Improving AI-Driven Subgrid Parameterizations in Climate Models Using Long-Term Observational Data

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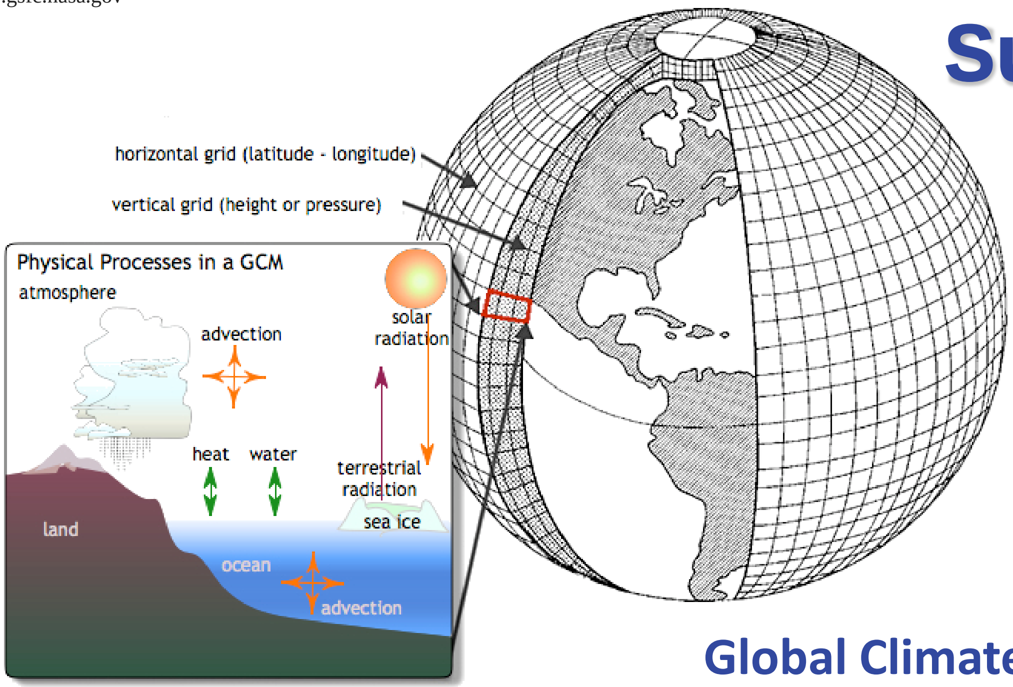
EPFL, Lausanne, Switzerland, November 2024

Subgrid Scale Effects on Climate



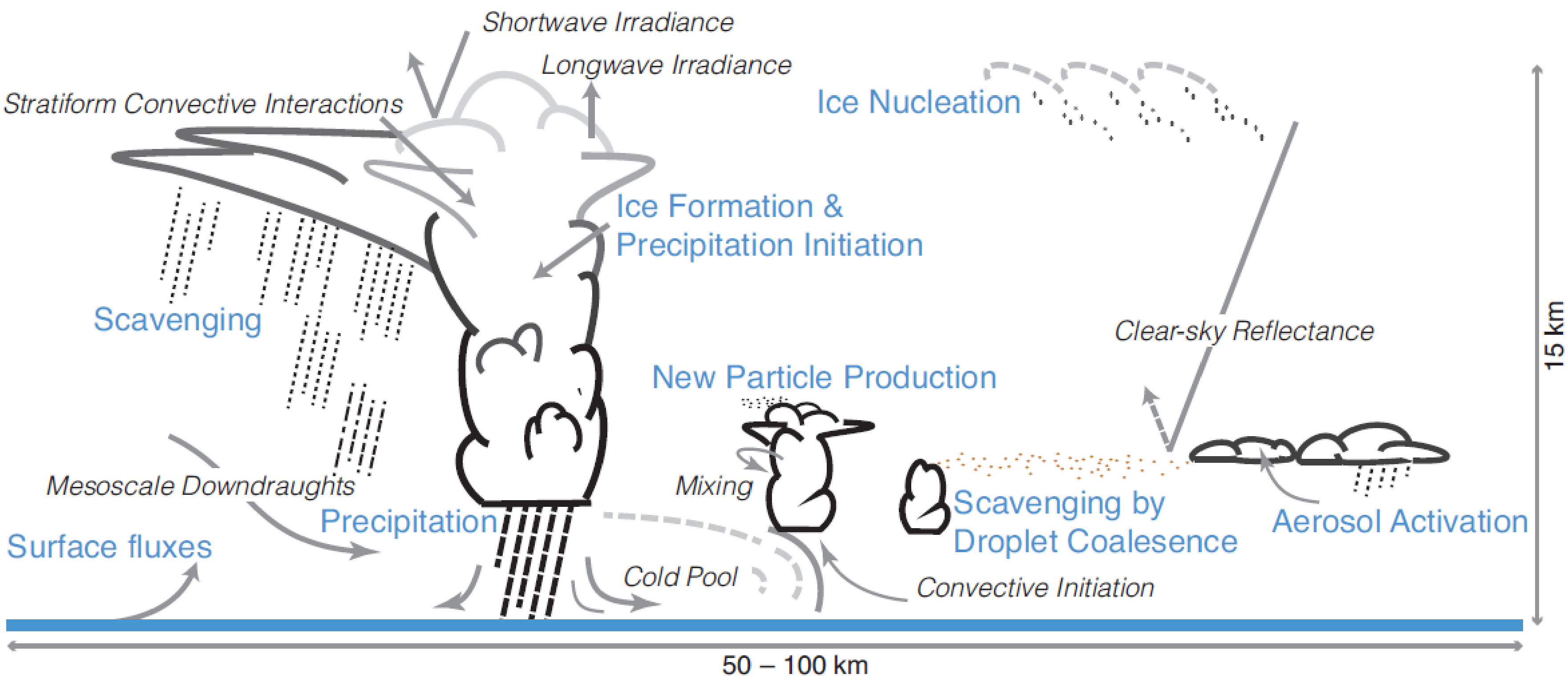
Global Climate Models:

- Spatial resolution ~ 50-200 km; time step ~ 1-6 h.
- ~10 km for NWP
- Computationally intensive.
- All sub-grid processes must be **parameterized**, i.e., represented by few average parameters.

Most of the uncertainty in climate assessments results from sub-grid scale parameterization bias

http://www.cmmap.org

Cloud Processes are Sub-grid scale



Cloud Formation:
Spatial scale ~ 10 -1000 m Time scale ~ 20 min

IPCC 2014

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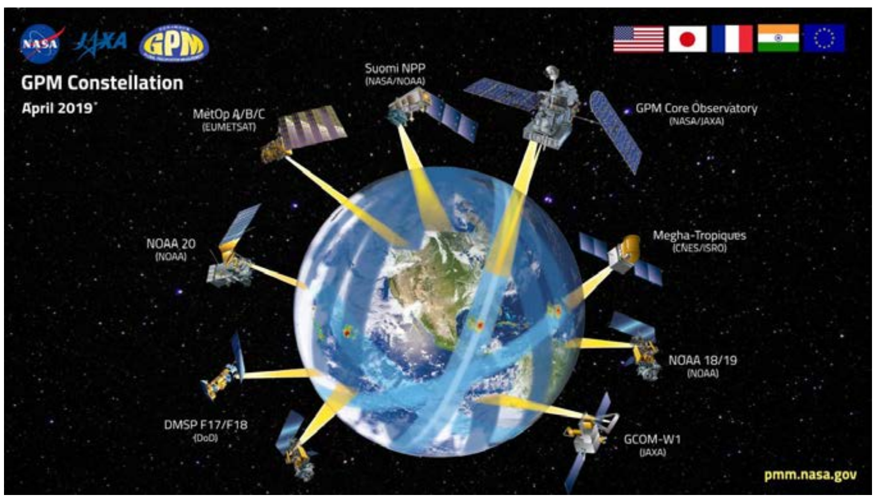
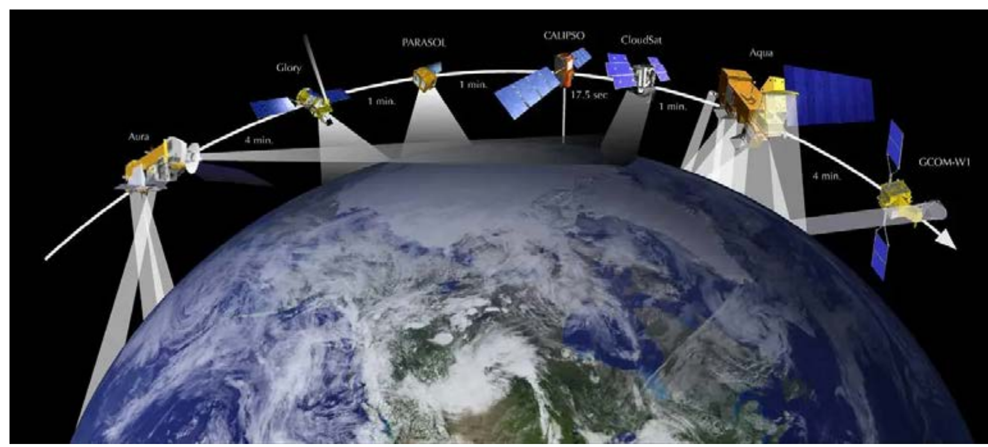
Observational Data

Over the past 40 years the community has amassed a vast array of atmospheric data:

- ~100 different field campaigns (IOP, aribone)
- Long term ground-based observational data
- Satellite retrievals



A-Train



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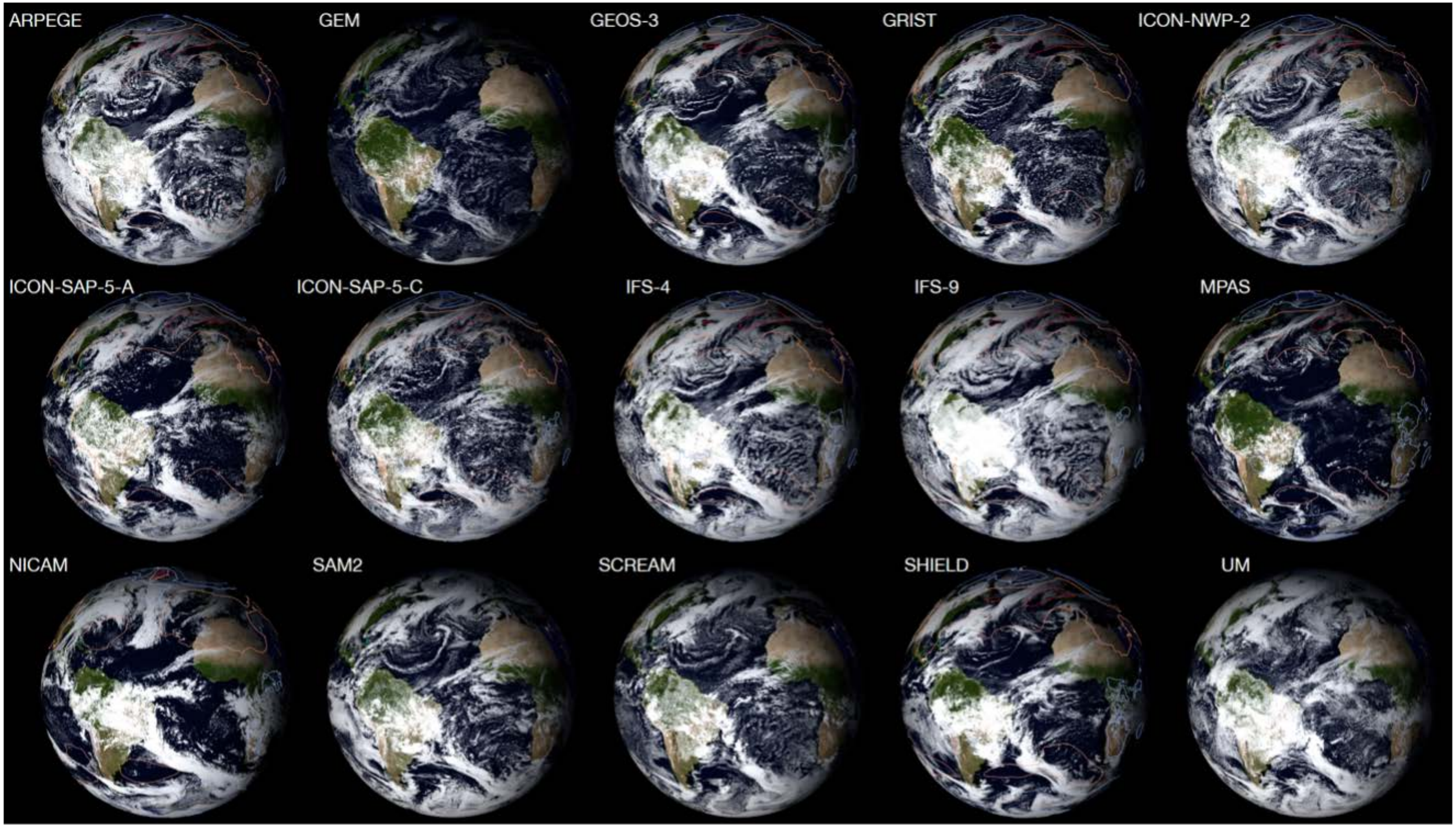
Global GCRMs



Up to 1 km global spatial resolution. Typically a few weeks of simulation.

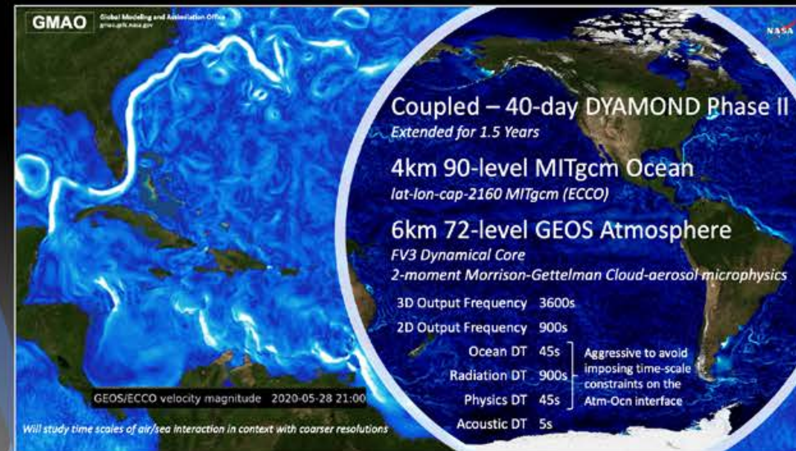
Stevens et al. 2019.

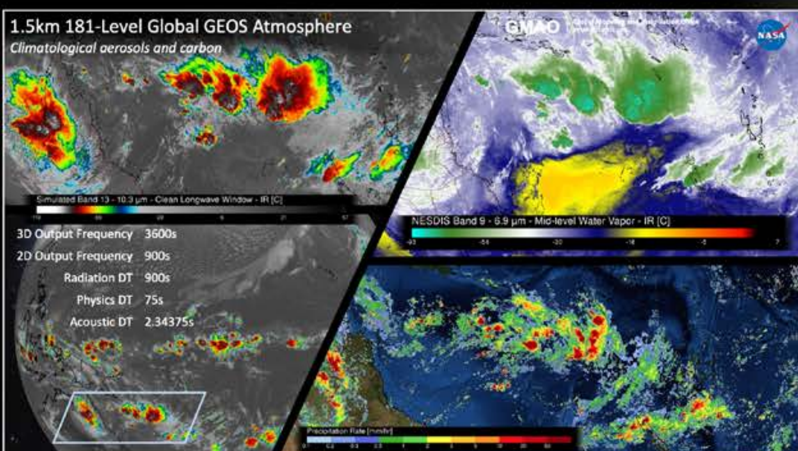
National Aeronautics and Space Administration

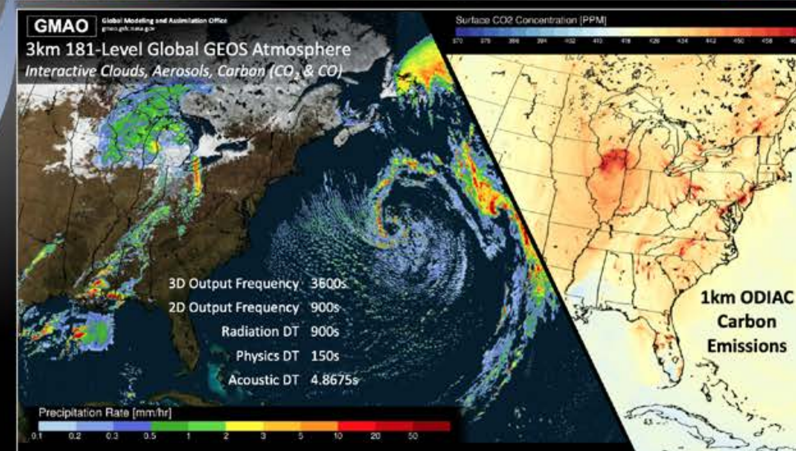
An overview of the GEOS Non-Hydrostatic DYAMOND Phase-II Simulations

GEOS DYAMOND Phase-II 40-day Simulations

Configuration	Total Cores - "System"	Throughput	Data Volume
Coupled Atm-Ocn 6km 72-Level Atm 4km 90-Level Ocn	**8,160 Intel Xeon Haswell** processor cores "Pleiades" NASA-NAS	**3 Simulated Days /** Wallclock Day	**0.3 Petabytes**
Atmosphere+Carbon 3km 181-Level Atm	**39,360 Intel Xeon Skylake** processor cores "Discover" NASA-NCCS	**7 Simulated Days /** Wallclock Day	**2.0 Petabytes**
Atmosphere 1.5km 181-Level Atm	**39,440 Intel Xeon Skylake** processor cores "Discover" NASA-NCCS	**1.5 Simulated Days /** Wallclock Day	**1.3 Petabytes**







GMAO Global Modeling and Assimilation Office
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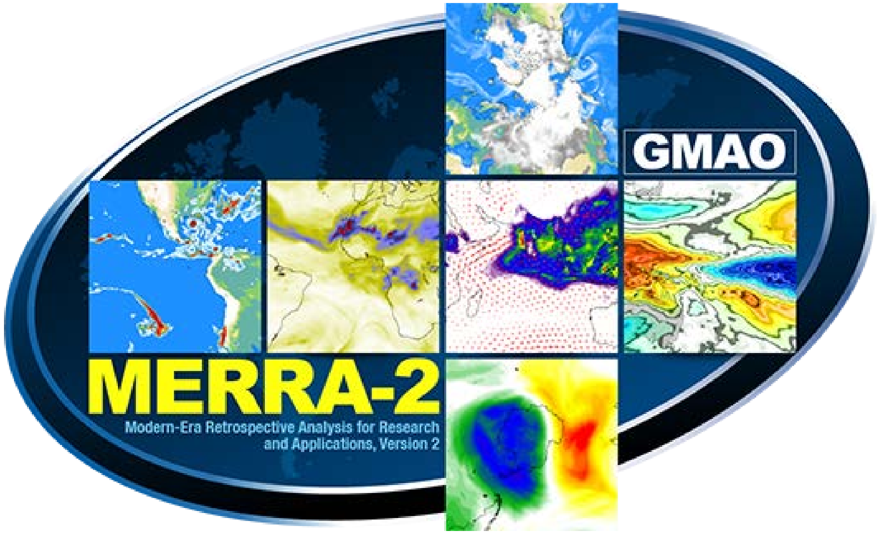
William Putman

with contributions from the GMAO SI Team, Andrea Molod, Dimitris Menemenlis, Lesley Ott, Ehud Strobach, and the GMAO Modeling Team

Modern-Era Retrospective Analysis for Research And Applications MERRA-2

MERRA is a NASA reanalysis using GEOS-5. The Project focuses on historical analyses of the hydrological cycle on a broad range of weather and climate time scales and places the NASA EOS suite of observations in a climate context.

MERRA-2 is the first long-term global reanalysis to assimilate space-based observations of aerosols and represent their interactions with other physical processes in the climate system.



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Data Overload

"a comic image that depicts data overload in climate science"

Created with DALL-E3

Leveraging Machine Learning

Science RESEARCH ARTICLES

Cite as: R. Lam *et al.*, *Science* 10.1126/science.adi2336 (2023).

Learning skillful medium-range global weather forecasting

Remi Lam[1*]†, Alvaro Sanchez-Gonzalez[1*]†, Matthew Willson[1*]†, Peter Wirnsberger[1]†, Meire Fortunato[1]†, Ferran Alet[1]†, Suman Ravuri[1]†, Timo Ewalds[1], Zach Eaton-Rosen[1], Weihua Hu[1], Alexander Merose[2], Stephan Hoyer[2], George Holland[1], Oriol Vinyals[1], Jacklynn Stott[1], Alexander Pritzel[1], Shakir Mohamed[1*], Peter Battaglia[1*]

[1]Google DeepMind, London, UK. [2]Google Research, Mountain View, CA, USA.

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Could Machine Learning Break the Convection Parameterization Deadlock?

P. Gentine[1], M. Pritchard[2], S. Rasp[3], G. Reinaudi[1], and G. Yacalis[2]

Spatially Extended Tests of a Neural Network Parametrization Trained by Coarse-Graining

Noah D. Brenowitz[1] and Christopher S. Bretherton[1]

[1]Department of Atmospheric Sciences, University of Washington, Seattle, WA, USA

Deep learning to represent subgrid processes in climate models

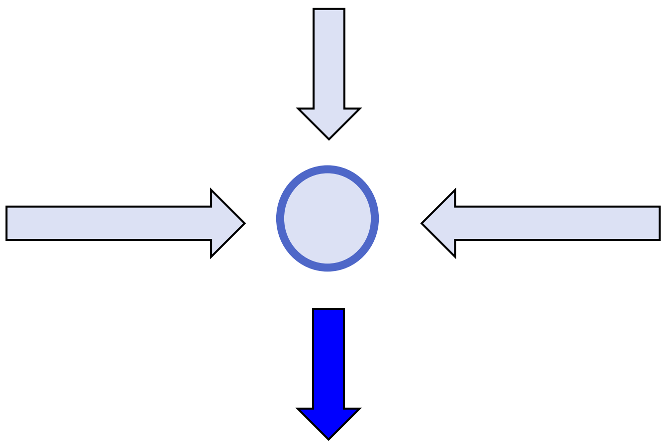
Stephan Rasp[a,b,1], Michael S. Pritchard[b], and Pierre Gentine[c,d]

- Subgrid scale emulators from high-resolution simulations
- Parameterizations for expensive and rigorous physical processes
- Foundational models for numerical weather prediction
- Subgrid scale models developed directly from observations

Subgrid Variability via Constrained Adversarial Training

Atmospheric Reanalysis

Experimental Observations



Global km-scale simulations

Subgrid Variability in terms of the atmospheric state (i.e., T, P, Winds, …) at coarse resolution

Outline

1. **Wnet: A constrained neural network to estimate subgrid scale vertical wind velocity**

2. Trends in Vertical Velocity Variability

3. Vertical Velocity Variability as a Climate Feedback

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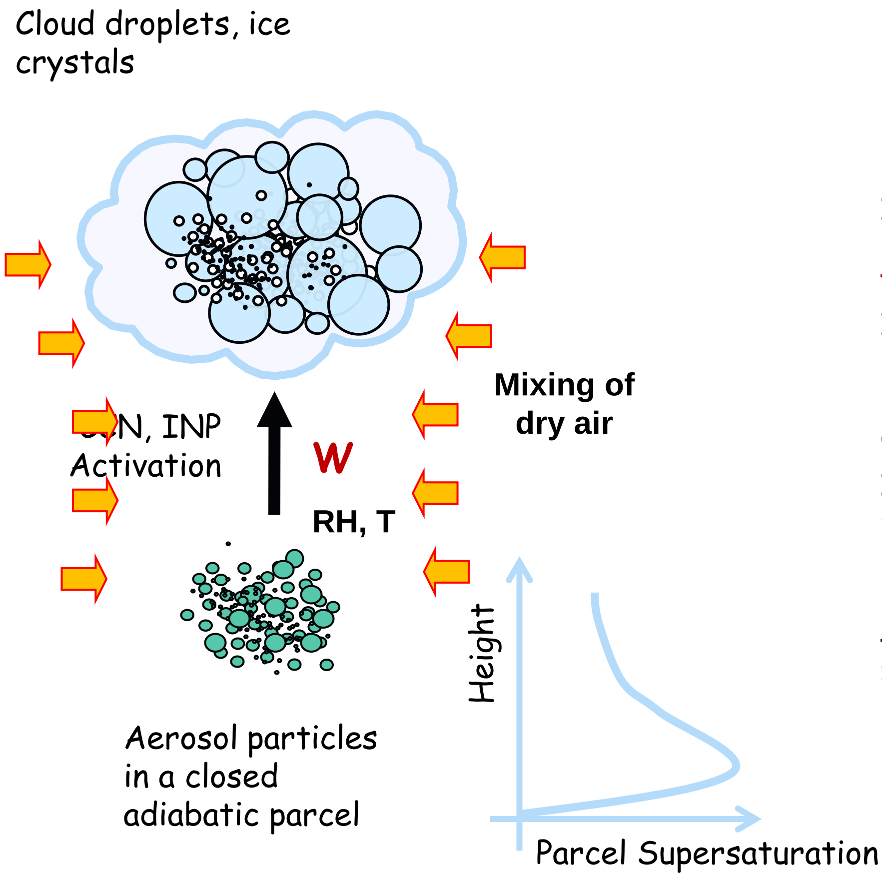
Cloud Formation via Aerosol Activation



Aerosol => Expansion Cooling => Generation of Supersaturation => CCN activation => Droplet Growth

Main Factors:

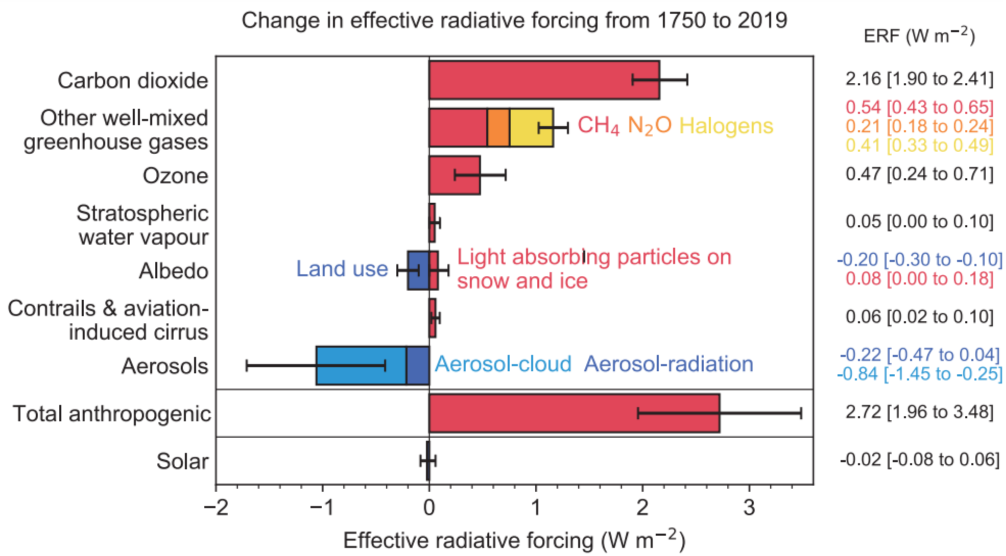
Aerosol size and composition

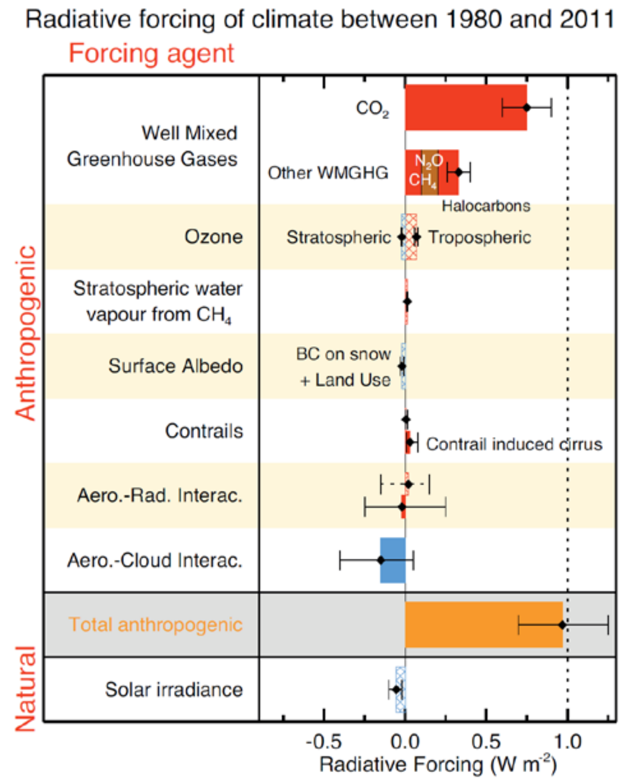
Dynamical forcing

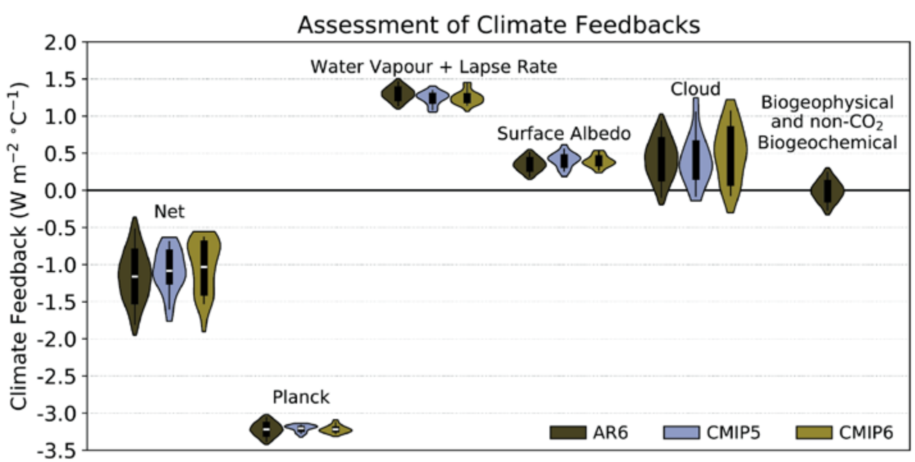
CCN only depend on aerosol properties whereas CDNC needs dynamical forcing

Activation is dependent on number concentration

Why is Aerosol Activation Important?



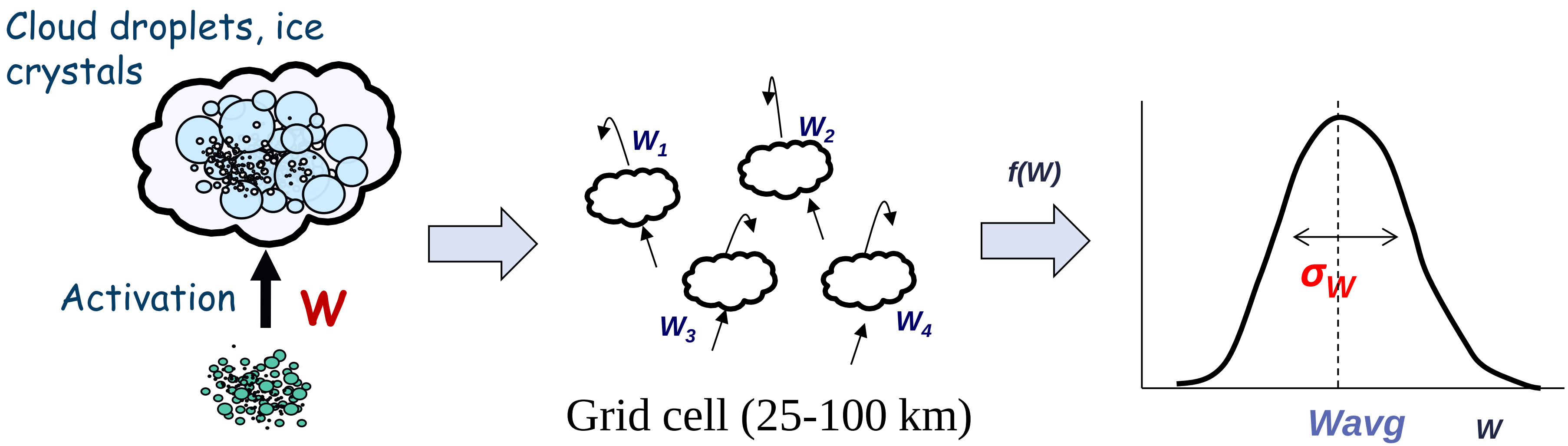




The aerosol indirect effect is the largest contributor to the uncertainty in climate assessments (long and short-term) and the cloud feedback.

IPCC AR5, AR6

Cloud Droplet Activation in GCMs



RH, T, CCN, INP

$\Delta X < 1$ km

$$\overline{N_\mathrm{a}} = \frac{\int_0^\infty N_\mathrm{a}(a_1, \ldots, a_n, T, p, w) f(w)\mathrm{d}w}{\int_0^\infty f(w)\mathrm{d}w}. \approx N_\mathrm{a}|_{\mathrm{Wsub}}$$

$W_{sub} \approx 0.8\sigma_W$ ≡ ***Subgrid Updraft, Characteristic W, …***

Peng et al. 2005.

Parameterizing σ_w

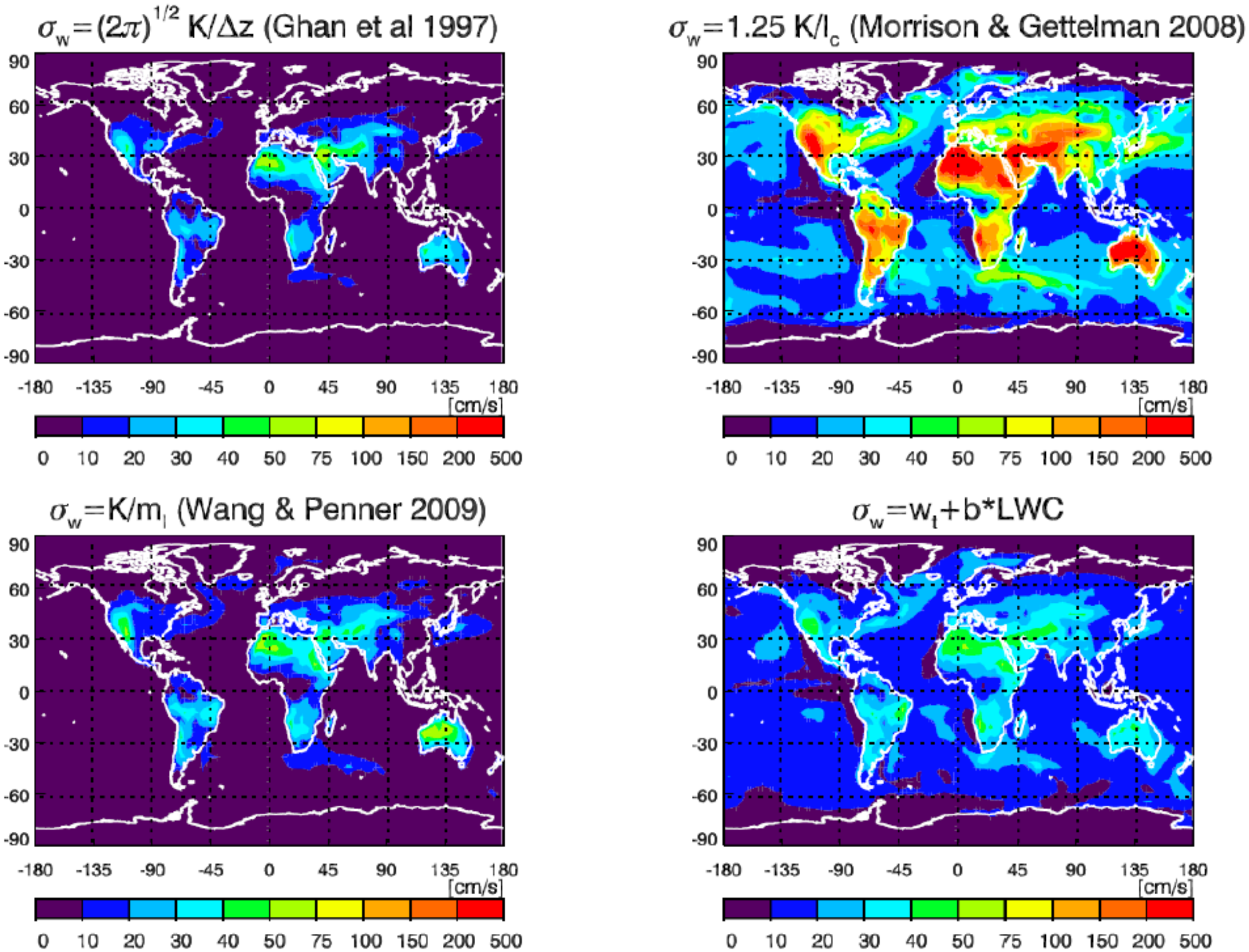


FIGURE 6: Annual averages of the grid-mean σ_W for the lowest five model levels ($\approx$2km), calculated with four different parameterizations implemented in CAM-Oslo.

Uncertainty in σ_w impacts cloud formation rates.

Different models for liquid and ice clouds.

CLUBB:
Consistent representation based on joint T, Q and W distributions.

- Complex
- PBL oriented
- Needs further evaluation

Hoose et al. 2010.

Parameterizing σ_w

"*Input updraft velocity fluctuations can explain as much as 48% of temporal variability in output ice crystal number and 61% in droplet number in GEOS-5 and up to 89% of temporal variability in output ice crystal number in CAM5.1.*" (Sullivan et al. 2016)

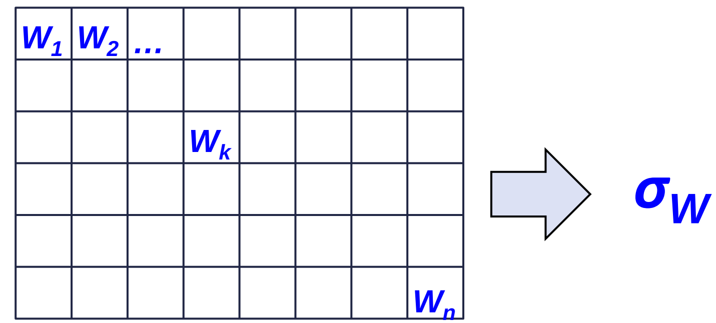
In radiative terms *"the breadth of the range* [of the effect of σ_w on the AIE] *is 0.4Wm−2, …comparable to a substantial fraction of the total diversity of current aerosol forcing estimates."* (West at al. 2014).

There is currently not a global, independent estimate of σ_w that allows us to reduce such an uncertainty

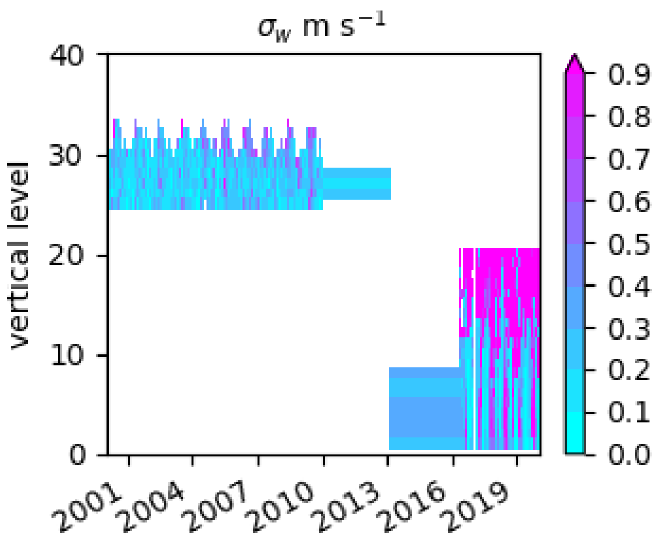
Estimating σ_w

Explicit: Kilometer-scale models

- Physically-based.
- Very expensive. Unfeasible for operational forecasts or long-term climate prediction but p**rovide excellent data for training.**
- **Biases still exist. Can't resolve all scales.**



High-res downsampling



Observational Data: W and σ_w can be retrieved using Doppler radar and lidar.

- Constrained by observations
- Very Limited domain. Satellite-based estimates are crude.
- Experimental error could be significant.

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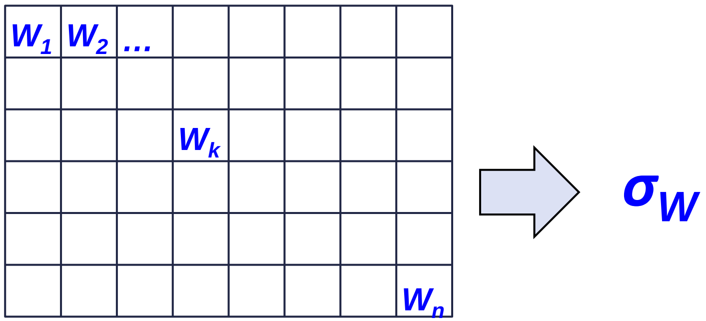

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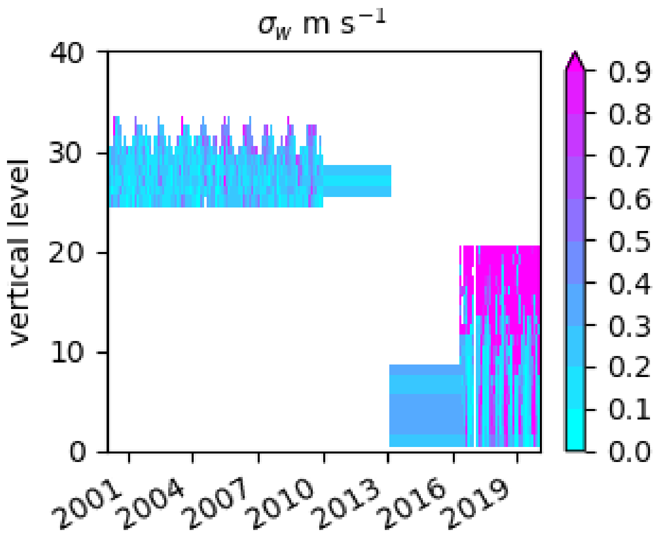


Experimental Observations,
Kilometer-Scale simulations
Climate Reanalysis

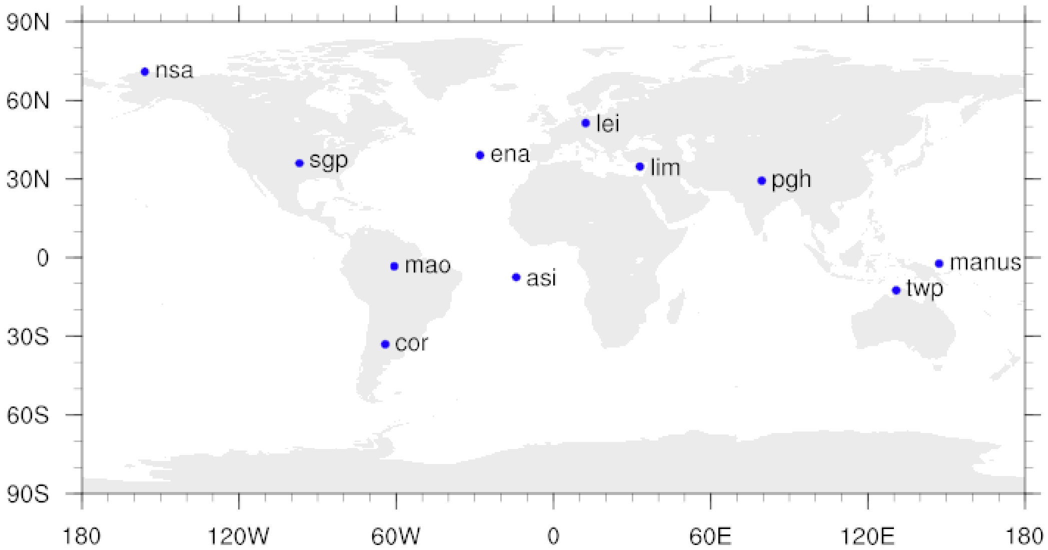
→ **ML** → σ_w **= f(coarse state)**

Data and Methods

GEOS Nature run (G5NR): 2 years of free-running, non-hydrostatic simulation of the NASA GEOS-5 model with prescribed SST at 7 km spatial resolution. ~ 5Pb of data.

MERRA-2: NASA 1980-present atmospheric reanalysis. Provides the atmospheric state for each of the sites.

Observational Data:



W retrieved using Doppler radar and lidar, at 11 different sites around the world. Mostly PBL sites, 4 cirrus, 1 tropical convection

Mostly from DOE-ASR archive. New data at the “lei” and “lim” sites (CloudNet).

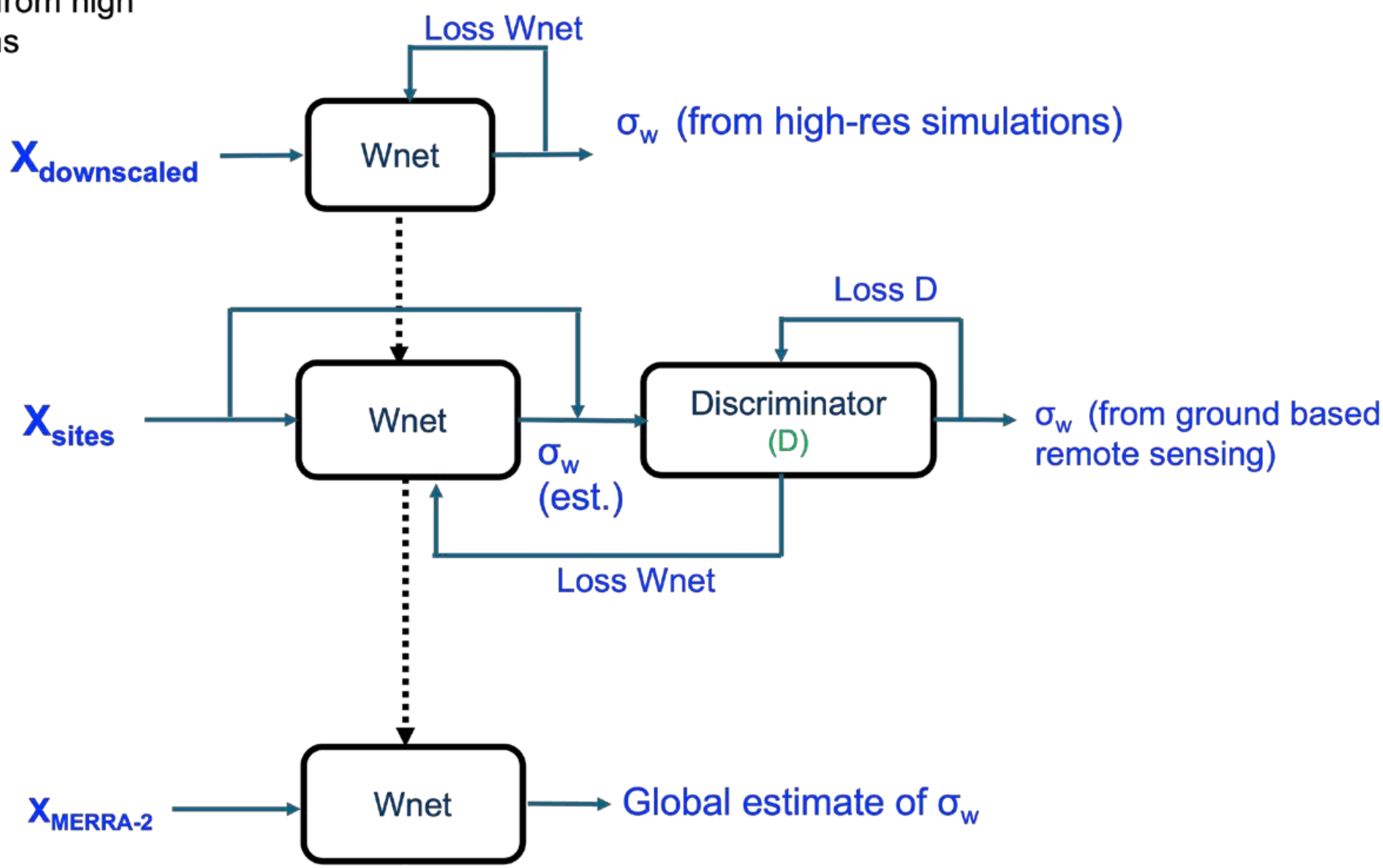
About 100 years of data on *W* at temporal resolution between 20 s and 5 min.

Developing a Global Estimate of σ_W

1- Surrogate model from high resolution simulations

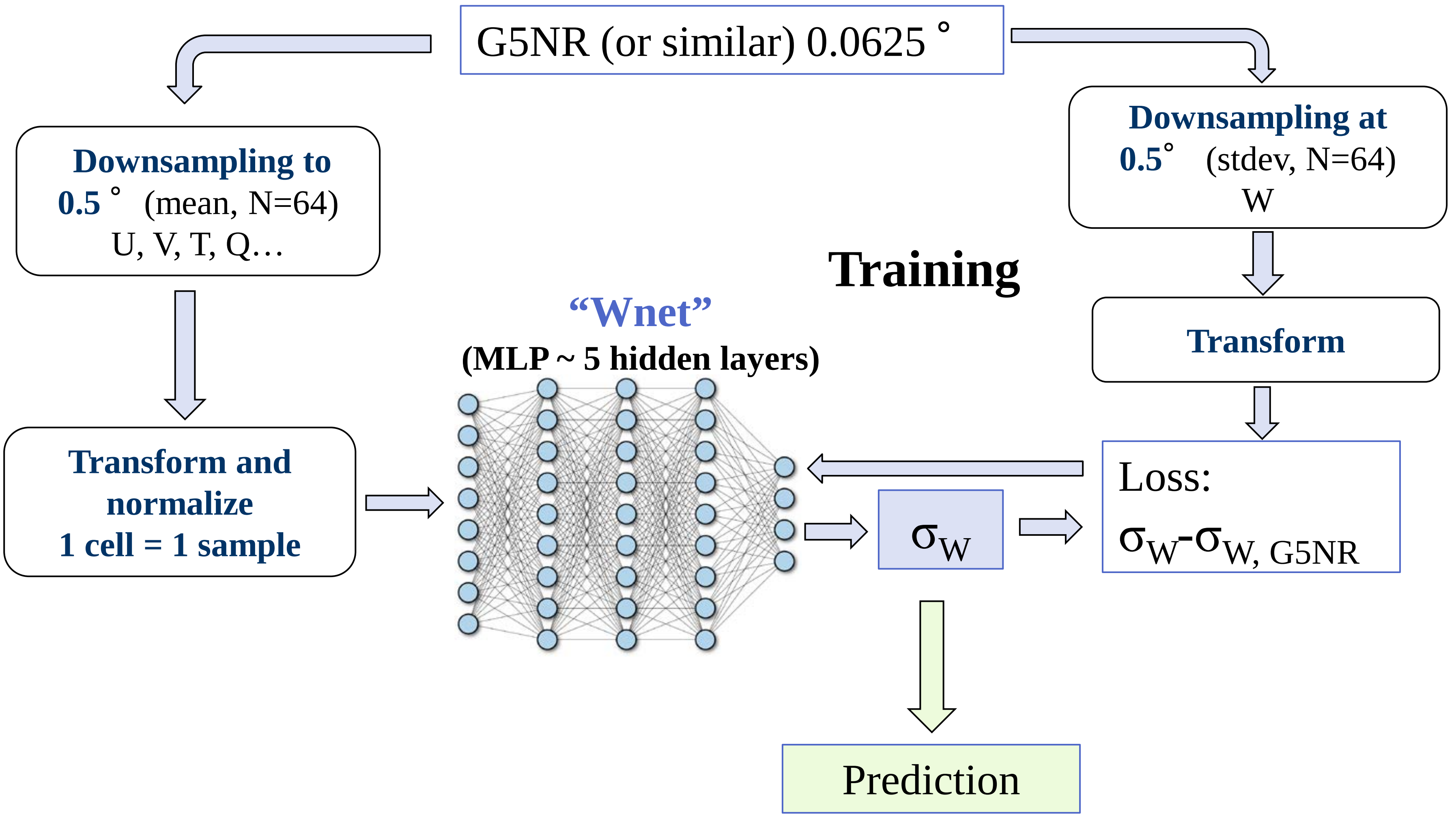
2- Probabilistic refinement using observational data at ground sites

3- Inference driven by reanalysis data

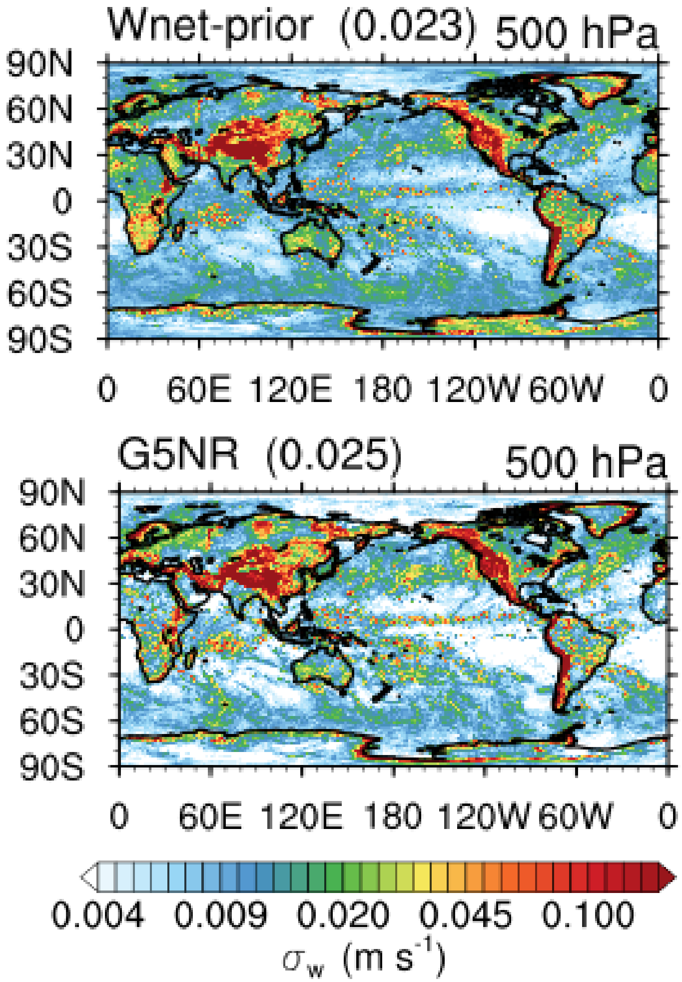


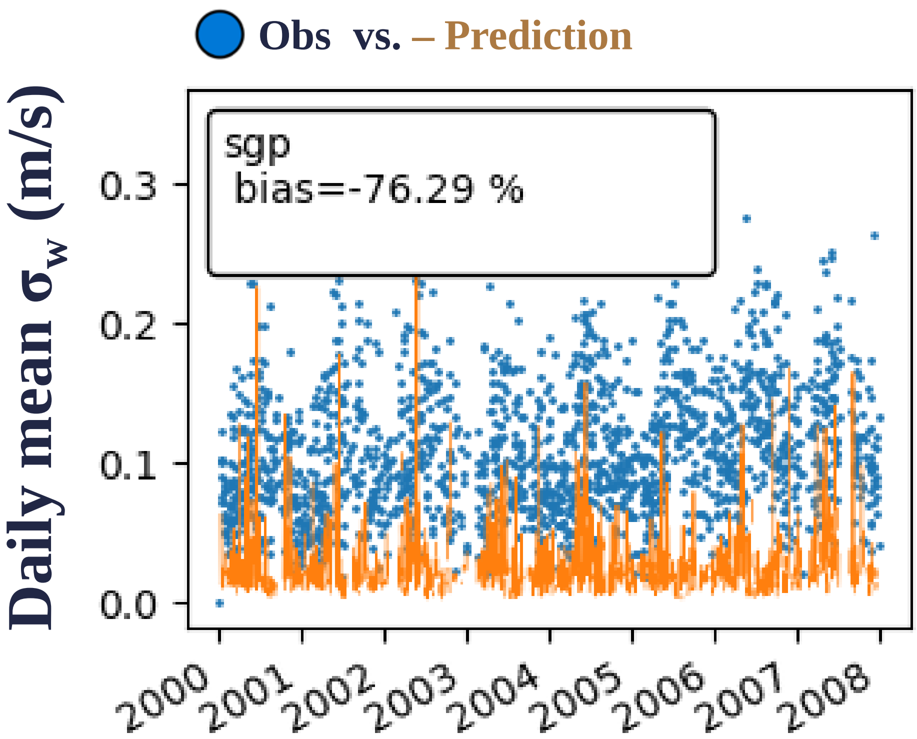
X = Atmospheric State (T, P, Winds, Km, Ri, $Q_{l,i,v}$) **at coarse resolution**

Developing Wnet-prior



Wnet (prior) reproduces the GSRM

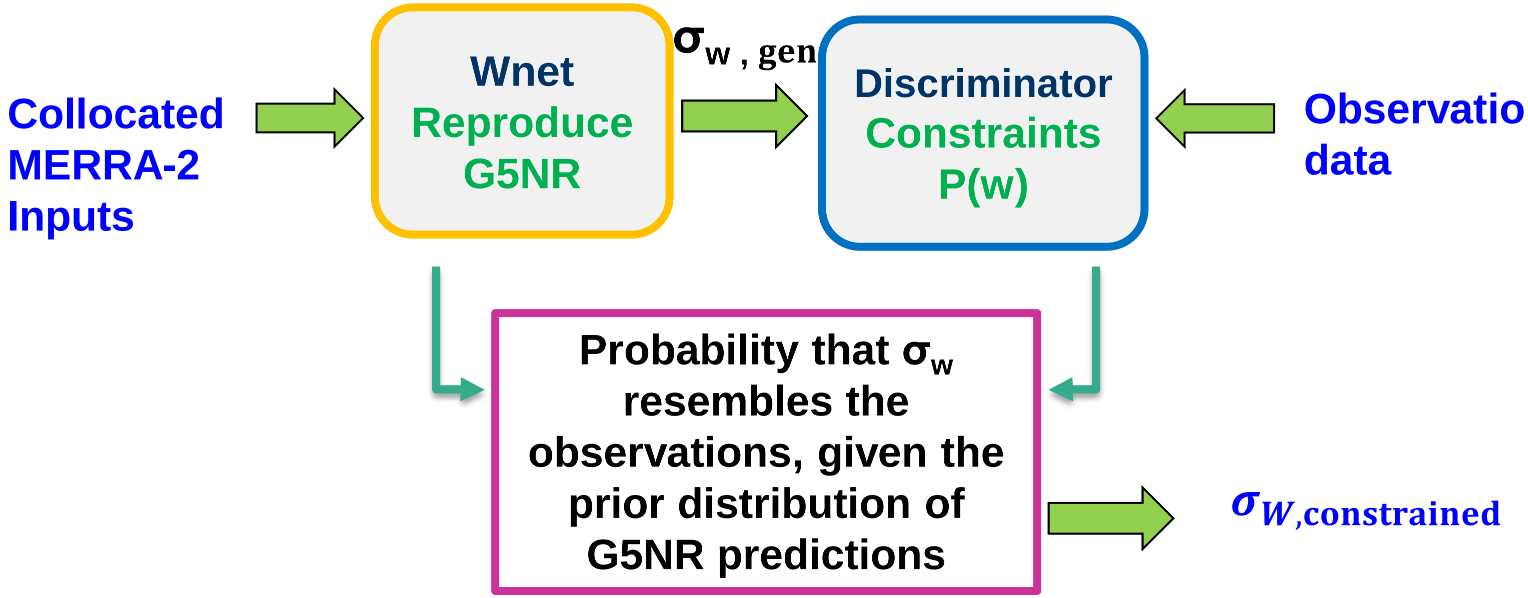




The NN reproduces the GSRM output within 0.005 m s^{-1}.
However, it tends to underestimate variability, reflecting the bias of the high-resolution simulations.

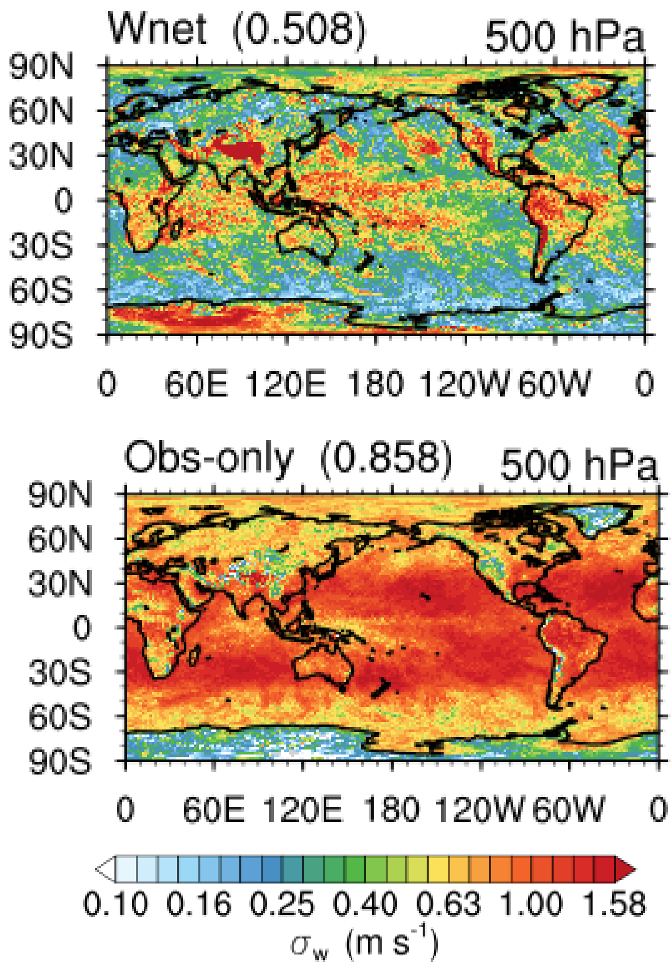
Barahona et al. *AIES* (2024).

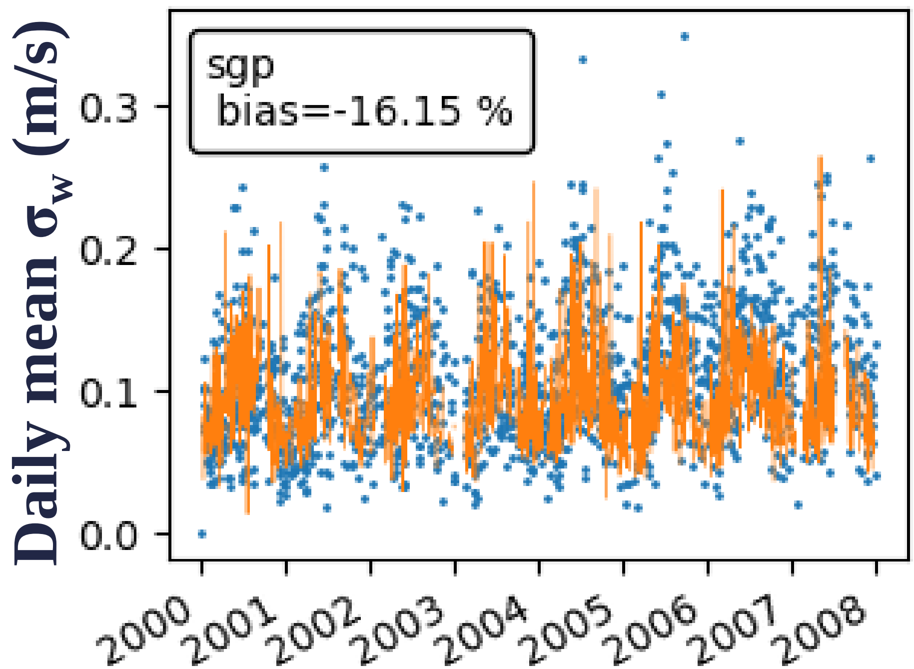
Probabilistic Parameterization Development: Constrained Adversarial Training



The discriminator coerces the generated statistics to be the same as the observations.

Results: GAN-Trained NN Parameterization Achieves High Accuracy

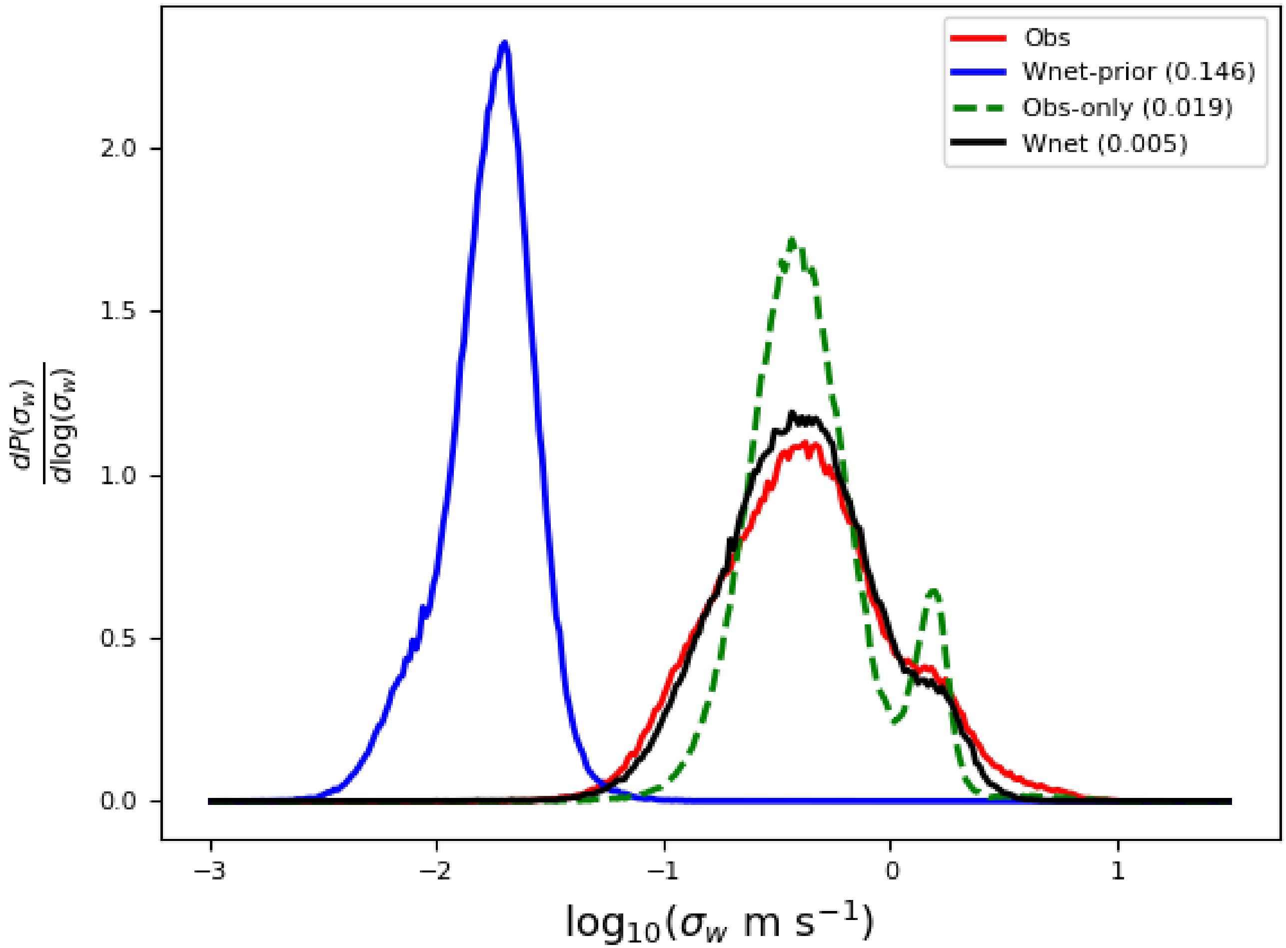




Using observational data is critical for the performance.
Wnet exhibits spatial structure that would be missing in a model trained using only observational data ("Obs-Only").

Barahona et al. *AIES* (2024).

What about the PDF?



The statistics generated by the Wnet parameterization approximate well the observations, minimizing the effect of uncertainty on $\sigma_{W.}$

Barahona et al. *AIES* (2024).

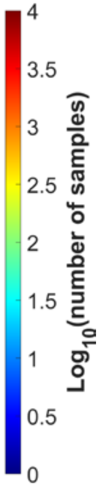
Implementation Online in GEOS

Current parameterization

GEOS + Wnet

Observations

2nd Run



Analysis performed by Minghui Diao and Derek Ngo

FKB: Fortran-Keras Bridge. (Otto et al. 2020).

GEOS + Wnet compares much better to in situ observations. Still some issues with computational performance.

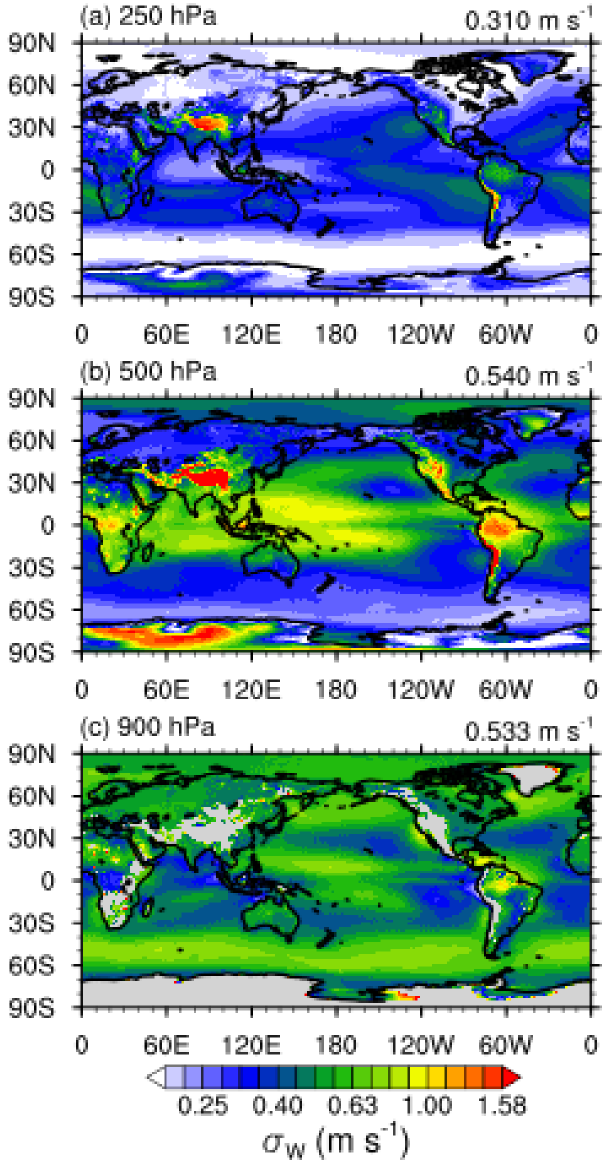
Outline

1. Wnet: A constrained neural network to estimate subgrid scale vertical wind velocity

2. **Trends in Vertical Velocity Variability**

3. Vertical Velocity Variability as a Climate Feedback

Global Estimate of σ_w



Global mean σ_w derived from MERRA-2 for 1980-2023.

We developed a long-term data set on σ_w spanning 42 years, on 3-hourly intervals, at half-degree, from 1 hPa to 1000 hPa.

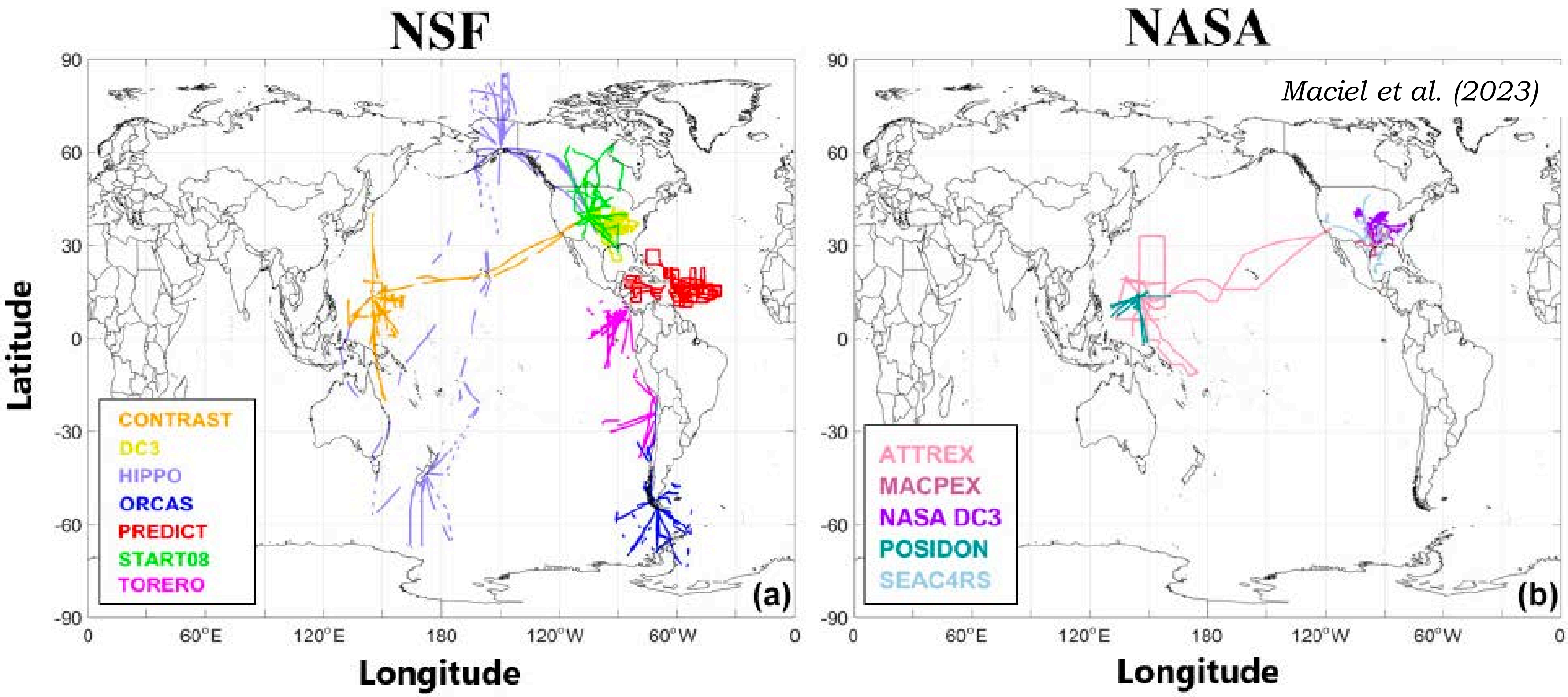
https://portal.nccs.nasa.gov/datashare/Wstd-MERRA2/

Familiar patterns:

- High variability in convective regions and storm tracks.
- Turbulence induced by orography and the jet stream.
- In general σ_w decreases with altitude.

Barahona et al. *Under review.*

Evaluation against Aircraft Data



MERRA2-derived σ_w was interpolated along flight tracks for different field campaigns.

Barahona et al. *Under review.*

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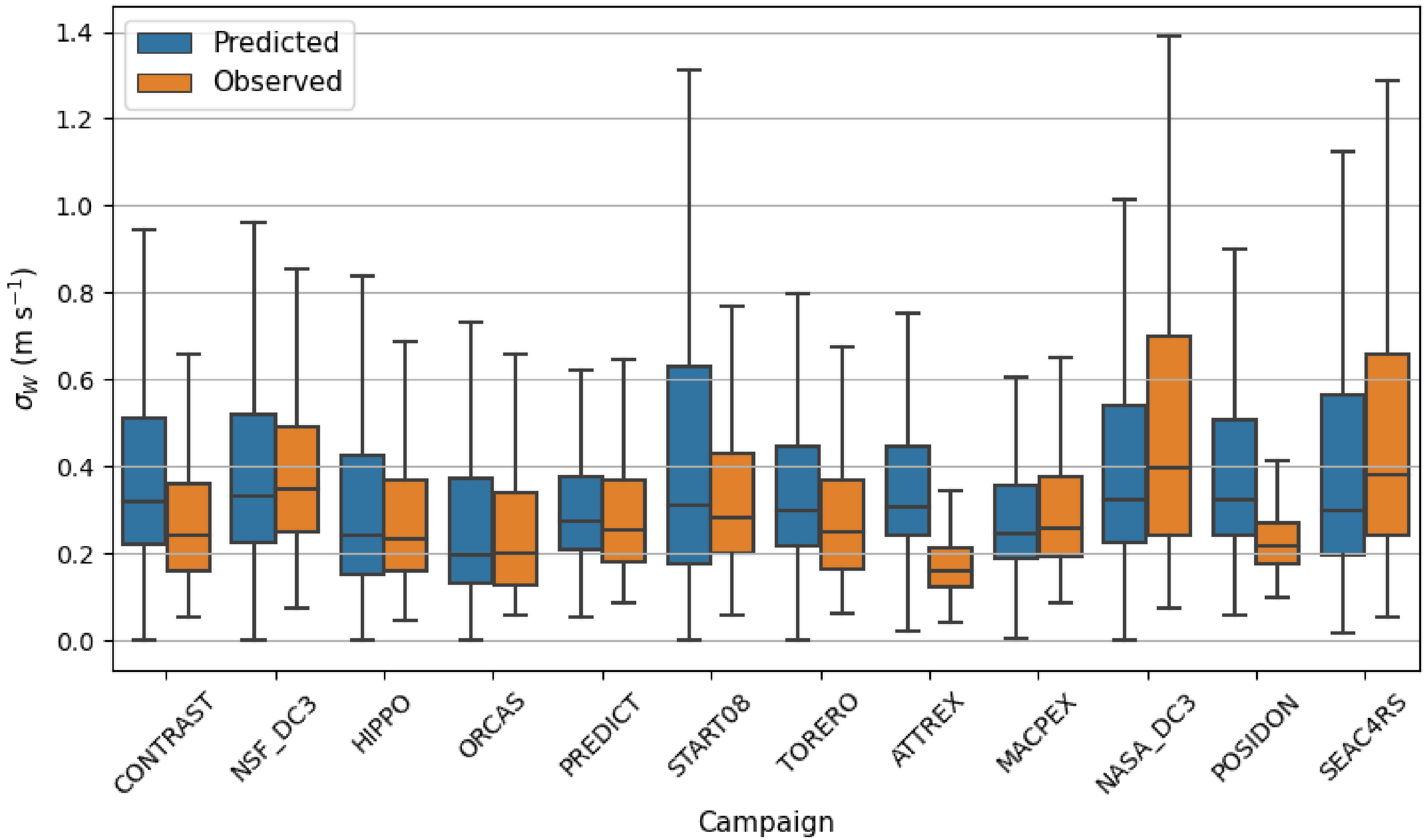
Evaluation against Aircraft Data



Rigorous test:
Data not used during training, and σ_w is measured directly instead of retrieved by remote sensing.

Barahona et al. *Under review.*

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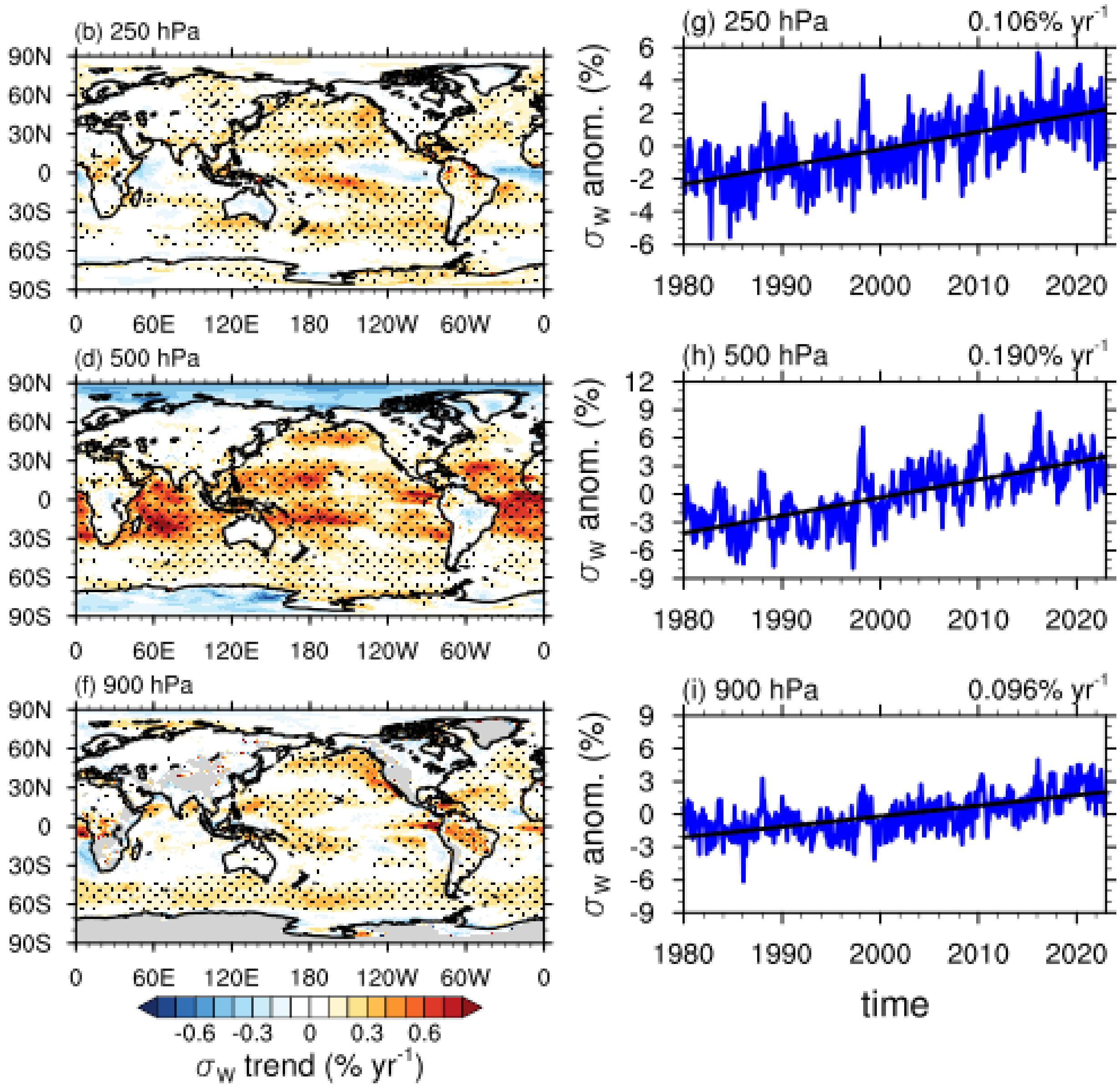
Trends in σ_w

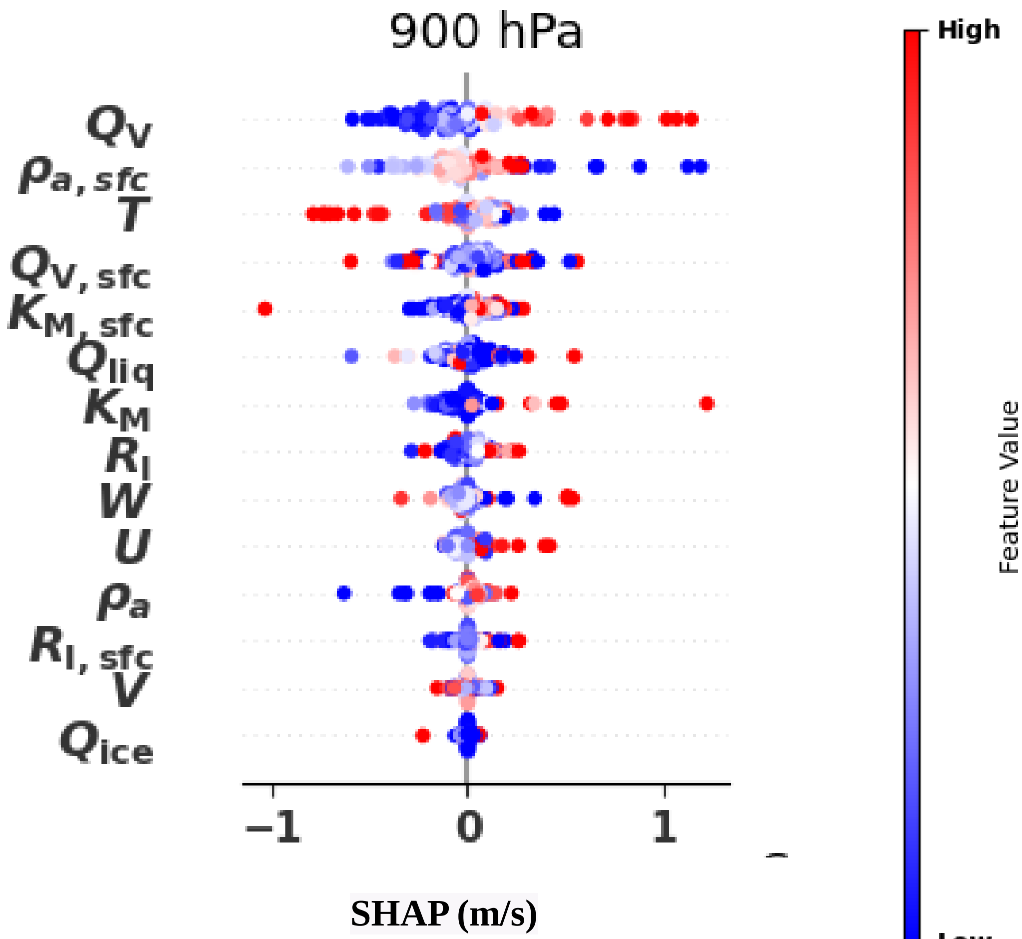


Significant trends in σ_w emerged during the last 40 years, with a general increase over the tropics/subtropics and decrease towards high latitudes.

Implies enhanced turbulence in the lower latitudes.

Barahona et al. *Under review.*

Explainable Machine Learning Analysis



The SHAP value indicates the sensitivity of σ_w to a given input. Red on the right means positive correlation, inputs are organized by importance.

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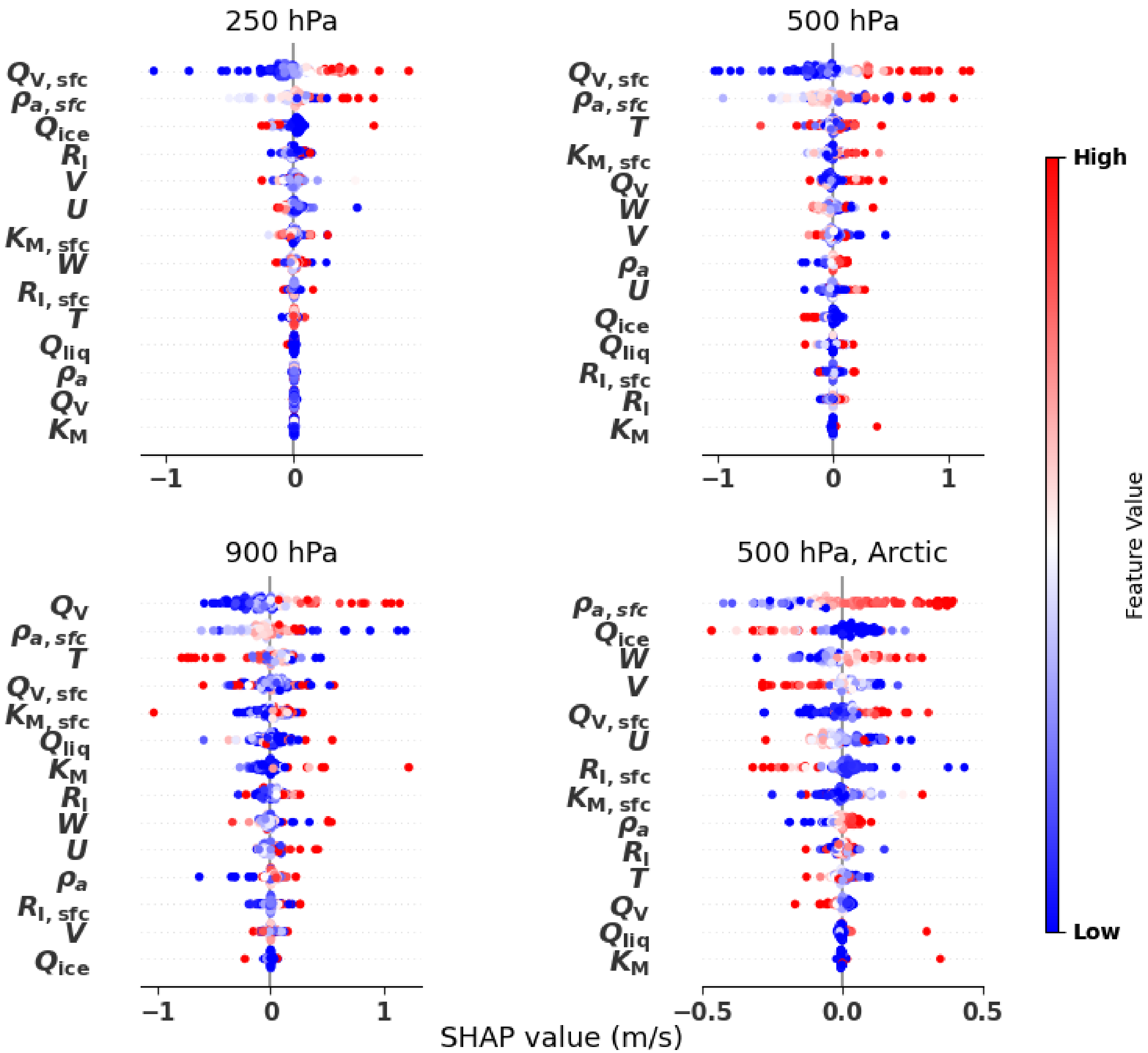
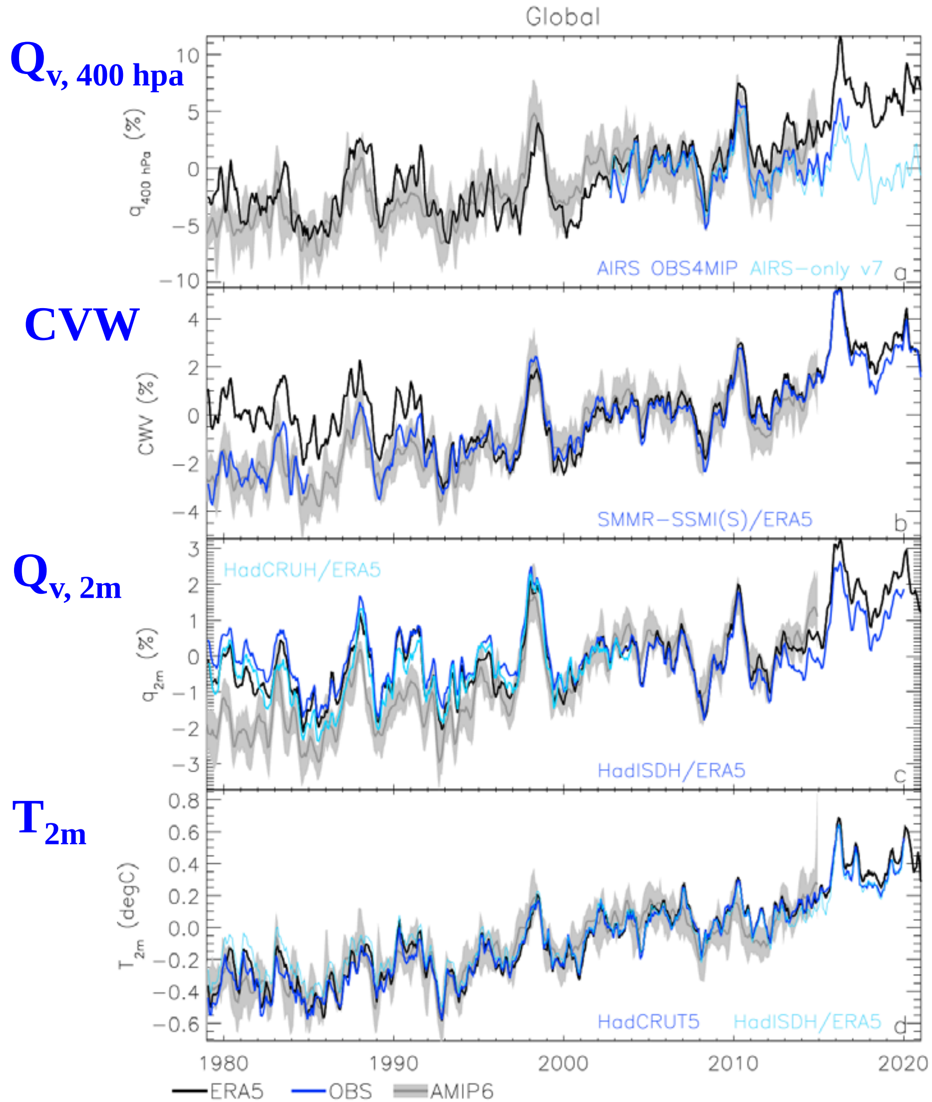
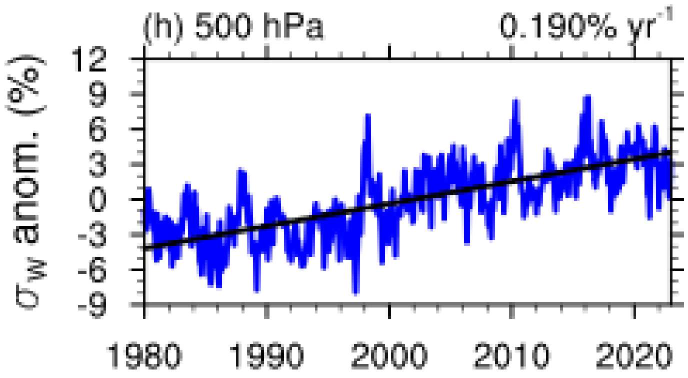
SHAP



Surface water vapor and air density are the main factors at all levels. Horizontal winds become important at higher altitude and in the Arctic. These are linked to convective activity, water vapor transport, and jet-stream strength.

Trends in σ_w





Evolving meteorological patterns, like jet-activity and convection, have systematically impacted the intensity and frequency of small scale processes, such as turbulence, hence cloud microphysics.

Allan et al. *JGR*, 2022.

Outline

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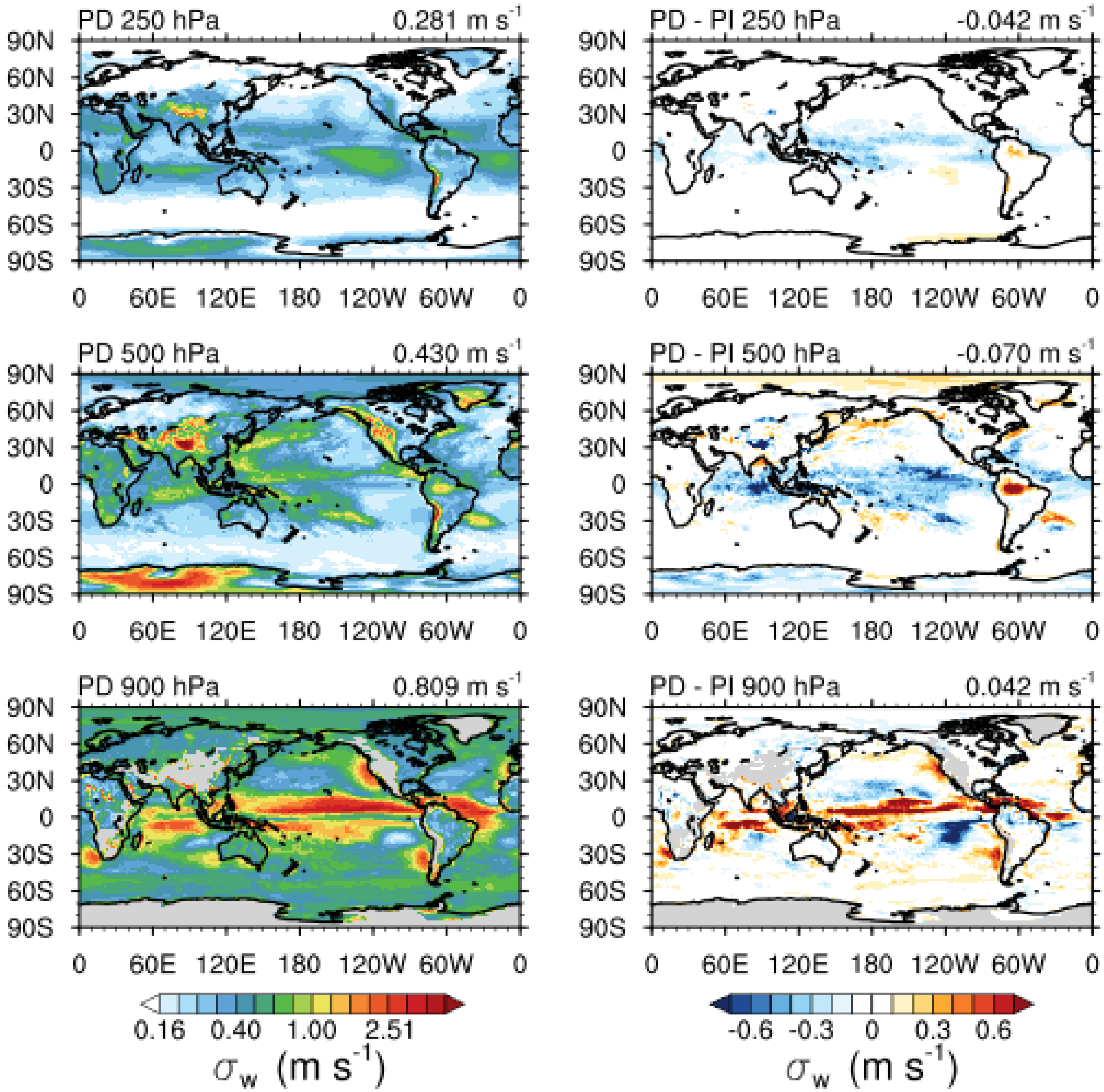
2. Trends in Vertical Velocity Variability

3. **Vertical Velocity Variability as a Climate Feedback**

Changes in σ_w during the Industrial Era



Due to its impact on cloud microphysics, σ_w affects the radiative properties of clouds.

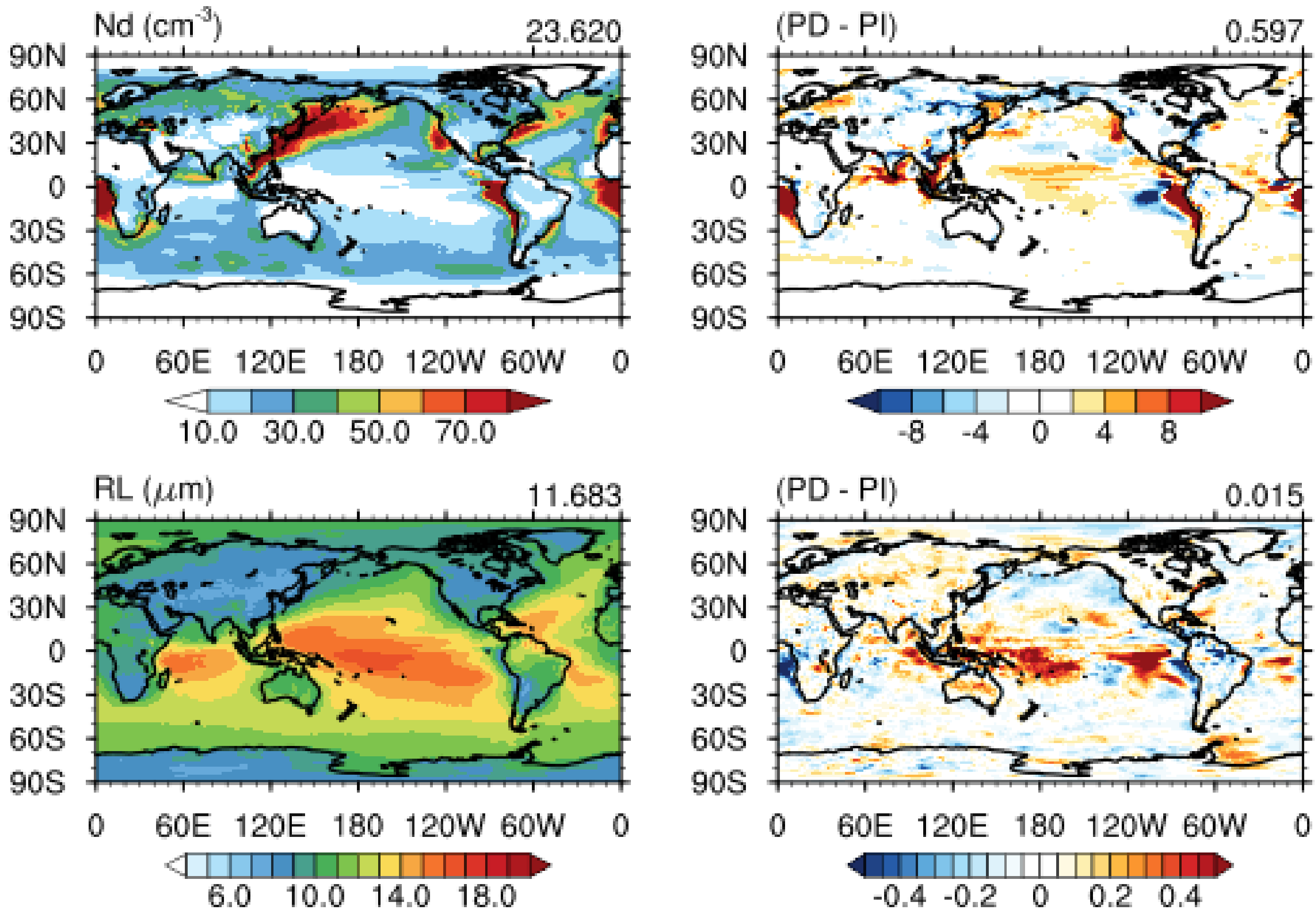
Climatologies of σ_w were calculated using the output of two pre-run simulations representing preindustrial (1850, PI) and present day (mean 2010's, PD) conditions.

Quantifying forcing associated with σ_w

Run	**SigmaW climatology**
Present Day (wnet_Pd)	Last 10 of a AMIP current day simulation with prescribed SST and climatological aerosol emissions (**PD**)
Preindustrial (wnet_Pi)	Last 10 years of piCon Simulation (preindustrial emissions and CO2) **PI**
SST4K (wnet_sst4k)	Derived from AMIP simulation using sst+4K

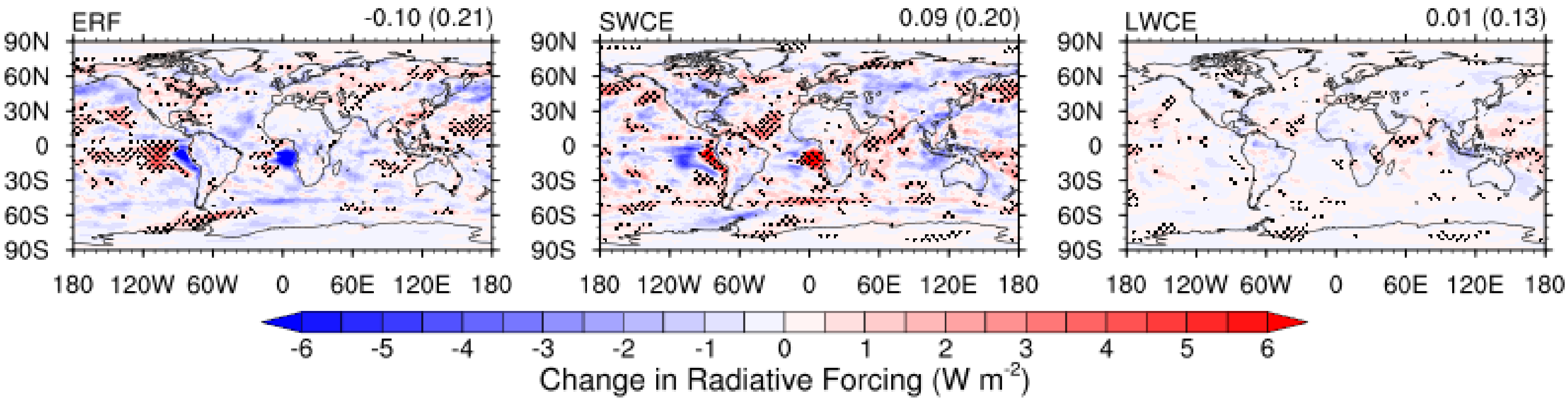
All runs: 50 years integration, prescribed MERRA2 SST and sea ice fraction, perpetual 2005, climatological aerosol (2010-2020)

Change in Liquid Cloud Properties associated with σ_w



Enhance droplet number and reduced effective radius in stratocumulus regions

Radiative forcing associated with σ_w



Evolving σ_w represents a radiative forcing of about -0.1 W m^{-2}, mostly through the shortwave.

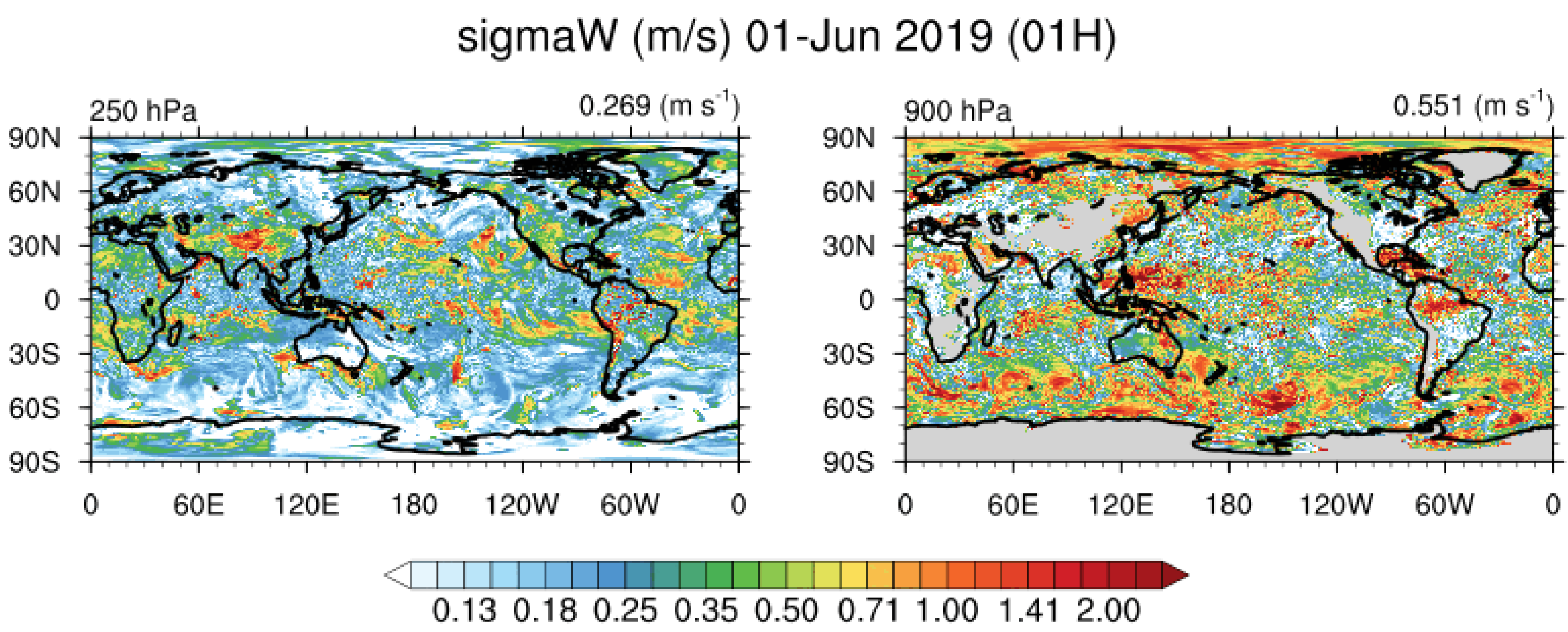
Barahona et al. *Under review.*

Conclusions

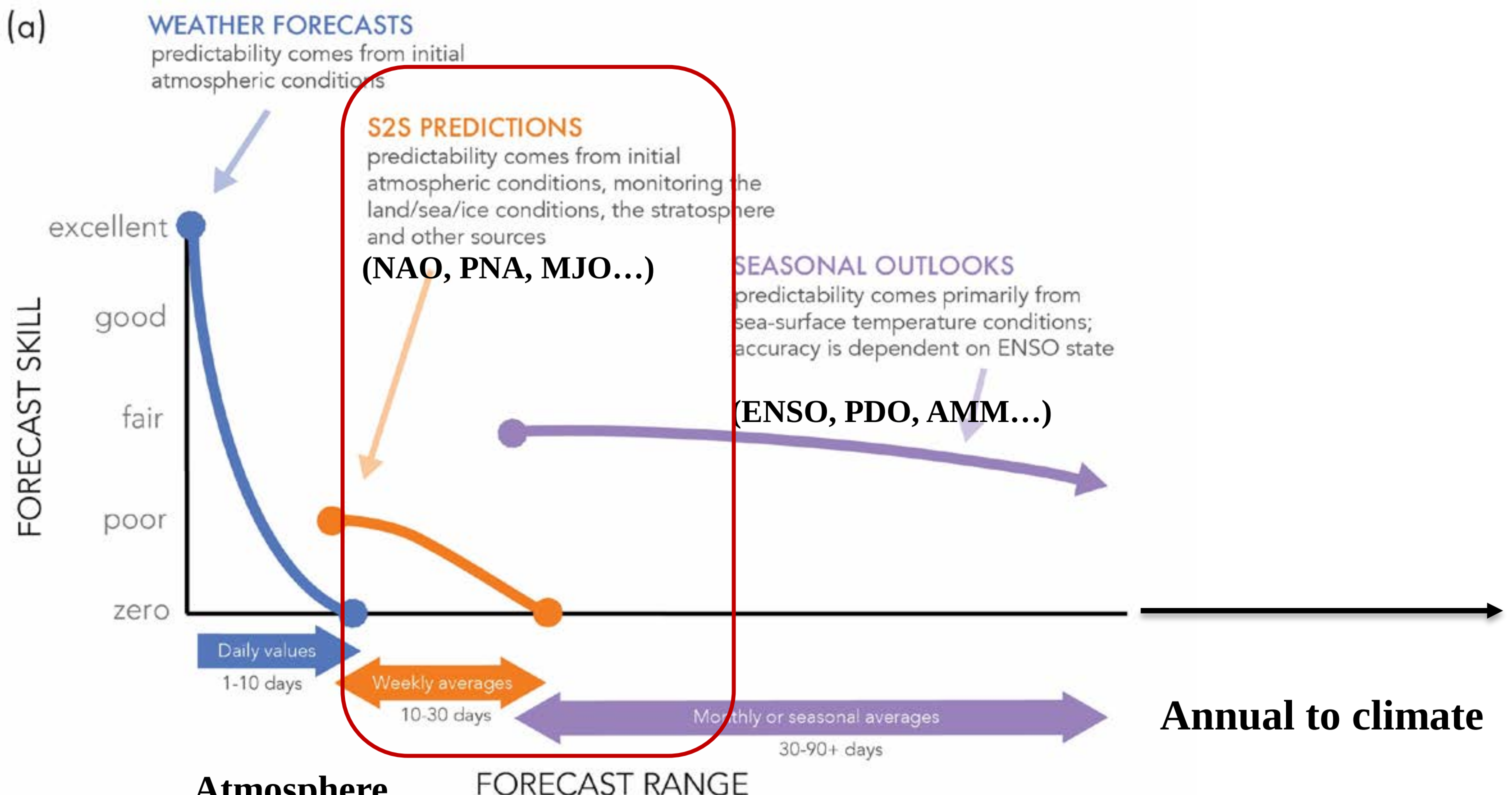
- An observations-constrained neural network, Wnet, was developed to estimate the subgrid scale variability in W from the coarse meteorological state.

- A long term data set was developed, revealing significant trends in σ_w over the last four decades, likely driven by the evolution of water vapor, convection and jet stream strength.

- The connection between large scale climate patterns and cloud microphysics through σ_w may represent an indirect radiative effect on climate, slightly counterbalancing greenhouse warming.



Prediction Scales

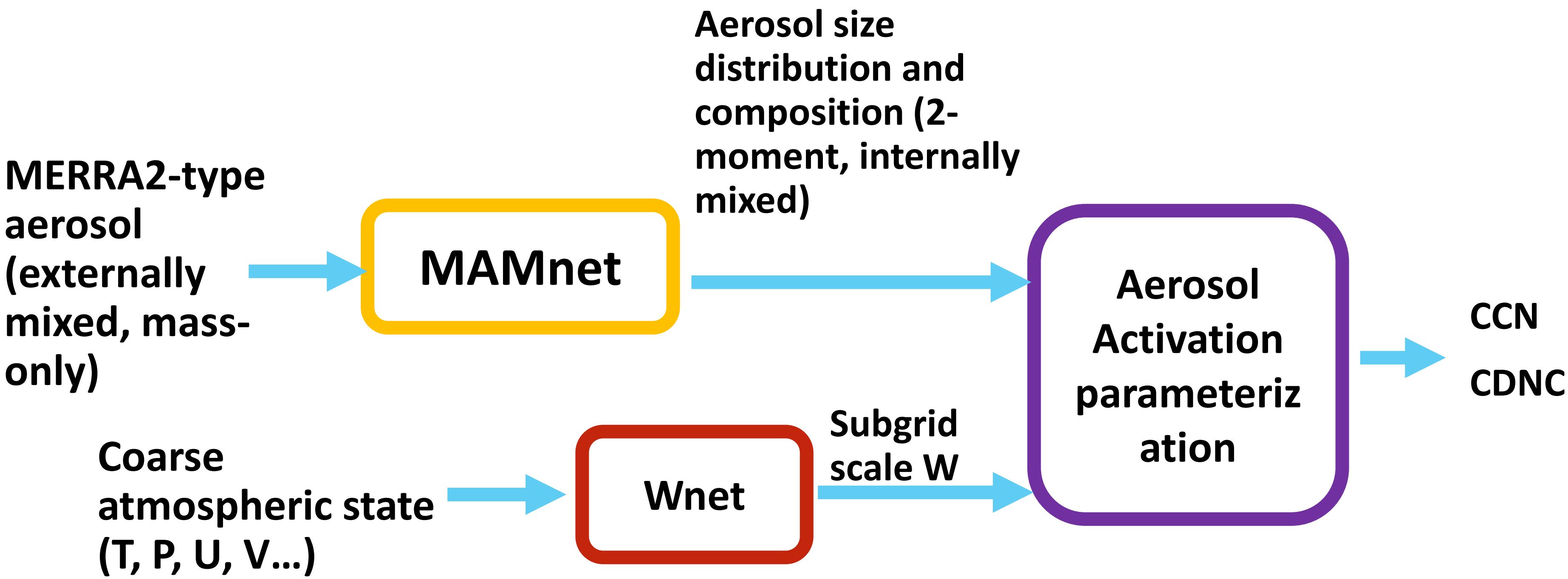


Atmosphere Only

Coupled (Atmosphere, Ocean, Sea ice , Land)

Relies heavily on observations

Estimating Droplet Number Concentration and CCN from MERRA-2



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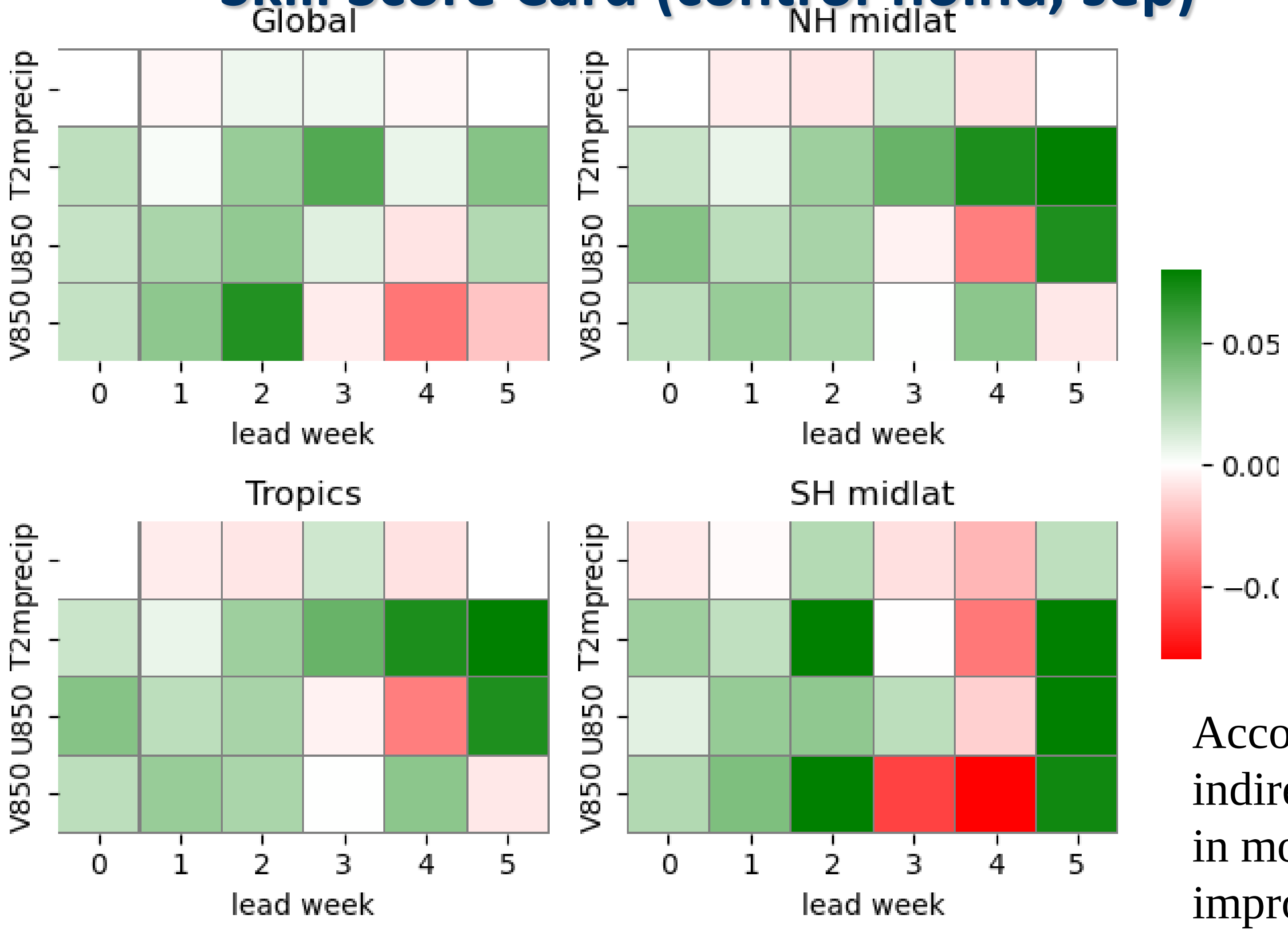
Skill Score Card (control-noind, sep)



Change in Anomaly Correlation

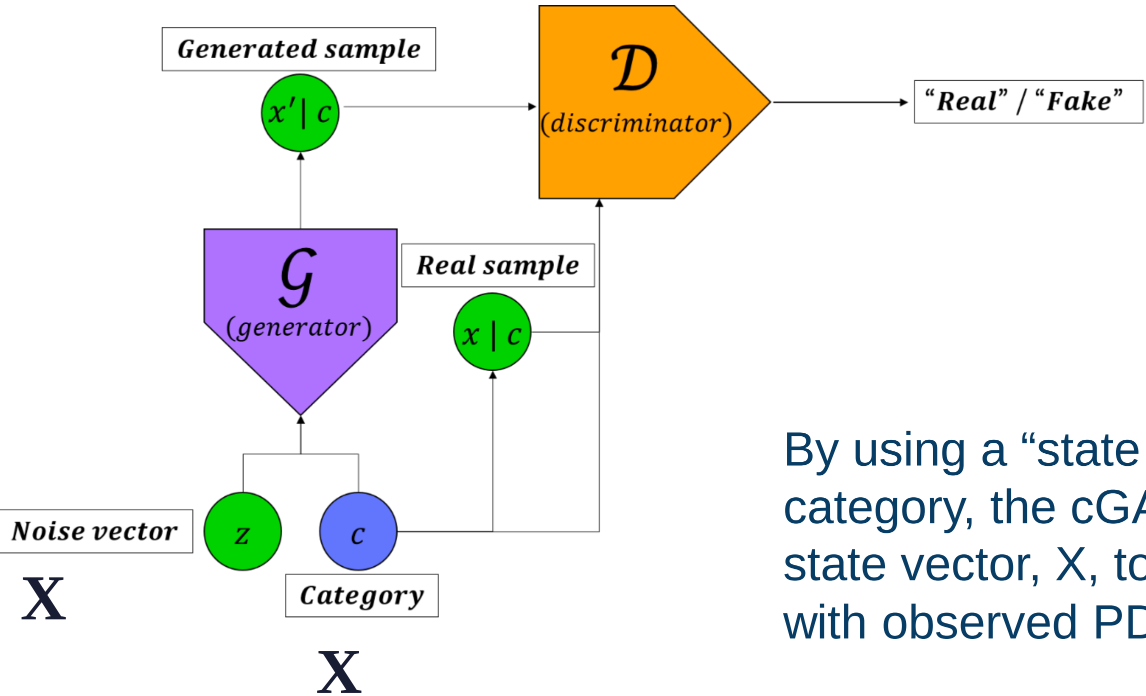
Accounting for the indirect effect results in mostly improvement of the skill, although some degradation in SH

Accounting for Error through Adversarial Training

The PDF of $\boldsymbol{\sigma_w}$ is more robust to experimental and sampling error than individual measurements:

- Even a few observations may represent the PDF
- Non-systematic error cancels out in the PDF

Parameterization must aim to reproduce the PDF-> Generative Adversarial Networks (GANs)



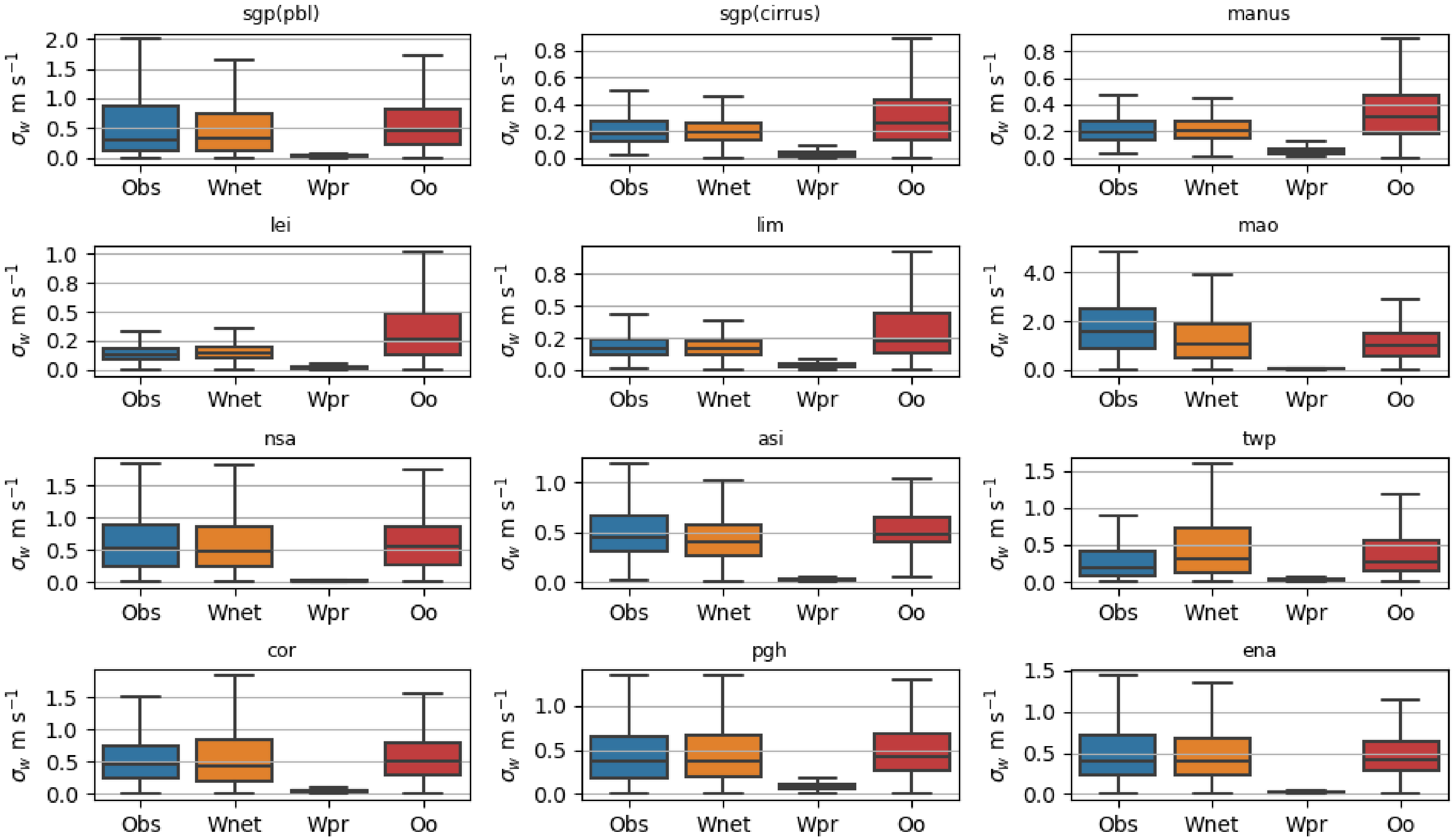
Conditional GAN

By concatenating labelled data to the target, it is possible restrict the PDF within a particular reference class

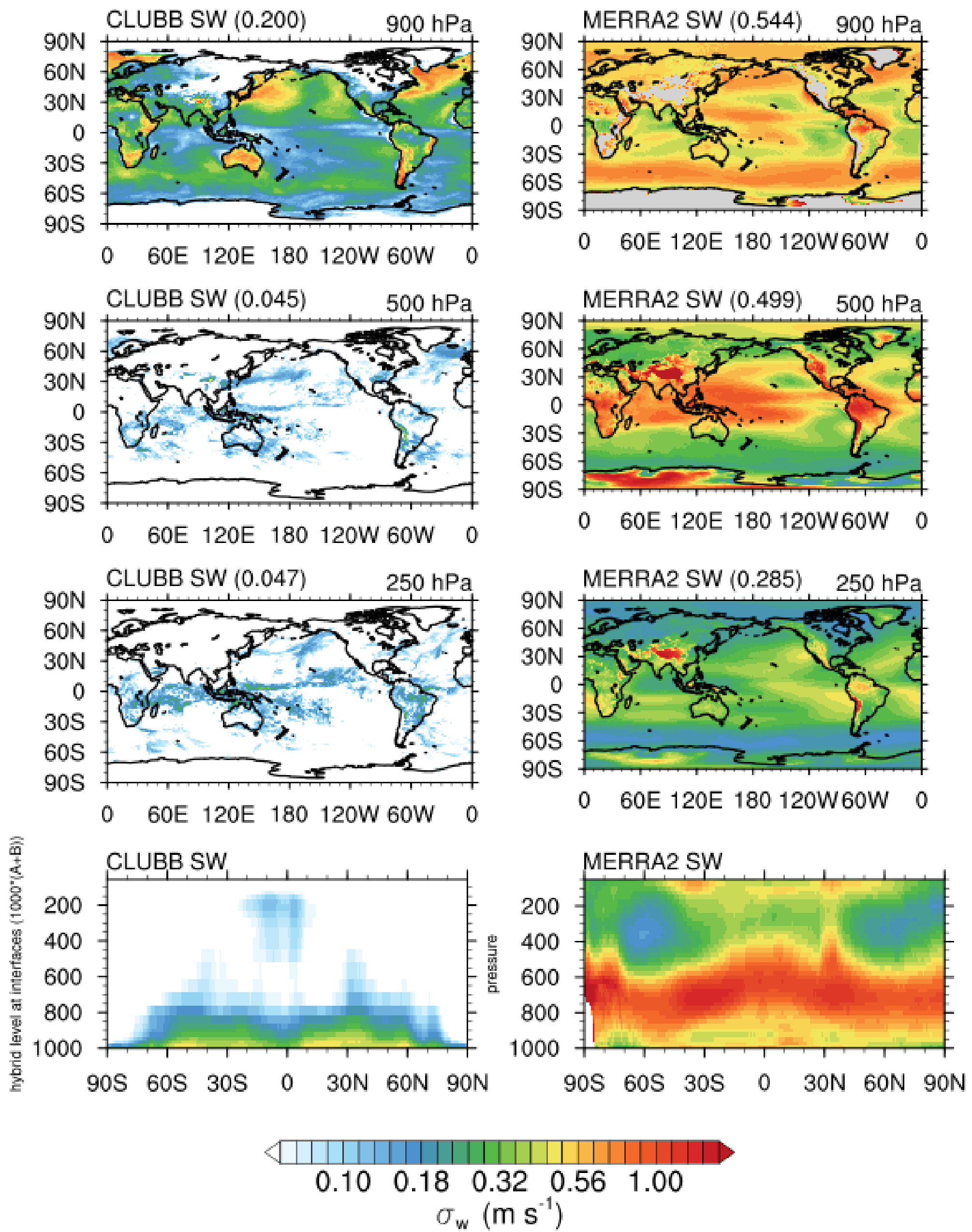
By using a "state vector" **X**, as both input and category, the cGAN yields a regression from the state vector, X, to the target ($\boldsymbol{\sigma_w}$) while conforming with observed PDF.

Park et al. Electronics 2020, 9, 688; doi:10.3390/electronics9040688

Results: ANN models at all sites



Barahona et al. *AIES* (2024).


CLUBB SW (0.200)
900 hPa
MERRA2 SW (0.544)
900 hPa
CLUBB SW (0.045)
500 hPa
MERRA2 SW (0.499)
500 hPa
CLUBB SW (0.047)
250 hPa
MERRA2 SW (0.285)
250 hPa
90N 60N 30N 0 30S 60S 90S
0 60E 120E 180 120W 60W 0
CLUBB SW
MERRA2 SW
hybrid level at interfaces (1000*(A+B))
pressure
200 400 600 800 1000
90S 60S 30S 0 30N 60N 90N
0.10 0.18 0.32 0.56 1.00
σ_w (m s^{-1})

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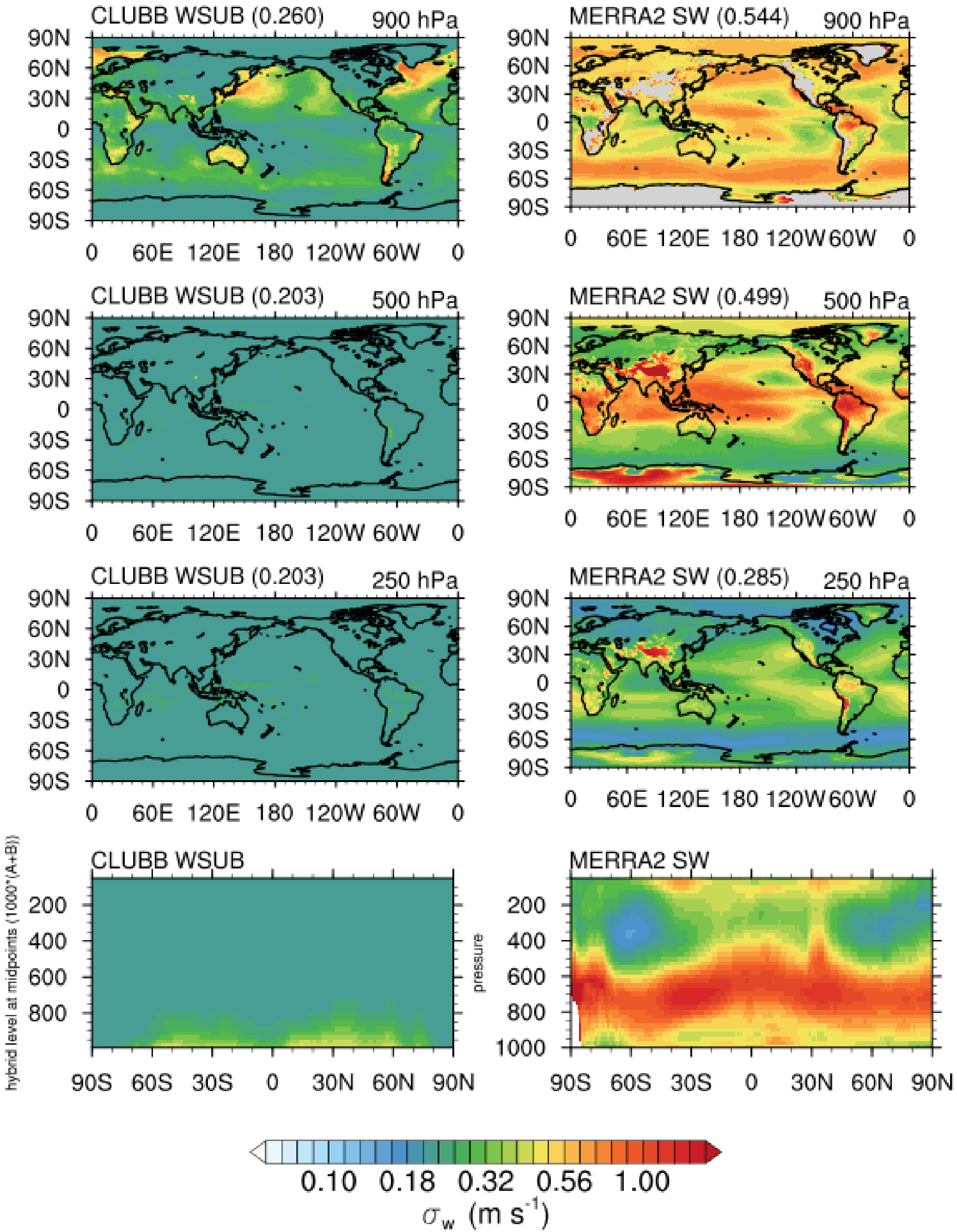
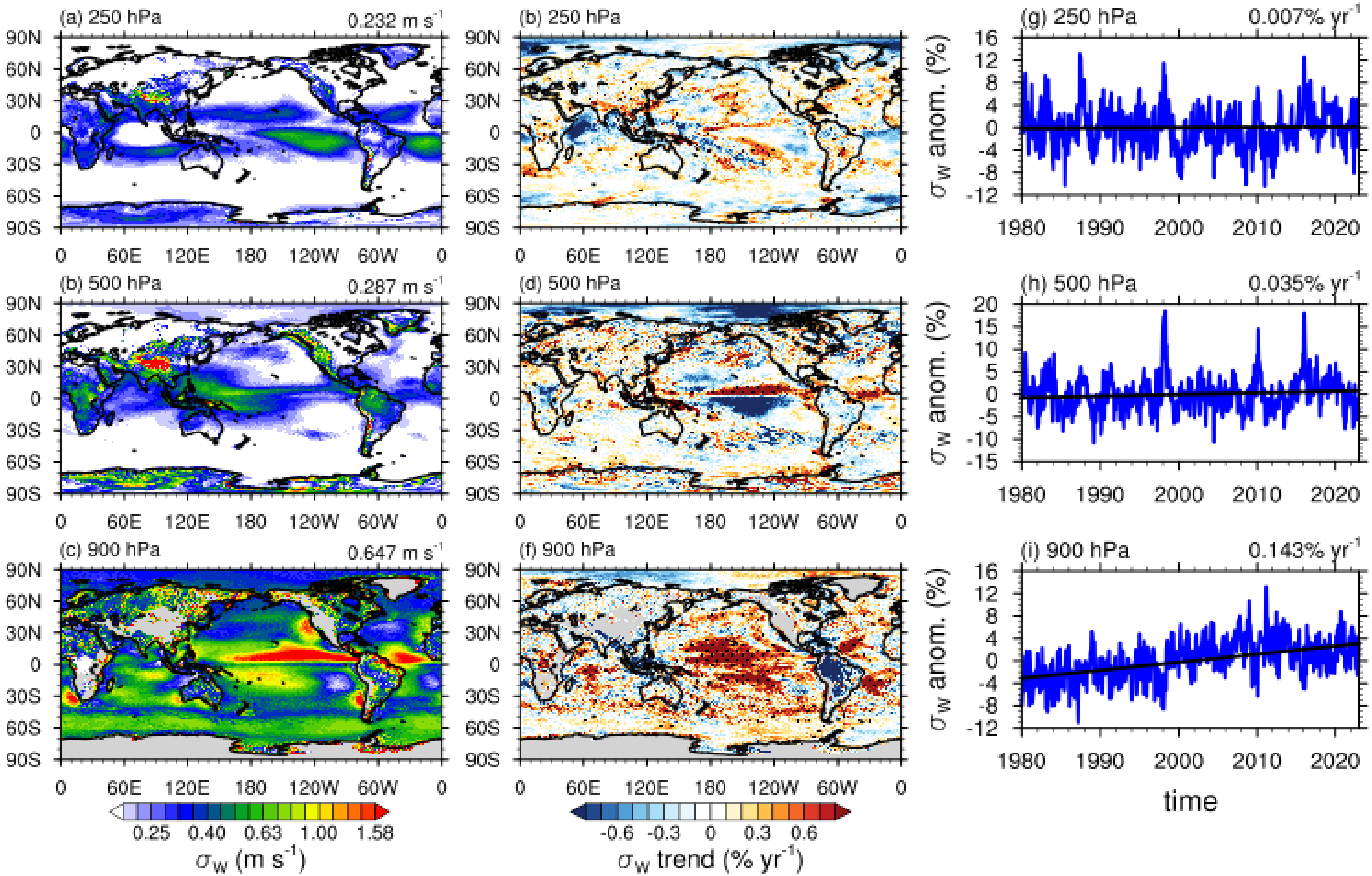
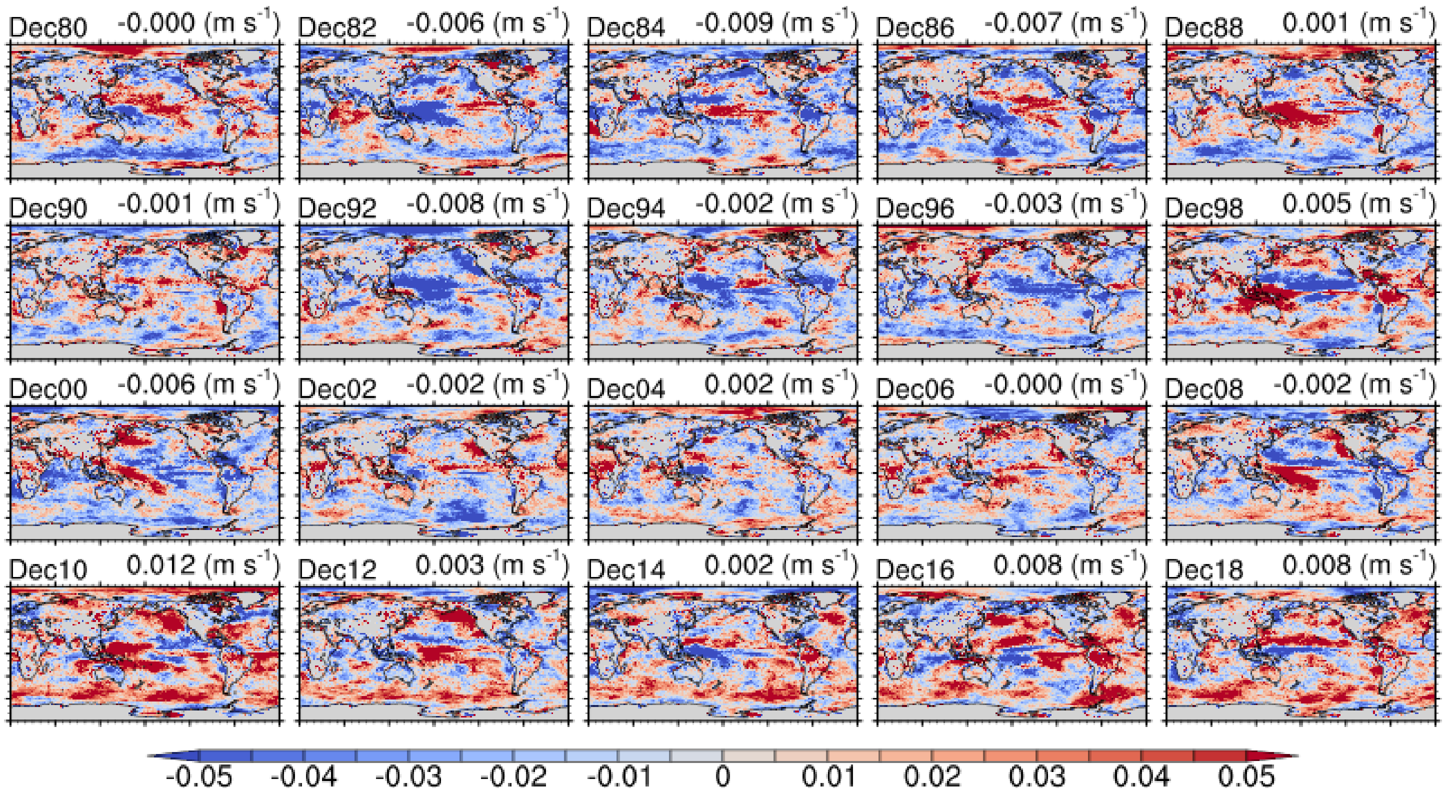


GMAO
gmao.gsfc.nasa.gov



σ_W anomaly at 900 hPa



Increased in CDNC seems to be correlated with dynamical forcing

Barahona et al. ***Submitted.***

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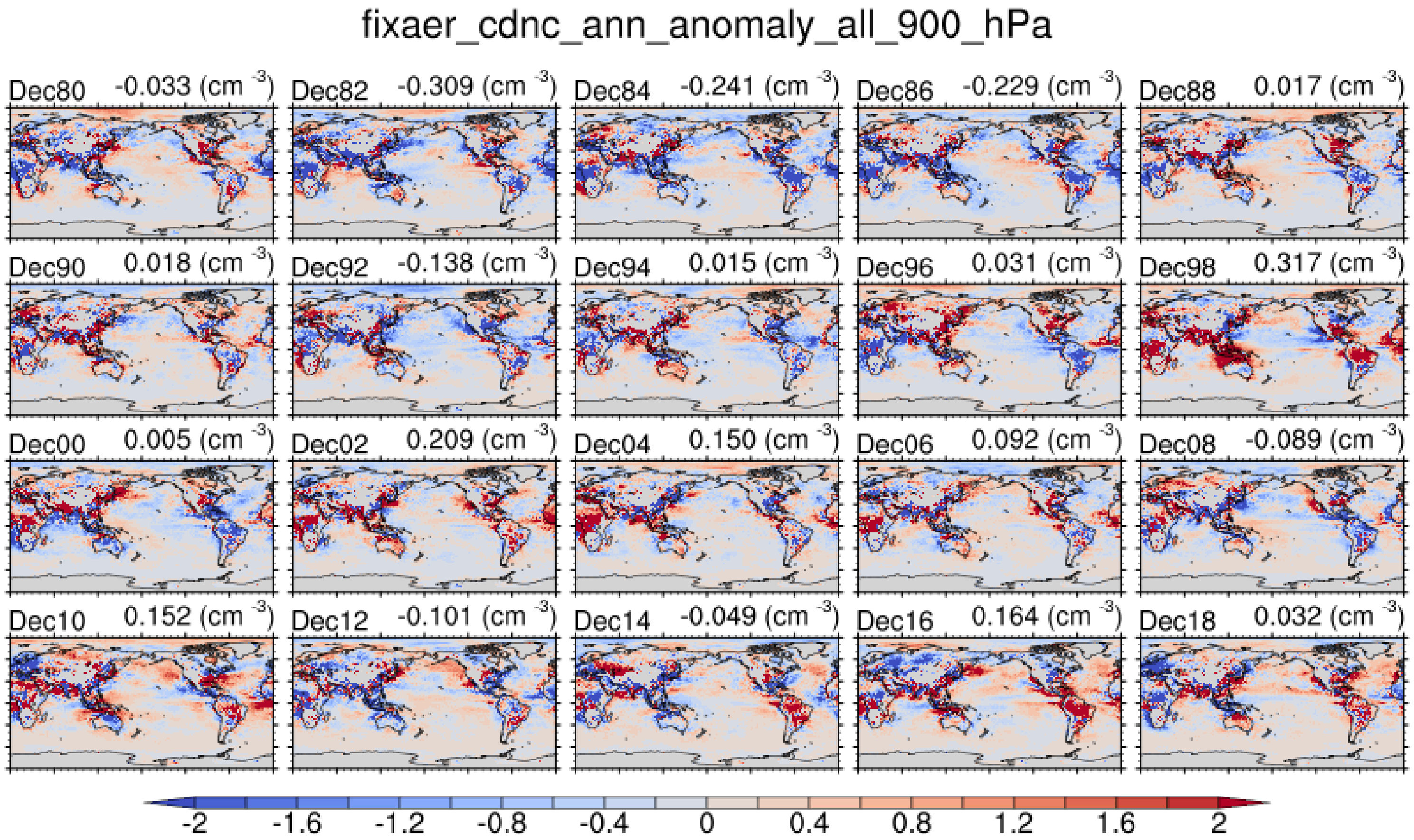
Estimating the effect of sigma_w



Anomaly in CDNC using constant aerosol climatology