# A Multi-mode Neural Network for the Long-term Sea Wave Hindcast in the Island Coastal Region of South China Sea

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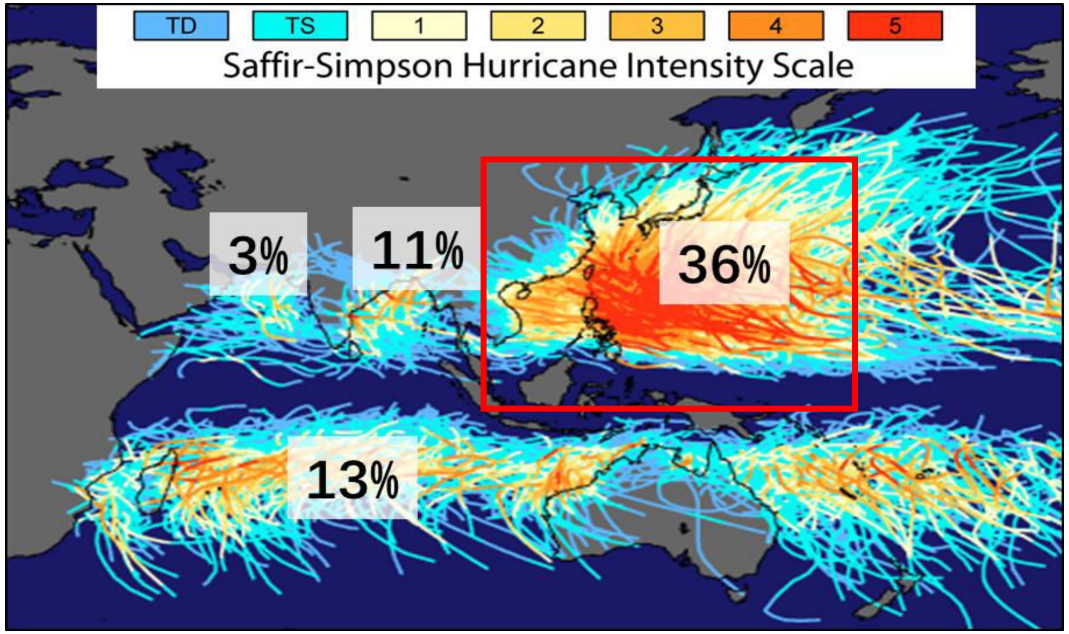
# outlines

1. Motivation
2. Data and Methods
3. Results
4. Conclusions

# 1. Motivation

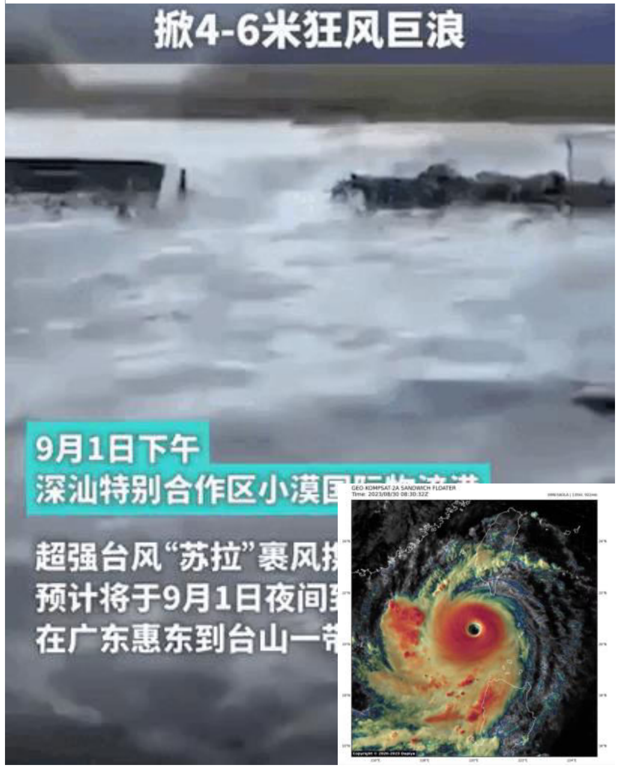
➢ **Typhoon and destructive wave**



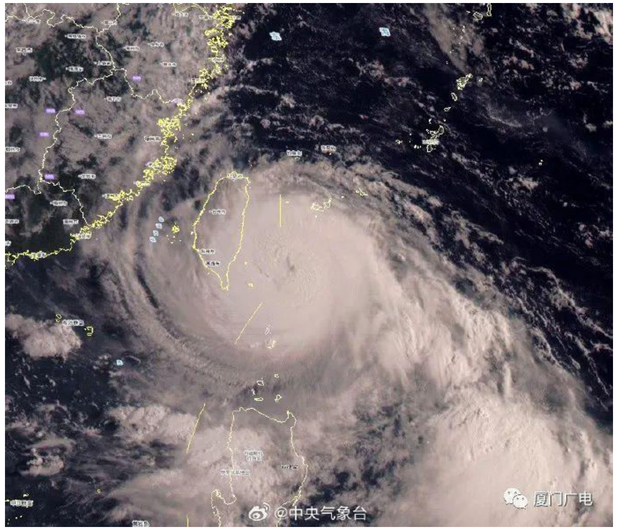

over 30% of the total TCs

**Super typhoon Saola (2023)**

**4-6m extreme wave**




**Super typhoon Haikui(2023)**




# 1. Motivation

- **Long-term Significant wave height (SWH) data, as a crucial information to reflect the character of sea waves, plays a vital role in coastal engineering design, operation and maintenance.**
- **Mainly from the observation or reanalysis data.**

Zhoushan Port

Oil platform (enping 15-2)


Gwadar port

# 1. Motivation

- In most cases, there are not enough observations (relatively short) for the analysis.
- The extension of SWH observations in short term is feasible.
- However, it is unavailable for longer-term extension due to rapidly increasing errors.

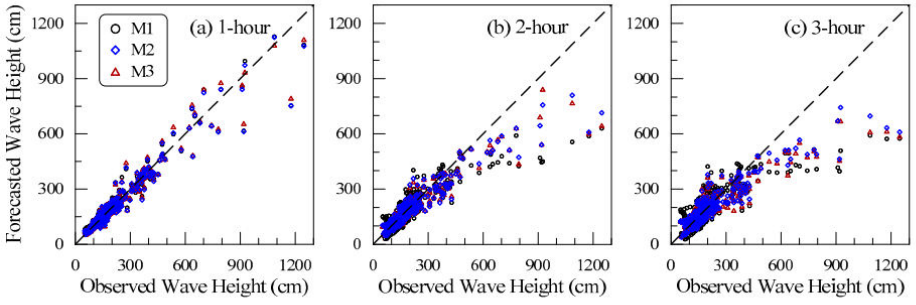



**Figure 4.** Forecasting results with lead time of (**a**) 1, (**b**) 2, and (**c**) 3 h for Longdong.

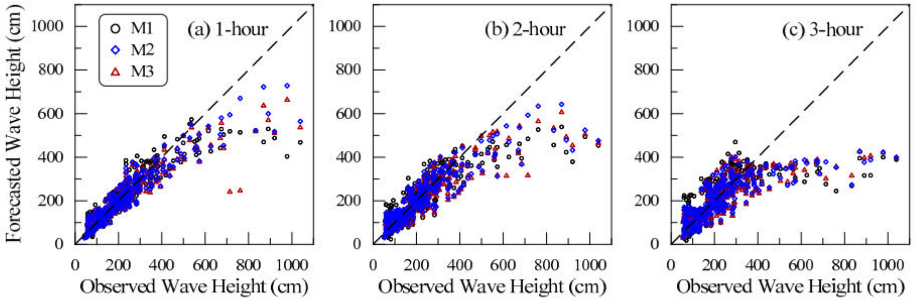



**Figure 5.** Forecasting results with lead time of (**a**) 1, (**b**) 2, and (**c**) 3 h for Guishan Island.

(Chen, et al. 2020)

**Table 2.** Comparison of error statistics between LSTM and EMD-LSTM, in addition to the degrees of improvement for the 3, 6, 9, 12, 24, 48 and 72 h forecast windows for NDBC buoys 41046 and 41047.

| | | LSTM | | | EMD-LSTM | | | Degree of Improvement | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Forecast Hours | *RMSE* (m) | *MAPE* (%) | R | *RMSE* (m) | *MAPE* (%) | R | *RMSE* (%) | *MAPE* (%) | R (%) |
| 41046 | 3 | 0.15 | 6.4 | 0.97 | 0.11 | 1.41 | 0.985 | 30.1 | 77.8 | 1.5 |
| | 6 | 0.22 | 9.2 | 0.92 | 0.12 | 6.68 | 0.979 | 44.6 | 27.4 | 6.4 |
| | 9 | 0.28 | 11.1 | 0.88 | 0.16 | 10.20 | 0.960 | 42.4 | 7.8 | 9.1 |
| | 12 | 0.33 | 13.2 | 0.84 | 0.19 | 12.01 | 0.950 | 41.1 | 9.2 | 13.1 |
| | 24 | 0.45 | 19.0 | 0.67 | 0.26 | 11.41 | 0.900 | 41.8 | 39.9 | 34.3 |
| | 48 | 0.58 | 31.1 | 0.41 | 0.38 | 18.90 | 0.790 | 33.7 | 39.2 | 92.7 |
| | 72 | 0.60 | 33.7 | 0.32 | 0.44 | 18.70 | 0.690 | 26.1 | 44.5 | 115.6 |
| 41047 | 3 | 0.19 | 7.2 | 0.97 | 0.10 | 3.96 | 0.991 | 46.8 | 44.9 | 2.1 |
| | 6 | 0.28 | 11.3 | 0.93 | 0.14 | 5.51 | 0.982 | 50.2 | 51.2 | 5.6 |
| | 9 | 0.35 | 13.1 | 0.88 | 0.18 | 7.38 | 0.971 | 49.2 | 43.7 | 10.3 |
| | 12 | 0.40 | 15.0 | 0.83 | 0.21 | 8.42 | 0.957 | 47.0 | 43.9 | 15.3 |
| | 24 | 0.55 | 22.0 | 0.67 | 0.28 | 11.76 | 0.922 | 48.2 | 46.5 | 37.6 |
| | 48 | 0.67 | 33.4 | 0.43 | 0.47 | 20.35 | 0.769 | 29.9 | 39.1 | 78.9 |
| | 72 | 0.71 | 38.8 | 0.34 | 0.48 | 21 | 0.757 | 32.2 | 45.9 | 122.6 |

(Zhou, et al. 2021)

# 1. Motivation

## Global Ocean Wave Reanalysis Data

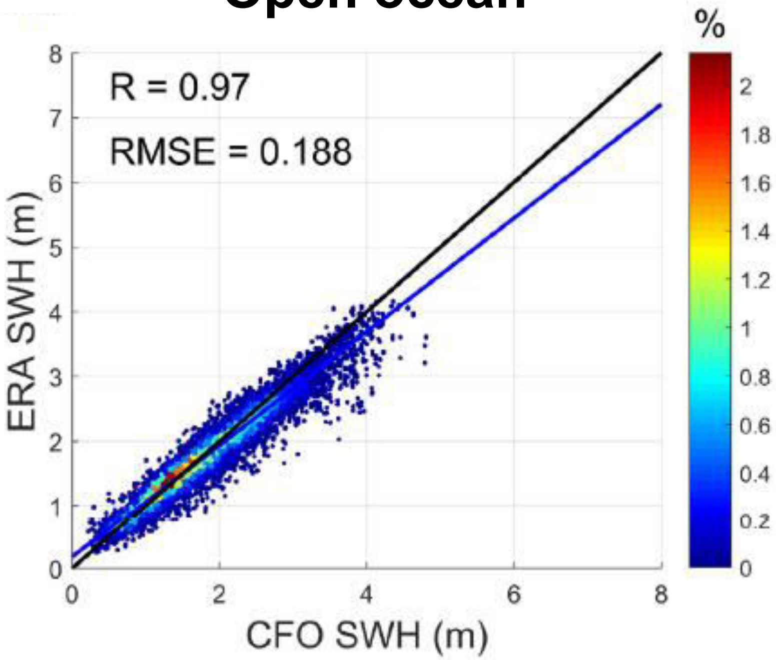
| Reanalysis Data | wave model | Time | Spatial Resolution | Temporal Resolution |
|---|---|---|---|---|
| ERA-40 | WAM | 1957-2002 | 1.5°×1.5° | 6h |
| ERA-Interim | WAM | 1979-2019 | 0.125°×0.125° | 6h |
| ERA5 | WAVEWATCH III | 1979-2019 | 0.5°×0.5° | 1h |
| WAVERYS | MFWAM | 1993-2021 | 0.2°×0.2° | 3h |
| NOAA | WAVEWATCH III | 1997-2019 | 1.25°×1° | 3h |

Low resolution

# 1. Motivation

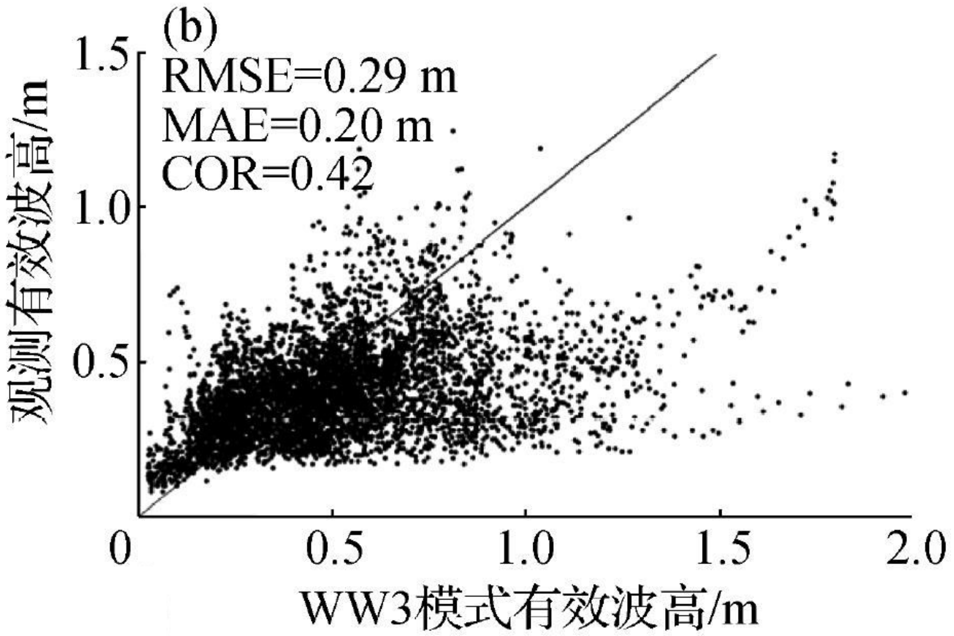
**Large biases of numerical model in the coastal region**

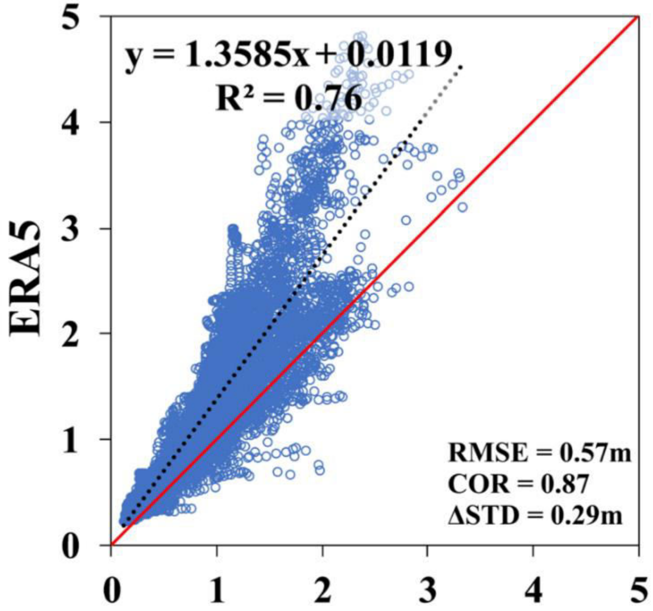
**Open ocean**




(Li, et al. 2022)

**Coatal region in the SCS**




(Li et al.， 2020; Liu et al., 2022)

# 1. Motivation

1. **Can the long-term modeled significant wave height (SWH) be improved by machine learning?**

2. **How can we use the prior knowledge of physical ocean to further improve the correction results of SWH?**

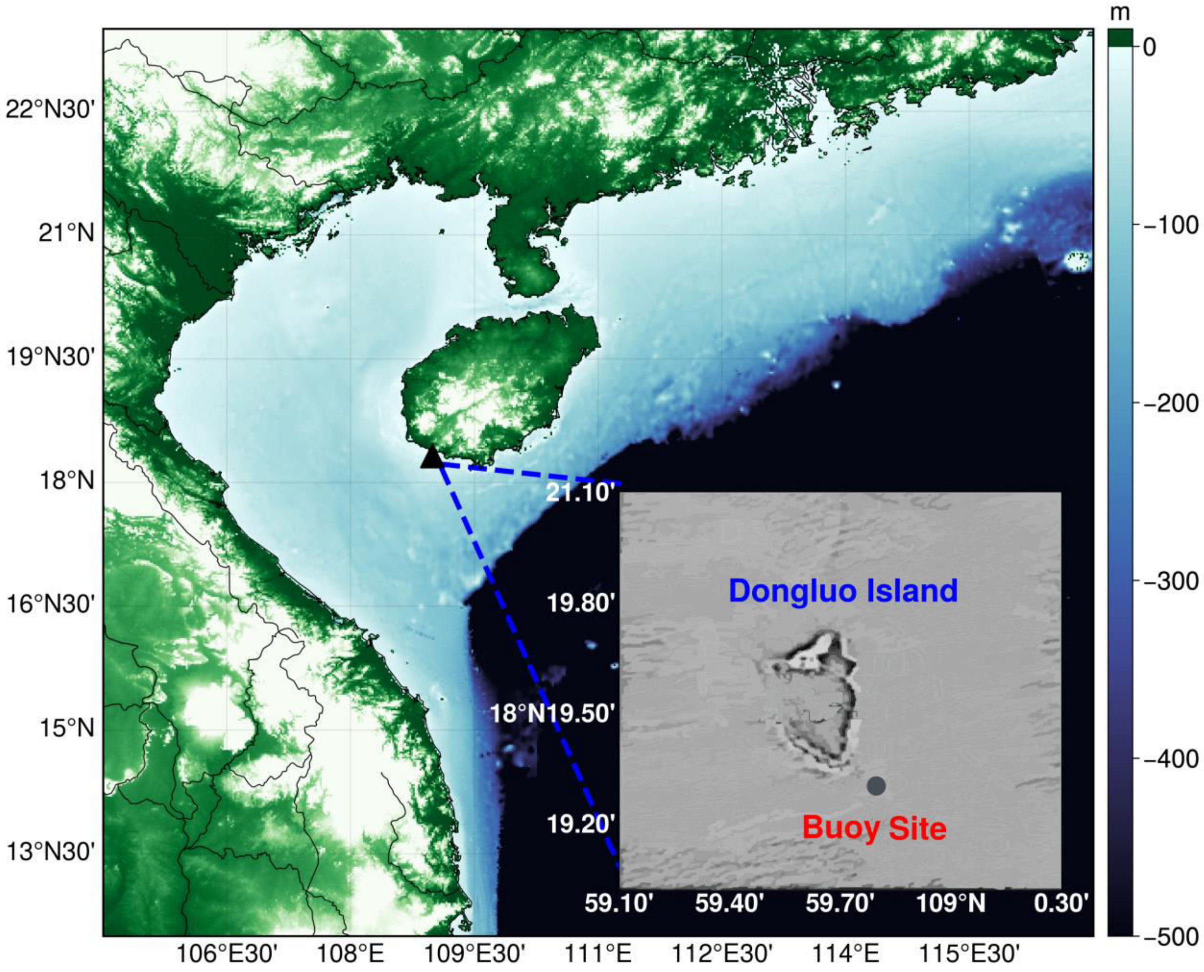
# 2. Data and Methods

## □ WAVEWATCH III

- ✓ **Region： 78°E-150°E, 22°S-41.5°N**
- ✓ **Resolution： 1/12°×1/12°， 1h**
- ✓ **Wind reanalysis: ERA5+Holland model**

## □ Buoy data (Dongluo island)

- ✓ **Resolution： 30min**
- ✓ **Time： 2020-2021**
  **2020 for training**
  **2021 for validation**



# 2. Data and Methods

## ☐ Long-Short Term Memory neural network

- ✓ **SM-LSTM: input layer, hidden layer, output layer**
- ✓ **Input time data are from the previous 12h:**

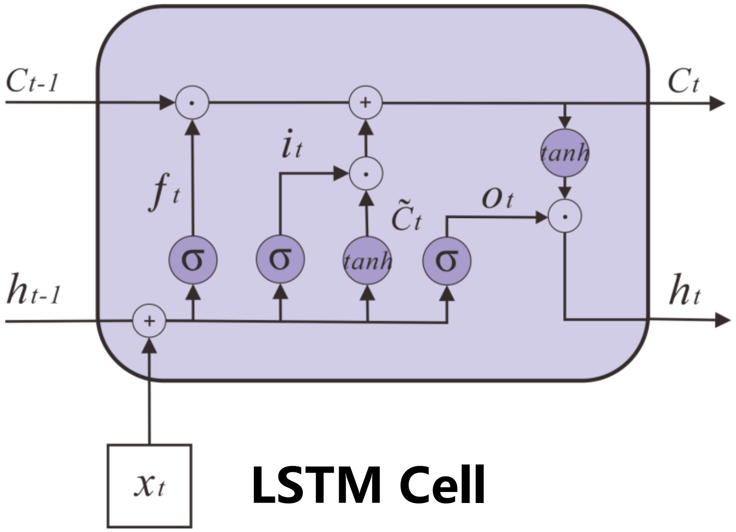
$$Y_t = f(X_{t-12}, X_{t-11}, X_{t-10}, \dots, X_{t-1})$$

**SWH correction**

**Model variables**

**Wind reanalysis**

- **SWH**
- **Mean wave direction**
- **Wind speed**
- **Wind direction**

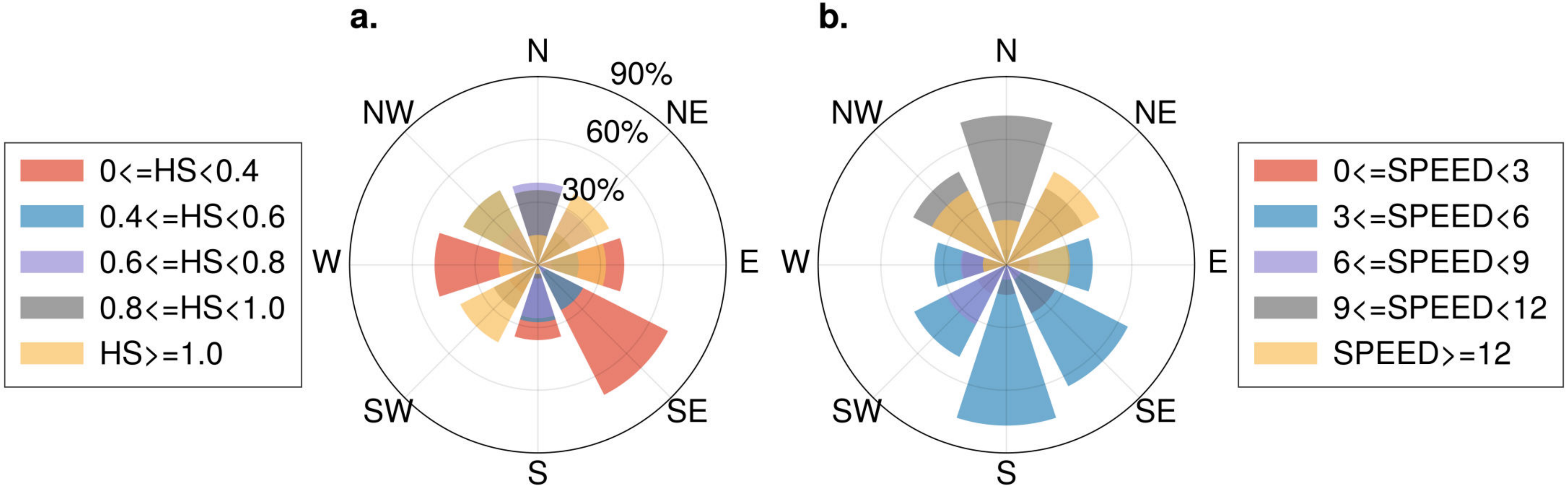


**LSTM Cell**

# 2. Data and Methods

## ➢ The analysis of wave properties

- **The proportion of different ranges of SWH (a) and wind speed (b) associated with the mean wave direction.**



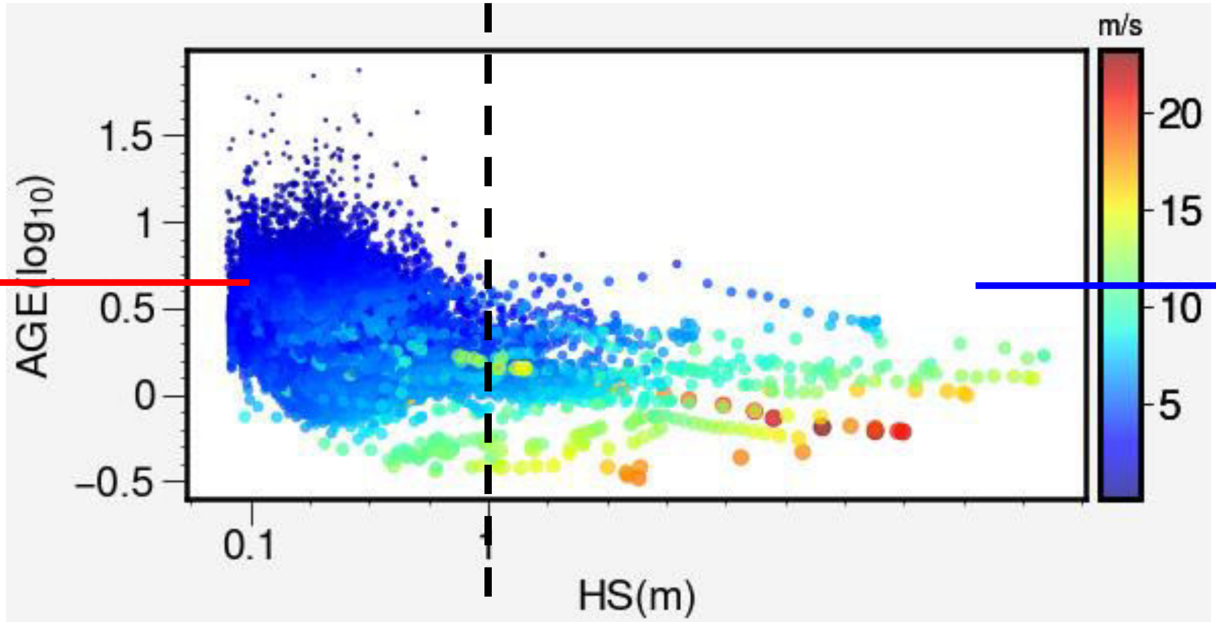

The SWH of greater than 1m are dominated by **the high wind conditions of northeasterly and northwesterly** (>12 m/s). While the SWH less than 1m are mainly affected by **the low wind conditions of westerly, southerly, and easterly** ranging from 3 to 6 m/s.

# 2. Data and Methods

## ➢ The analysis of wave properties

- **The scatterplots between the SWH and the wave age with different wind speeds.**

Low wind speed swell

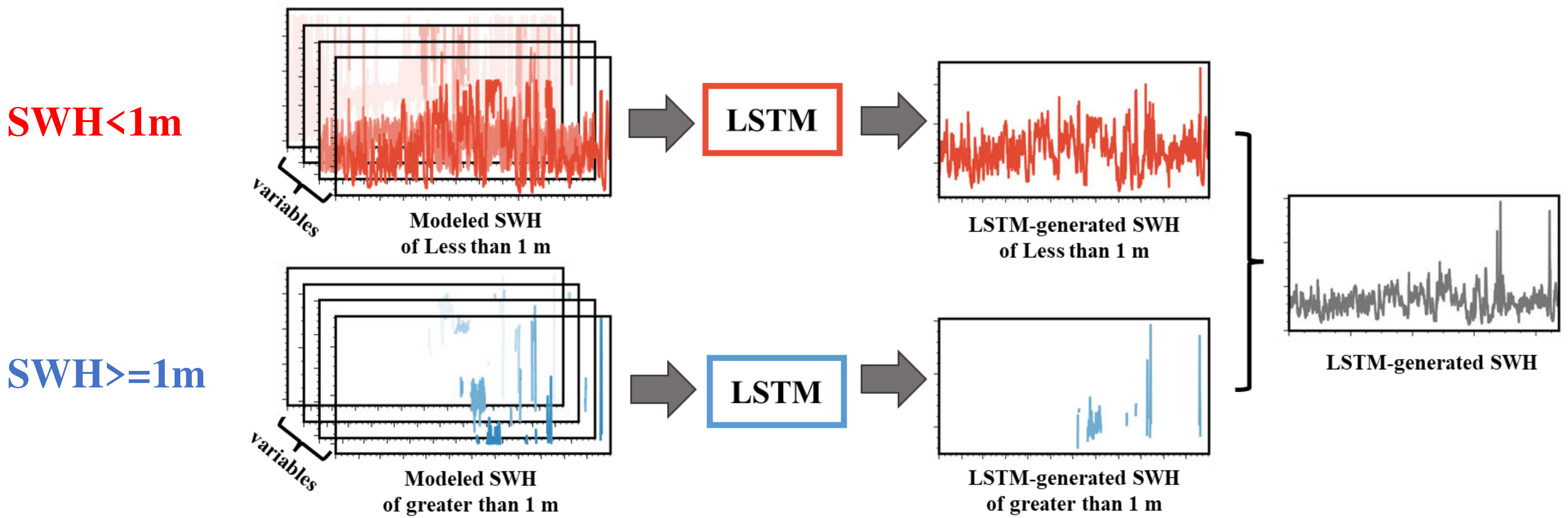



High wind speed wind wave

| | Wave age | | | Wind speed | Swell | Wind wave |
|---|---|---|---|---|---|---|
| | Minimum | Maximum | Mean value | Maximum(m/s) | ratio (%) | ratio (%) |
| **SWH of less than 1-m** | 0.36 | 75.2 | **3.12** | 23 | **82.4%** | 17.6% |
| **SWH of greater than 1-m** | 0.33 | 6.45 | **1.57** | 16 | 45.1% | **54.9%** |

# 2. Data and Methods

➢ **A multi-mode correction model (MM-LSTM)**



# 2. Data and Methods

## ➢ Sensitivity experiment

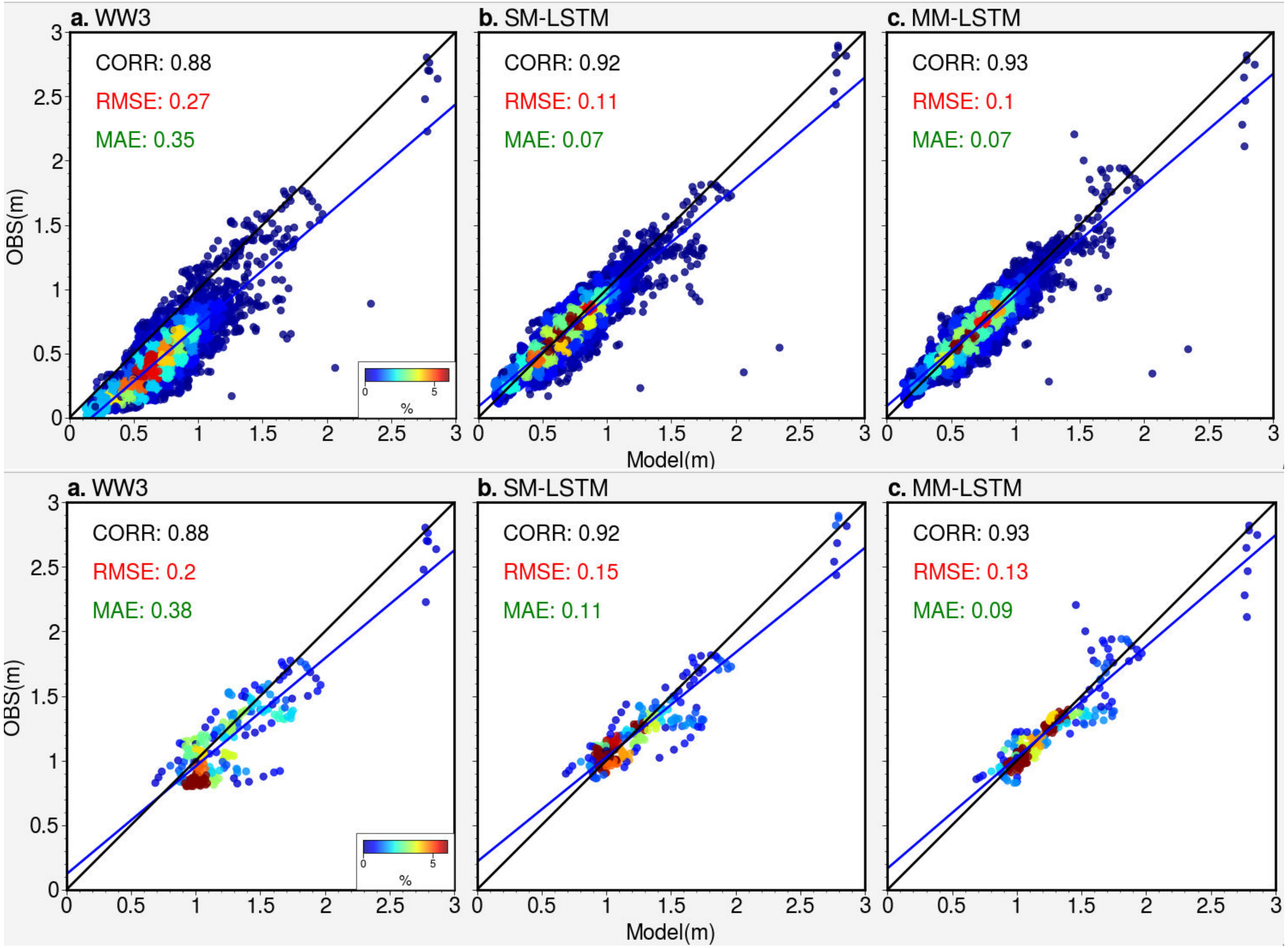
| Experiments | Input variable |
|---|---|
| **LSTM I** | SWH |
| **LSTM II** | Wind speed |
| **LSTM III** | SWH, Wind speed |
| **LSTM IV** | SWH, Wind speed, Wind direction |
| **LSTM V** | SWH, mean wave direction |
| **LSTM VI** | SWH, Wind speed, Wind direction, mean wave direction |

# 3. Results

➢ **Training results**

ALL

>1m

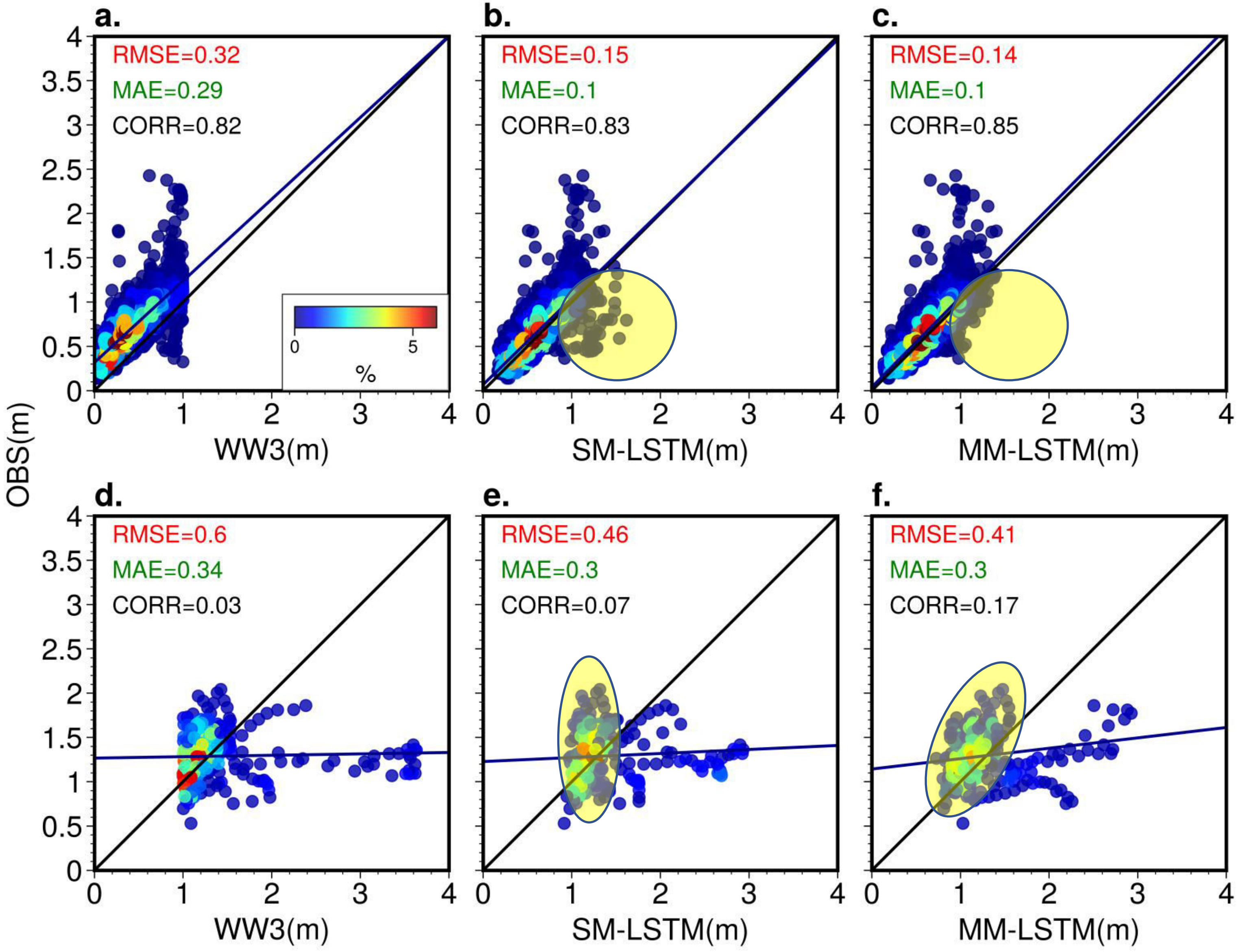


# 3. Results

- **Testing results (validation)**

**SWH<1m**

**SWH>=1m**

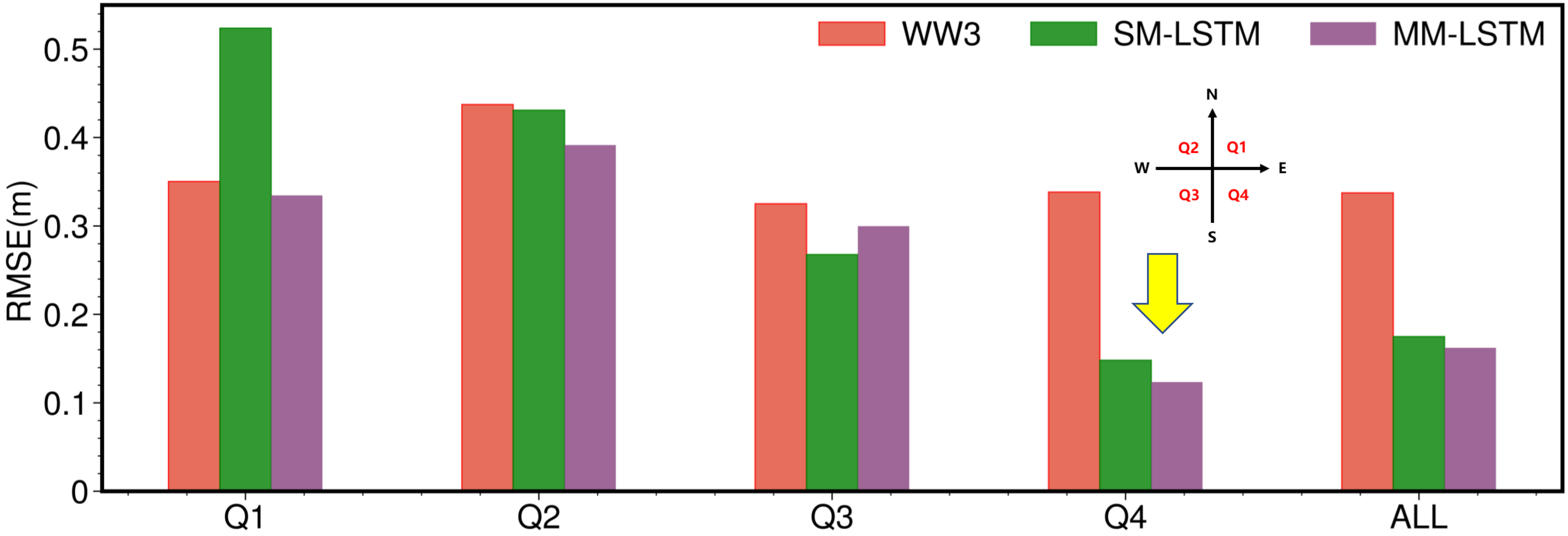


# 3.Results-sensitivity experiment

- **A multi-mode correction model**

| experiments | Input variables | Error statistics<br>RMSE: 0.34 MAE: 0.29 CORR: 0.78 (Numerical model data) | | | | | |
|---|---|---|---|---|---|---|---|
| | | Single-mode | | | Multi-mode | | |
| | | RMSE | MAE | CORR | RMSE | MAE | CORR |
| LSTM I | SWH | 0.19 | 0.11 | 0.78 | 0.2 | 0.12 | 0.77 |
| LSTM II | Wind speed | 0.26 | 0.18 | 0.51 | 0.22 | 0.17 | 0.64 |
| LSTM III | SWH, Wind speed | 0.21 | 0.12 | 0.76 | 0.2 | 0.12 | 0.78 |
| LSTM IV | SWH, Wind speed, Wind direction | 0.19 | 0.12 | 0.78 | 0.18 | 0.11 | 0.81 |
| LSTM V | SWH, mean wave direction | 0.2 | 0.12 | 0.75 | 0.18 | 0.11 | 0.81 |
| LSTM VI | SWH, Wind speed, Wind direction, mean wave direction | 0.17 | 0.11 | 0.81 | **0.16** | **0.11** | **0.83** |

# 3. Results




In general, the MM-LSTM can effectively correct the results of numerical models in all quadrants, but get little effect in some quadrants with few samples.

# 3. Results

| | Q1 DIRMN∈(0,90°) | Q2 DIRMN∈(90°,180°) | Q3 DIRMN∈(180°,270°) | Q4 DIRMN∈(270°,360°) |
|---|---|---|---|---|
| Training samples | 0.0% 0+0 | 0.31% 29+0 | 7.31% 602+71 × | 92.38% 7982+540 √ (>1m+<1m) |
| <1m | 0.54→0.28 | 0.44→0.38 | 0.26→0.26 | 0.12→0.12 |
| >1m | 0.24→0.55 | 0.37→0.50 | 0.29→0.39 | 0.91→0.51 |

**The green numbers: SM-LSTM**

**The red numbers: MM-LSTM**

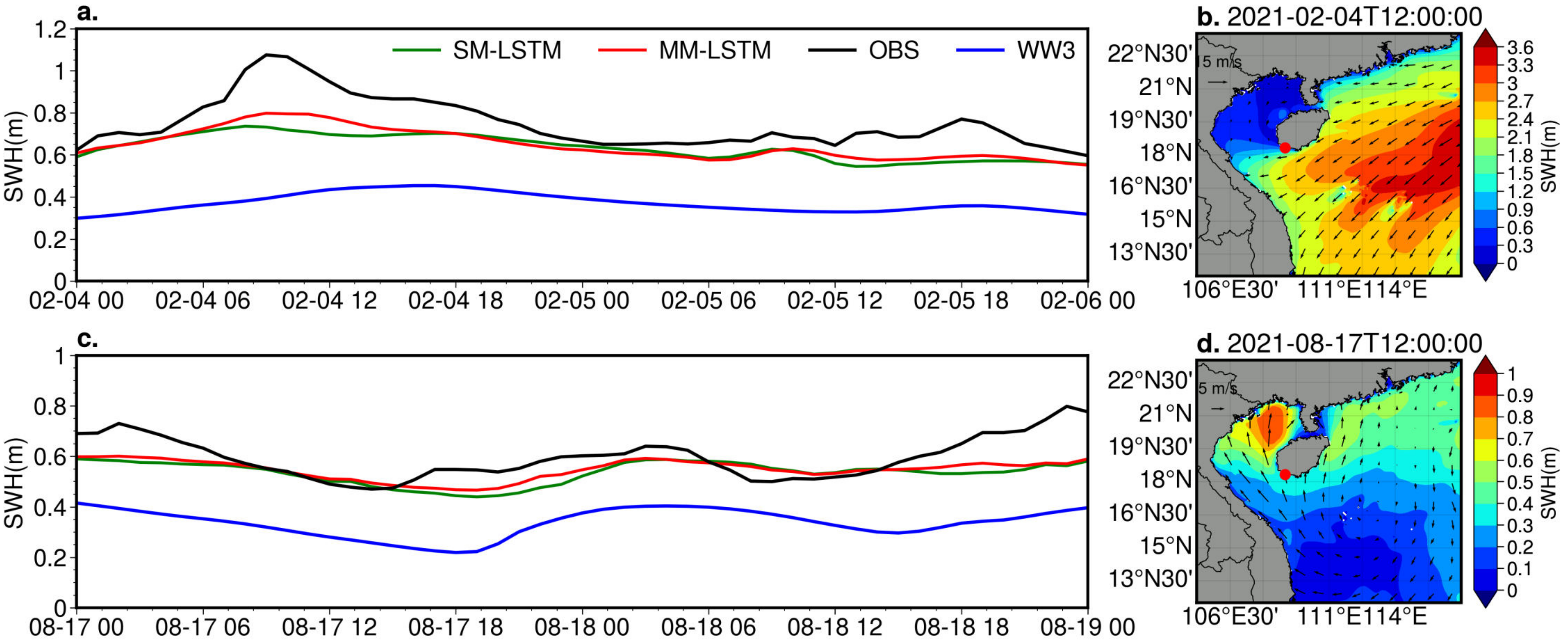
- **The results generated by LSTM depend on the number of training samples**
- ✓ The MM-LSTM not only can capture low sea state, but also has better performance than the SM-LSTM in the high sea state (Q4).
- ✓ However, the ability of the MM-LSTM to capture high sea state is also **limited by the total training samples.**

# 3. Results

## □Normal：East Asian monsoon

winter

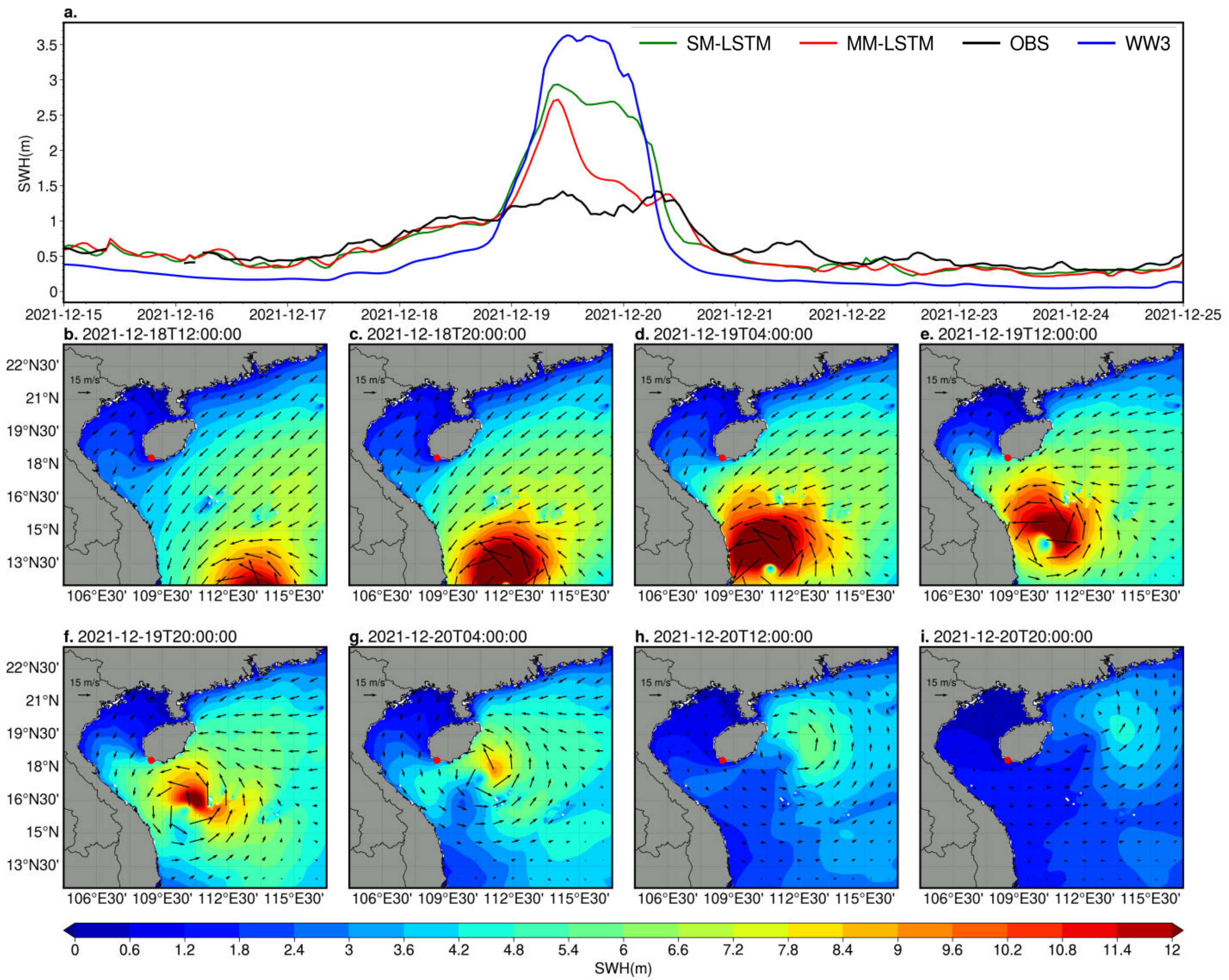
summer




**The MM-LSTM has a slight improvement over the SM-LSTM, but the difference is not significant.**

# 3. Results

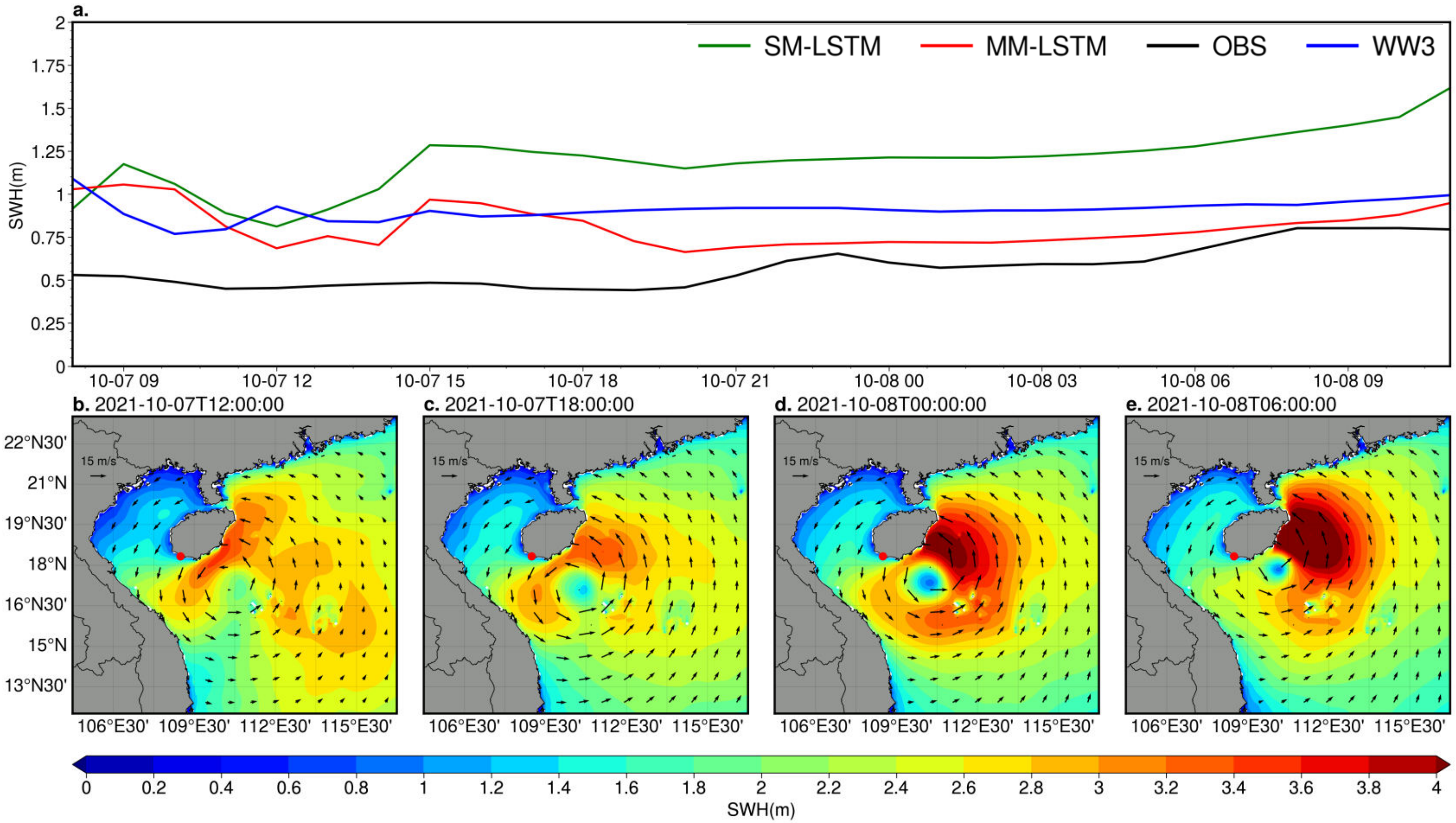
## □Typhoon case 1：Super typhoon Rai（2021）




- The SM-LSTM can correct the overestimated peak of SWH simulated by the numerical model to some extent.
- The MM-LSTM can also significantly reduce the peak of SWH and get much better results than the SM_LSTM.

# 3. Results

## □Typhoon case 2: Super typhoon Lionrock（2021）




**The SM-LSTM cannot correct the overestimated results of WW3 and even add errors to the results.**

**The MM-LSTM can reduce the errors of WW3 significantly.**

# 4. Conclusions

- Multiple factors (**SWH, DIRMN, wind speed, and wind direction**) should be considered in the machine learning correction model.
- The **SM-LSTM** can improve the RMSE and MAE of SWH generated by the numerical model. However, the improvement of SM-LSTM is not significant under **the high wind conditions**.
- The **MM-LSTM** significantly reduces the RMSE and MAE of modeled sea waves by **52.9% and 62.1%**, respectively, which outperforms the SM-LSTM.
- The MM-LSTM outperforms the SM-LSTM in the **high sea state** and can effectively correct the overestimation by the numerical model during a passage of typhoon.

# Thank you！