Statistical spatial downscaling of significant wave height in a regional sea from the global ERA5 dataset

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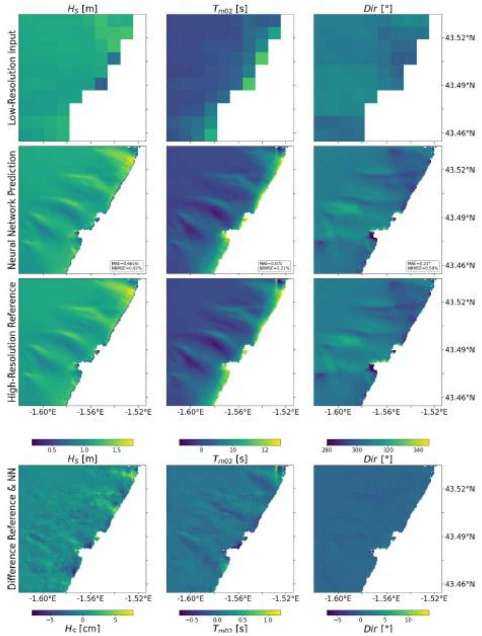
Introduction

- High-resolution significant wave height (SWH):
  - wave energy project planning, ship navigation, marine structure design etc.
- Dynamical downscaling:
  - physics based numerical models
  - Time consuming for fine scales
- Statistical downscaling:
  - Statistical relationships
  - Time efficient
  - machine learning, in particular, convolutional neural network (CNN)

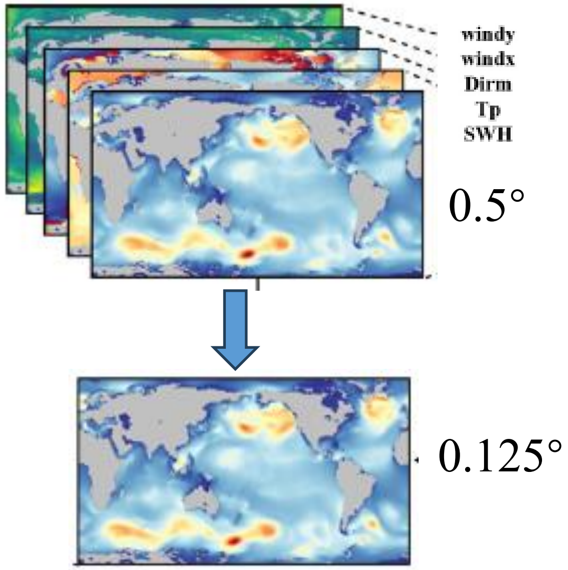
Introduction: Statistical downscaling

- Classifications based on predictor and target variables:
  - **Self-variable**: e.g., SWH to SWH
  - **Cross-variable**: e.g., wind to SWH
- Training framework:
  - **Perfect**: predictor data from coarsened data of regional models
  - **Imperfect**: predictor data from sources other than the above (useful for downscaling physical fields from publicly available global dataset)

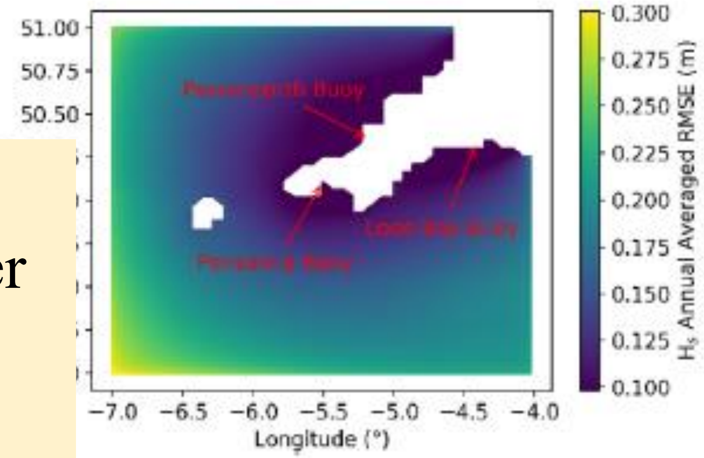
Lack of study on statistical spatial wave downscaling: with self-variable approach under imperfect framework, with the cross-variable approach using solely wind as predictors



Wave parameters 800 m -> 50 m (Kuehn et al., 2023)



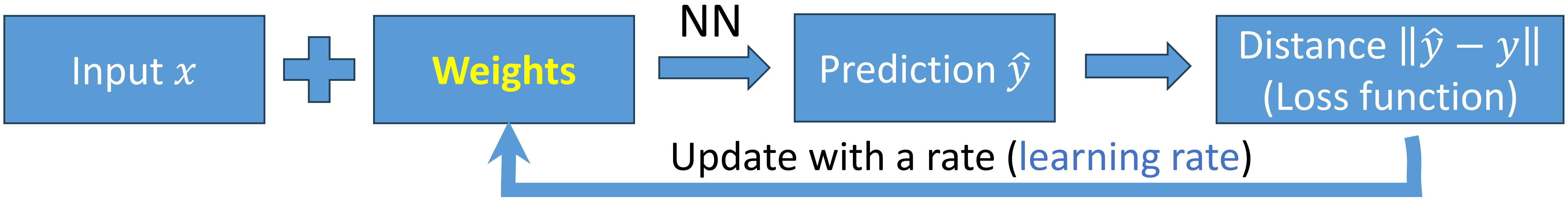
Multiple variables -> SWH (Wu et al., 2024)



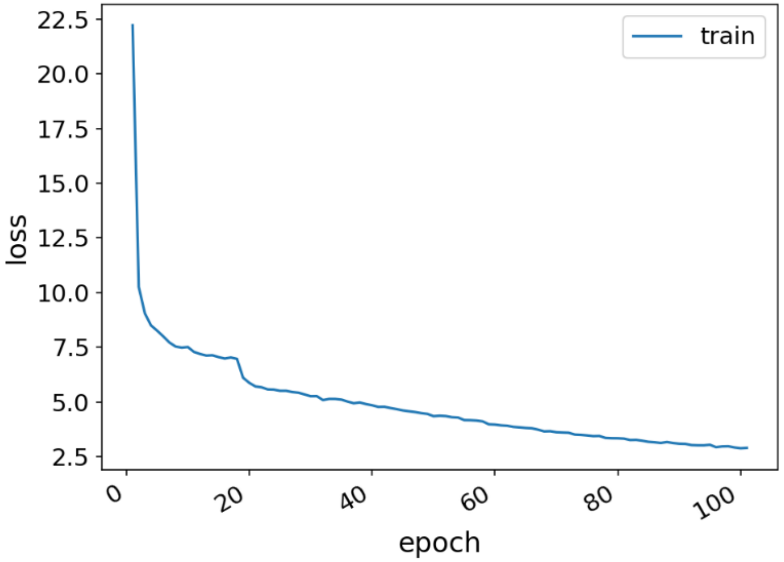
Buoy data->spatial SWH Random forest & linear regression (Chen et al., 2021)

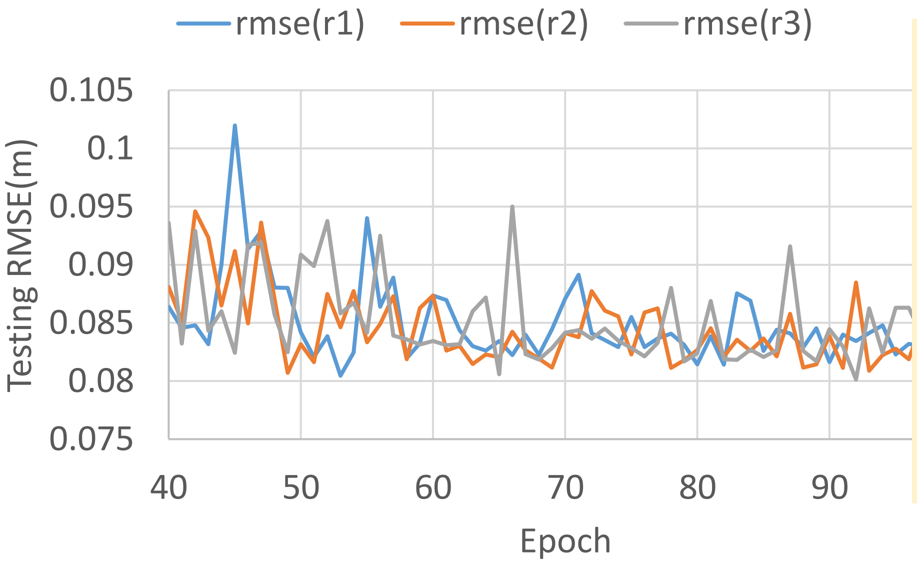
Introduction: Statistical downscaling

- Neural network (NN): like a function F that maps the input x to target y. The goal is to find *coefficients* (weights) in the function $\hat{y} = F(x)$ such that *the distance between prediction $\hat{y}$ and target y* (loss function) is minimized.



- This process is repeated a few times through *the entire training dataset* (epoch).





How to reduce **instability** in NN model prediction? What about traditional deterministic model like **linear regression**?

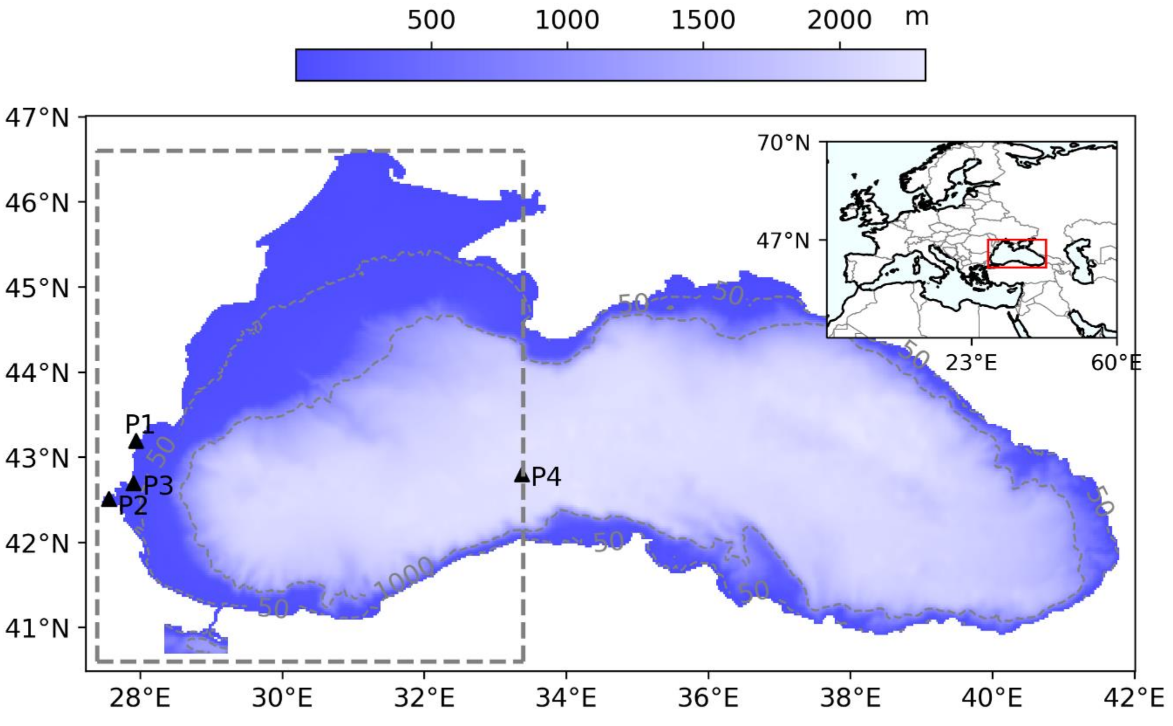
Aim of the research

- We proposes an **ensemble** CNN-based model and a **linear regression** model for **spatial SWH downscaling** from publicly available global ERA5 dataset to regional model output. Both self-variable and cross-variable (using **wind**) SWH downscaling are explored. Specifically, the following questions are addressed:
  - (i) How **effectively** can an **ensemble method** reduce the **prediction instability** of CNN-based models for spatial SWH downscaling?
  - (ii) Does the **nonlinear** CNN-based model outperform the **linear** regression model in spatial wave downscaling with both **self-variable** and **cross-variable** approaches?

Material and methods

- Total data length: default 11680 **samples** (3 hourly), each corresponds to a 2D physical field at certain time.
- 75% (8760 samples) for training, 25% for testing.

Data source	Variables	Spatial Resolution	Spatial grids	Time coverage
ERA5	SWH (m)	0.5°×0.5°	12×12	2018-2021
ERA5	10-m wind U and V (m/s)	0.25°×0.25°	24×24	2018-2021
CMEMS	SWH (m)	0.025°×0.025°	240×240	2018-2021



Bathymetry of the Black Sea. P1, P2 and P3 are in shallow area less than 50 m, with water depths of 10, 20 and 40 m, respectively, and P4 has the highest SWH in the domain during the selected period.

Material and methods

- Super-resolution residual network (**SRResNet**), based on Ledig et al. (2017)
- Ensemble method: average epoch predictions after training loss is approximately stabilized, e.g., average predictions from the last few epochs.
  - No need to train multiple NNs
  - Directly applicable to other NNs
- **Loss function**: f-prediction, *y*-target (ground truth)
  - $L_G = \|f - y\|_2$
- Input:
  - self-variable: low-resolution SWH data; cross-variable: low-resolution wind components U&V
  - normalized using a range cover the maximum & minimum values of the variables
- Output: high resolution data (SWH)
- Scale factor: self-variable: 20 (12*12->240*240 grid points); cross-variable 10.

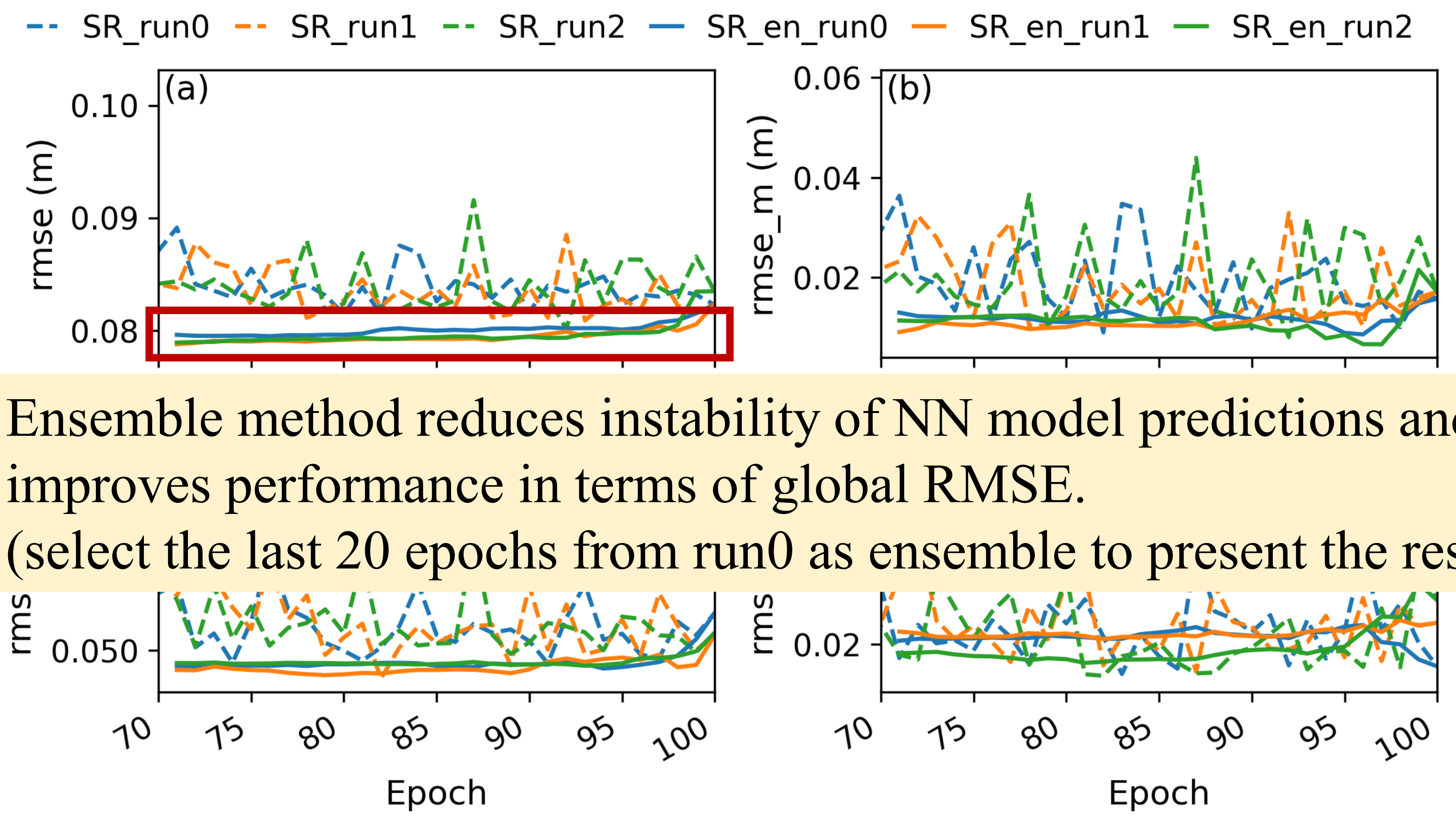
Material and methods

- Multivariate Linear regression (MLR):
- Estimates the linear relationship between two sets of variables; the target set has more than one variable, e.g., given N_I predictor variables at N_T times $\boldsymbol{X}$, to predict N_O ($N_O > 1$) target variables at the corresponding N_T times $\boldsymbol{Y}$.
- $y_{ij} = w_{0j}x_{i0} + w_{1j}x_{i1} + w_{2j}x_{i2} \ldots + w_{N_I j}x_{iN_I}$, with $x_{i0} = 1,\ i = 1, \ldots, N_T,\ j = 1, \ldots, N_O$
- In matrix form: $\boldsymbol{Y} = \boldsymbol{X}\boldsymbol{w}$, where $\boldsymbol{w}$ is the array of unknown coefficients.
- For 2D spatial downscaling, N_I / N_O = no. of low/high-resolution grid points

Material and methods

- Evaluation metrics:
- For all test dataset:
- **Mean absolute error (MAE):** $\frac{1}{T}\sum_j^T |\boldsymbol{y_j} - \boldsymbol{f_j}|$, $\boldsymbol{f}$- prediction, $\boldsymbol{y}$- target, *T*-sample No.
- **Root mean square error (RMSE):** $\sqrt{\frac{1}{T}\sum_j^T \left(\boldsymbol{y}_j - \boldsymbol{f}_j\right)^2}$
- Time average, 1st percentile and 99th percentile of the test data, e.g.,:
- $MAE\_m = \frac{1}{N}\sum_i^N |\overline{y}_i - \overline{f}_i|$, *N*-total number of grid points in a sample, overbar-time average
- $RMSE\_m = \sqrt{\frac{1}{N}\sum_i^N \left(\overline{y}_i - \overline{f}_i\right)^2}$
- Compare with direct interpolation methods e.g., nearest neighbor, radial basis function (RBF) interpolation with a linear kernel (good at extrapolation).

Results: ensemble vs original SRResNet

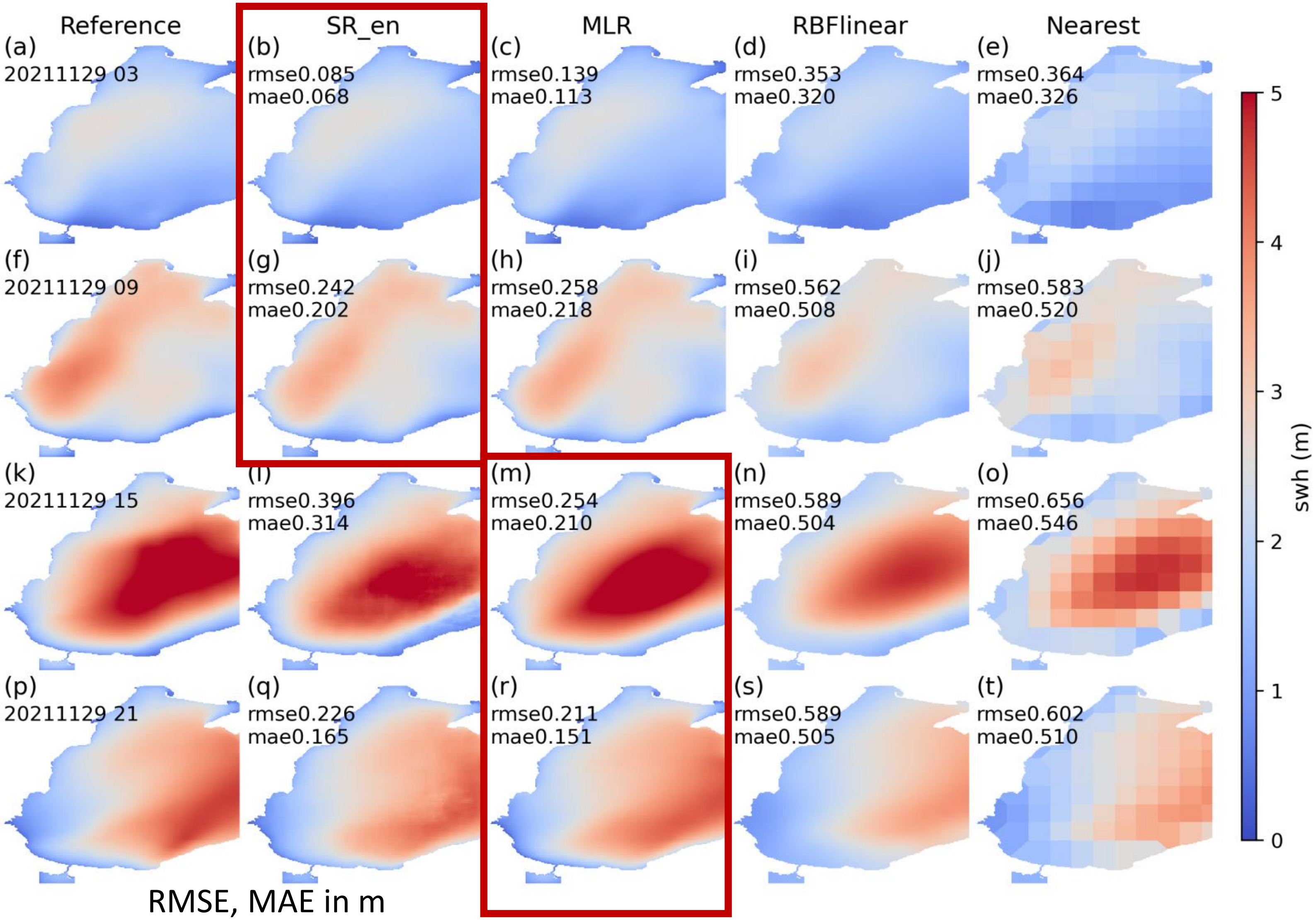


➢ Ensemble method reduces instability of NN model predictions and improves performance in terms of global RMSE.
(select the last 20 epochs from run0 as ensemble to present the results)

Comparison of error metrics between SRResNet and the ensemble SRResNet for multiple runs in self-variable SWH downscaling. For the ensemble model, the error value at an epoch number is obtained by using the averaged prediction from that epoch to the last epoch 100.

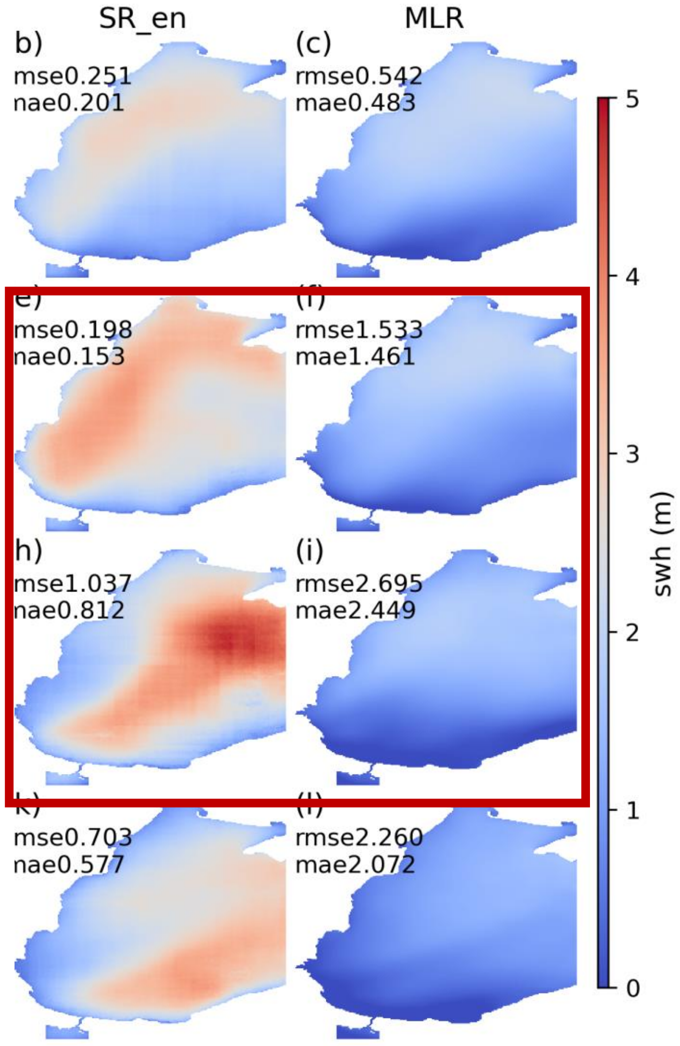
Results: downscaled SWH at selected times

Self-variable downscaled SWH at four times (a storm period)



RMSE, MAE in m

Cross-variable downscaled SWH



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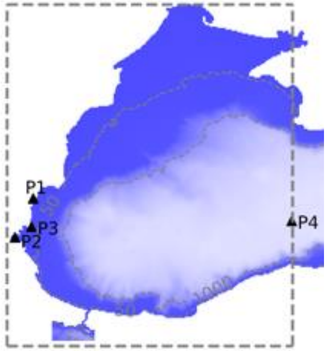
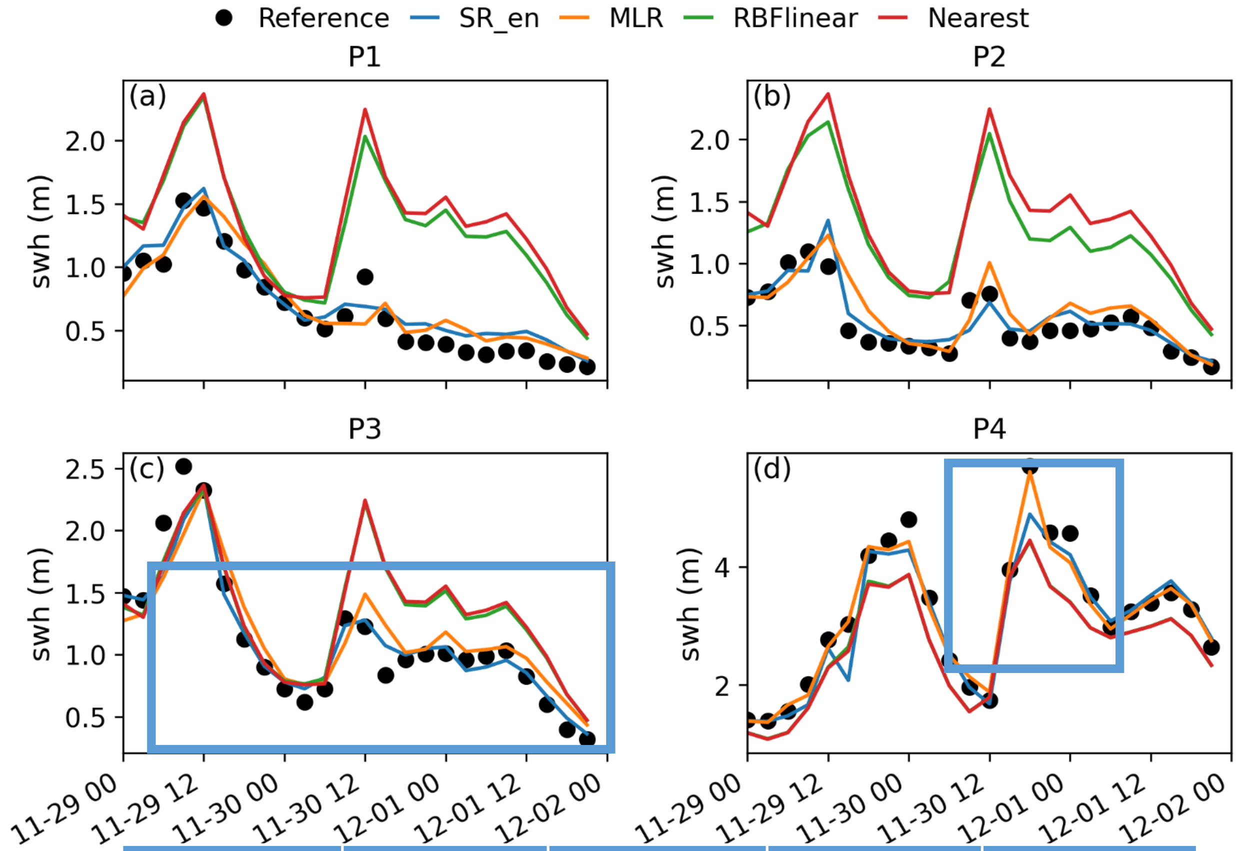
Results: downscaled SWH at selected locations

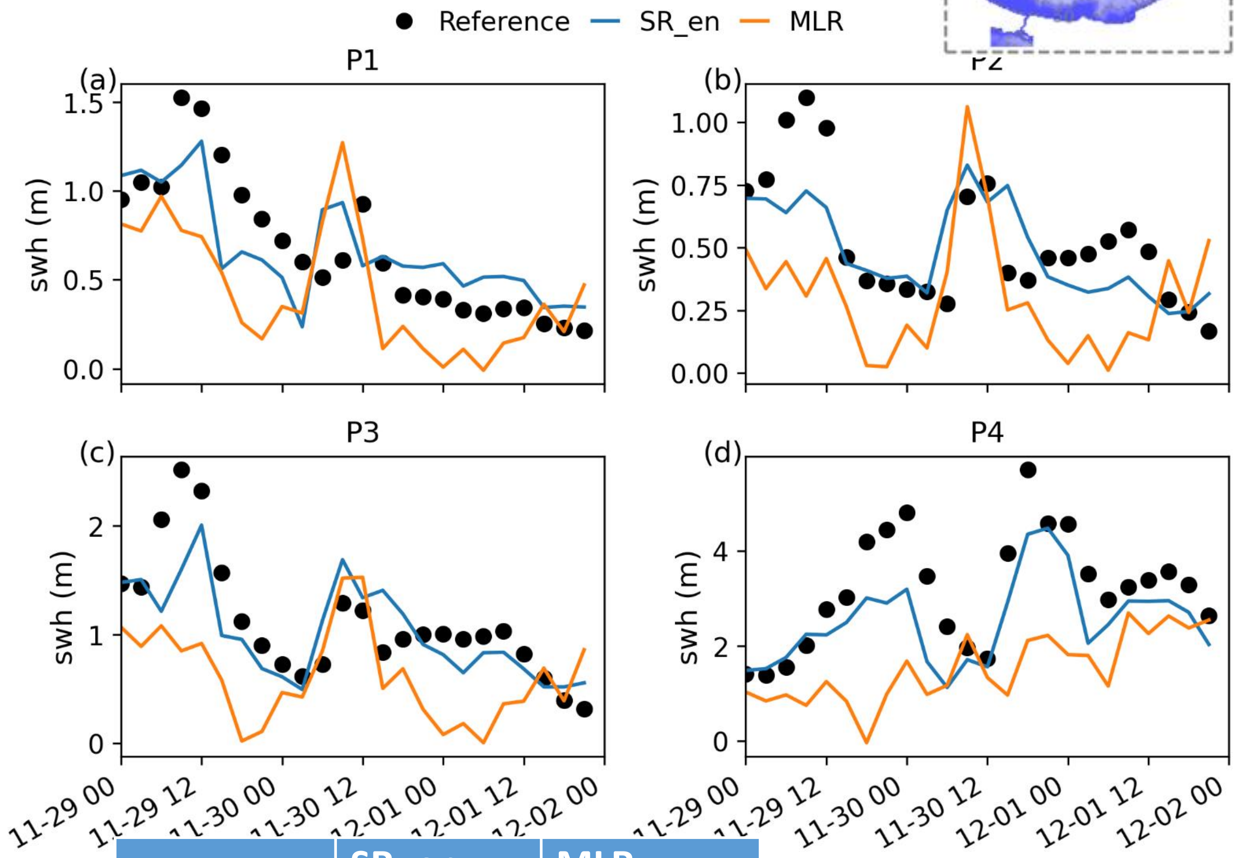


- Self-variable downscaled SWH at P1-P4



	SR_en	MLR	RBF	Nearest
Location	RMSE (m)	RMSE (m)	RMSE (m)	RMSE (m)
P1	**0.117**	0.145	0.703	0.775
P2	**0.119**	0.159	0.755	0.885
P3	**0.145**	0.219	0.380	0.393
P4	0.314	**0.172**	0.586	0.590

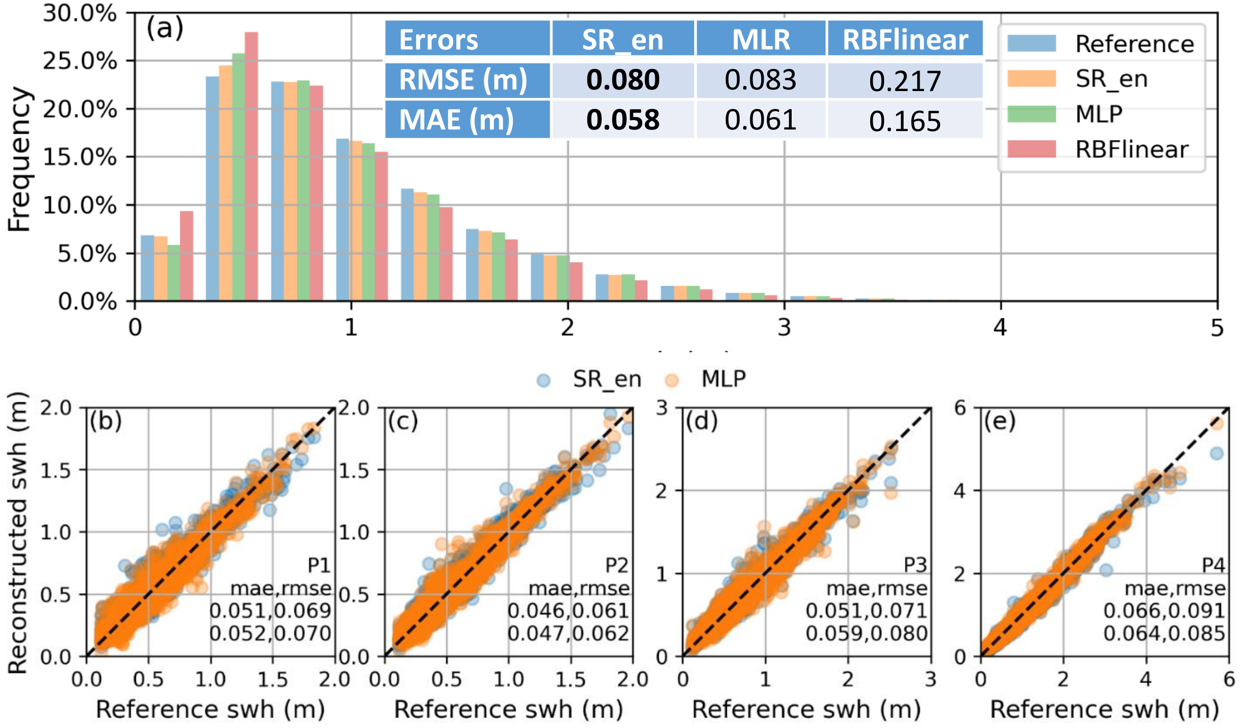
- Cross-variable downscaled SWH



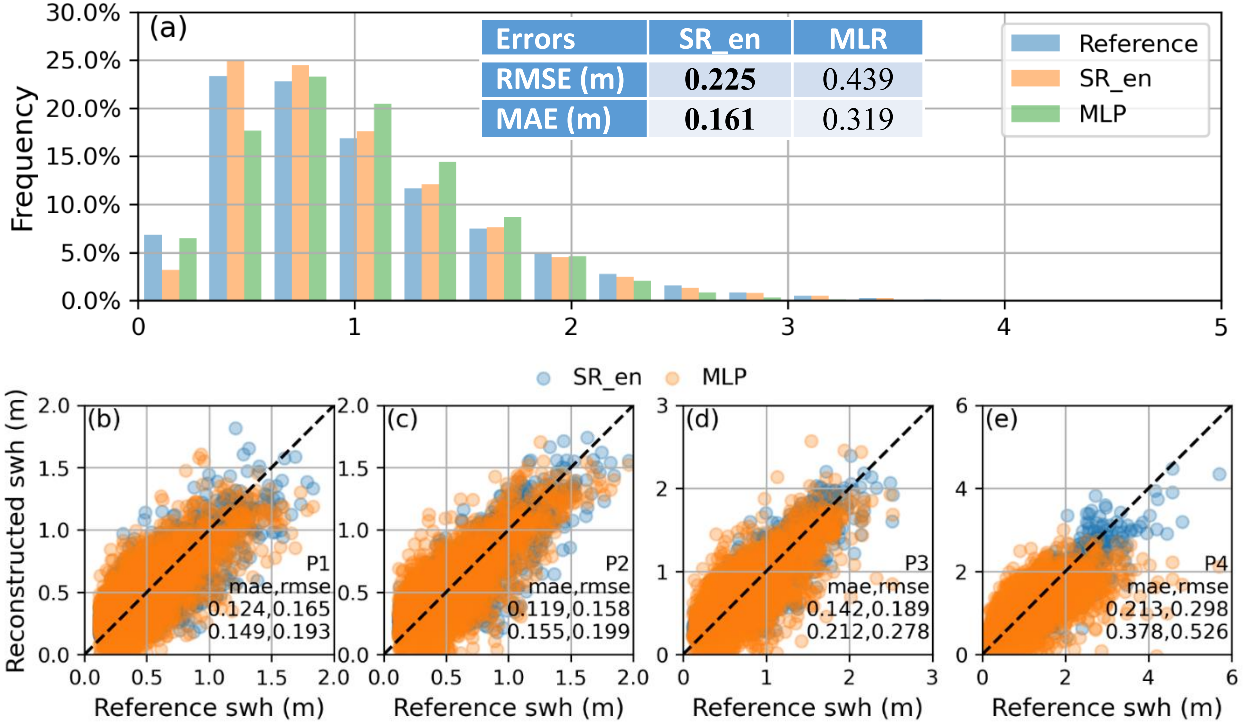
	SR_en	MLR
Location	RMSE (m)	RMSE (m)
P1	**0.255**	0.417
P2	**0.190**	0.358
P3	**0.360**	0.744
P4	**0.894**	2.055

Results: distribution of downscaled SWH

Distribution of self-variable downscaled SWH at all grid points and locations P1-P4



Distribution of cross-variable downscaled SWH at all grid points and locations P1-P4



- Ensemble SRResNet and MLR have similar performance in self-variable SWH downscaling in the Black Sea;
- In cross-variable downscaling, the former still works, while MLR fails.

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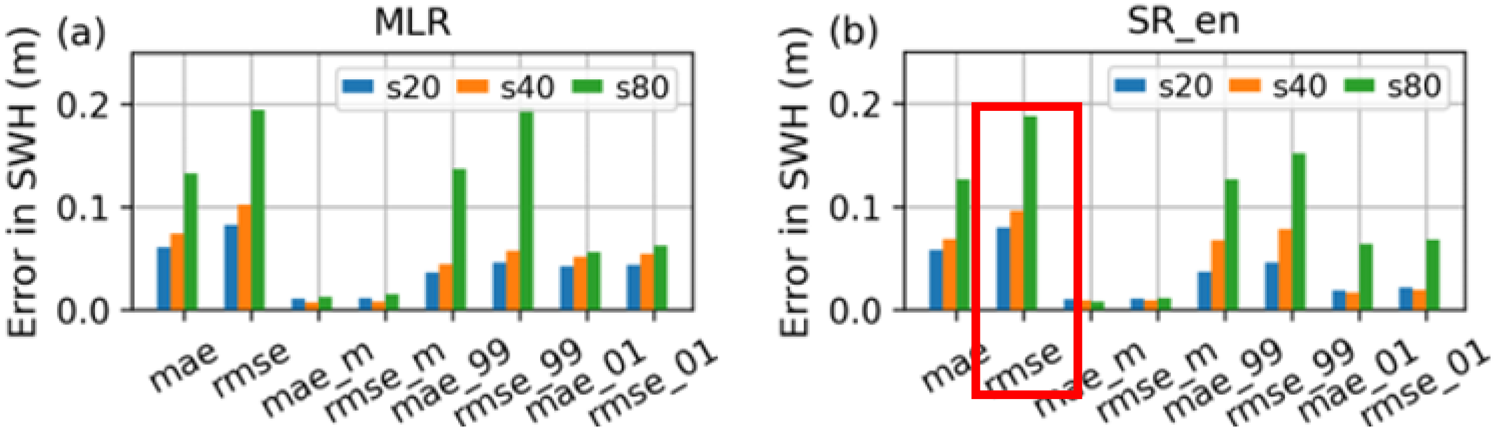
Results: Self-variable vs cross-variable

- Scale factor (self-variable) :
  - Performance with a scale of 40 close to that with 20.
  - A scale of 80 gives smaller global RMSE than that of cross-variable approach with a scale of 10 (0.225 m, ensemble).



Result sensitivity to scale factors for self-variable wave downscaling. Scales 40 and 80 are coarsened ERA5 data.

- Self-variable vs cross-variable:
  - Likely relationship between low- and high-resolution SWH is approximately linear, whereas that between low-resolution wind and high-resolution SWH is nonlinear.
  - For application: self-variable approach when possible.

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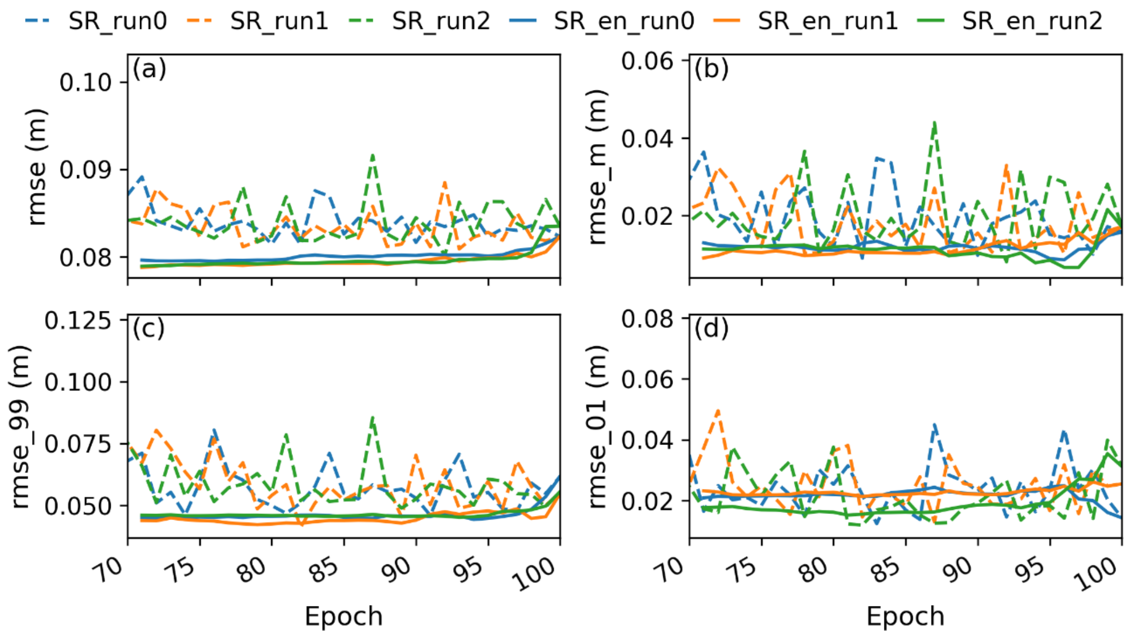
Summary

- The ensemble approach significantly reduces the prediction instability of the neural network



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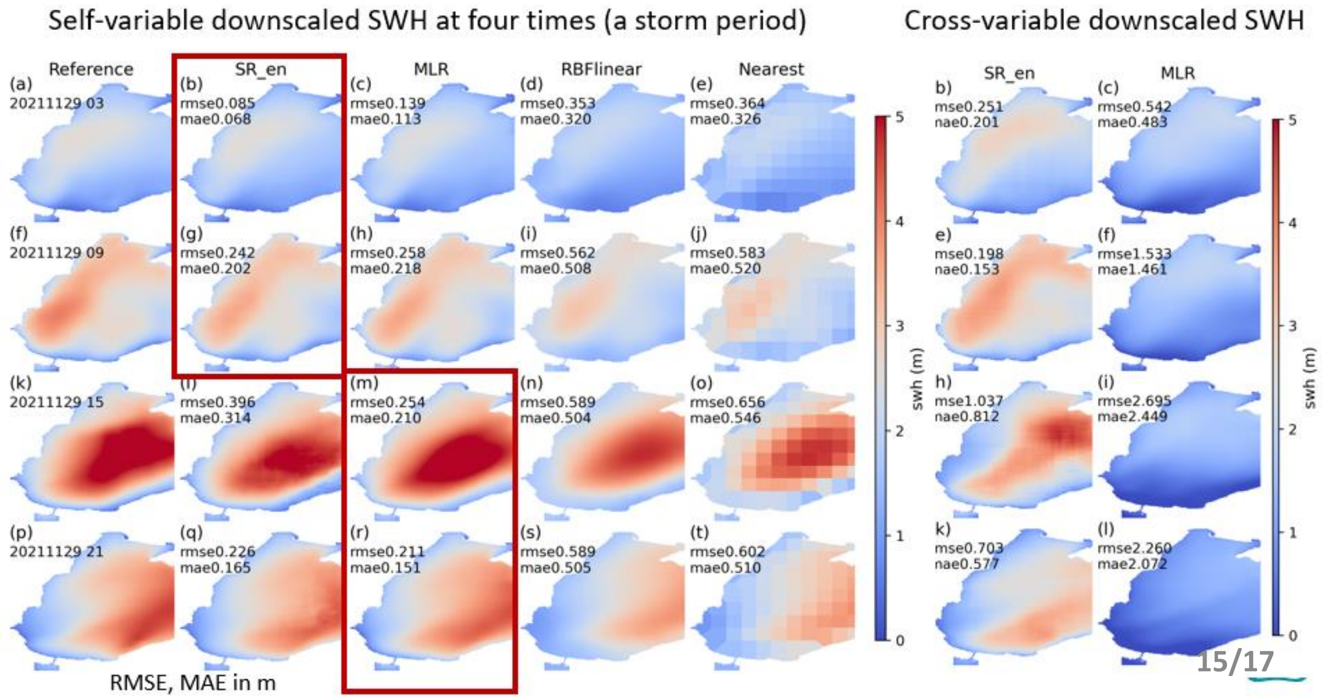
- In cross-variable downscaling, the former still works, while the latter fails.



Main references

- Ledig, C., Theis, L., Huszar, F., Caballero, J., Cunningham, A., Acosta, A., Aitken, A., Tejani, A., Totz, J., Wang, Z., Shi, W., 2017. Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network. https://doi.org/10.48550/arXiv.1609.04802
- Kuehn, J., Abadie, S., Liquet, B., Roeber, V., 2023. A deep learning super-resolution model to speed up computations of coastal sea states. Applied Ocean Research 141, 103776. https://doi.org/10.1016/j.apor.2023.103776
- Wu, X., Zhao, R., Chen, H., Wang, Z., Yu, C., Jiang, X., Liu, W., Song, Z., 2024. GSDNet: A deep learning model for downscaling the significant wave height based on NAFNet. Journal of Sea Research 198, 102482. https://doi.org/10.1016/j.seares.2024.102482
- Chen, J., Pillai, A.C., Johanning, L., Ashton, I., 2021. Using machine learning to derive spatial wave data: A case study for a marine energy site. Environmental Modelling & Software 142, 105066. https://doi.org/10.1016/j.envsoft.2021.105066

- Yuan, B., Ricker, M., Chen, W., Jacob, B., Pham, N.T., Staneva, J., 2025. Statistical spatial downscaling of significant wave height in a regional sea from the global ERA5 dataset. Ocean Engineering 329, 121100. https://doi.org/10.1016/j.oceaneng.2025.121100

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Thank you!

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