# A Limited-Area Data-Driven Weather Model for High-temporal Predictions

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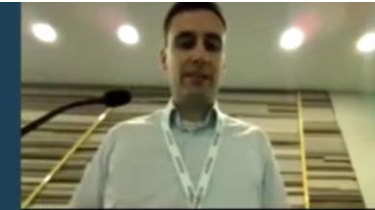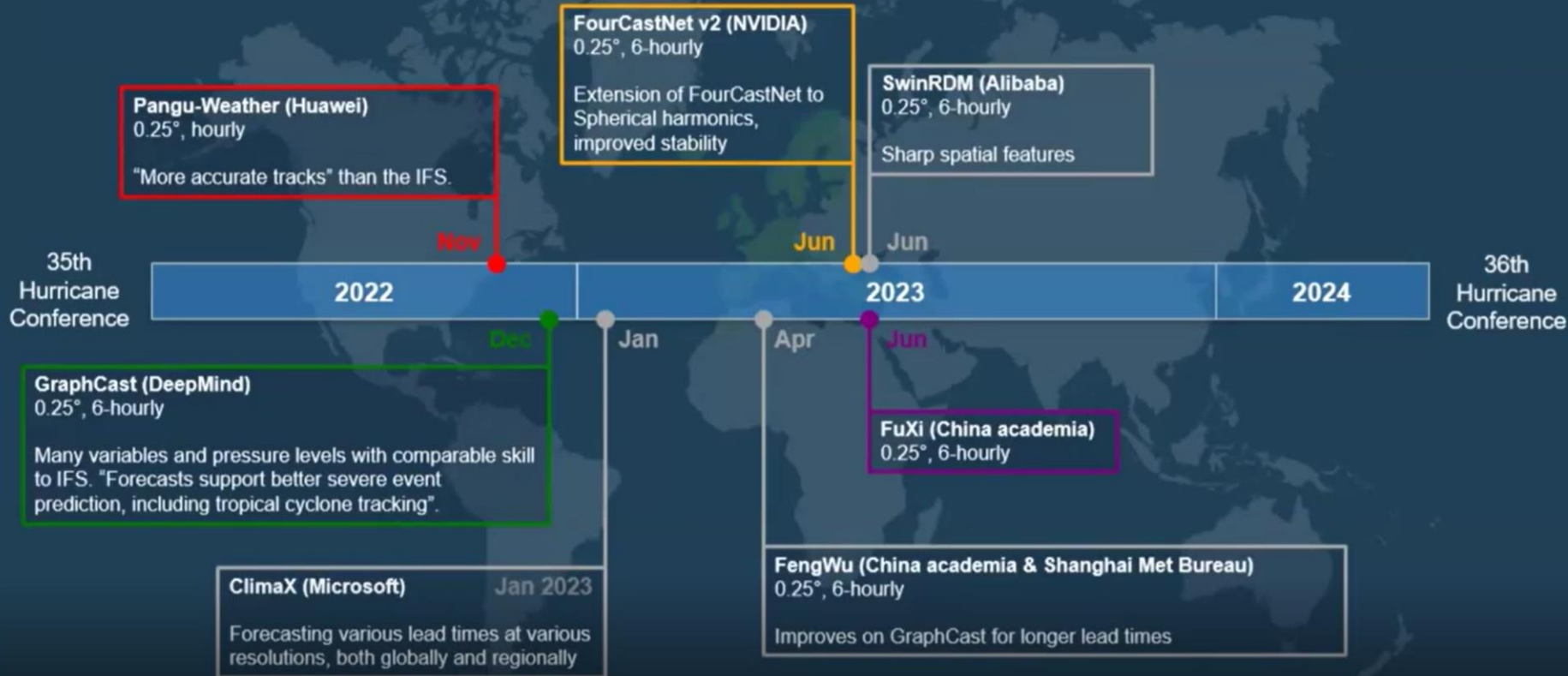
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September 3 - 5, 2024, Central Weather Administration, Taipei

**Michael Maier-Gerber, L. Magnusson, and M. Chantry (2024):**

**Evaluation of Tropical Cyclones in Global Data-Driven Forecasting Models.**

The 36th Conference on Hurricanes and Tropical Meteorology, 18D.1.

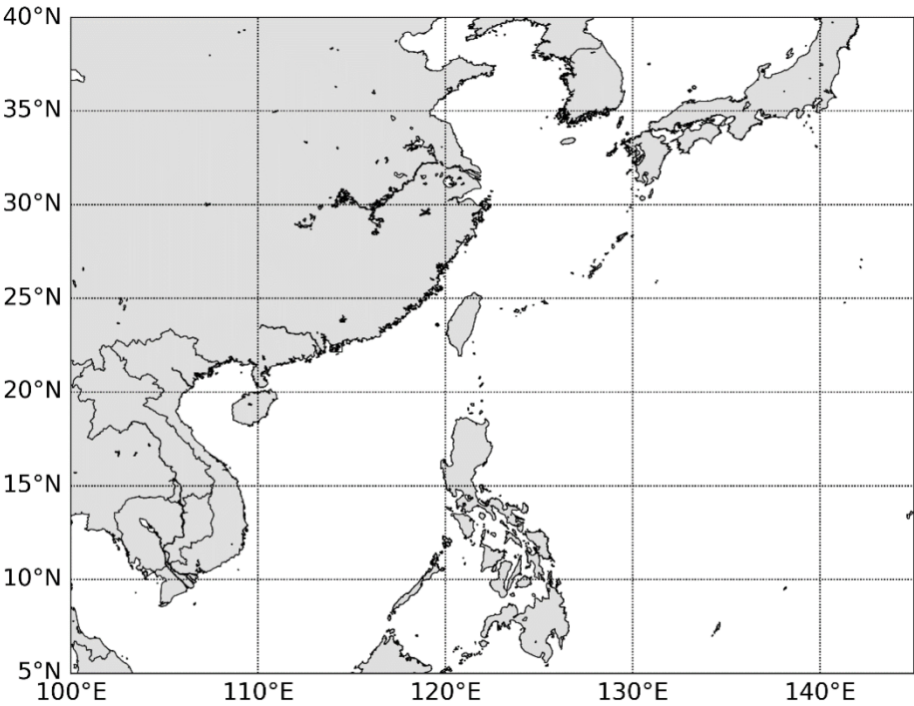## What do we need for a **Limited-Area** data-driven weather model?

1. Appropriate boundary replacement strategies

2. Auto-regression to 96 hours with reasonable forecast results

3. Competitive performance against global data-driven weather models (baseline)

4. Higher temporal resolution: 6-hourly → 1-hourly

# Scientific questions

1. Can we use the deep network architecture of a global data-driven weather model to build a high-temporal limited-area data-driven weather model?

2. Are the relationships of mass fields and momentum fields in the model reasonable?

3. How do we deal with boundary replacement for inferencing (forecasting)?

# Data

| Name | ERA5 |
|---|---|
| Domain | 5°N - 40°N, 100°E - 145°E |
| Resolution | 0.25° x 0.25° (about 25 km around Taiwan) |
| Levels | 50, 150, 300, 500, 700, 850, 925, 1000 hPa |
| Upper-air Variables | u, v, t, q, z |
| Surface Variables | u10, v10, t2m, msl |
| Training | 2013 - 2017 |
| Validation | 2019 |
| Testing | 2020 |



Pros and cons of using ERA5 data ?

# Model Architecture



**Input**

$V_{upper, t}$

(8,141,181) * 5 variables

$V_{surface, t}$

(141,181) * 4 variables

(Huai-Yuan Kuo)
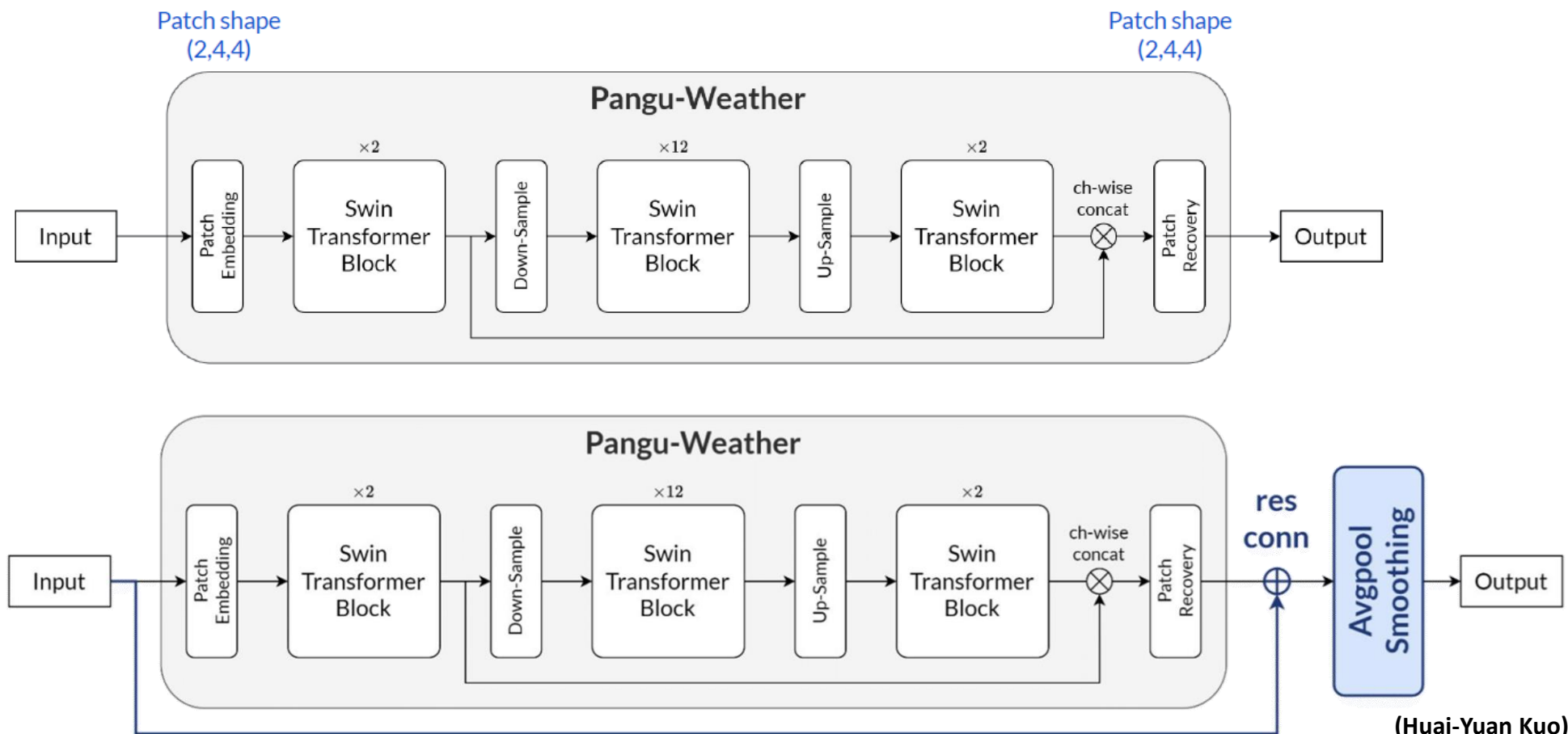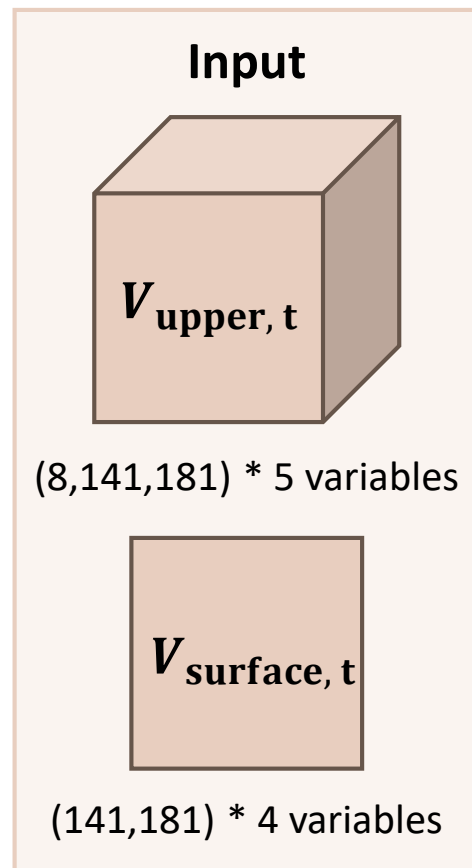
Training strategies:

1. Data is standardized. (Statistic results are calculated from 2016~2018 ERA5 data)

2. The model is optimized by L1 loss.

Computational costs:

1. 300k steps

2. ~70 h on 8 V100 GPUs on TWCC

Introduction ○

Objectives ○

Data and Methods ○○●○

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Summary and Future Works ○

P.5

# Inferencing



**Without Boundary Replacement**

$V_{t=0}$ → Model → $V'_{t+1h}$ → Model → $V'_{t+2h}$

**With Boundary Replacement**

$V_{t=0}$ → Model → $V'_{t+1h}$ → $V^*_{t+1h}$ → Model → $V'_{t+2h}$

$V_{t+1h}$

**outer 8 px (~ 200 km)**

**Boundary condition**

**ERA5**
**Pangu-Weather FM6**

regional DWP fct 001~003h → Pangu FM6 fct 000h

regional DWP fct 004~009h → Pangu FM6 fct 006h

regional DWP fct 010~015h → Pangu FM6 fct 012h
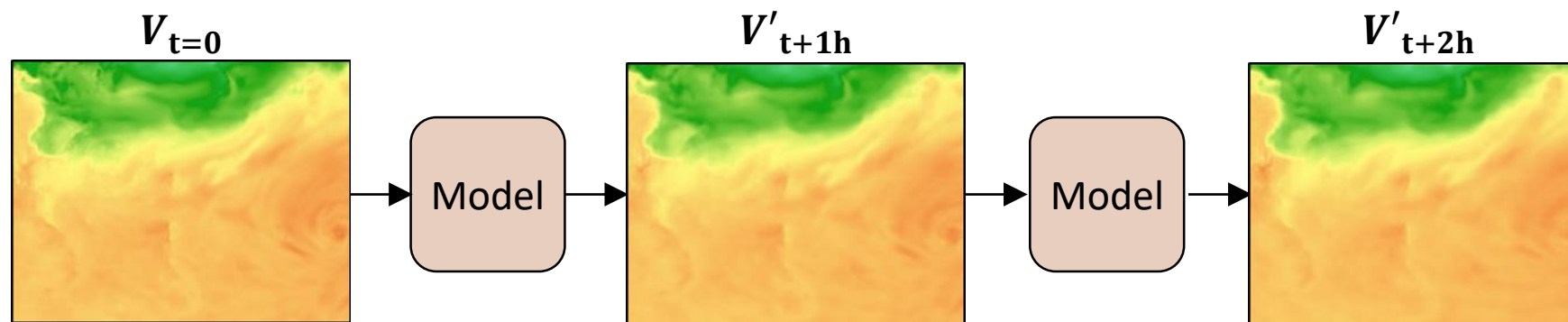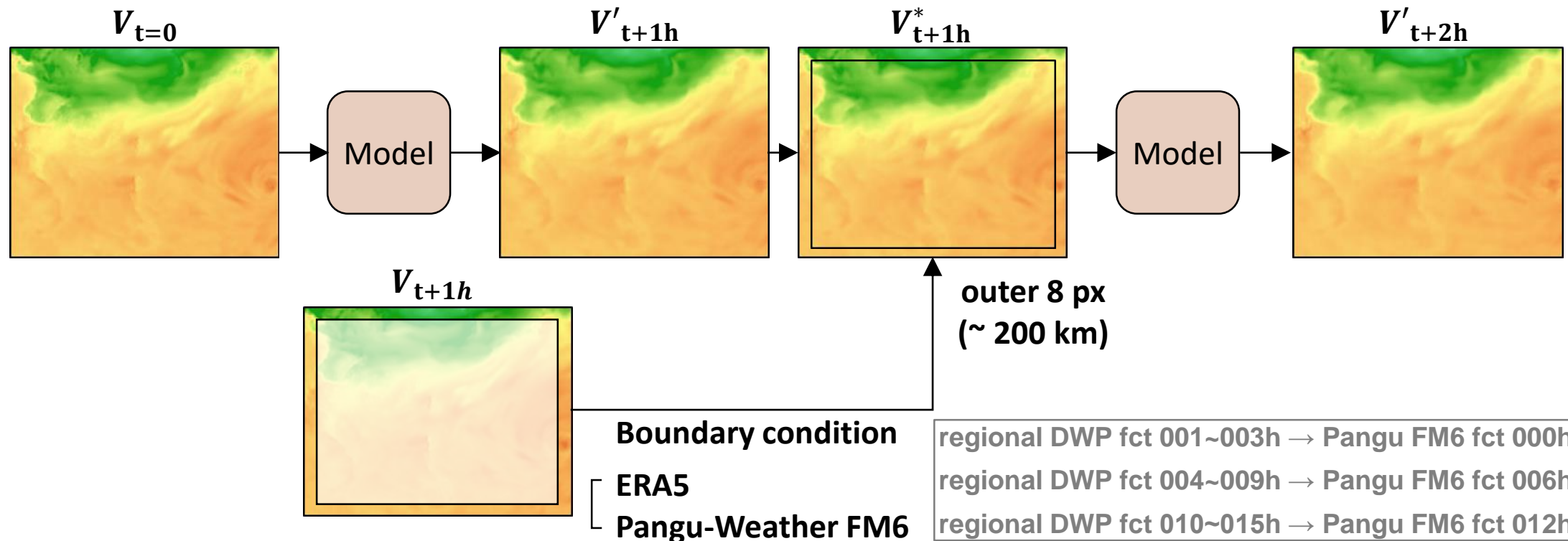
# Model Improvements



**+ 96 h**



**+ 96 h**
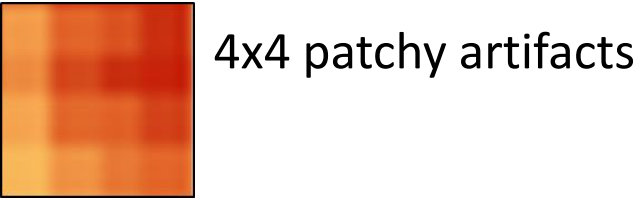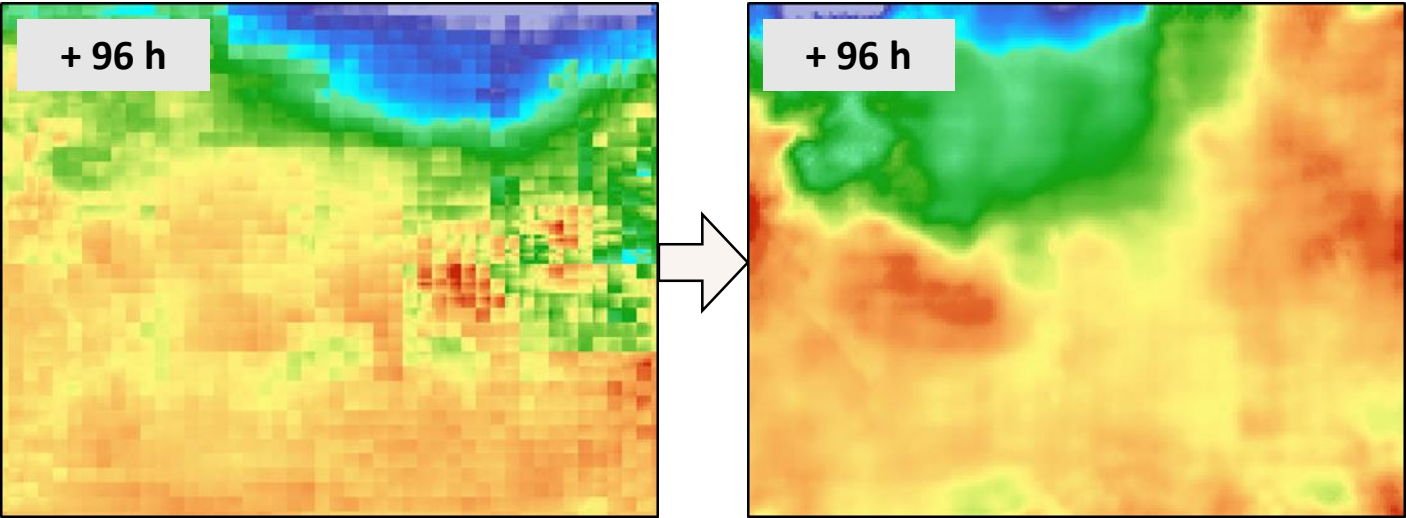
4x4 patchy artifacts

1. Fix patchy artifacts

2. Improved forecast results

**RegPGW**

**RegPGW + LS**

Lateral smoothing (3x3 Average pooling)

**RegPGW + LS + Res ?**
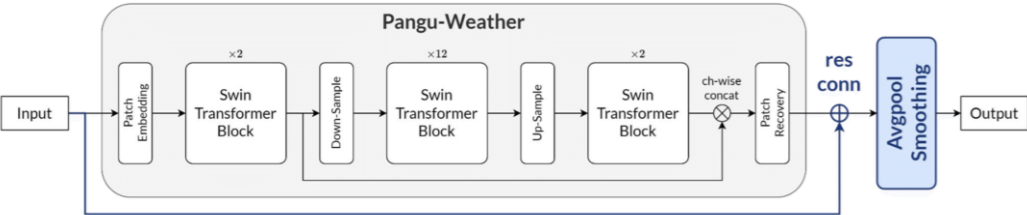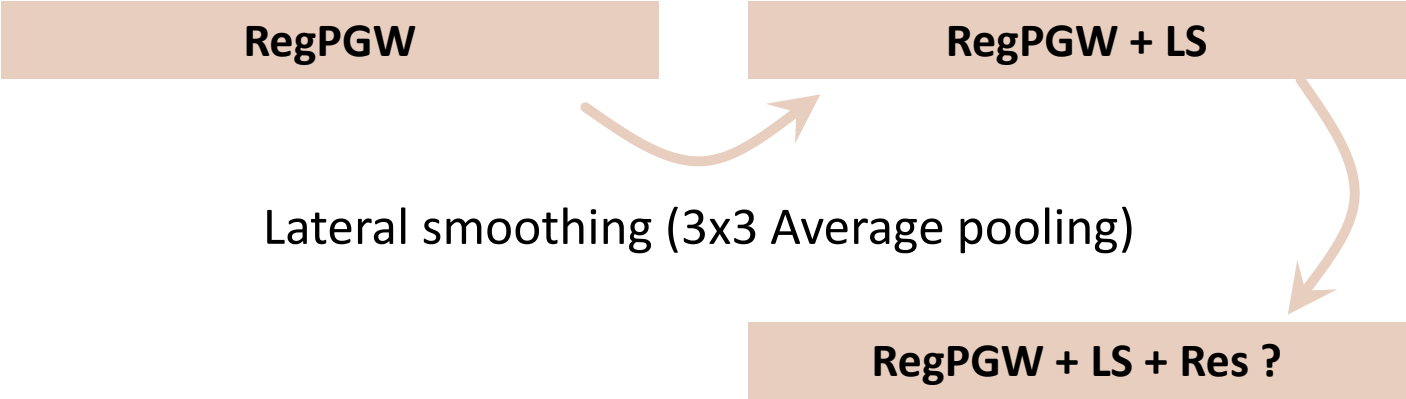


Pangu-Weather

## Global data-driven weather model

**Pangu-Weather FM24**

**Pangu-Weather FM1**

## Limited-area data-driven weather model

| RegPGW + LS | X ERA5 |
| RegPGW + LS | X Pangu-Weather FM6 |
| RegPGW + LS + Res | X ERA5 |
| RegPGW + LS + Res | X Pangu-Weather FM6 |

# 2019 Case Studies – t850 RMSE
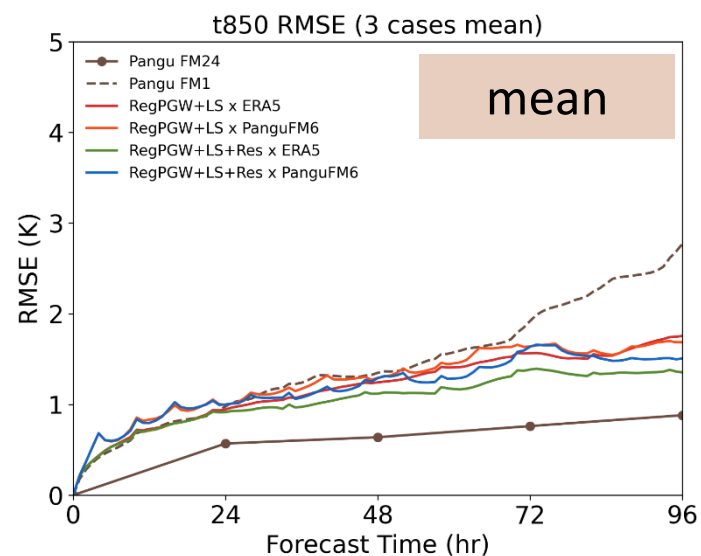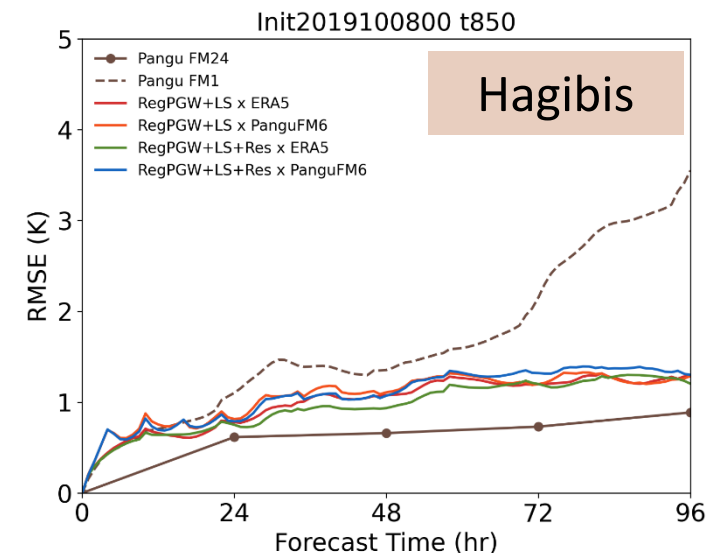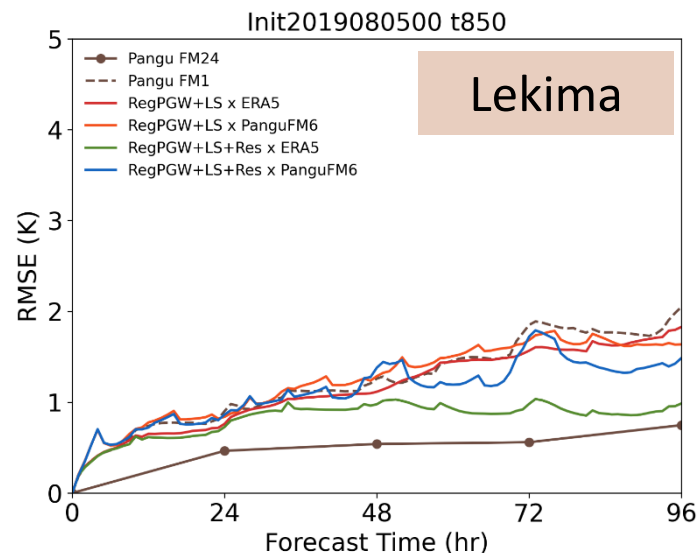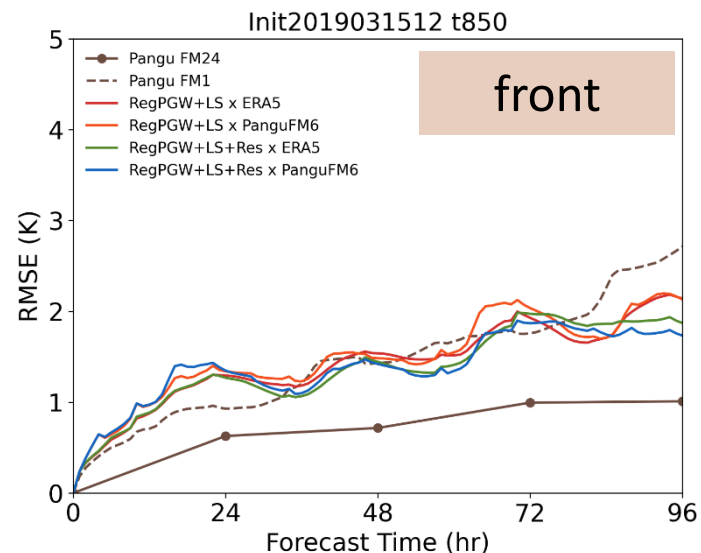


1. No significant difference.
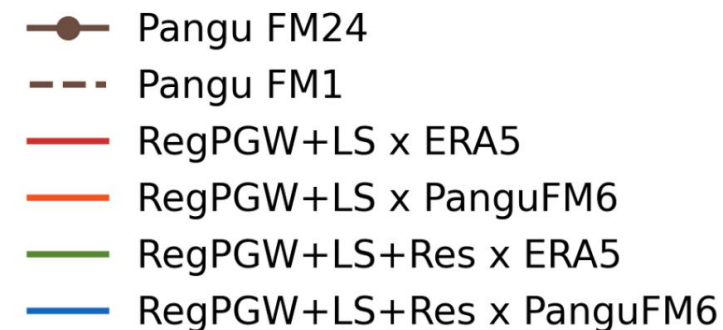
# 2019 Case Studies – z500 RMSE
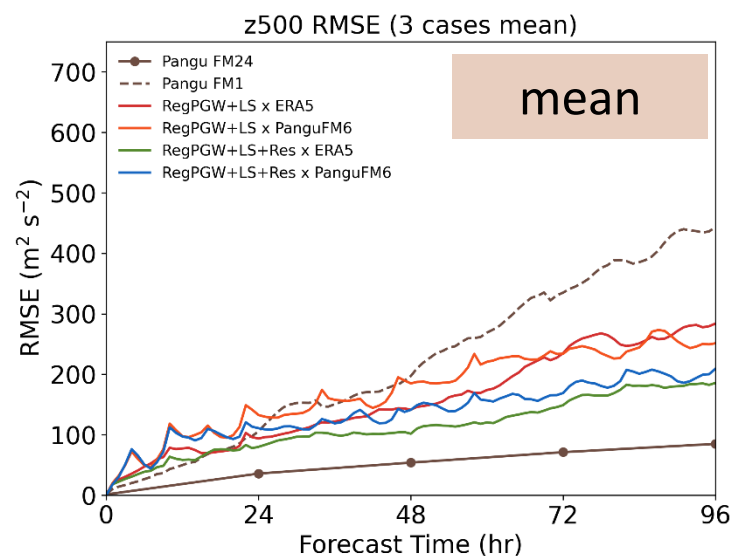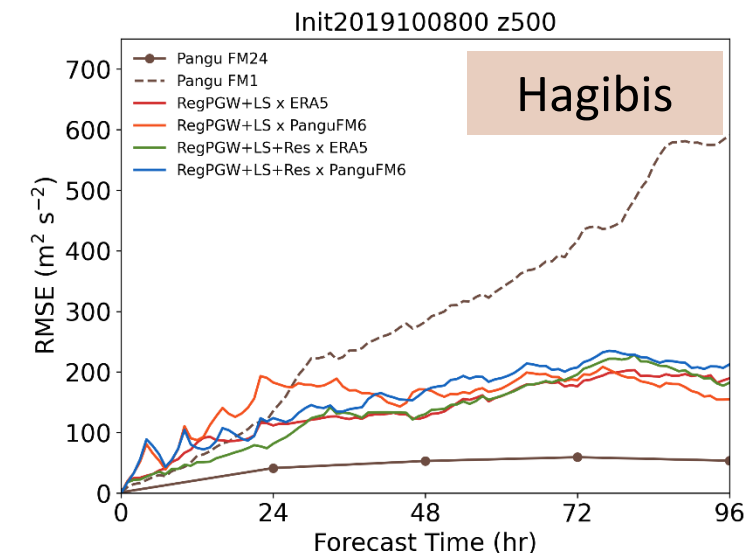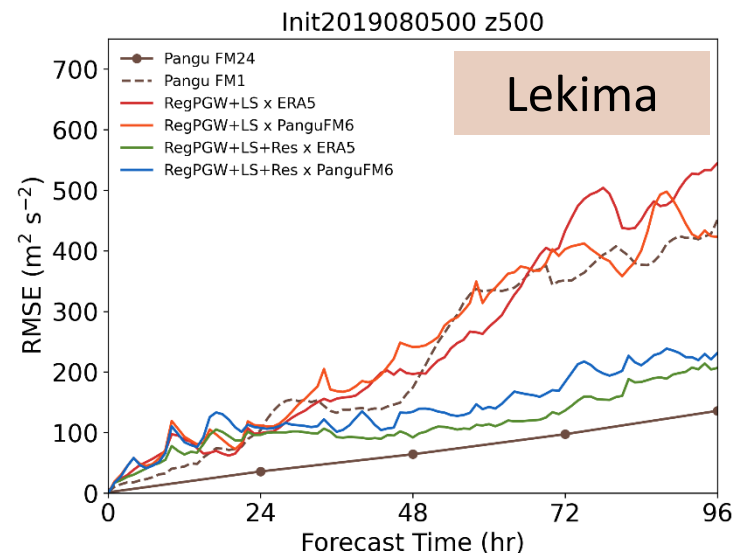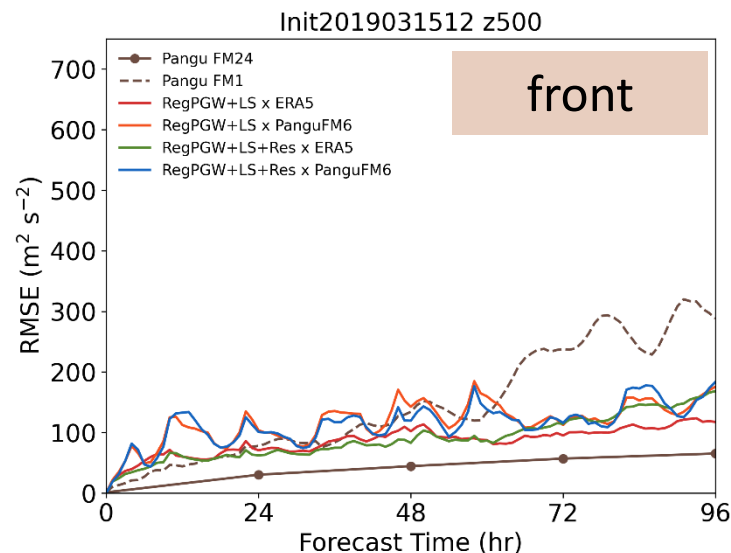


1. The forecast results are mainly influenced by **different models** rather than influenced by different boundary replacement strategies.
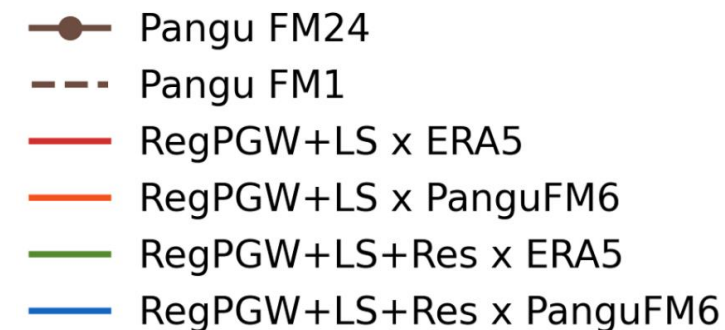
# 2019 Case Studies

20190315 front《850 hPa temperature and wind》
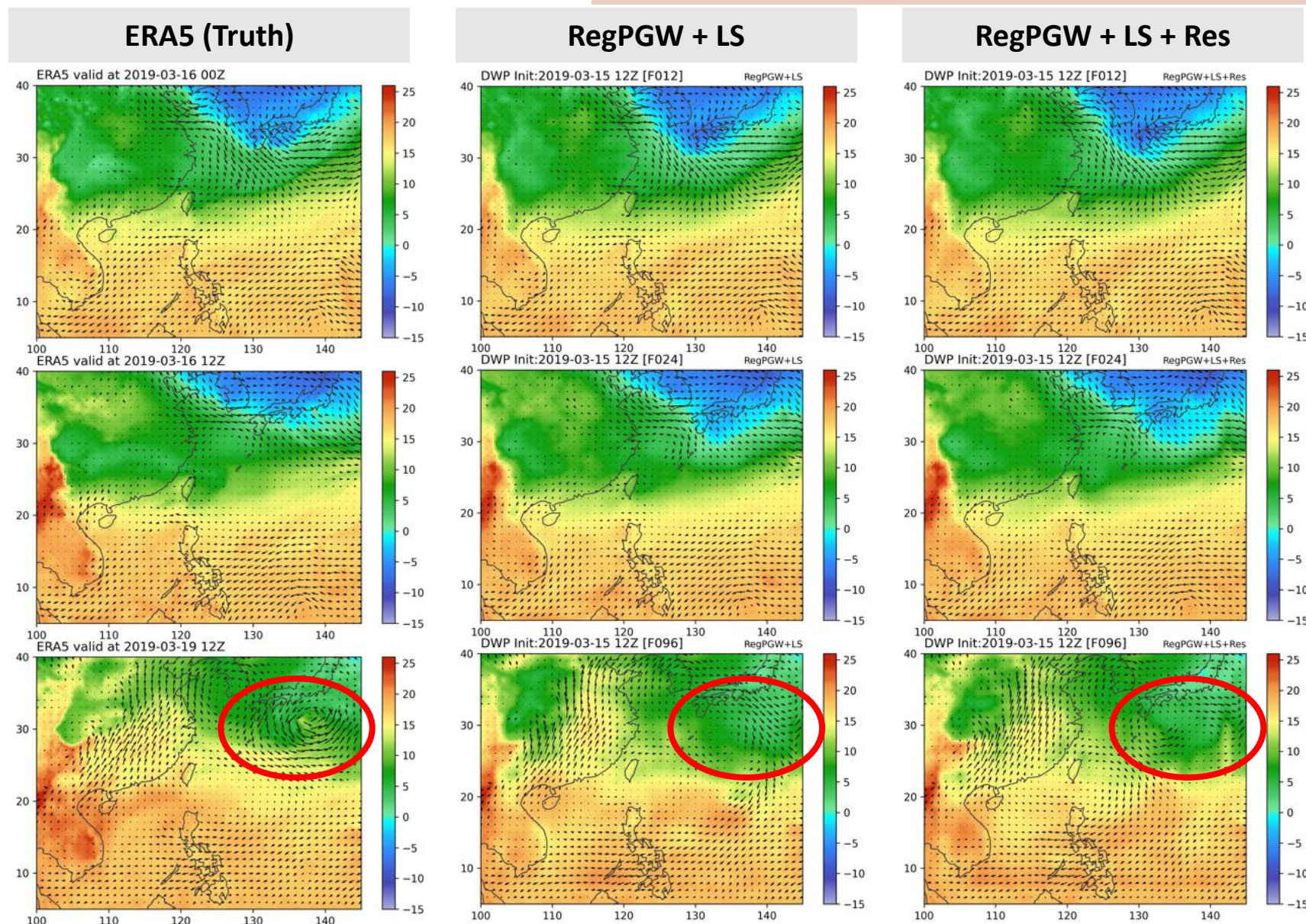


Failed to capture the extratropical cyclone

# 2019 Case Studies

## 20190805 Lekima《Surface wind and MSLP》
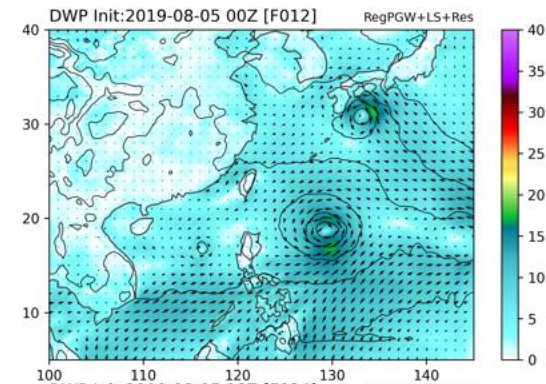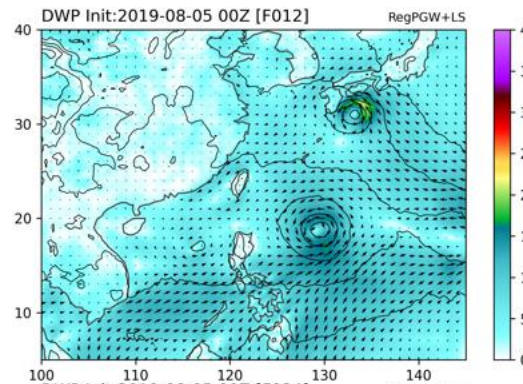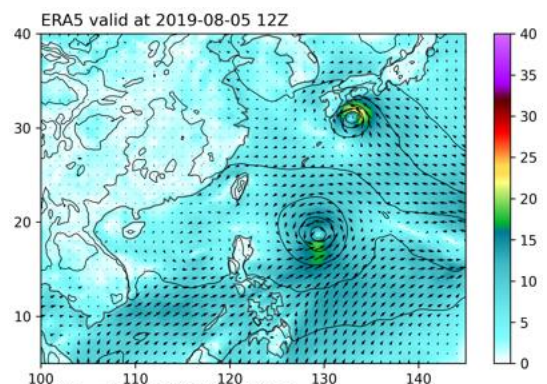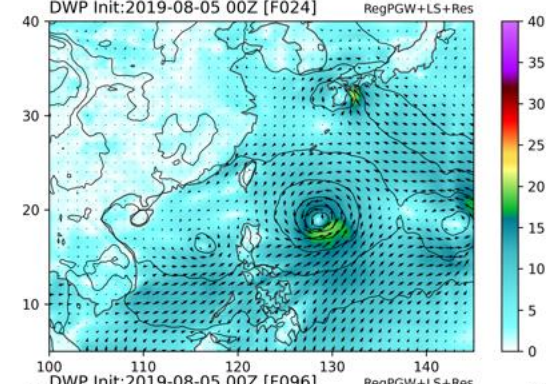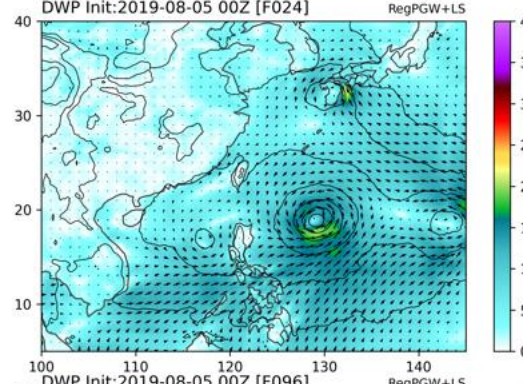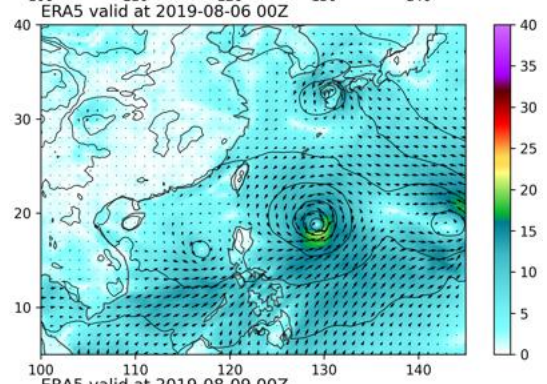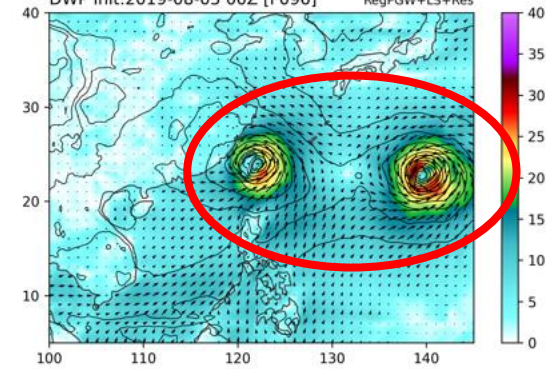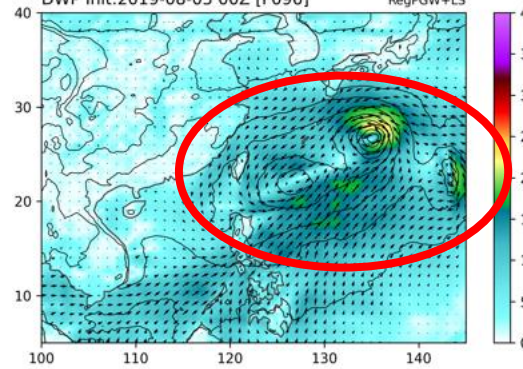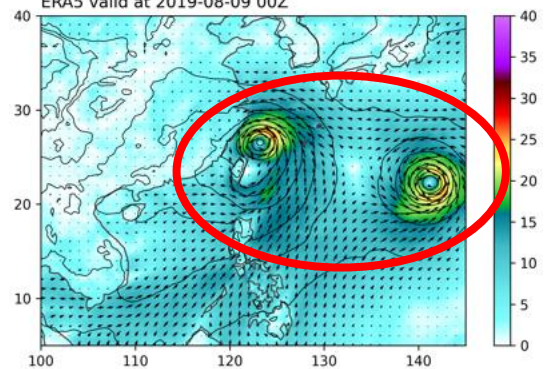
# 2019 Case Studies

20190805 Lekima《500 hPa Vorticity and wind》
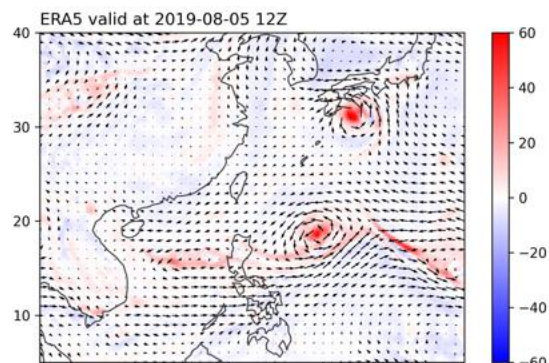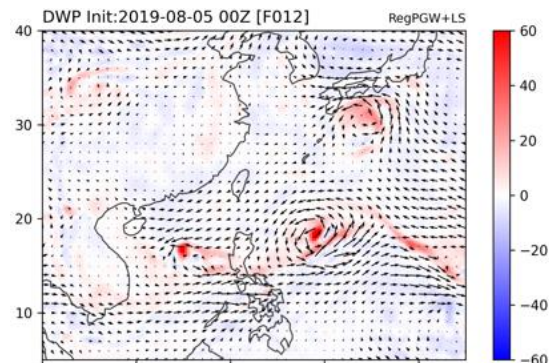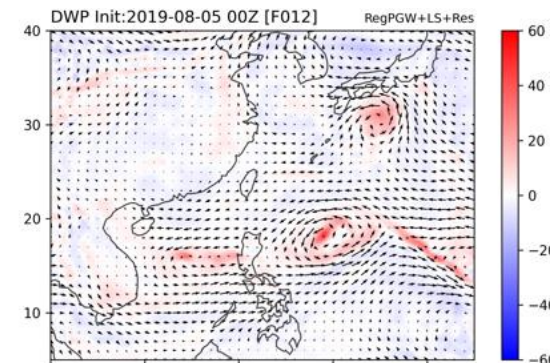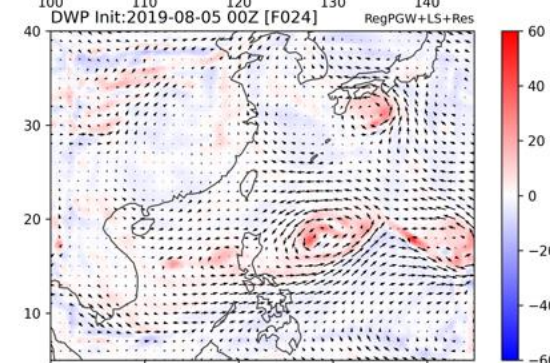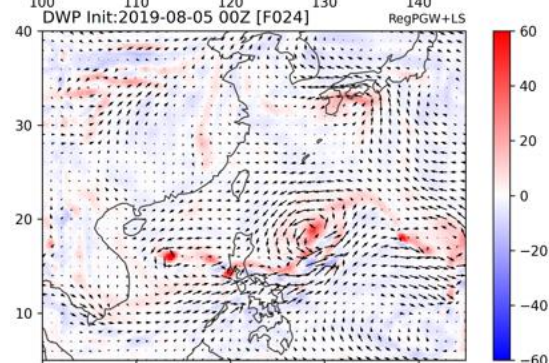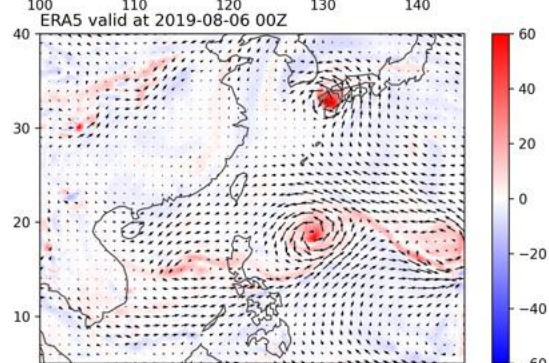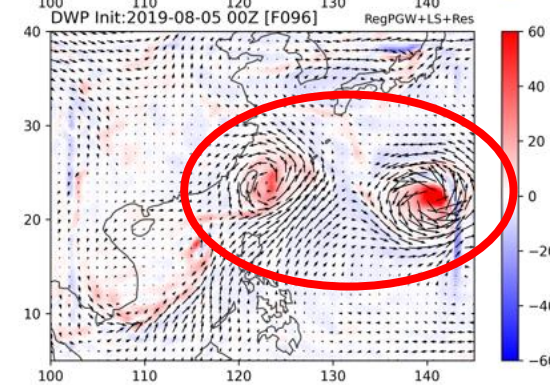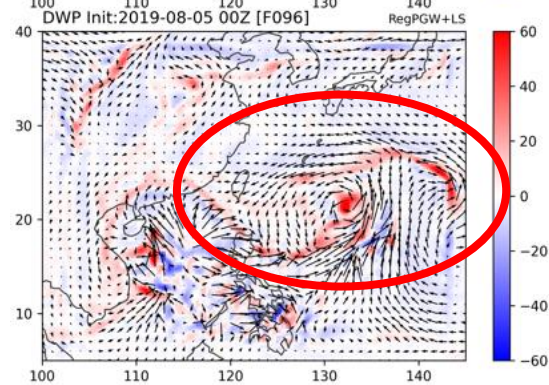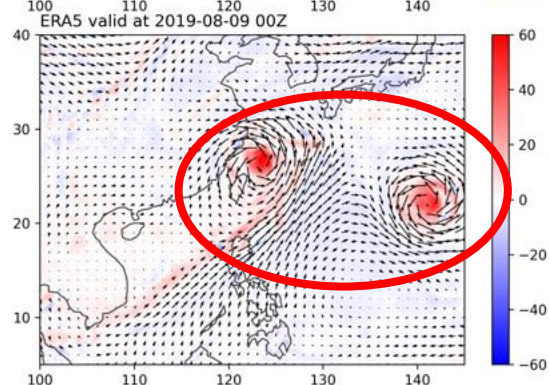


Well-coupled between lower and upper levels.

# 2019 Case Studies

20191008 Hagibis《Surface wind and MSLP》

**Introduction**
○

**Objectives**
○

**Data and Methods**
○○○○

**Results**
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**Summary and Future Works**
○

P.13
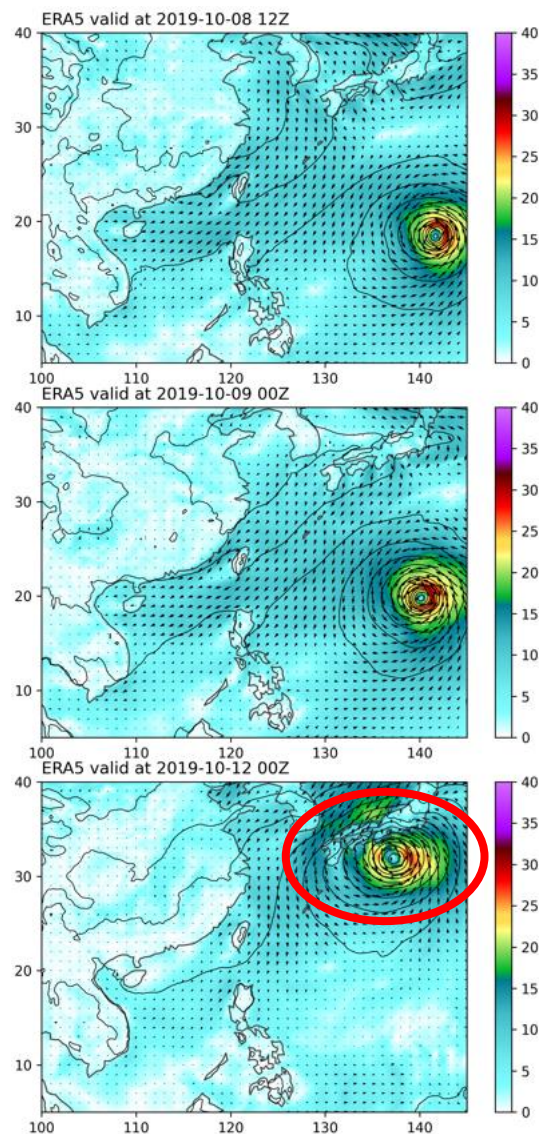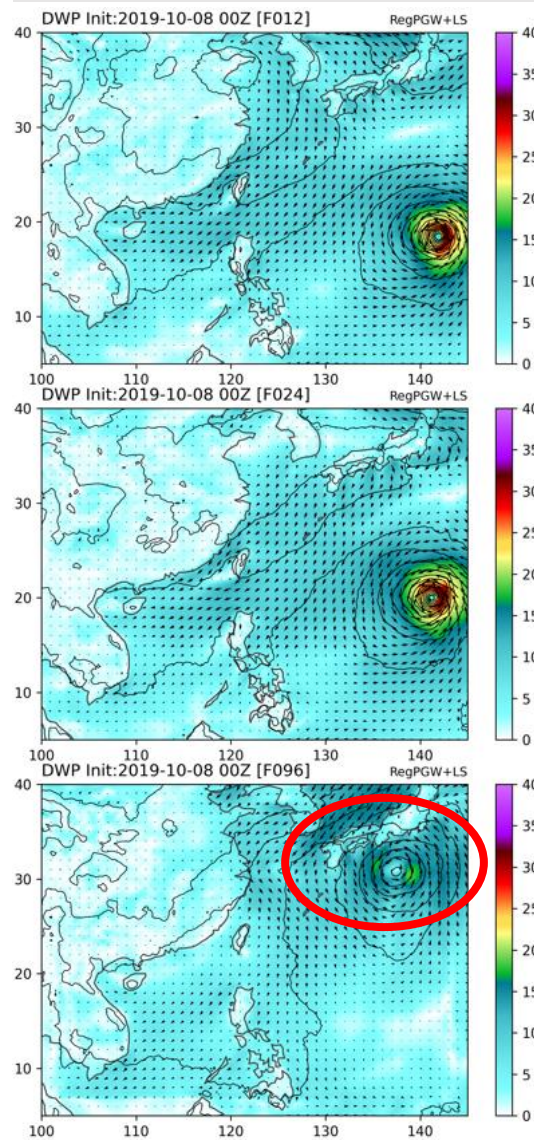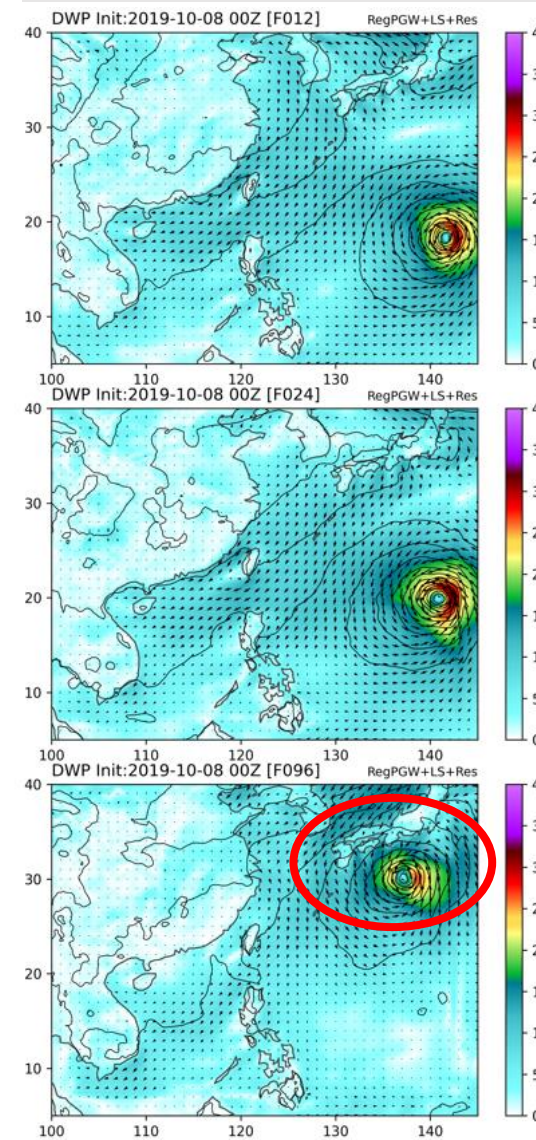
# 2019 Case Studies

20191008 Hagibis《500 hPa Vorticity and wind》
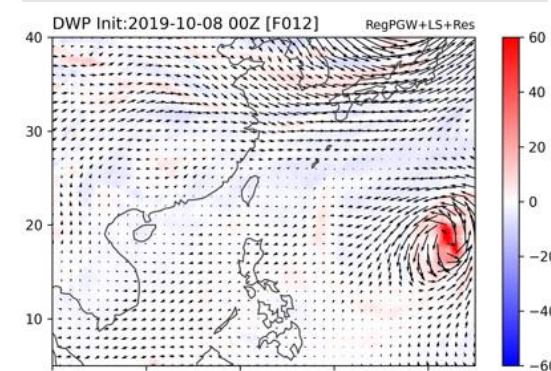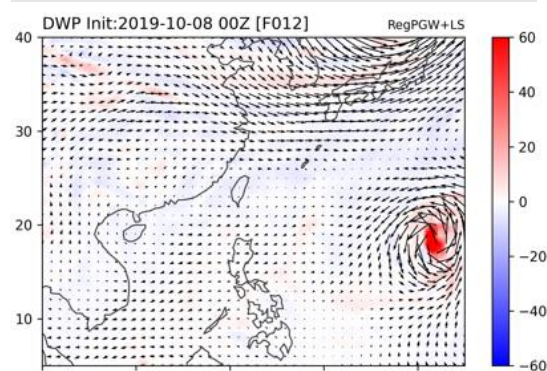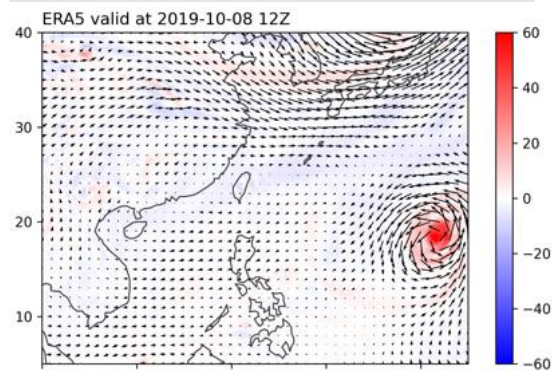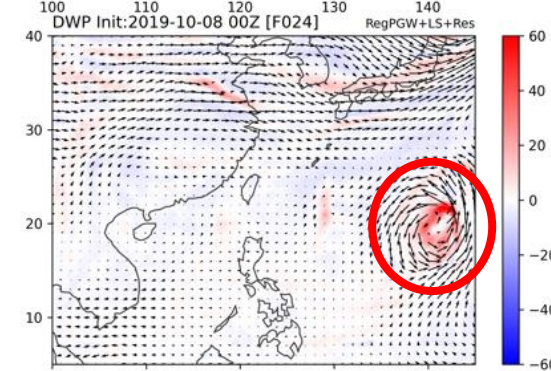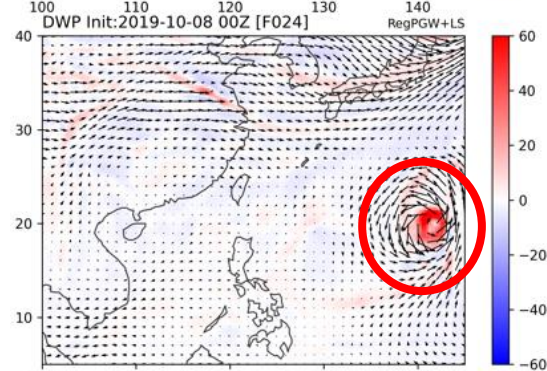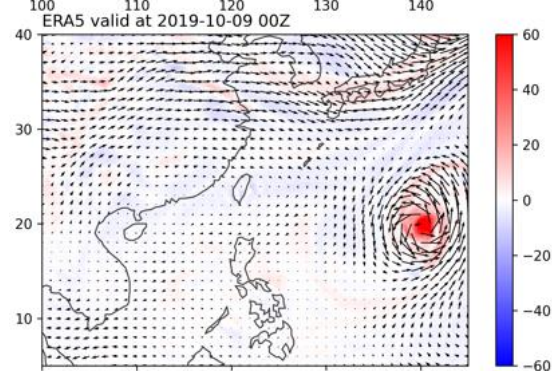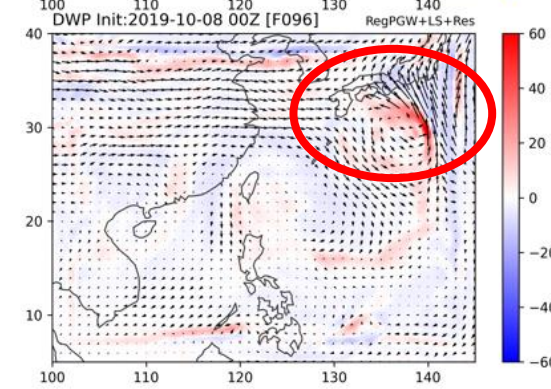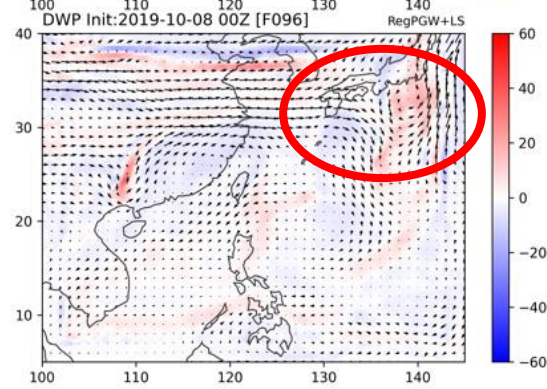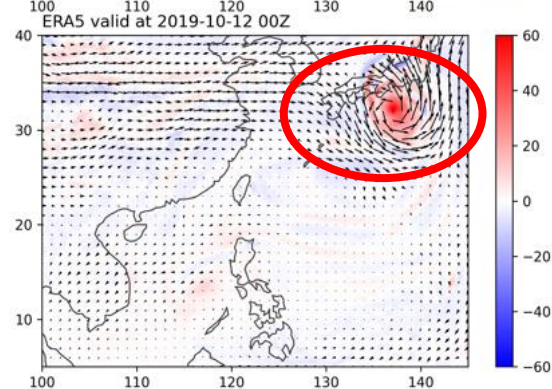


Too close to the boundary.

# 2019 Whole Year Evaluation – RMSE with standard deviations

t850

z500



t850 RMSE (2019 mean)
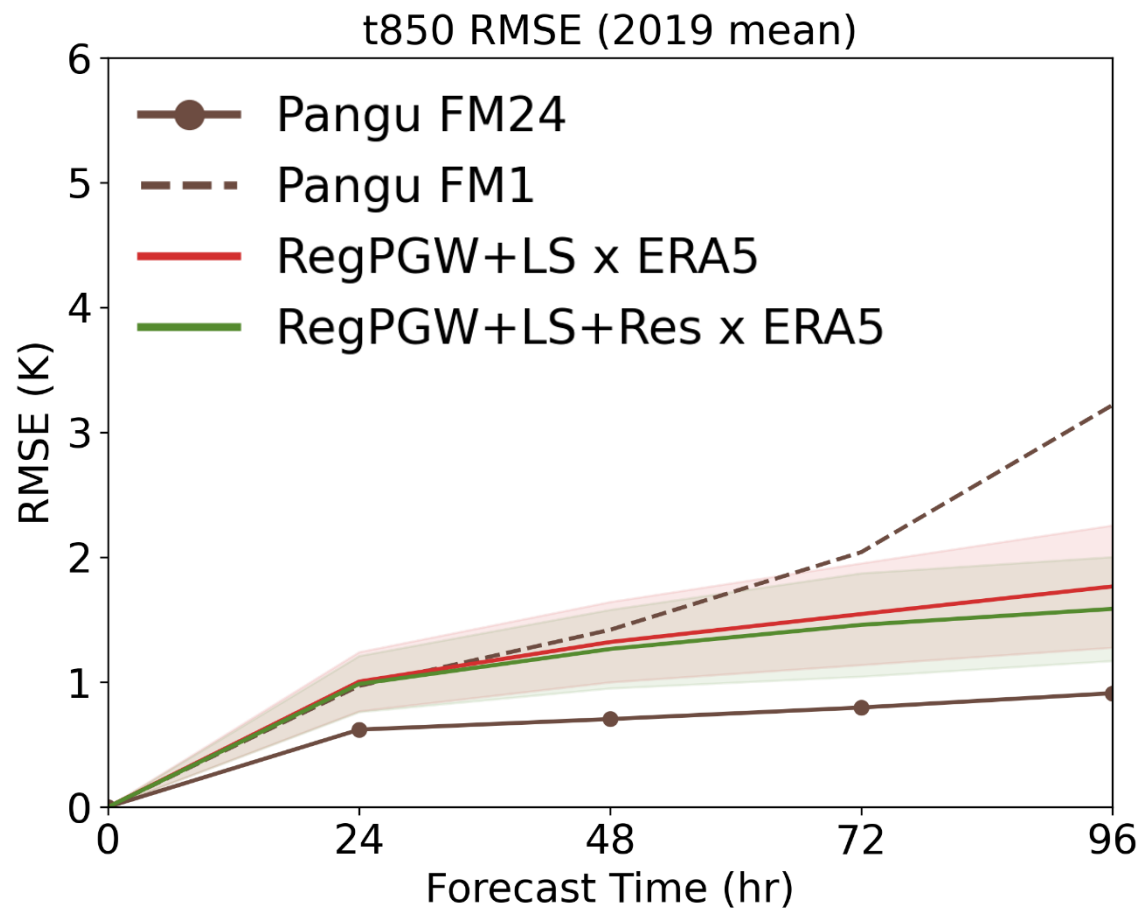
z500 RMSE (2019 mean)
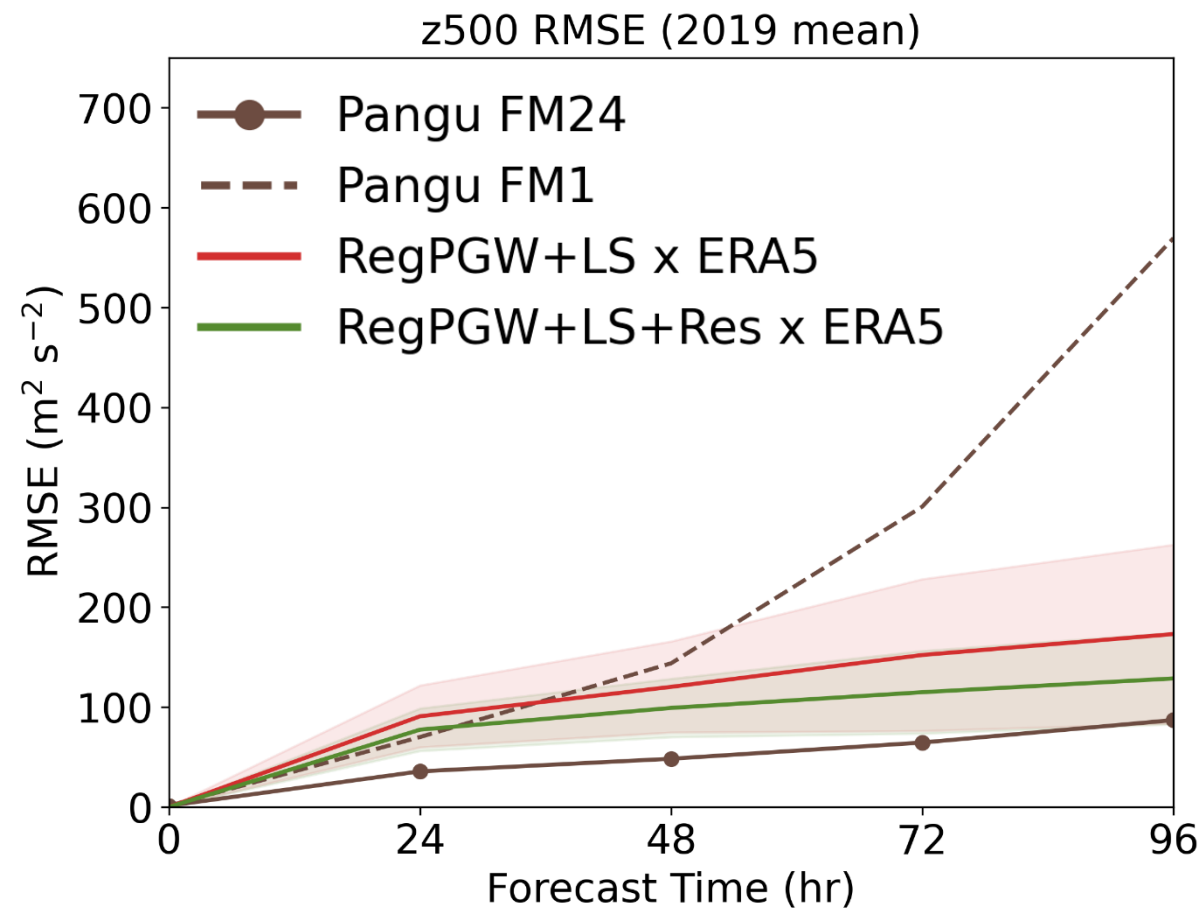
**RegPGW+LS+Res: smaller RMSE and smaller stds**

# 2019 Whole Year Evaluation – RMSE with standard deviations
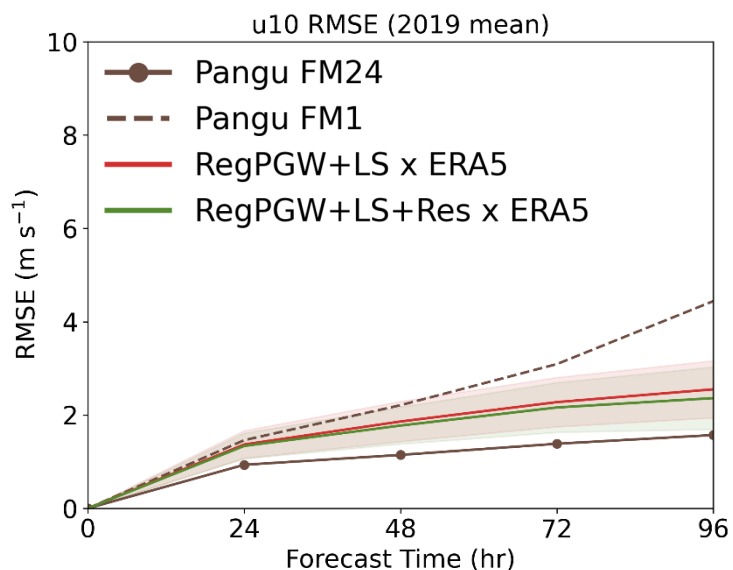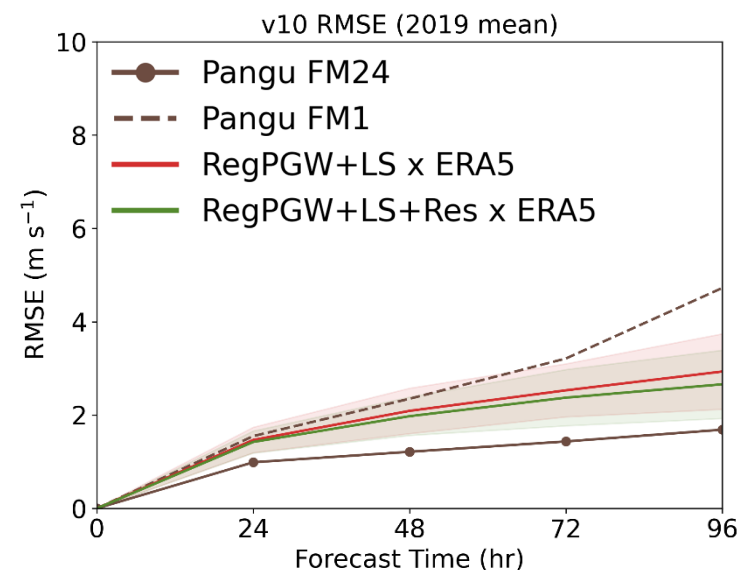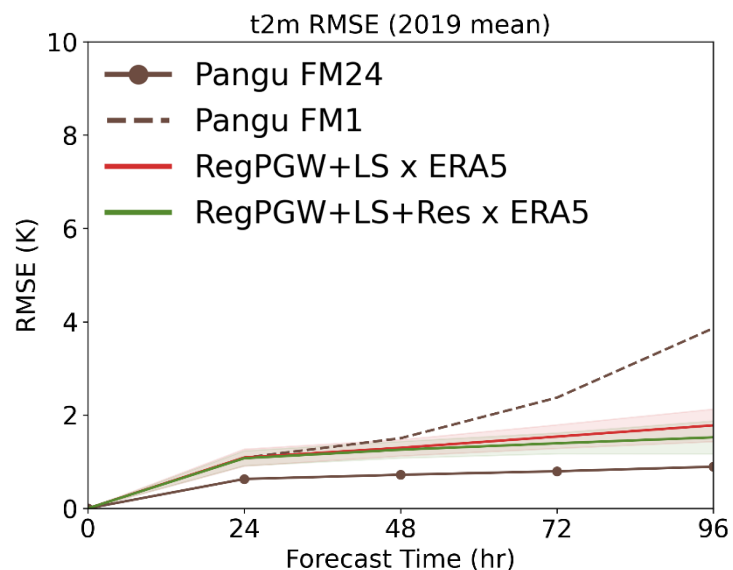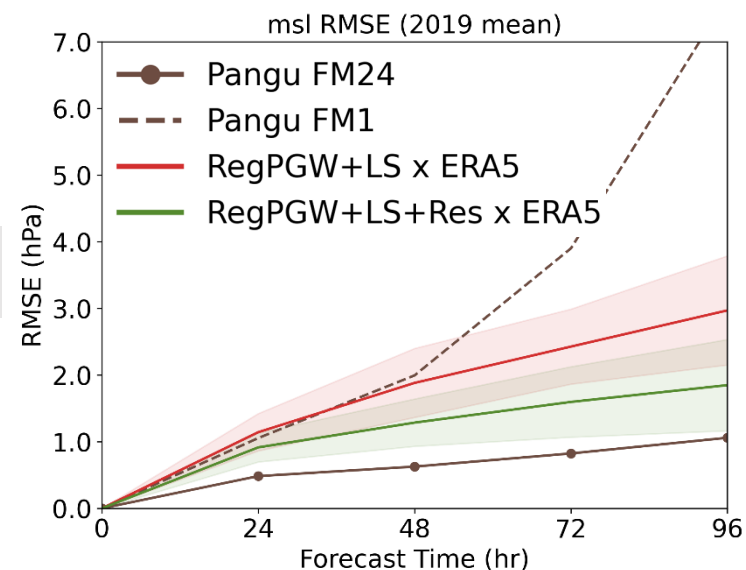
# 2019 Whole Year Evaluation – RMSE of all variables (normalized by PanguFM1)



[F024h] 2019 Mean RMSE Normalized by Pangu1
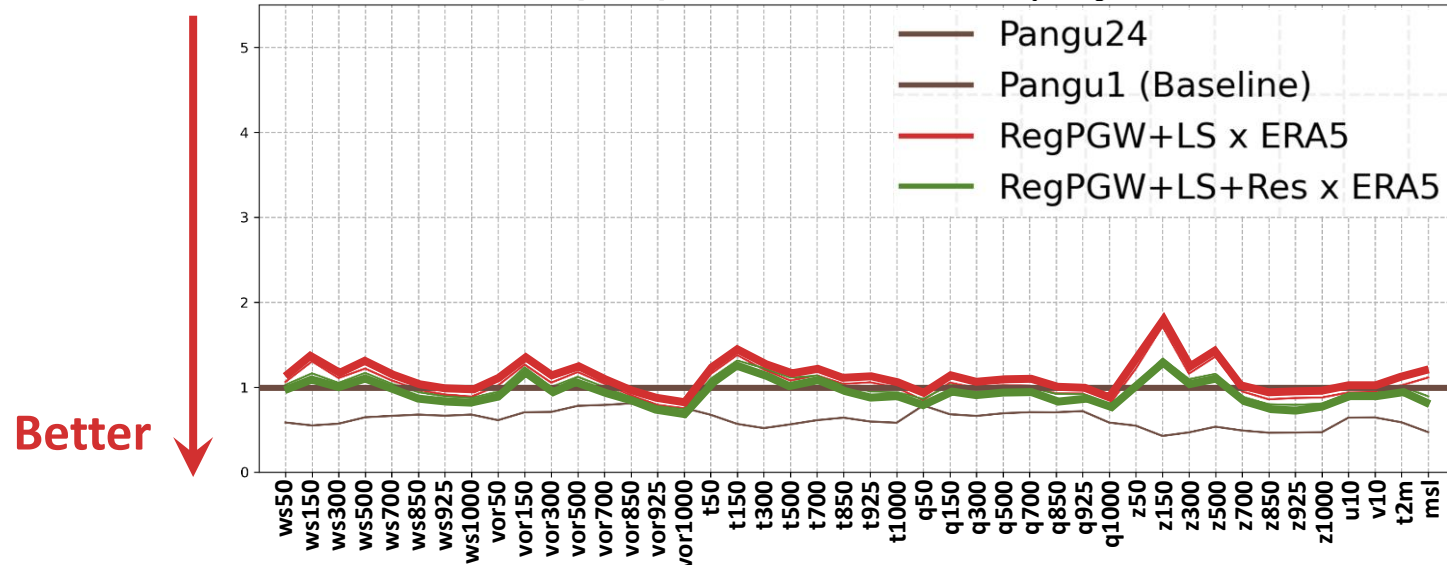
**Better**

**+24h**

1. The two models show similar forecast abilities in most variables, and the RMSEs are similar to PGW FM1.
2. The main difference exists in the upper-level geopotential.



[F096h] 2019 Mean RMSE Normalized by Pangu1
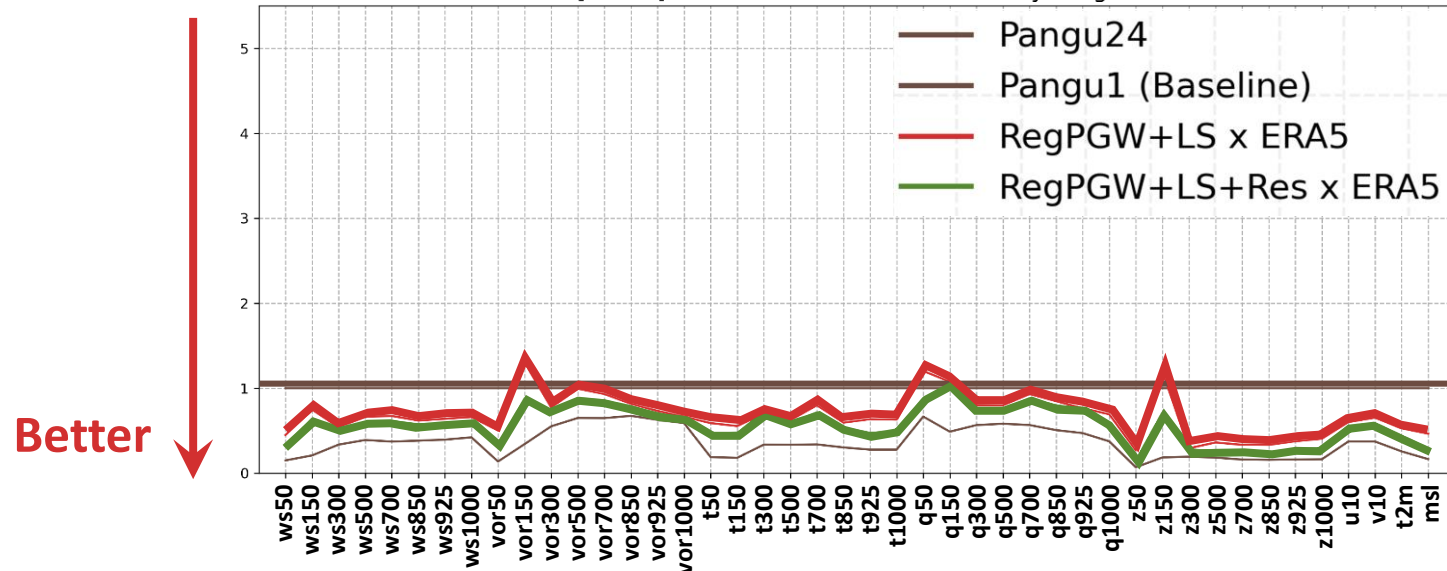
**Better**

**+96h**

1. Both two models show better forecast abilities than PGW FM1 in most variables.
2. RegPGW+LS+Res performs better than RegPGW+LS, especially in long-term forecasts.

# Forecast Results of Gaemi (2024)
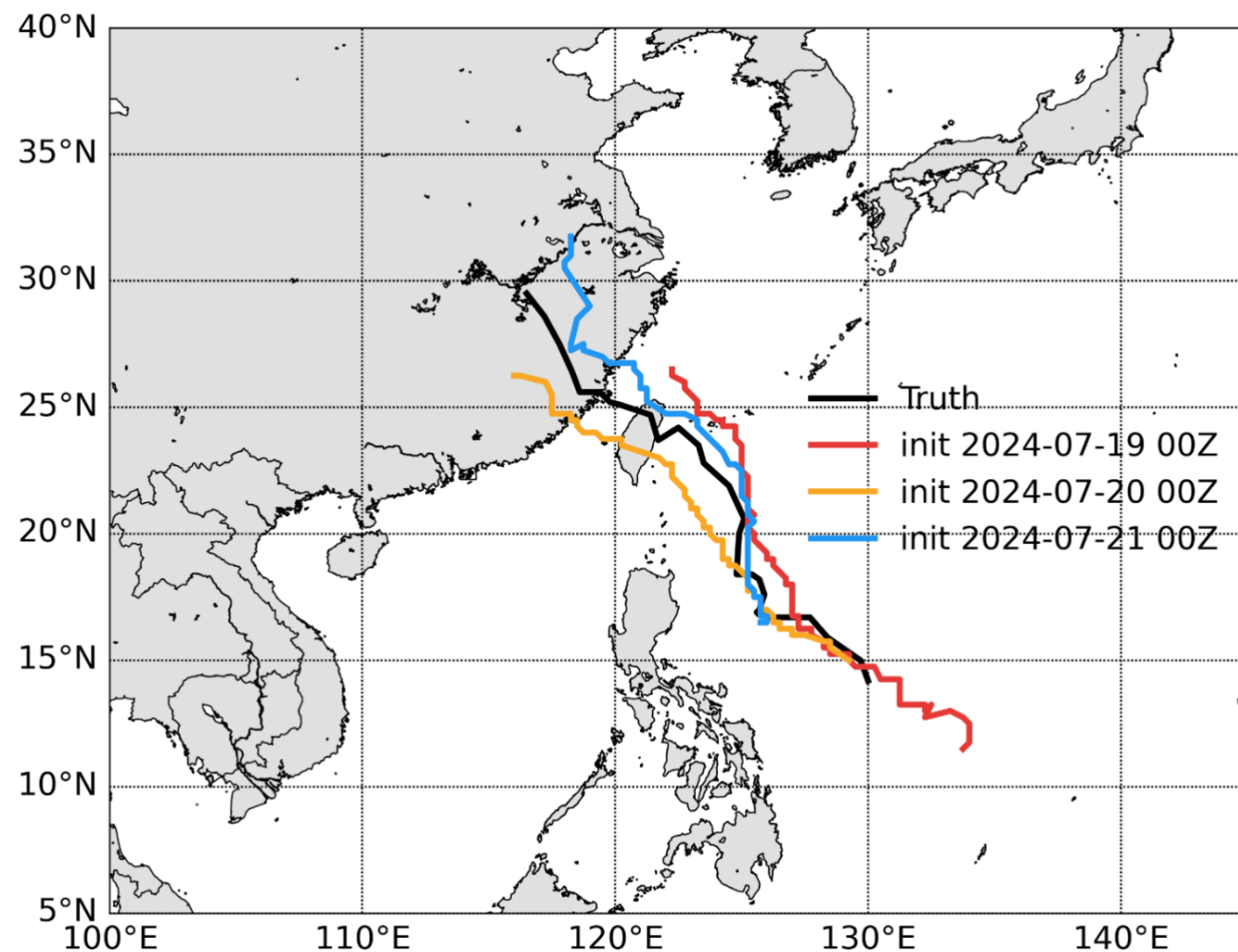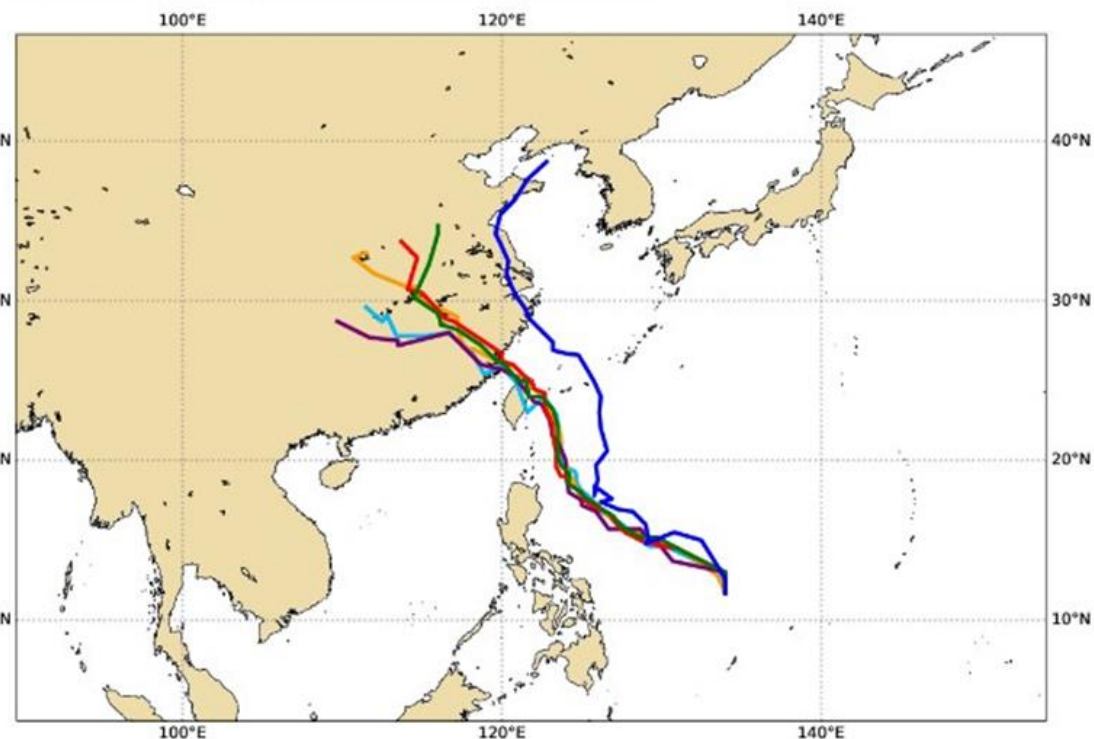
1. **Can we successfully use the deep network architecture of a global data-driven weather model to build a high-temporal limited-area data-driven weather model?**

**YES,** with some model architecture modifications based on process-based evaluations.

    1) **Average pooling smoothing** → brings information from the boundary into the central region

    2) **Residual connection** → more effective in learning complex representations

    RegPGW+LS+Res performs better and is more stable than RegPGW+LS (smaller RMSE stds)

      ⇨ **Process-based evaluation**

2. **Are the relationships of mass fields and momentum fields in the model reasonable?**

**YES,** in most cases.

    However, the model performs worse at the upper levels (50, 150, 300 hPa).

      ⇨ **Increase vertical resolution**

3. **How do we deal with boundary replacement during inferencing (forecasting)?**

**Simply** replace the boundary with ERA5 or any forecast from global data-driven weather models.

# Thanks for listening

# Appendix

# Smoothing strategies

(Huai-Yuan Kuo)

| Smoothing | Segmented-smoothing |
|---|---|
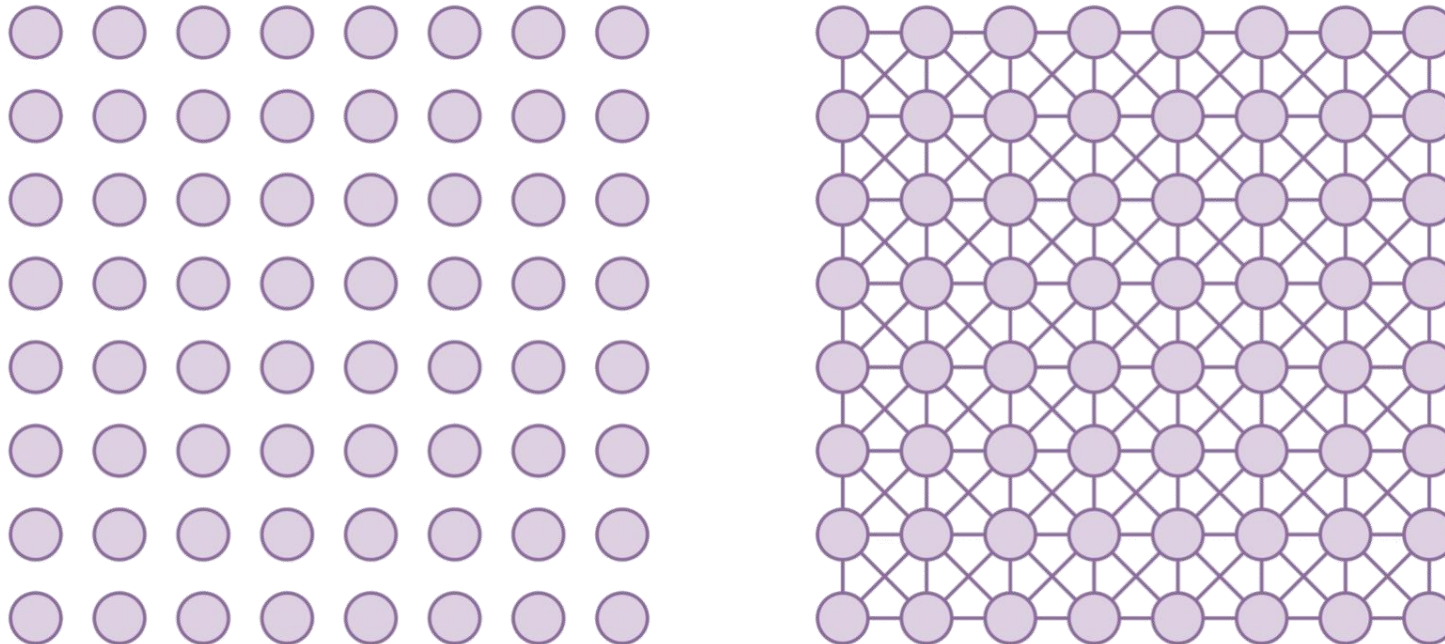


The effects of AvgPool:

1. Smooths out the patch-to-patch difference

2. Brings information from the boundary into the central region
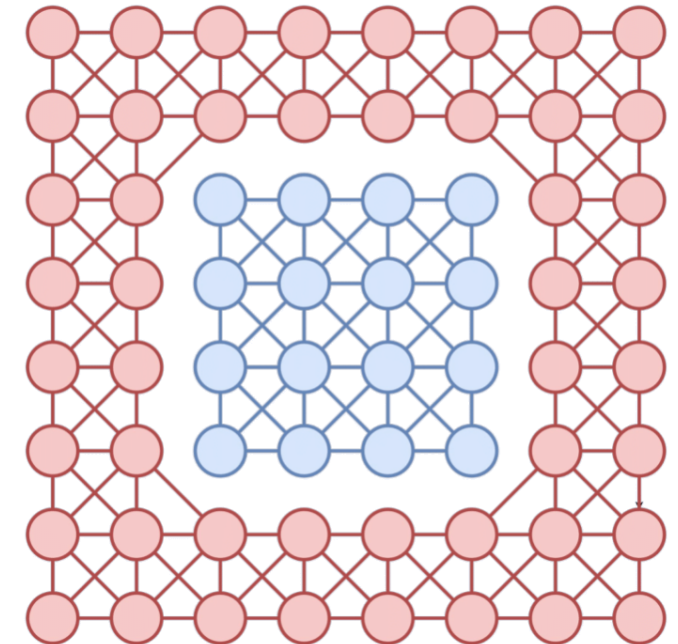
Segmented-smoothing:

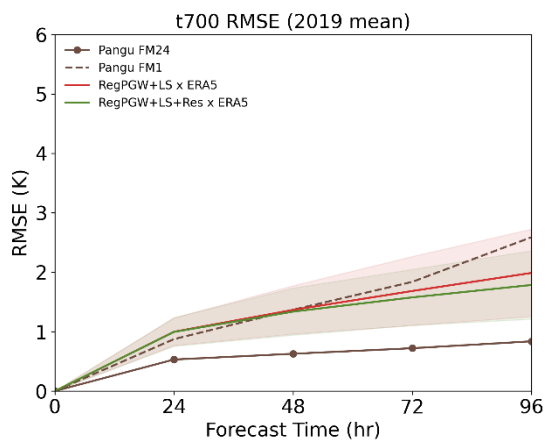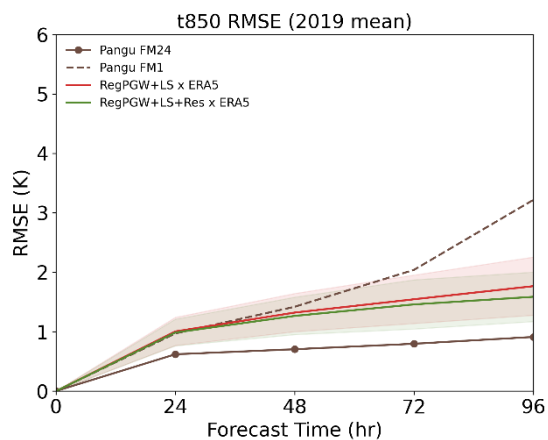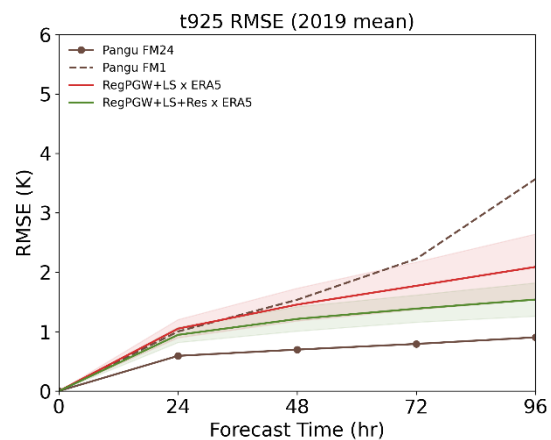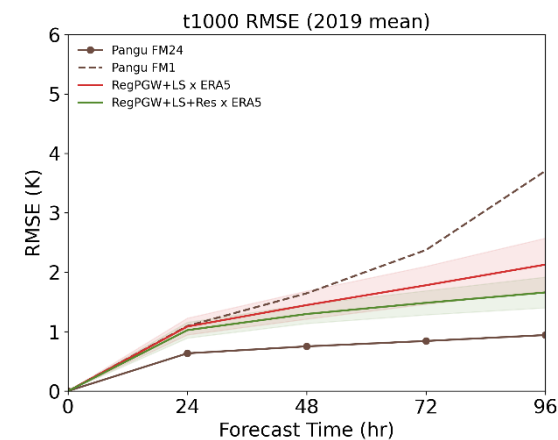There is no connection between the

boundary and the central region

# Smoothing strategies
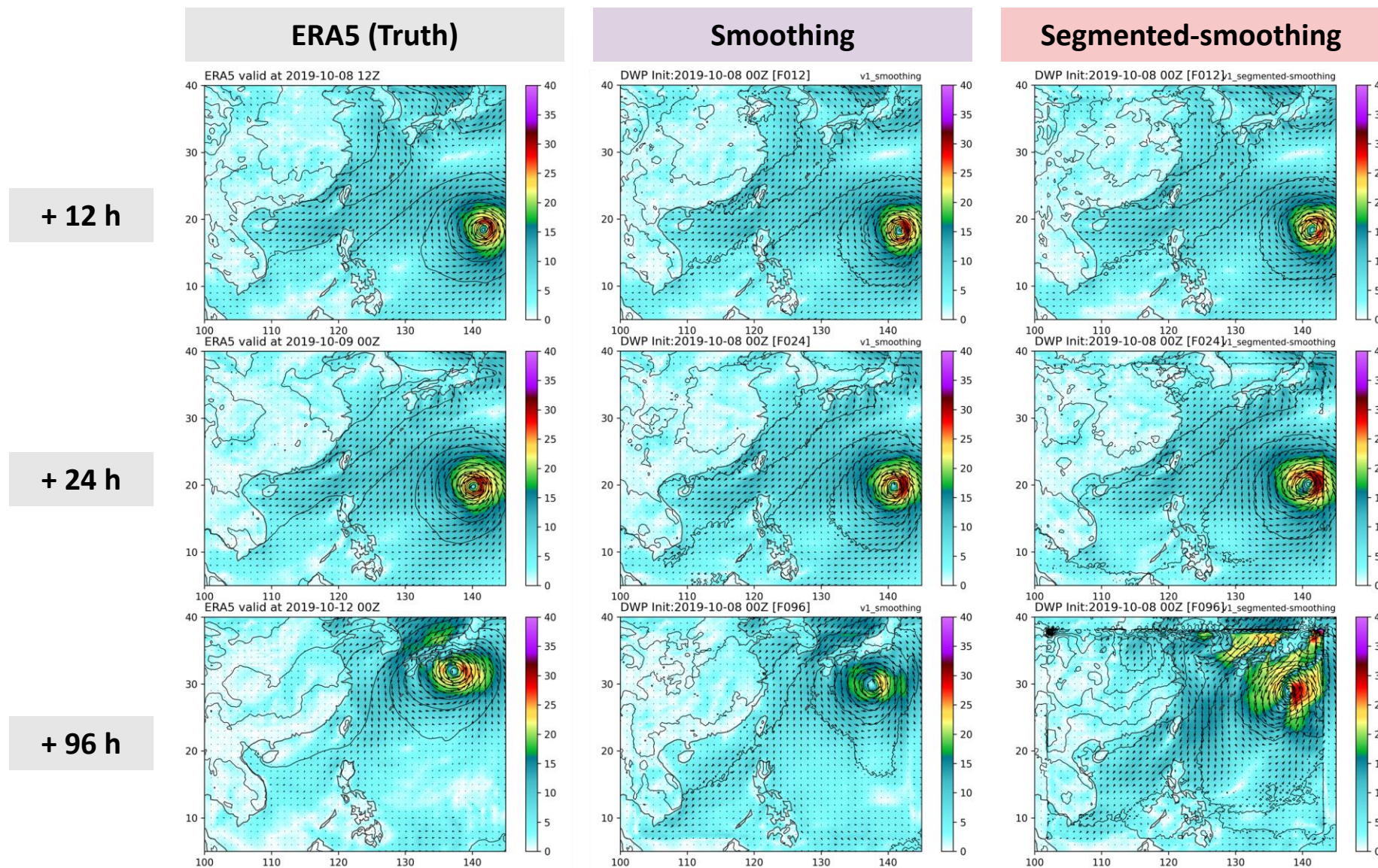
# Location of residual connection

(Huai-Yuan Kuo)
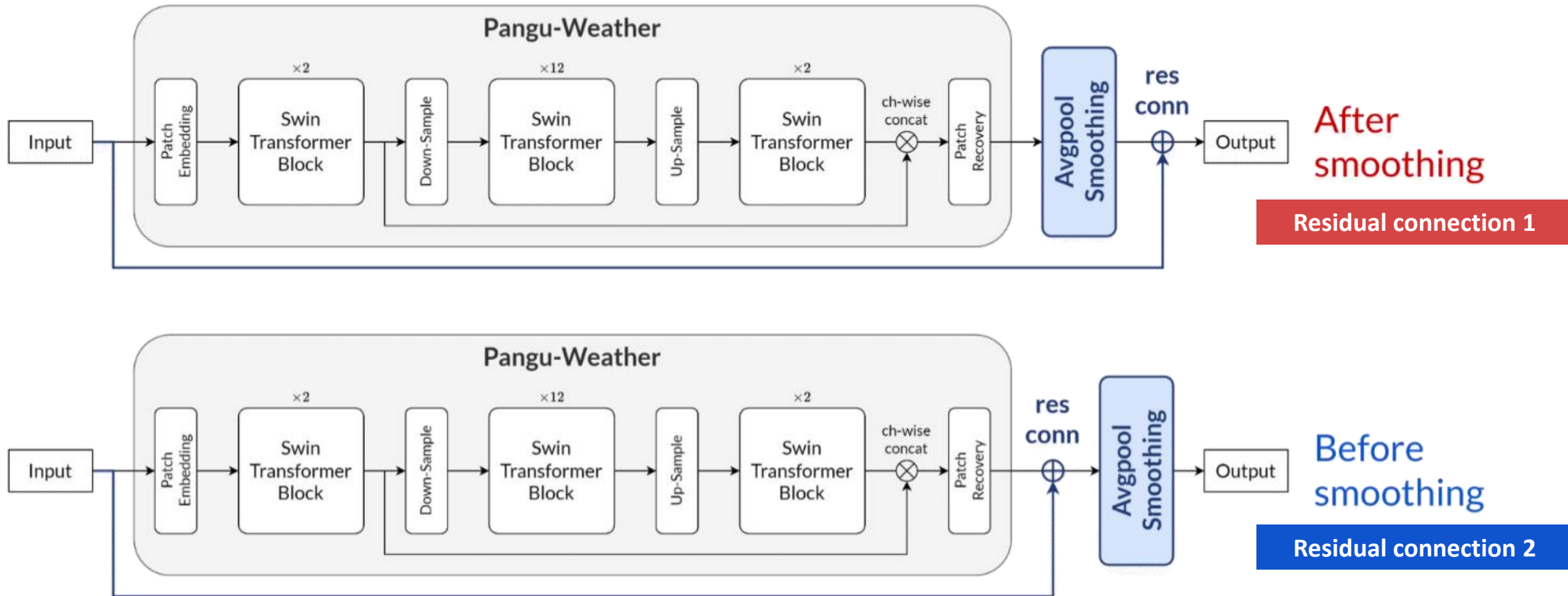
# Location of residual connection
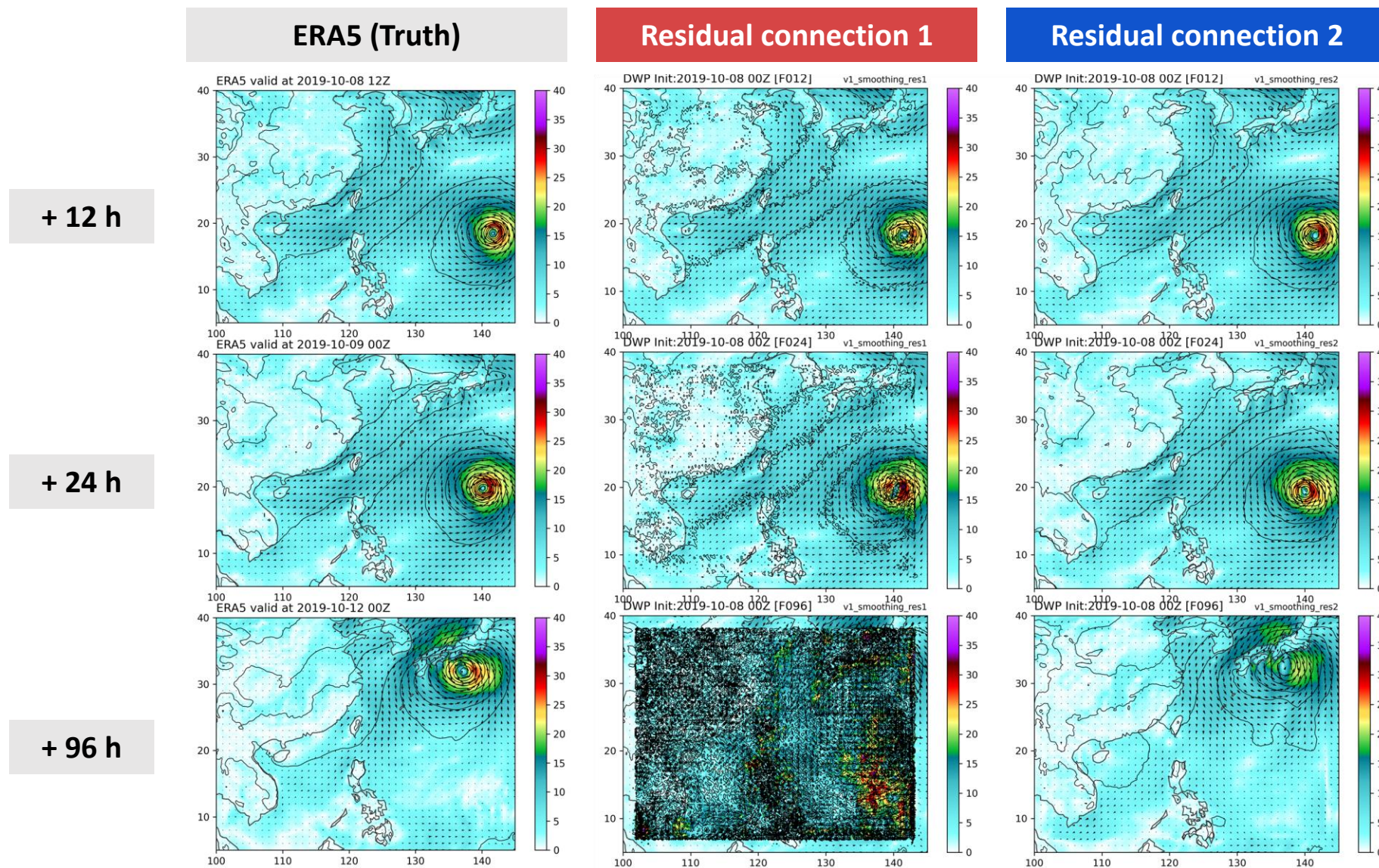
# 2019 Whole Year Evaluation – RMSE with standard deviations
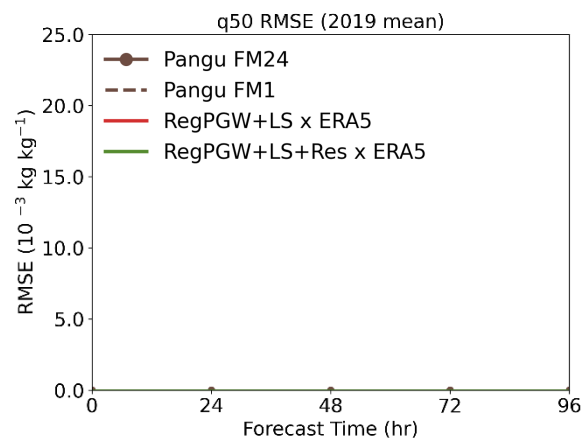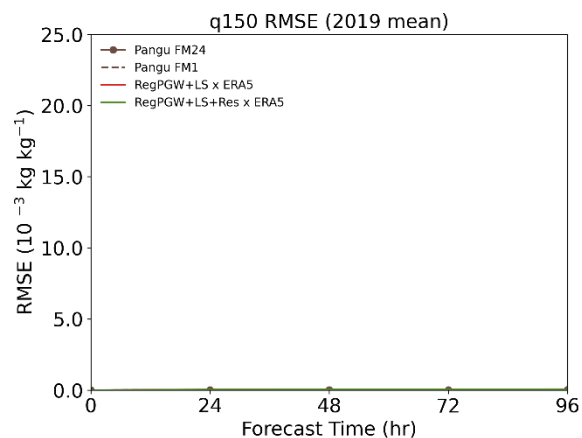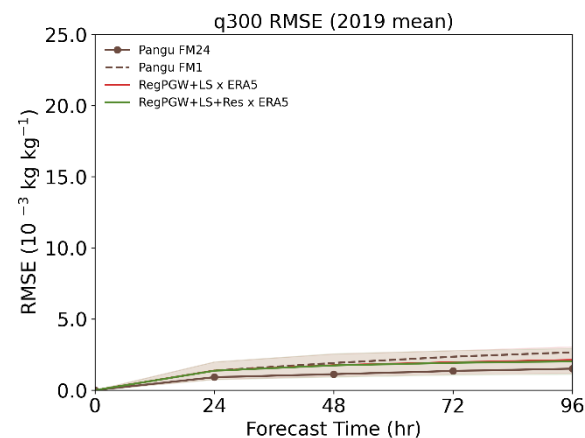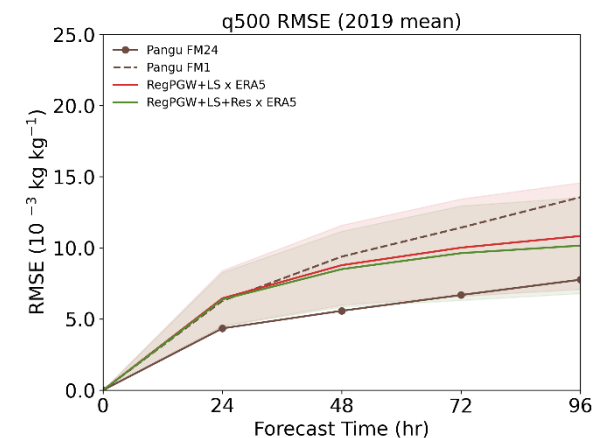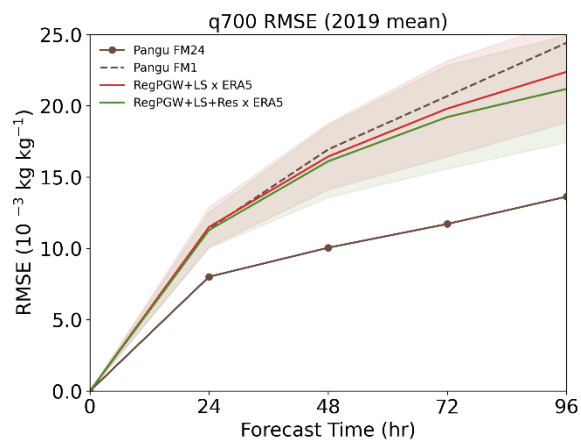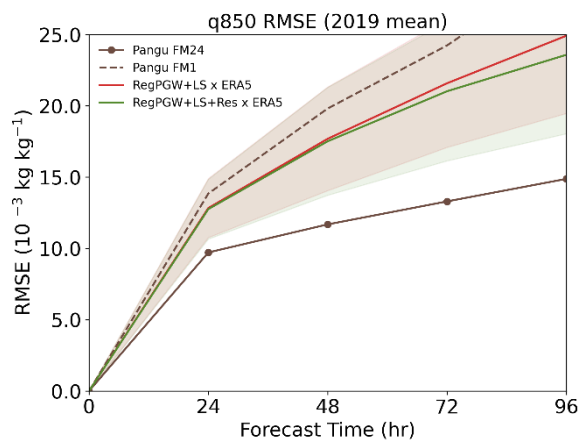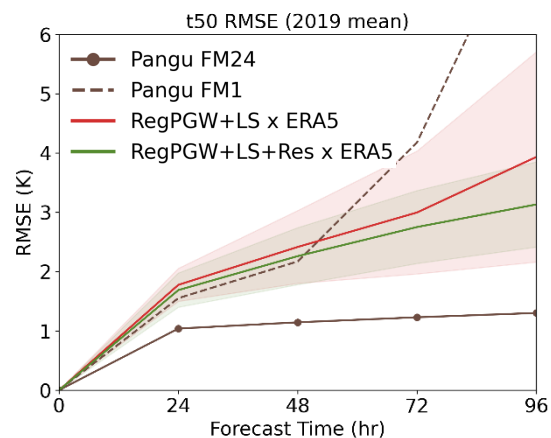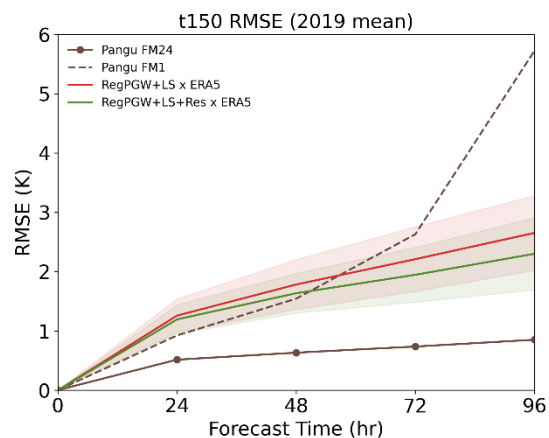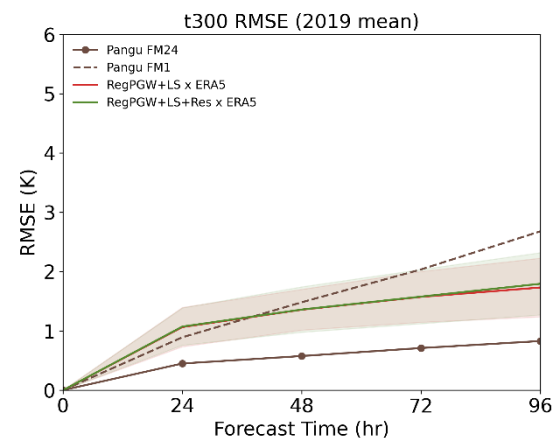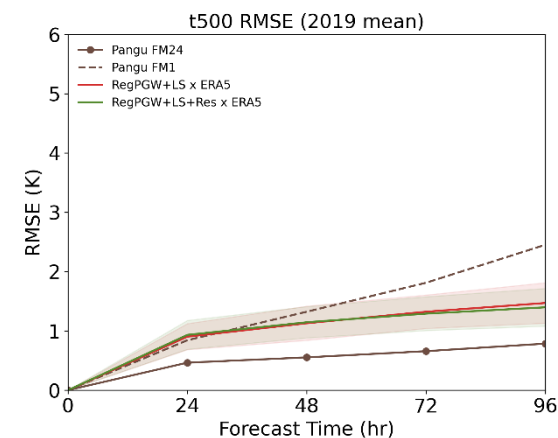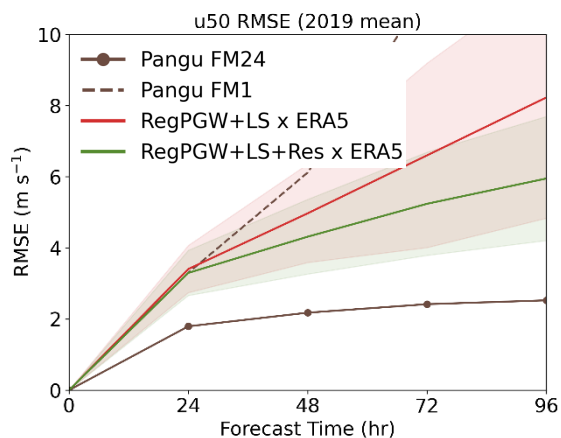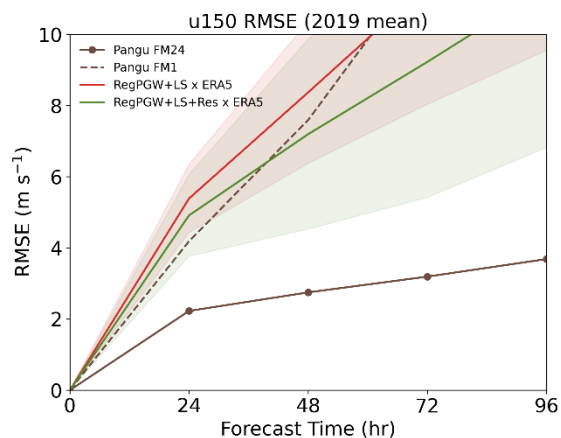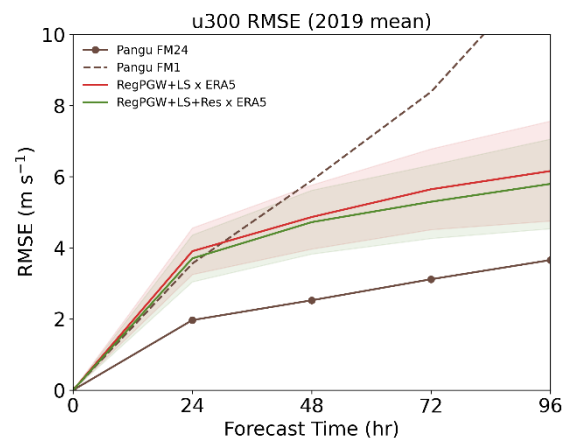
# 2019 Whole Year Evaluation – RMSE with standard deviations
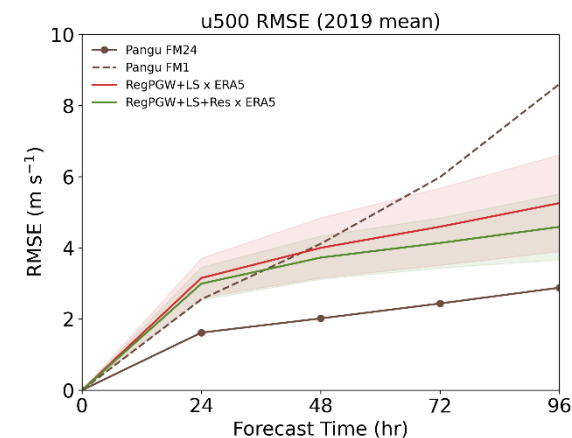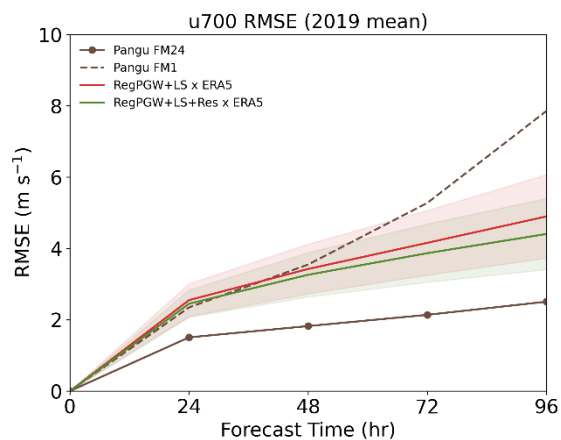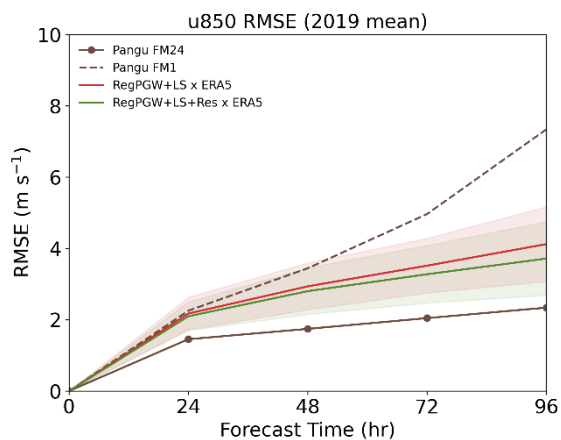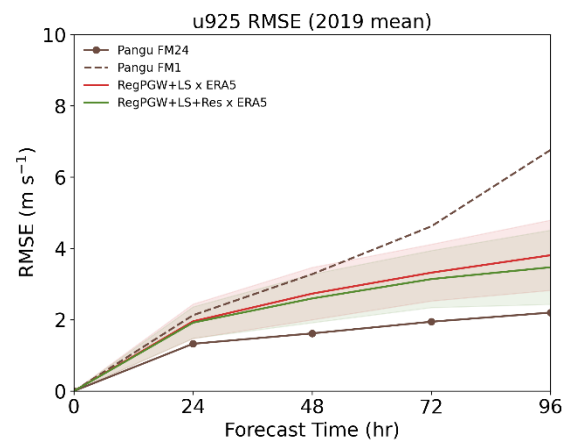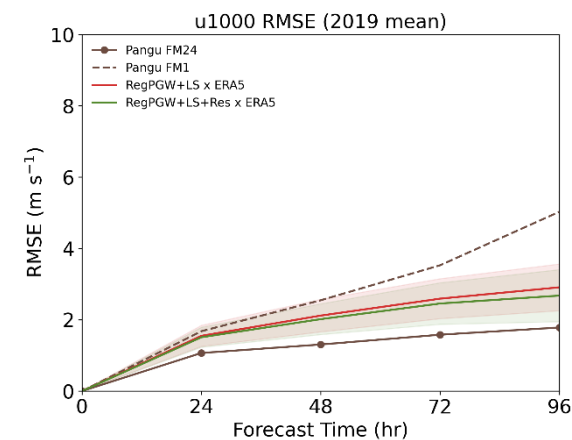
# 2019 Whole Year Evaluation – RMSE with standard deviations
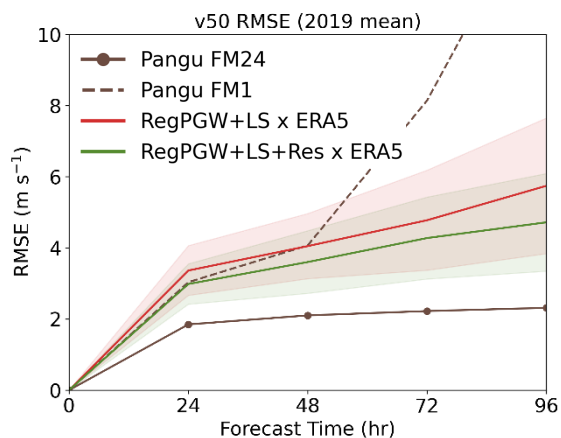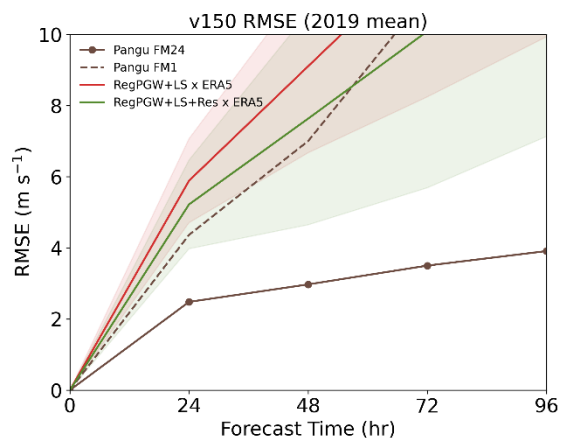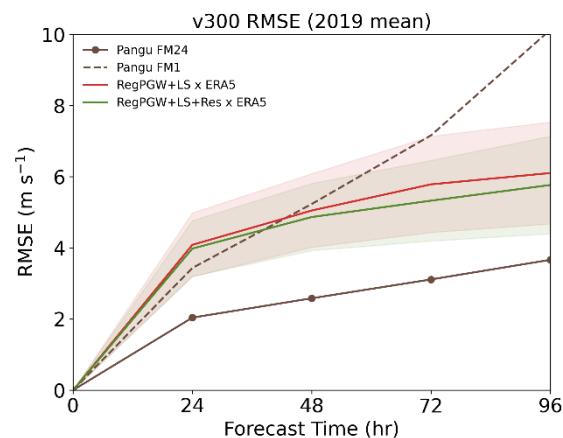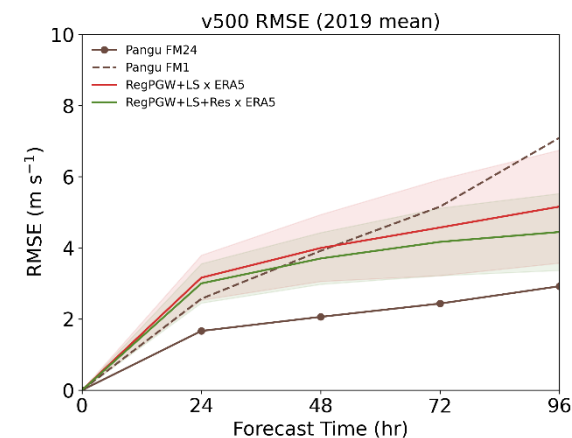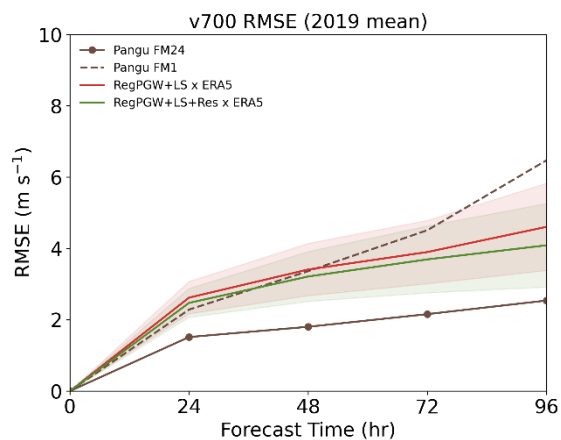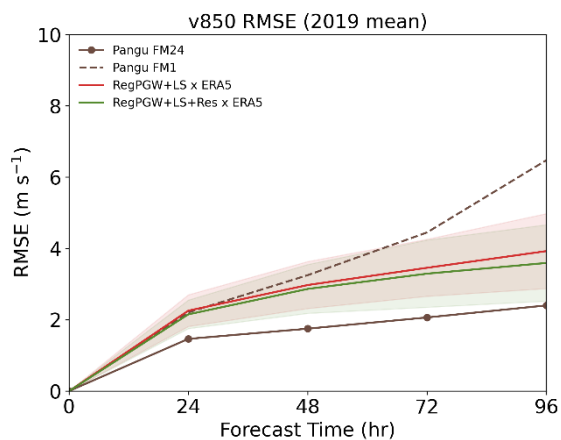
# 2019 Whole Year Evaluation – RMSE with standard deviations

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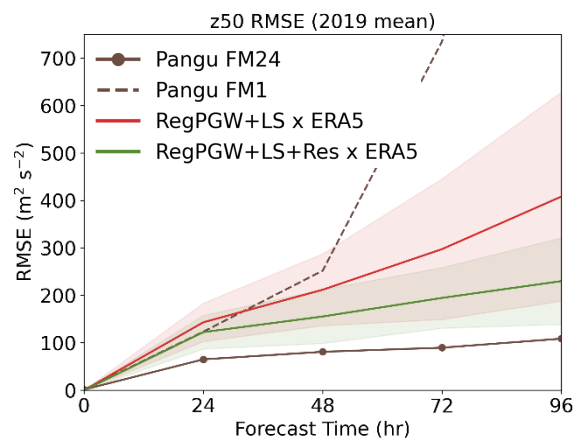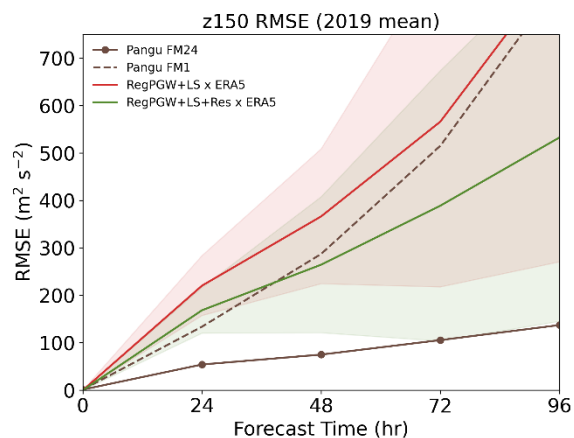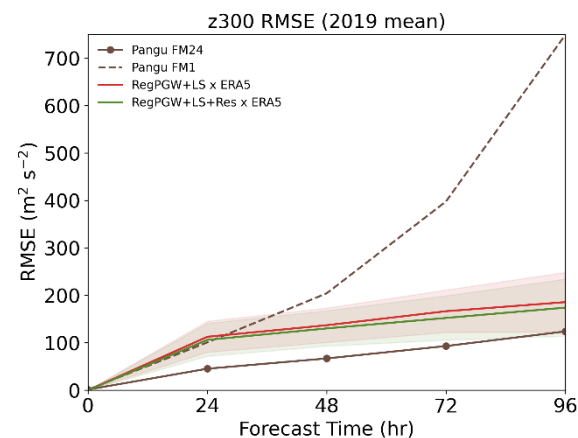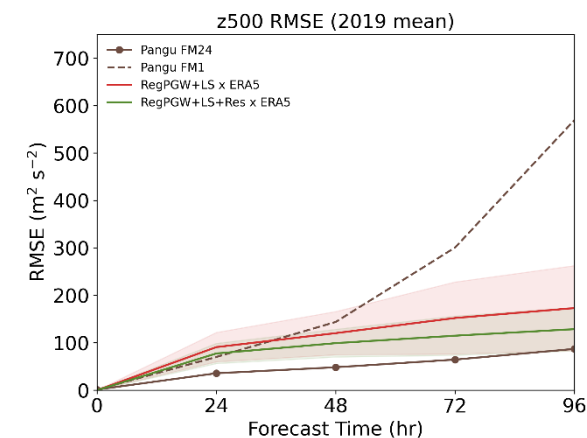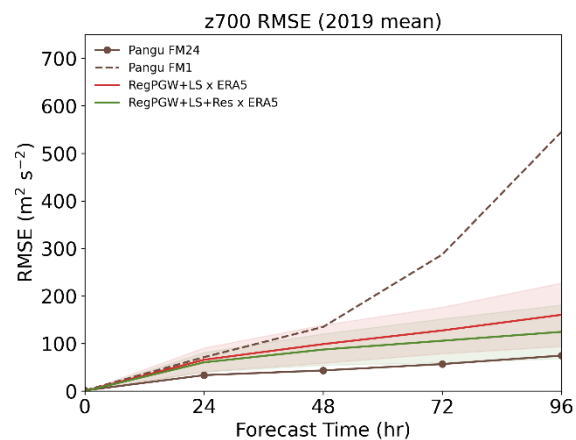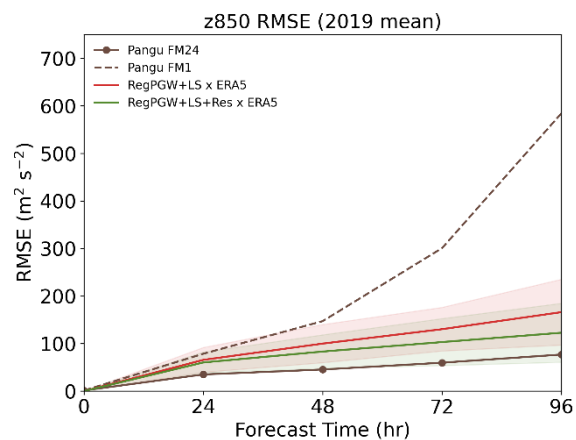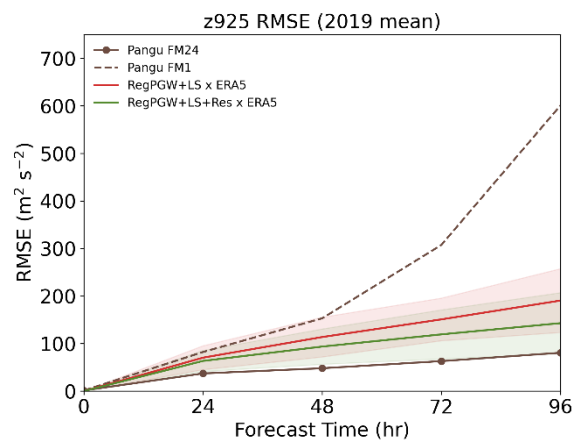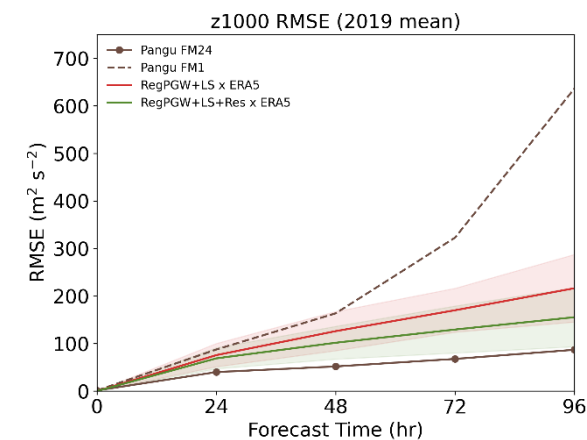
# Future Works

- **Increase vertical resolution.**

- **Carefully examine the physical processes in the model (with some validation/verification standards)**