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Prediction of Sea Surface Currents around the Korean Peninsula using artificial neural networks

AI-TT Workshop @ Montréal, Canada
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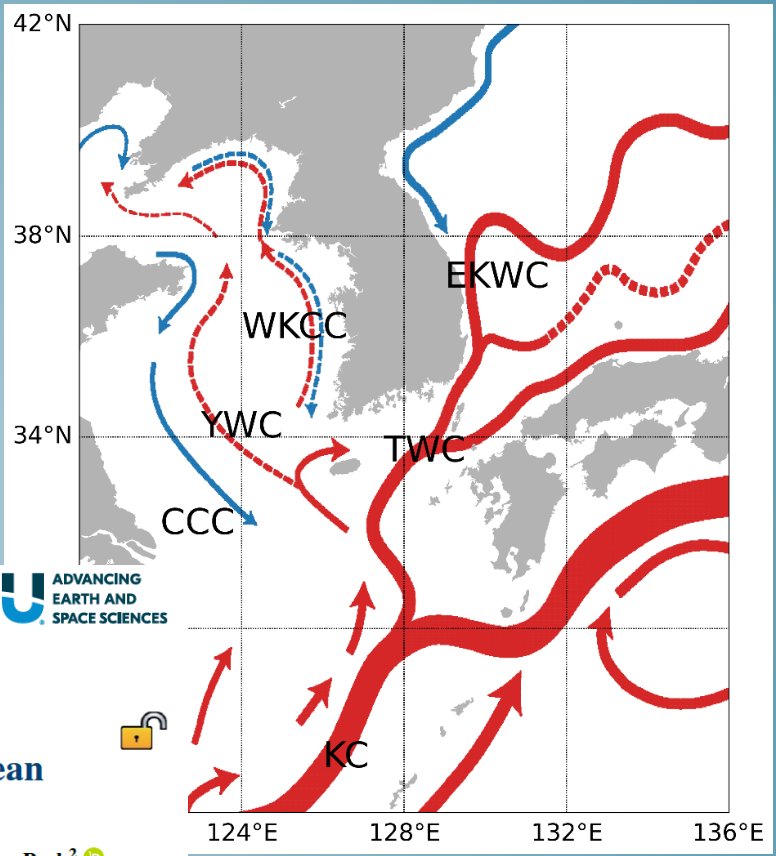
INHA UNIVERSITY
KIOST KOREA INSTITUTE OF OCEAN SCIENCE & TECHNOLOGY
Korea Hydrographic and Oceanographic Agency
CHONNAM NATIONAL UNIVERSITY

AI model for surface current prediction

- Seas around Korean peninsula show different characteristics: Yellow Sea = tides dominant East/Japan Sea = mesoscale processes



AGU ADVANCING EARTH AND SPACE SCIENCES

JGR Machine Learning and Computation

RESEARCH ARTICLE

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Prediction of Sea Surface Current Around the Korean Peninsula Using Artificial Neural Networks

Jeong-Yeob Chae[1], Hyunkeun Jin[2], Inseong Chang[3], Young Ho Kim[3], Young-Gyu Park[2], Young Taeg Kim[4], Boonsoon Kang[5], Min-su Kim[4], Ho-Jeong Ju[1], and Jae-Hun Park[1]

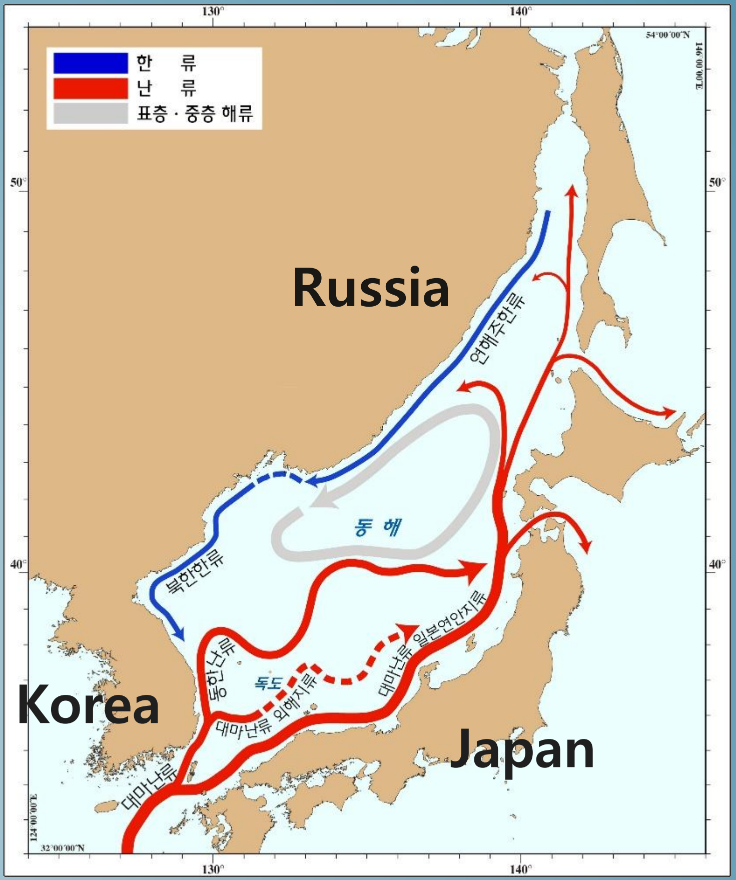
Key Points:

- Using a convolutional neural network (CNN), sea surface currents were predicted with 1/24° spatial resolution

- We demonstrated an efficient surface current prediction framework around Korean peninsula using a 3-dimensional convolutional neural network (3-D CNN)

Study Area: East/Japan Sea

- Geographic Features
  - Semi-enclosed marginal sea
  - Bounded by Korea, Japan and Russia
  - Mean depth: ~1,700 m
- Oceanographic Significance
  - Miniature ocean
  - Complex circulation (EKWC, NKCC)
  - Strong seasonal variability
  - Active mesoscale eddies



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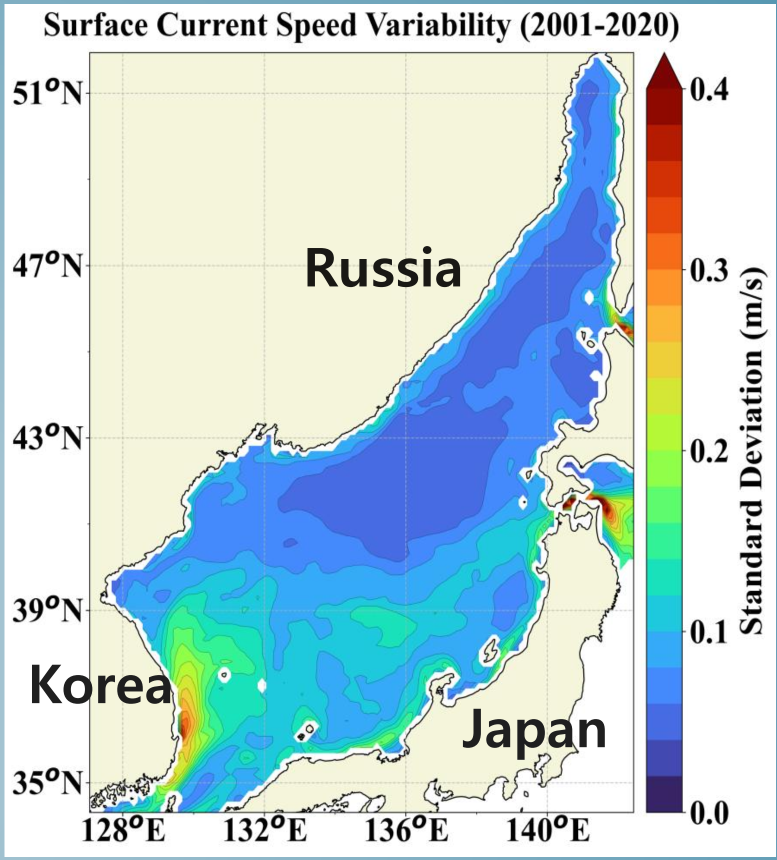
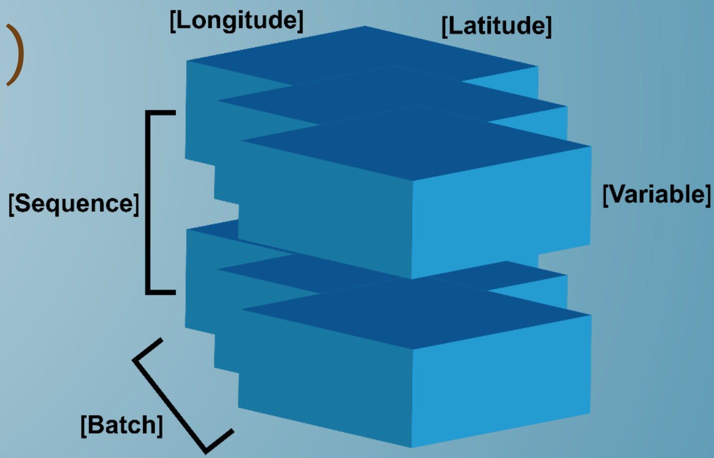


- Sea surface currents & height prediction using AI
  - Numerical model: Expansive computation cost
  - General Neural Networks: may produce physically inconsistent features

⇒ **Physics-Informed Neural Networks (PINNs)**

Data

- Inputs from numerical simulation results
  - Ocean: “KHOA” OMAP (sea surface currents, sea surface height) during 2001-2020 (20 years)
  - Atmosphere: “ECMWF” ERA5 (wind speed at 10 m above sea surface)
  - Bathymetry: “NCEI” ETOPO2022 (depth)



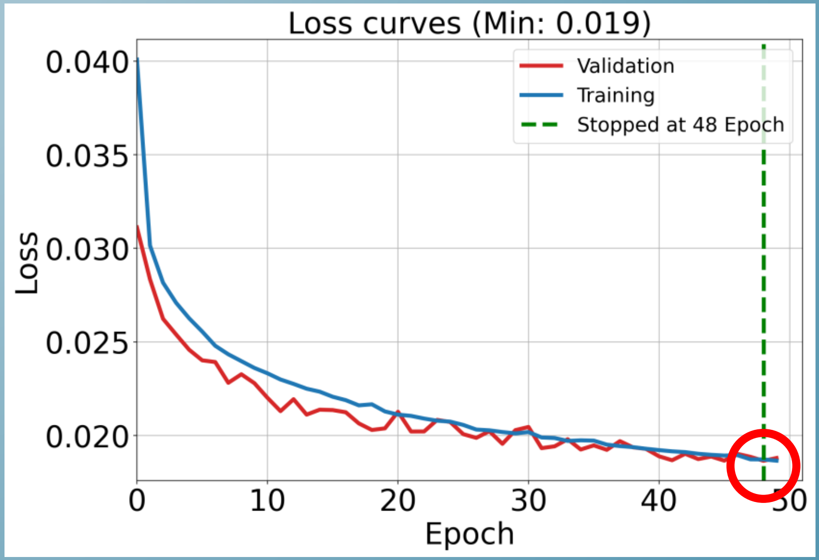
< Dataset structure >

- Preprocessing
  - Spatial and temporal interpolations
    Temporal resolution: Daily
    Spatial resolution: 1/36° (3 km)
  - 5-Dimensional Input Data for Training
    [Batch, Variables, Sequence, Latitude, Longitude]

Hyperparameters

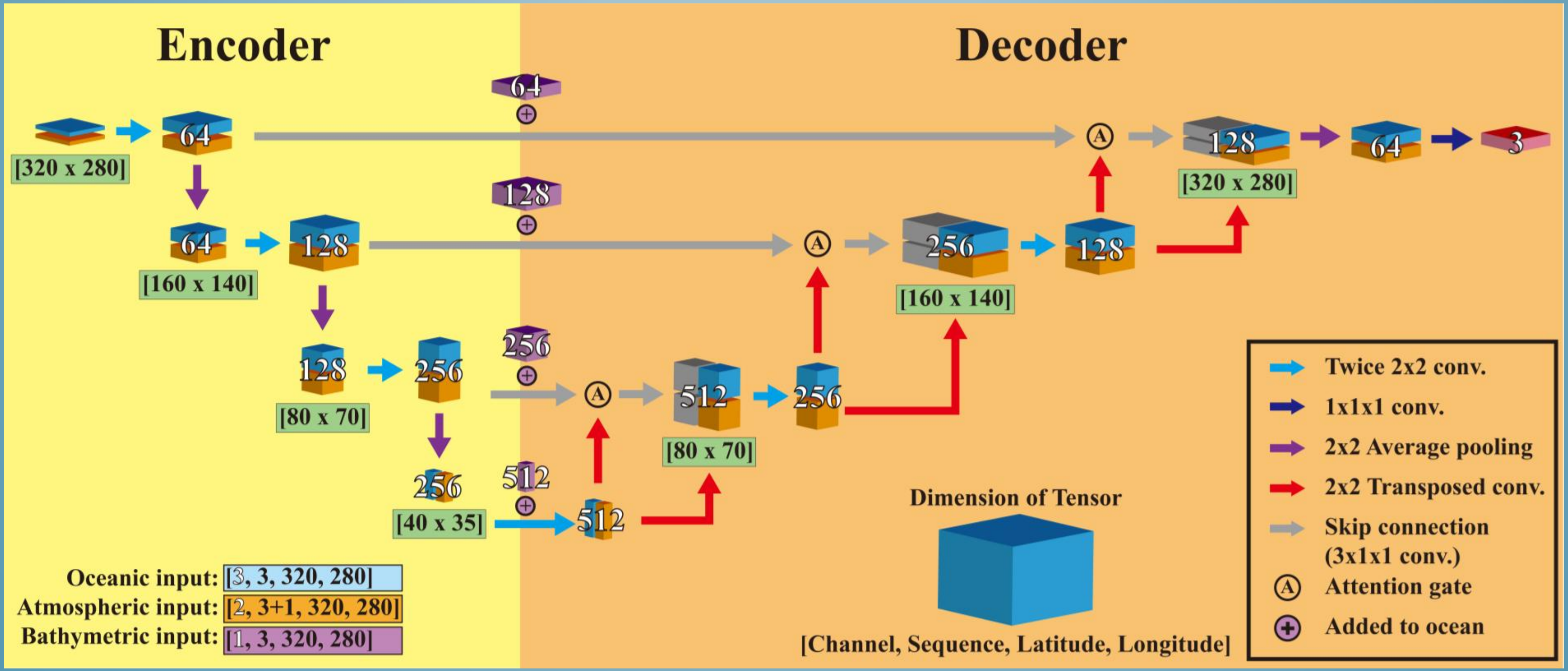
- Selecting the best version based on minimum loss and maximum correlation, while adjusting initial channel and batch size
- Training set: 2001-2016 (20% used for validation)
  Test set: 2017-2020 (4 years)
- Recursive structure: Prediction data were fed back as inputs for future predictions

Hyperparameter	Values
Initial channel	64
Batch size	32
Input variables	U, V, SSH, Depth
	U_{10}, V_{10}
	U_{10}, V_{10} of the next day
Input sequence	3 days
Learning rate	0.0001
Activation function	ELU (Exponential Linear Unit)
Loss function	MAE (Mean Absolute Error)
Optimizer	AdamW



Physics-Informed Neural Networks (PINNs)

- Attention U-Net model based on 3D-CNN (Convolutional Neural Networks)
- Incorporating physical information as constraints to maintain physical consistency
- Integrating physical constraints into the loss function



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✓ Data loss (L_{data}) = Mean Absolute Error ($y, \hat{y}$)

✓ Ageostrophic loss (L_{ageo}) = MAE ($\text{ageostrophic cur.}, \widehat{\text{ageostrophic cur.}}$)

✓ Divergence loss (L_{div}) = MAE ($\text{divergence}, \widehat{\text{divergence}}$)

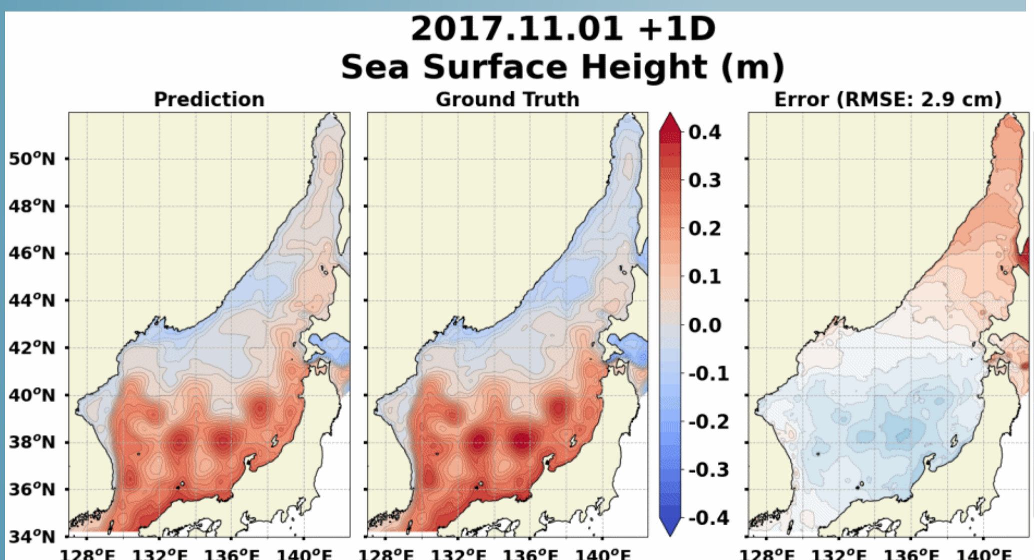
$$\left[\text{Divergence} = \frac{du}{dx} + \frac{dv}{dy}, \quad \text{Ageostrophic cur.} = \left(u + \frac{g}{f}\frac{\partial \eta}{\partial y}, v - \frac{g}{f}\frac{\partial \eta}{\partial x}\right)\right]$$

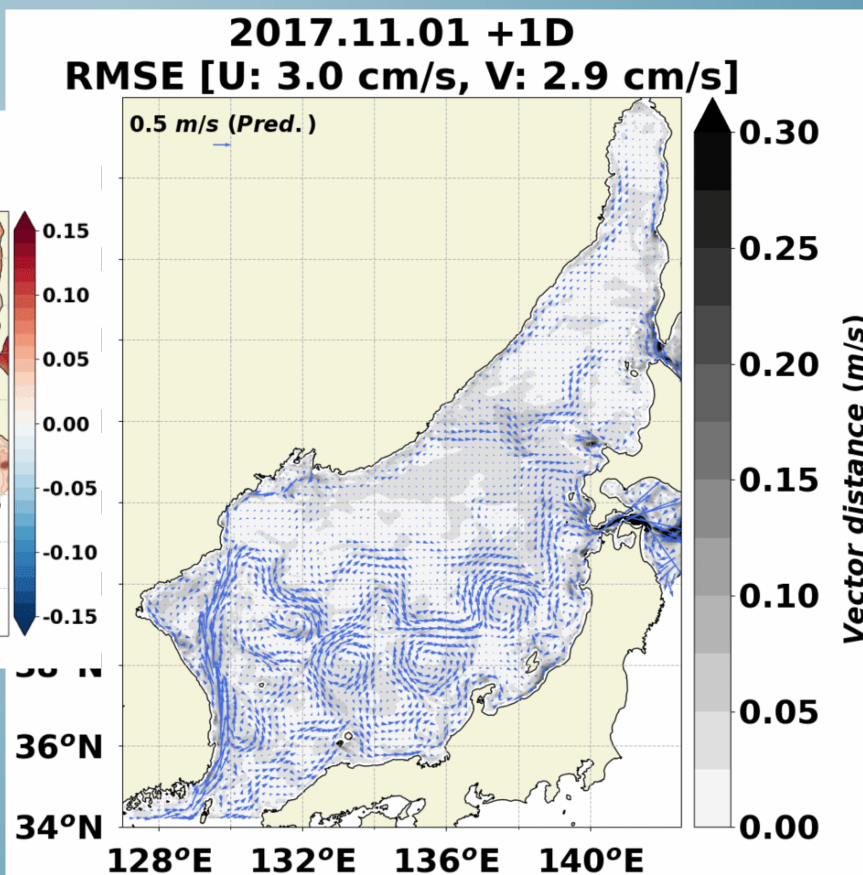
✓ After some tests:

Loss function = $\lambda_{data} L_{data} + \lambda_{ageo} L_{ageo}$

Prediction of surface currents & SSH

- Sequential 1-day predictions over a 10-day period
- Successfully reproduces energetic eddies & meandering currents
- Prediction errors remain small across most of the domain for both SSH and surface currents





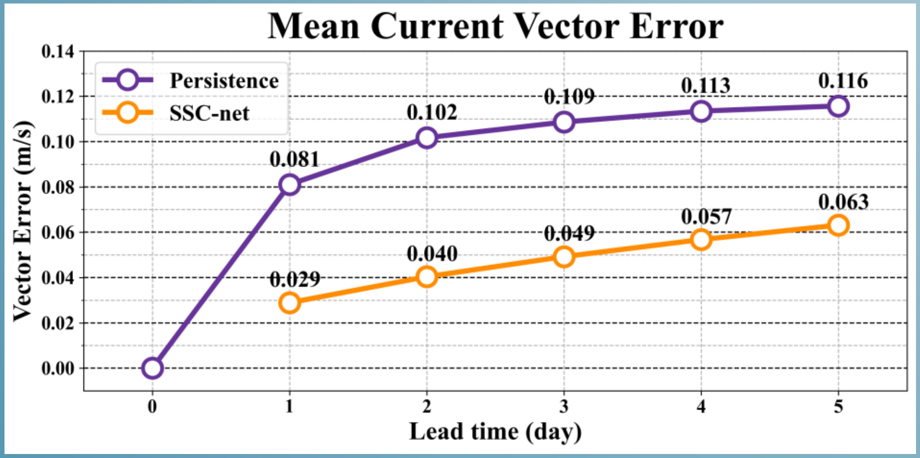
Model performance evaluation

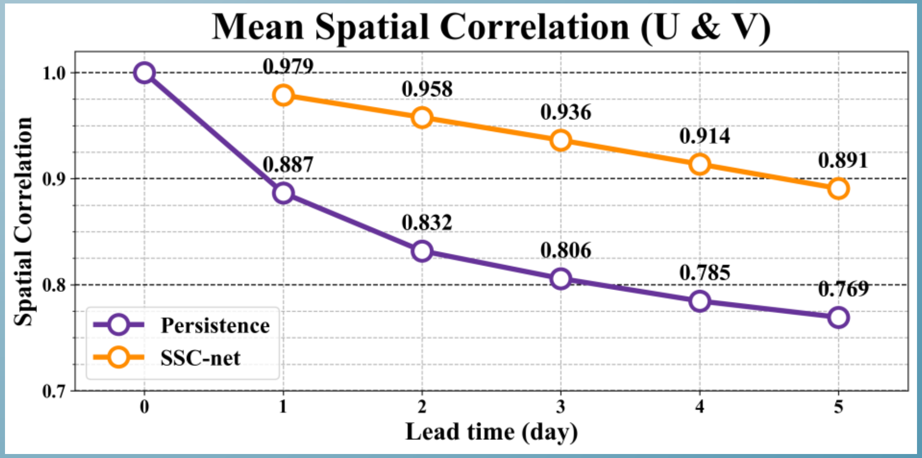
- Persistence model (the simplest baseline model): " tomorrow's conditions will be the same as today's "

  ⇒ Criteria for prediction performance

- **SSC-net (Sea Surface Current net)** achieves lower error & higher spatial correlation compared to the persistence model
- Maintains stable prediction performance due to its recursive structure

Sea Surface Currents





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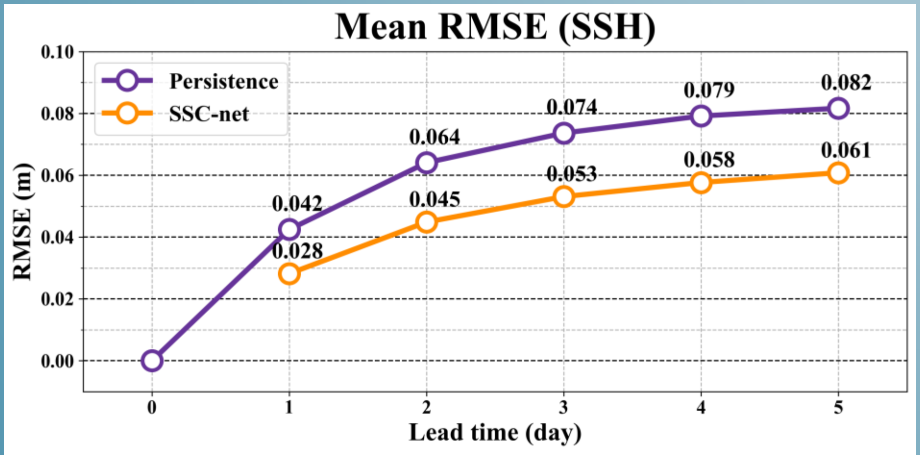
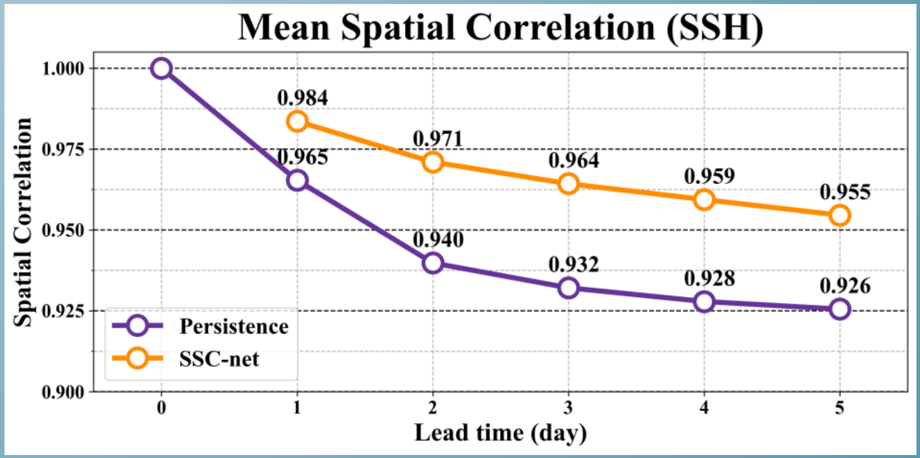
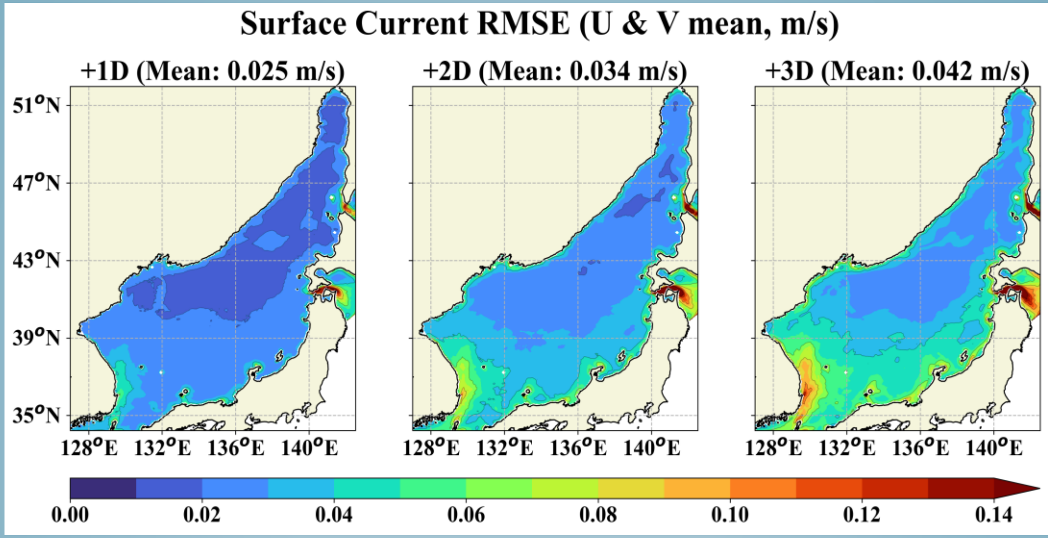
Sea Surface Heights

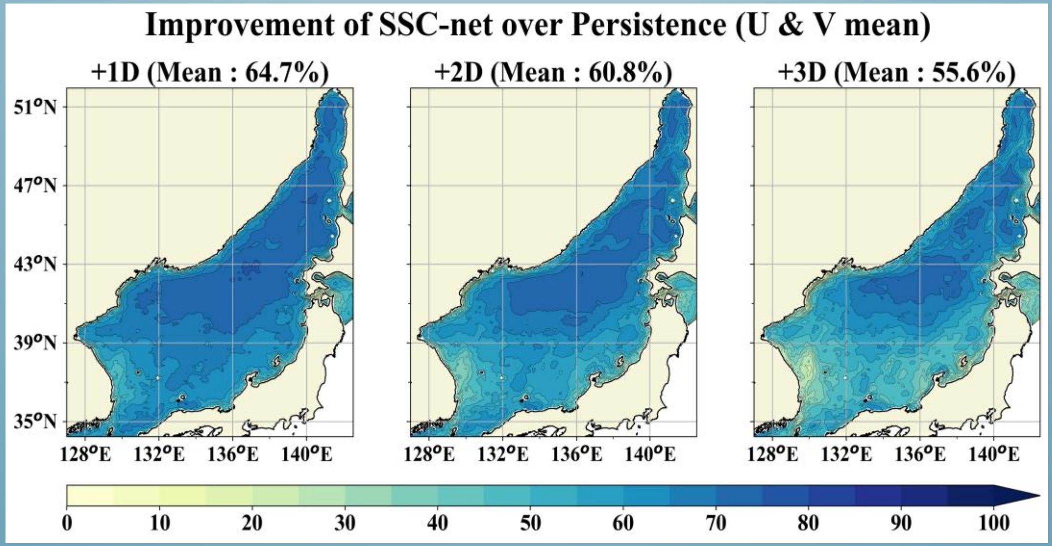




Model performance evaluation

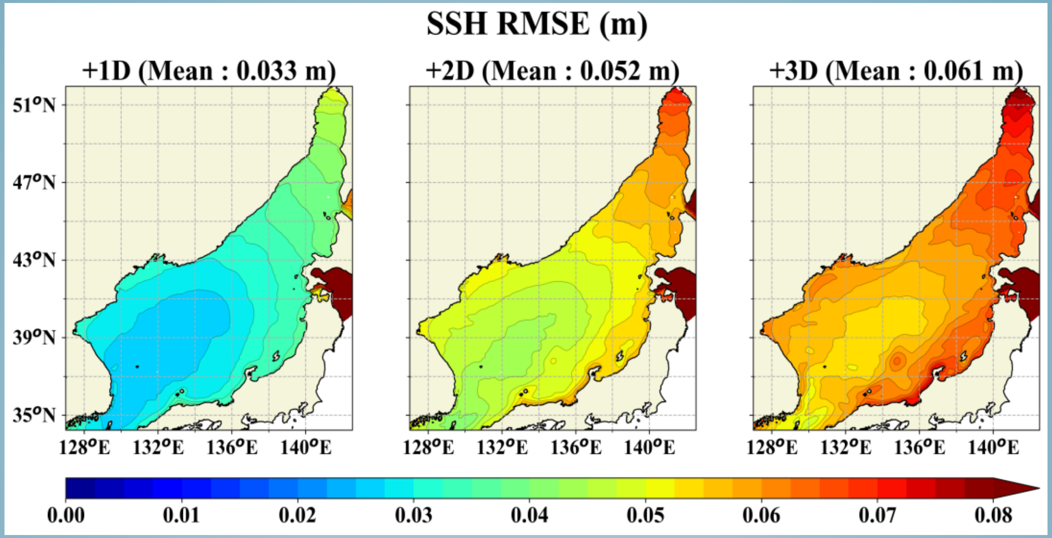
- **Surface Currents:** RMSE ~ 4 cm/s, ~ 60% improvement over the persistence model

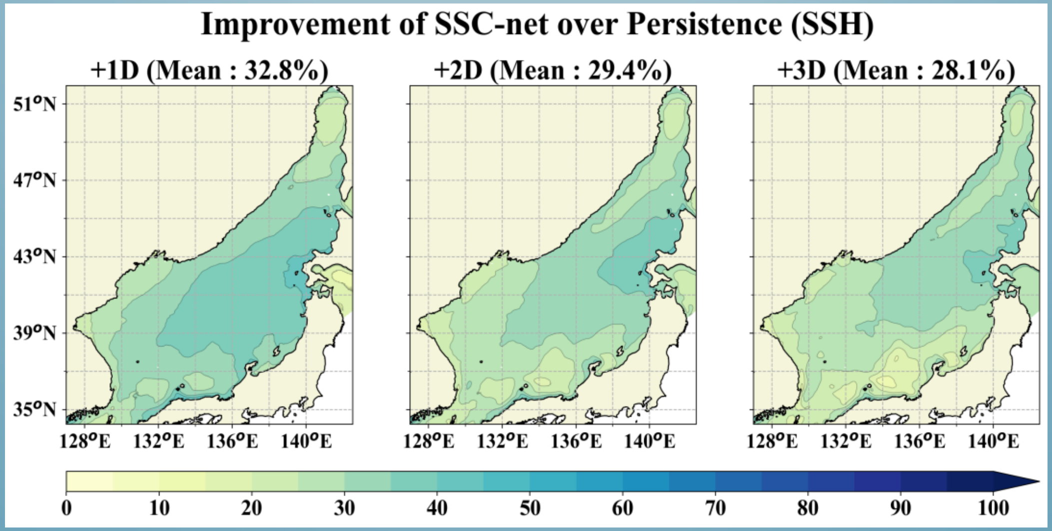




Model performance evaluation

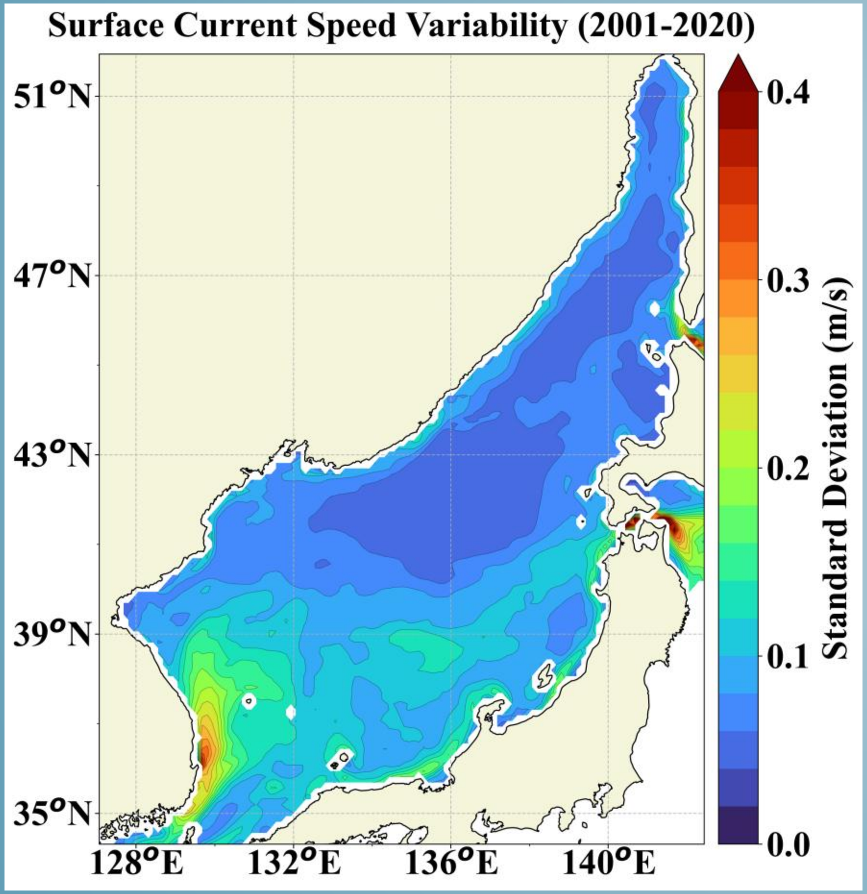
- **Sea Surface Height :** RMSE ~ 6 cm, ~ 30% improvement over the persistence model

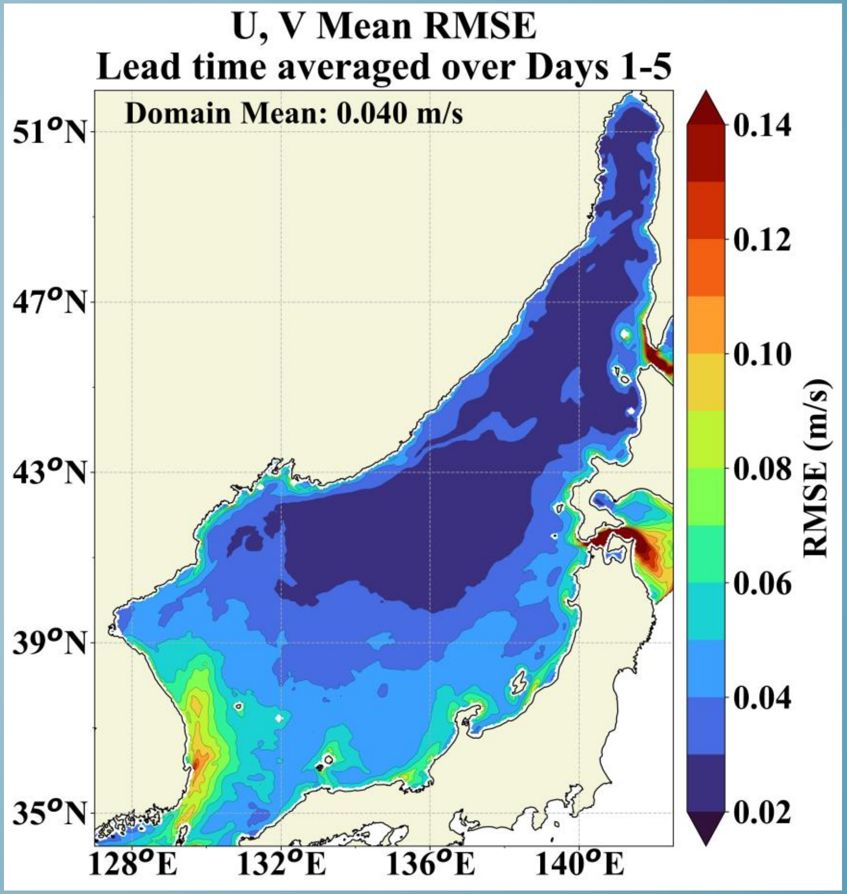




Model performance evaluation

- Higher current variability leads to lower prediction performance

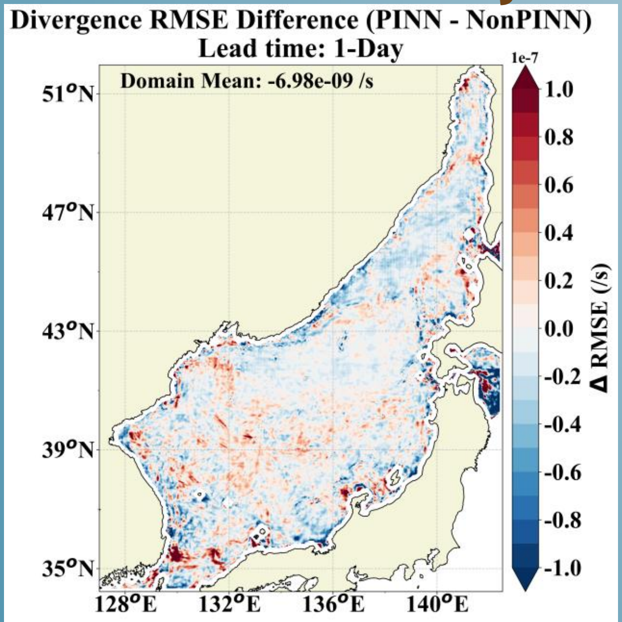




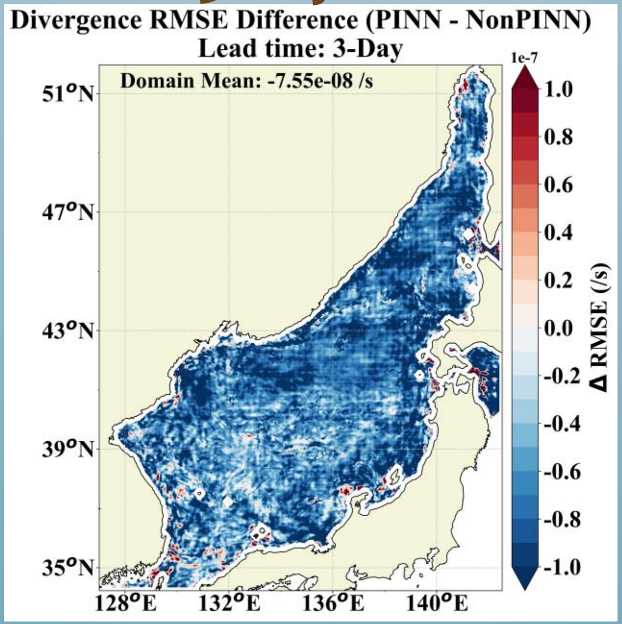
Impact of the PINN on SSC prediction

- Reduces spurious divergence across most of the basin
- Leads to lower divergence values than the Non-PINN and improving physical consistency
- Regions dominated by strong geostrophic currents show relatively persistent errors
- Physics-informed constraint is important at longer lead times

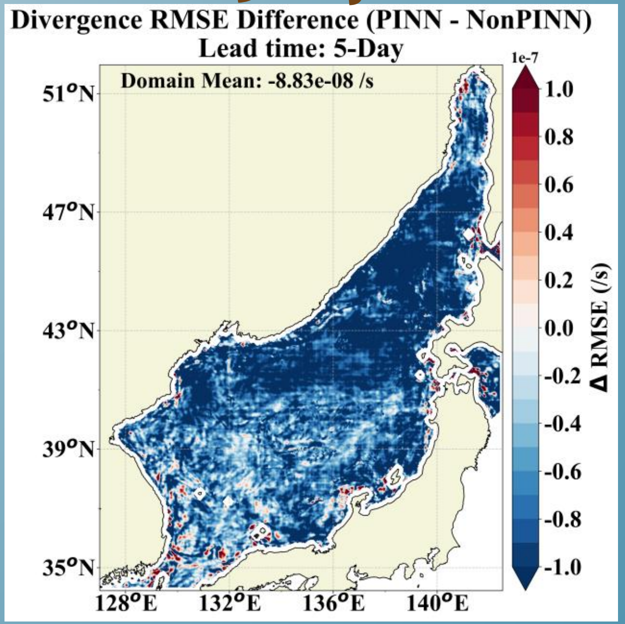
Lead time: 1 day



3 days



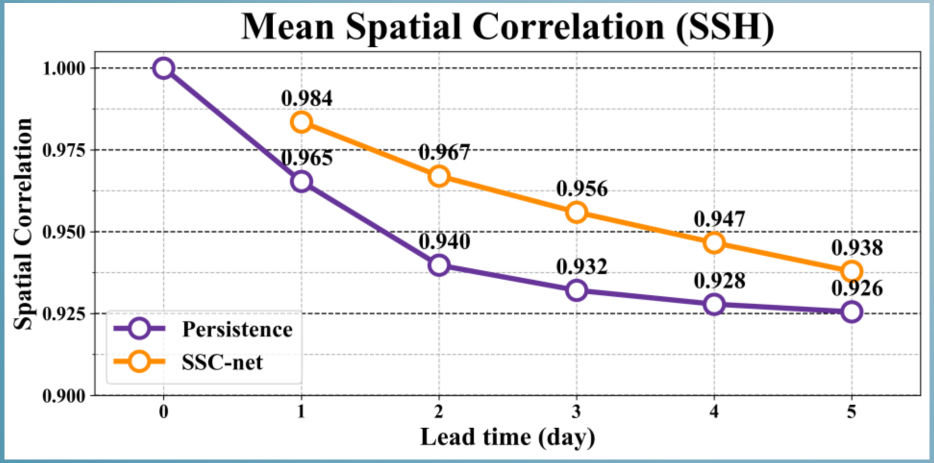
5 days



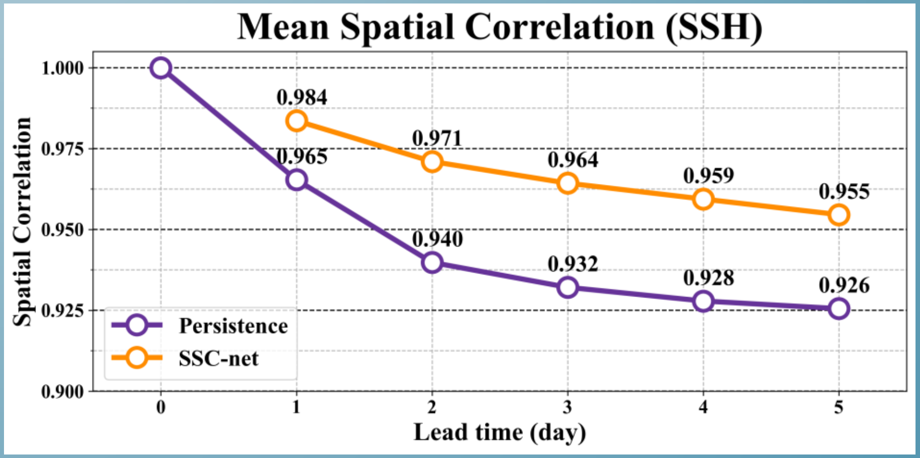
Impact of the PINN on SSH prediction

- Improvement of SSH prediction becomes more pronounced at longer lead times
- Physical constraints prevent error accumulation in recursive predictions, maintaining geostrophic consistency over time
- PINN improves the spatial structure of SSH rather than its absolute magnitude, suggesting that geostrophic constraints are more effective in shaping spatial patterns than reducing amplitude errors

Non-PINN

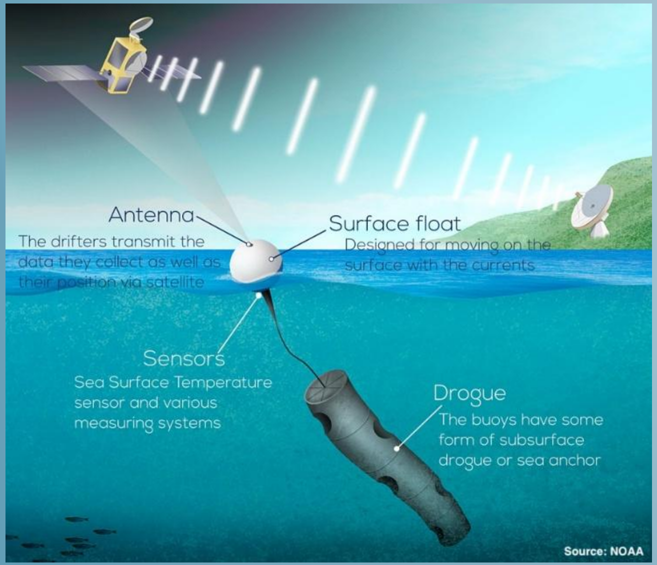


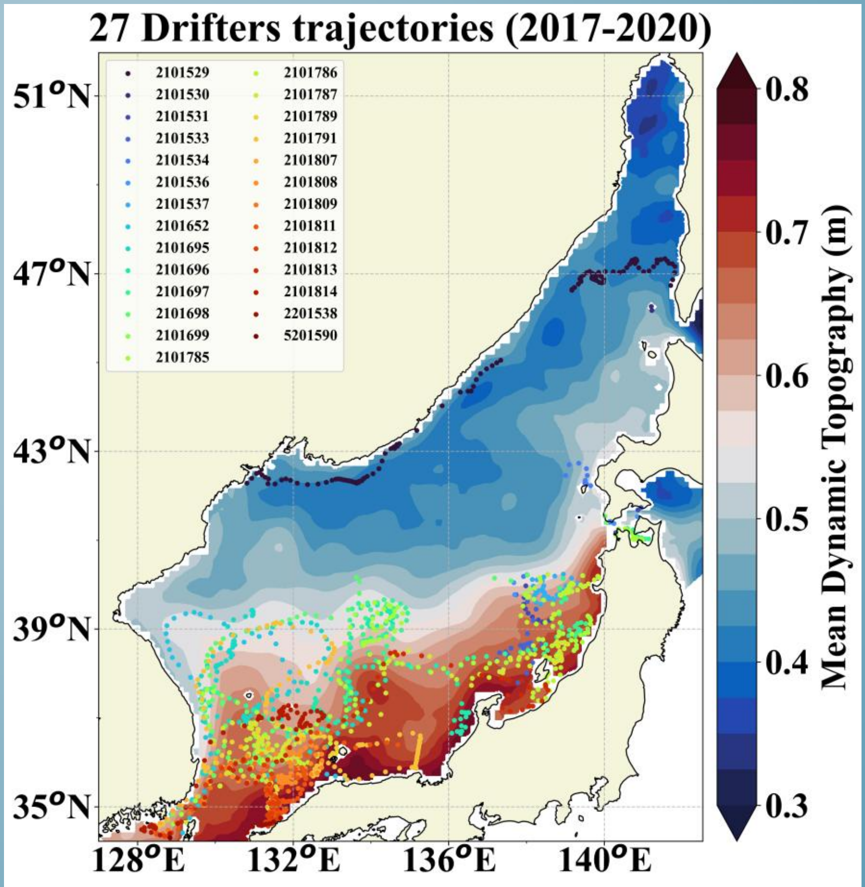
PINN



Evaluation using surface drifters

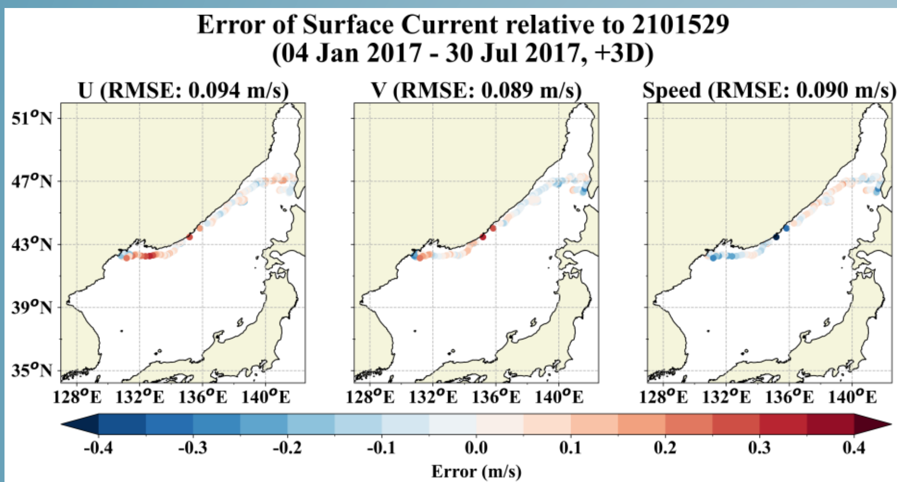
- 27 surface drifters (NOAA GDP) during 2017-2020
- 3-day low-pass filtered
- Compared with numerical models (OMAP, ES3k, GLORYS12v1)

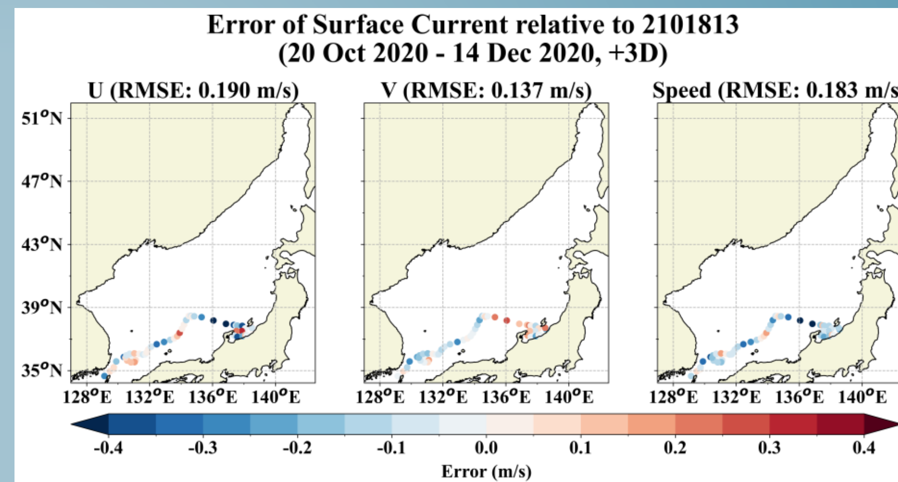


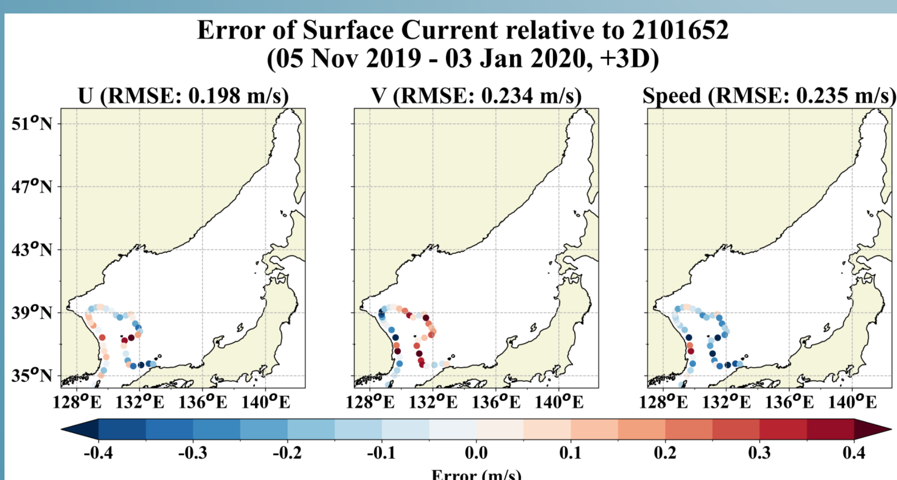


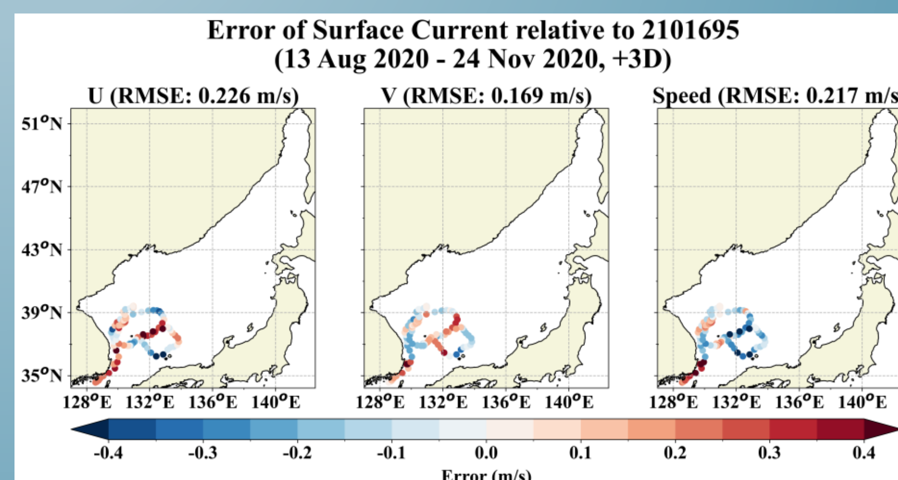
Evaluation using surface drifters

- Examples showing surface current errors
- Larger errors in dynamically active regions (coastal & boundary currents)









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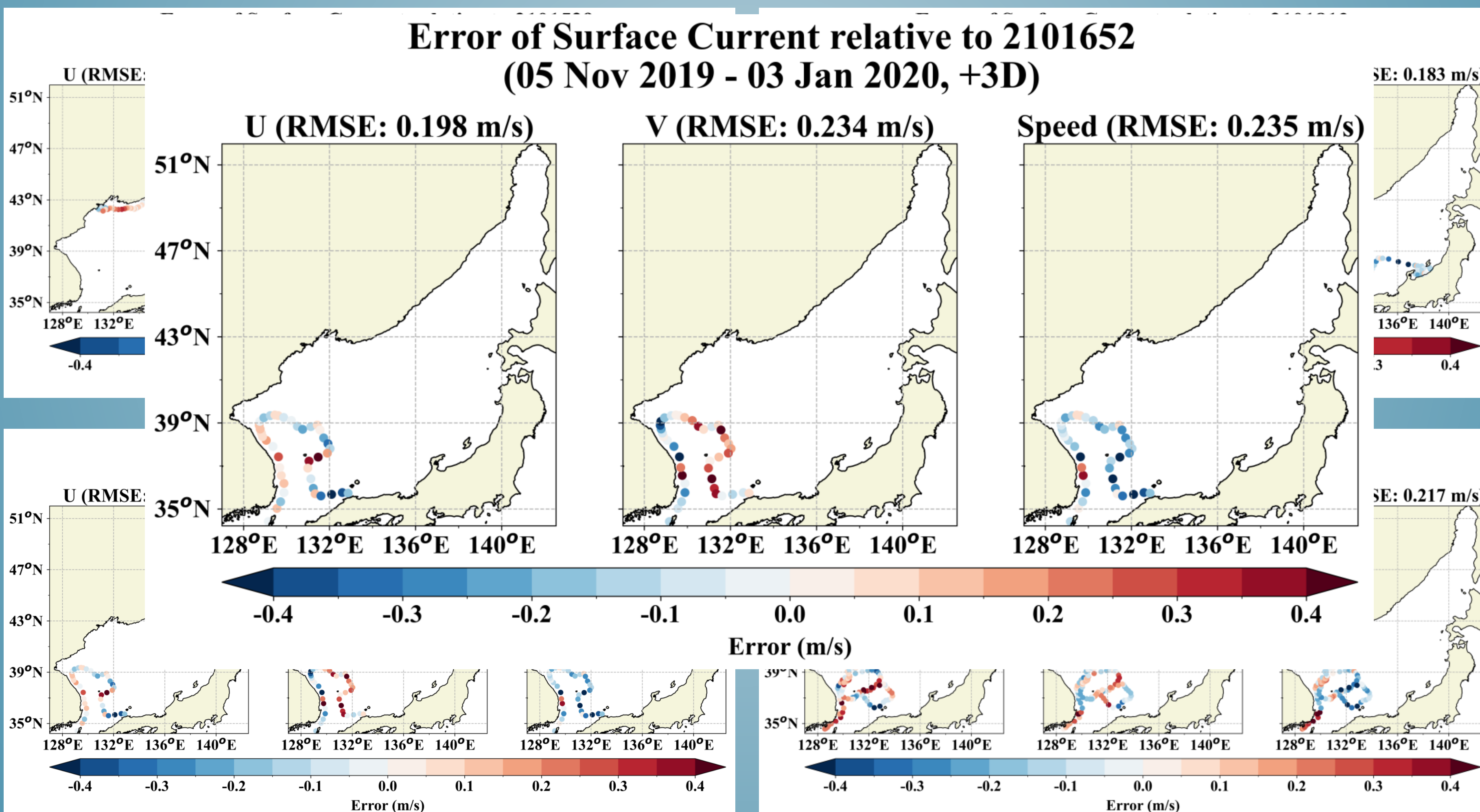
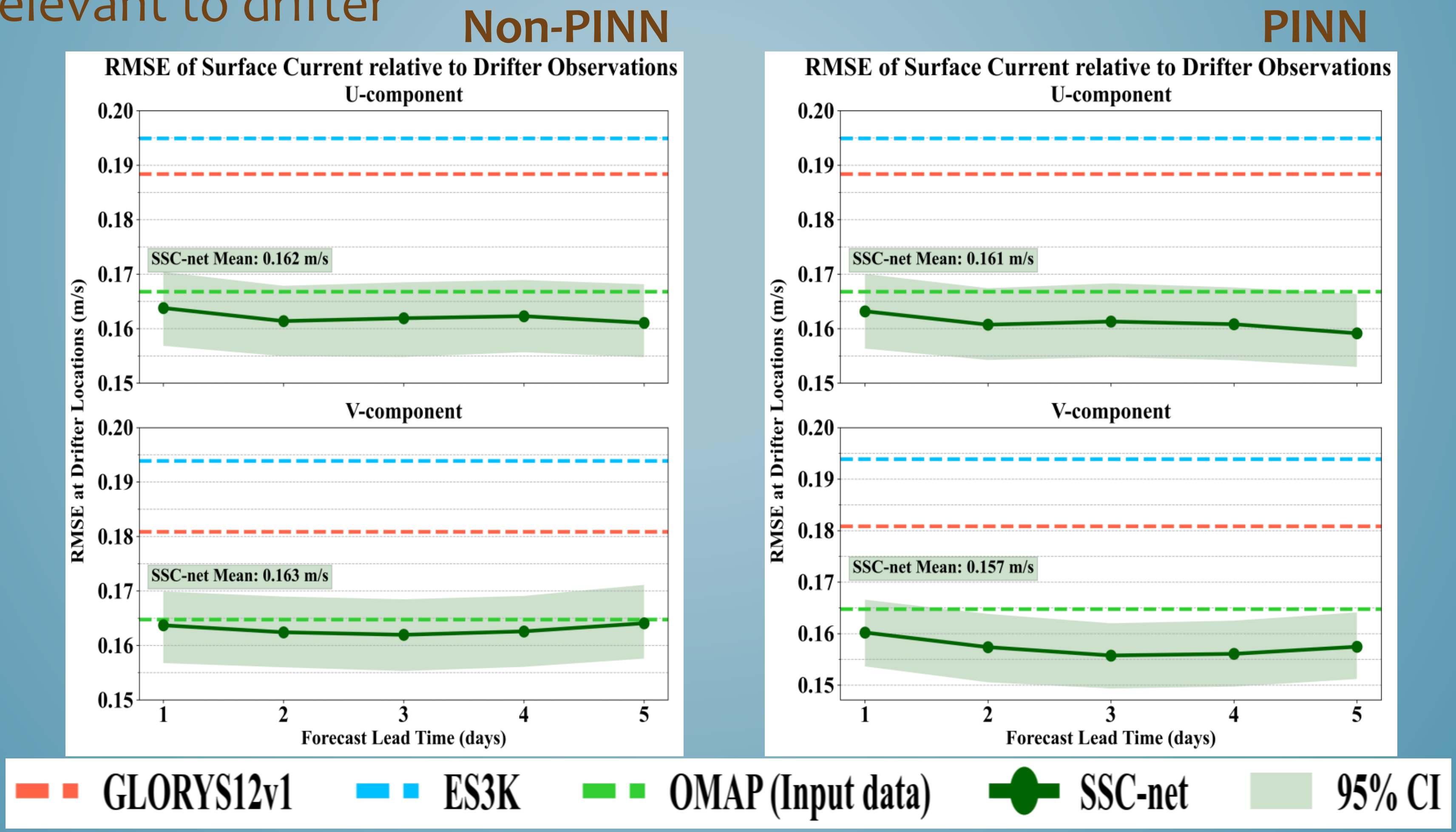


Evaluation using surface drifters

- SSC-net outperforms numerical models despite not being trained using drifter data
- Loss function of PINN enhances geostrophic consistency relevant to drifter



Summary

- **Sea Surface Current & SSH Predictions**
  - Outperforms the persistence model across all lead times (RMSE ~4 cm/s, ~60% improvement)
  - Successfully captures mesoscale features including eddies and the currents
- **Impact of Physical Constraints (PINN)**
  - Reduces spurious divergence and improves physical consistency across the basin
  - Geostrophic balance constraint enhances prediction skill, particularly at longer lead times
- **Independent Validation with Drifters**
  - SSC-net outperforms numerical models (OMAP, ES3k, GLORYS12v1) without drifter training data
  - Physics-informed constraints improve geostrophic consistency and real-ocean reproducibility

THANK YOU