Toward efficient calibration of higher-resolution ESMs

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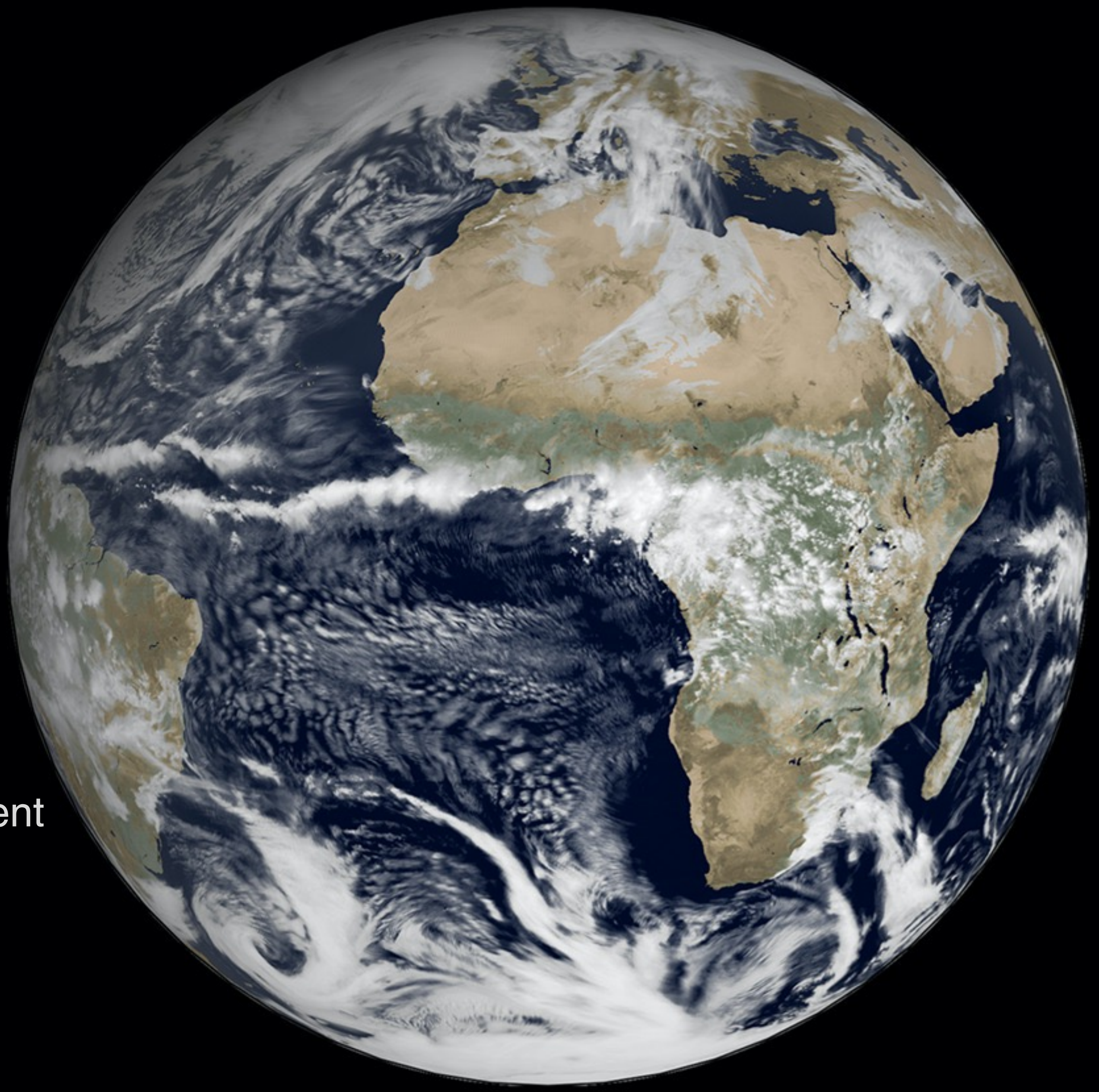
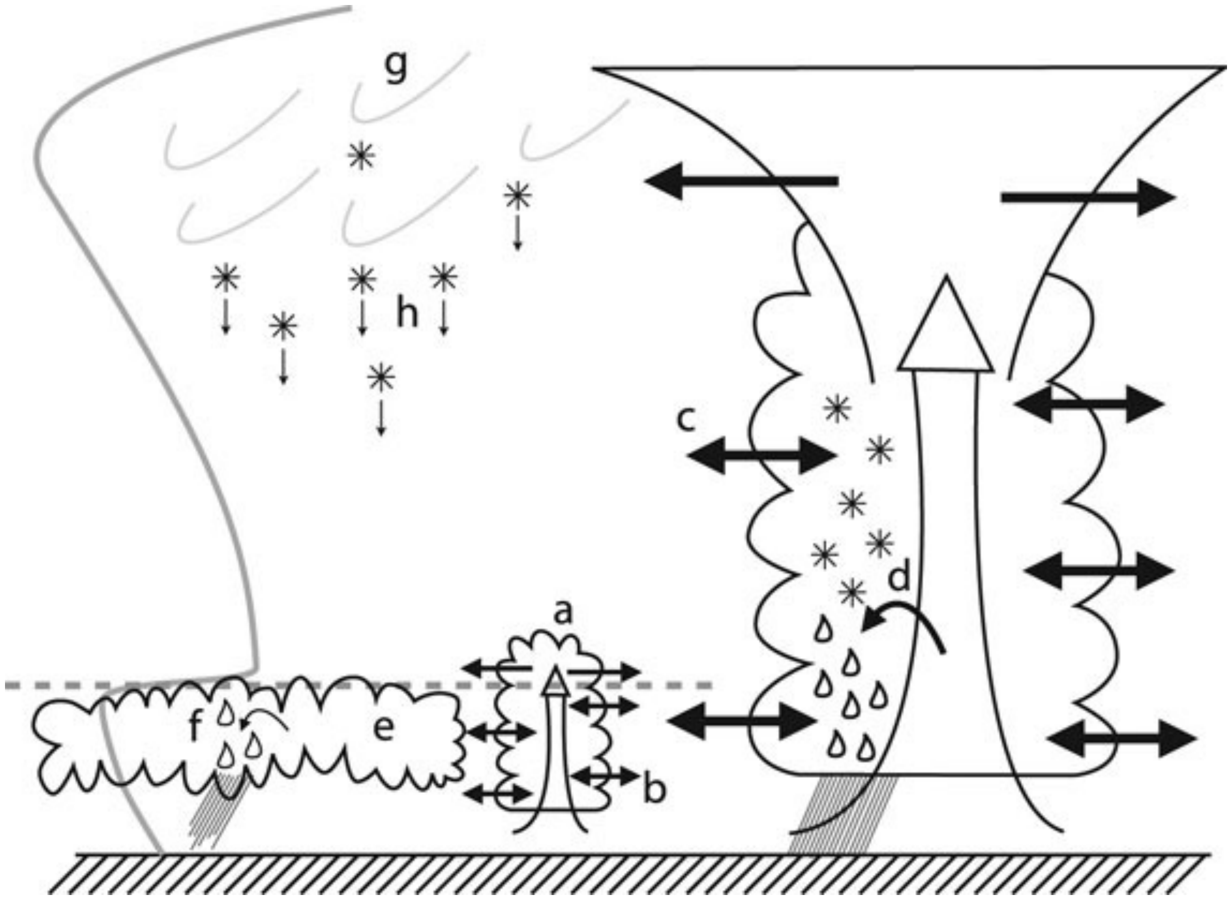


1.4 km resolution global simulation from Wedi et al., *JAMES*, (2020)

Introduction

- High-resolution (<10 km) simulations with ESMs are required to support adaptation planning and decision-making, especially for hydrologic change.
- CMIP6-class ESMs have spatial resolution ~100 km, so **downscaling** is required.
- Tuning/calibration is a major barrier to development of higher-resolution ESMs.
- Here we present a proof-of-concept study showing that a convolutional neural network can be used to reduce CPU time for ESM calibration.

Model calibration (aka Tuning)



Mauritsen et al., JAMES, (2012)

- Unresolved (sub-grid scale) processes involve poorly constrained parameters
- Esp. clouds, precipitation, radiation.

CLIMATE MODEL SIMULATIONS

CESM SIMULATIONS

- CESM1.0.4 F-compset: CAM4 physics, 1850 SSTs and sea ice.
- Run identical 100-member PPEs at f09, f19 and f45 resolutions
- Each realization is run for 36 months
- Analyze annual climatologies
- Upscale f19 and f45 outputs to f09 grid (`192 x 288`)

Parameter	Description (CAM4 parameter name)	Min	Default	Max
x_1	Fraction of hygroscopic SO_4	0.0	0.0	1.0
x_2	Spatial uniformity of BC (1 = globally uniform)	0.0	0.0	1.0
x_3	Scaling factor for global BC mass	0.0	1.0	40.0
x_4	Altitude for insertion of uniform BC layer	0.0	–	39.0
x_5	RH threshold for low cloud formation (cldfrc_rhminl)	0.80	0.88	0.99
x_6	Effective radius of liquid cloud droplets over ocean (cldopt_rliqocean)	8.4	14.0	19.6
x_7	Timescale for consumption rate of shallow CAPE (hkconv_cmftau)	900	1800	14 440
x_8	RH threshold for high cloud formation (cldfrc_rhminh)	0.50	0.50	0.85
x_9	Timescale for consumption rate of deep CAPE (zmconv_tau)	1800	3600	28 800

Covey et al. (2013); Fletcher et al., *ACP*, (2018)

CNN ARCHITECTURE

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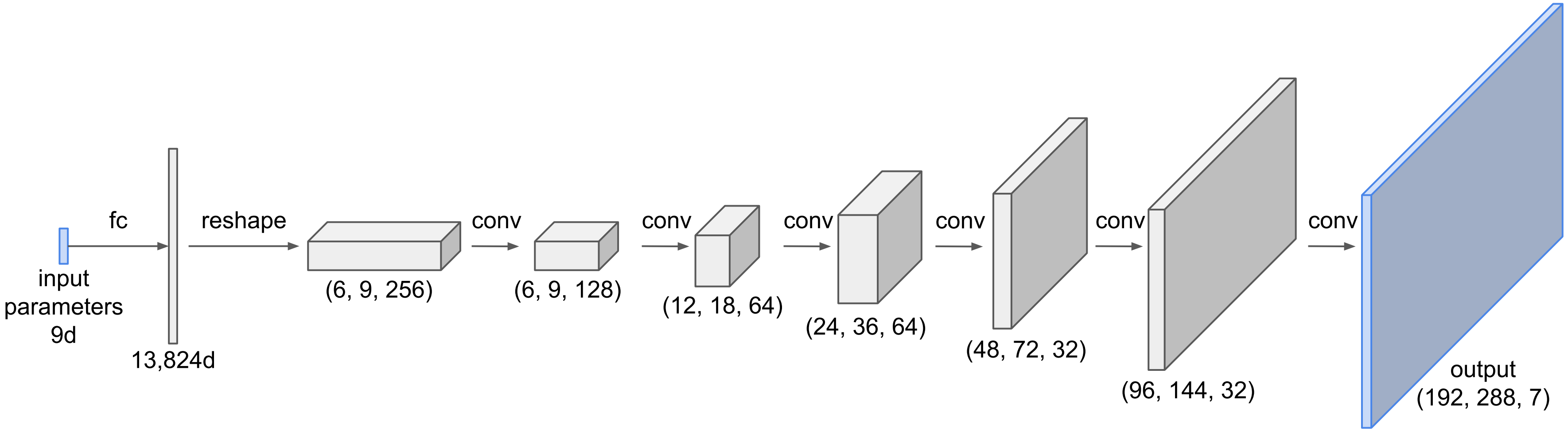
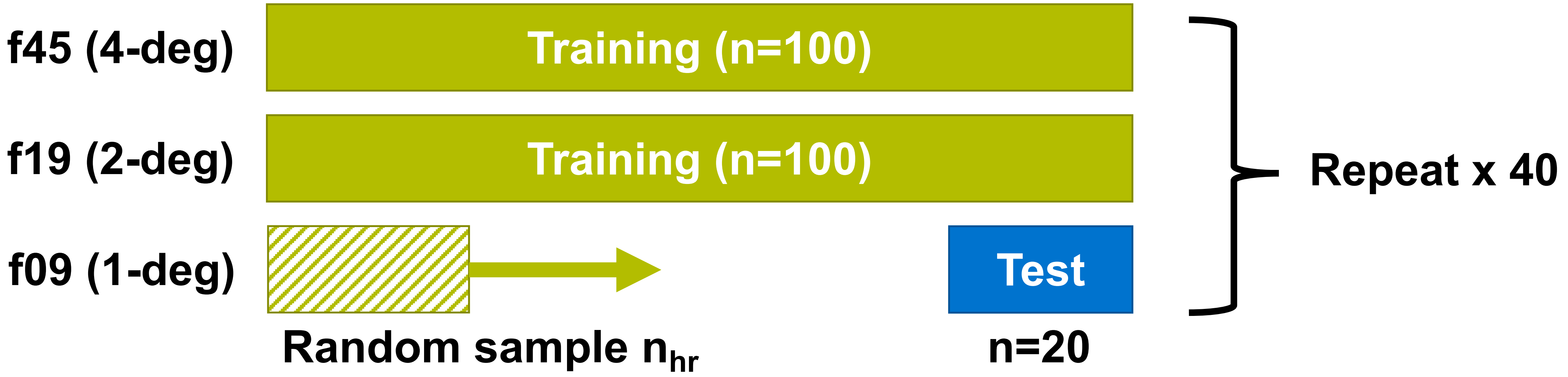


- Input: 9d vector of parameter values projected to `13,824d` then `6 x 9 x 256`.
- Series of transpose convolutions (+ batch normalization and leaky rectified linear unit)
- Output is array of predictions `192 x 288 x 7`, where 7 is number of variables.
- CNN implemented in TensorFlow 2.2 using Keras API.

LOW-TO-HIGH RES EMULATOR

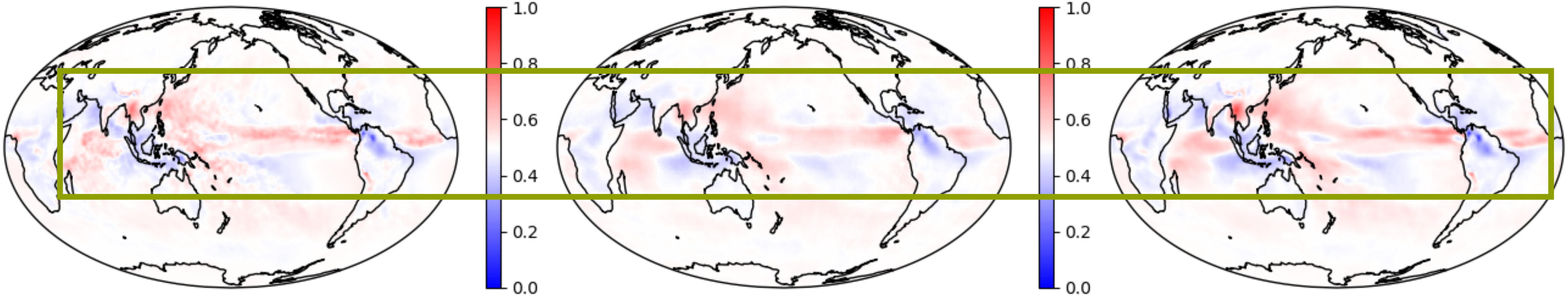


- Inspired by Anderson and Lucas (2018): Train CNN on lower-resolution (f45 and f19) cases, plus an increasing number (n_{hr}) of f09 cases.
- Quantify SS for predicting n=20 unseen high-res cases at different values of n_{hr}
- Compare to a baseline prediction: annual climatological mean difference

RESULTS

HIGH-RES PREDICTION EXAMPLE

CAM4 (1-deg) **CNN (L_{MSE})** **CNN (L_{SS})**



Realization 2 of 20

- Averaged over all realizations, cross-validated SS = 0.82 (0.73 for precipitation)
- Skill is ~25% higher using L_{SS} than L_{MSE} .

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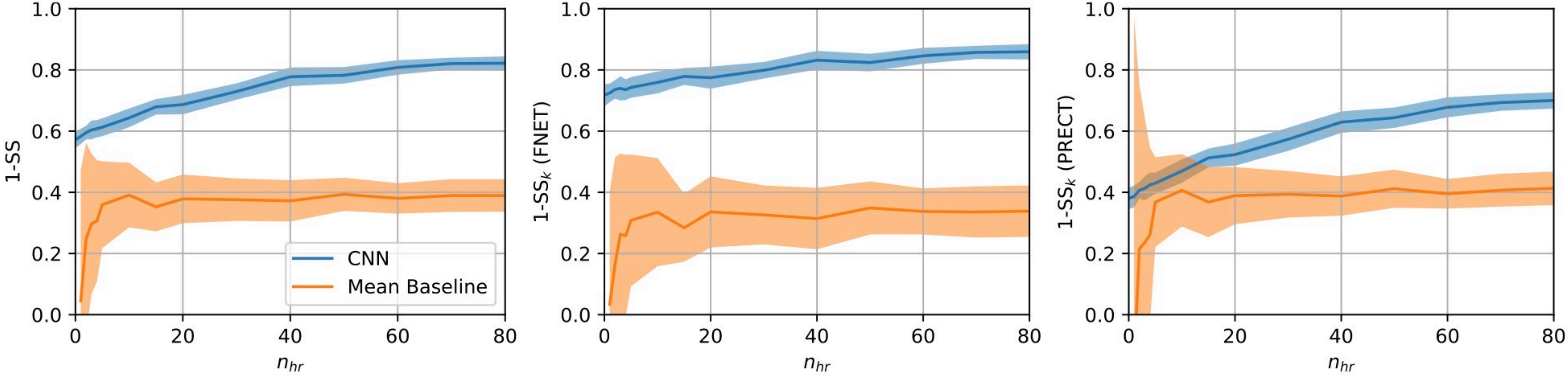
LOW-TO-HIGH RES EMULATOR



(a) Mean **(b)** FNET **(c)** PRECT

- Mean SS ~ 0.6 with **only** low-res cases; increases to 0.8 including high-res cases.
- Skill plateaus at n_{hr} ~ 40: limited benefit from running more high-res cases.
- CNN skill exceeds baseline when n_{hr} > 10, even for precipitation.

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Conclusions

- We present a ML-based method that could support calibration of high-resolution ESMs.
- The CNN accurately predicts the spatially-resolved impacts of nine tuning parameters on atmospheric outputs in CAM4, even for precipitation.
- Using the CNN reduces required CPU time by 20-40%. Potential extensions to seasonal, regional outputs, high-resolution, and time-evolving simulations.
- Operational settings require simultaneous calibration of multiple components, fully-coupled integrations (not just atmosphere).

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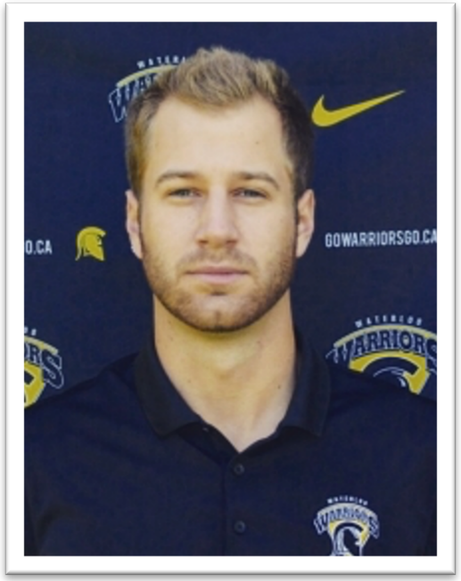

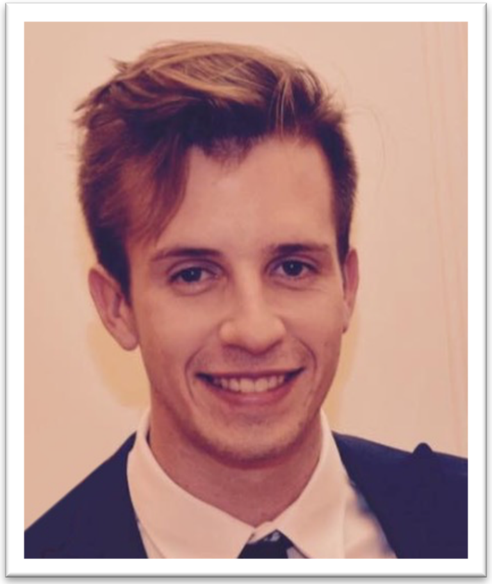

Thank you!

C. G. Fletcher, W. McNally, J. G. Virgin: *Toward efficient calibration of higher-resolution ESMs* (in prep)

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https://uwaterloo.ca/scholar/c5fletch/

@ClimoChris

EXTRA SLIDES

CNN TRAINING/VALIDATION

f09 (1-deg) **Training** **Test**

Random sample n=80 **n=20**

- Train CNN to predict <u>differences</u> due to parameters: `perturbed – default`.
- Normalize predictors (**x**) and target difference maps (**Y**)
- Train on two different loss functions: L_{MSE} and L_{SS} (SS from Pierce et al. 2009)
- Quantify accuracy of predictions using *MSE* and *SS* metrics between CESM simulation and predictions by CNN

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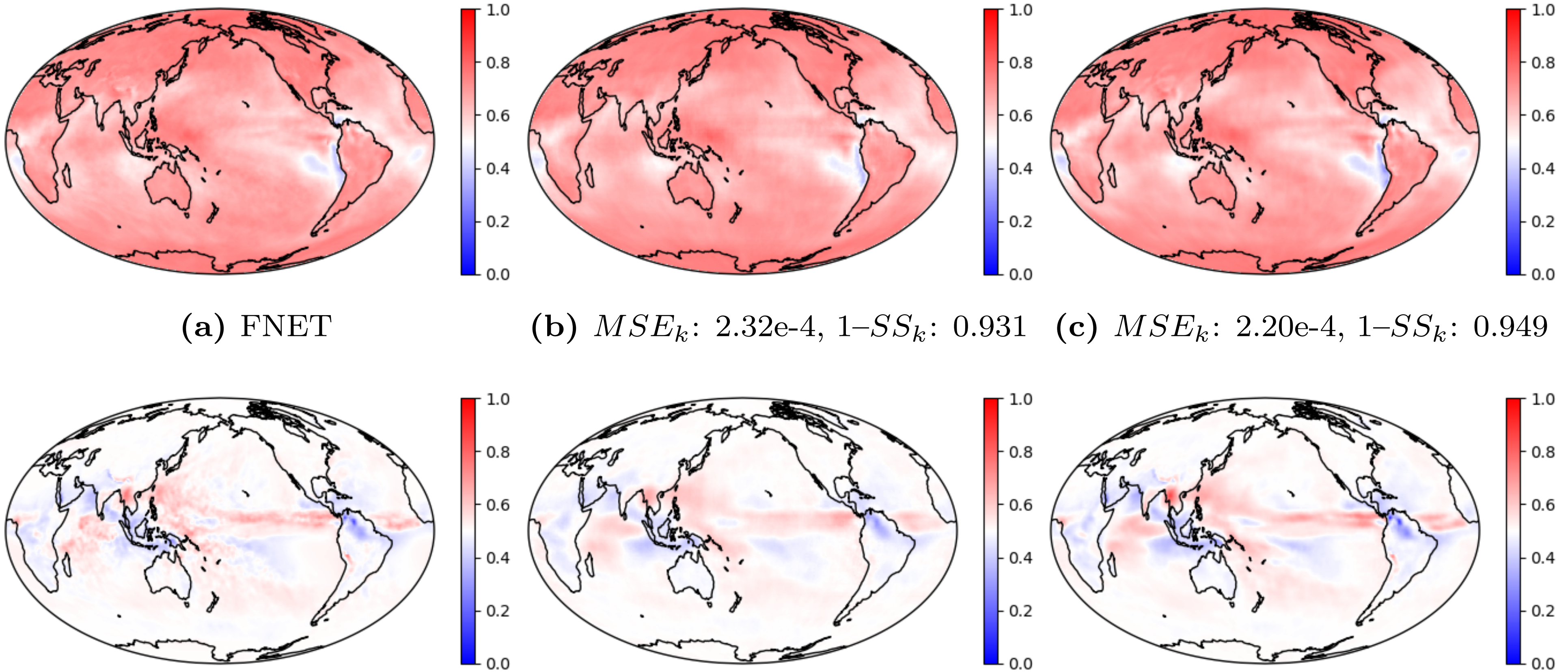
HIGH-RES EMULATION EXAMPLE

CAM4 (1-deg) | CNN (L_{MSE}) | CNN (L_{SS})

RESTOM

PRECT



(a) FNET

(b) MSE_k: 2.32e-4, 1–SS_k: 0.931

(c) MSE_k: 2.20e-4, 1–SS_k: 0.949

(d) PRECT

(e) MSE_k: 2.28e-4, 1–SS_k: 0.610

(f) MSE_k: 1.91e-4, 1–SS_k: 0.816

Realization 2 of 20

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