cumulus, etc., rather than directly solving physical-based governing equation sets to predict fundamental variables such as temperature, wind speed, and humidity. These parameterization schemes introduce significant uncertainties in precipitation forecasting due to the limited knowledge of precipitation processes, which bottlenecks the performance of precipitation forecasting in NWP models. To overcome this challenge, we propose a deep learning model based on Vision-Transformer that directly ingests fundamental meteorological variables solved by NWP models as predictors and maps them quantitatively to the precipitation map from a satellite-merged precipitation product. In this study, we conducted Weather Research and Forecasting (WRF) model simulations at 27km grid resolution for five years from 2017 to 2021 over China and the southeast region of Asia, and we used simulation results for the wettest season from June to September in 2017-2019 as training data, while validating and testing the model performance on data from 2020 and 2021. The deep learning model aims to circumvent uncertainties in physical parameterization schemes, which are due to the incomplete understanding of physical processes, and directly reproduce the high-resolution satellite rainfall observation product, the Climate Prediction Center morphing method (CMORPH) data. Our evaluation results on the test dataset show that the deep learning model effectively extracts features from meteorological variables, leading to improved precipitation skill scores of 21.7%, 60.5%, and 45.5% for light rain, moderate rain, and heavy rain, respectively, on an hourly basis. We also evaluate two case studies under different synoptic conditions and show promising results in estimating heavy precipitation during strong convective precipitation events. Overall, the proposed deep learning model can provide vital insights for capturing precipitation-triggering mechanisms and enhancing precipitation forecasting skills. Additionally, we discuss the sensitivities of the fundamental meteorological variables used in this study, training strategies, and performance limitations.

Proposed UNet model with Swin-Transformer Backbone

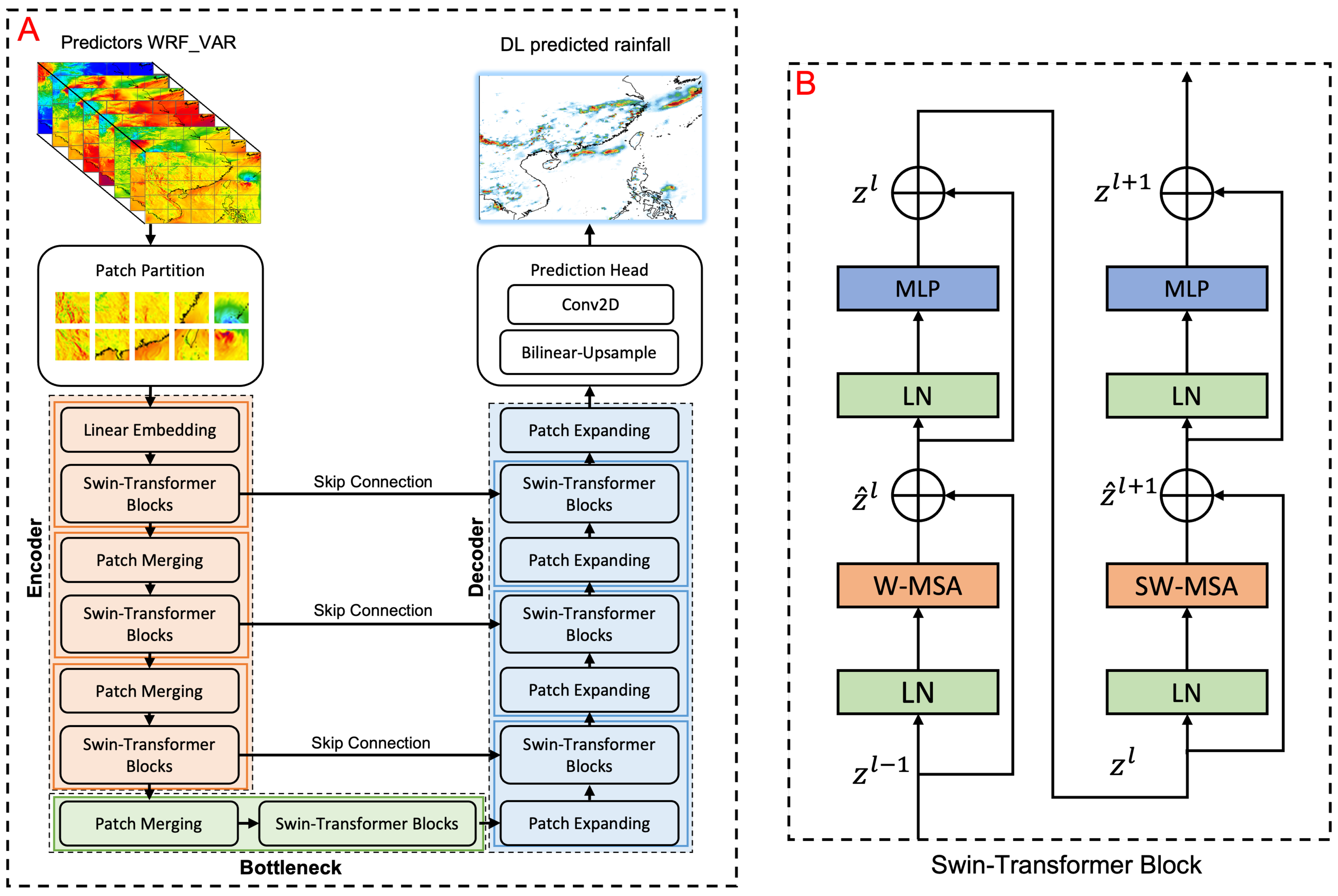

Figure 1. Architechture of proposed deep learning model based on classical UNet encoder-decoder structure (A), and the computational principle for the Swin-Transformer backbone (B).

Three-dimensional Grided meteorological variables including temperature, moisture content, atmospheric flow etc., simulated by the WRF model are served as the predictors to quantitatively reconstruct the precipitation patterns using the proposed deep learning model.

Model Evaluation - Frontal Rainbelt Case on 2021-06-03

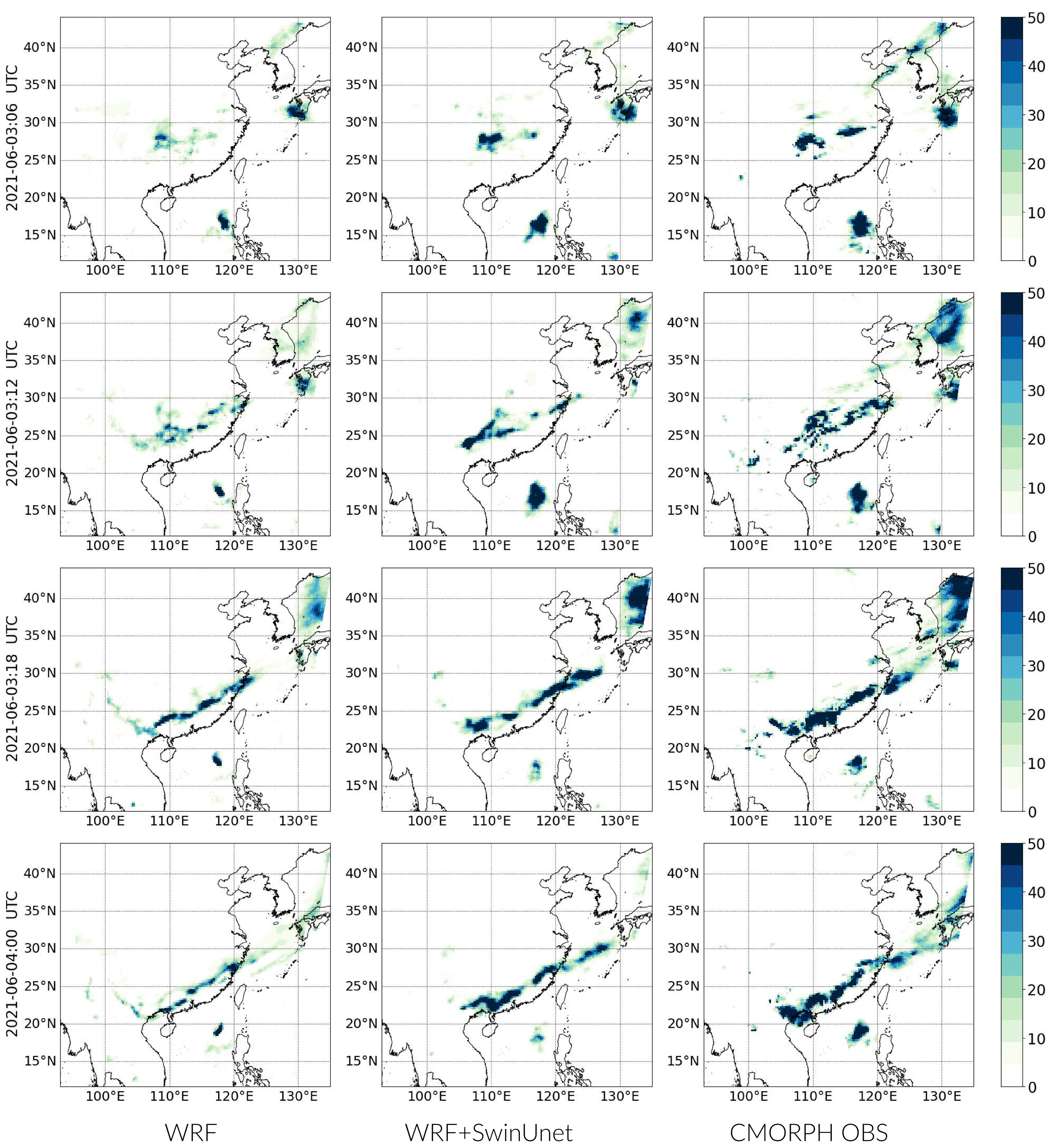

Figure 2. 6-h accumulated precipitation predicted by WRF, WRF + Swin-Transformer Unet, and observational data from CMORPH datasets on 2021-06-03.

Overall Model Evaluation

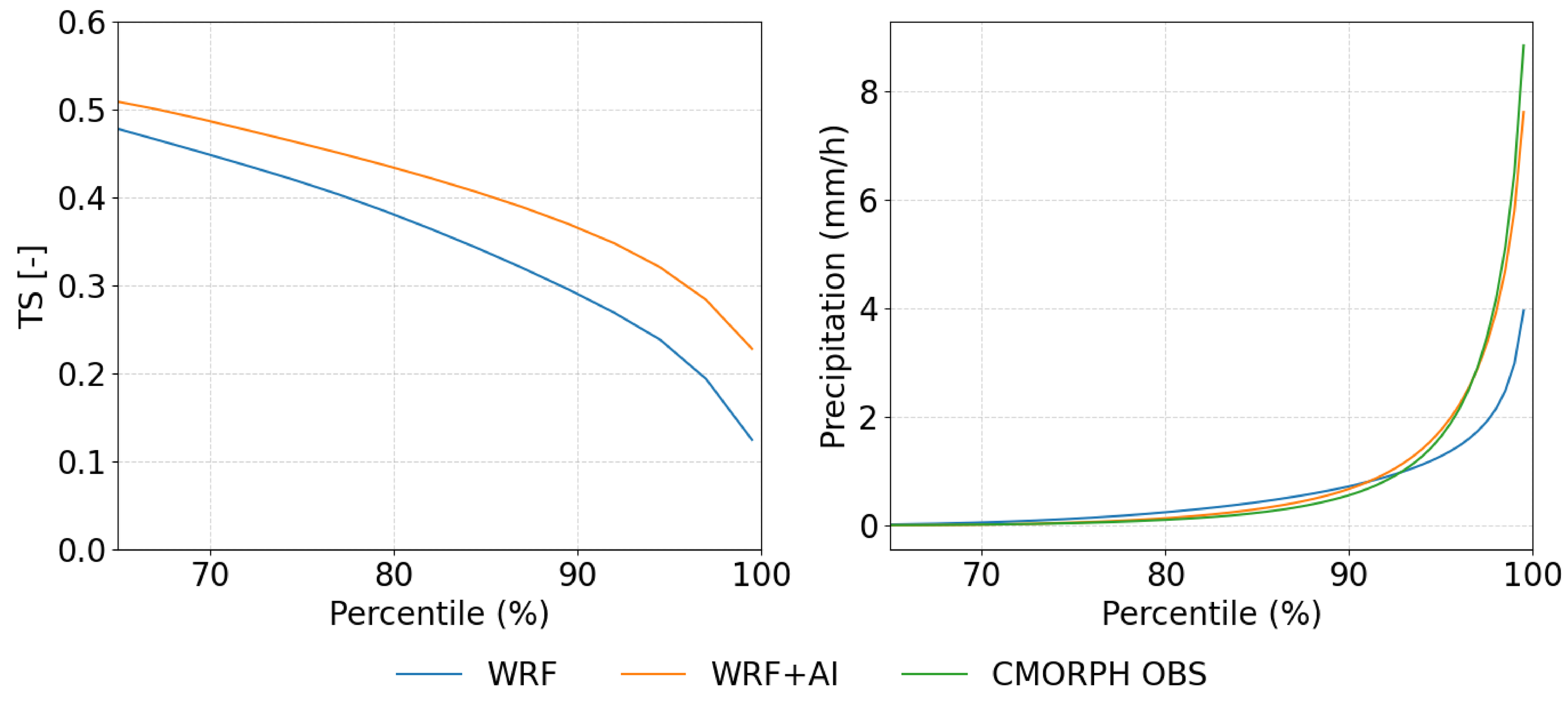

Figure 3. Threat Score (TS) for precipitation events above the percentile thresholds for WRF and WRF + AI framework (left), and hourly precipitation intensity for WRF, WRF + AI, CMORPH observation at each corresponding percentiles (right).

- The skill score improved at all ranges of precipitation intensity.
- Wet bias reduced at lower rainfall intensity.
- Significantly rectifying precipitation intensity for the extreme rainfall events at the highest quantile.

Spatial Variability at 95th percentile of precipitation intensity

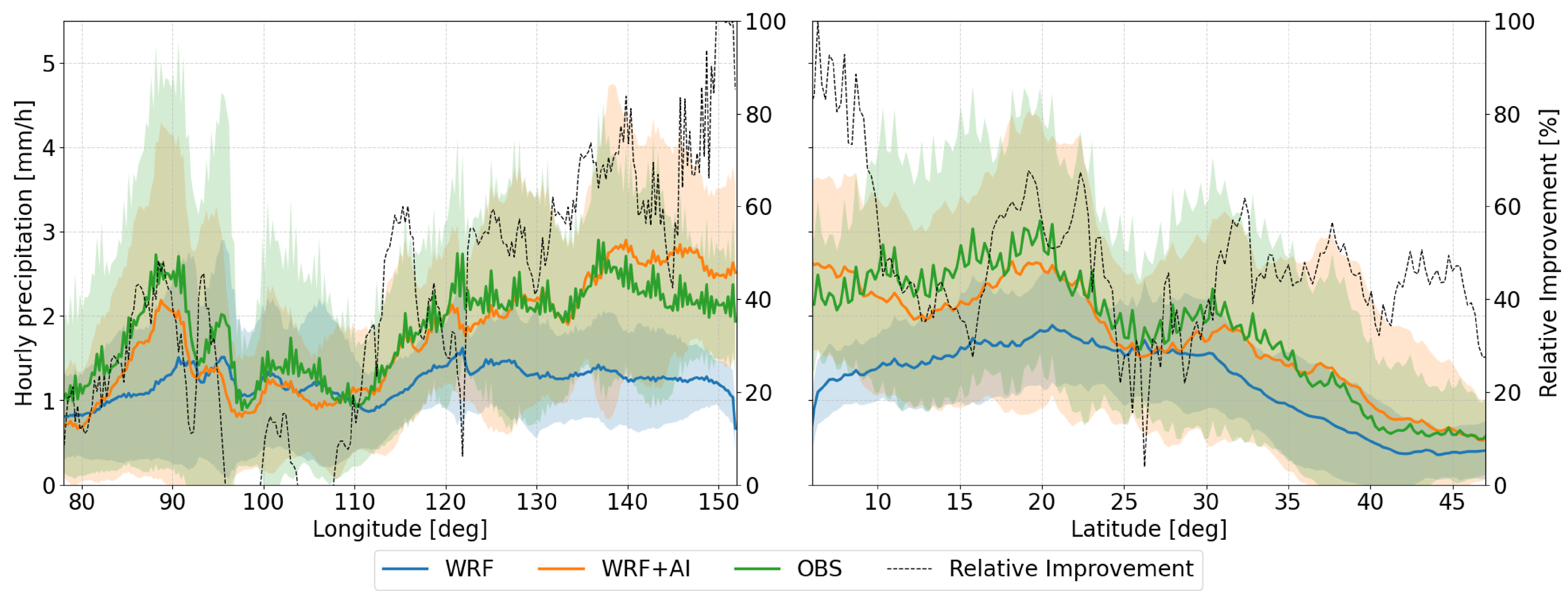

Figure 4. Meridionally (left) and Zonally (right) averaged precipitation intensity at $95th$ percentile.

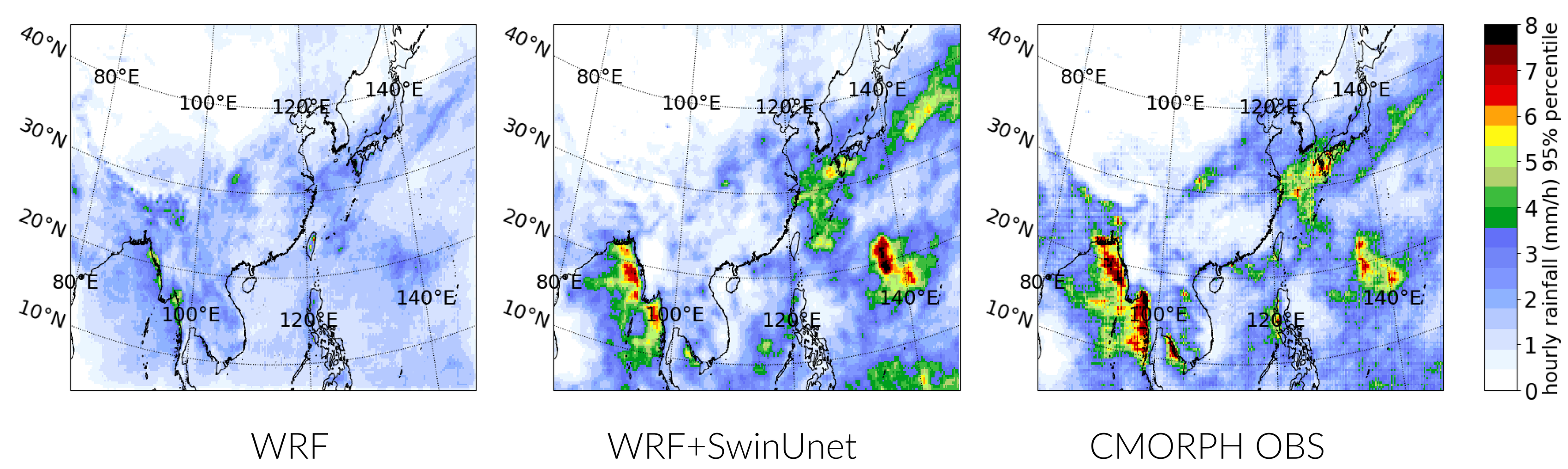

Figure 5. Spatial distribution of $95th$ hourly precipitation intensity for the baseline WRF (left), WRF + AI (mid) and CMORPH observation (right).

Summary & Conclusion

- Employing a transformer-based deep learning model to directly map fundamental meteorological variables derived from (NWP) models onto precipitation maps.
- The proposed framework significantly enhances precipitation estimation across all levels of precipitation intensity, demonstrating particularly remarkable performance in accurately representing extreme precipitation events, which are often located in the long tail of the distribution.
- The deep learning approach effectively captures the patterns of extreme precipitation, leading to enhanced conformity with observations in both spatial distribution and its intensity, shown in the example 95th percentile.
- Evaluation of a Frontal Rainbelt case reinforces these findings, showcasing substantial alignment with observations in terms of both intensity and spatial arrangement.

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