Pioneering Adaptive Strategies for Korea Integrated Model in the Face of Climate Change

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1 Background

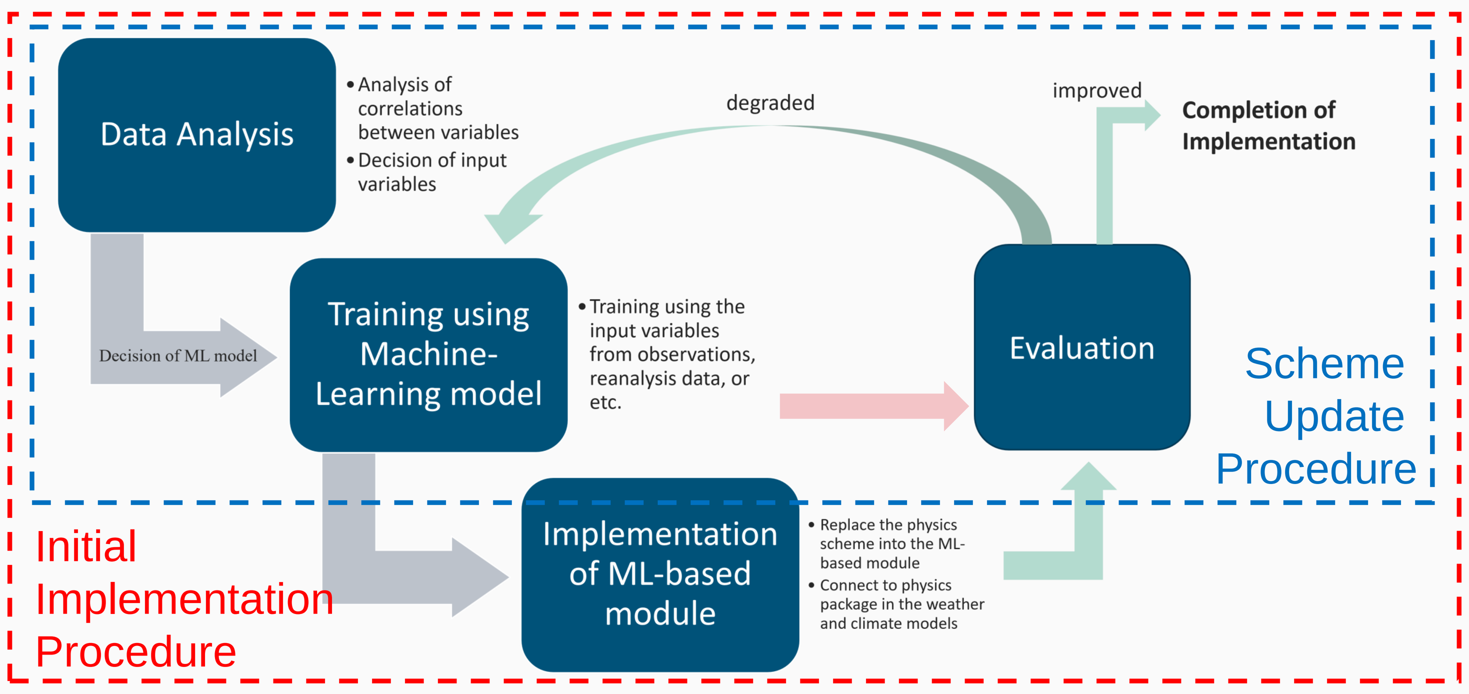
- Climate change poses significant challenges to numerical weather prediction models. As global warming alters established weather patterns, models struggle to accurately predict extreme events like cyclones and heatwaves, which are becoming more intense and unpredictable (Emanual, 2017)
- To address these challenges, scientists are integrating new technologies such as artificial intelligence and machine learning to improve model accuracy and adaptability (Brotzge et al., 2023).
- Korea Institute of Atmospheric Prediction Systems (KIAPS) scientists are also trying to develop climate-resilient models based on the Korean Integrated Model (KIM).
- This presentation will outline **various methodologies for developing models adaptable to climate change**, with a focus on the machine learning approach.

2 Strategy

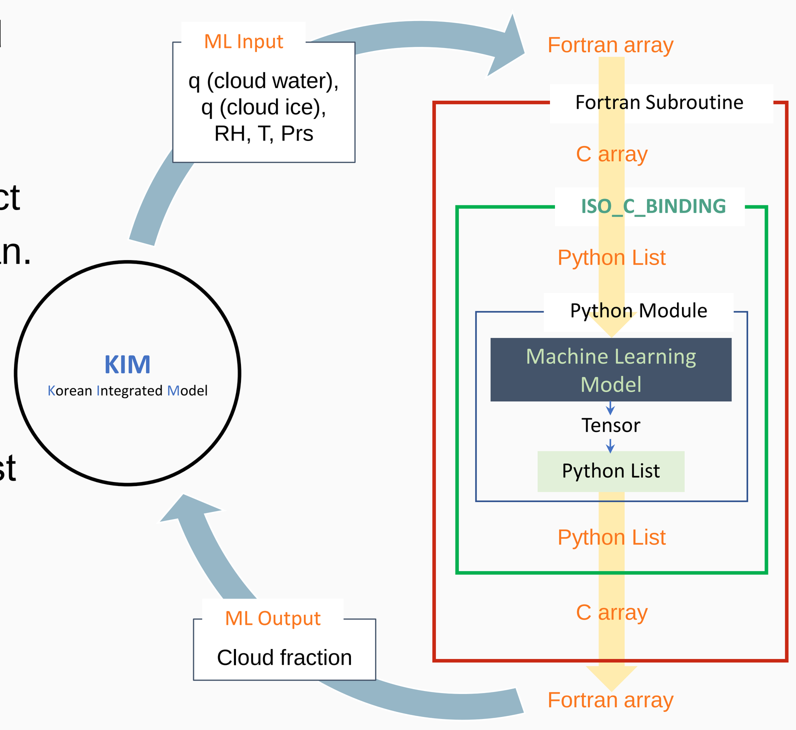
- We are exploring multiple approaches for developing a climate-resilient model.
  - One key strategy is **Machine Learning (ML)** integration for developing **climate-resilient physical parameterization schemes**.
  - Another involves refining initial and background conditions. For this purpose, we are **integrating ocean, sea ice, wave, and river flow models**. Additionally, we are also diagnosing and **refining various climatology** (ozone, carbon dioxide, aerosol, and so on) used in the KIM.
  - The other approach is **ensemble forecasting**, which provides a robust framework for enhancing the accuracy and reliability of weather and climate predictions amid climate change. This is achieved by quantifying uncertainty, reducing errors, and improving decision-making processes.

3 Methodology and preliminary results

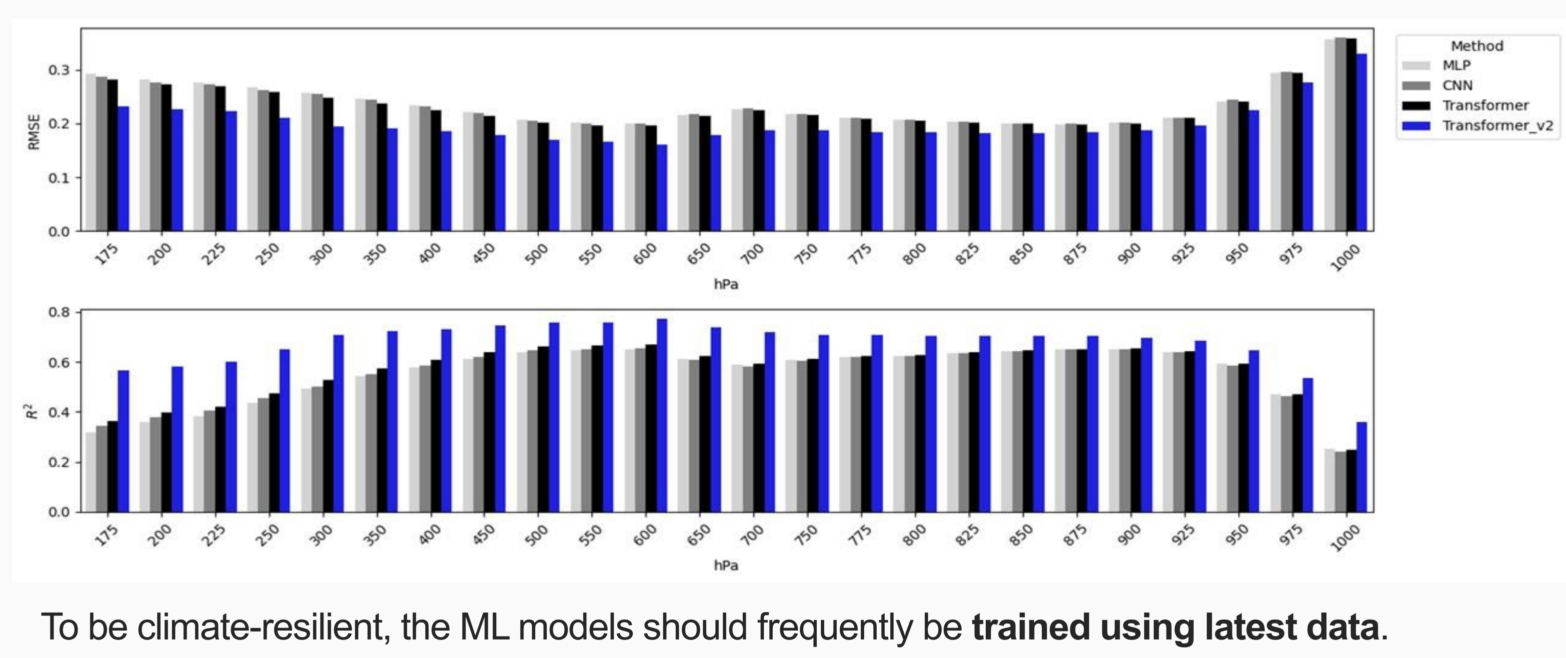
Developing ML-based scheme



- **Direct Variable Exchange Method** was adapted for **linking between ML model and KIM physics package**.
- Utilizing **ISO_C_BINDING**:
  - Convert Python modules into shared object (.so) files, enabling direct calls from Fortran.
  - Efficient data conversion:
    - KIM → C array → Python list → ML model input
    - ML model output (Tensor) → Python list conversion
    - Python list → C array → Fortran array → KIM transmission
- Seamless data exchange between Fortran and Python optimizes interactions between KIM and ML models.



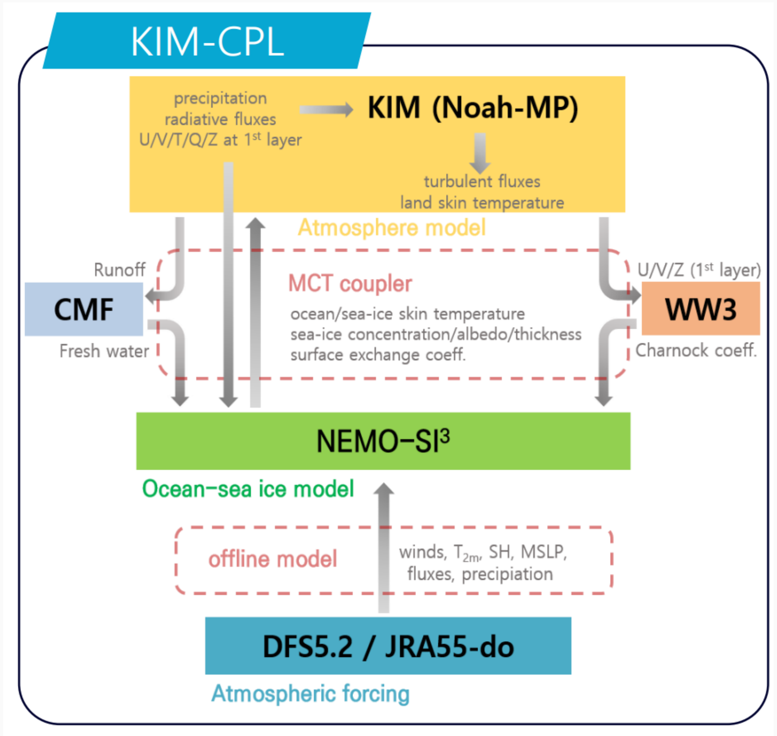
- Three ML models were compared for simulating cloud fraction: Multi-Layer Perceptron (**MLP**), Convolutional Neural Network (**CNN**), and **Transformer**.
- Transformer simulations at both lower and upper levels continue to exhibit slightly lower performance compared to mid levels, yet they remain more robust than CNN and MLP models.



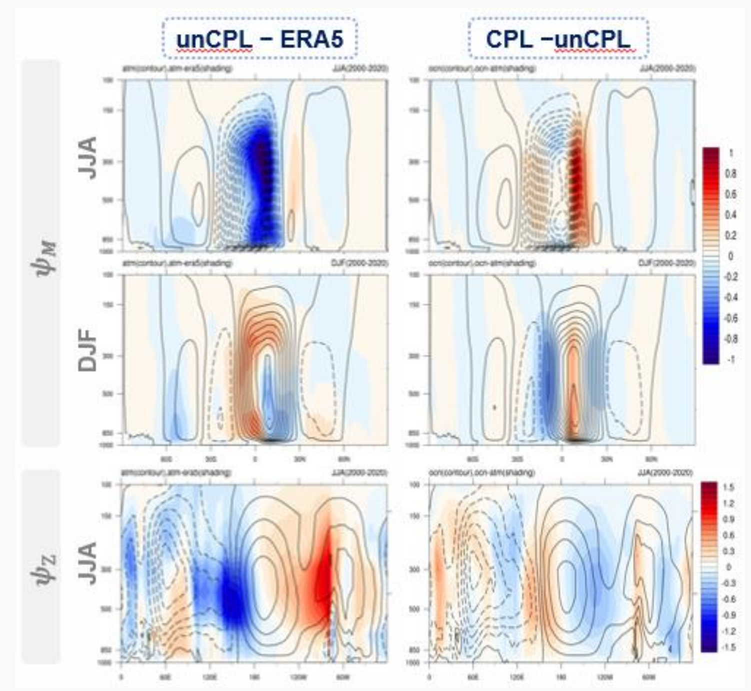
- To be climate-resilient, the ML models should frequently be **trained using latest data**.
- For use in regional modelling, **fine-scale local data** can be necessary for training the ML models.

Combining boundary models

- The coupled modeling system, which integrates atmosphere (KIM), ocean-sea ice (NEMO-SI³), wave (WW3), and river flow (CMF) models, demonstrates improved circulation patterns.

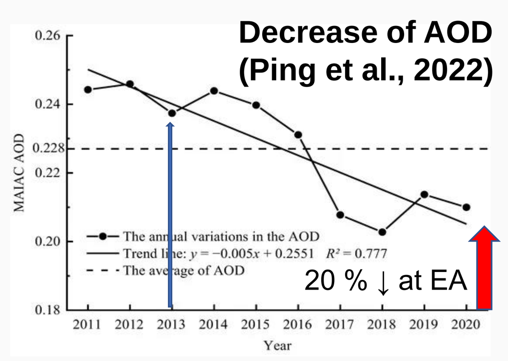


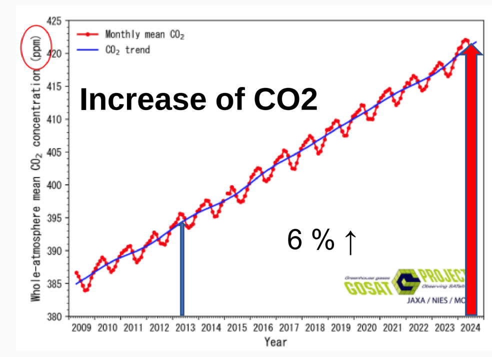
[Effect on the Hadley and Walker circulation]



Refining climatology

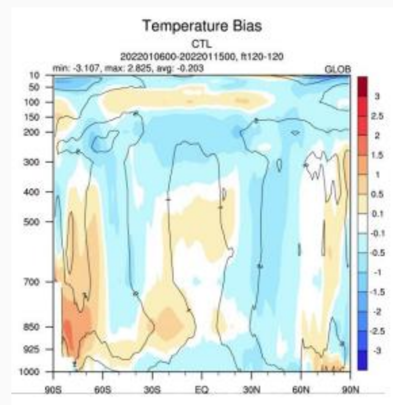
- As climate change accelerates, the variability of climatology used in weather and climate models is increasing, which can significantly impact model predictability. To address this, we aim to diagnose the appropriateness of these climate values and intend to optimize the climatology.



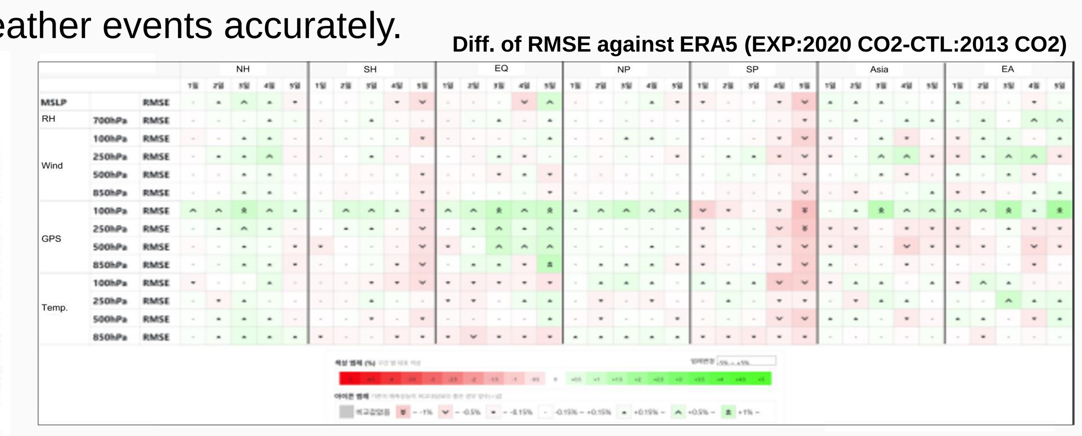


If these factors are not adequately reflected in numerical models, the models may simulate a cooler atmosphere than reality.

- When considering CO2 variability, improving model performance is not guaranteed. This is because bias errors in the model caused by influential variables such as clouds or surface processes may align with the direction of improvement expected from CO2 adjustments, ultimately leading to a degrading in model performance.
- However, The variability of climatology appears to have a significant impact on the predictability of numerical weather prediction models. Considering other climatology, this influence cannot be overlooked, as it may alter model performance and the ability to forecast extreme weather events accurately.

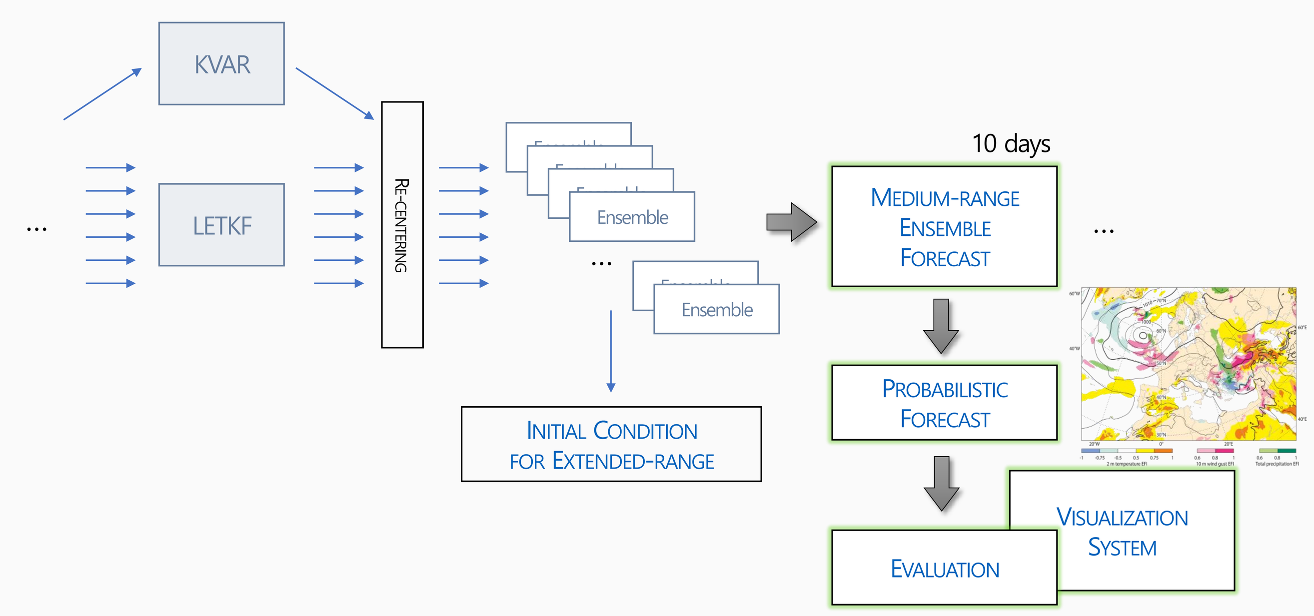


Diff. of RMSE against ERA5 (EXP:2020 CO2-CTL:2013 CO2)



Ensemble forecasting system

- By quantifying uncertainty, reducing biases, and enhancing risk assessment capabilities, ensemble methods are a critical tool for adapting numerical weather prediction models to the challenges posed by climate change.



4 Concluding remarks

- To address challenges in numerical weather prediction models caused by climate change, various methodologies are being applied to the KIM, including **machine learning-based physical parameterization, coupled modeling systems, improved climatology, and ensemble forecasting.**
- While these approaches may not provide direct solutions in a face of climate change, ongoing efforts and continuous refinement are expected to help overcome these difficulties.
- **International collaboration** like this workshop will be essential to address it effectively, since this issue is a global concern.

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