Seamless Global Modelling Workshop
June 4th 2025

Machine Learning Emulation of Climate Change Projections for Southeast Asia

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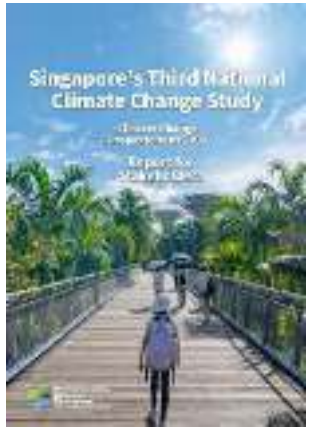
CCRS launched the Third National Climate Change Study (V3) in 2024

V3 study provides **future climate change projections** for Singapore and the Southeast Asia by 2100.

- based on **latest IPCC AR6**, and **6** CMIP6 models
- under **three emission scenarios**.
- world's **highest-resolution** (2 & 8km) projections for **SEA**
- advanced bias adjustment for SG

Stakeholder Report



Science Report

Research Articles, Videos, Brochures

V3 Data Sharing Portal

https://v3-climate-projections-uat.mss-int.sg/

V3 Visualisation Portal

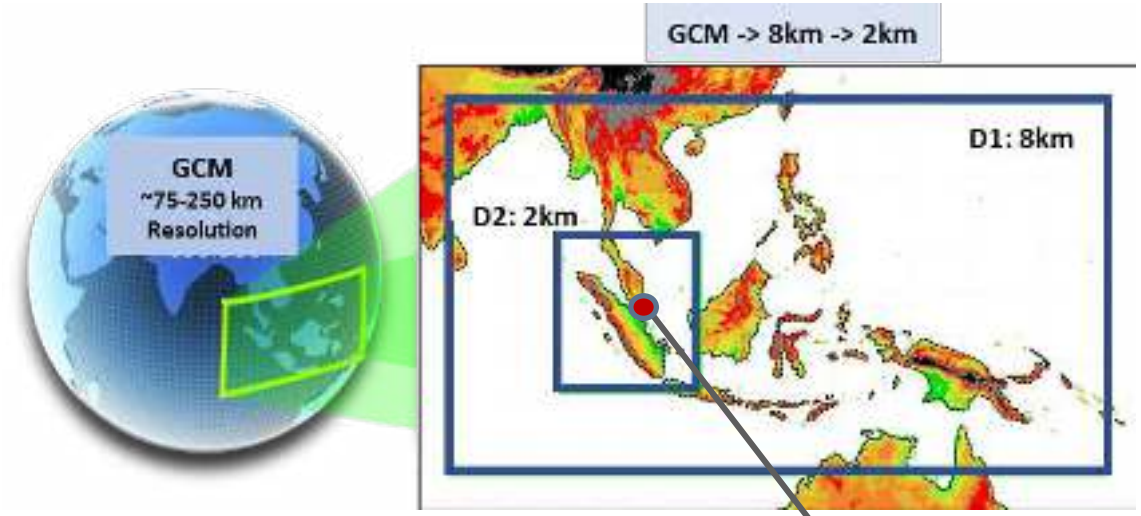
https://www.mss-int.sg/v3-climate-projections

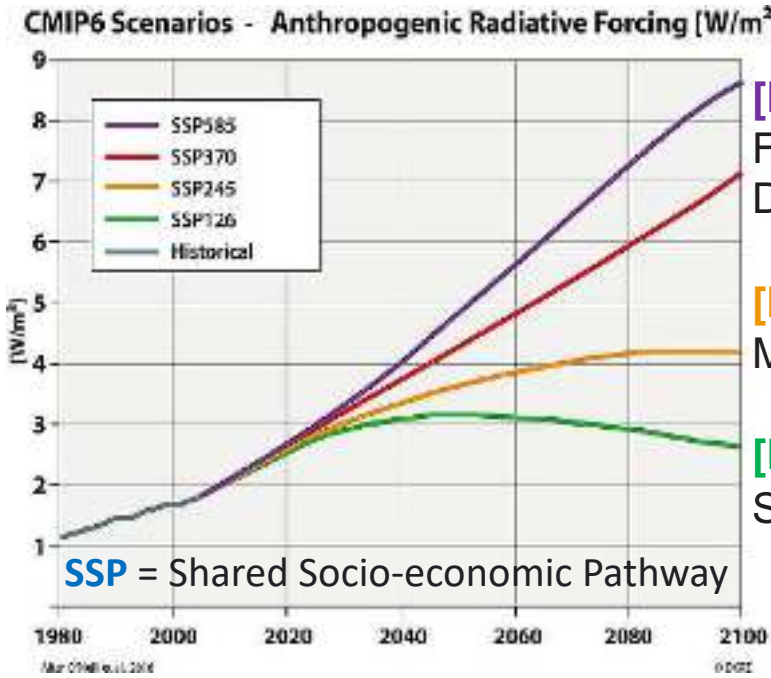
Scan to visit

- Support Singapore's **climate adaptation efforts**
- Support studies on **climate change impacts**:
  - sea level rise;
  - water and flood management;
  - biodiversity and food security;
  - human health and energy;
  - science-policy translation.
- Share V3 data/findings with **ASEAN** states.
- Share V3 data with research community (e.g., **CORDEX, IHLs**).

V3 created world's highest-resolution (2 & 8km) projections for SEA

Dynamical downscaling: convection-permitting **SINGV-RCM**





[High] SSP5-8.5: Fossil-fuel Development

[Medium] SSP2-4.5: Middle of the Road

[Low] SSP1-2.6: Sustainability

12-km grid (in **V2**)

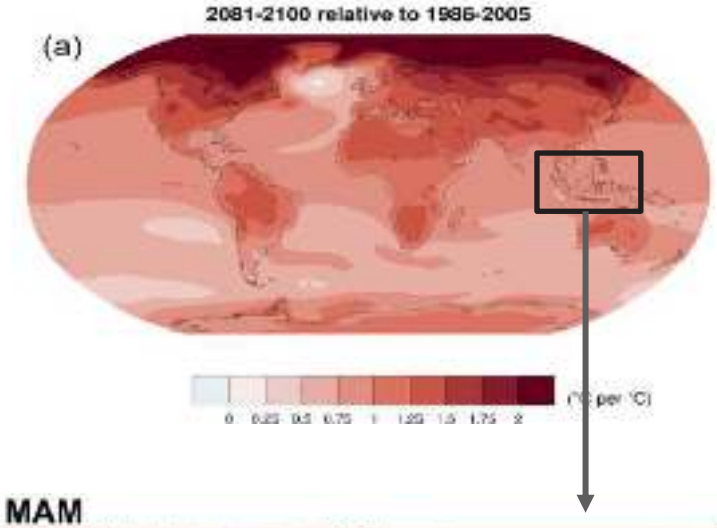
8-km grid (in **V3**)

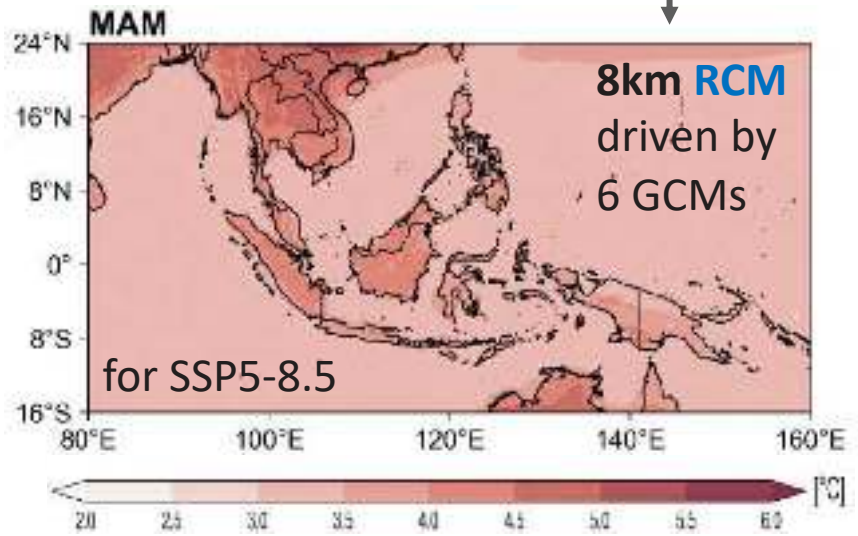
2-km grid (in **V3**)

V3 SINGV-RCMs capture detailed spatial patterns in SEA and SG

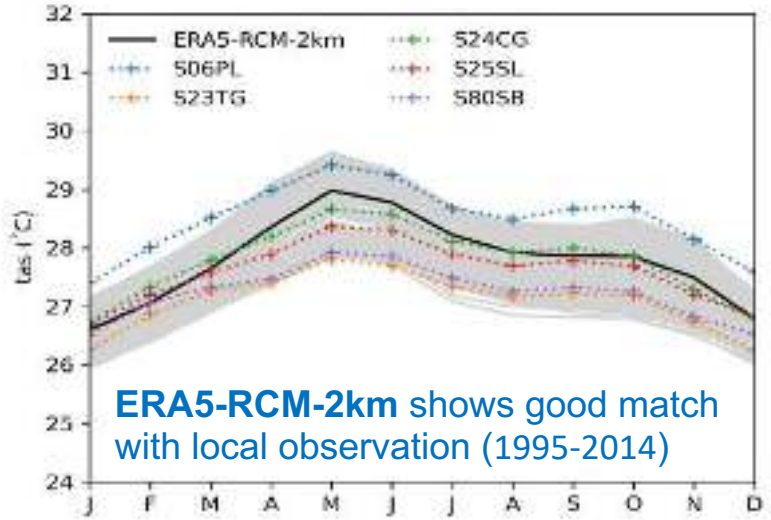
Surface air temperature change

200km GCM

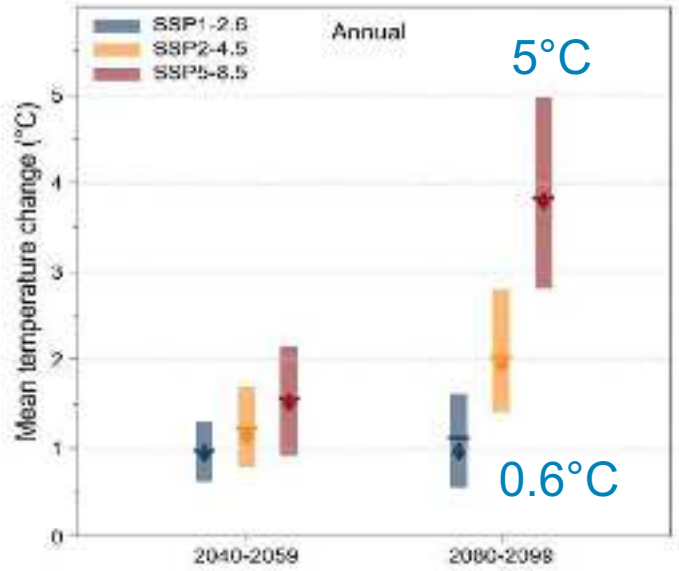




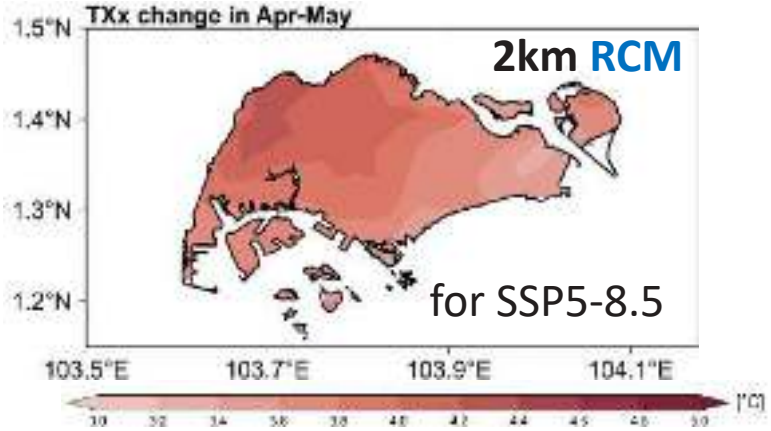
SG temperature



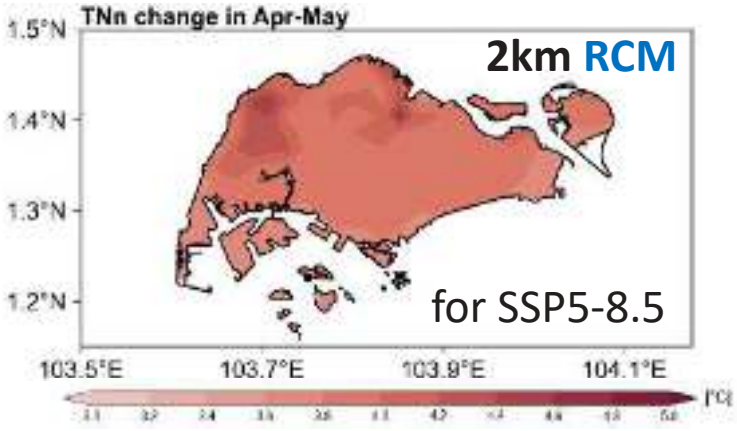
SG temperature change



TXx: Maximum of daily maximum temperatures



TNn: Minimum of daily minimum temperatures



A Sustainable Pathway to the Fourth Climate Change Study (V4)

V3 is huge – heavy computing needs, 7PB dataset

Outputs: 10mins, hourly, daily, monthly

Scenarios	RCM @8km (SEA domain)	RCM @2km (WMC domain)
Historical SINGV-RCM-ERA5	1955-2014 (60 yr)	1995-2014 (20 yr)
Historical SINGV-RCM-GCM	1955-2014 (60 yr)	1995-2014 (20 yr)
Future SSP126, SSP245, SSP585	2015-2099 (85 yr)	2040-2059 (20 yr), 2080-2099 (20 yr)

V3 - multi-GCM ensemble
Considering performance & ECS

CMIP6 model	ECS (K)
ACCESS-CM2	4.66
EC-Earth3	4.26
MIROC6	2.60
MPI-ESM1-2-HR	2.98
NorESM2-MM	2.49
UKESM1-0-LL	5.36

Convection-permitting for both 8km and 2km. Prescribed SST (every 3hr). 1-yr spin-up.
8km (1120x560). time step: 240s. with 400CPUs (Cray XC40). 8km: 1yr to finish 30yr simulation
2km (960x960). time step: 120s. with 320CPUs(Cray XC40). 2km: 1yr to finish 15yr simulation

How Can Machine Learning Support the V4?

- Improving Efficiency
- Cost-Effectiveness
- Large ensemble - Robustness

1. **Machine Learning Emulation**
   - Fill in gaps for future scenarios, e.g., SSP370.

2. **Machine Learning Downscaling**
   - Downscale from coarse to high resolution, GCM-> 8km-> 2km
   - Large ensemble

Machine Learning Emulation

Target is to fill in the SSP370 projection using simulations of other scenarios

Model Inputs: anthropogenic forcing agents (yearly)

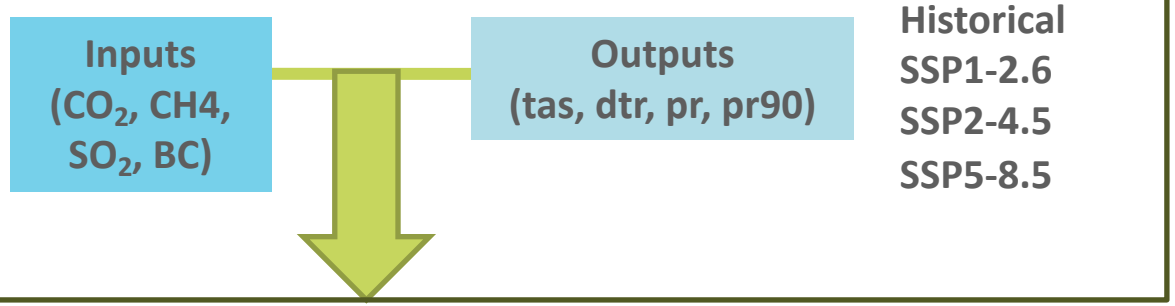
Variable	Description
CO2	carbon dioxide, global cumulative emission
CH4	methane, global emission
SO2	sulfur dioxide, spatial distribution
BC	black carbon, spatial distribution

Model Outputs: **spatial changes** in key climate variables

Variable	Description
tas	surface air temperature (°C)
dtr	daily range of surface air temperature (°C)
pr	mean precipitation (mm/day)
pr90	extreme precipitation at 90th percentile (mm/day)

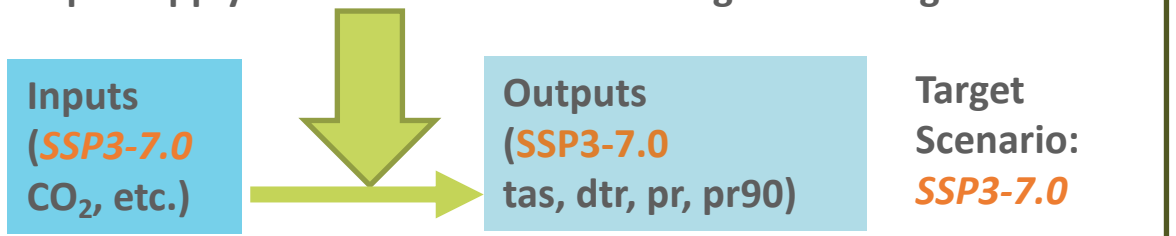
ML model – CNN-LSTM (Convolutional Neural Network - Long Short-Term Memory):
ClimateBench - Watson-Parris and Coauthors, 2022

Step 1: Train an emulation model to respond to forcing scenario



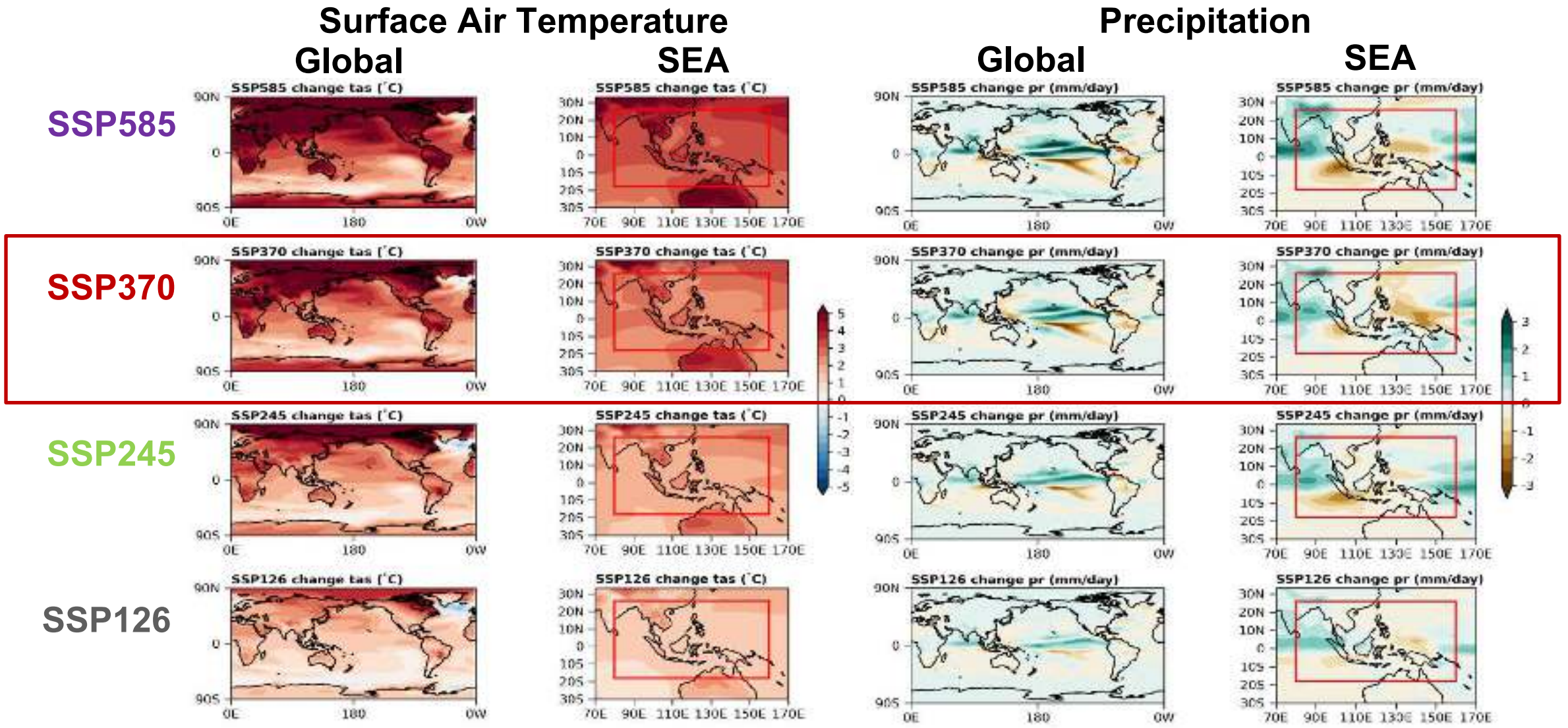
Emulation model (ML : CNN-LSTM)

Step 2: Apply the emulation model to a given forcing scenario



Machine Learning Emulation

Target is to fill in the SSP370 projection using simulations of other scenarios



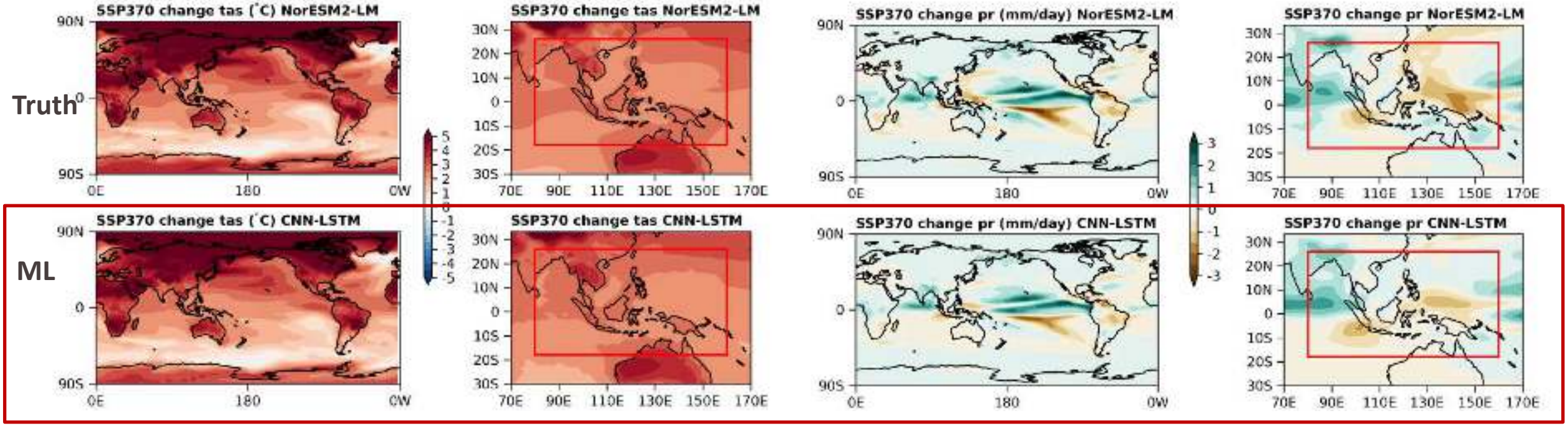
GCM NorESM2-LM - 2080-2100 annual mean change from pre-industrial

Machine Learning Emulation

ML model can emulate the spatial changes in the SSP370 projection

Changes in annual mean temperature (tas) for SSP370 scenario

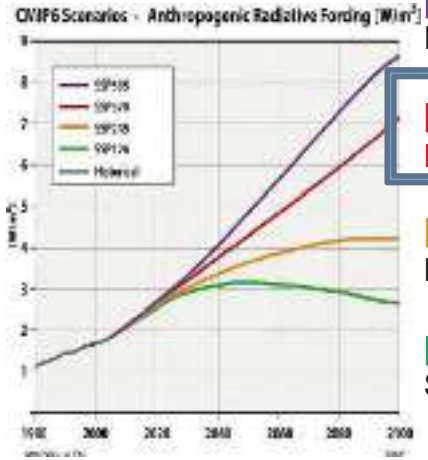
Changes in annual mean precipitation (pr) for SSP370 scenario



GCM NorESM2-LM, lat: 96, lon: 144. historical 165yr 1850-2014, SSP scenario: 86 yr, 2015-2100.

Machine Learning Emulation

ML model can emulate the long-term warming trend in the SSP3-7.0 projection

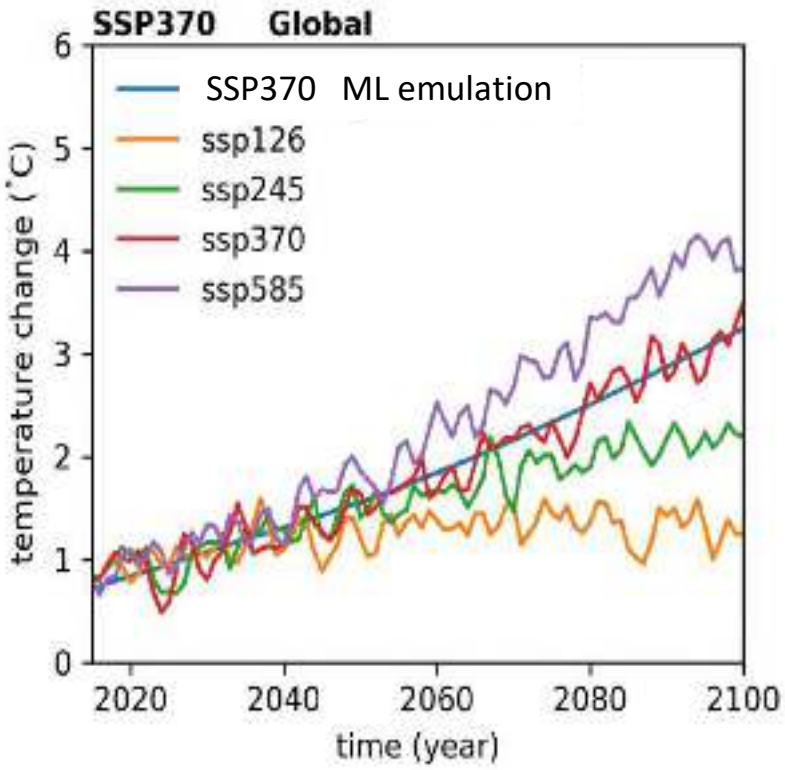


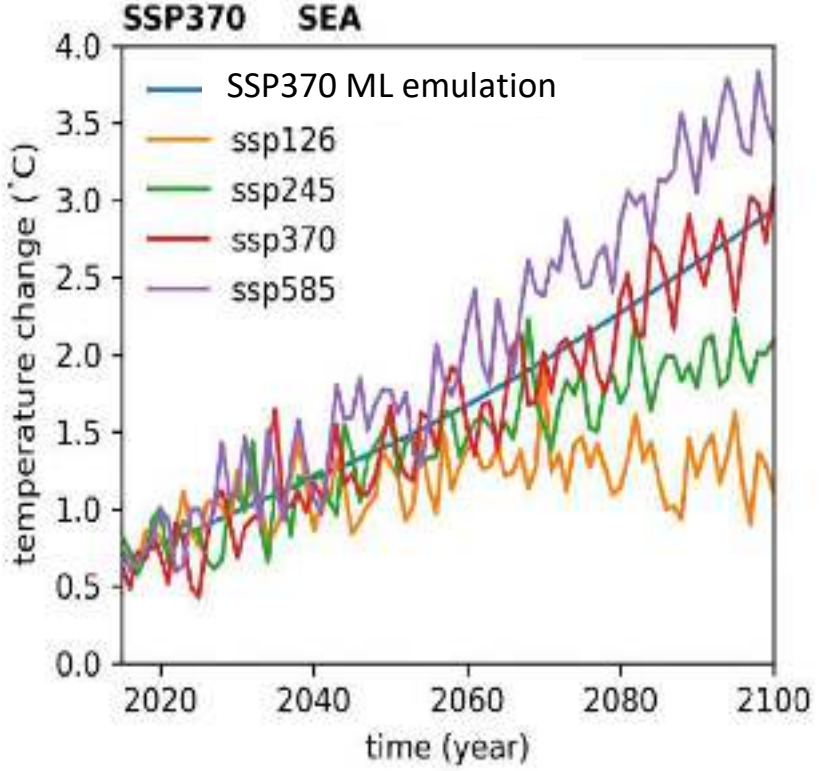
[High] SSP5-8.5:
Fossil-fuel Development

[Medium] SSP3-7.0:
Middle of the Road

[Medium] SSP2-4.5:
Middle of the Road

[Low] SSP1-2.6:
Sustainability





GCM NorESM2-LM, lat: 96, lon: 144. historical 165yr 1850-2014, SSP scenario: 86 yr, 2015-2100.

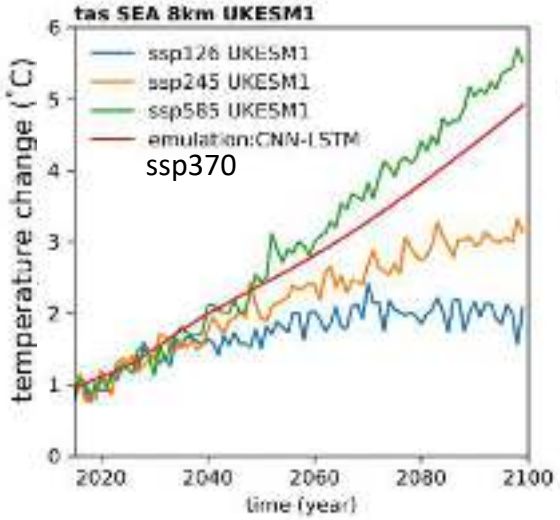
Machine Learning Emulation for V3 SEA 8km projections

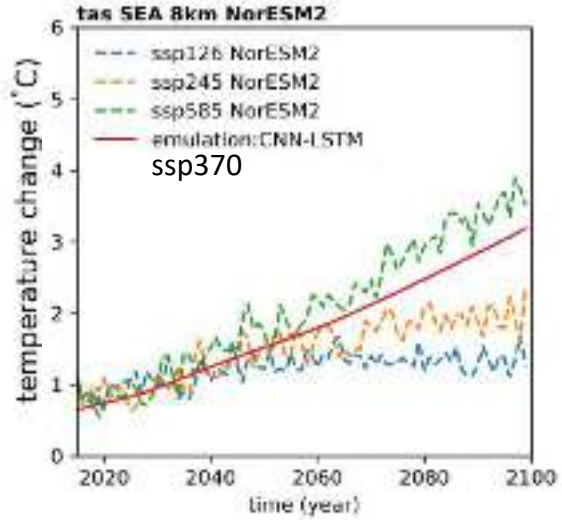
ML model can emulate spatial changes and long-term warming trend in SSP370 for individual models (but no daily variability)

Model	ECS (K)
ACCESS-CM2	4.66
EC-Earth3	4.26
MIROC6	2.60
MPI-ESM1-2-HR	2.98
NorESM2-MM	2.49
UKESM1-0-LL	5.36

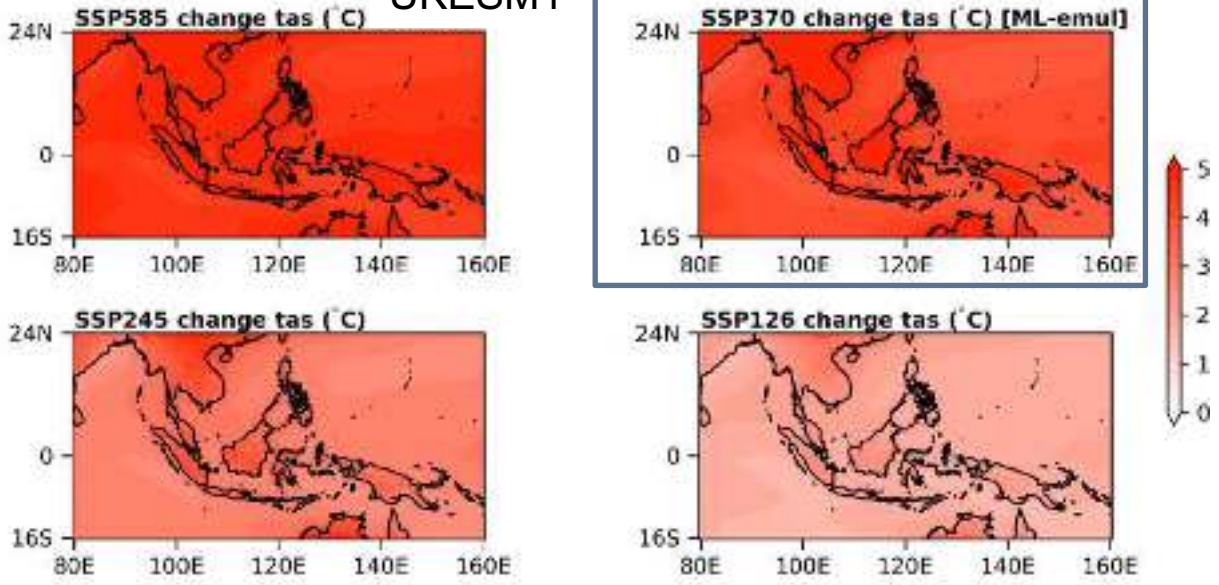
SINGV-RCM 8km, lat: 560, lon: 1120.
historical 60yr 1955-2014,
SSP scenario: 85 yr, 2015-2099.

Maps show the change:
2080-2099 annual mean change
from 1955-1974 climatology

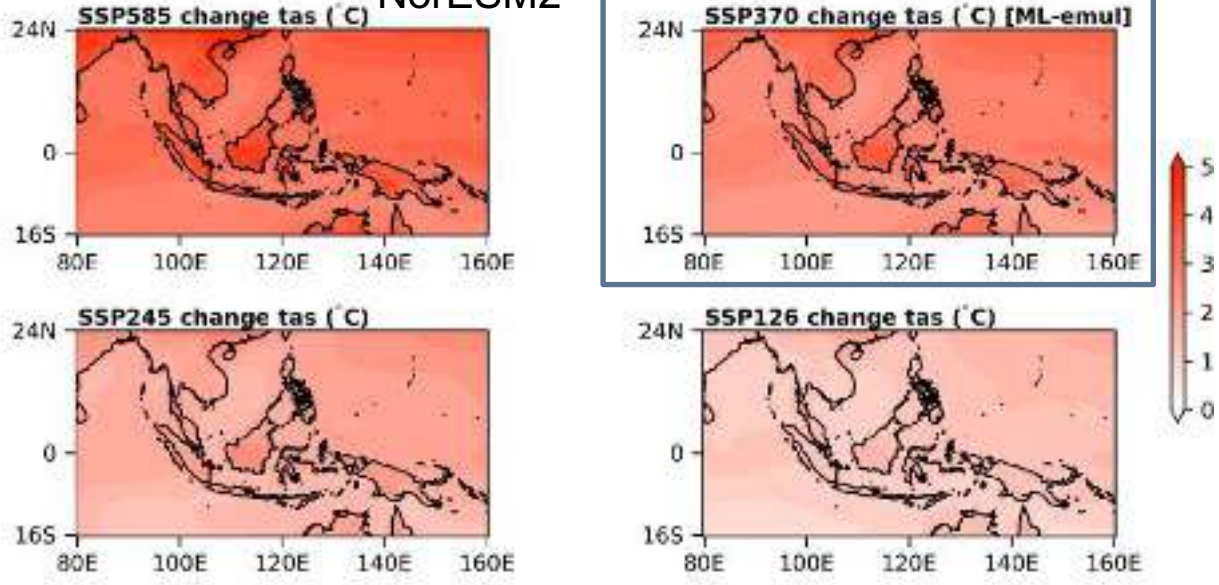




UKESM1



NorESM2



Emulator with iterative capability and variability? ACE2 is the best choice so far. (but 1deg res)

Test runs using ACE2-ERA5 (6hrly, 1deg), 2001-2004

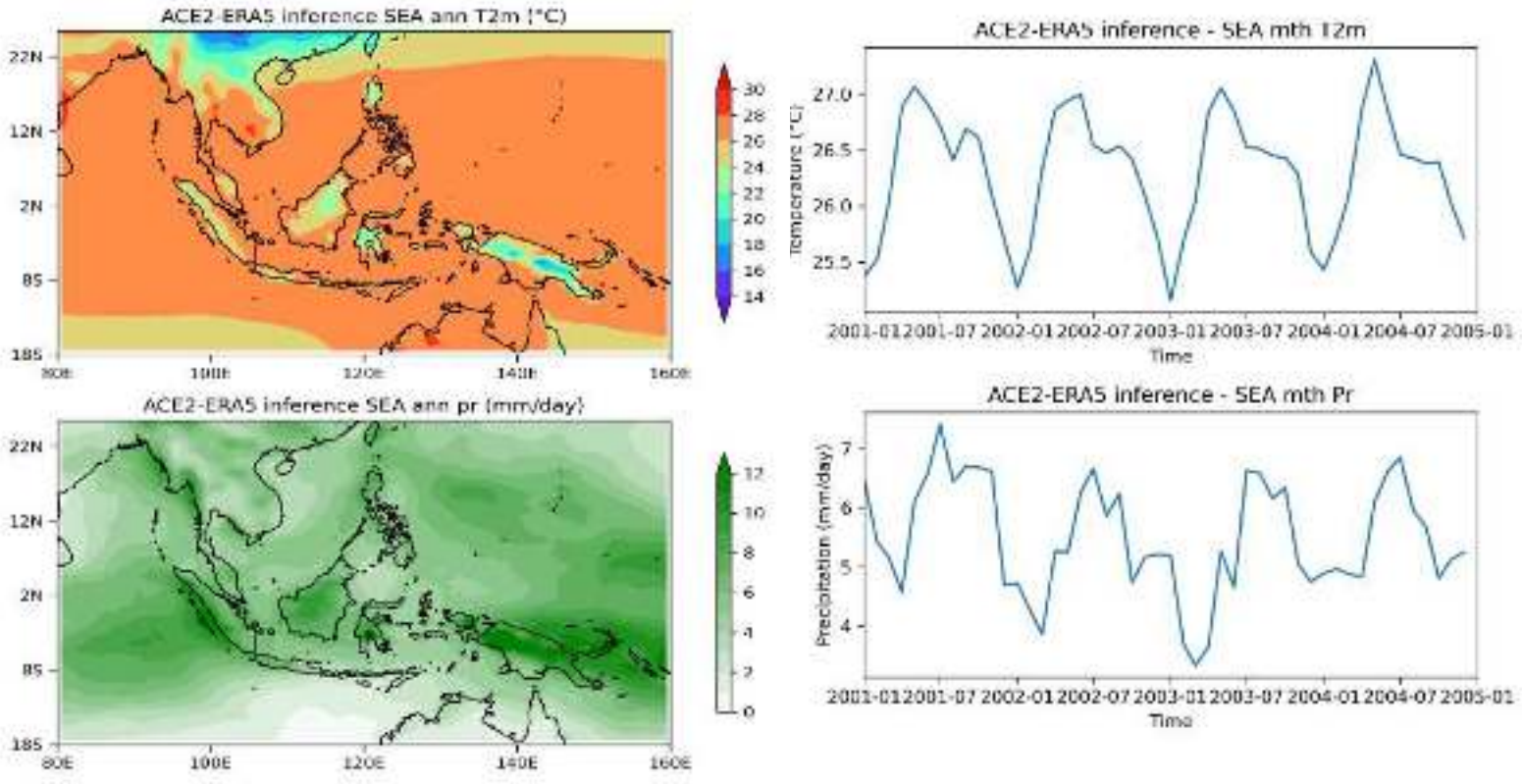
Model: ACE2-ERA5 from Ai2
Paper: Watt-Meyer, et al. 2025 (https://doi.org/10.48550/arXiv.2411.11268)

Spherical Fourier Neural Operator, trained on ERA5 1940-2020.

AMIP type runs are forced by CO_2, SST, and etc.

Variable: temperature, precipitation, over 30 variables, 8 levels.

Remarks: global, 1degree, 6hrly, stable iteration with physics constraint (dry air and moisture conservation).



NCAR also has a CAMulator (https://doi.org/10.48550/arXiv.2504.06007), for long iteration simulations trained on CAM6. with global dry air mass conservation, moisture budget, and energy conservation. (SST forcing, no CO2)

1deg res simulations cannot represent Tropical Cyclone well.
Quick fix? ML TC downscaler to reconstruct the wind speed at the target resolution.

Step 1: crop TC snapshots (gridcells centred at TC eye) from 25km ERA5 based on IBTrACS TC data at 3hrly time step

Step 2: create snapshot pairs in coarse (16x16, 100km) and fine resolution (64x64, 25km)

Step 3: Train downscaler using coarse-fine pair of TC snapshots

Coarse grid
T2m, U10, V10, etc.

Fine grid
T2m, U10, V10, etc.

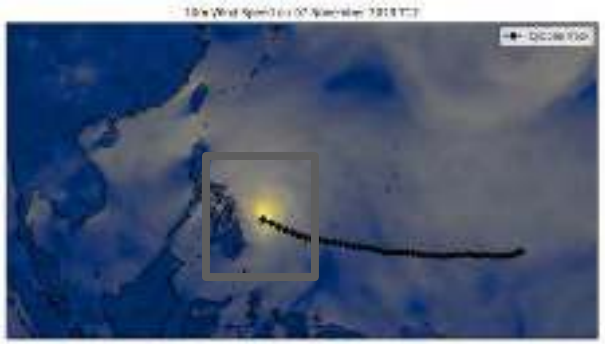
Downscaler (ML : UNet)

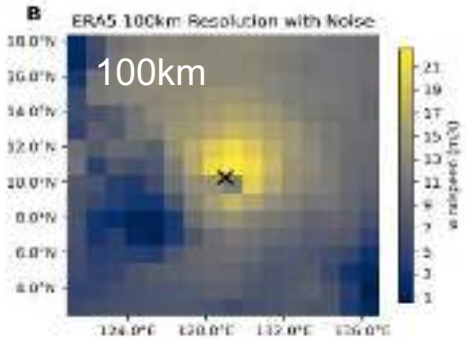
Step 4: identify TC centre using tracking algm. and crop snapshot in coarse res data

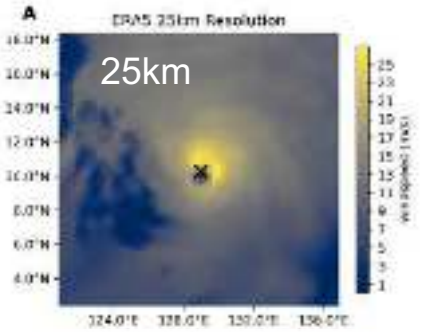
Step 5: Apply the downscaler to reconstruct the wind profile and intensity

Coarse grid
T2m, U10, V10, etc.

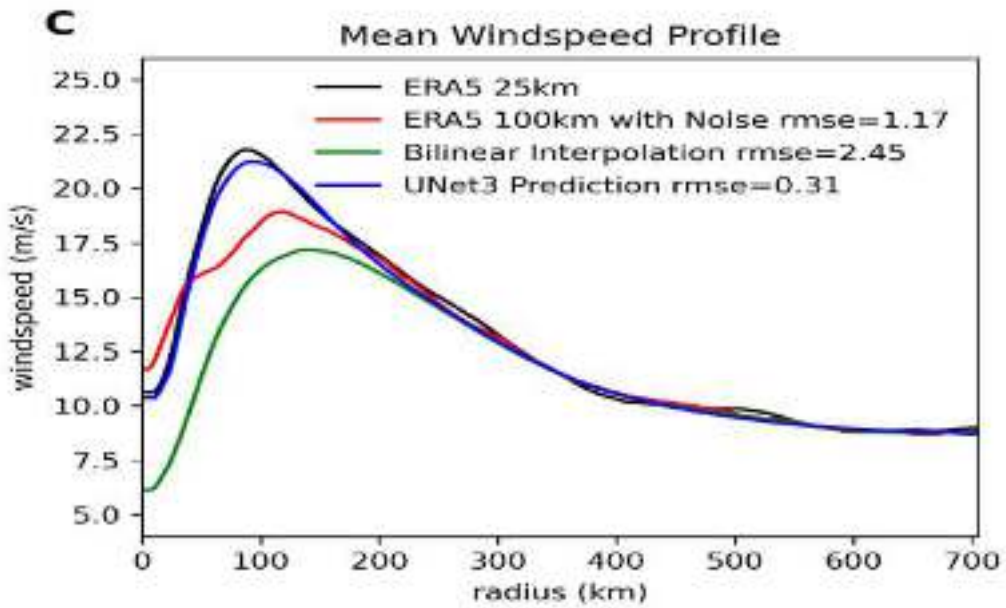
Fine grid
T2m, U10, V10, etc.

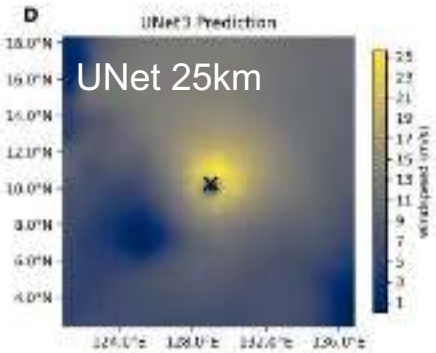


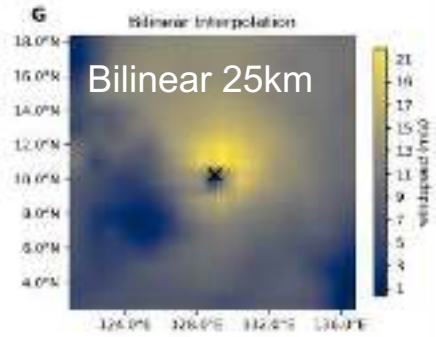




Western North Pacific (WNP) basin (0◦-50◦N, 100◦E-180◦E) for the year 2013







Want ML downscaling with large ensemble?

Generative ML models can do it.

Diffusion model. ClimateDiffuse: Watt and Mansfield 2024
UNet as the benchmark.

Step 1: Train a downscaling emulator

Fine grid: Land sea mask
Fine grid: surface topography
Embedding: Month, Time of day

Period:
ERA5, hourly,
1950-2017

Coarse grid
T2m, U10, v10

Fine grid
T2m, U10, V10

Downscaling emulator (ML : Unet, Diffusion model)

Step 2: Apply the model

Period:
ERA5 2018-2022

Coarse grid
T2m, U10, v10

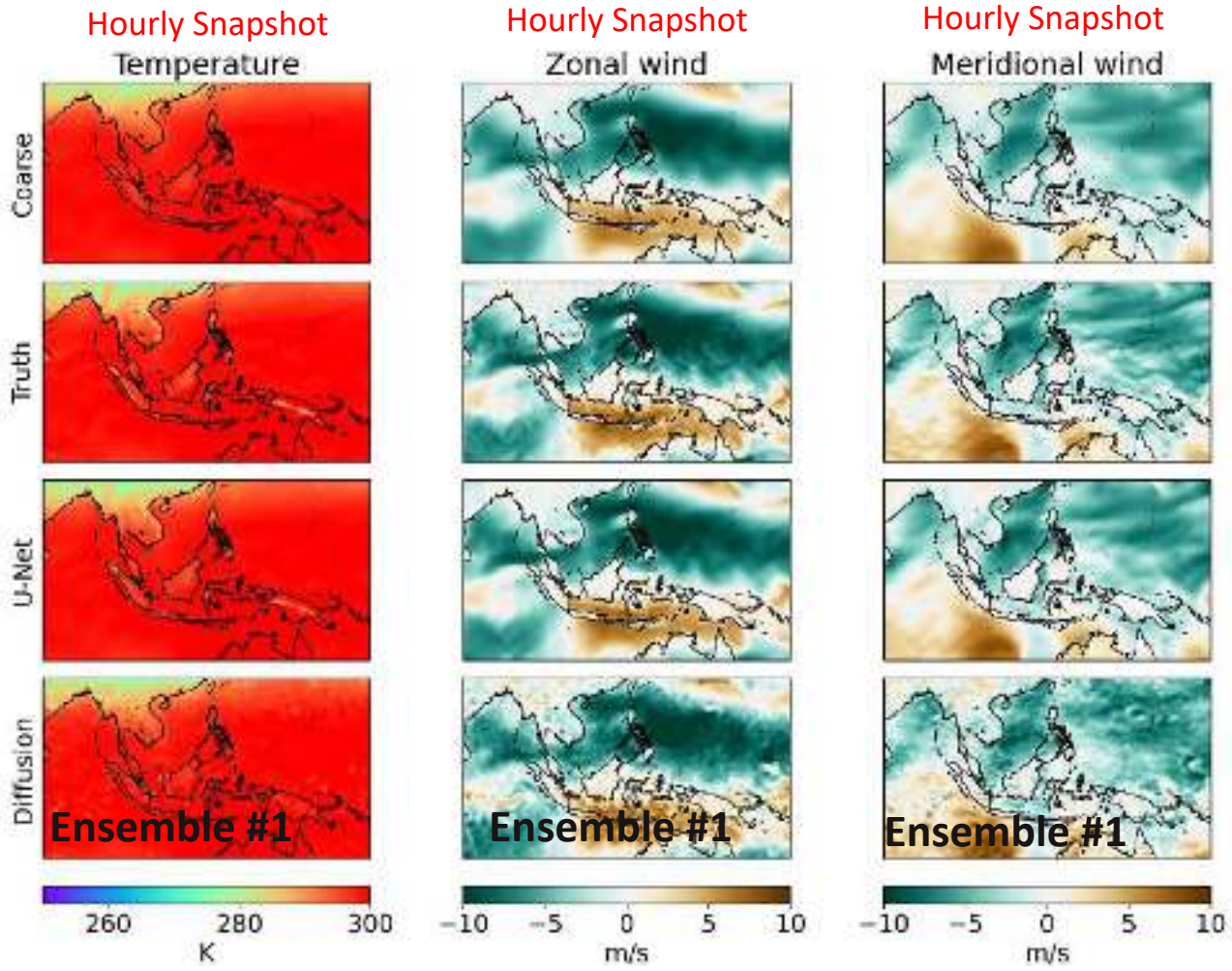
Fine grid
T2m, U10, V10

200km
coarse

25km
Truth

200->25km
ML - UNet
(deterministic)

200->25km
ML – Diffusion
(stochastic)



For V3 SINGV-RCM downscaler (25->8km), we test NVIDIA CorrDiff diffusion model

ML Diffusion model
– CorrDiff: Mardani et al. 2025

Step 1: Train a downscaling emulator

Fine grid: Land sea mask
Fine grid: surface topography
Embedding: Month, Time of day

Training:
2010-2012
daily data

Coarse grid 25km ERA5 T2m, pr, etc. → **Fine grid 8km SINGV-RCM-ERA5 T2m, pr, etc.**

Downscaling emulator (ML : CorrDiff model)

Step 2: Apply the model

Validation 2013.
Test 2014.

Coarse grid 25km ERA5 T2m, pr, etc. → **Fine grid 8km SINGV-RCM-ERA5 T2m, pr, etc.**

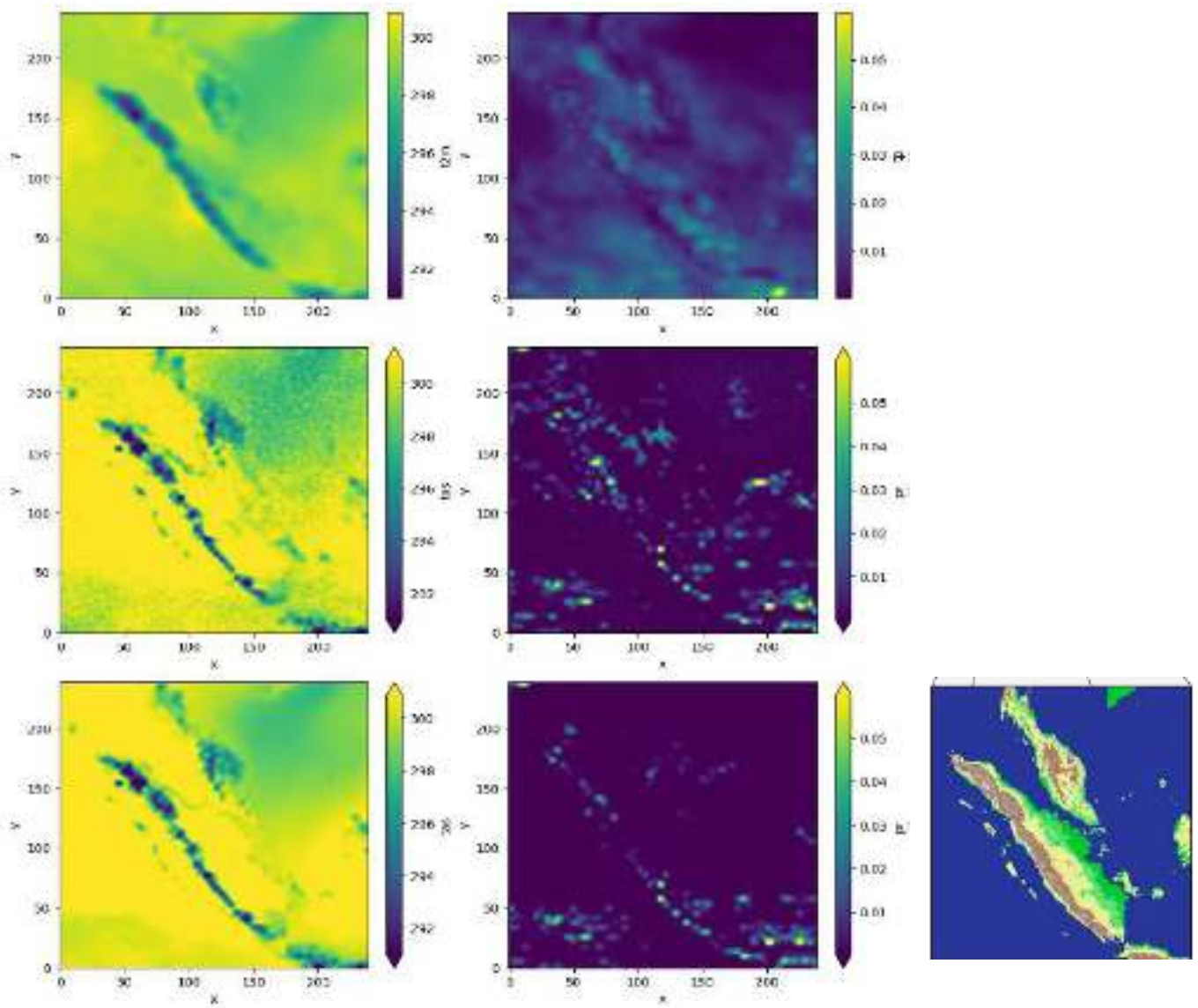
Daily Snapshot
Surface Air Temperature (K)

Daily Snapshot
Precipitation (kg/m²/s)

ERA5 25km
-coarse

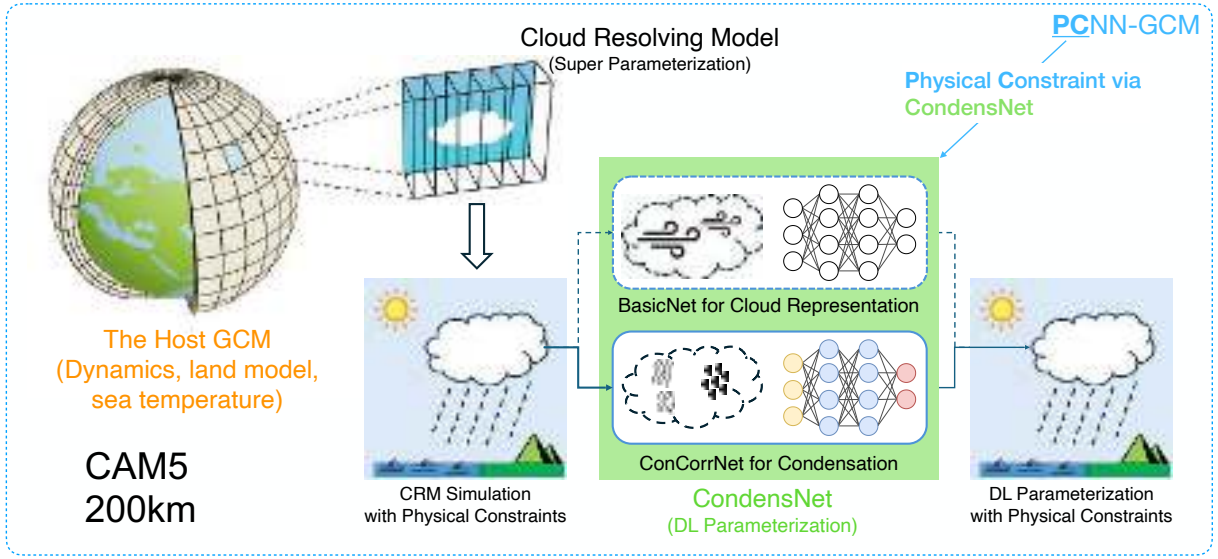
CorrDiff 8km

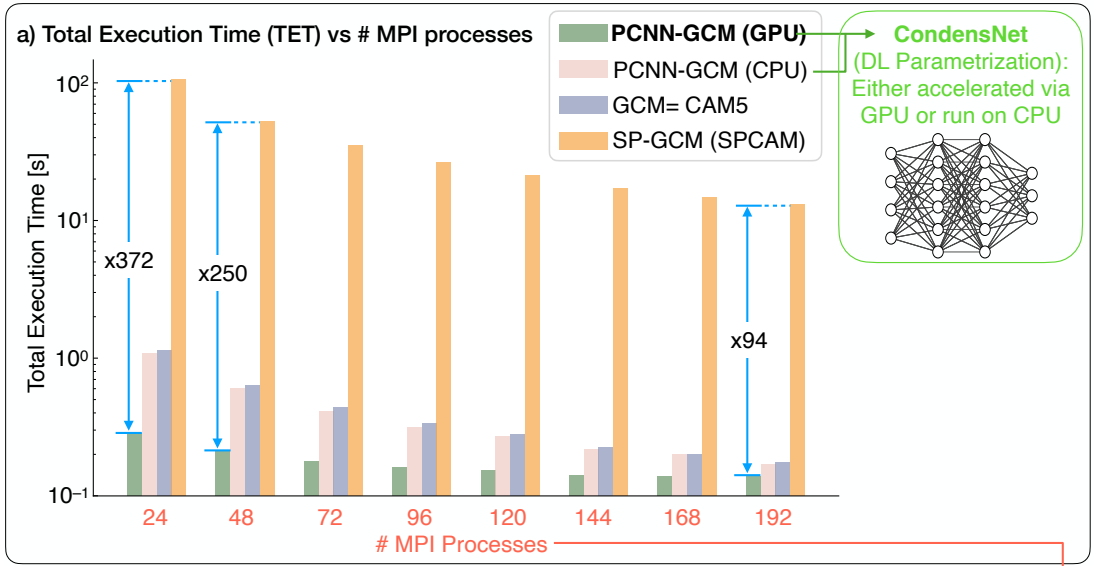
SINGV-RCM-ERA5 8km
-Truth



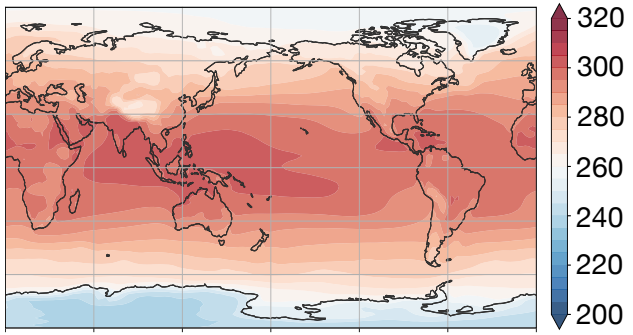
Solution with coherent physics? ML-hybrid model with physical constraints

CondensNet: Enabling stable long-term climate simulations via hybrid deep learning models with adaptive physical constraints, https://doi.org/10.48550/arXiv.2502.13185

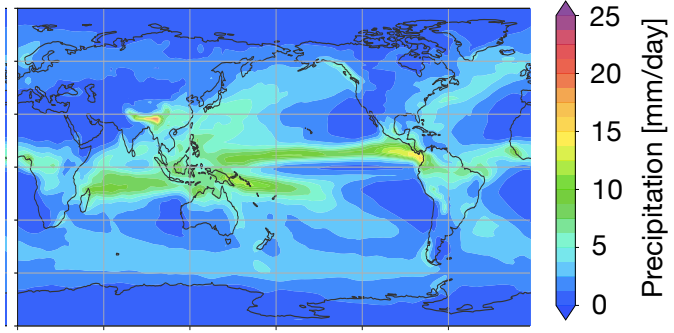


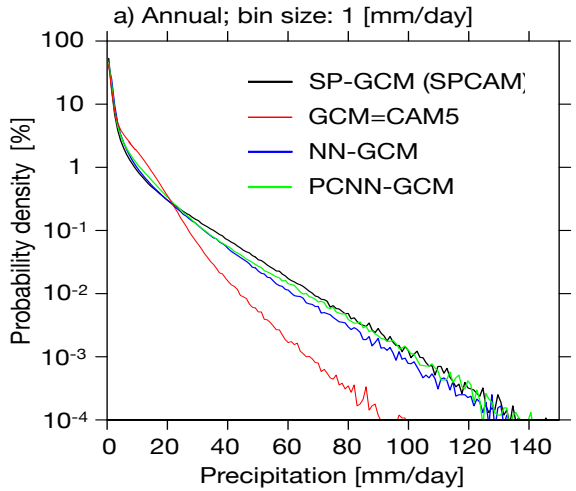


Surface Air Temperature (K)



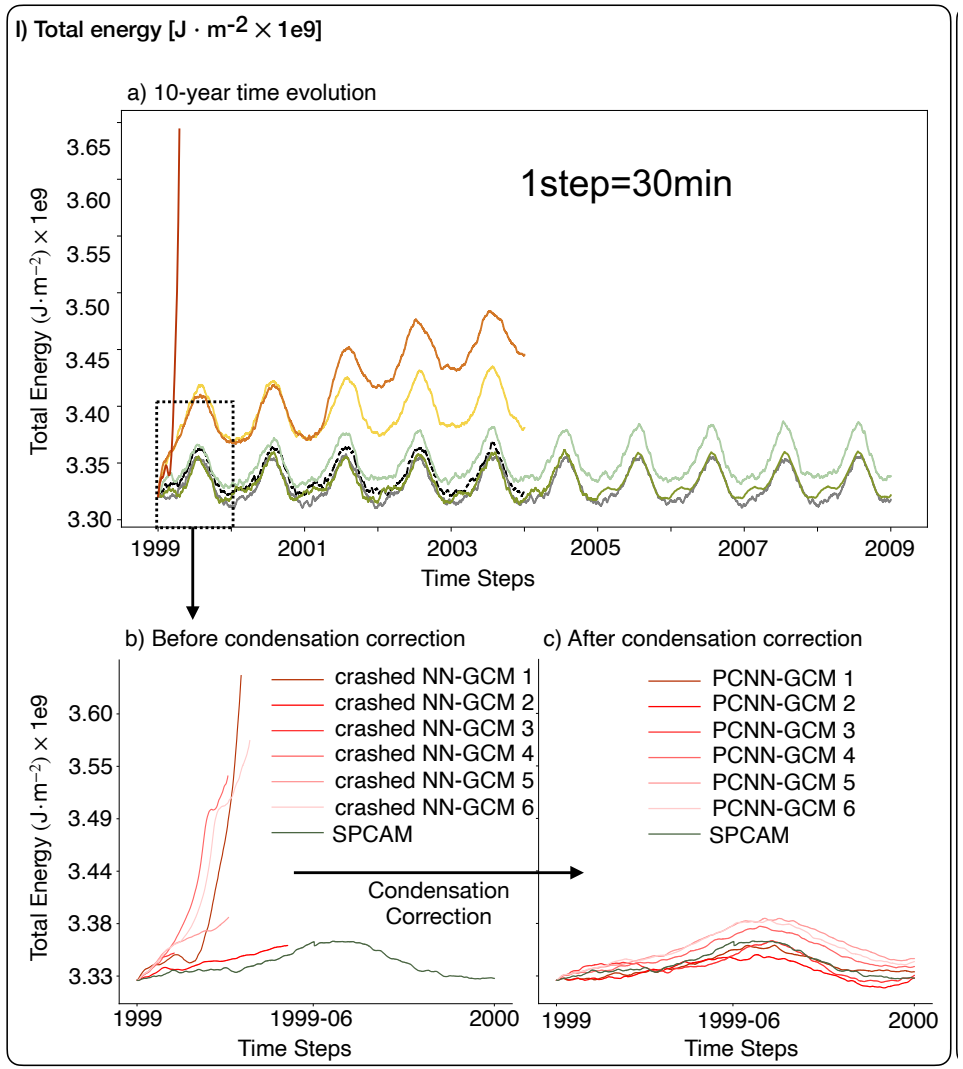
Precipitation (mm/day)

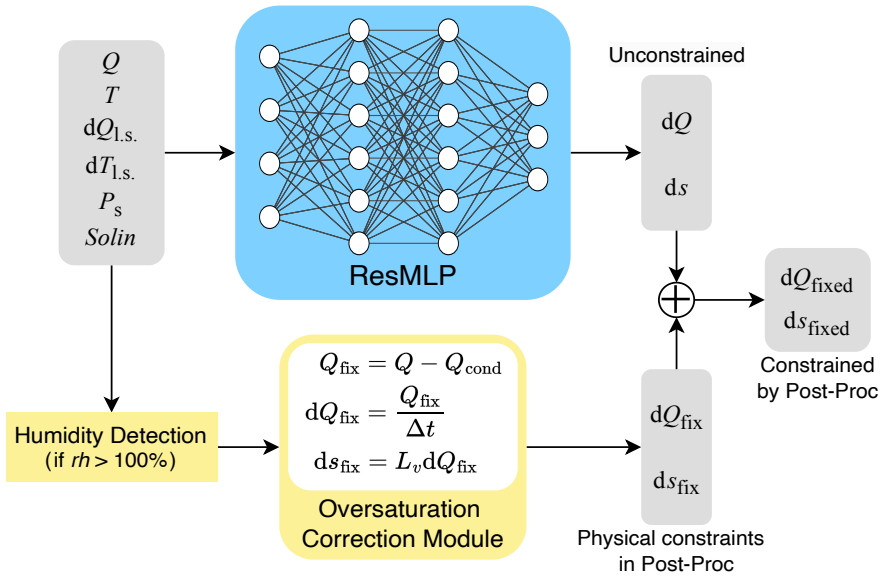




Xin Wang, Gianmarco Mengaldo, NUS

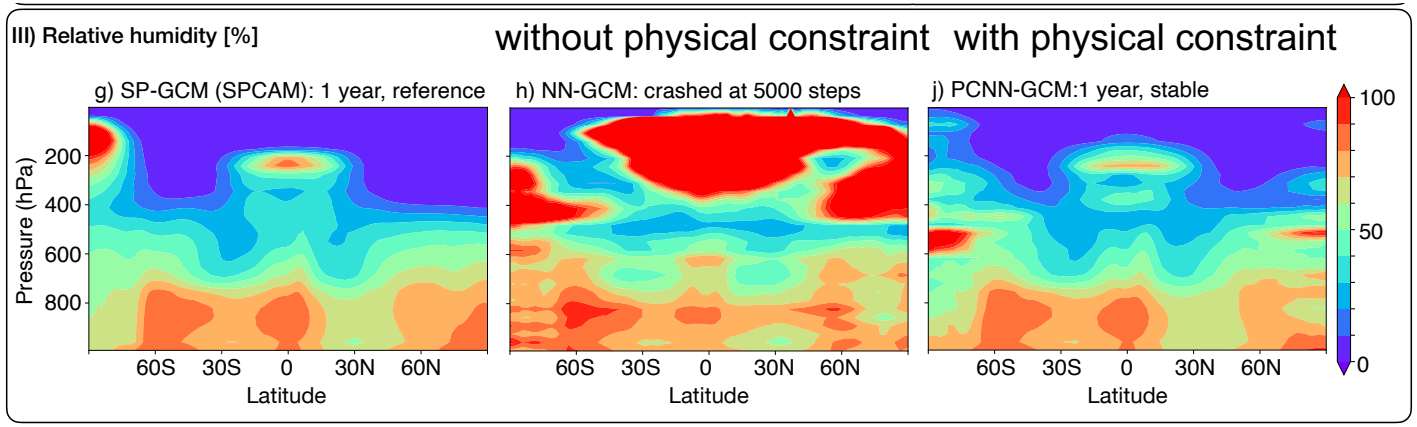
ML-hybrid model with physical constraints: fix the RH, stable runs





BasicNet: tasked to predict basic tendencies of water vapor (dQ) and dry-static-energy (ds), capturing fundamental cloud physics.

Condensation Correction Network: unlike methods that penalize non-physical predictions via the loss function or post- processing, it operates as an independent neural network that computes explicit correction terms and applies them selectively.



Xin Wang, Gianmarco Mengaldo, NUS

Summary

Exploring a Sustainable Pathway to the Fourth Climate Change Study

How Can Machine Learning Support the V4?

Make the regional projection faster, cheaper, and more robust with a large ensemble

1. **ML Emulation**
- ML models can fill in gaps for future scenarios, e.g., SSP370.
- Each climate model has its own ML emulator, and can form a model ensemble
-

2. **ML Downscaling**
- ML models (diffusion models) can downscale from coarse to high resolution, 2deg-> 8km-> 2km
- Generative ML models can create large ensemble

3. **ML models with physical constraint**
- Full iterative ML emulator with physical constraint, e.g., ACE2, CAMulator
- ML-hybrid model with physical constraints, e.g., CondensNet.

Centre for Climate Research Singapore (CCRS)

http://ccrs.weather.gov.sg

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Build National Research Capability

~ Modeling:
weather/climate/urban/land/ocean

~ Research:
tropical weather and climate
climate change effects to Singapore and Southeast Asia.

~ AI for Science (latest)
AI4Climate/Weather

Provide scientific inputs

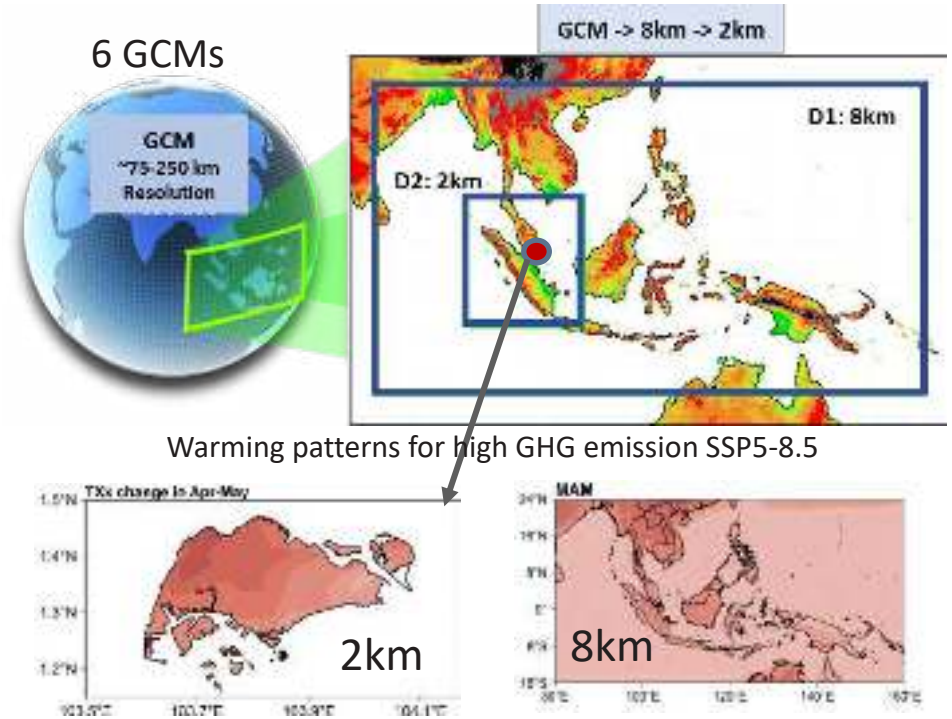
to national and regional climate adaptation and resilience policies

Facilitate National Research Program

2020 - National **Sea Level** Research Programme
2022 - Climate **Impact** Science Research Programme
2025- **Weather** Science Research Programme (New)

Third National Climate Change Study (V3)

World's highest-res (2 & 8km) projections for SEA
V3 is huge – heavy computing needs, 7PB dataset



- V3 Reports, Images, Brochures, Videos: https://www.mss-int.sg/v3-climate-projections
- V3 Data Sharing Portal (New): https://v3-climate-projections-uat.mss-int.sg/

Sustainable Pathway to the Fourth Climate Change Study

~ AI Emulation:
Complement traditional climate models. Provides rapid, cost-effective solutions for scenario expansion.
Example: fill gaps for future scenarios like SSP370.

~ AI Downscaling:
Enhances spatial resolution improved local assessments.
Example: train generative RCM emulator to generate large ensemble.

Way forward is through collaboration on a wide range of topics