Application of machine learning in wave forecasting considering atmosphere instability

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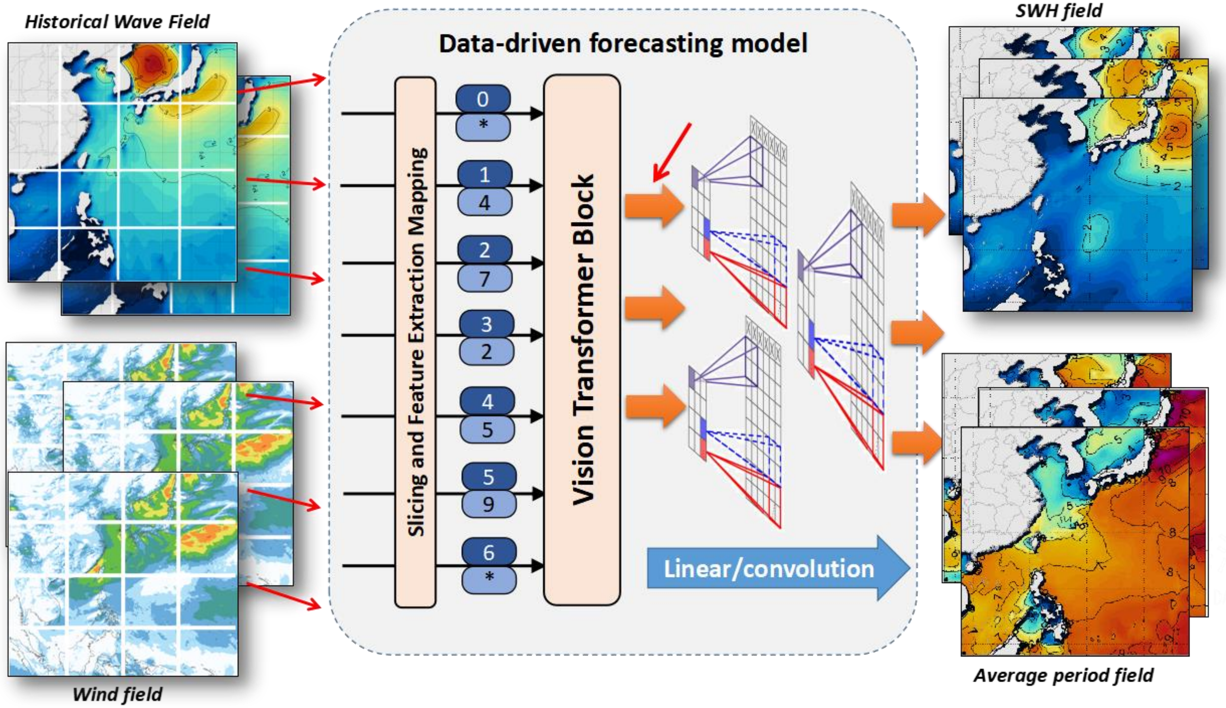
Outline

- Technical Framework
- ViT Regional Sensitivity Experiment
- Super-Resolution Model
- Results and Discussion

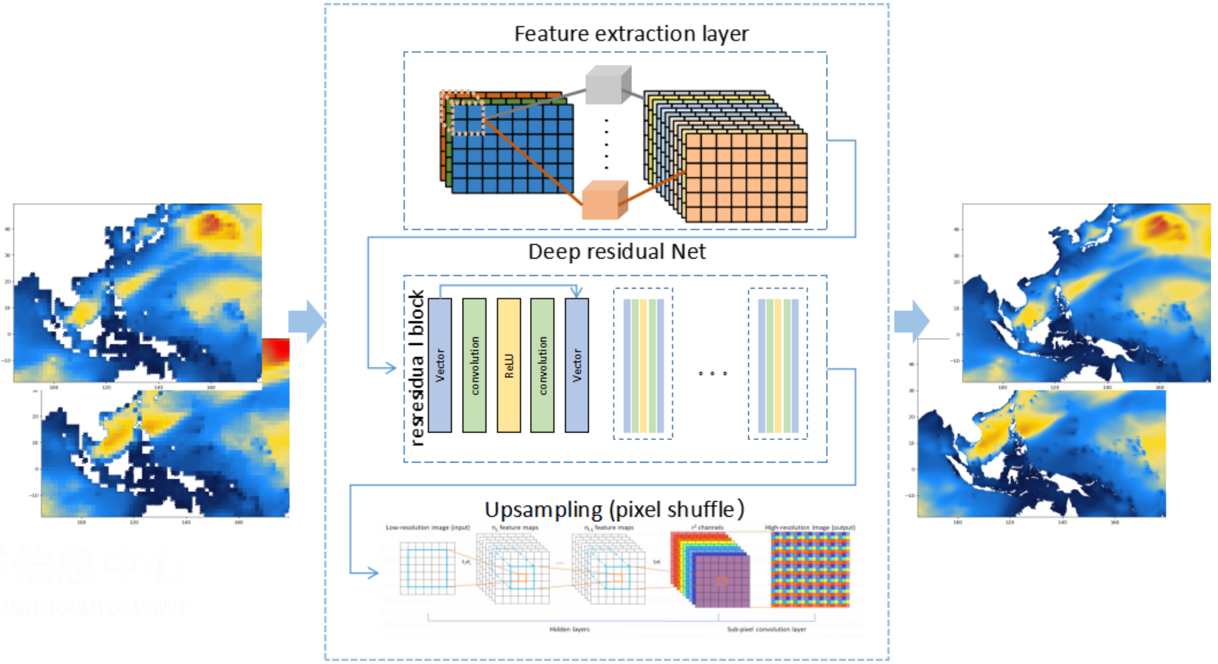
Wave Intelligent Forecasting Model - Technical Solution

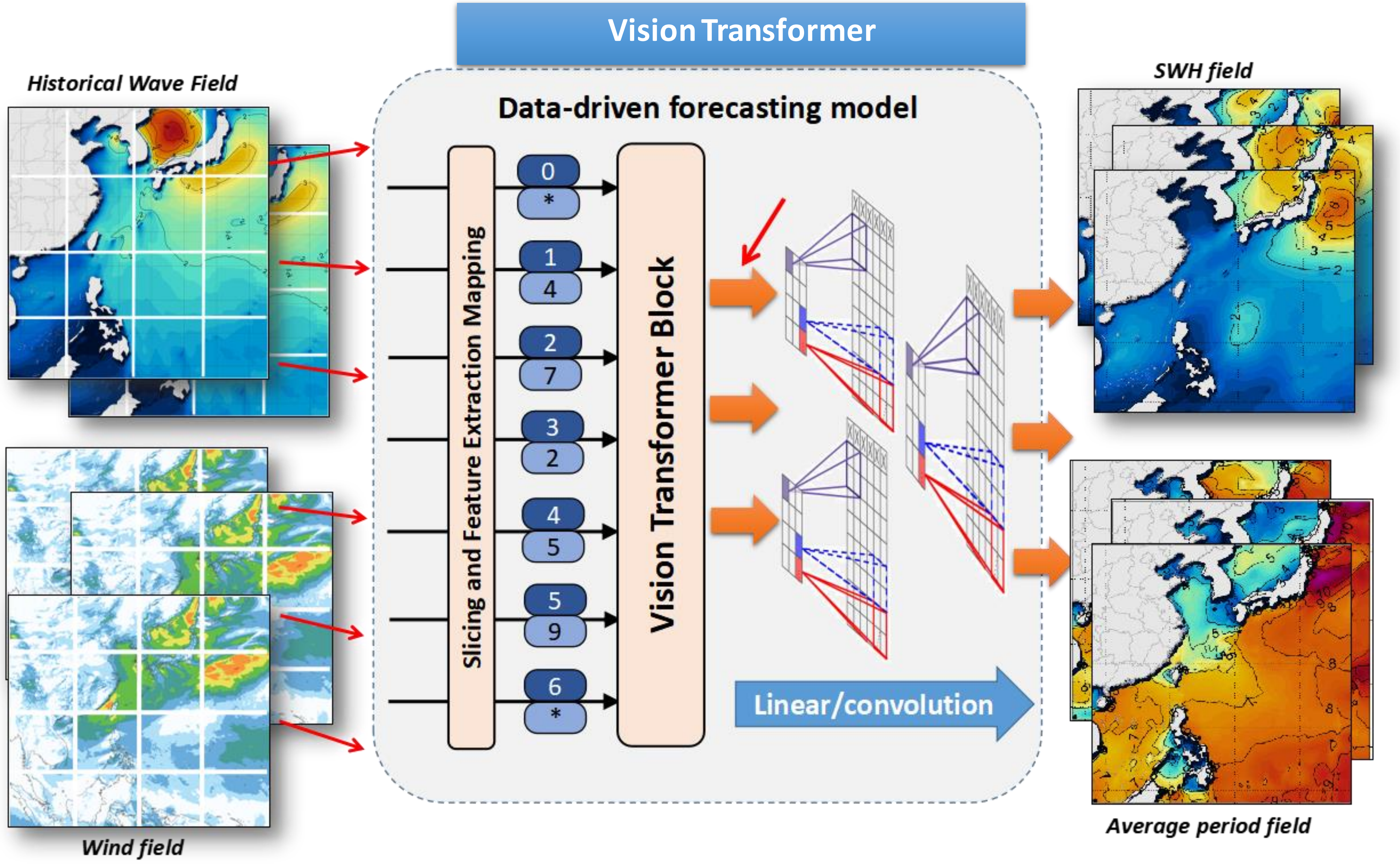
Technic framework

Vision Transformer

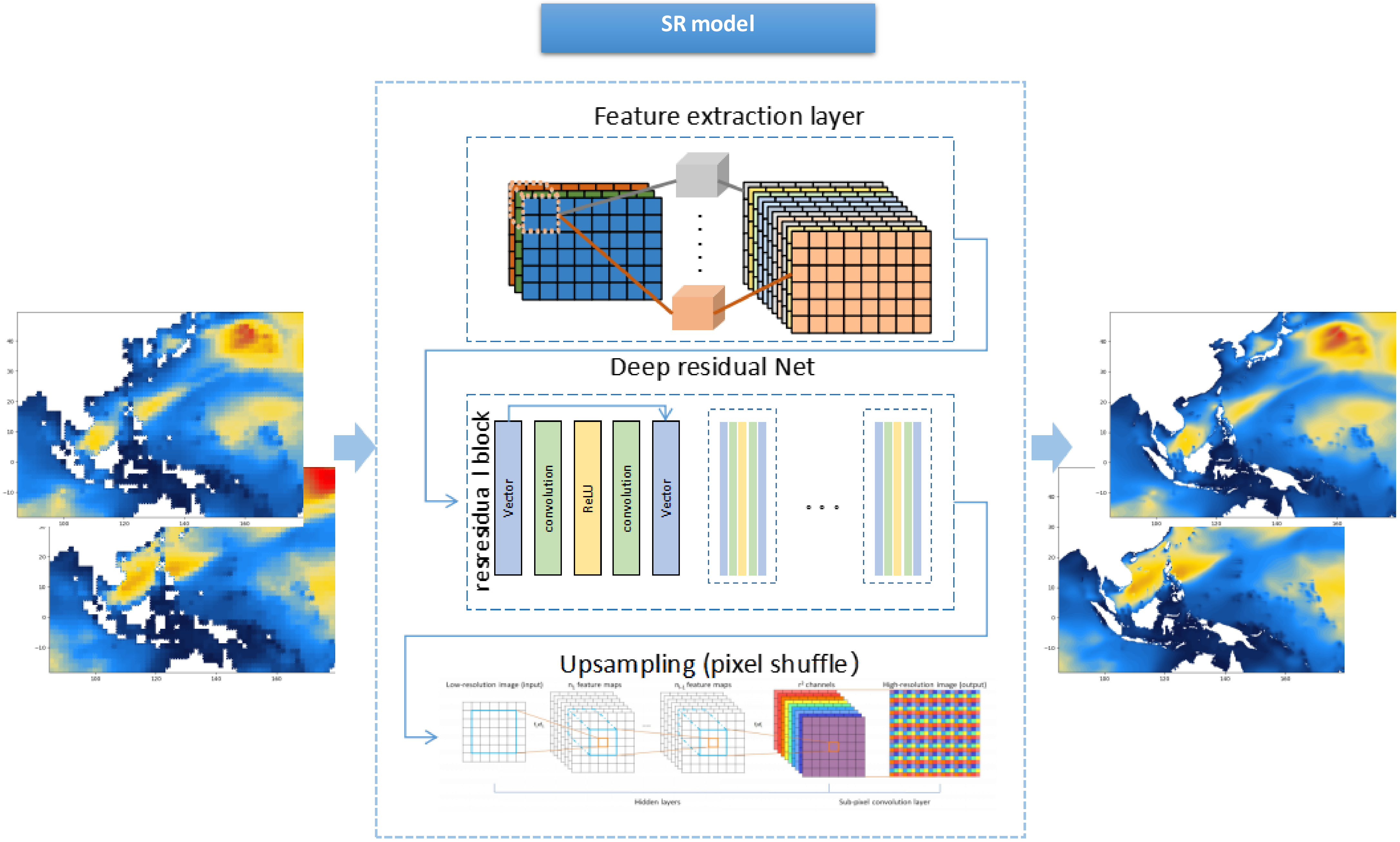


SR model





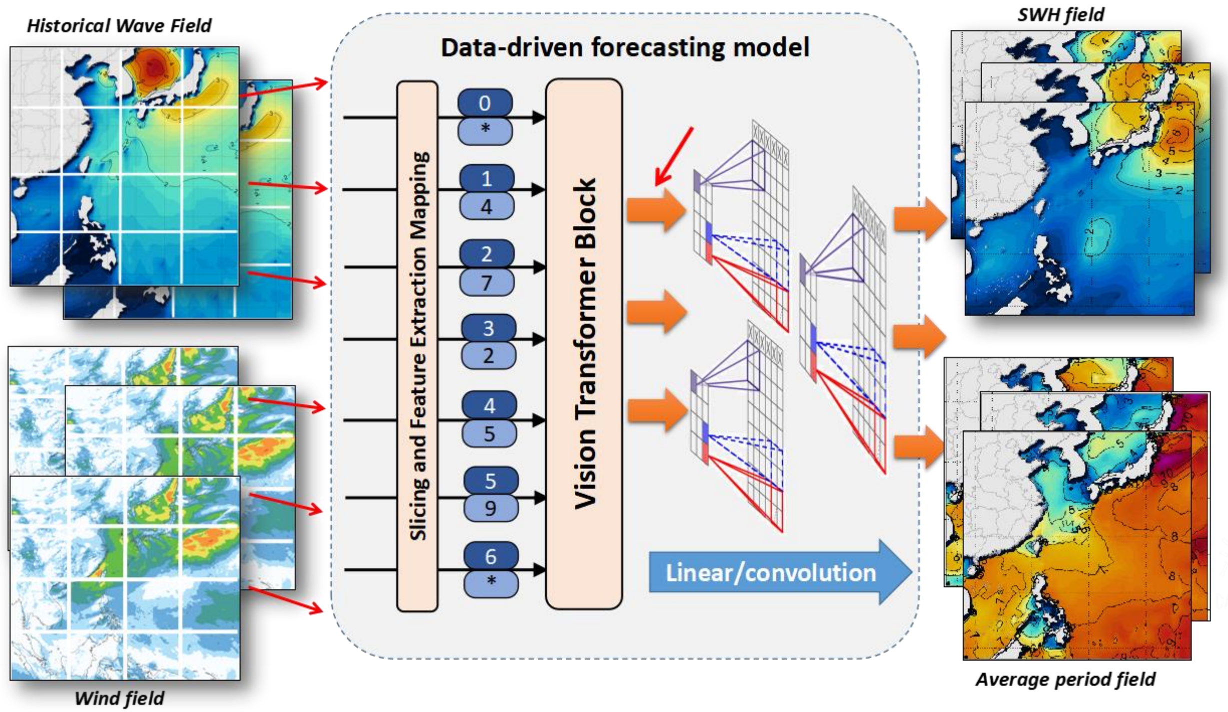
Vision Transformer
Historical Wave Field
Data-driven forecasting model
SWH field
Slicing and Feature Extraction Mapping
0
*
1
4
2
7
3
2
4
5
5
9
6
*
Vision Transformer Block
Linear/convolution
Wind field
Average period field


SR model
Feature extraction layer
Deep residual Net
resresidua l block
Vector
convolution
ReLU
convolution
Vector
Upsampling (pixel shuffle)
Low-resolution image (input)
High-resolution image (output)
Hidden layers
Sub-pixel convolution layer

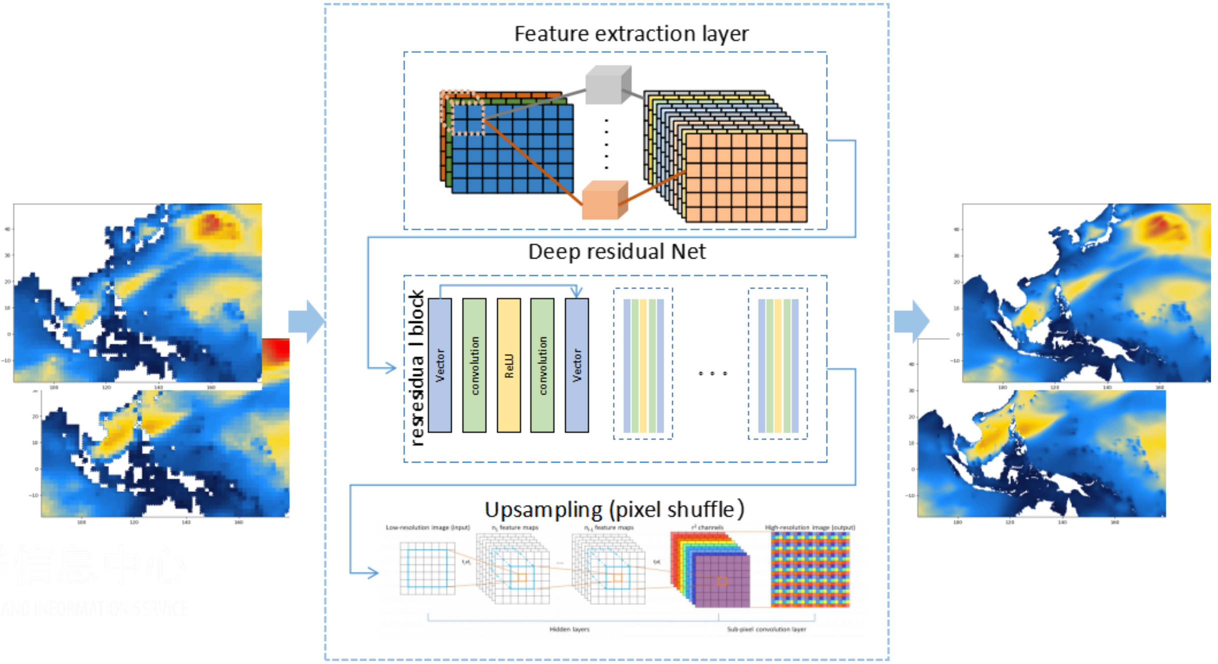
Wave Intelligent Forecasting Model - Technical Solution

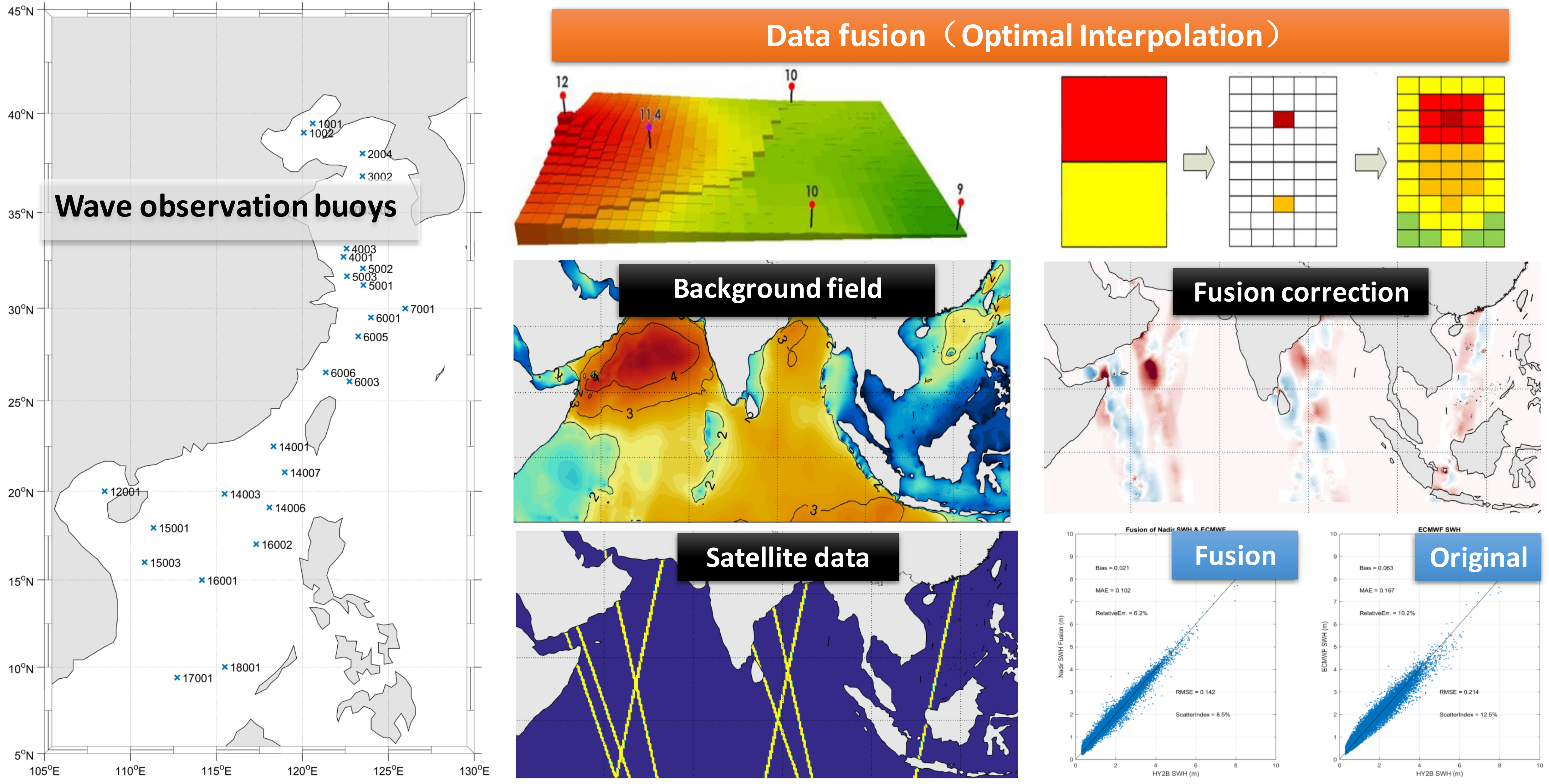
Technic framework

Vision Transformer

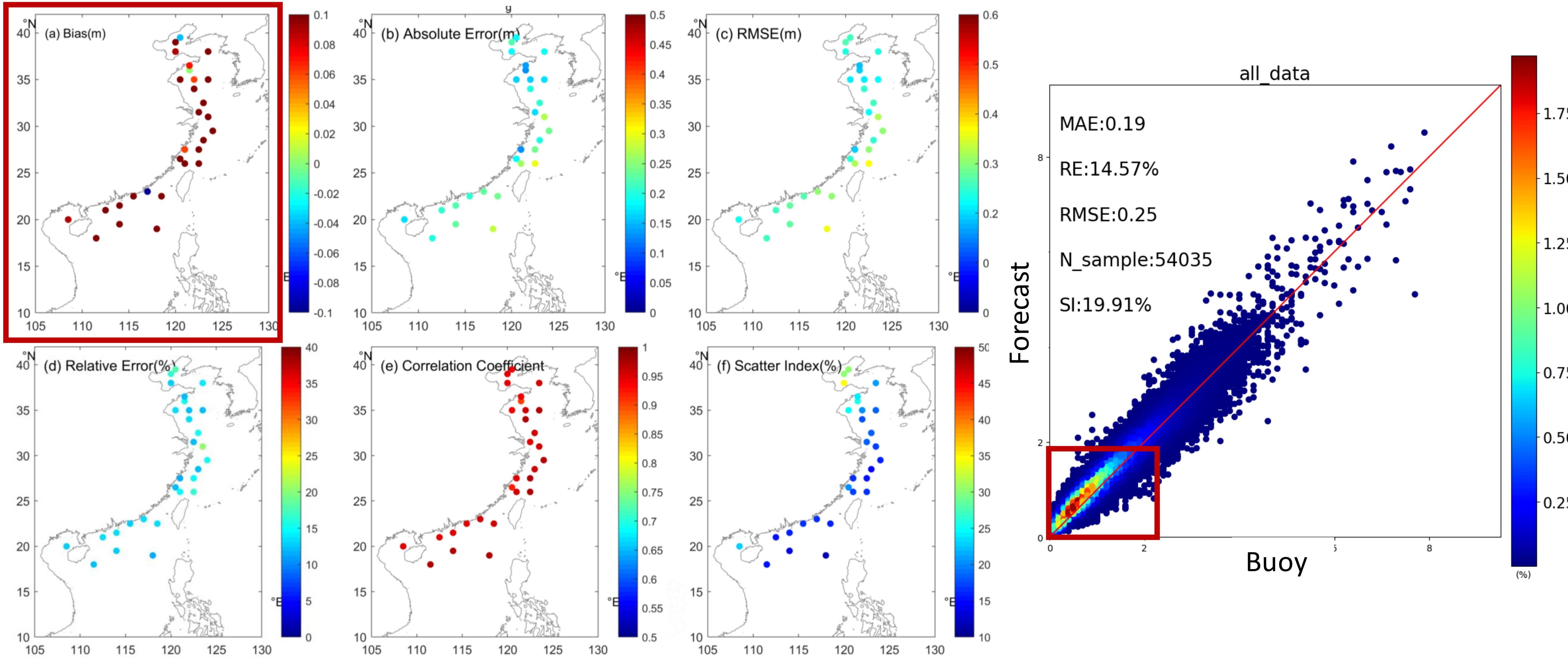


SR model





we use the satellite data Ocean-2 satellite altimeter and buoys data into the forecast wave field with "Ensemble optimal interpolation method"



we use the ECMWF-IFS data for the model

Wave Intelligent Forecasting Model - ViT Regional Sensitivity Experiment

1. One-time calculation（Sequence to Sequence）

Sequence to Sequence

Steps	$T_{0\text{-}m}$	……	$T_{0\text{-}1}$	T_0	T_1	T_2	T_3	……	T_n
Wind(u,v)		……							
Wave(swh)									

AI Wave Model

Wave FCST

SWH_{T1}
SWH_{T2}
SWH_{T3}
……
SWH_{Tn}

Using the wind field sequence at T_0… T_{0+n} and the $T_{0\text{-}m}$…T_0wave field to obtain the wave field prediction sequence at T_1… T_{0+n}

2. Iterative calculation（Step by Step）

Step by Step

Steps	$T_{0\text{-}m}$	…	$T_{0\text{-}1}$	T_0	…	T_{n1}
Wind(u,v)		…			…	
Wave(swh)		…			…	

T_{n1}	…	T_{2n}	T_{2n+1}	…	T_{3n}
	…			…	
	…				

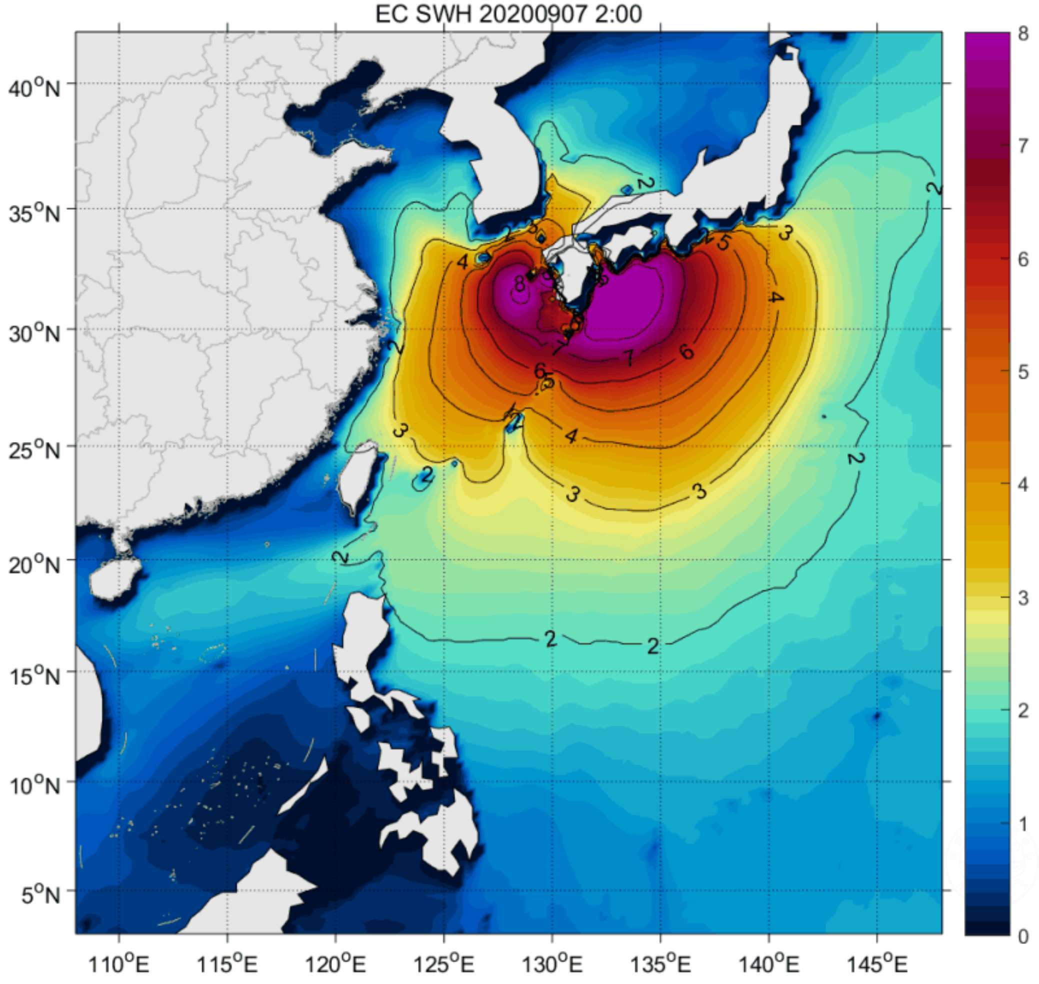
Wave FCST

SWH_{T1}
SWH_{T2}
SWH_{T3}
……
SWH_{Tn}

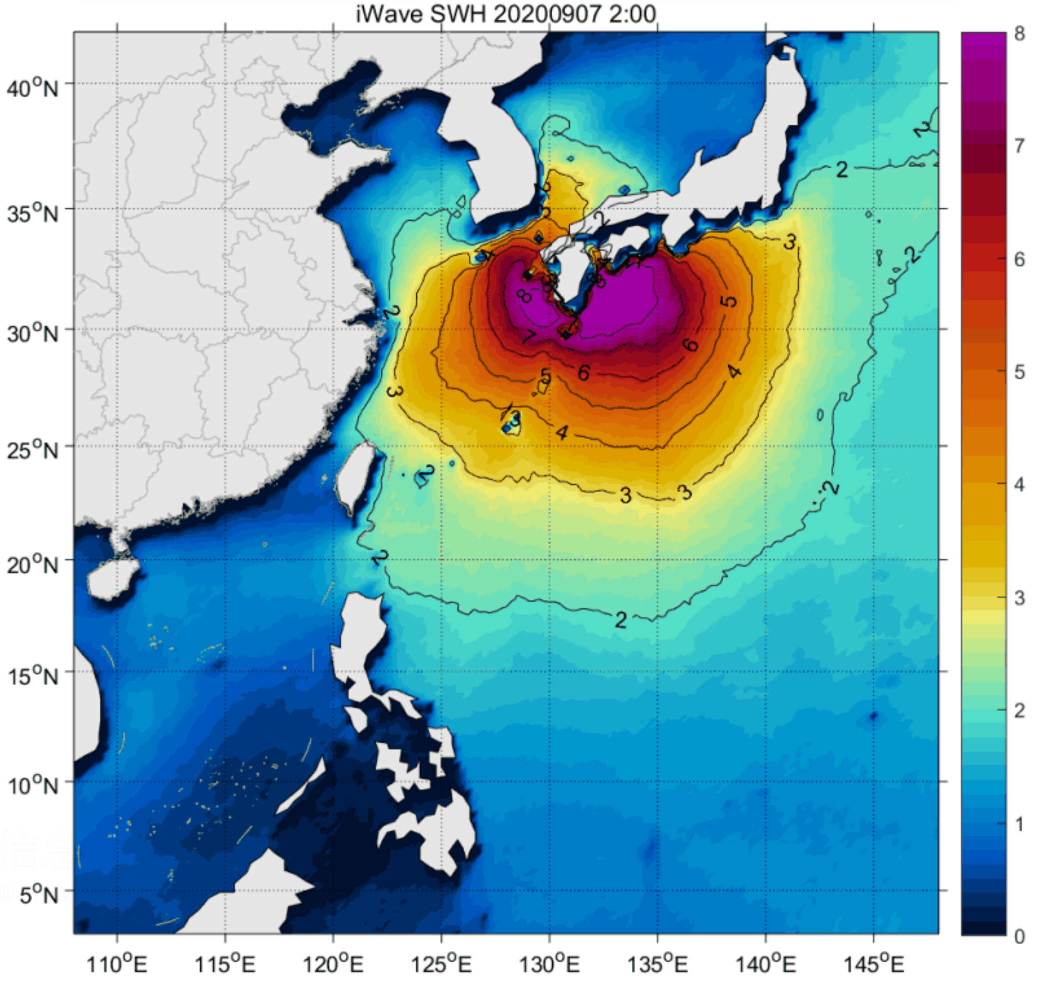
Consistent with traditional numerical forecasting models, using short time series forecasting to iteratively calculate future wave forecasts for all time periods

Wave Intelligent Forecasting Model - ViT Regional Sensitivity Experiment

Traditional numerical model

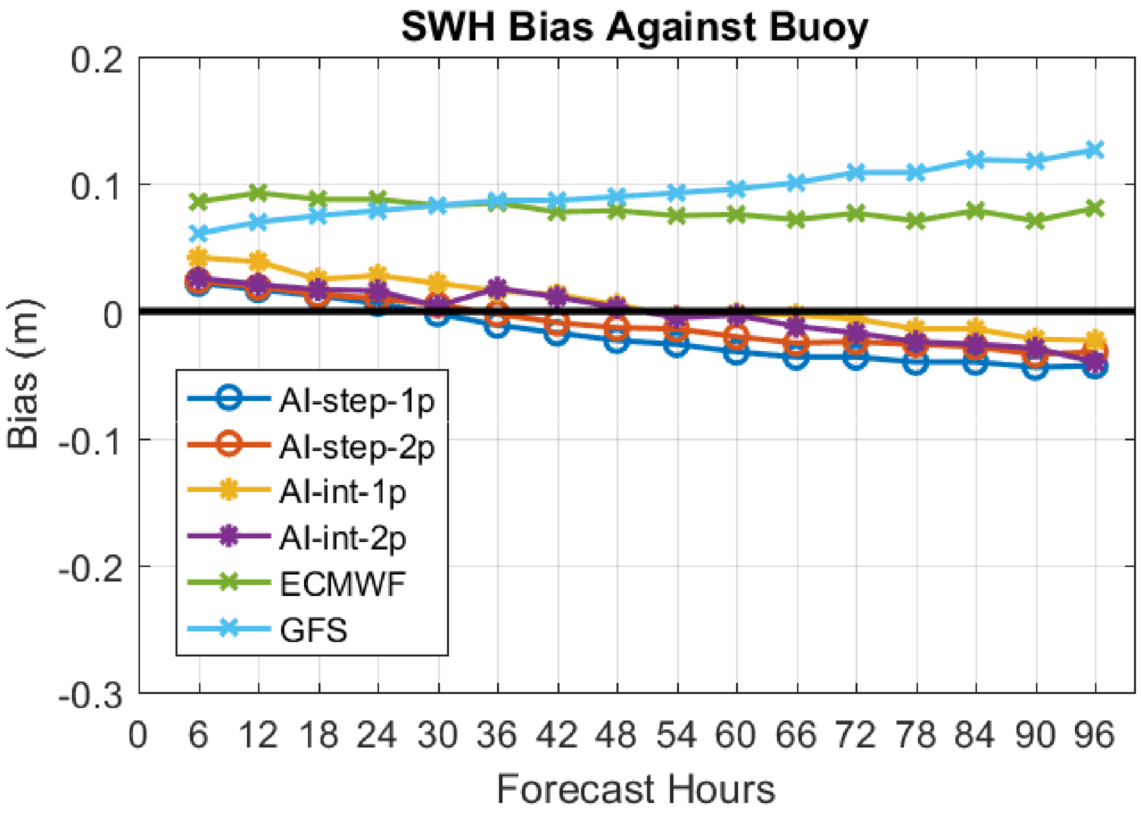


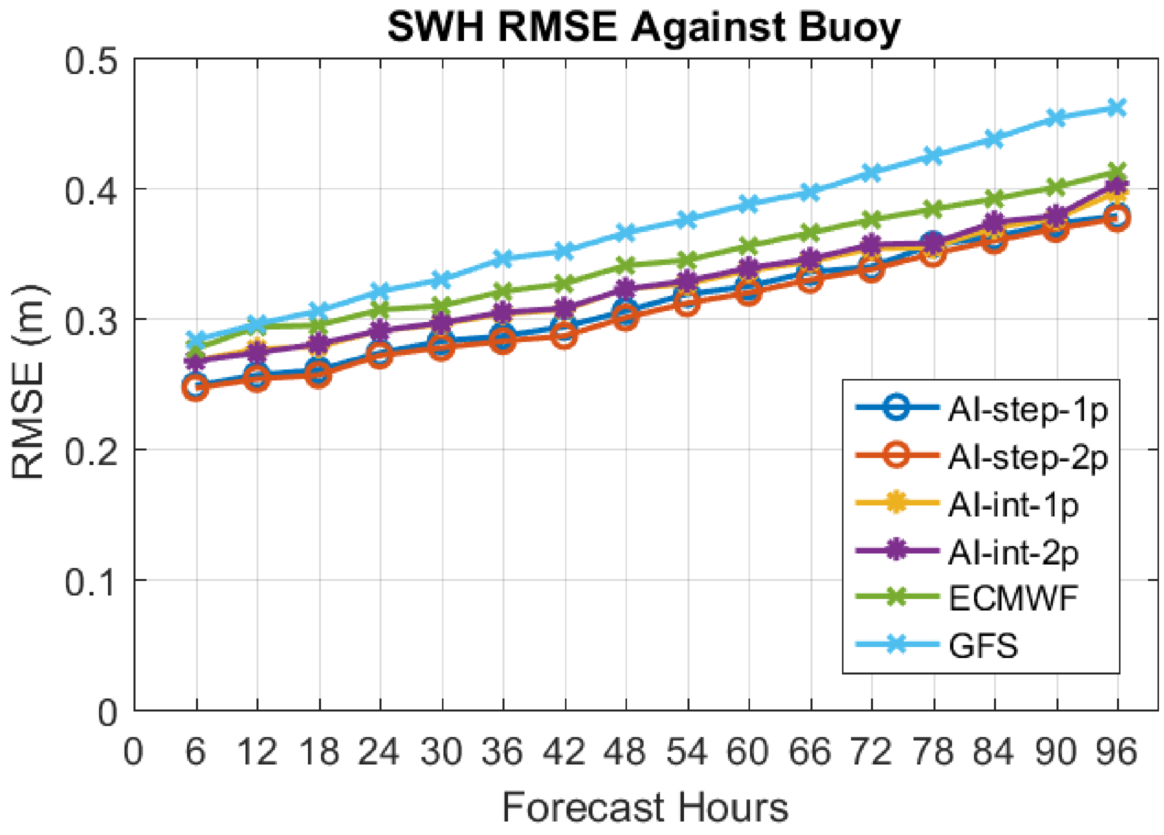
AI



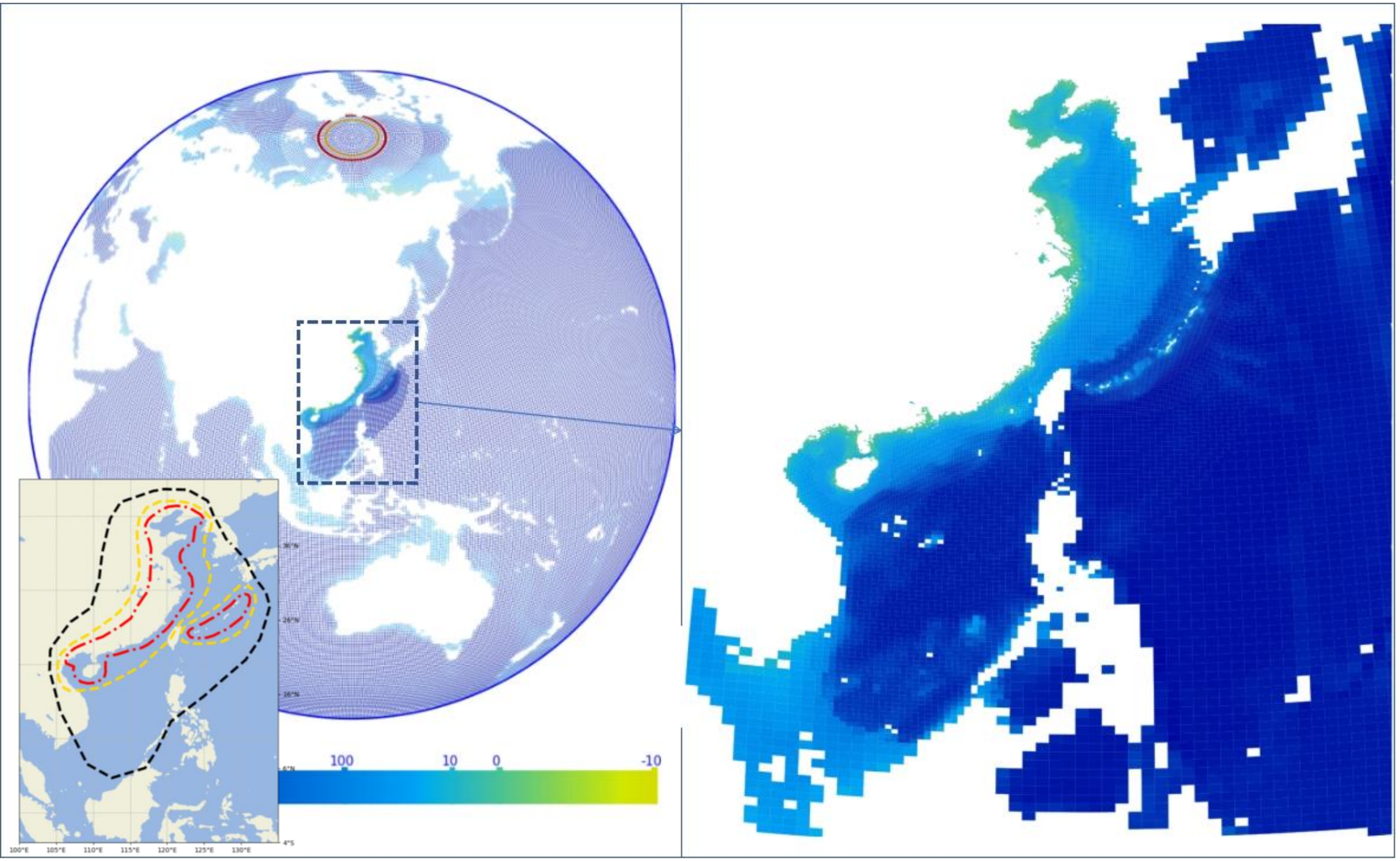
both types were able to simulate the spatial distribution of significant wave height and its evolution over time quite effectively.

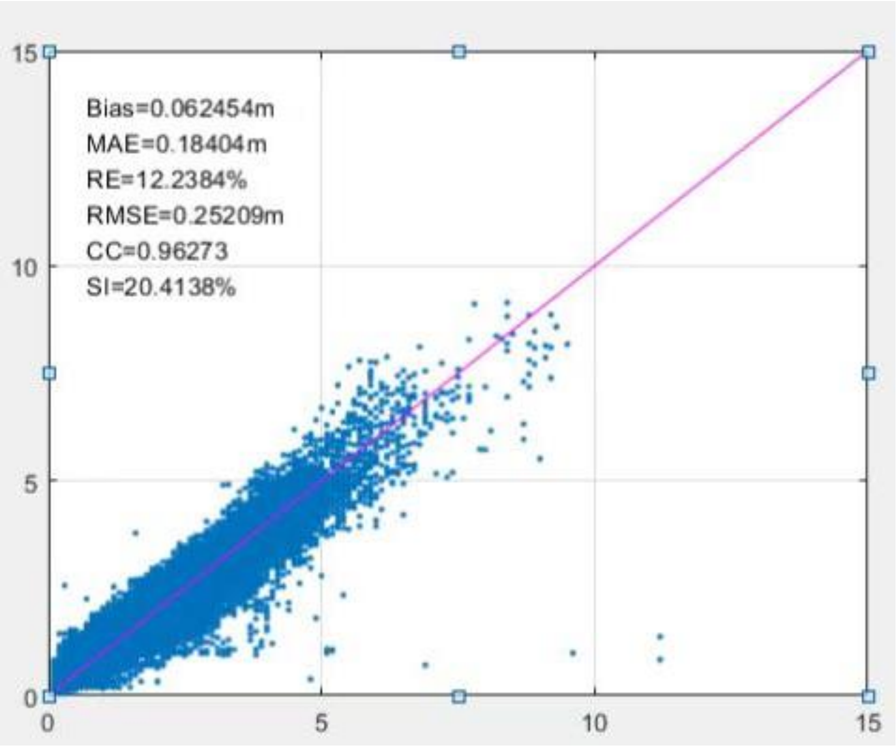
Wave Intelligent Forecasting Model - ViT Regional Sensitivity Experiment





We validated the results of significant wave height from several types of models against buoy data. The verification errors of our current intelligent models are comparable to those of traditional numerical models. Due to the correction of learning data in intelligent models, there is an advantage in terms of bias reduction. step-step models showed better performance compared to one-time models, and models forecasting two elements performed better than those forecasting only one element. However, the differences are not significant.



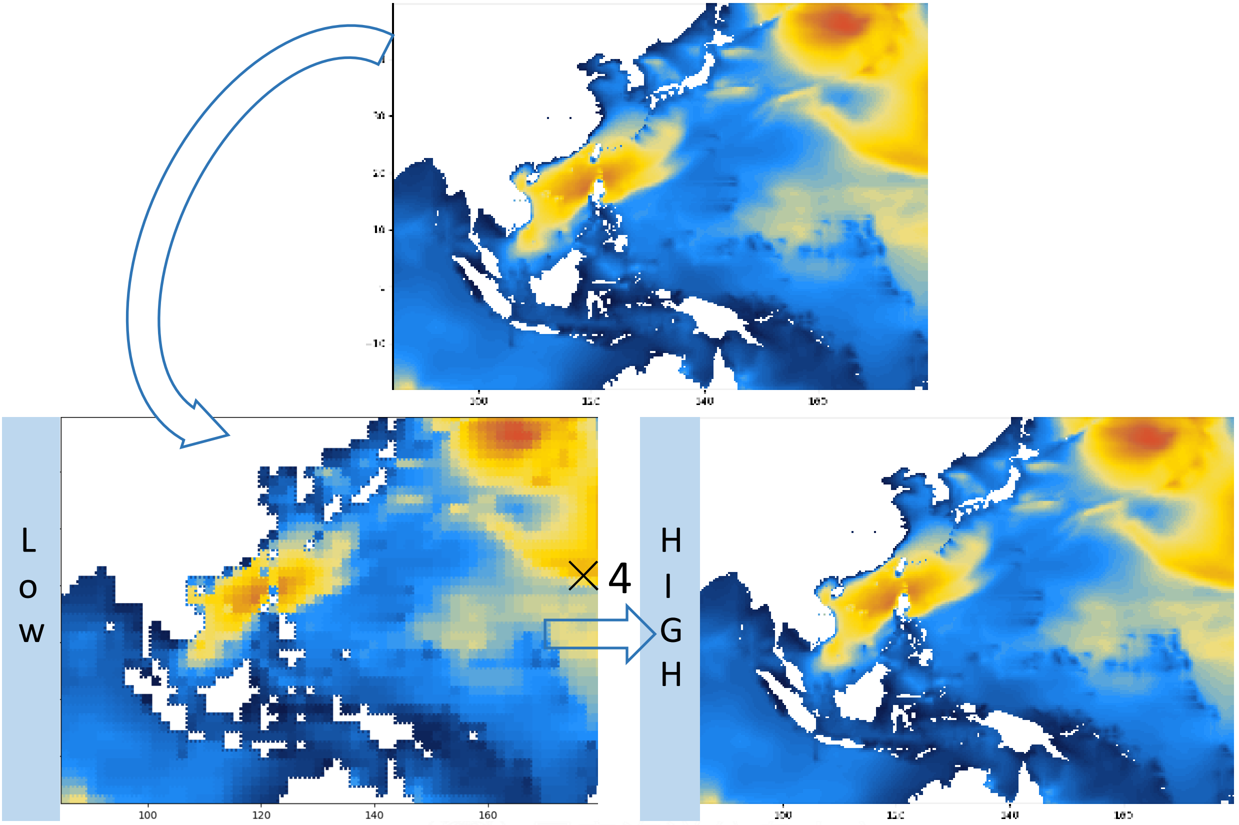


Region	Resolution
Within the red line range	lat:0.058,lon:0.087 （about 6km）
Within the yellow line range	lat:0.116,lon:0.174
Within the black line range	lat:0.232,lon:0.348
Global （Outside the black line range）	lat:0.464,lon:0.696

model	WW3
source term	（ST4+）
force wind	ERA（10m u， v）
time span	2years（2021~2022）
time resolution	Hourly

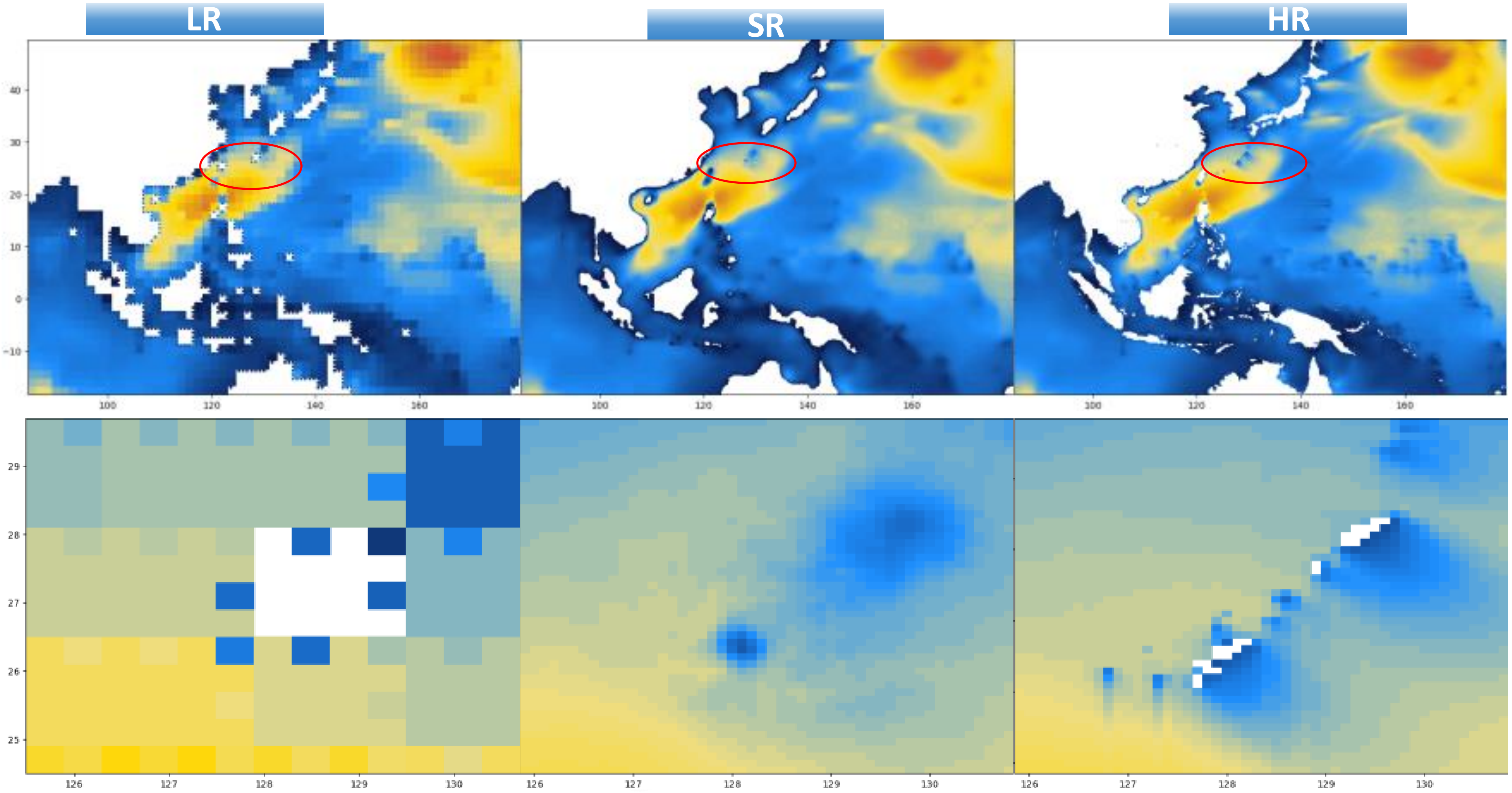
Wave Intelligent Forecasting Model - Super-Resolution Model

Data



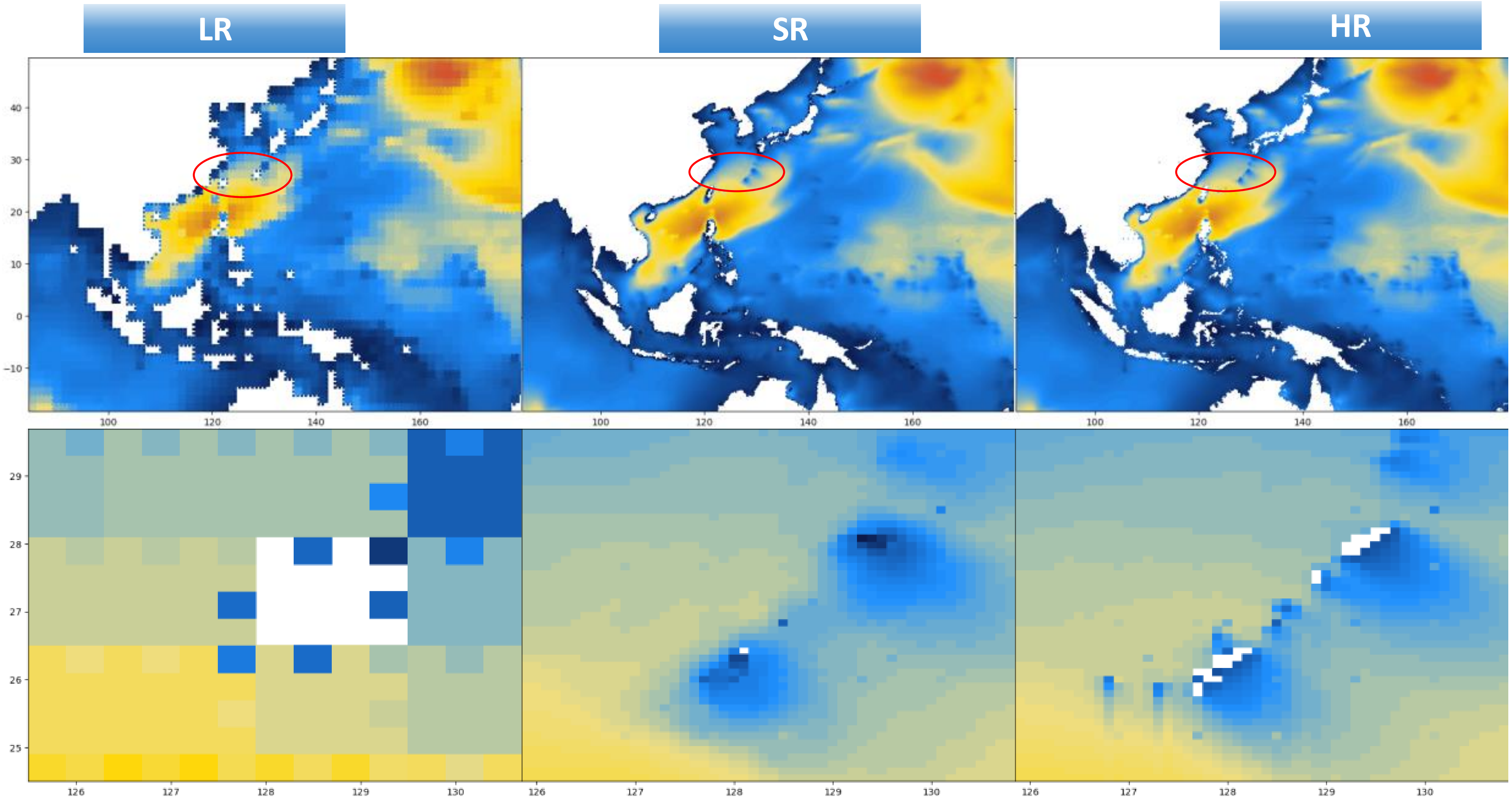
Unlike the regional model, the global model faces challenges in training due to limitations in GPU memory as the data volume increases. We first established a low-resolution global model, followed by the development of a super-resolution model. The super-resolution model utilizes deep residual networks for data feature extraction and use pixel shuffling for 4x upsampling. Before constructing the global model, we initially built a regional model for the Northwest Pacific. Since there is not a significant

Wave Intelligent Forecasting Model - Super-Resolution Model



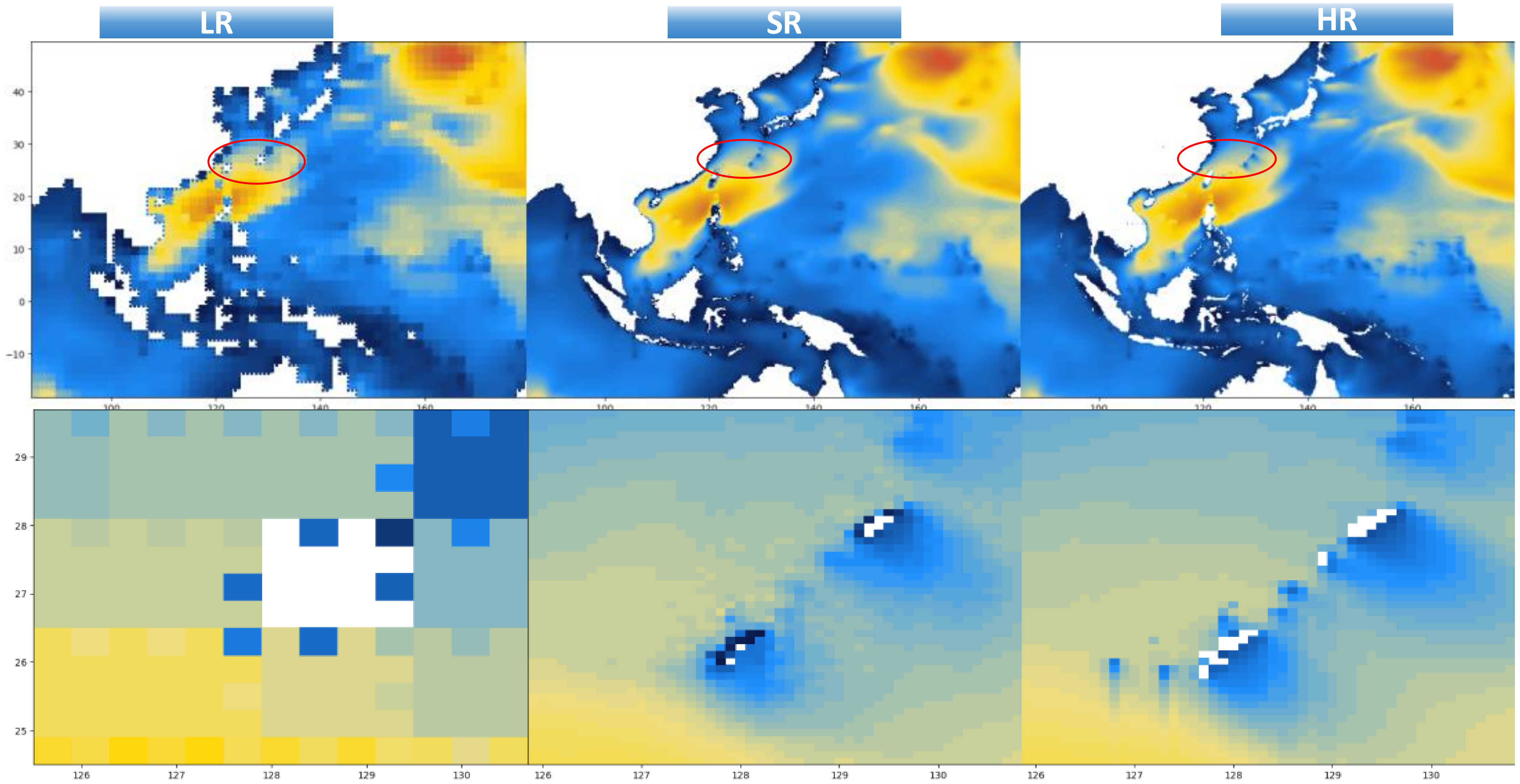
we sliced the training data into 26 segments and applied random rotations and flips to these segments. It can be observed that the results are not satisfactory. The overall terrain appears blurry, and there is a lack of effective supplementation of high-frequency information to compensate for the masking effects on wave fields.

Wave Intelligent Forecasting Model - Super-Resolution Model



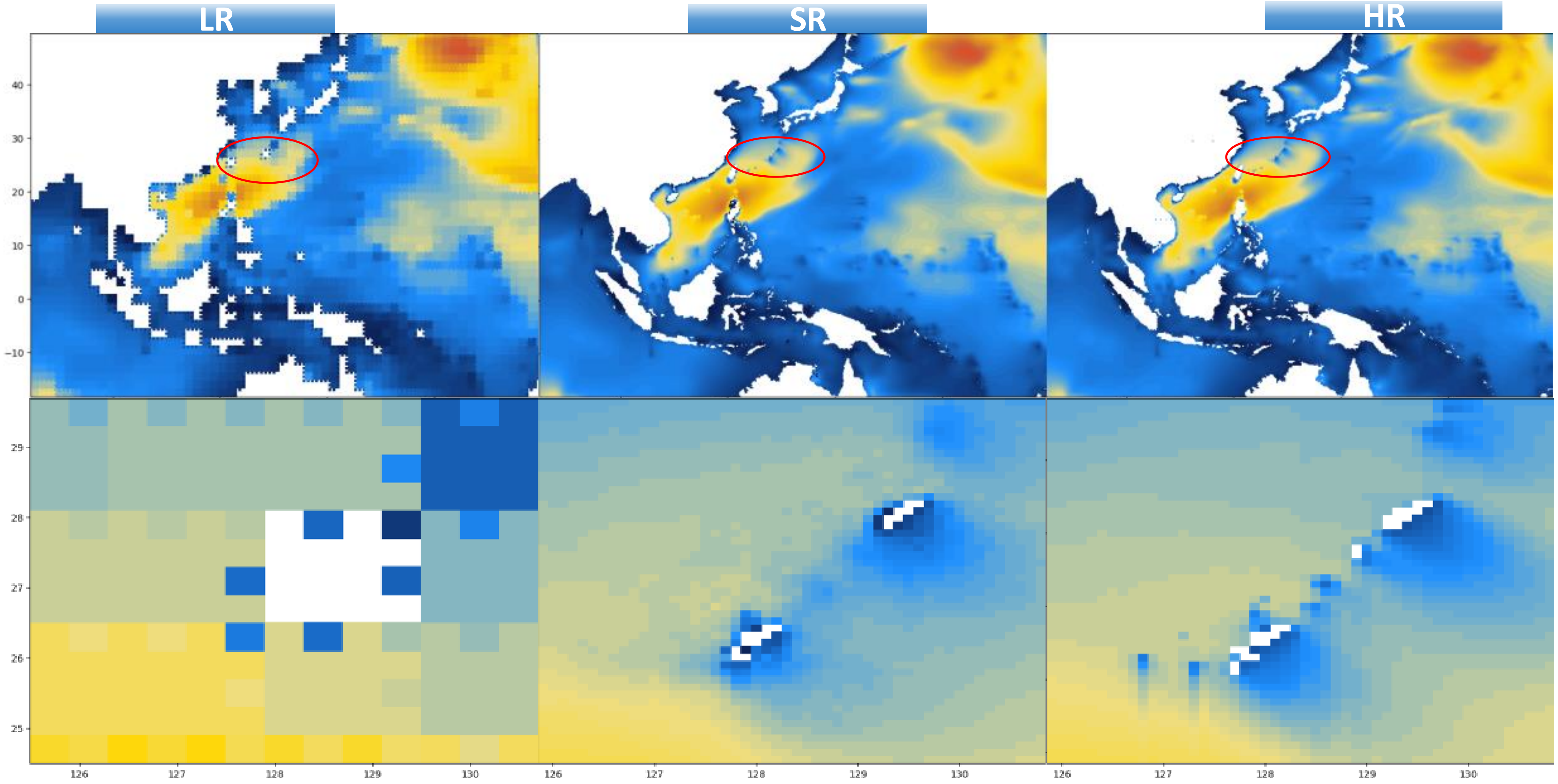
This experiment involved slicing the training data into 26 segments without applying flips or rotations.
It is evident that the super-resolution results are better compared to the previous experiment.

Wave Intelligent Forecasting Model - Super-Resolution Model



This experiment only involved slicing the training data into 13 segments without applying flips or rotations.
It is notable that the super-resolution results have improved further, a the islands are now beginning to emerge faintly.

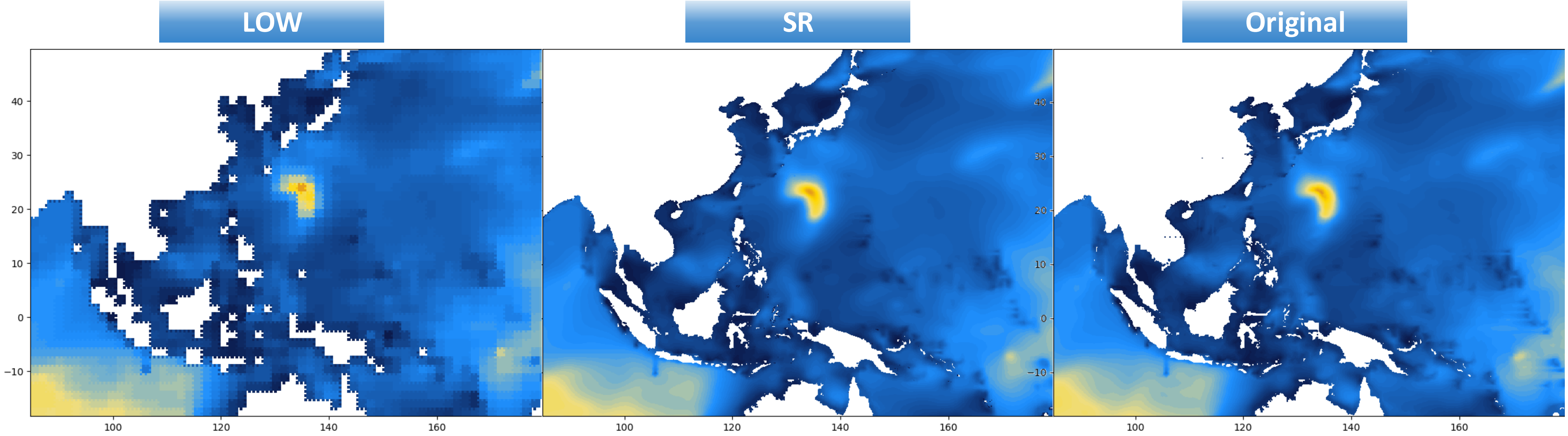
Wave Intelligent Forecasting Model - Super-Resolution Model



This is the training result without any data augmentation.

the super-resolution performance without data augmentation yields the best results.

Wave Intelligent Forecasting Model - Super-Resolution Model

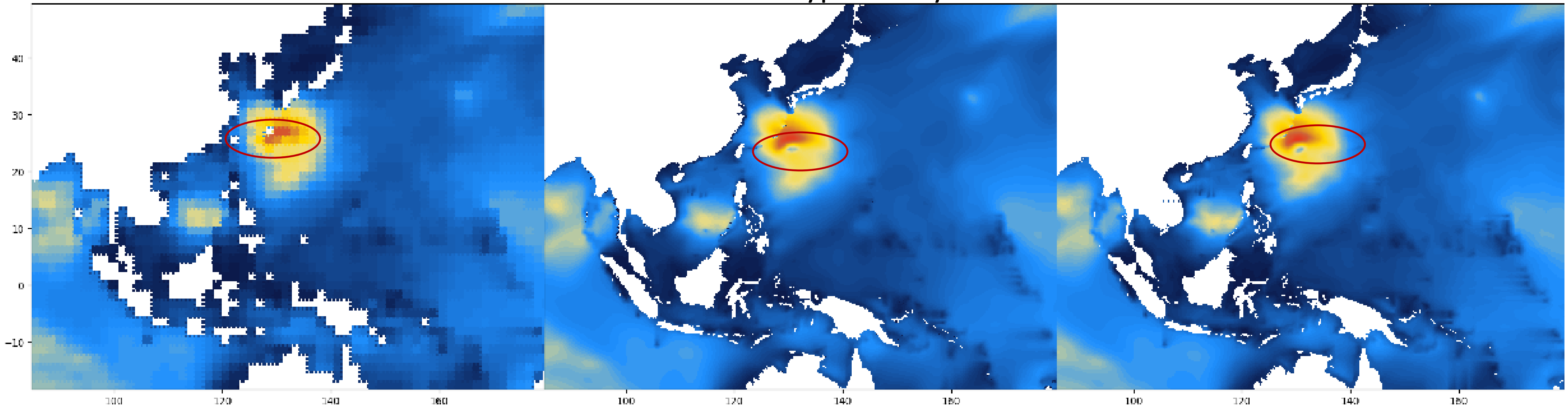


sensitivity experiments	data augmentation , 26 segments	no data augmentation, 26 segments	data augmentation , 13 segments	no data augmentataion, no segment
PSNR	42.875	44.3700	46.8581	47.2571
NIQE	16.8675	15.5082	13.8839	13.6314

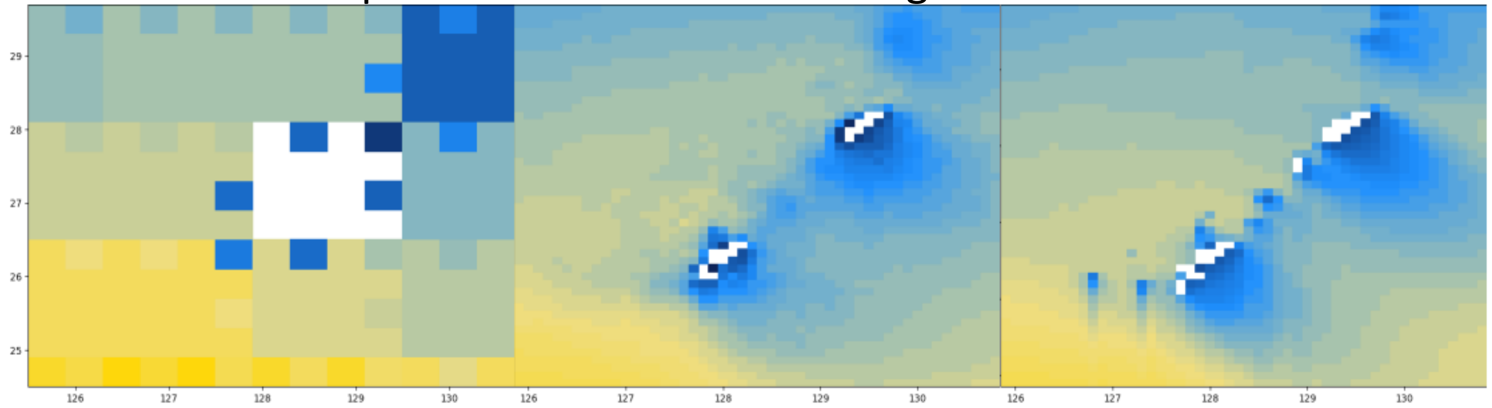
We conducted sensitivity experiments for different data augmentation methods and model parameters under the same number of iterations.

Wave Intelligent Forecasting Model - Super-Resolution Model

Reconstruction of Typhoon Eye Structure

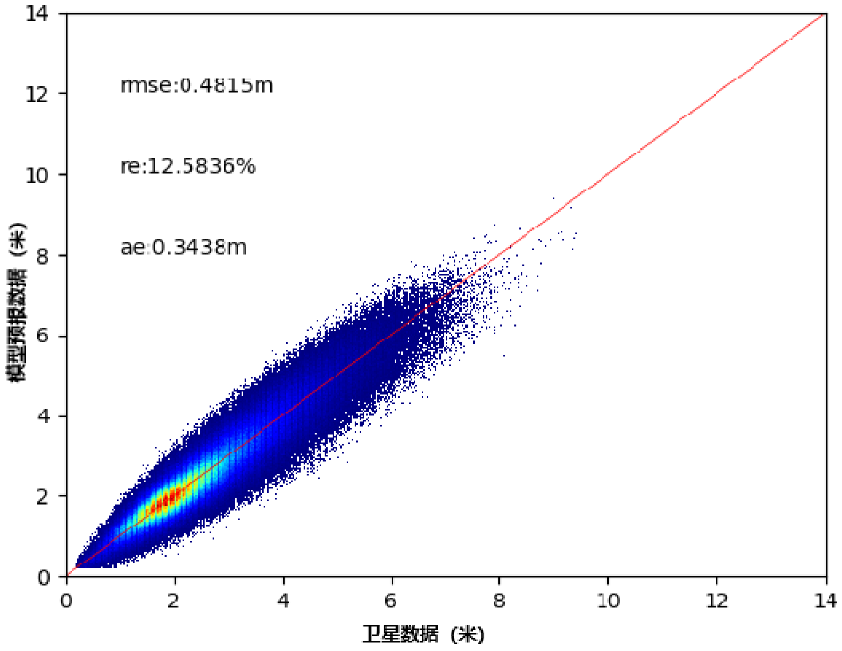


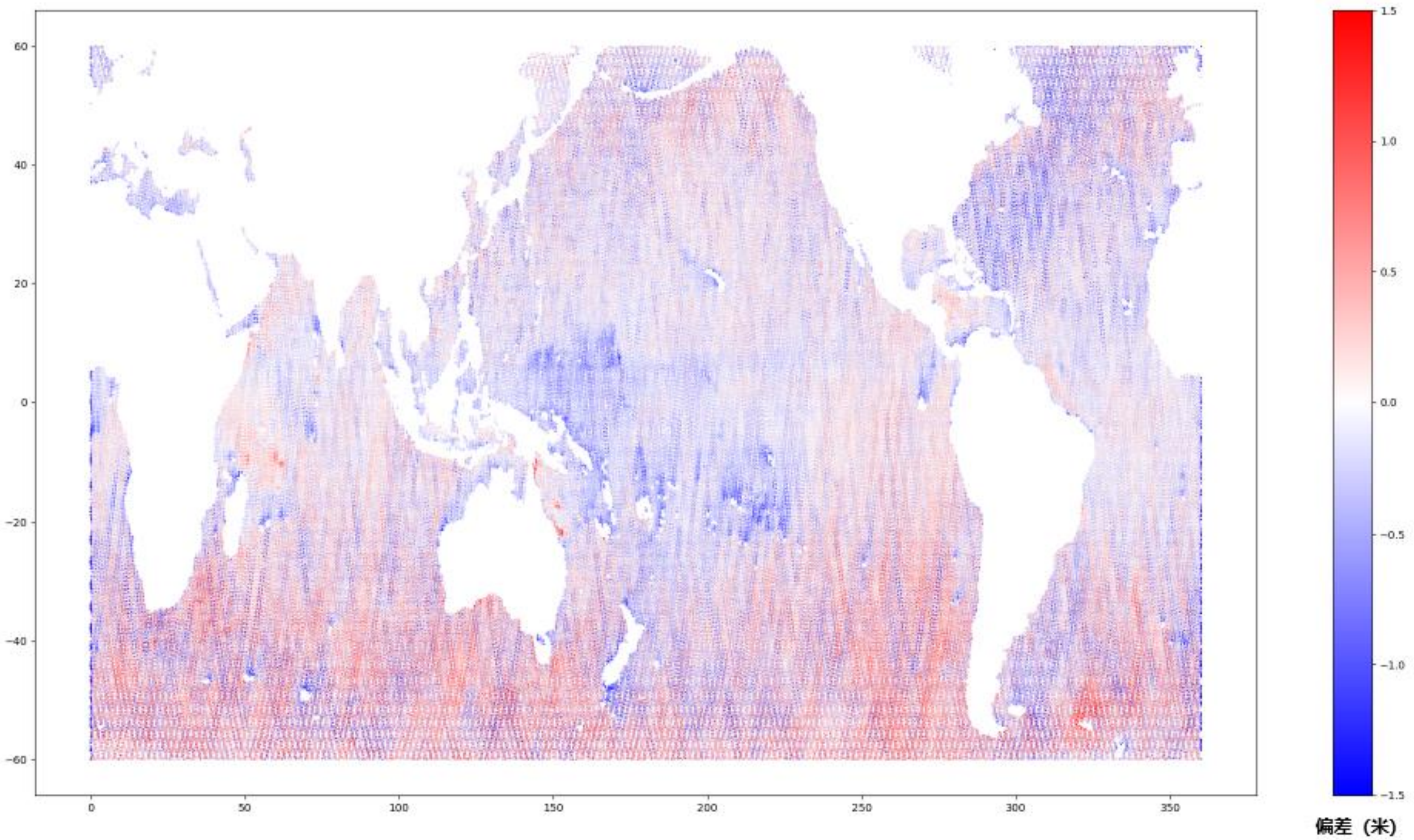
Reproduction of Island Blocking Effect on Waves



we can observe that the super-resolution model not only possesses the capability to generate high-resolution data but also can supplement high-frequency details that are missing in coarse-resolution data. This is something that traditional interpolation methods may struggle to achieve."

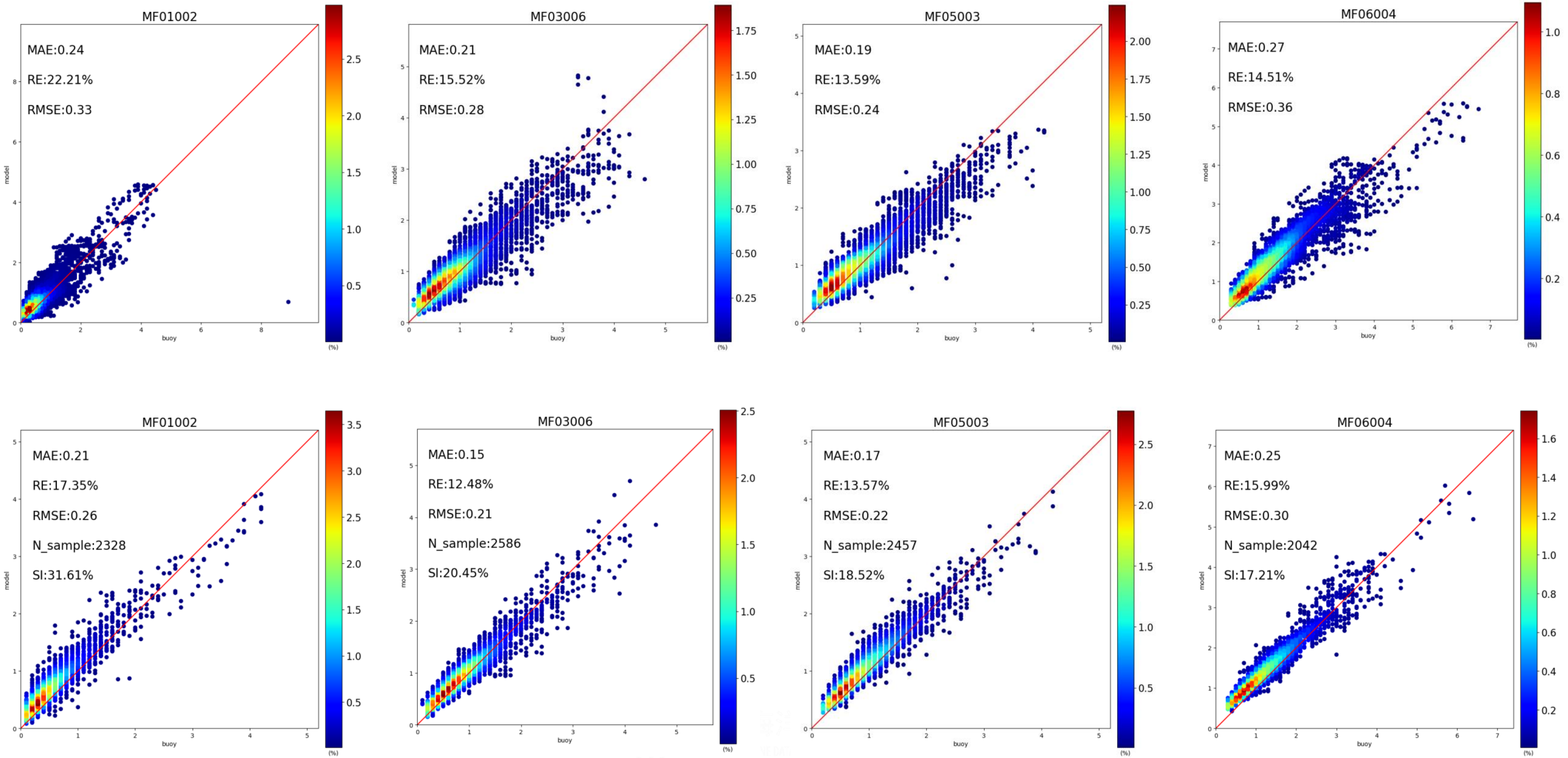
Wave Intelligent Forecasting Model - Global Model(Vit + SR)





we conducted a one-year forecasting experiment using the 0.4-degree global intelligent wave forecasting model combined with the super-resolution model. The driving wind field was based on the ECMWF's forecast wind fields for the year 2023. Currently, only the forecast results for 24 hours have been validated. the deviation distribution of global significant wave height appe ars reasonable, with no apparent regions exhibiting significant anomalies.

However, the performance is slightly inferior compared to ECMWF's IFS forecast



We also selected a few buoys in the coastal of China for simple validation. The top row shows is the intelligent forecasting, the bottom row shows the ECMWF IFS forecasting.

Although only a few buoys were selected, it is evident that the results of the intelligent forecasting exhibit greater divergence, and the overall validation metrics are inferior to those of ECMWF.

Results and Discussion

Summary

- our model is trained using reanalysis data, which may not be suitable for forecasting wind fields.We have encountered similar issues when tuning parameterization schemes for numerical models using reanalysis data.
- may be that our model structure is relatively simple, and the training data have a relatively short time
- the same model structure may lack universality as the simulated region expands. (region 1.5day ,global 2weeks)