Nov. 09, 2023

Prediction of sea surface current around the Korean peninsula using artificial neural network based on numerical model outputs

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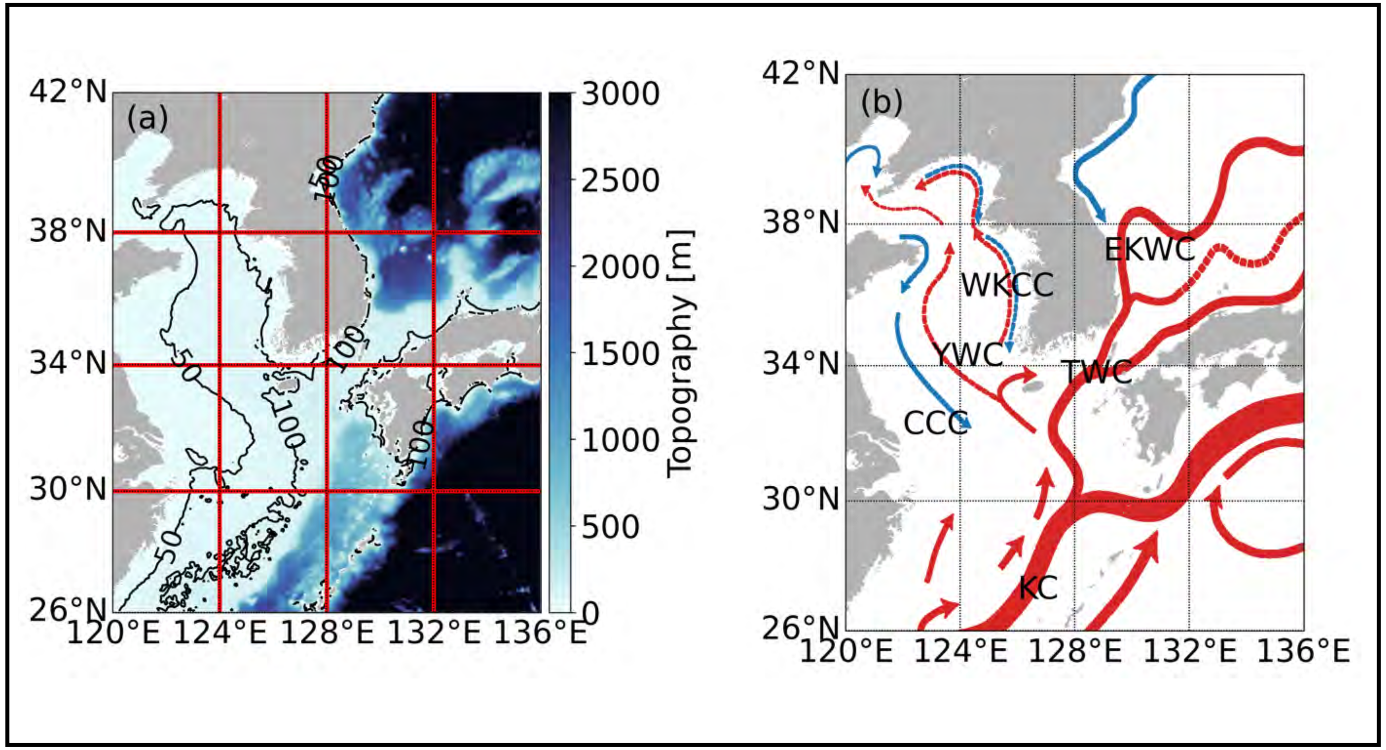
Study area

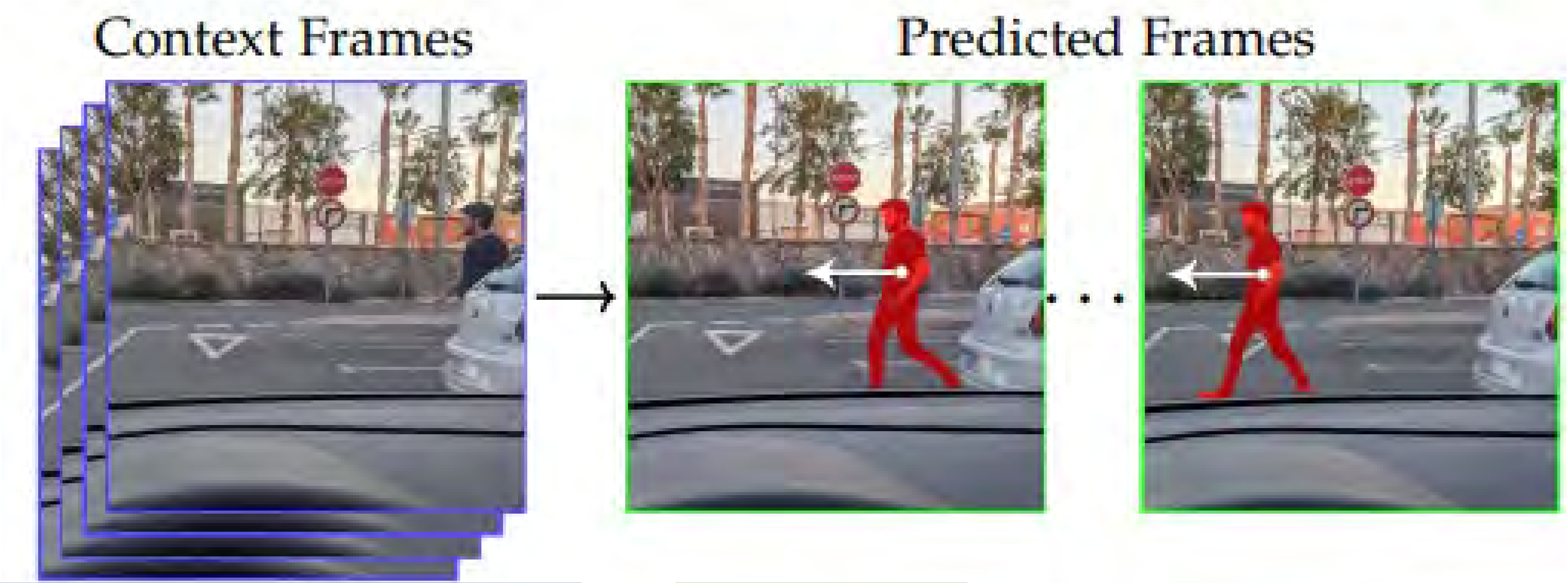


- Seas around Korean peninsula show different characteristics:
  Yellow Sea = tides dominant
  East Sea = mesoscale processes

- Numerical model with fine-spatial resolution is needed for prediction.
- However, it requires high computational power

Hard to be used in the near-real time prediction

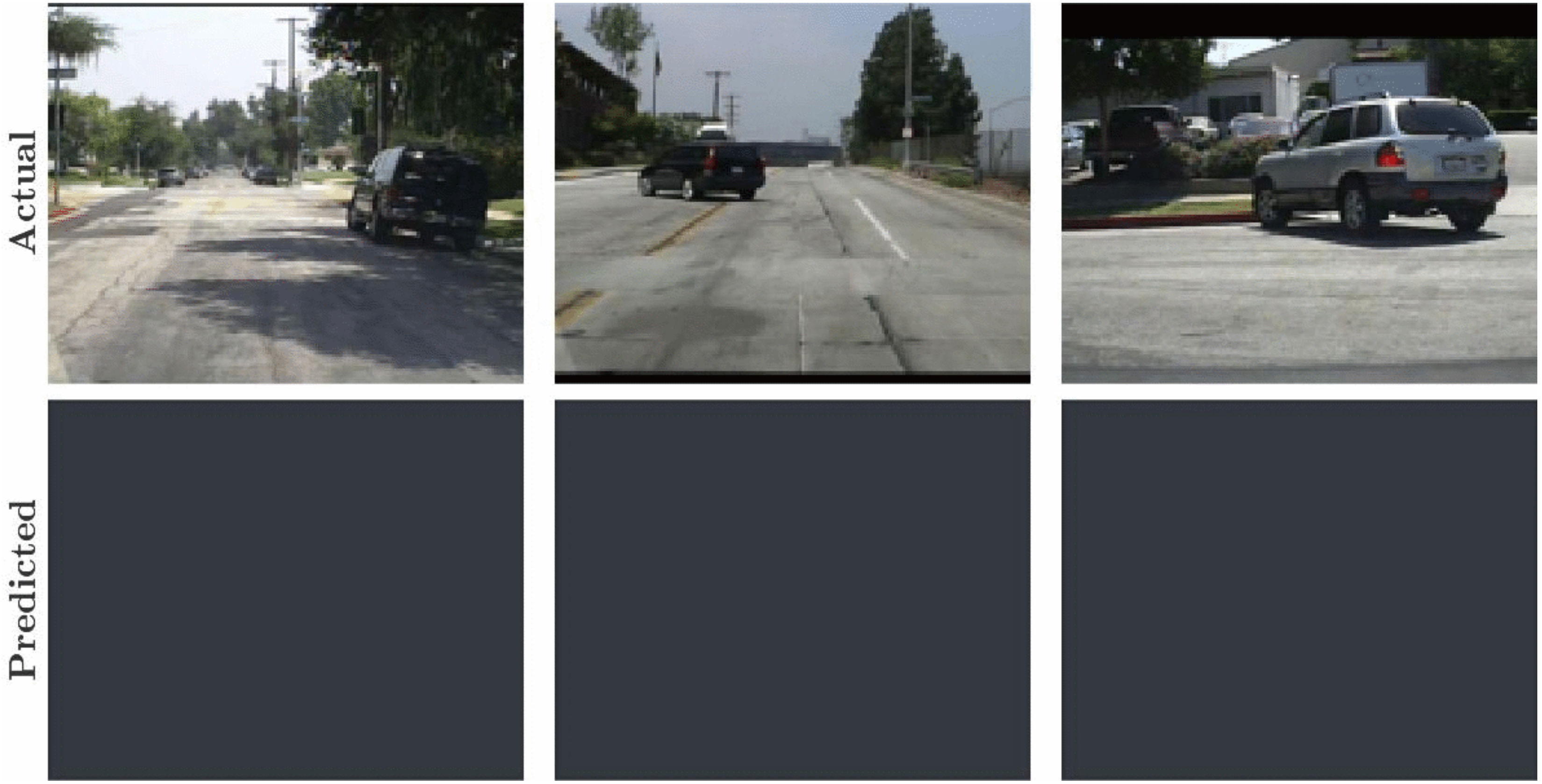
Video prediction - AI



From past and present frames → A next frame

A Review on Deep Learning Techniques for Video Prediction. 2020

Video prediction - AI



Prediction of SSC?

https://coxlab.github.io/prednet/

Video prediction – application on OGCM

Questions

1. For sea surface current (SSC), can it be forecasted?
2. Typhoon can be considered in the network?
3. Could it have reasonable performance,
   when compared with the in-situ SSC data?

⬇

AI can be another efficient way of SSC prediction

Data

Oceanic inputs – OPEM reanalysis data

Time resolution: daily

Spatial resolution: 1/24°

- Sea surface current (U, V)
- Sea surface height (SSH)

Atmospheric inputs – ECMWF ERA5 reanalysis data

Time resolution: hourly → daily

Spatial resolution: 1/4° → 1/24°

- 10 m above surface wind velocity (U10, V10)

- Train set: 2011–2020 (10 years)
- Test set: 2021-2022 (2 years)

Metrics

RMSE

$$RMSE(t) = \sqrt{\overline{(f(t) - o(t))^2}}$$

Anomaly correlation coefficient (ACC)

$$ACC(t) = \frac{\overline{(f(t)-c(t)) \cdot (o(t)-c(t))}}{\sqrt{\overline{(f(t)-c(t))^2}}\ \sqrt{\overline{(o(t)-c(t))^2}}},$$

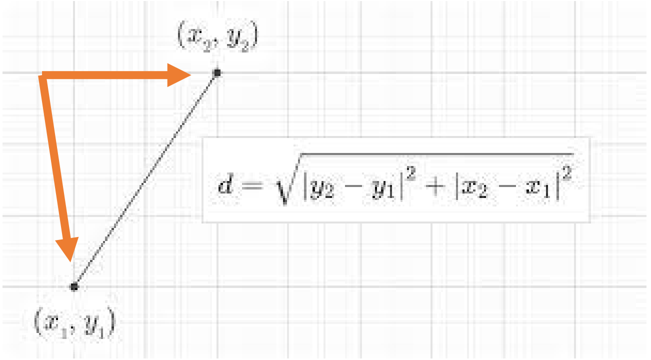
(t is the time, f(t) and o(t) are forecasted and observed state value,

the c(t) is the daily climatological mean value during the train period)

Vector distance (D)

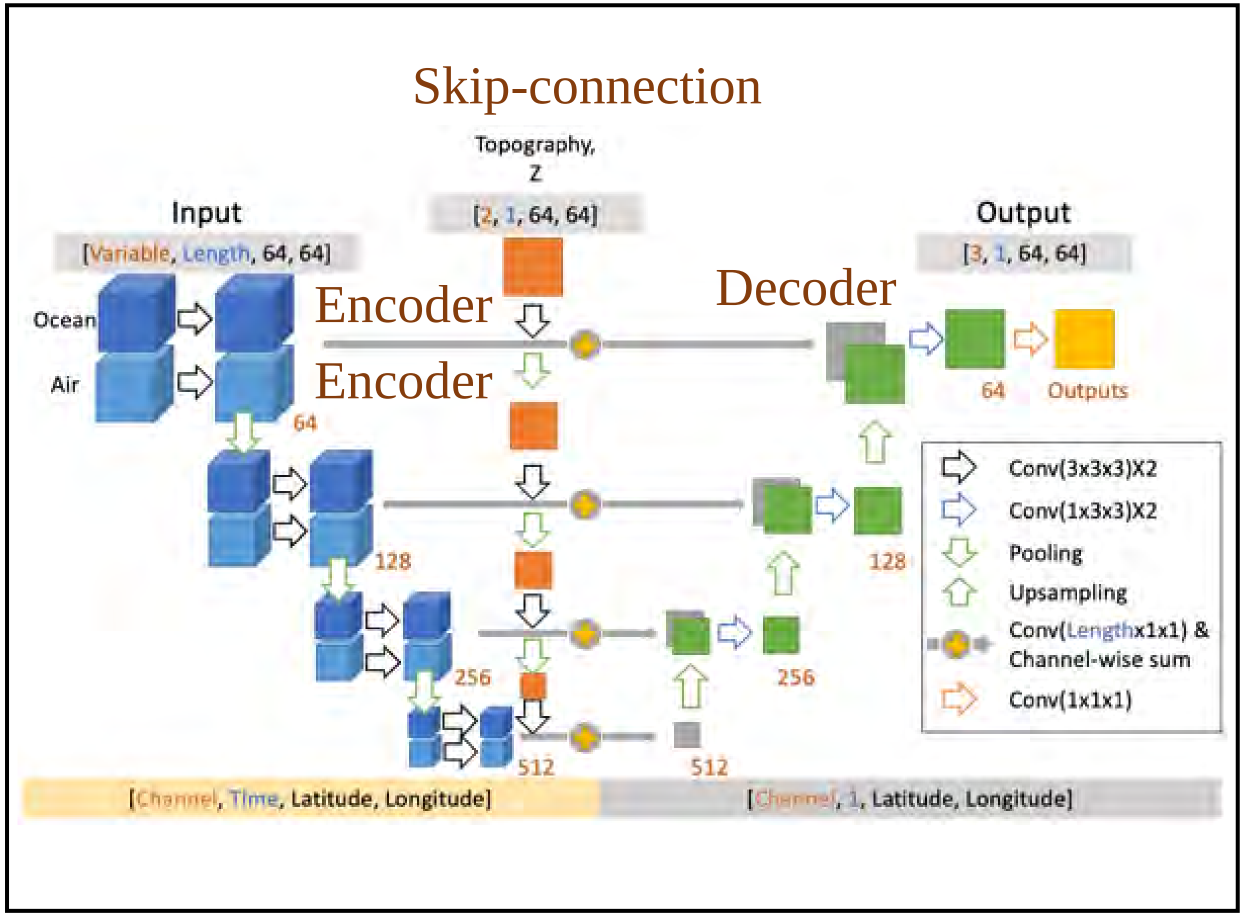
$$D = \left|\overrightarrow{U_f} - \overrightarrow{U_o}\right|$$

($\overrightarrow{U_f}$ and $\overrightarrow{U_o}$ are the forecasted- and observed-state vector of SSC)



SSC-net

- Sea surface current (SSC) estimation and prediction

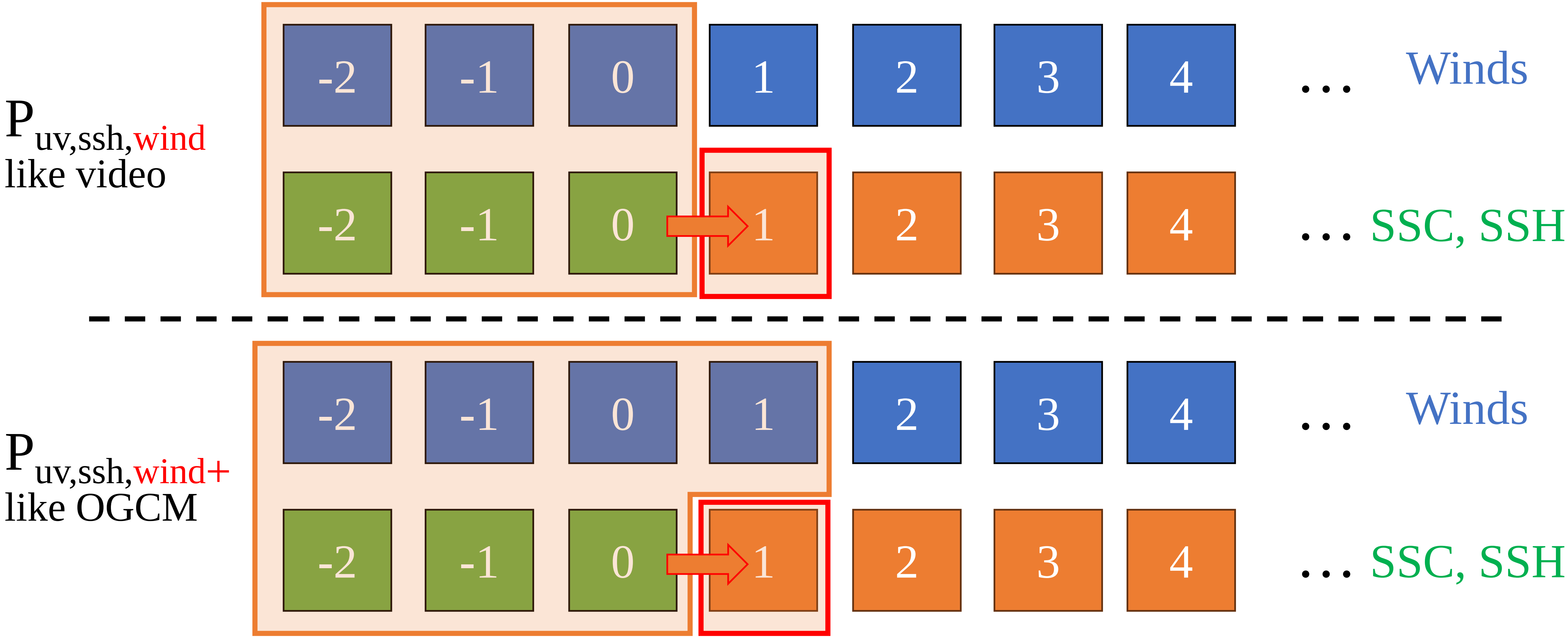


- Dual encoder
  - Enabling different shapes of ocean and air parts
    ex) [time, lon, lat]
    ex) [$time_a$, lon, lat], [$time_b$, lon, lat]
  - Can include winds of the next day
    ex) the next day's daily winds
    ex) [3, lon, lat] , [3+1, lon, lat]
  - Can change the time-resolution
    ex) daily to 6-hourly winds
    ex) [3, lon, lat] , [3 X 4, lon , lat]

SSC = Sea surface current

SSC prediction – concept

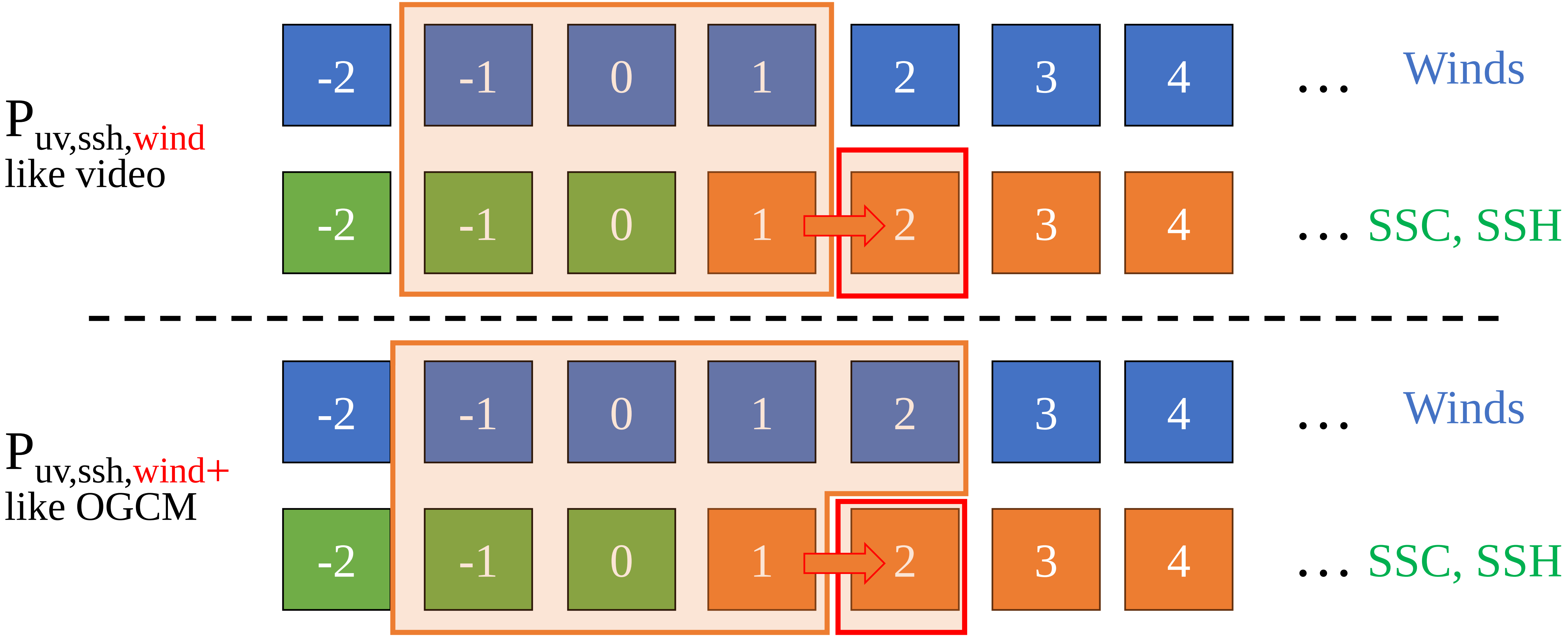
Forecast using AI (ocean) with 3-input days.



SSC = Sea surface current

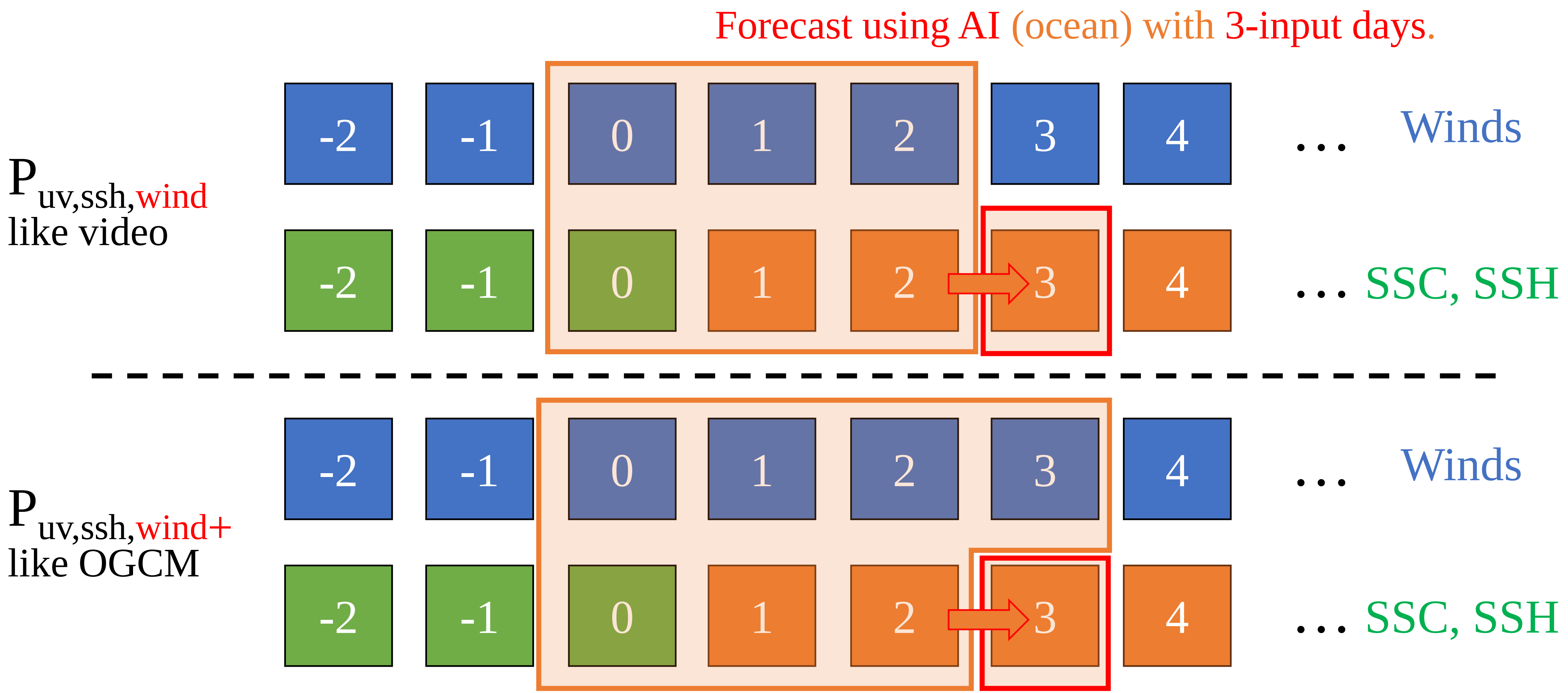
SSC prediction – concept

Forecast using AI (ocean) with 3-input days.



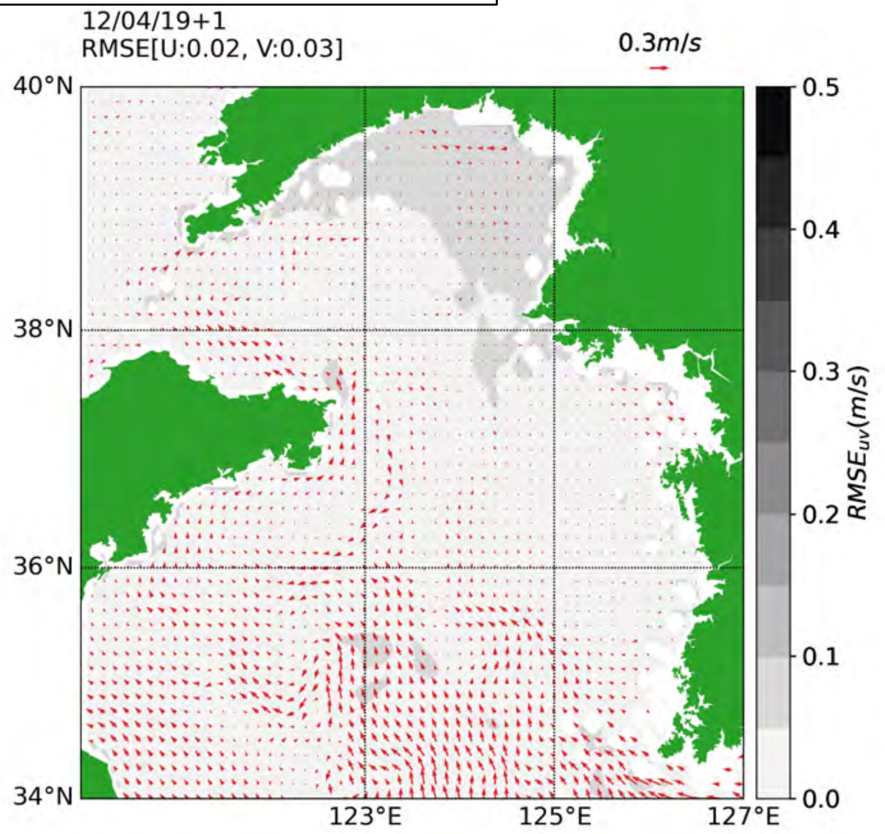
SSC = Sea surface current

SSC prediction – concept

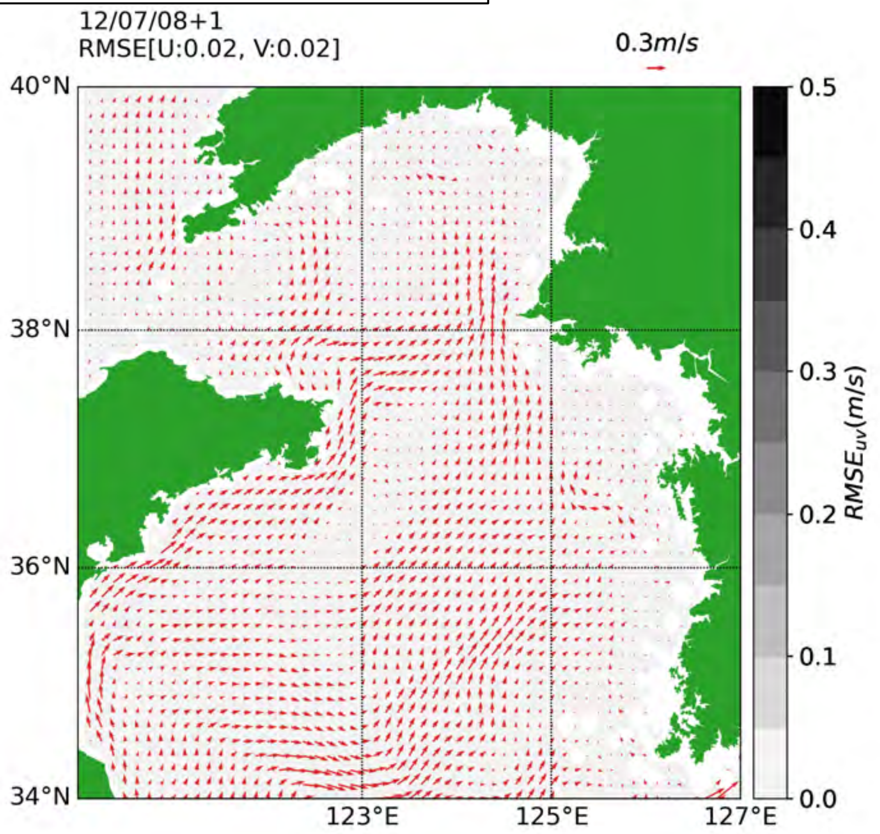


SSC-net predictions (5-day predictions)

Apr. 19th + [1–5]



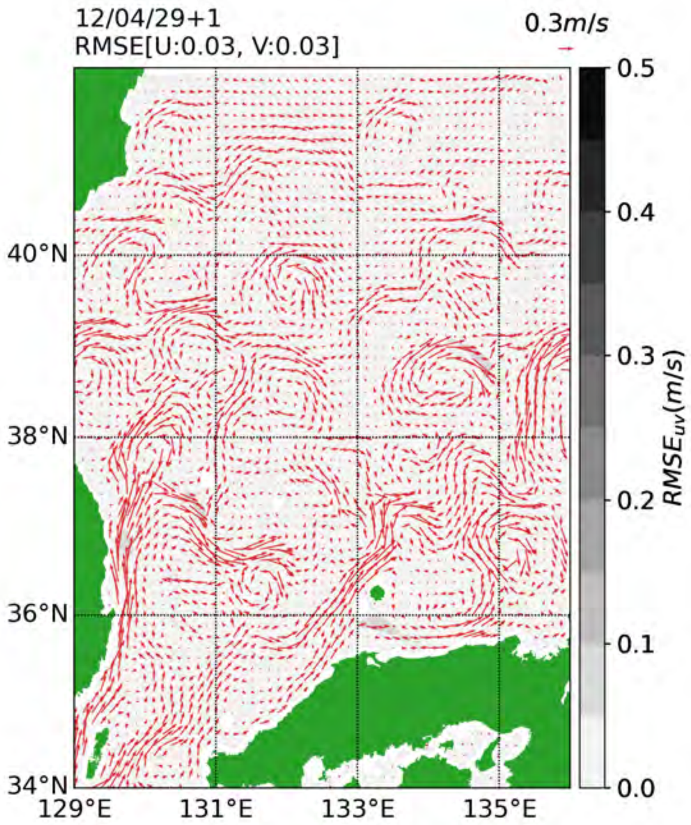
Dec. 08th + [1–5]



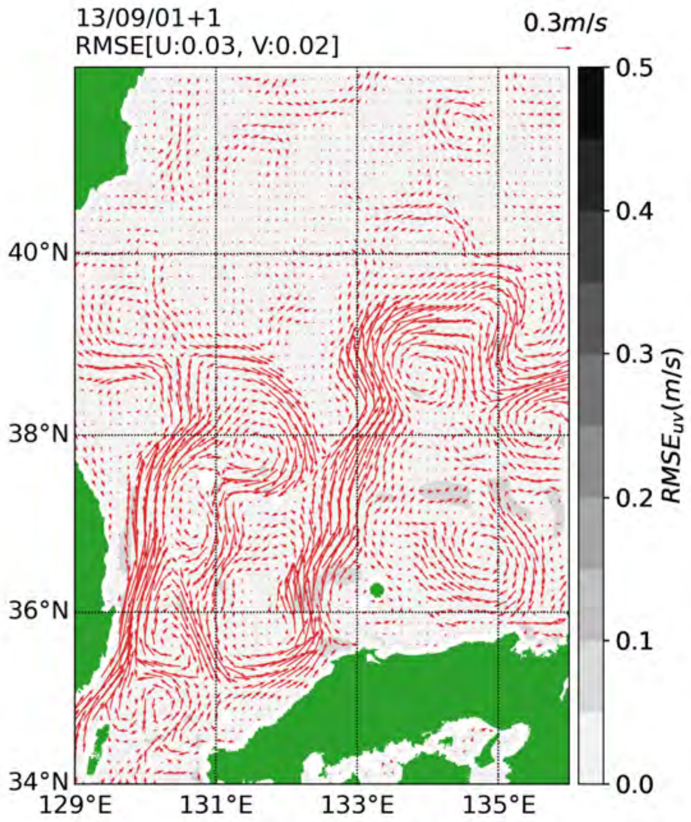
No tidal current!!

SSC-net predictions (5-day predictions)

Apr. 29th + [1–5]

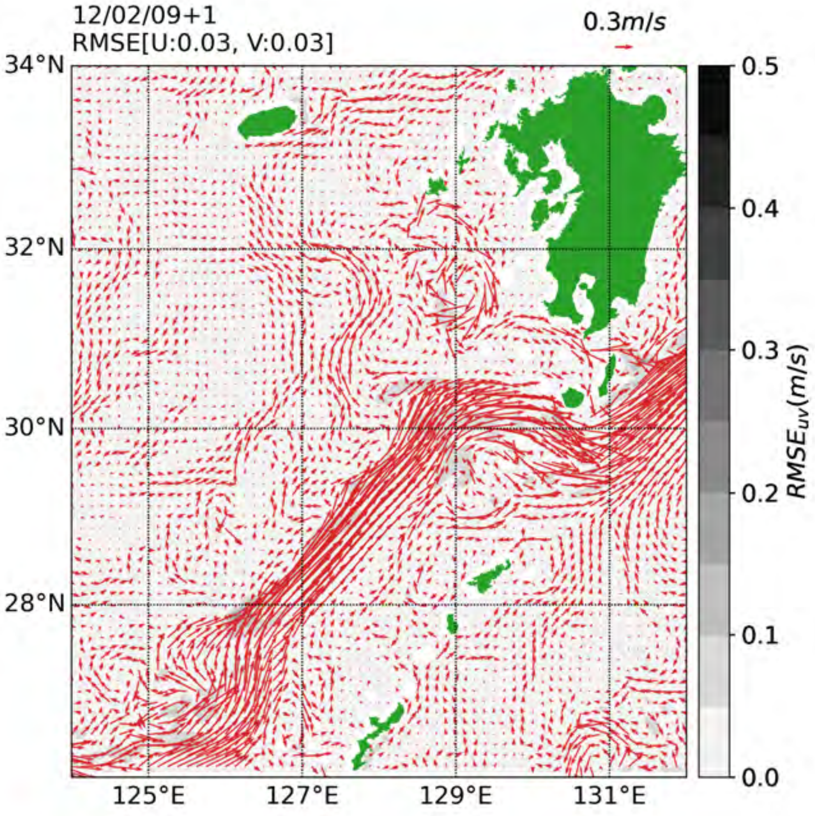


Sep. 01st + [1–5]

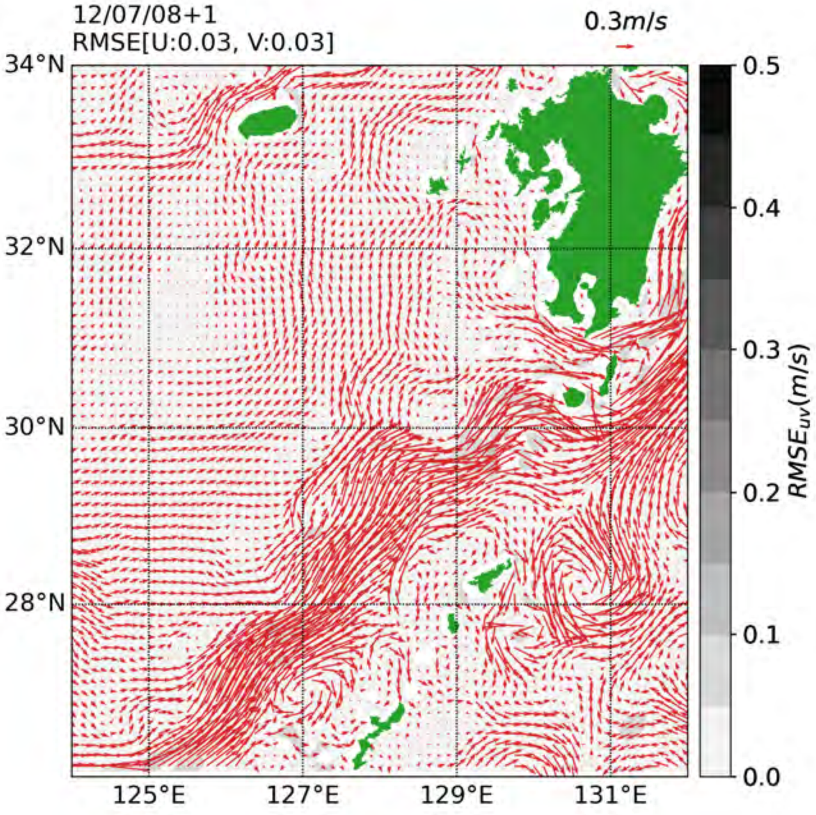


SSC-net predictions (5-day predictions)

Feb. 09th + [1–5]

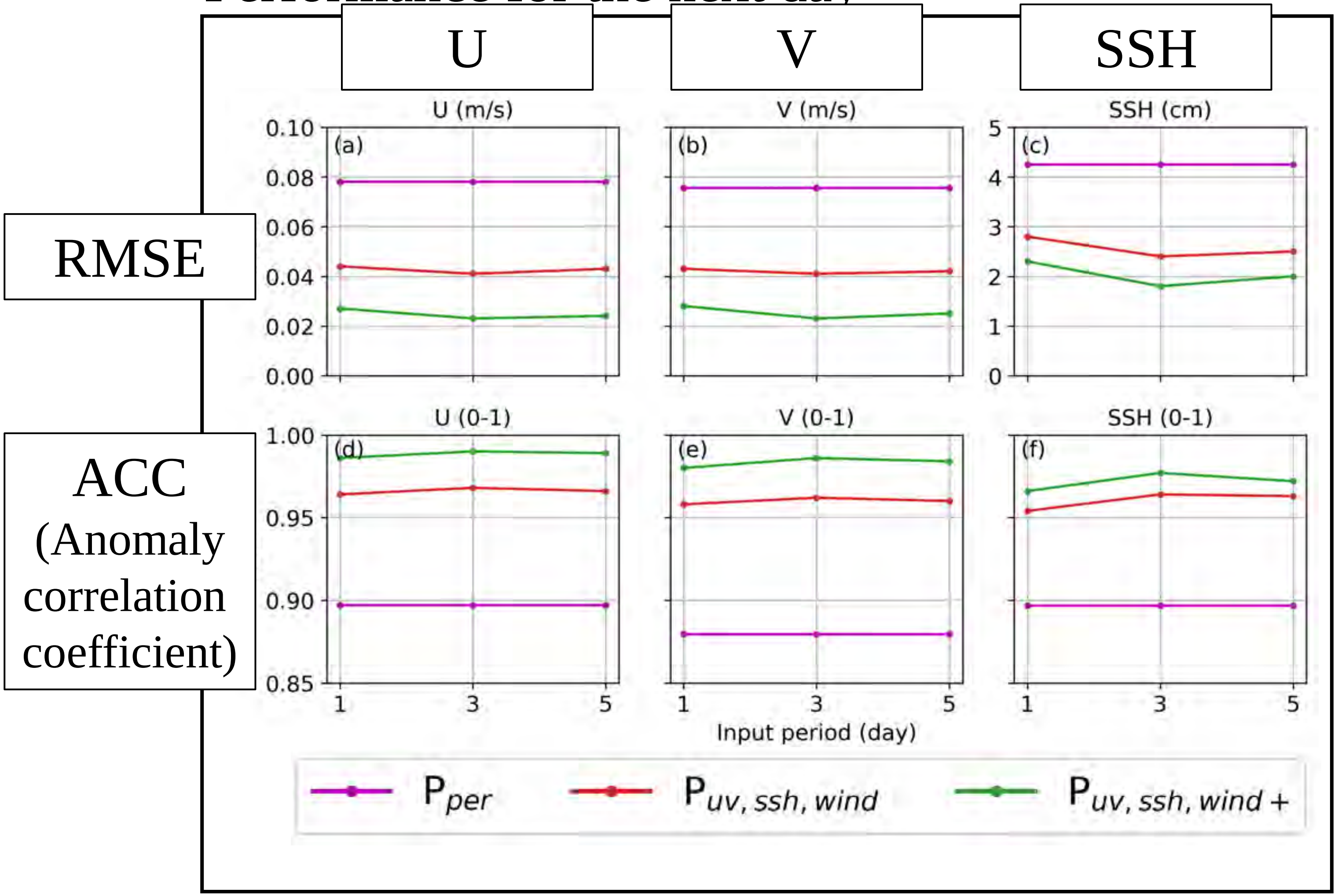


July 08th + [1–5]



SSC-net performance depending on input periods

Performance for the next day



- P_{per}: Persistence prediction (Difference between today and tomorrow)
- $P_{uv,ssh,wind}$: SSC,SSH,wind→ SSC, SSH
- $P_{uv,ssh,wind+}$: SSC,SSH,wind+→ SSC, SSH

⇒ Optimal input periods are <u>3</u> to 5 days.

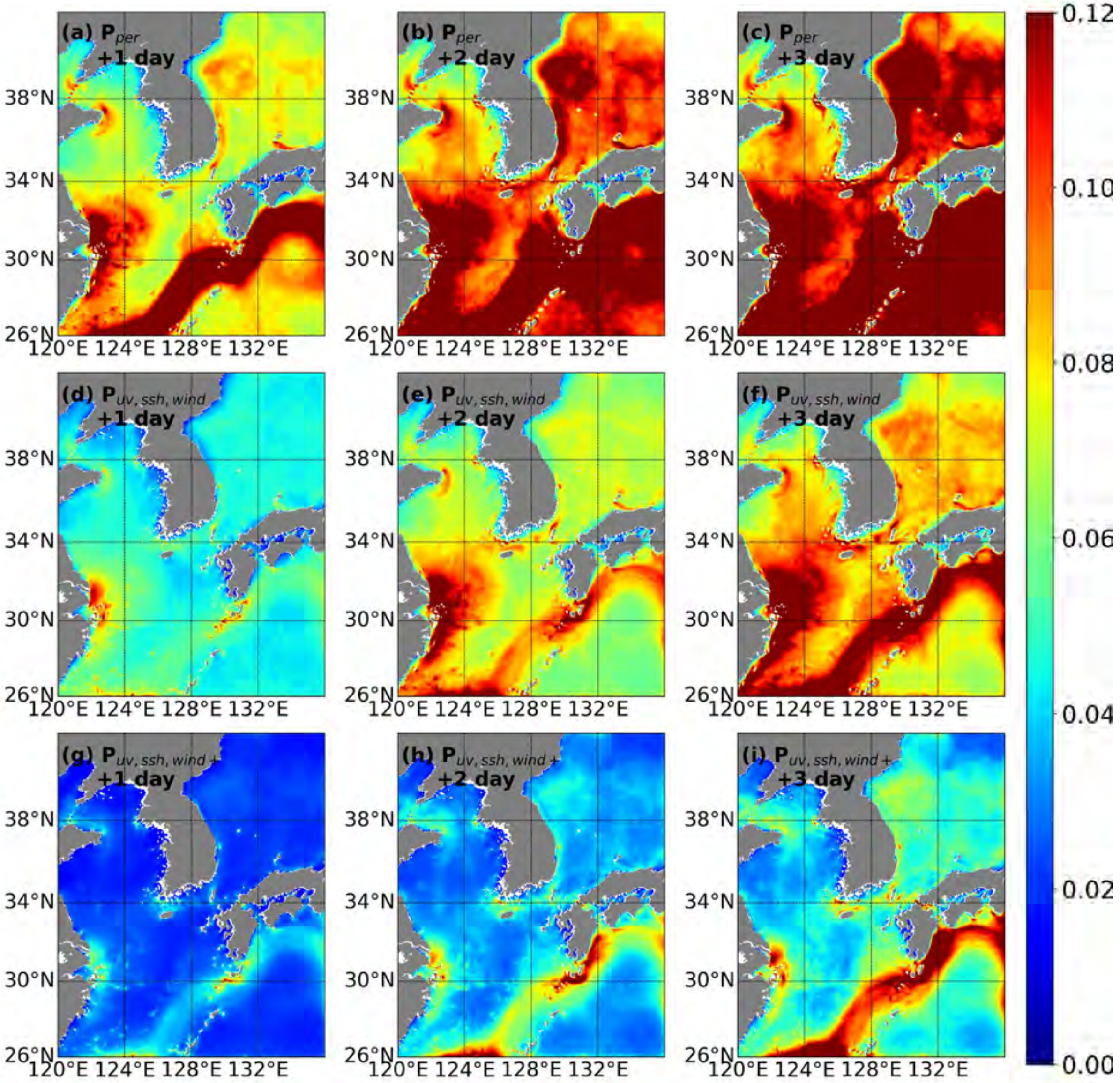
SSC errors depending on forecast days

[input days = 3]

Persistence error
(non-prediction case)

SSC,SSH,wind→ <u>SSC</u>, SSH

SSC,SSH,wind+→ <u>SSC</u>, SSH



Temporal-averaged D (m/s)

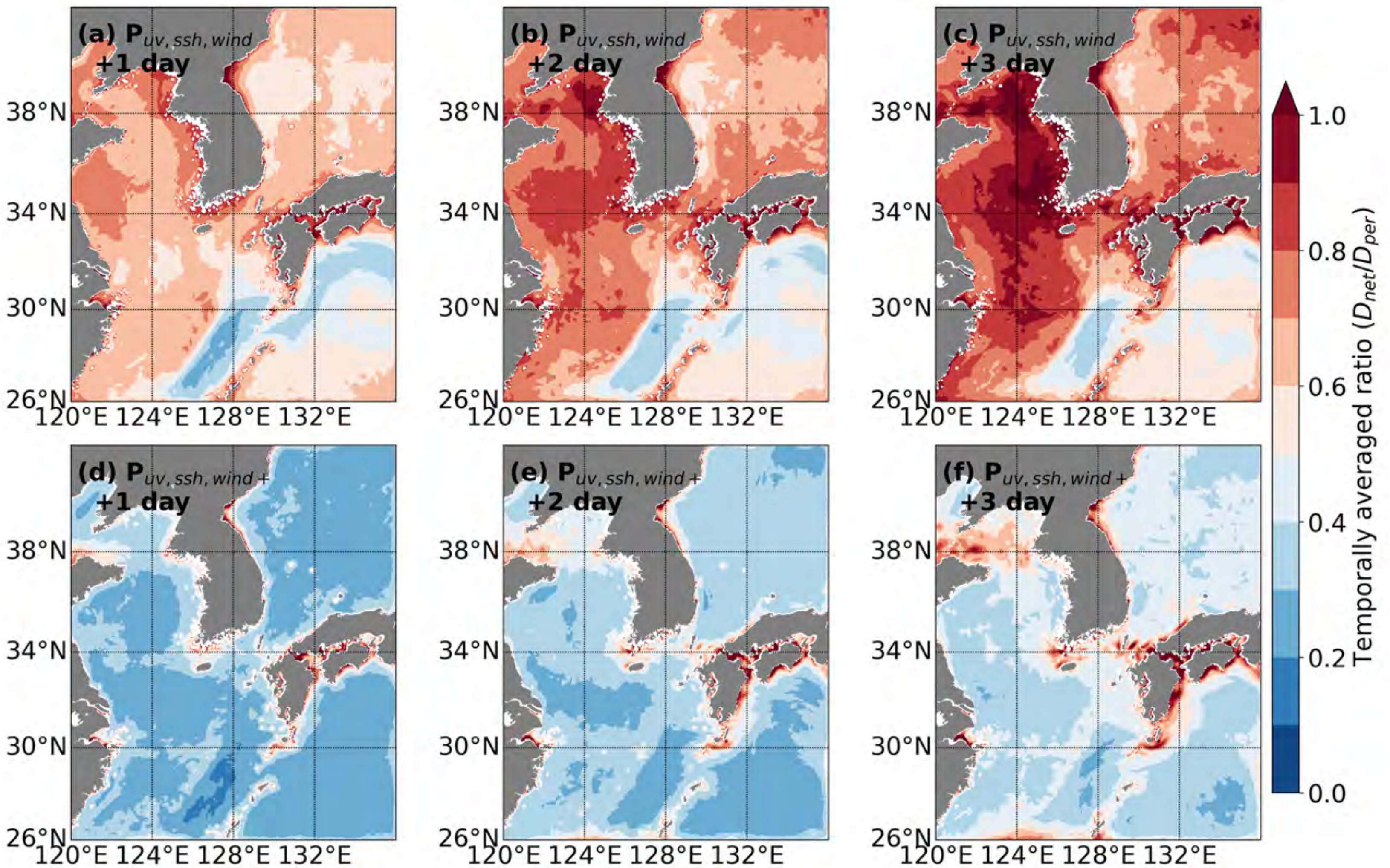
Normalized SSC errors depending on forecast days

[input days = 3]

Ratio
(Error of network/error of persistence
=Error of network/Daily variation)

SSC,SSH,wind→ SSC, SSH

SSC,SSH,wind+→ SSC, SSH



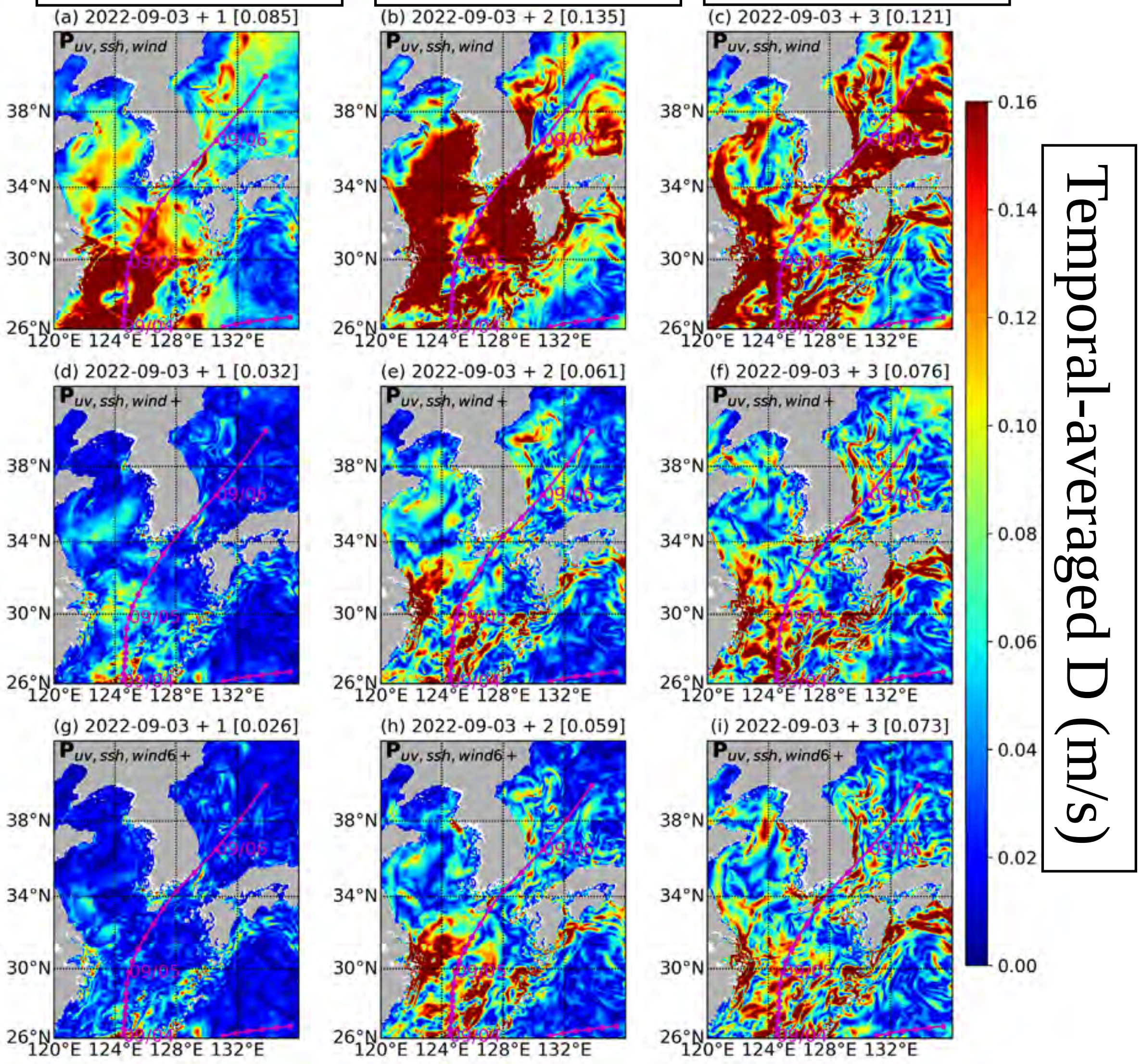
Effect of temporal resolutions of wind (daily/6hourly)

Sep. 03 +1 | Sep. 03 +2 | Sep. 03 +3 [input days = 3]

Prediction
using U, V, SSH, Wind

Prediction
using U, V, SSH, Wind+

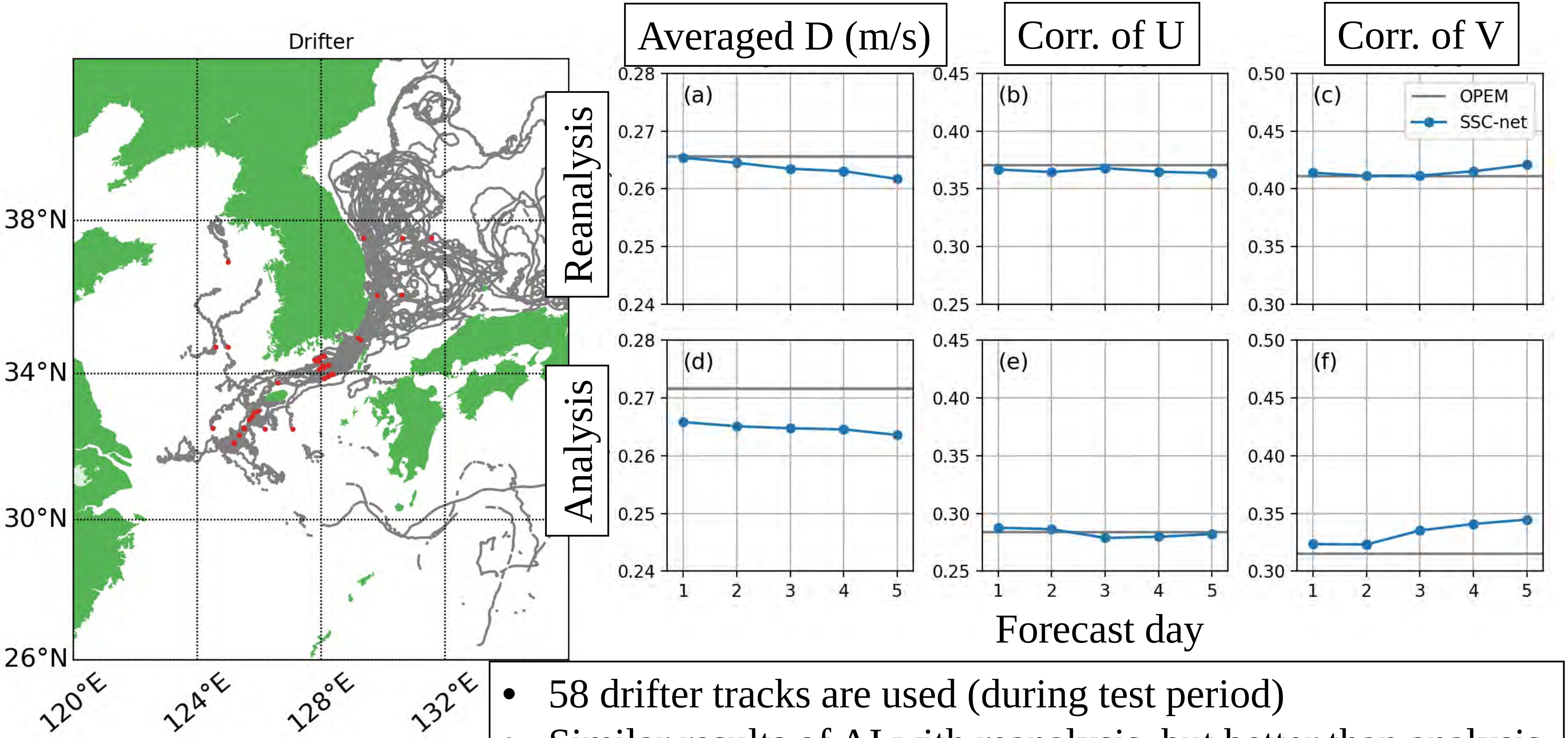
Prediction
using U, V, SSH, Wind6+



Typhoon: HINNAMNOR

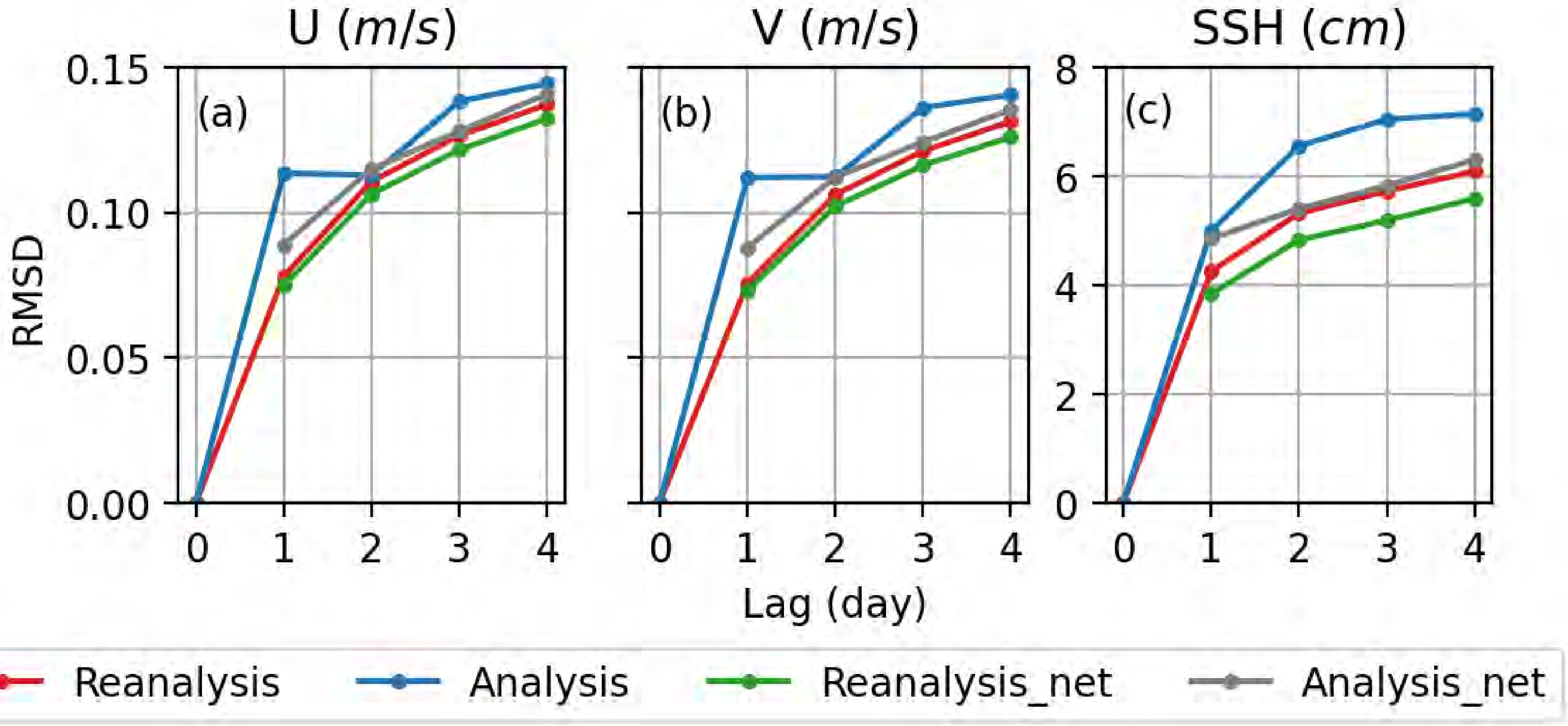
[input days = 3]

Comparisons of SSC with the drifter tracks



- 58 drifter tracks are used (during test period)
- Similar results of AI with reanalysis, but better than analysis

Daily variation of models



- Analysis data shows higher daily variation – no data-assimilation for SSH
- The network learned the pattern of reanalysis data

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.

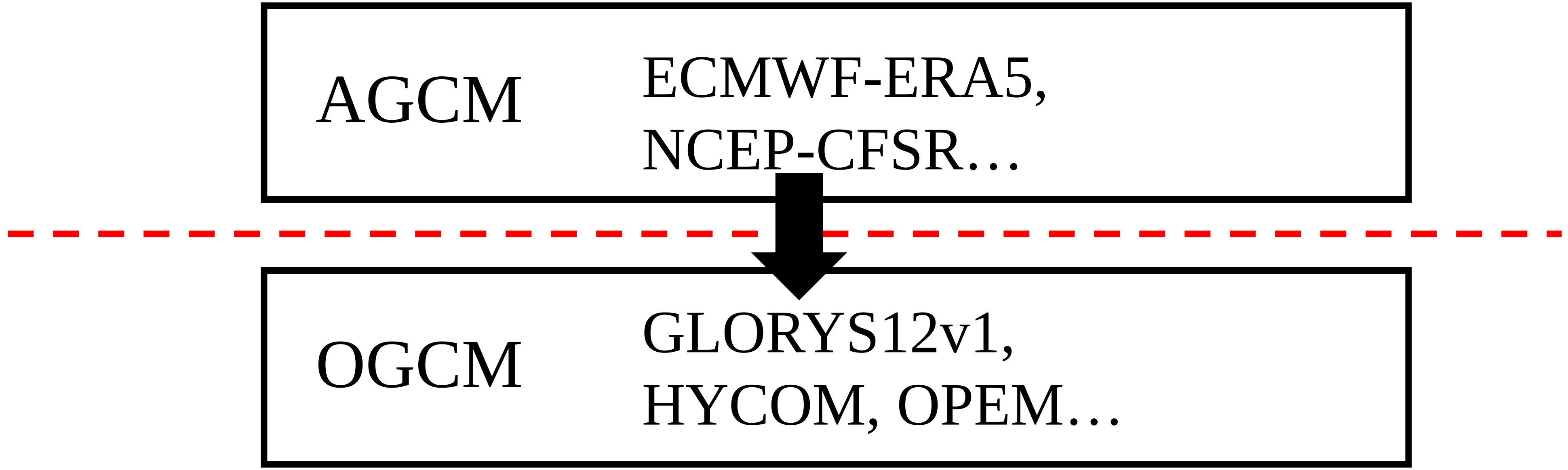
- The trained pattern can be override to the analysis data.
- It means it can be used in the near-real time prediction task with the pattern of reanalysis model.

- High resolution ocean prediction system using CNNs can be a practical and efficient way with a lightweight computing power.

OGCM

Ocean general circulation model (OGCM)

- one-way interaction



- Data-assimilation, high resolution…to make more realistic processes
- Hard to be applied in near-real time prediction tasks
- Need efficient ways for sea surface current (SSC) forecasts

Comparison with drifter tracks

3. When compared with the in-situ SSC data?

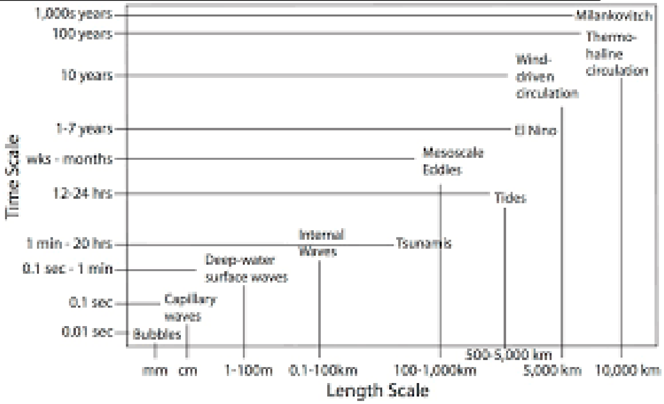
Model	**OPEM Reanalysis (used for the training)**	**OPEM Analysis (for forecast system)**
Surface boundary conditions	ECMWF - ERA5	KMA - GDAPS
Open boundary conditions	CMEMS - Global reanalysis	CMEMS - Global analysis and forecast
Data-assimilation	SST, SSH	SST

Normalized SSC errors depending on forecast days

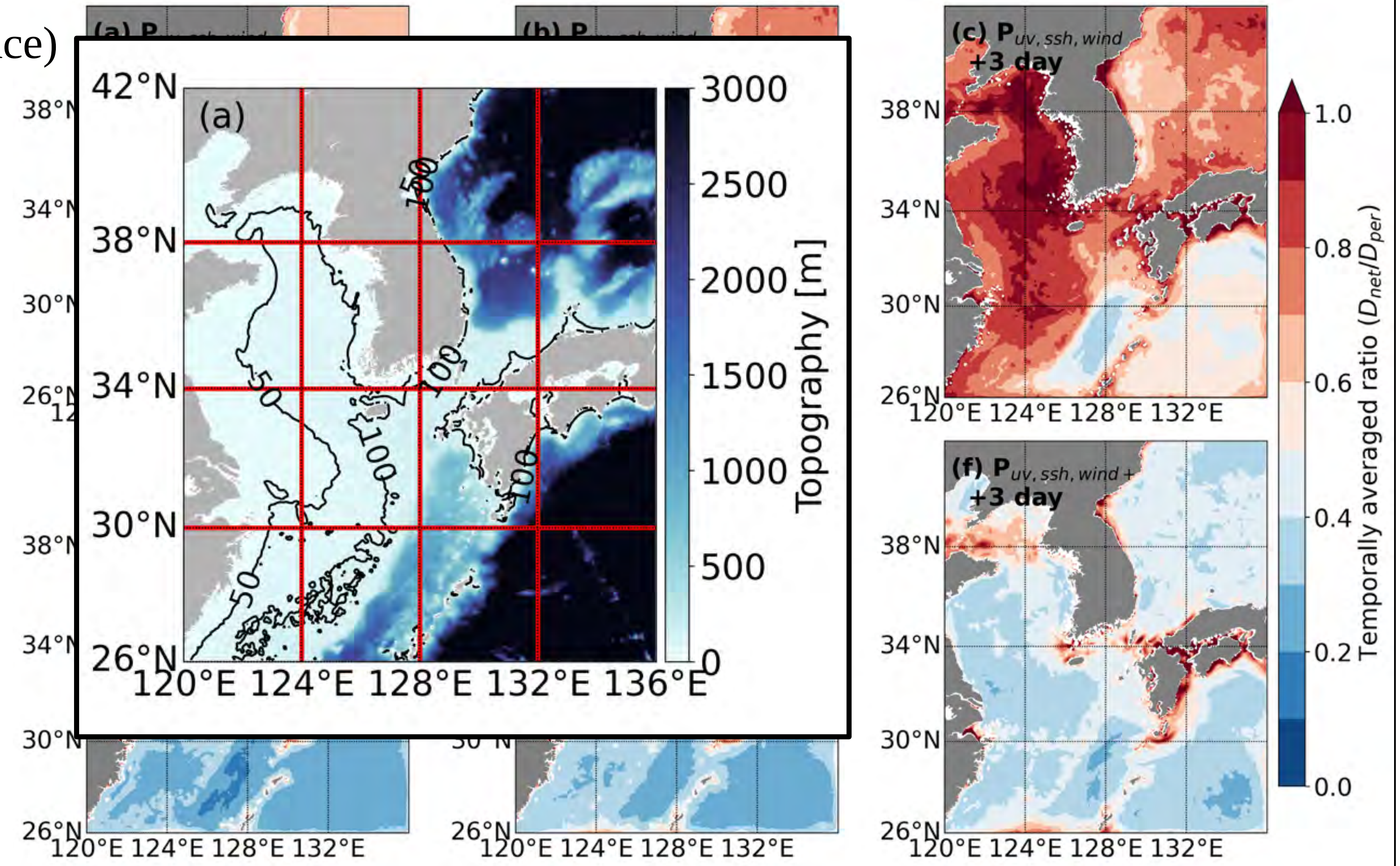
[input days = 3]

Ratio
(Error of network/Error of persistence)

SSC,SSH,wind→ SSC, SSH

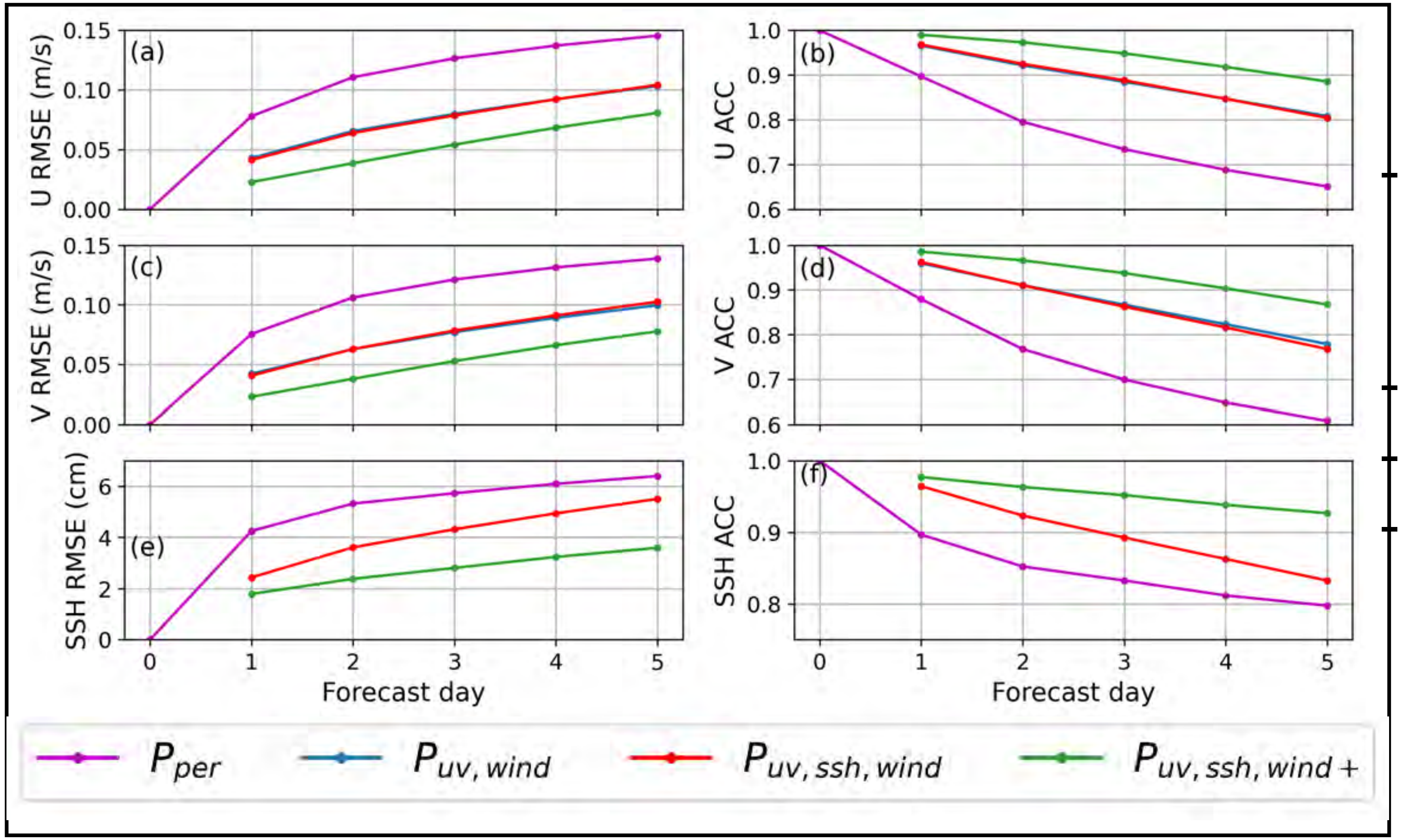


SSC,SSH,wind+→ SSC, SSH



SSC-net errors depending on predicting days

Predictions [input days = 3]



P_{per}: Persistence prediction (Difference between today and tomorrow)

$P_{uv,wind}$: SSC, wind→ SSC

$P_{uv,ssh,wind}$: SSC,SSH,wind→ SSC, SSH

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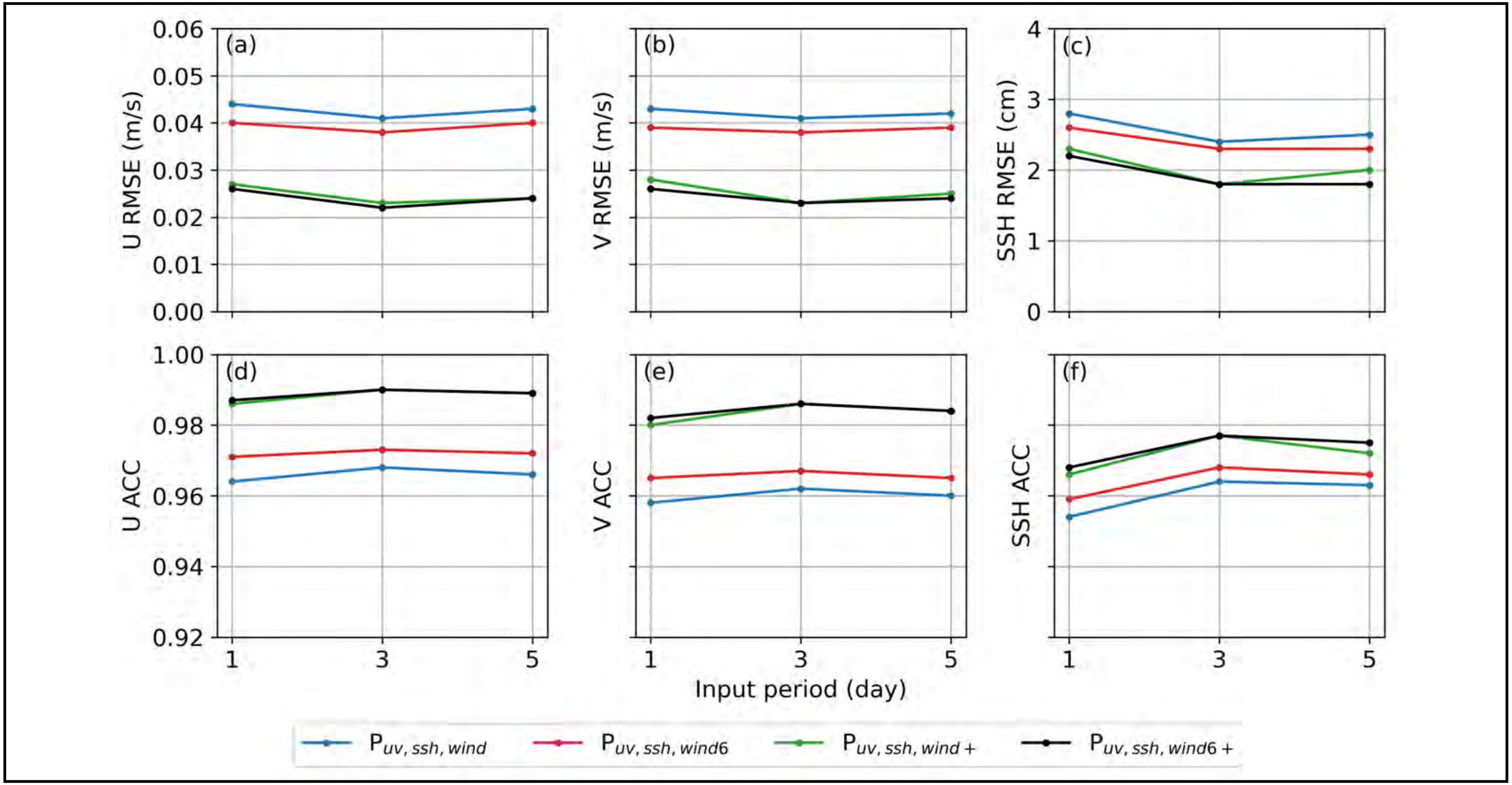
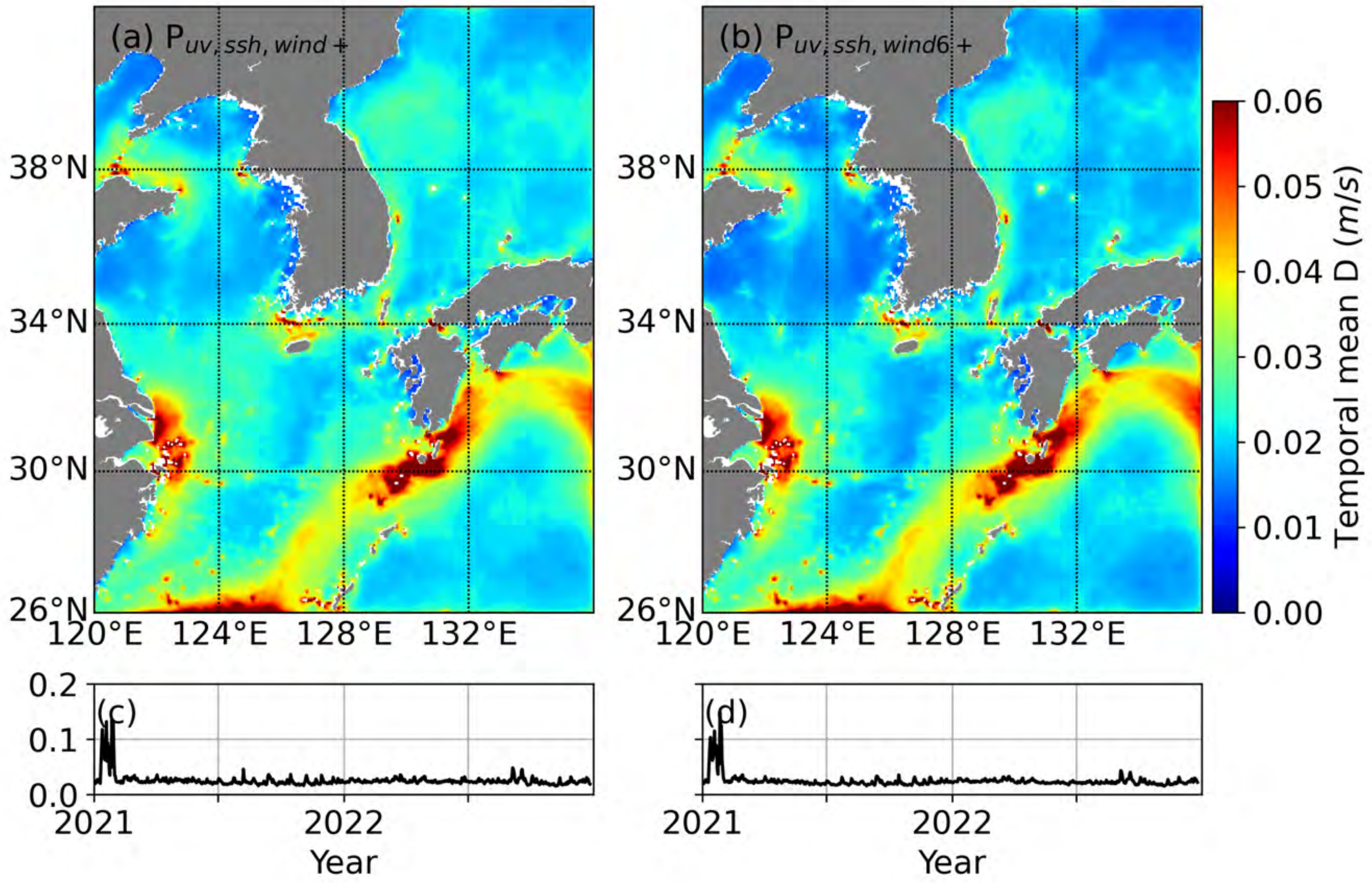
Effect of temporal resolutions of wind (daily/6hourly)



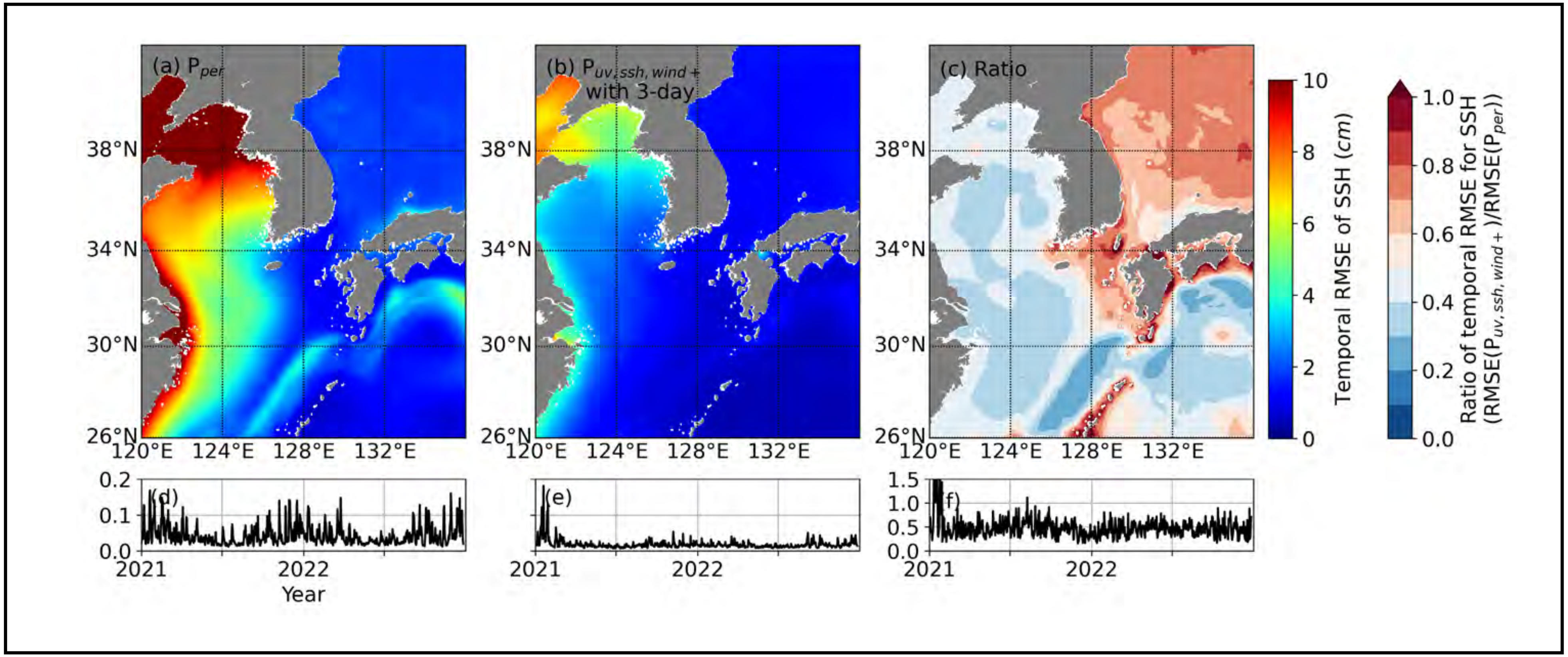
Effect of temporal resolutions of wind (daily/6hourly)

[input days = 3]



Effects of input days on the current prediction

[SSH] Prediction using U, V, SSH, Wind+

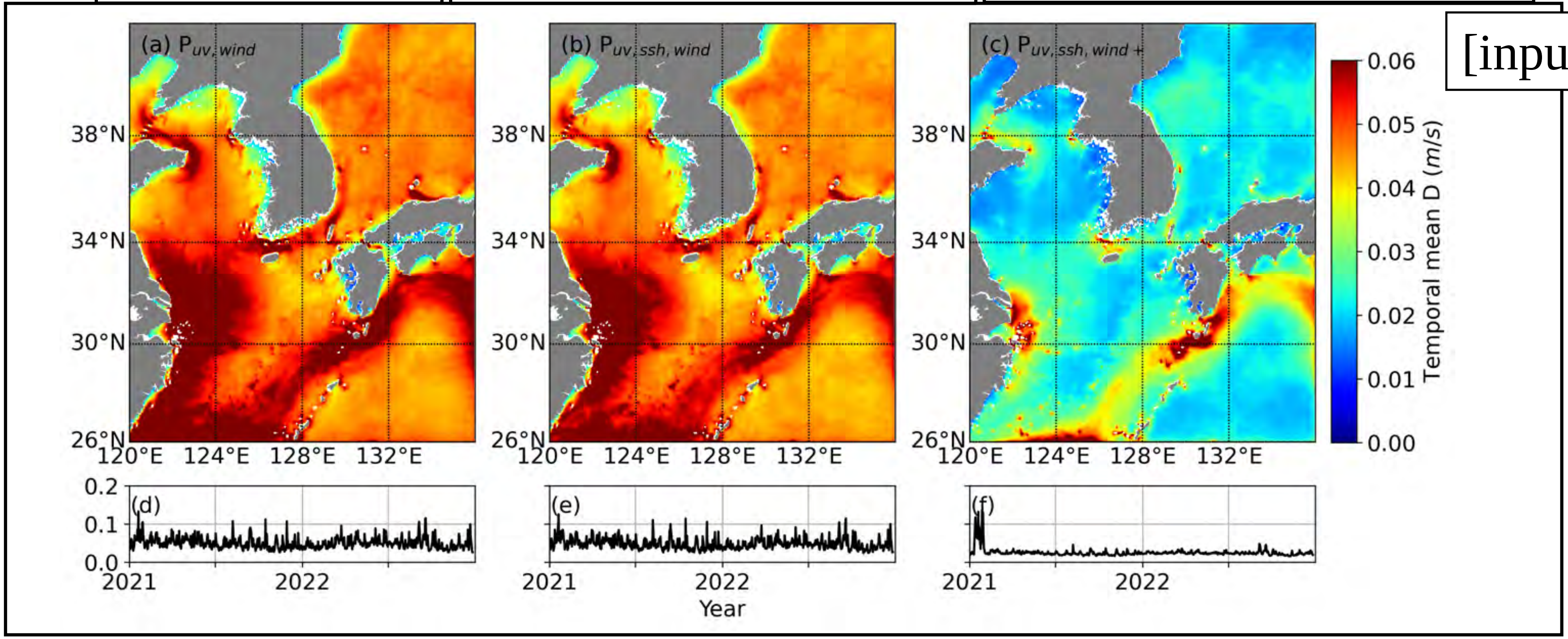


- Error distribution of SSH ($RMSE_{SSH}$) for the 1st prediction day (Input days = 3)

SSC-net performance depending on diff. variables

SSC, wind→ SSC | SSC,SSH,wind→ SSC, SSH | SSC,SSH,wind+→ SSC, SSH

[input days = 3]



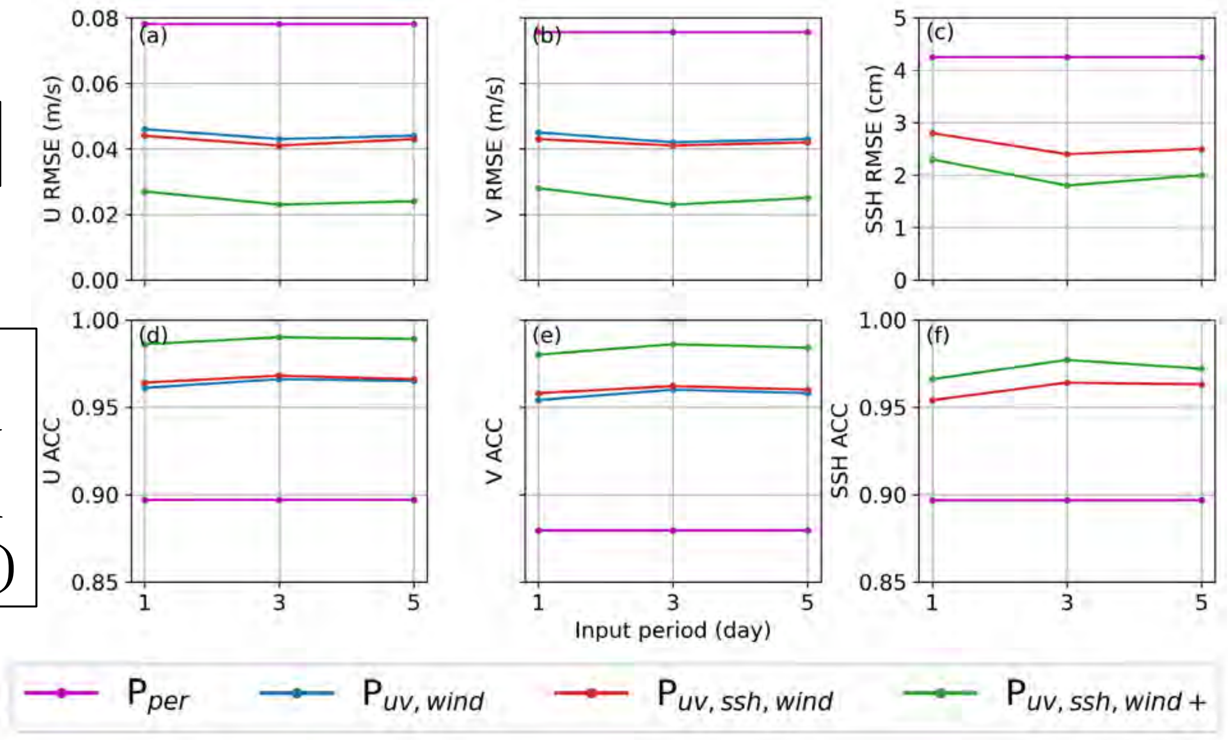
- Error distribution of SSC prediction for the 1st prediction day
- Performance is similar for the $P_{uv,wind}$ and $P_{uv,ssh,wind}$
- With the next day's wind, overall error is decreased

SSC-net performance depending on input periods

Performance for the next day

RMSE

ACC (Anomaly correlation coefficient)

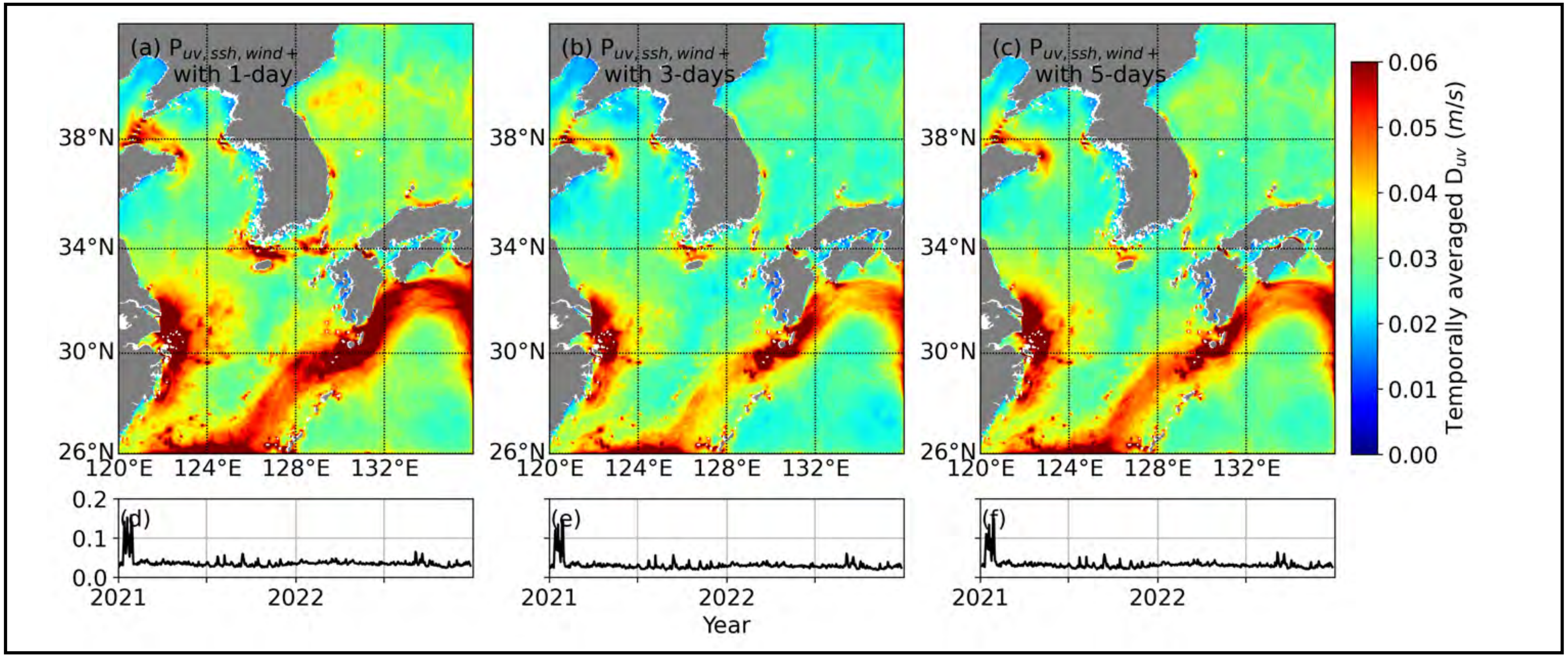


- P_{per}: Persistence prediction (Difference between today and tomorrow)
- $P_{uv,wind}$: SSC, wind→ SSC
- $P_{uv,ssh,wind}$: SSC,SSH,wind→ SSC, SSH
- $P_{uv,ssh,wind+}$: SSC,SSH,wind+→ SSC, SSH

⇒Optimal input periods are 3 to 5 days.

Effects of input days on the current prediction

Prediction using U, V, SSH, Wind+



- Error distribution of uv-component averaged RMSE (RMSEuv) for the 1st prediction day (Input days = 1, 3, and 5)
- Overall error decreases with 3 to 5 input-days

Question: comparison with OPEM forecast

Sun	Mon	Tue	*Wed	Thu	Fri	Sat
			Initial data	1) Permanent DA-run	1) Permanent DA-run	1) Permanent DA-run
Sun	Mon	Tue	*Wed	Thu	Fri	Sat
1) Permanent DA-run	1) Permanent DA-run	1) Permanent DA-run	Initial data	2) Tentative DA-run	2) Tentative DA-run	2) Tentative DA-run
Sun	Mon	Tue	*Wed	Thu	Fri	Sat
2) Tentative DA-run	2) Tentative DA-run	2) Tentative DA-run	Initial data	3) 10day Prediction-run	3) 10day Prediction-run	3) 10day Prediction-run
Sun	Mon	Tue	Wed	Thu	Fri	Sat
3) 10day Prediction-run	3) 10day Prediction-run	3) 10day Prediction-run	3) 10day Prediction-run	3) 10day Prediction-run	3) 10day Prediction-run	

□□. KOOS OPEM □□ □□□