Algorithmic transformation from physical models to data-driven models using the coupling library: a case of a climate model

Hisashi YASHIRO (National Institute for Environmental Studies)

with

Takashi Arakawa(ClimTech Inc.), Shinji Sumimoto, Kengo Nakajima (U-Tokyo), and h3-Open-BDEC team

45th ASE Seminar (Advanced Supercomputing Environment):
International Workshop on "Integration of Simulation/Data/Learning and Beyond"
2023/11/29

Demands on HPC resource for weather/climate research

Resolution

km-scale is required for more accurate predictions

Climate simulation is more than 100 years

Duration

We need more computational power!

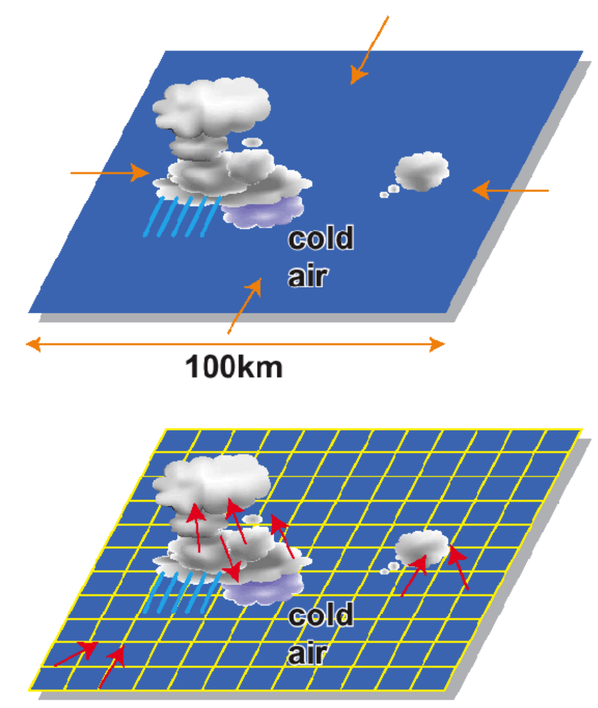
Complexity

we want to use more sophisticated model components

100 members is not enough

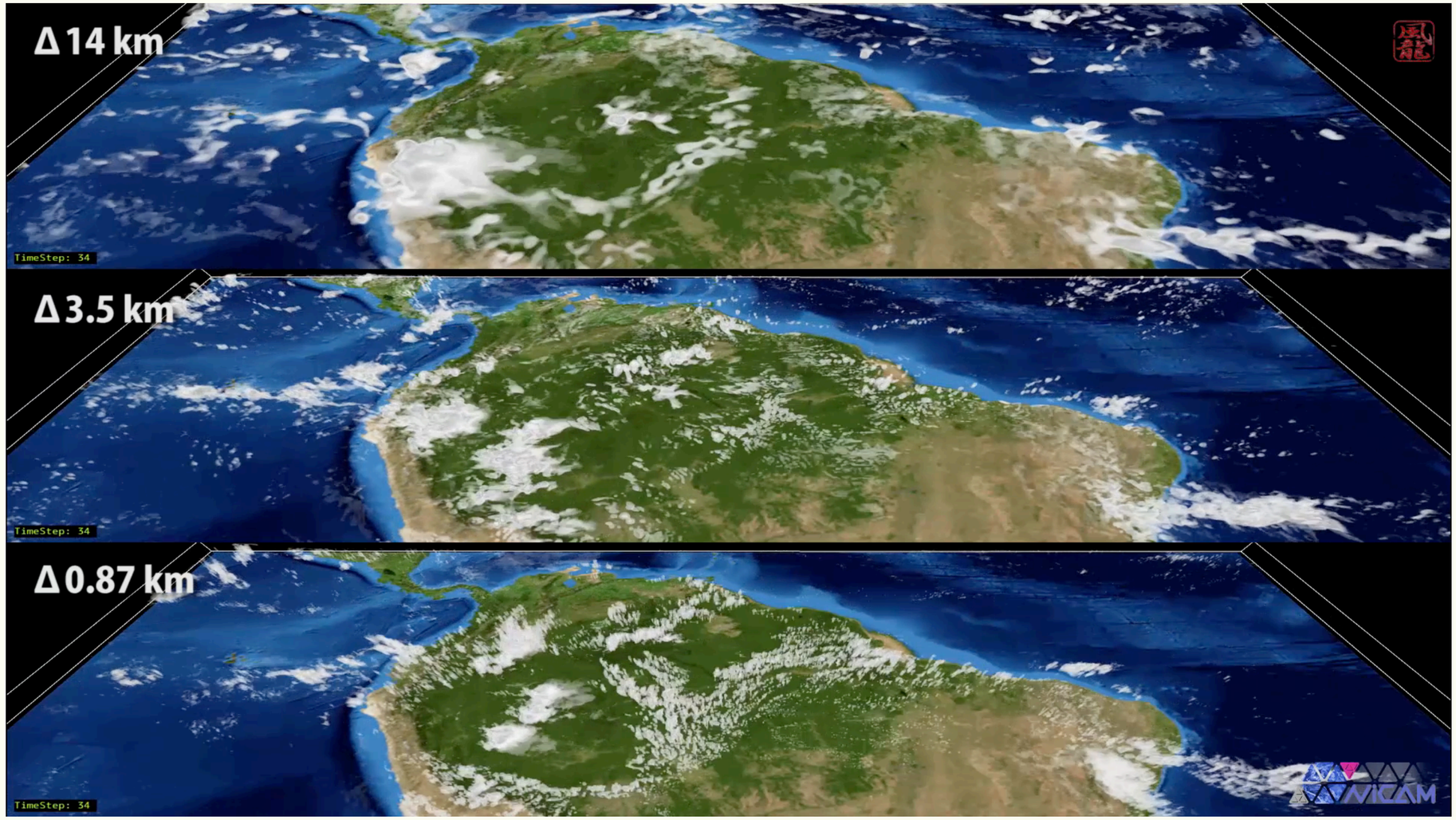
Ensemble

Why we need high-resolution atmospheric simulations?



- When the grid spacing is O(100km), we have to parameterize the clouds and convection process
  - Coarse-grained models cause large uncertainty
- However, high resolution simulation takes large computational cost
  - 1/10 horizontal grid spacing -> x1000 problem size

Simulated precipitation diurnal cycle over the Amazon region



- Observations show late afternoon peak
  - Too early peak is simulated in *O*(100km) resolution
  - The simulation in *O*(10km) resolution shows midnight peak
  - Super high-resolution (*O*(1km)) reproduce the timing well

…But big obstacles stand in our way

The trend of the HPC is changing and changing

- Weather/climate models are huge and very hard to port
- The memory throughput mainly determines simulation speeds, and its performance will not improve faster as we expected
- No large hot-spots of computation: we have to optimize everywhere in the application

ACM Gordon Bell prize for climate (2023~)

- This prize encourages collaboration and further efforts between climate science and computational science
- The first winner was the very big team: They've rewritten the atmospheric model with C++

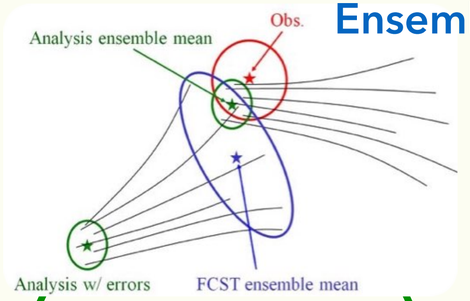
Development of the coupling library h3-Open-UTIL/MP

Two practical cases for using our coupling library

- The reduction of the computational cost of high-resolution weather data assimilation

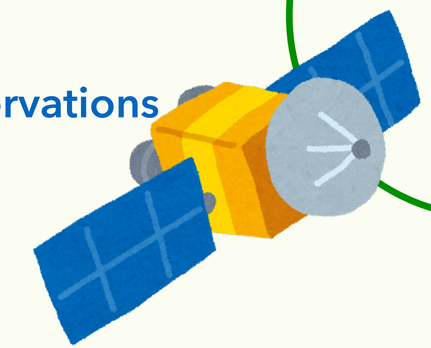
- The reduction of the computation through the making of data-driven surrogated models

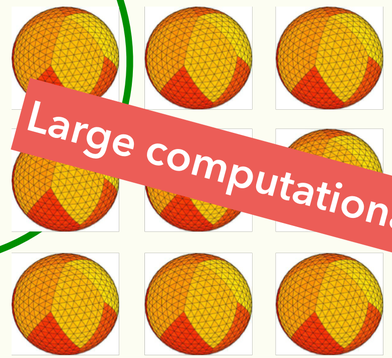
The reduction of the computational cost of high-resolution weather data assimilation



Ensemble Karman filtering

Observations

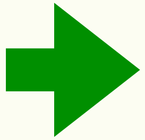


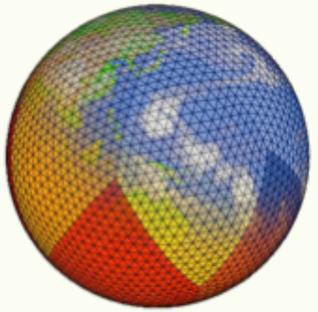


Large computational cost

Hi-res. Ensemble simulations

Ensemble Mean



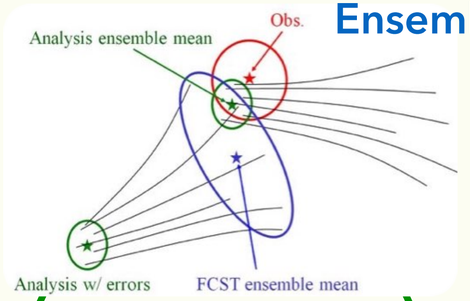


Realistic atmospheric state

Ensemble data assimilation (DA)

- Total computational cost = 1-member simulation x # of ensemble members
- high-resolution x large ensemble is costful

The reduction of the computational cost of high-resolution weather data assimilation



Ensemble Karman filtering

Observations

Low-res. Ensemble simulations

h3-Open-UTIL/MP
Coupling

Realistic atmospheric state

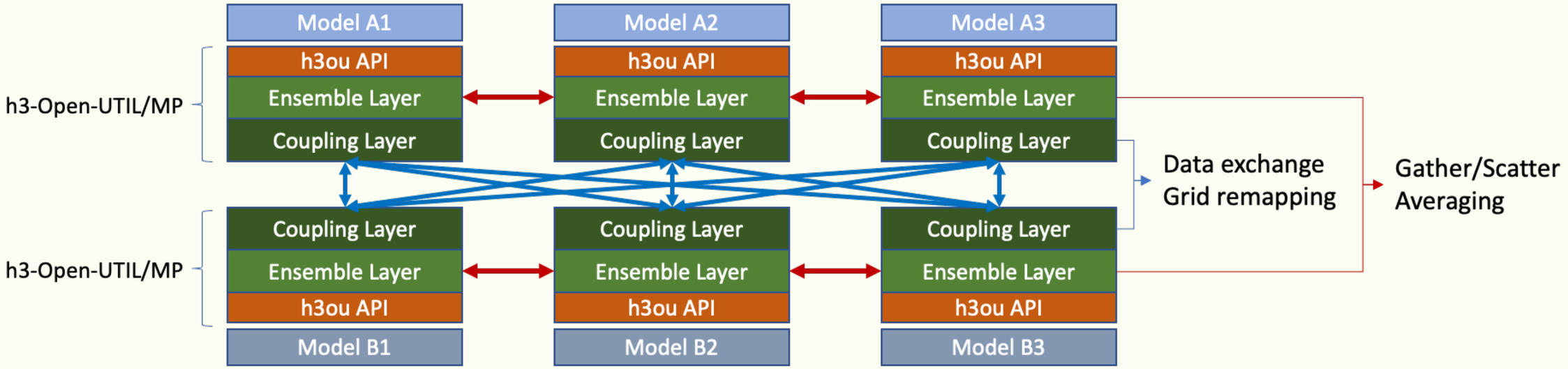
- Large scale: nudged by Low-res. DA
- Small scale: explicitly simulated

Online coupling of Low-Res. Ensemble DA + Filtered Nudging

- DA result and high-res. prediction is compared in the low-resolution

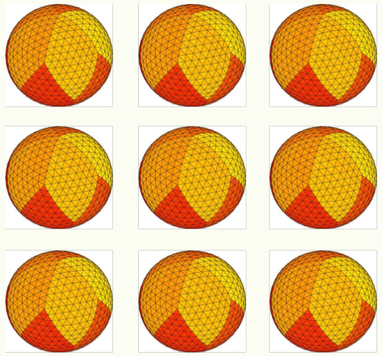
➡ Difference is applied as a nudging tendency (=Newtonian relaxation)

Ensemble + Coupling by h3-Open-UTIL/MP



- Coupling Layer : data exchange between different models
  - grid remapping
  - MxN (local to local) send/recv
- Ensemble Layer : data exchange between same models
  - Gather and Scatter on the same area of different ensemble
  - Average calculation of ensemble data

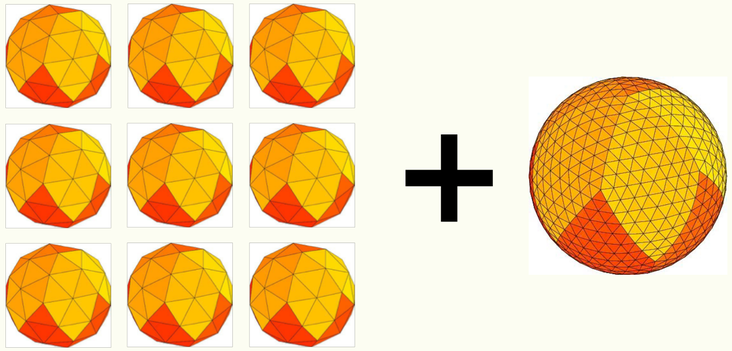
Estimation of the computational cost



High-res. Ensemble DA

- 14km mesh, 64 members
- 640 MPI procs per member

➡ 0.5 simulation day per wall-clock hour (SDPH) with 1280node of wisteria-o



Low-res. Ensemble DA + One Hires. Nudging

Ensemble DA part

- 224km mesh, 64 members
- 40 MPI procs per member

➡ 181 SDPH with 640node of wisteria-o

Filtered Nudging part

- 14km mesh, 1 member
- 2560 MPI procs per member

➡ 9.1 SDPH with 640node of wisteria-o

Total

- Two simulations are almost overwrapped

➡ 9.1 SDPH with 1280node of wisteria-o

➡ **x18** faster than high-res. ensemble DA!

The reduction of the computation through the making of data-driven surrogated models

AI weather models!

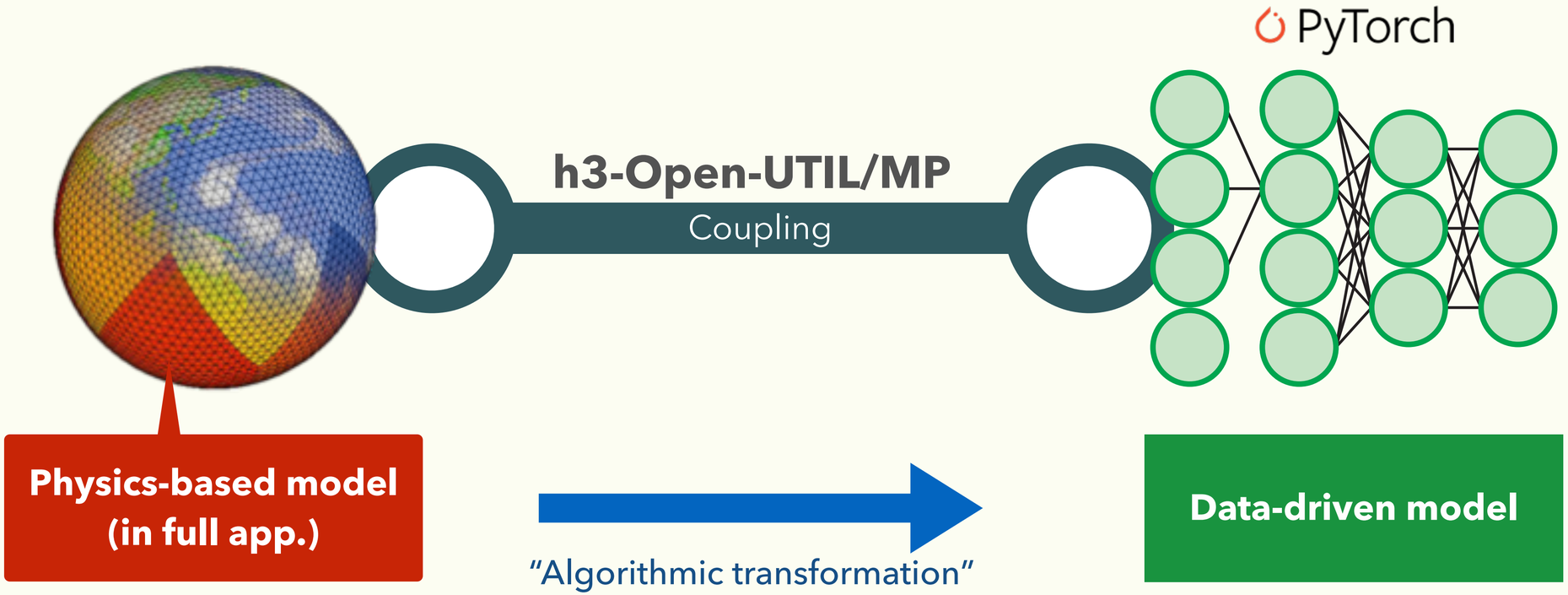
- GraphCast, Pangu Weather, FourCastNet, etc…
- Hot topics in the world
- It surrogates simulation results ~= full model

But we are climate/weather scientist

- We want understand the process of the phenomena in the atmosphere
- We will not throw away the physics models from now and future
- We want to apply new technics step by step in the huge-codebase software

➡ Component-level surrogation by AI technics to make a “booster”

Training system with coupling library

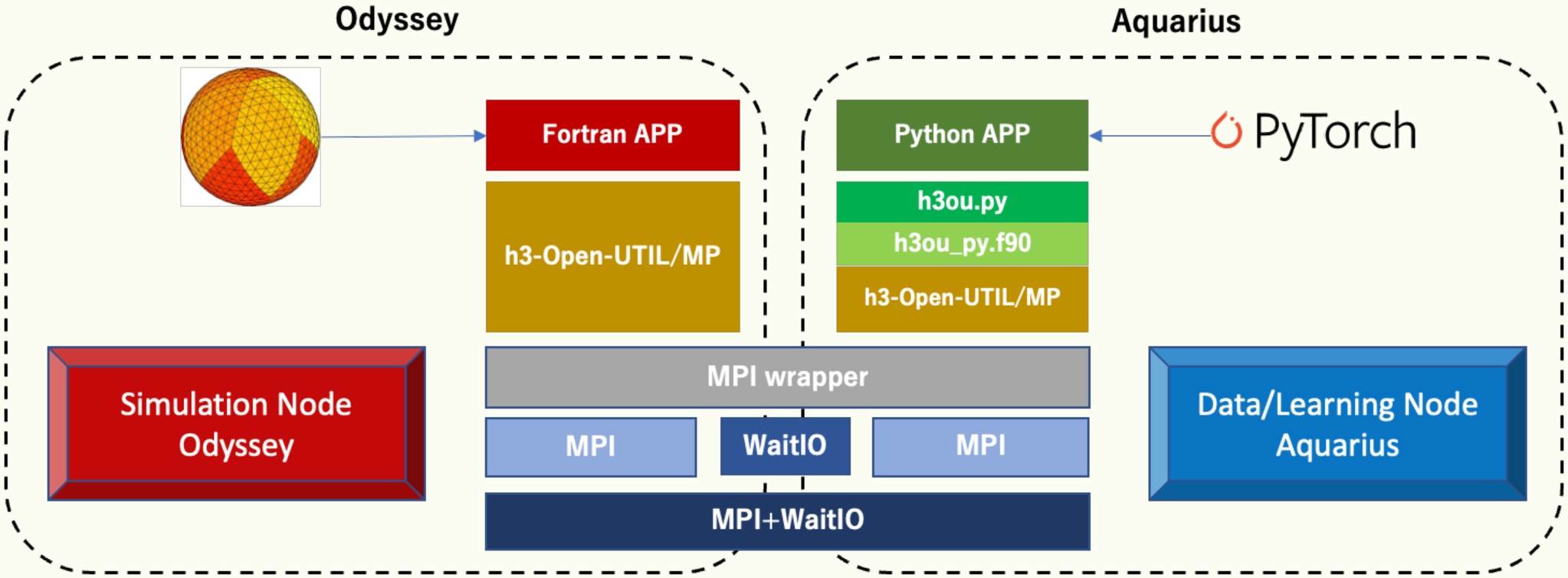


- Based on our knowledge
- Relatively slow, difficult to speedup anymore

- Provide teaching data on-the-fly
- Plug-in to target component of the application

- Fast because less computation
- Dense computation fits GPUs
- Lots of GPU-ready libraries

Training system with coupling library

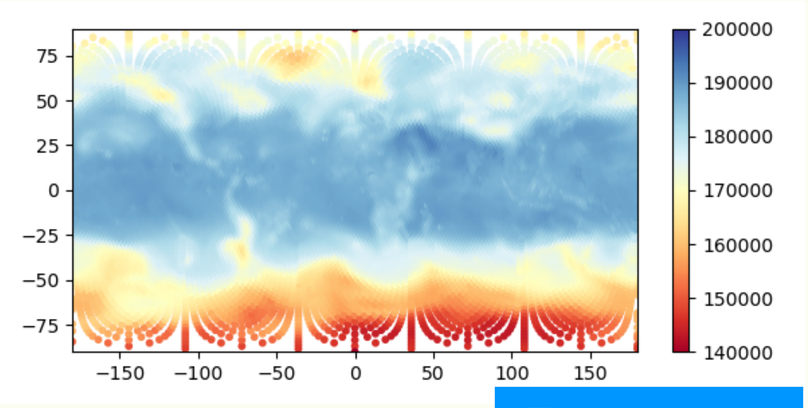


Coupling with a legacy fortran application and a modern python ML library

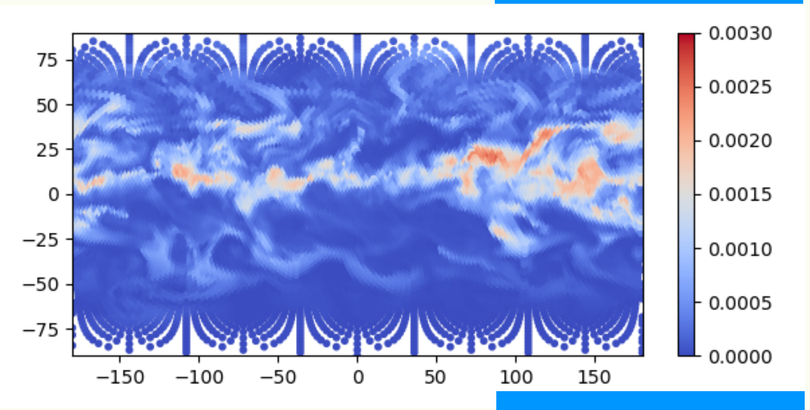
By using **h3-Open-SYS/WaitIO** together, users will be able to perform calculations using heterogeneous supercomputers easily

The case of the cloud microphysics scheme

States

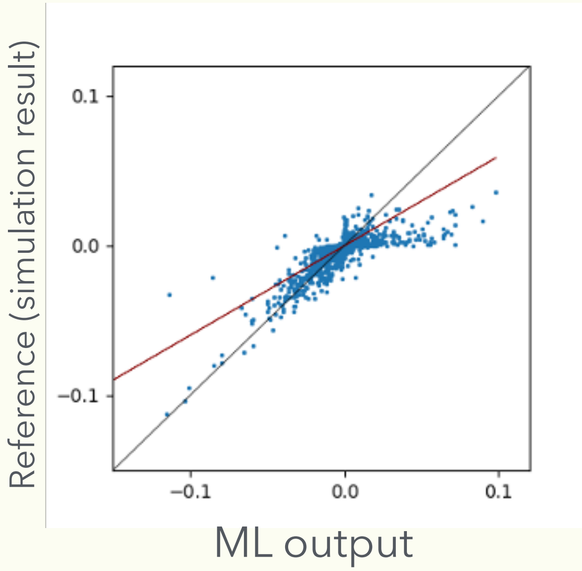


Temperature



Water vapor

- Input: air density, temperature, water vapor amount
- Output: tendency of the inputs
- 3-layers MLP



- For more accurate reproducibility:
  - More input variables
  - Inputs from the multiple atmospheric layers

Summary

Weather/climate models still need huge amount of the computational resources

- However, accelerating weather/climate models will be more difficult in the next decade
  - Performance portability, memory wall, algorithms that cannot increase computational intensity…

Solving some issues by using coupling library

- h3-Open-UTIL/MP is powerful tool for bridging models across the scale and algorithm