



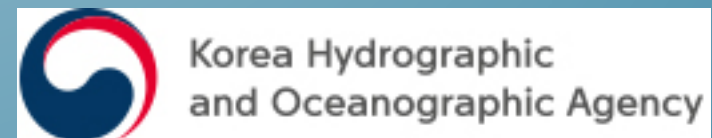
# ARTIFICIAL NEURAL NETWORK FOR OCEAN SURFACE CURRENT PREDICTION AROUND THE KOREAN PENINSULA

PICES Annual Meeting  
Sep. 27, 2022

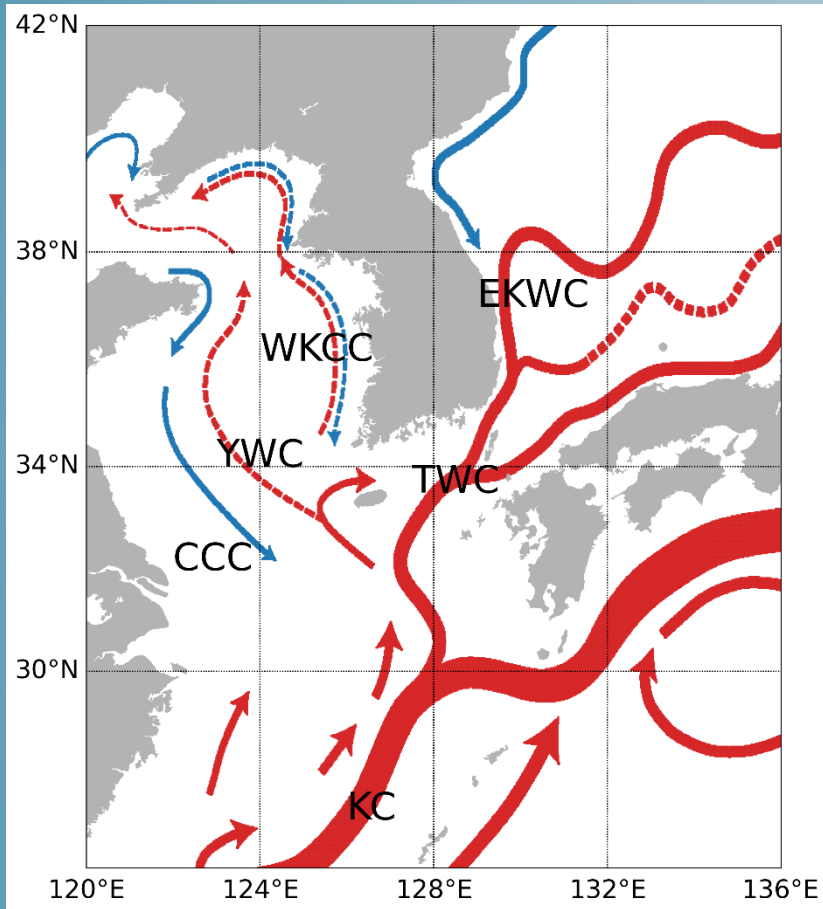
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<sup>2</sup>Korea Hydrographic and Oceanographic Agency, Korea



# AI model for surface current prediction?




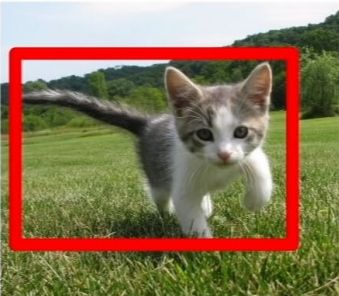
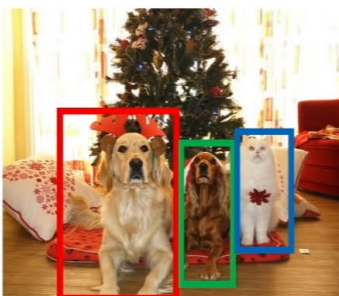

Data from KHOA

- Ocean surface current prediction is essential for various objectives.
- Seas around Korean peninsula show different characteristics: Yellow Sea = tides dominant East Sea = mesoscale processes
- Numerical model with fine-spatial resolution including is needed for prediction.
- However, it requires high computational power.

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

# Convolutional Neural Networks (CNN)

## – Semantic Segmentation

Semantic Segmentation	Classification + Localization	Object Detection	Instance Segmentation
			
GRASS, CAT, TREE, SKY	CAT	DOG, DOG, CAT	DOG, DOG, CAT
No objects, just pixels	Single Object	Multiple Object	

hi im is: CC public domain

Fei-Fei Li & Justin Johnson & Serena Yeung      University of California, Berkeley      Lecture 11 - 17 May 10, 2017

## CS231n: Convolutional Neural Networks for Visual Recognition

- In Computer Vision (CV) area, there are many different tasks: Image Classification, Semantic Segmentation, Object Localization, Object Detection, Instance Segmentation, etc.

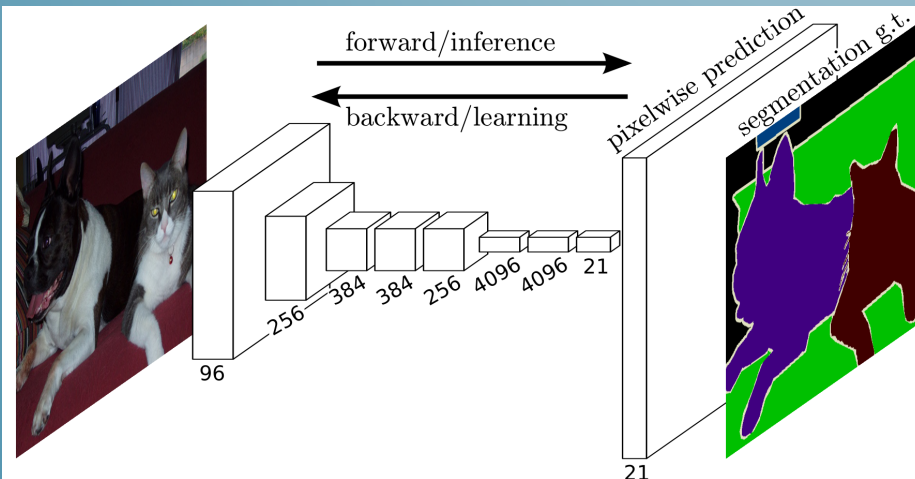
# CNN – Semantic Segmentation

- One of computer vision task
- Fully convolutional network (FCN)
- Encoder-Decoder structure
- Pixel-wise classification

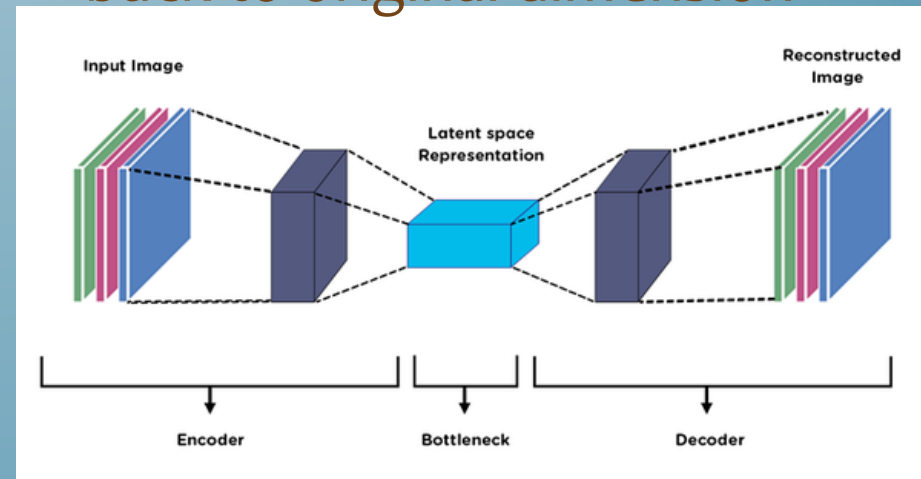


- **Pixel-wise regression**

- Encoder:  
Encodes or compresses the input data into a latent-space representation
- Decoder:  
Decodes or reconstructs the encoded data (latent space representation) back to original dimension

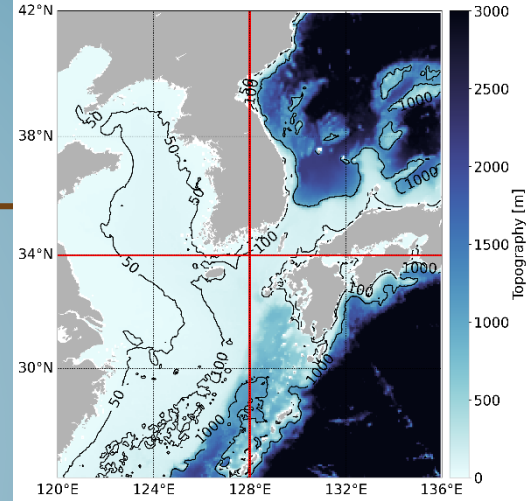


Fully Convolutional Networks for Semantic segmentation (Long et al., 2015)



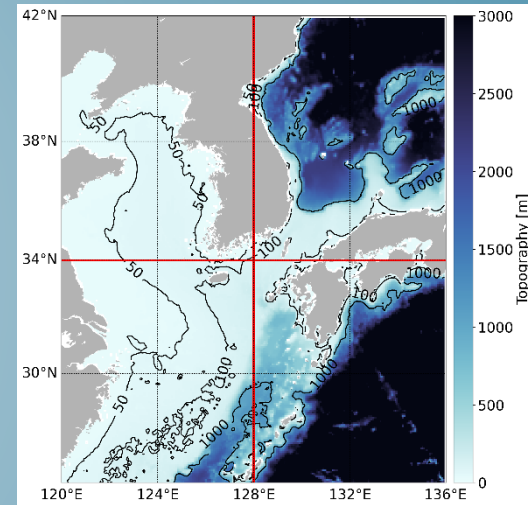
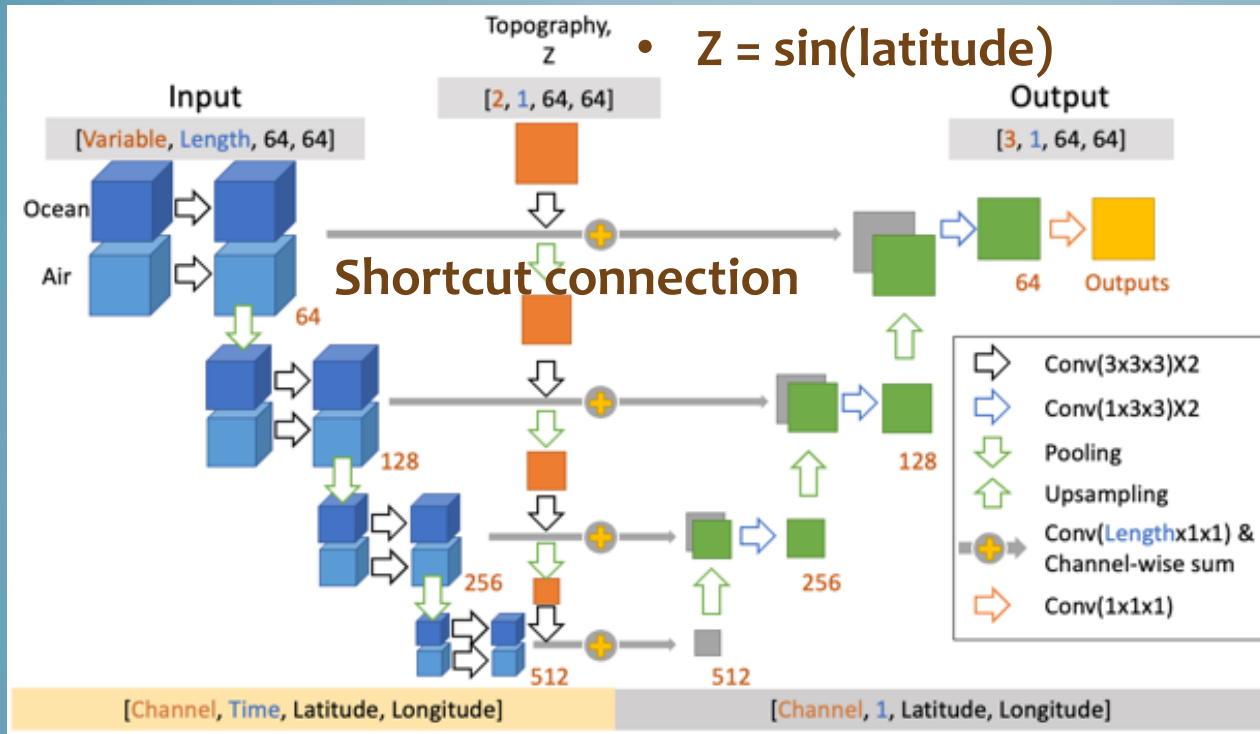
<https://medium.com/@birla.deepak26/>

# Oceanic & Atmospheric Data



- Oceanic inputs – OPEM reanalysis data
  - Time resolution: daily
  - Spatial resolution:  $1/20^\circ \rightarrow 1/16^\circ$
  - Sea surface current (U, V, SSH)
- Atmospheric inputs – ECMWF ERA5 reanalysis data
  - Time resolution: hourly  $\rightarrow$  daily
  - Spatial resolution:  $1/4^\circ \rightarrow 1/16^\circ$ 
    - Only 10 m above surface wind velocity (U10, V10)
- Train set: 1993–2012 (20 years)
- Test set: 2013-2014 (2 years)

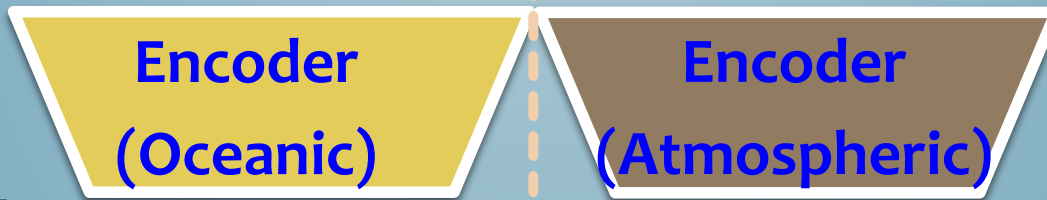
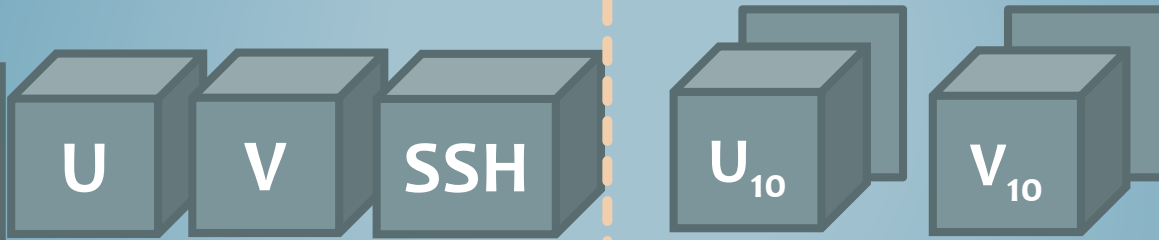
# AI Methods



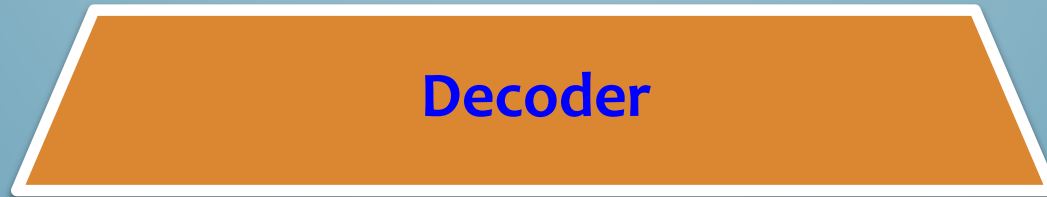
- The U-shaped network:
  - Encoder-decoder structure with shortcut connection
- The full domain (256×256) are divided into four patches (128×128) and used in the training processes
- Double encoder for each oceanic and atmospheric data
- Topography data is included in the shortcut connection

# AI Methods

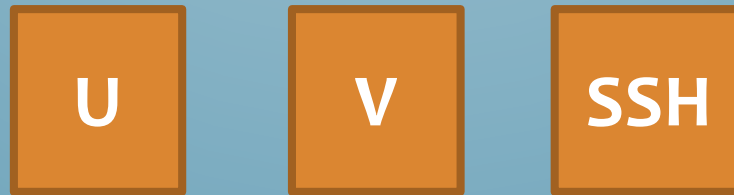
3-D inputs [Time, Lat, Lon]



Double Encoder

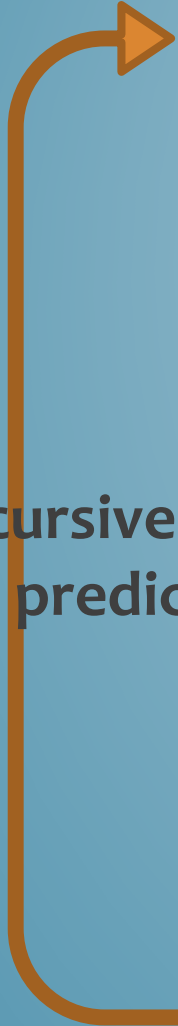


Single Decoder



2-D outputs [Lat, Lon]

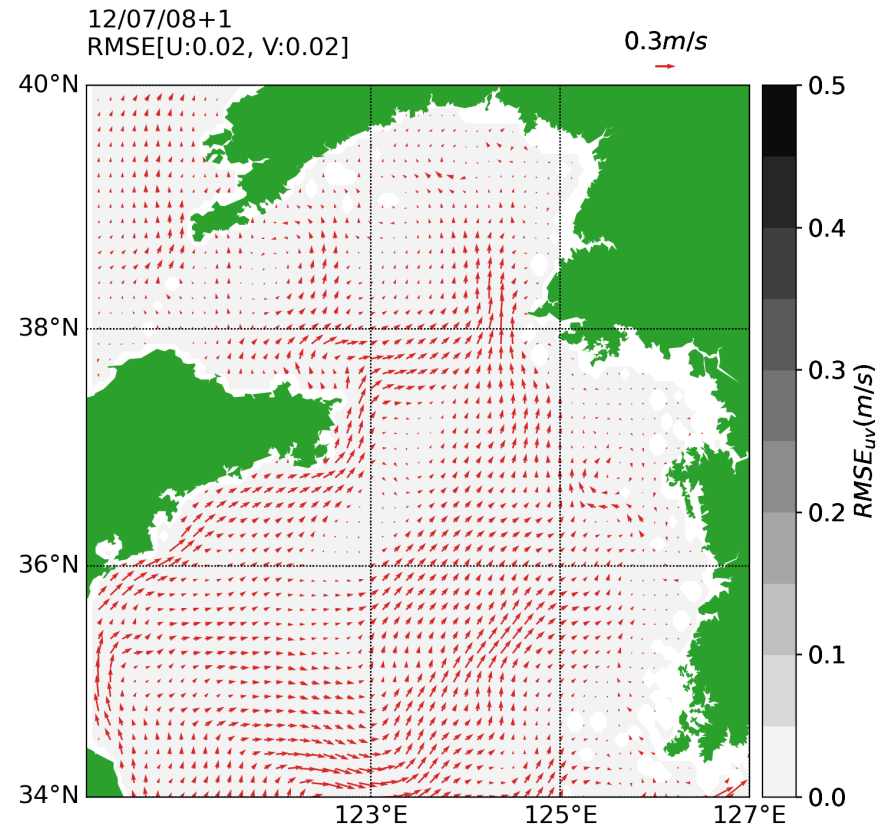
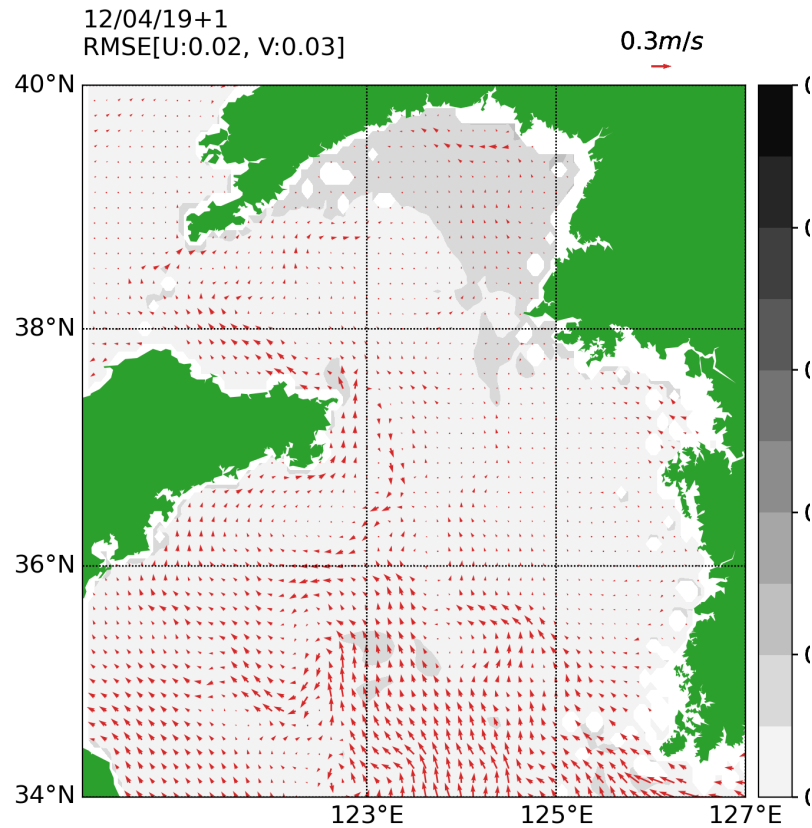
Recursive way for prediction



# AI model prediction of surface current for 5 days: Yellow Sea

Start date: Apr. 19, 2012

Start date: Jul. 08, 2012

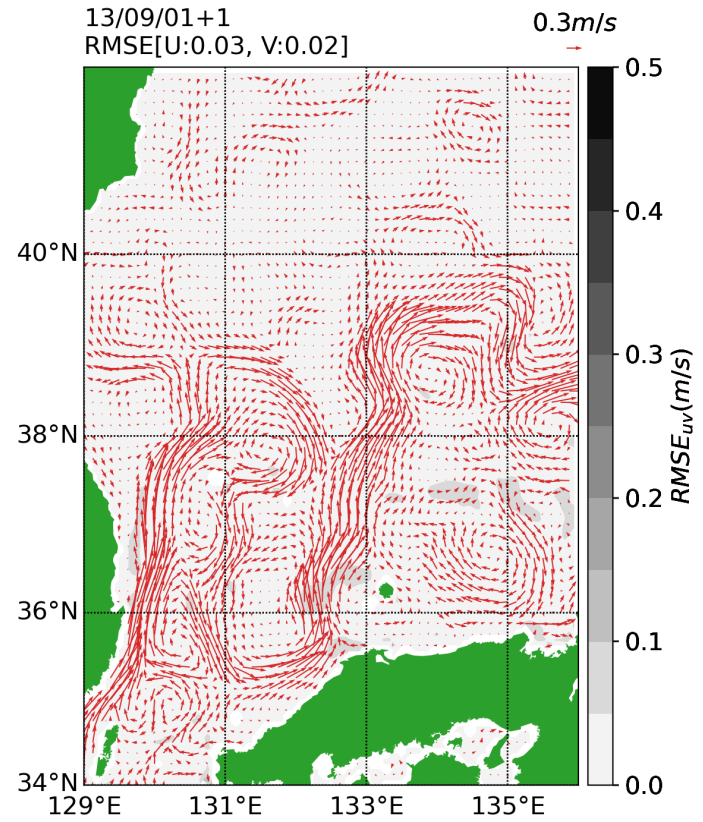
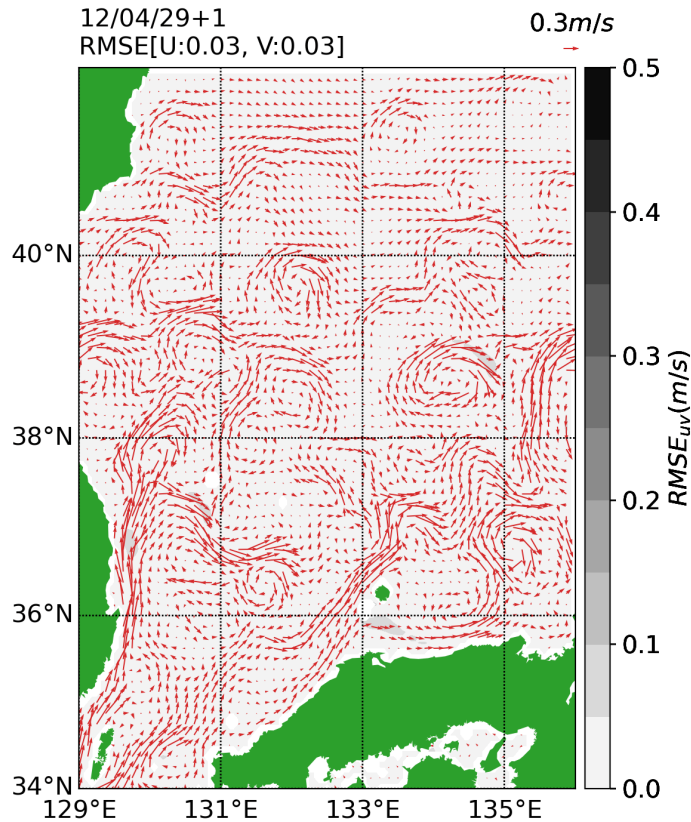




# AI model prediction of surface current for 5 days: East Sea

Start date: Apr. 29, 2012

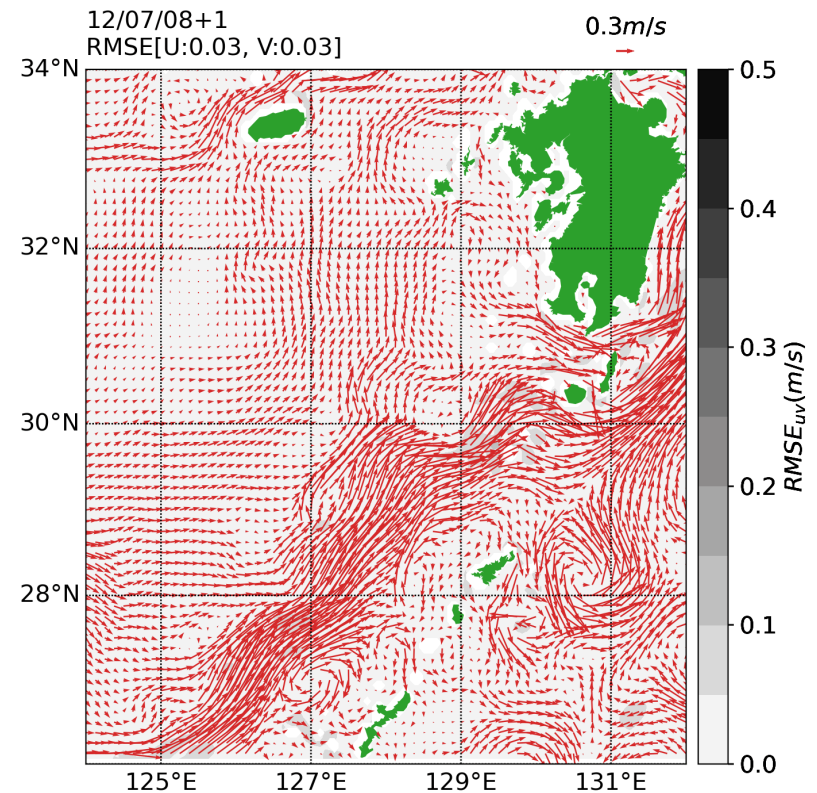
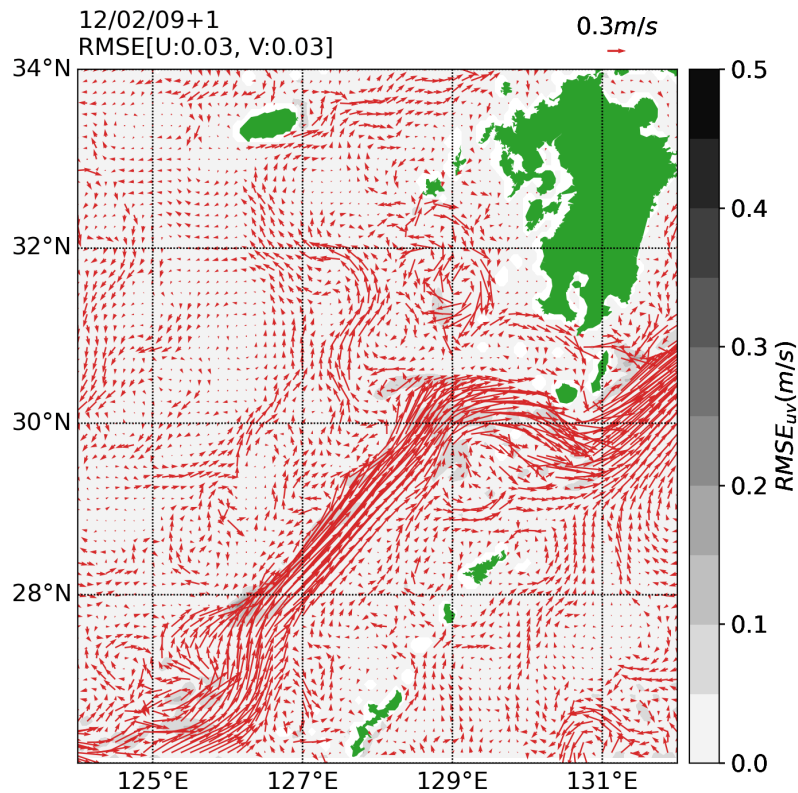
Start date: Sep. 01, 2013



# AI model prediction of surface current for 5 days : East China Sea

Start date: Feb. 09, 2012

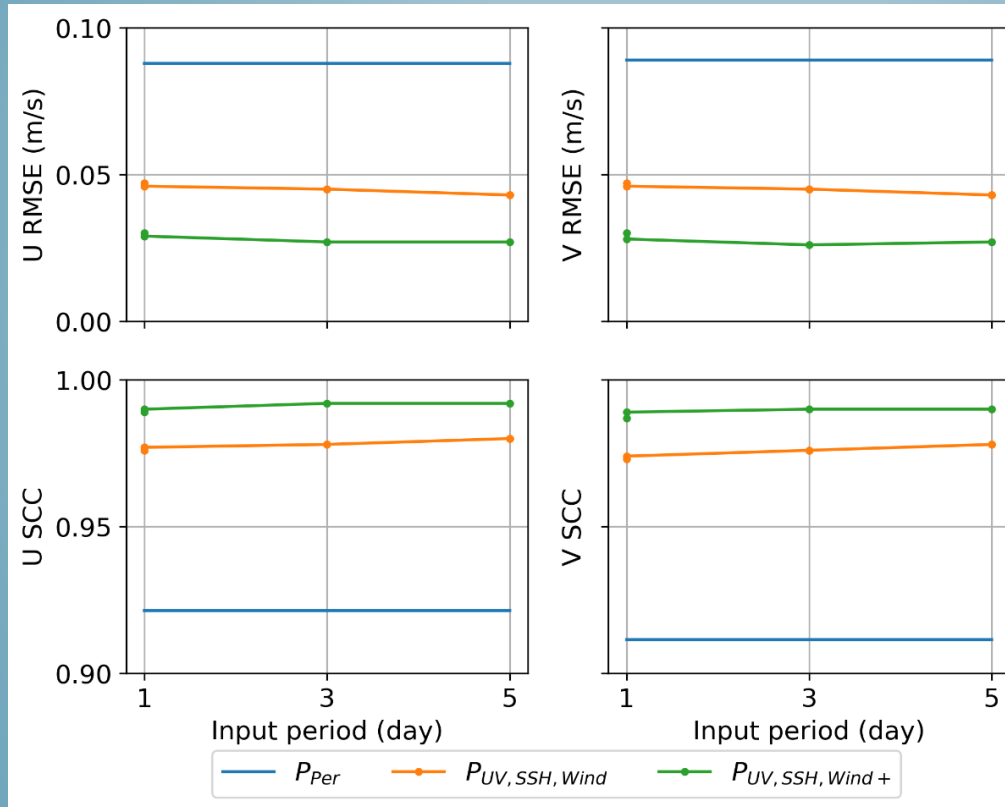
Start date: Jul. 08, 2012



# AI model performance depending on input periods and winds

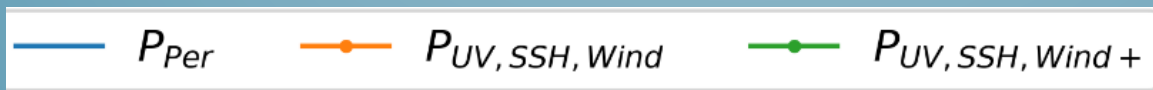
RMSE of U

SCC of U  
(spatial correlation coefficient)



- Optimal input periods are 3 to 5 days.

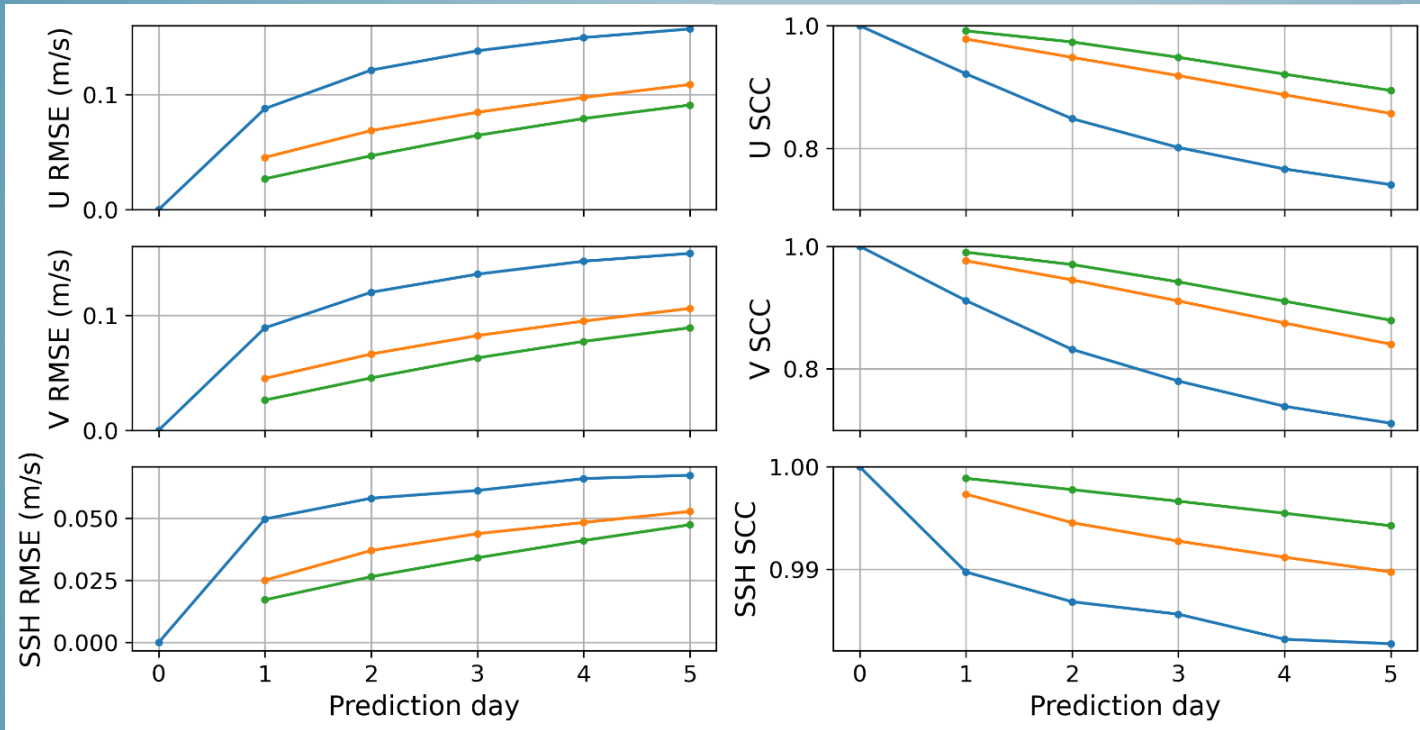
- The next-day wind input performs the best.



- $P_{per}$ : Persistence prediction (RMSE between today and tomorrow)
- $P_{UV,SSH,Wind}$ : Prediction with surface current, SSH, and 10-m wind
- $P_{UV,SSH,Wind+}$ :  $P_{UV,SSH,Wind}$  with the next-day wind

# AI model errors depending on predicting days

=> RMSE= $\sim 0.07$  m/s for the prediction on day 3



RMSE of U

RMSE of V

RMSE of SSH

$P_{per}$      $P_{UV,SSH,Wind}$      $P_{UV,SSH,Wind+}$

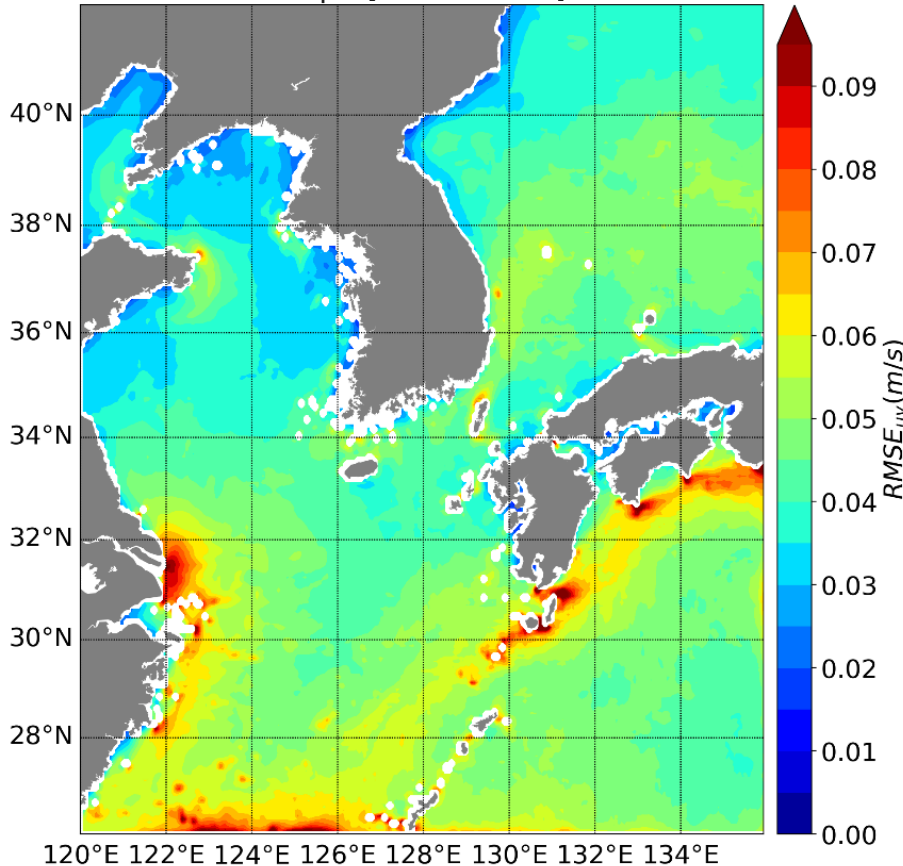
- $P_{per}$ : Persistence prediction (RMSE between today and tomorrow)
- $P_{UV,SSH,Wind}$ : Prediction with surface current, SSH, and 10-m wind
- $P_{UV,SSH,Wind+}$ :  $P_{UV,SSH,Wind}$  with the next day's wind

# Effects of wind+ on the current prediction

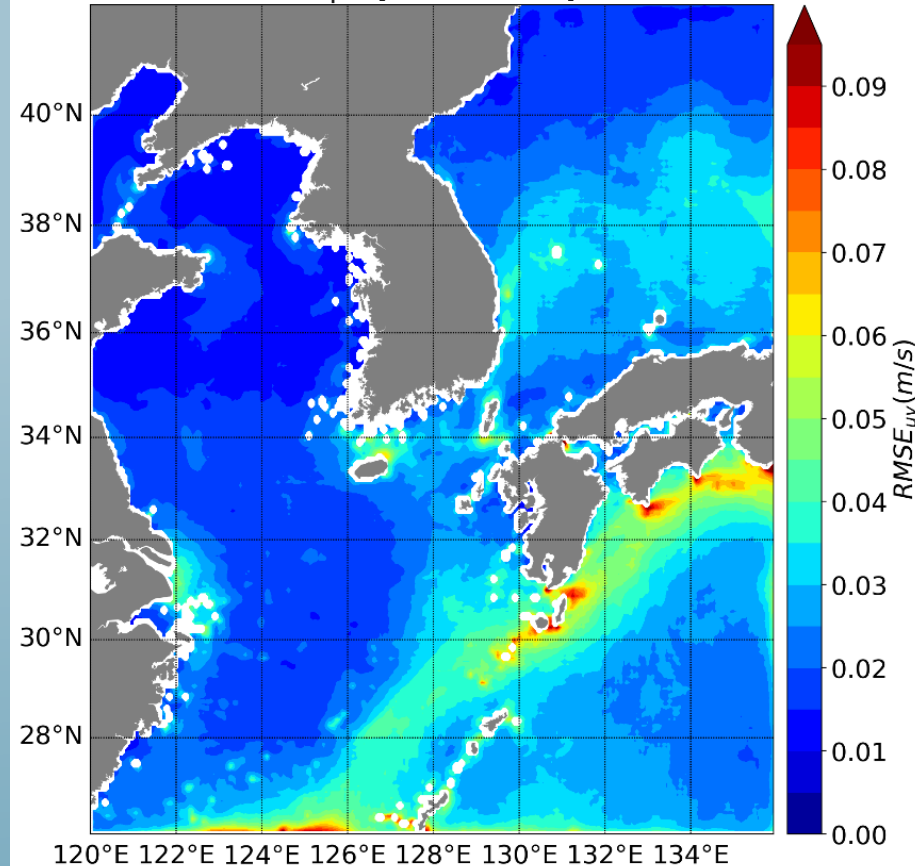
Prediction using U, V, SSH, wind

using U, V, SSH, wind+

Seq: 1 [RMSE: 0.0461]



Seq: 1 [RMSE: 0.0254]

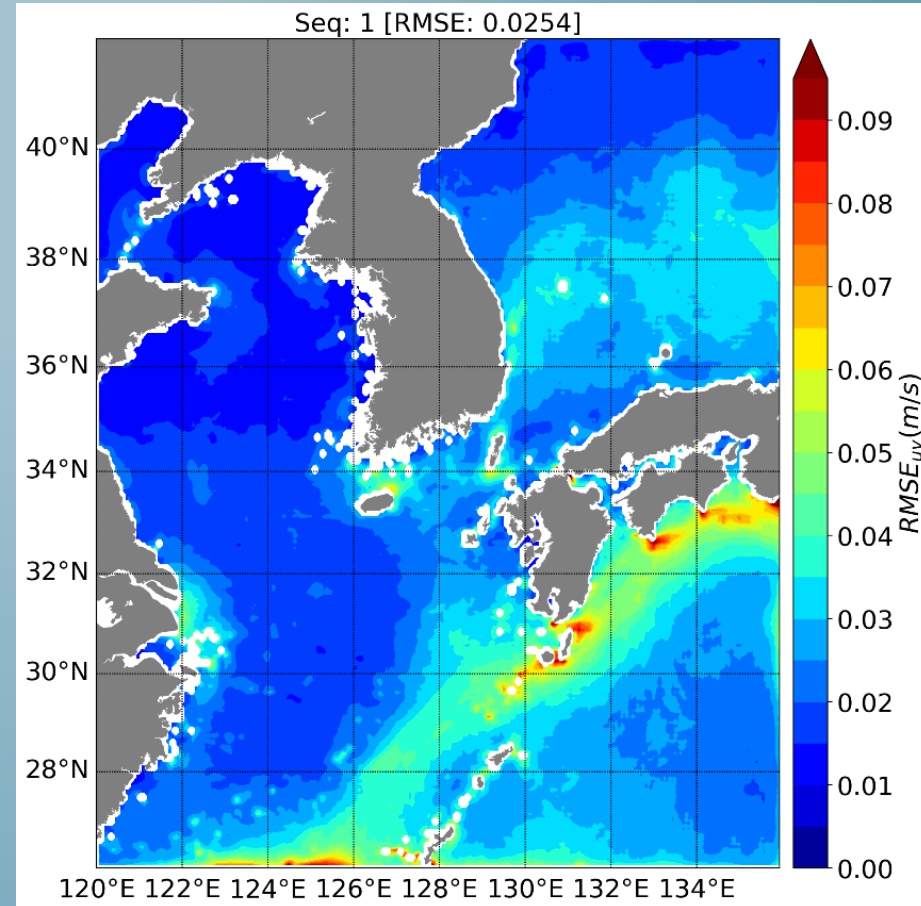


Error distribution of uv-component averaged RMSE ( $RMSE_{uv}$ ) for the 1<sup>st</sup> prediction day (Input days = 3)

# Effects of wind+ on the current prediction

using U, V, SSH, wind+

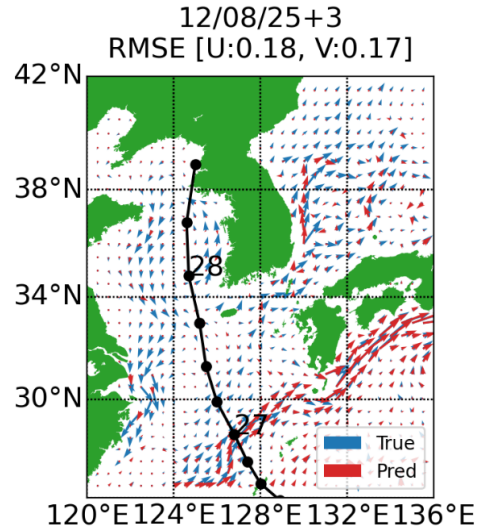
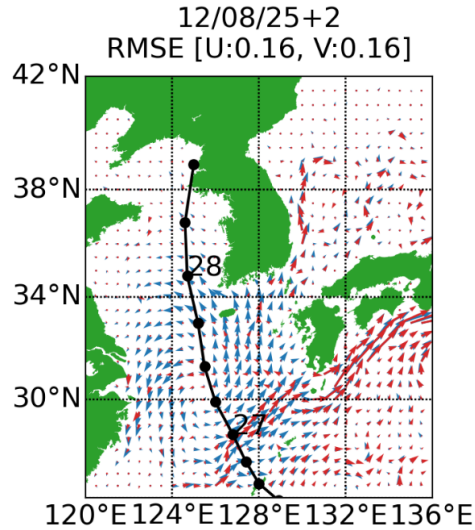
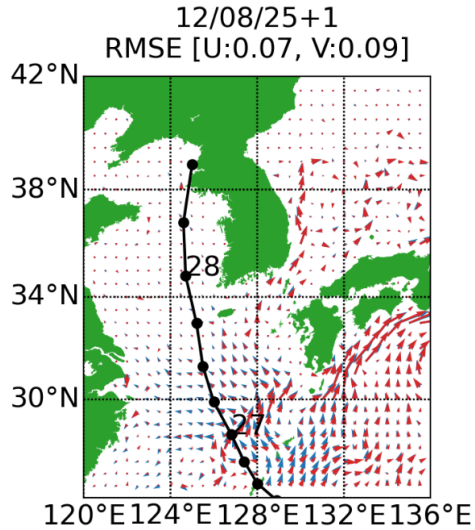
- The input of the next-day wind (wind+) results in a significant improvement in the Yellow Sea as expected. In addition, open sea areas also show some improvement.
- Yangtze River discharge prediction is also improved with wind+
- The effects of wind+ on the strong geostrophic currents such as the Kuroshio and the East Korea Warm Current are rarely seen.



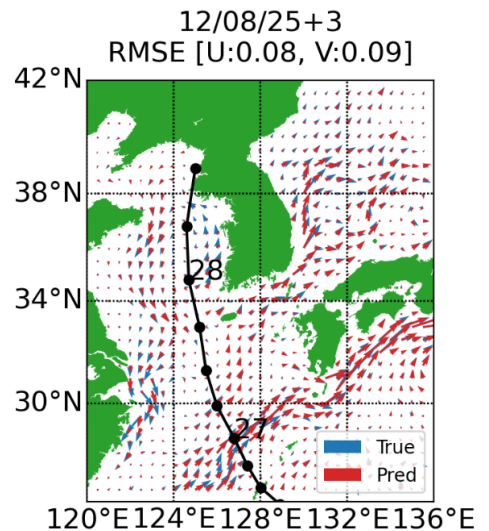
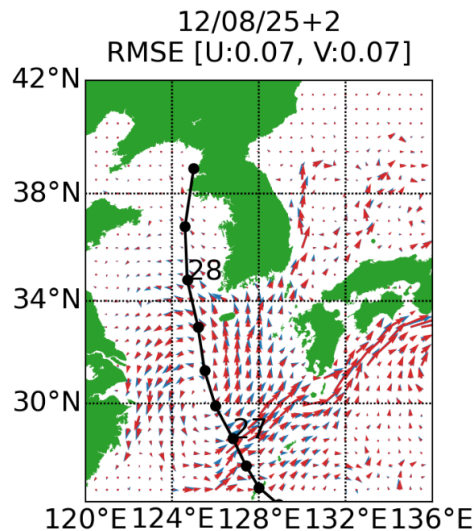
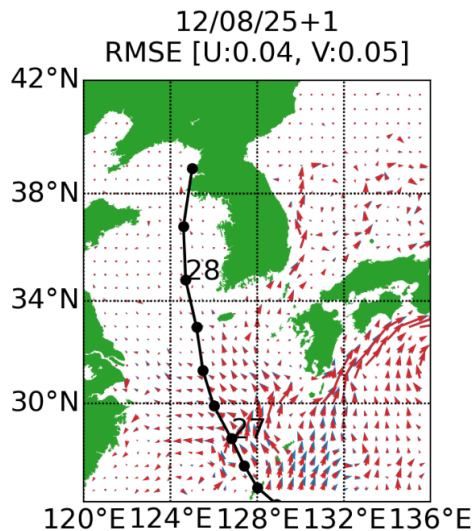
# Prediction of typhoon-induced currents improves when the next-day winds (wind+) are used

Typhoon: BOLAVEN

$P_{UV,SSH,Wind}$

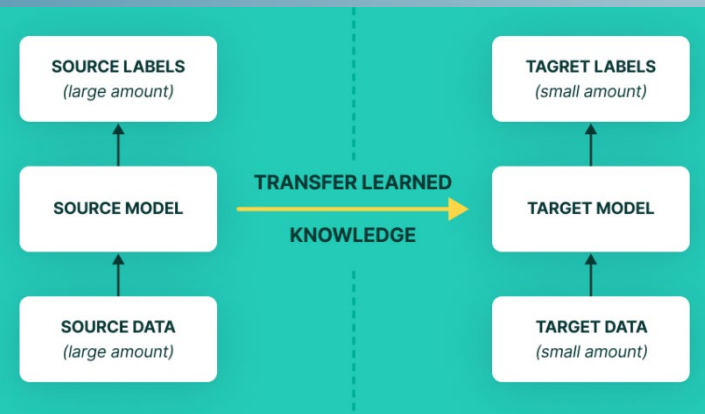


$P_{UV,SSH,Wind+}$



# Transfer learning

Source data



<https://www.v7labs.com/blog/transfer-learning-guide>

Target data

Oceanic input – OPEM reanalysis data

Atmospheric input – ECMWF ERA5 data

- Train set: 1993–2012 (20 years)
- Test set: 2013-2014 (2 years)

$P_{UV,SSH,Wind+}$



Transfer learning

Oceanic input – OPEM analysis data

Atmospheric input –KMA GDAPS data

- Train set: 2017–2020 (4 years)
- Test set: 2021 (1 year)



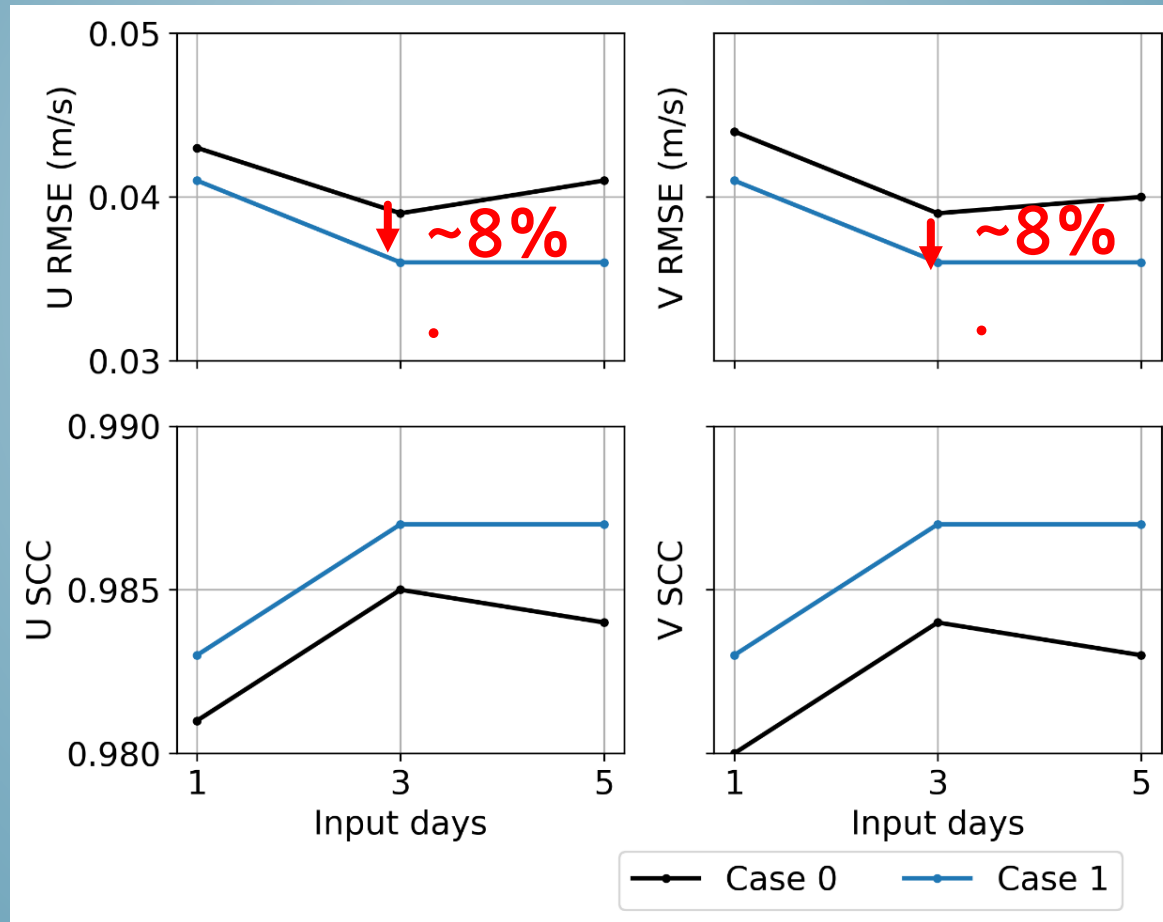
# Improvement of current prediction using transfer learning

RMSE:

$P_{\text{per}} \approx 0.1$

SCC:

$P_{\text{per}} \approx 0.89$

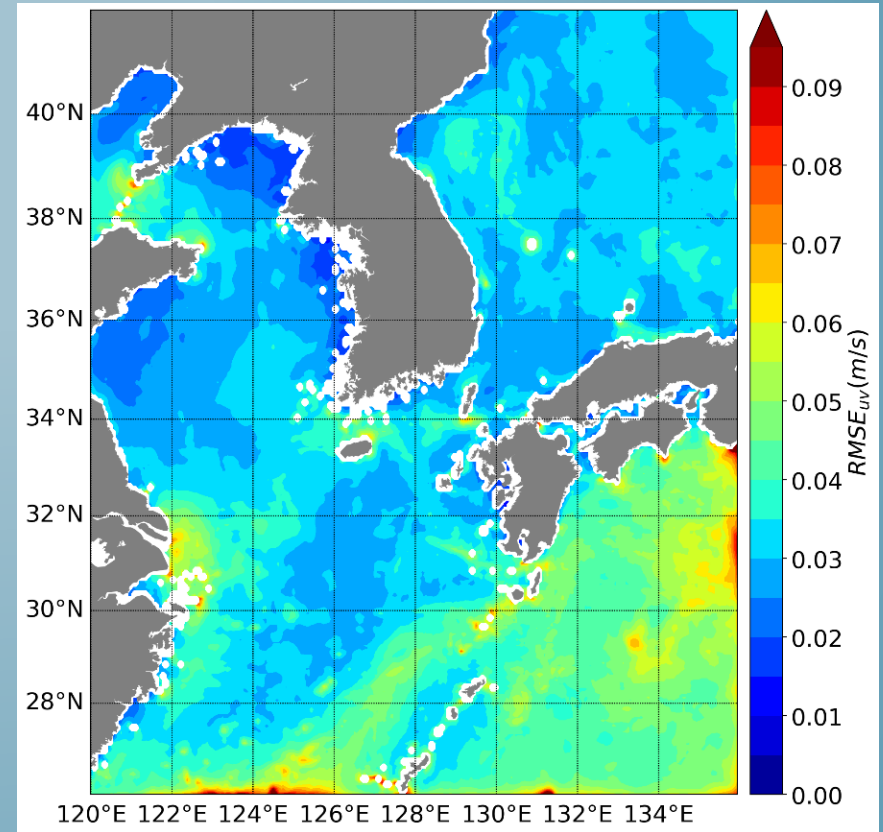
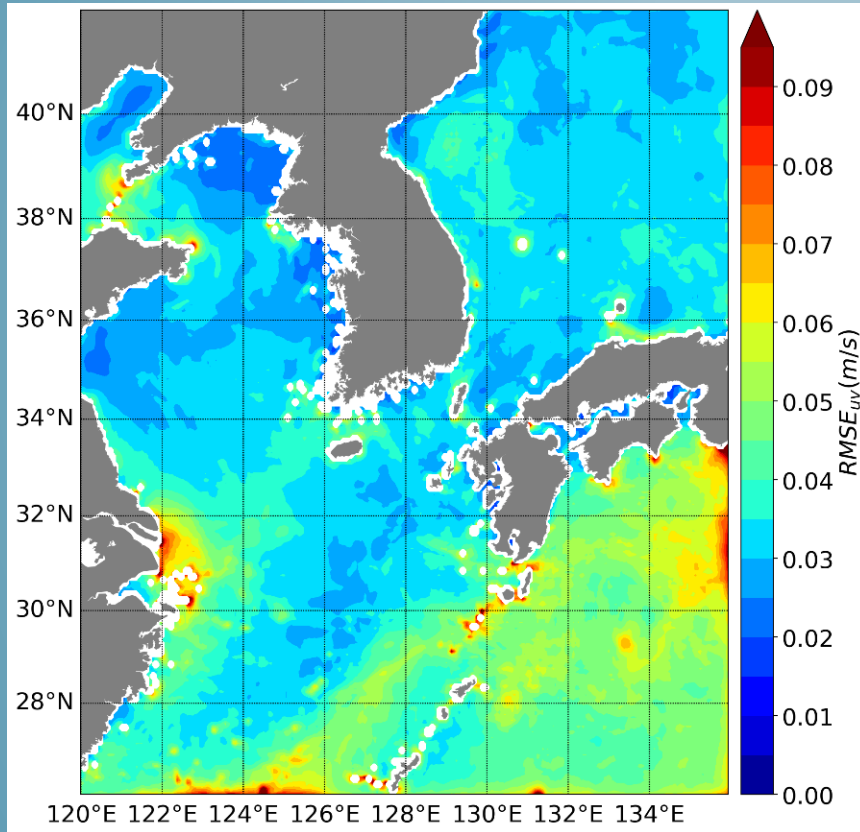


Case0: No transfer learning case

Case1: Transfer learned case

(from 20 years of reanalysis data)

# Improvement of current prediction using transfer learning



Case0 (No transfer learning)

Case1 (transfer learning)

Error distribution of uv-component averaged RMSE ( $RMSE_{uv}$ ) for the 1<sup>st</sup> prediction day (Input days = 3)

# Conclusions

- The U-shaped 3-D CNN model is applied to predict the sea surface current around Korean peninsula.
- The AI model including the next-day wind data shows the better performance than the other models. In addition, it could successfully simulate extreme events caused by the typhoon passage.
- Transfer learning can improve the performance of the sea surface current prediction.
- High resolution ocean prediction system using CNNs can be a practical and efficient way with a lightweight computing power.