



A Machine Learning Framework for Enhancing Station Wind Speed Estimation From WRF Model Outputs

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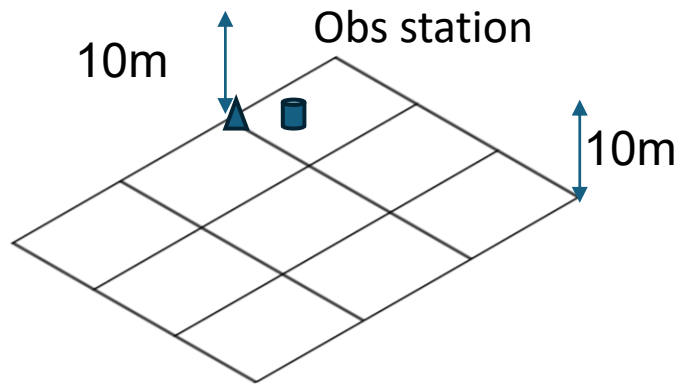


OUTLINE

- ❖ Motivation
- ❖ Data & Method
- ❖ Results
- ❖ Conclusions
- ❖ References



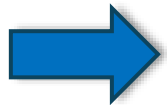
- Surface wind speed provided by the WRF model represents the wind speed at 10 meters above the model ground level, estimated via MO similarity theory (Monin and Obukhov 1954).
- **Limitation:** The aforementioned wind speed is not designed to, and thus can not effectively capture the wind speed characteristics observed at weather stations.



The 10 m wind forecasts from the WRF model are insufficient to represent the observed wind at weather stations (including both synoptic and automatic stations)

Reasons:

1. The wind speed (WS) measured at the obs station is not the 10-meter wind speed.
2. There is a difference in ground elevation between the obs station and the model grid points.
3. Obs station and model grid points are not located at the same location.



Improving estimates of surface winds in Taiwan





- Artificial intelligence-based methods are widely used for the estimation of wind speed.
 - Wan et al. (2025) used multilayer perceptron algorithm Machine Learning to estimates of wind speed profiles from surface observations, compared with the Monin–Obukhov method and showed that the mean relative errors of near-surface wind speed in the ML model could be reduced by 8.4%, 10.6% and 8.3% at 30 m, 50 m and 70 m, respectively.
 - Zhao et al. (2025) conducted a method based on the random forest approach to improve short-term surface wind speed forecasts - pooling the data from sliding time window and the entire region (SR_RF), SR_RF exhibits a great potential in downscaling and providing reliable predictions.

Objective:

- Increase the representativeness of the observation station wind speed from the observation station data and the model grid points through machine learning.
- Develop a Random Forest (RF) machine learning framework incorporating **Density-based Weighting** to establish non-linear mappings between WRF grid variables, station topography, and surface observations to enhance station-level wind estimation.



1) Training + Testing: 4 YEARS

- Training Set: Years 2022, 2023, 2025
- Testing Set: Year 2024

2) Variables

a) Model Input Data:

- Model Data (Initial Fields):
 - ✓ Model Layer 1: Wind Speed (**WS1**), model layer height (**Z1**)
 - ✓ Sea Level Pressure (**SLP**), Model Surface Elevation (**TER**)
- Station Data: Longitude (**LON**), Latitude (**LAT**), Station Elevation (**ELEV**), Anemometer Height (**HEIGHT**),
- obs Wind Speed (**WDSD**), **WRF_10m**

b) Model Output Data: Observed Wind Speed at Station

Target Function: $WS = f(a, b, c, d, \dots)$

$$\text{WS at obs station} \quad \text{cylinder icon} \quad = \quad f \quad \left(\text{Obs station data, model grid point variables} \right)$$

1) Random Forest

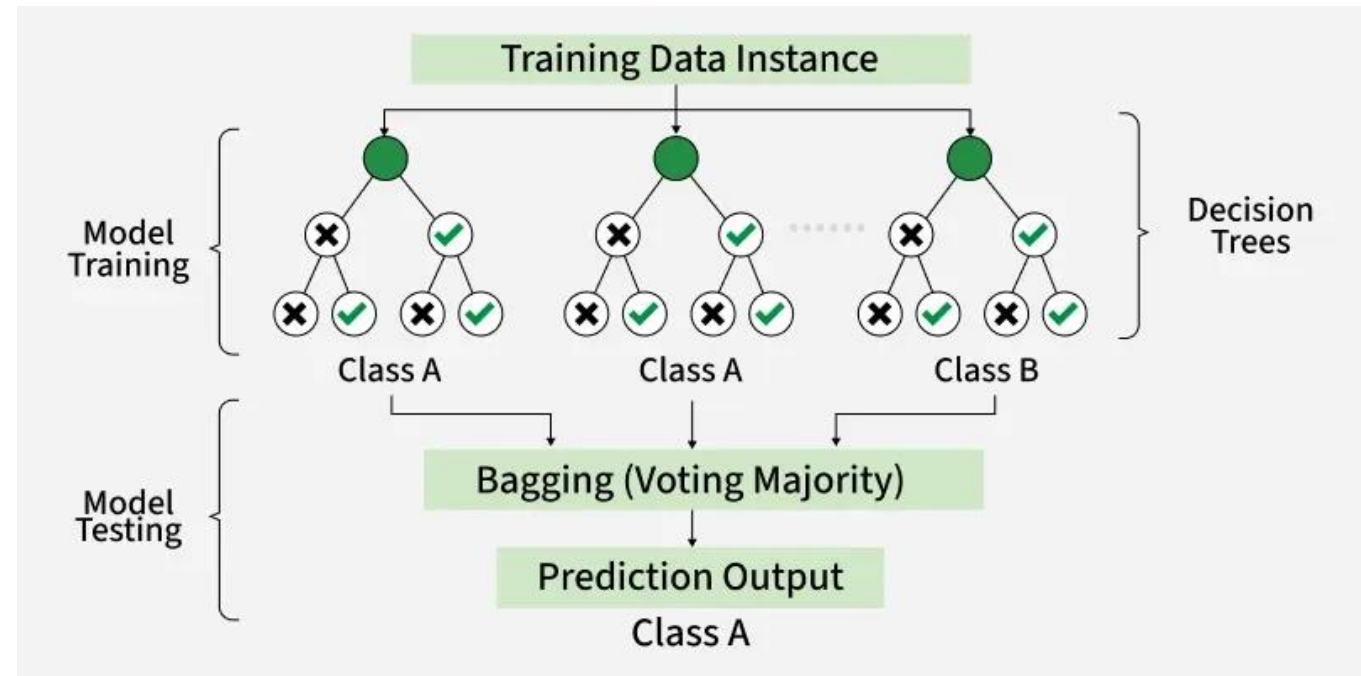
Random forests are a combination of tree predictors such that each tree depends on the values of a random vector sampled independently and with the same distribution for all trees in the forest (Breiman, 2001).

2) Density-based Weighting

Problem: Most classification algorithms assume equivalent sample sizes for each class => imbalanced classification datasets pose a significant challenge in prediction modeling (Dong and Qian, 2022).

High wind speeds (extreme weather events, tropical cyclones) occur rarely, creating extreme class imbalance that leads standard ML models to under-predict tail values.

Solution: Apply sample weights inversely proportional to the local probability density of wind speed categories (Beaufort scale weighting)



Scale 1-3: 0 - 5.4 m/s
scale 4-5: 5.5-10.7 m/s
scale 6-7: 10.8 - 17.1 m/s
scale: 8-9: 17.2 - 24.4 m/s (tropical storm)
scale 10-11: 24.5 - 32.6 m/s
scale >=12: >= 32.7 m/s (typhoon)



1) Overall Model Performance (Training & Testing)

- Random Forest results
- Feature importances
- Airport station

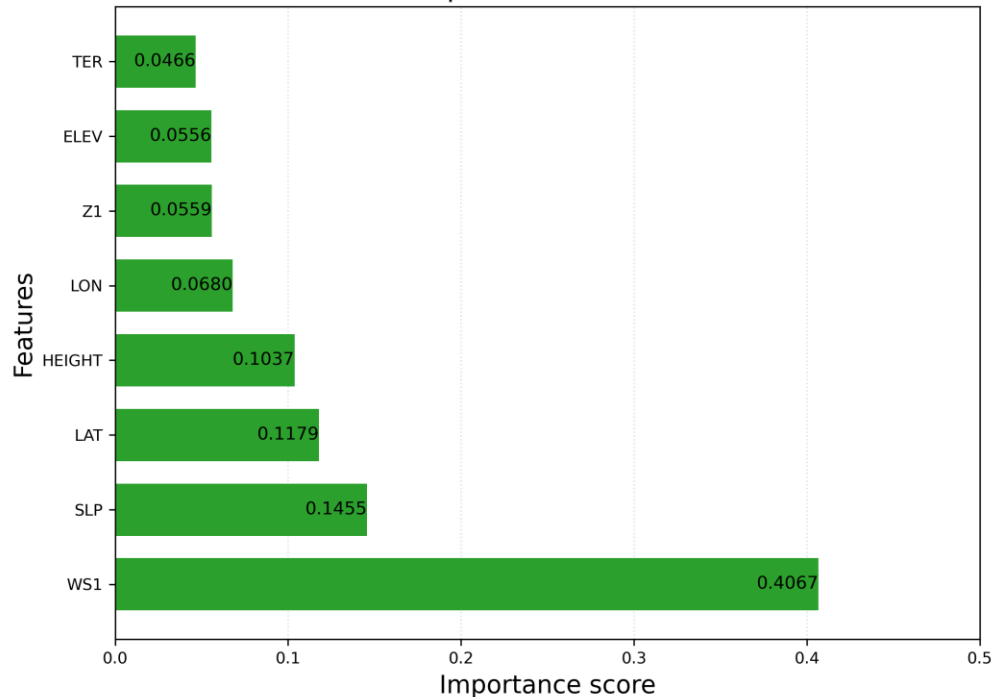
2) Model Verification

- Gaemi typhoon (2024)
- Northeast monsoon (2026)



Feature importance analysis

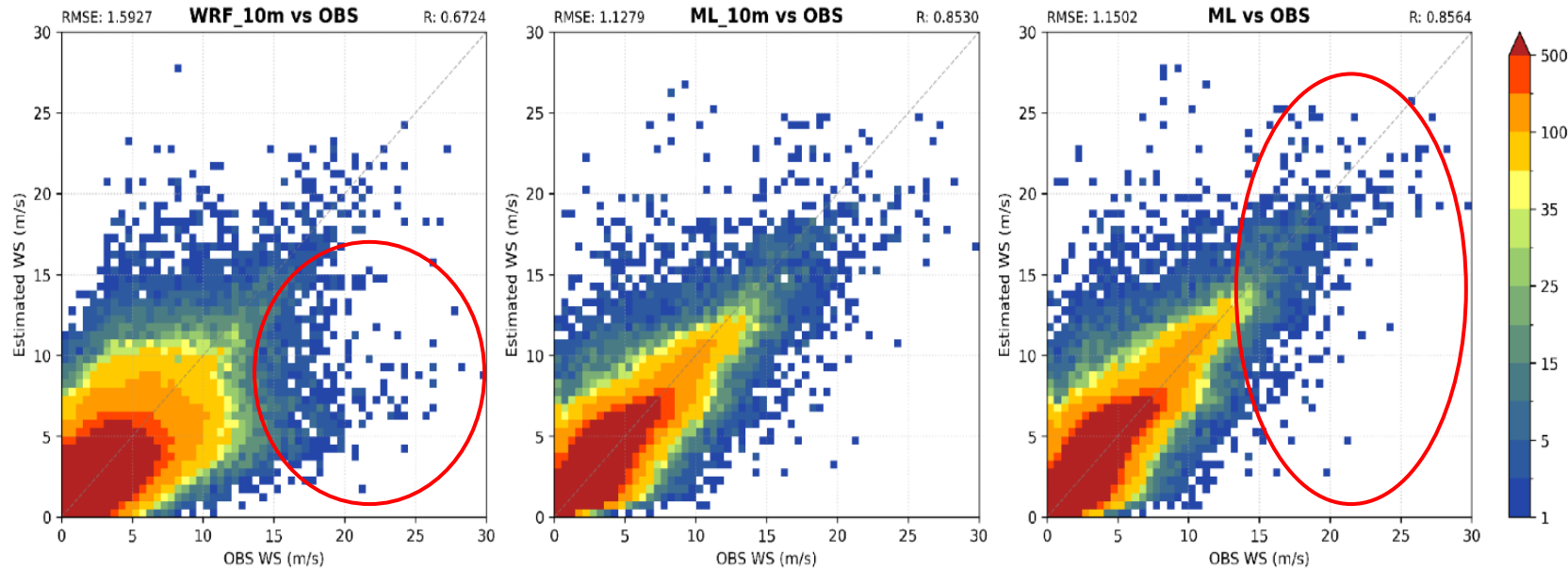
Features importance - Random Forest



- WS1 is 0.4067: Primary predictor; lowest model layer wind speed drives the baseline magnitude.
- SLP is 0.1455: Captures synoptic pressure gradients driving regional wind systems.
- LAT is 0.1179 and LON is 0.0680: Encode spatial position and geographic exposure.
- HEIGHT is 0.1037: Corrects vertical wind profile discrepancies caused by non-standard anemometer heights.
- ELEV is 0.0556, Z1 is 0.0559, TER is 0.0466: Resolve topographic features and boundary layer height effects.

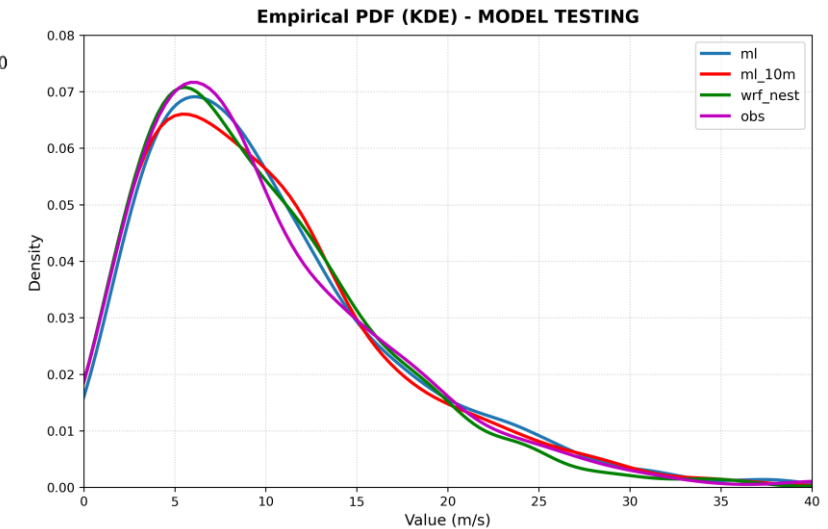


Scatter & Density Comparison



- **WRF_10m vs. OBS:** RMSE = 1.5927 m/s, R = 0.6724
Large scatter, notable underestimation at high wind speeds
- **ML_10m vs. OBS:** RMSE = 1.1279 m/s, R = 0.8530
Significant reduction in error, tighter clustering around ideal-line
- **ML vs. OBS:** RMSE = 1.1502 m/s, R = 0.8564
Same as ML_10m

Probability Density Function

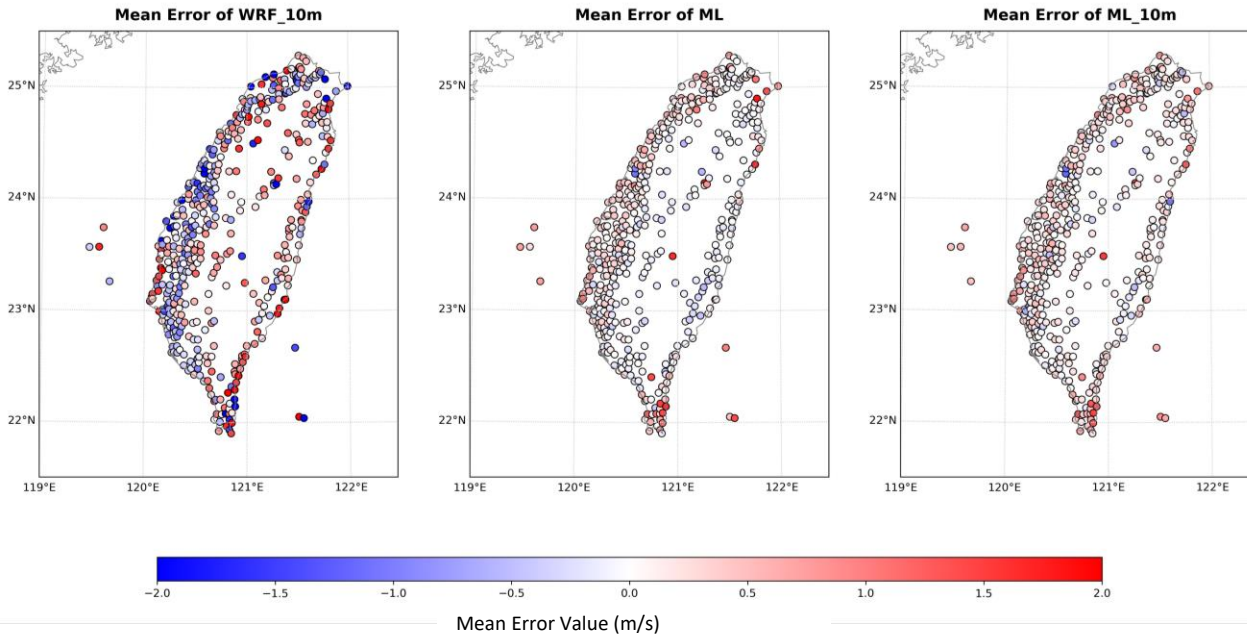


- Both ML models (ML and ML_10m) fit the empirical observation (OBS) curve much closer than WRF_10m.
- The density-weighted RF effectively resolves the peak around 5 m/s and preserves the heavy tail for values >20 m/s



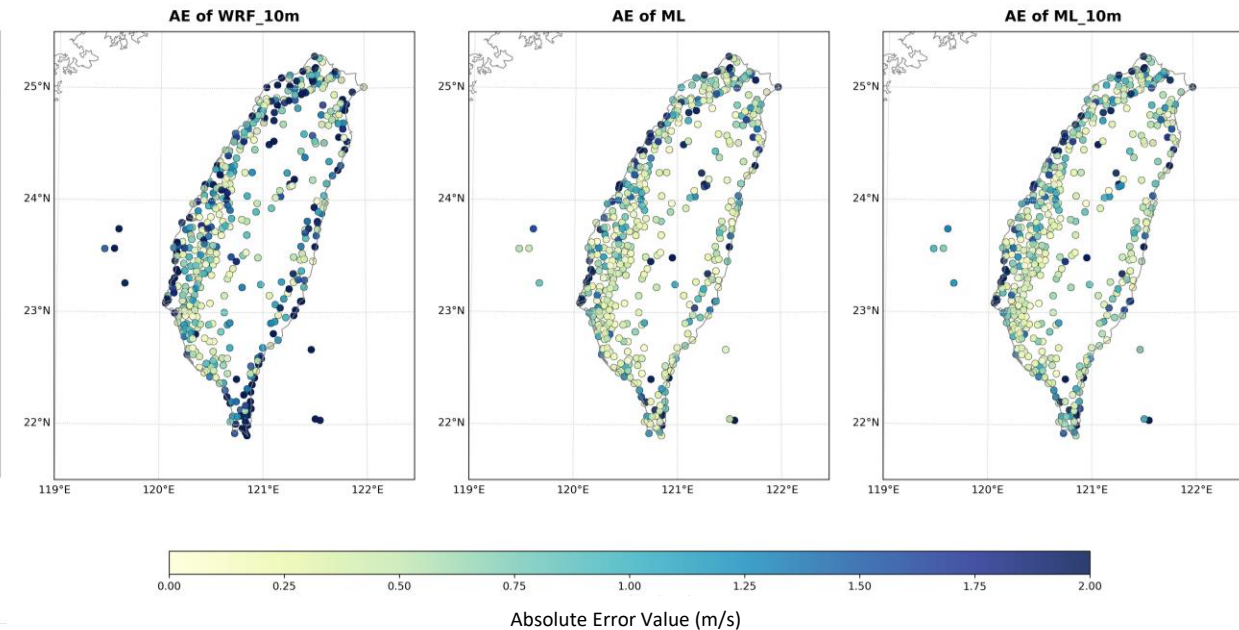
Spatial Error Distribution Analysis

2D Mean Error (Model - Obs)



- WRF_10m exhibits severe spatial bias: both positive and negative bias along coastal regions and mountainous, complex terrain.
- ML models substantially eliminate spatial bias across Taiwan, reduce mean errors significantly at most mainland and island stations.

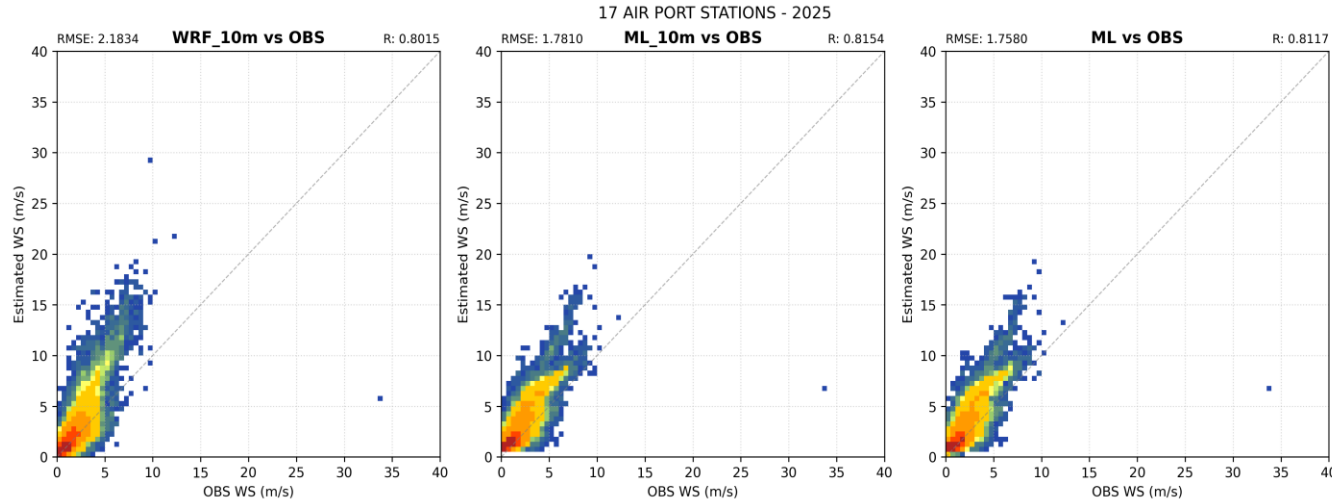
2D Absolute Error (Model - Obs)



- High absolute errors >1.5 m/s in WRF_10m are widespread.
- ML models reduce AE values across western plains and eastern valleys to <0.5 m/s.

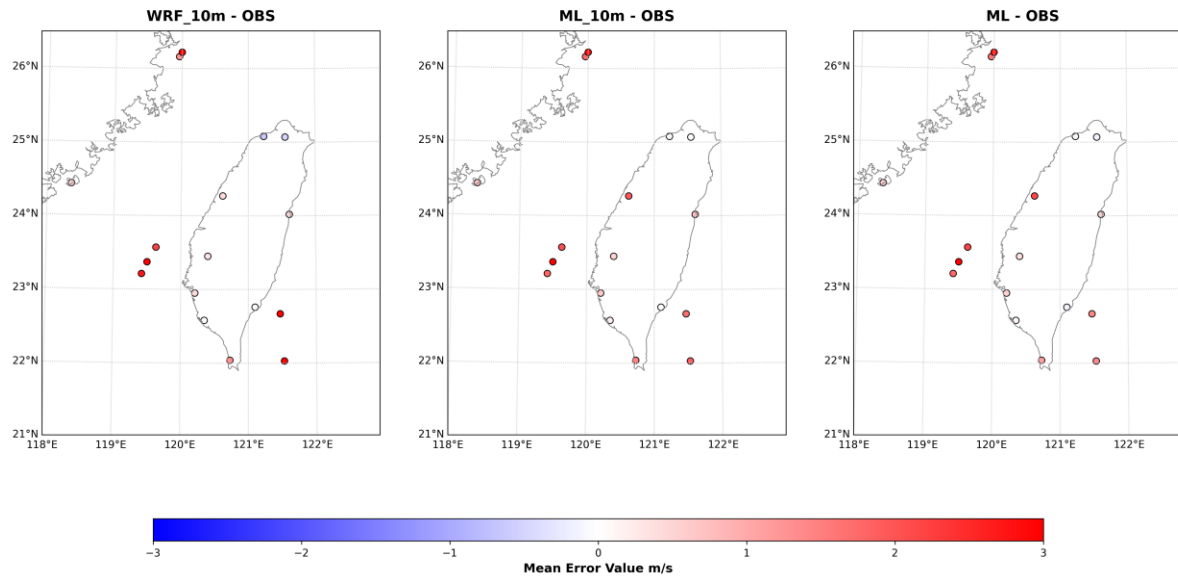


Evaluation at 17 Airport Stations (2025)

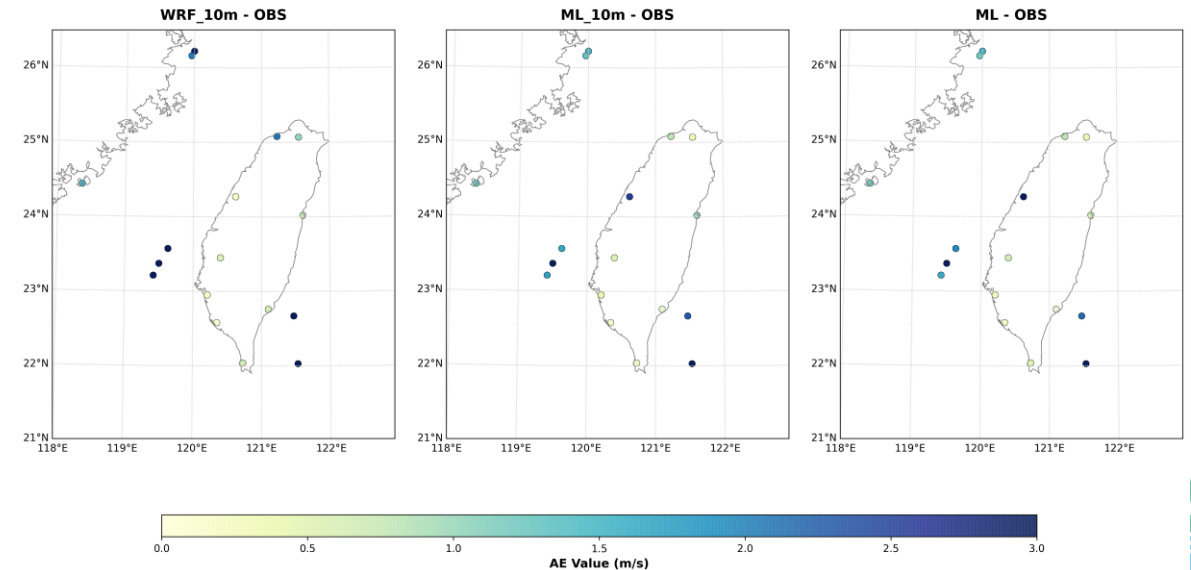


- ML reduces RMSE by ~19.5% across airport stations compared to direct WRF outputs.
- Reduces false alarms and extreme under-predictions in coastal runways where local breeze and friction effects dominate.

MEAN ERROR (Model - Obs)

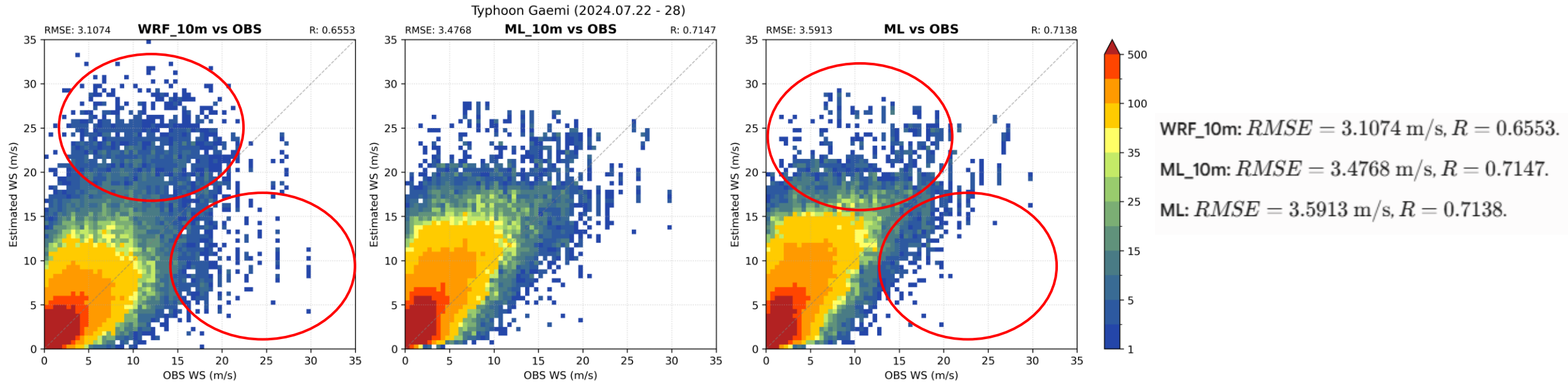


Absolute Error (Models vs OBS)





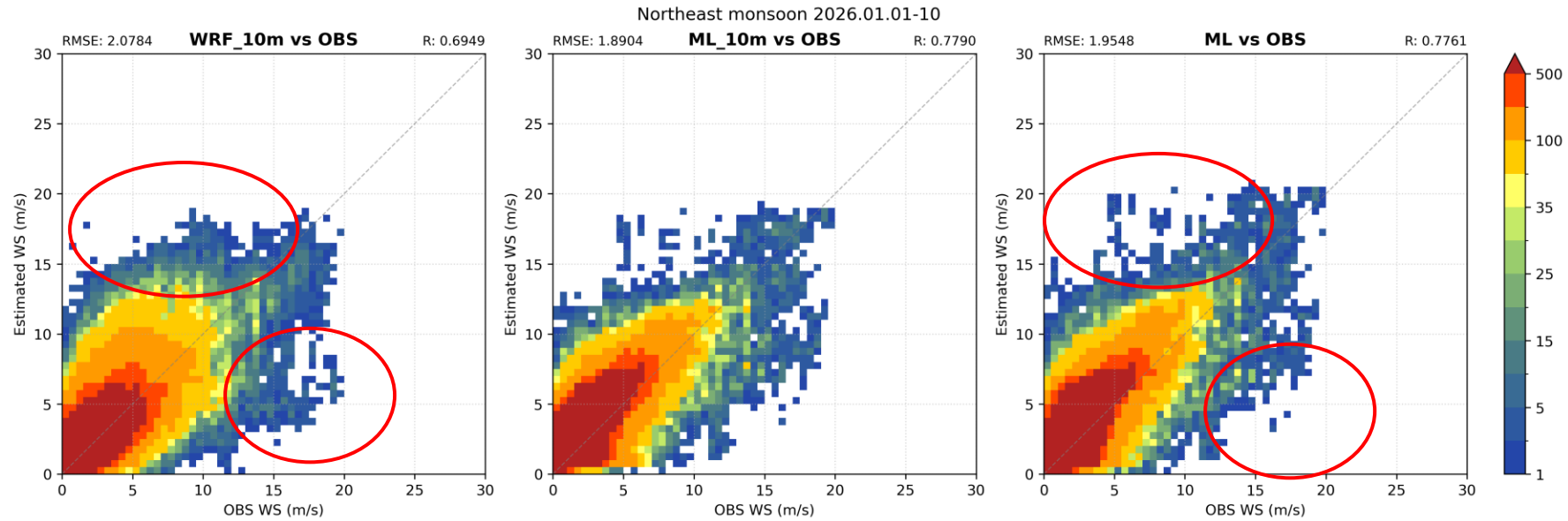
Case 1: Gaemi typhoon (2024)



- ML models improve the linear correlation (R increases from 0.655 to 0.714 $\sim 10\%$), demonstrating better tracking of wind trends during extreme typhoon passes.
- Slight increase in overall RMSE is attributed to spatial phase shifts in typhoon center predictions from WRF, but peak wind speeds are better maintained due to density weighting.



Case 2: Northeast monsoon (2026.01.01-10)



WRF_10m: $RMSE = 2.0784$ m/s, $R = 0.6949$.

ML_10m: $RMSE = 1.8904$ m/s, $R = 0.7790$.

ML: $RMSE = 1.9548$ m/s, $R = 0.7761$.

Strong winter monsoon winds channel through the Taiwan Strait. ML significantly reduces persistent WRF overestimation along the western coast, improving R by ~12%.



Model Accuracy: The proposed Random Forest framework significantly outperforms standard WRF_10-m wind outputs, reducing overall RMSE from 1.59 m/s to 1.13 m/s and raising correlation R from 0.67 to 0.85.

Mitigating Data Imbalance: Density-based sample weighting effectively preserves high-wind speed tail distributions, avoiding severe under-prediction during severe weather.

Bias Correction: Spatial error analysis confirms that ML successfully corrects vertical anemometer height mismatches and complex terrain-induced biases in Taiwan.

Operational Readiness: Strong verification performance on airport stations, Typhoon Gaemi, and Northeast Monsoon events validates the framework's capability for real-time station wind forecasting.



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Thank you ~~~

