# Improving Seasonal Forecasting Using Probabilistic Deep Learning

WCRP World Climate Research Programme

WORLD METEOROLOGICAL ORGANIZATION

unesco Intergovernmental Oceanographic Commission

International Science Council

ECMWF

Donald D. Lucas

Baoxiang Pan, Gemma Anderson, André Goncalves, Céline Bonfils, and Jiwoo Lee

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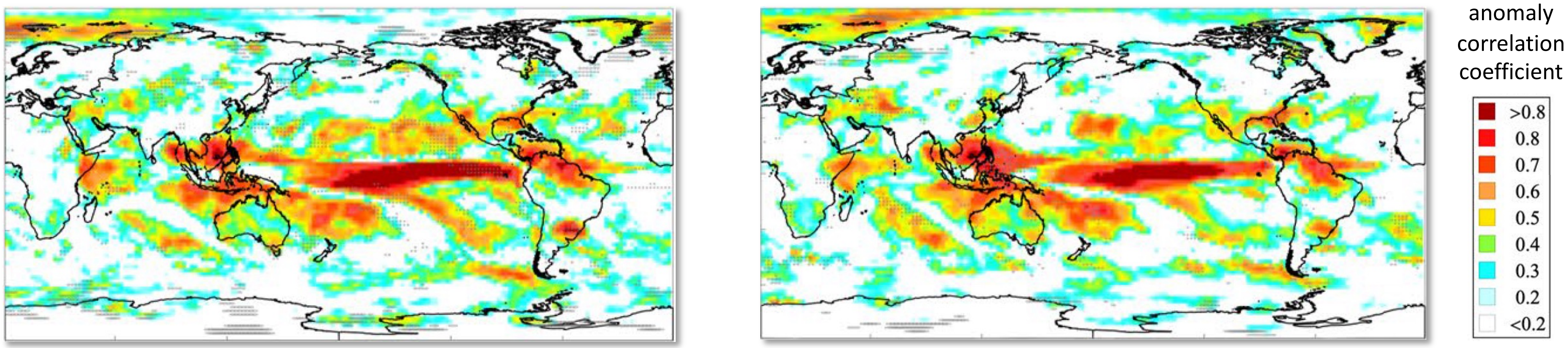
Lawrence Livermore National Laboratory

# Deep learning is becoming competitive with dynamical seasonal forecast systems

Skill in predicting October-March average precipitation initialized from July

Observational period 1982-2012




Which map is from NOAA’s North American Multi-Model Ensemble (NMME), and which is from deep learning of climate models?

# This presentation provides an overview of our recent JAMES paper

AGU ADVANCING EARTH AND SPACE SCIENCE

JAMES Journal of Advances in Modeling Earth Systems®

24 JAN 2022

RESEARCH ARTICLE
10.1029/2021MS002766

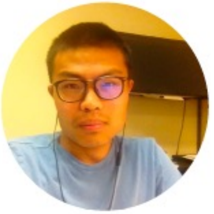
**Special Section:**
Machine learning application to Earth system modeling

## Improving Seasonal Forecast Using Probabilistic Deep Learning

**Baoxiang Pan[1], Gemma J. Anderson[1], André Goncalves[1], Donald D. Lucas[1], Céline J. W. Bonfils[1], and Jiwoo Lee[1]**

[1]Lawrence Livermore National Laboratory, Livermore, CA, USA

**Key Points:**

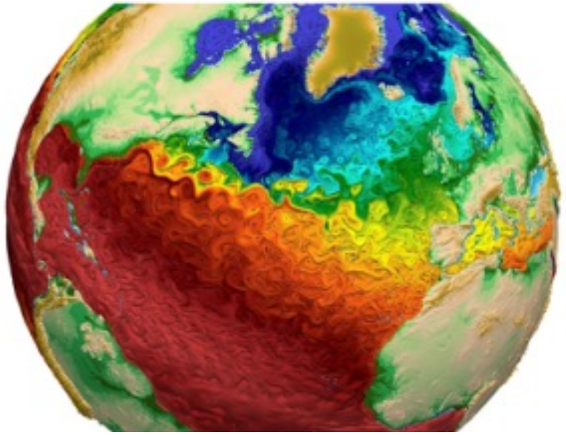




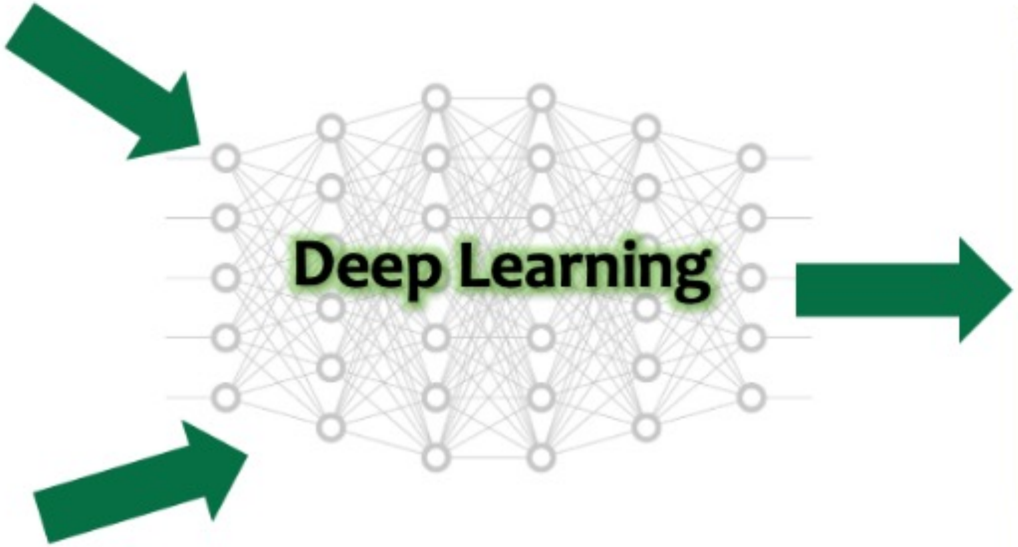

# Our JAMES paper was motivated by a project to improve seasonal predictions of water resources in California

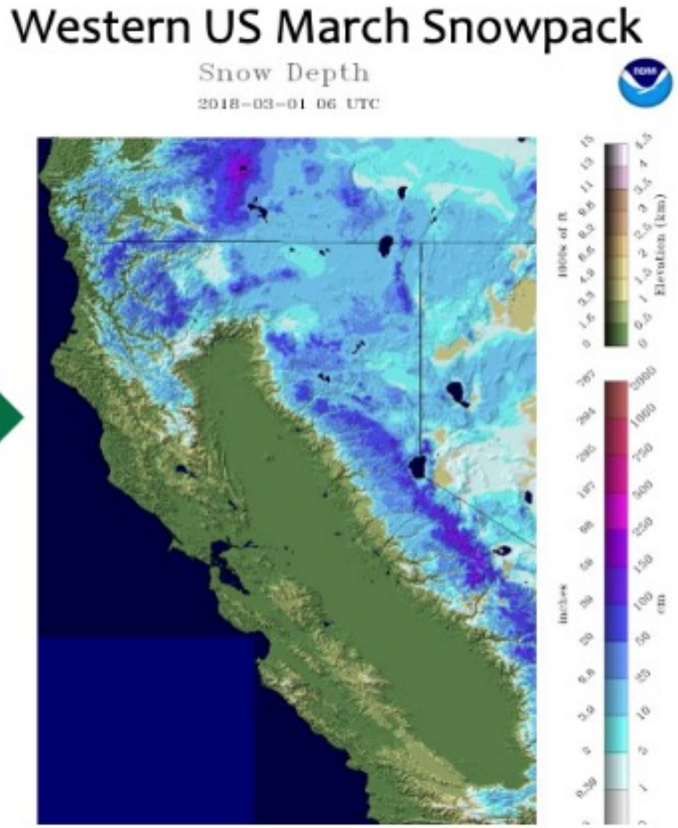
Observational Data

Climate Simulations



Persistent climate patterns steer storms toward or away from California.
E.g., the “Ridiculously Resilient Ridge”




Can deep learning exploit low frequency signals in the climate system to improve seasonal predictions?

Laboratory Directed Research & Development

# Two recent papers suggested deep learning applied to climate simulations may be useful

Geophysical Research Letters

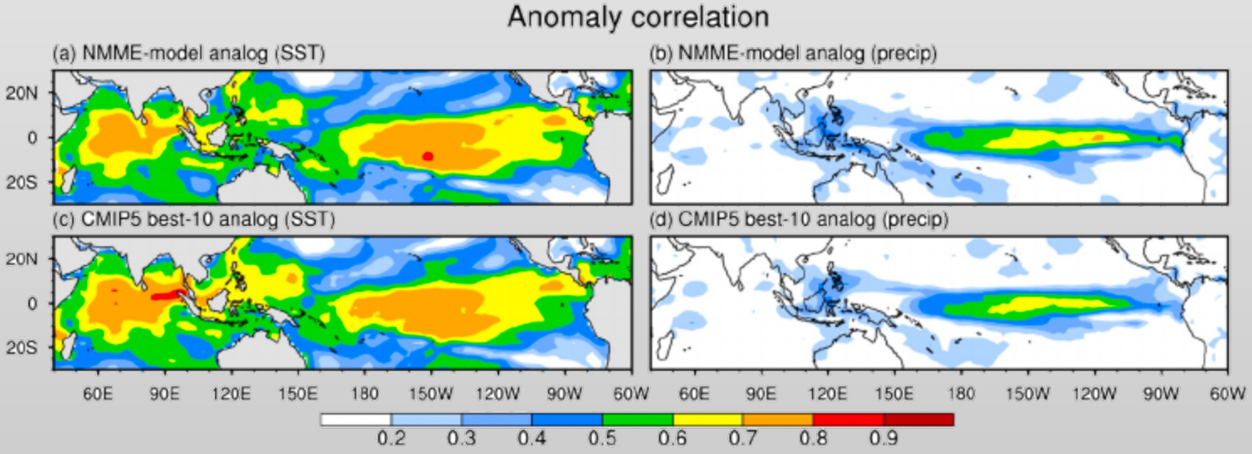
RESEARCH LETTER
10.1029/2018GL080598

**Diagnosing Secular Variations in Retrospective ENSO Seasonal Forecast Skill Using CMIP5 Model-Analogs**

Hui Ding[1,2], Matthew Newman[1,2], Michael A. Alexander[2], and Andrew T. Wittenberg[3]

Key Points:
- Seasonal tropical Indo-Pacific

**Step 1**: Search from existing climate simulations whose SST is close to observed SST
**Step 2**: Apply their following season's states as analog forecasts




Letter | Published: 18 September 2019

**Deep learning for multi-year ENSO forecasts**

Yoo-Geun Ham, Jeong-Hwan Kim & Jing-Jia Luo

*Nature* **573**, 568–572(2019) | Cite this article

**Step 1**: Take predictor–predictand pairs from climate simulations.
**Step 2**: Build a convolutional neural network regression model.
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**Step 4**: Apply the fine–tuned model for forecast.

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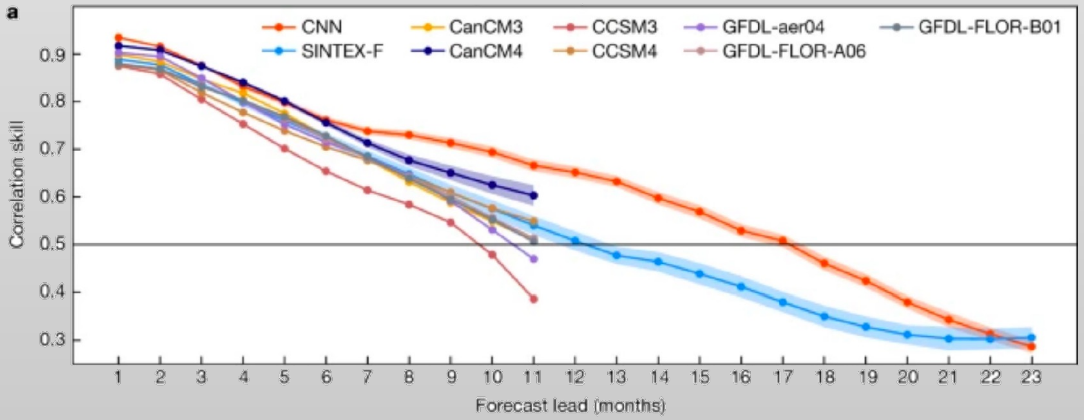
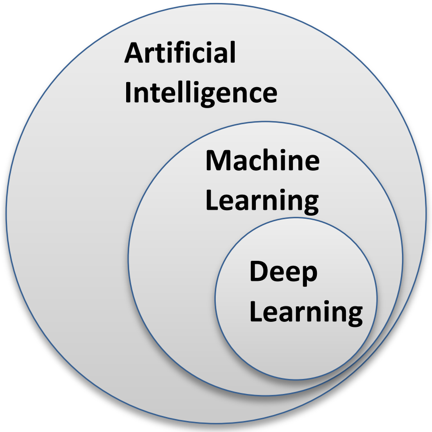
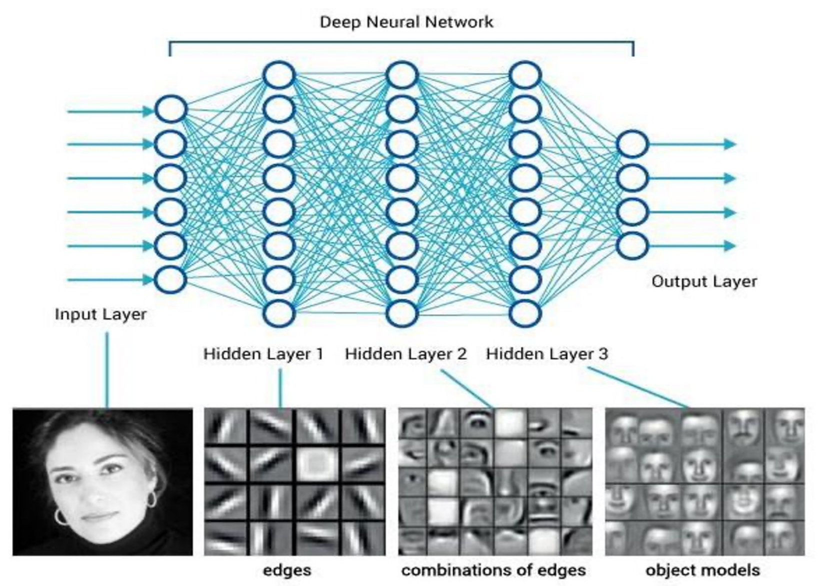


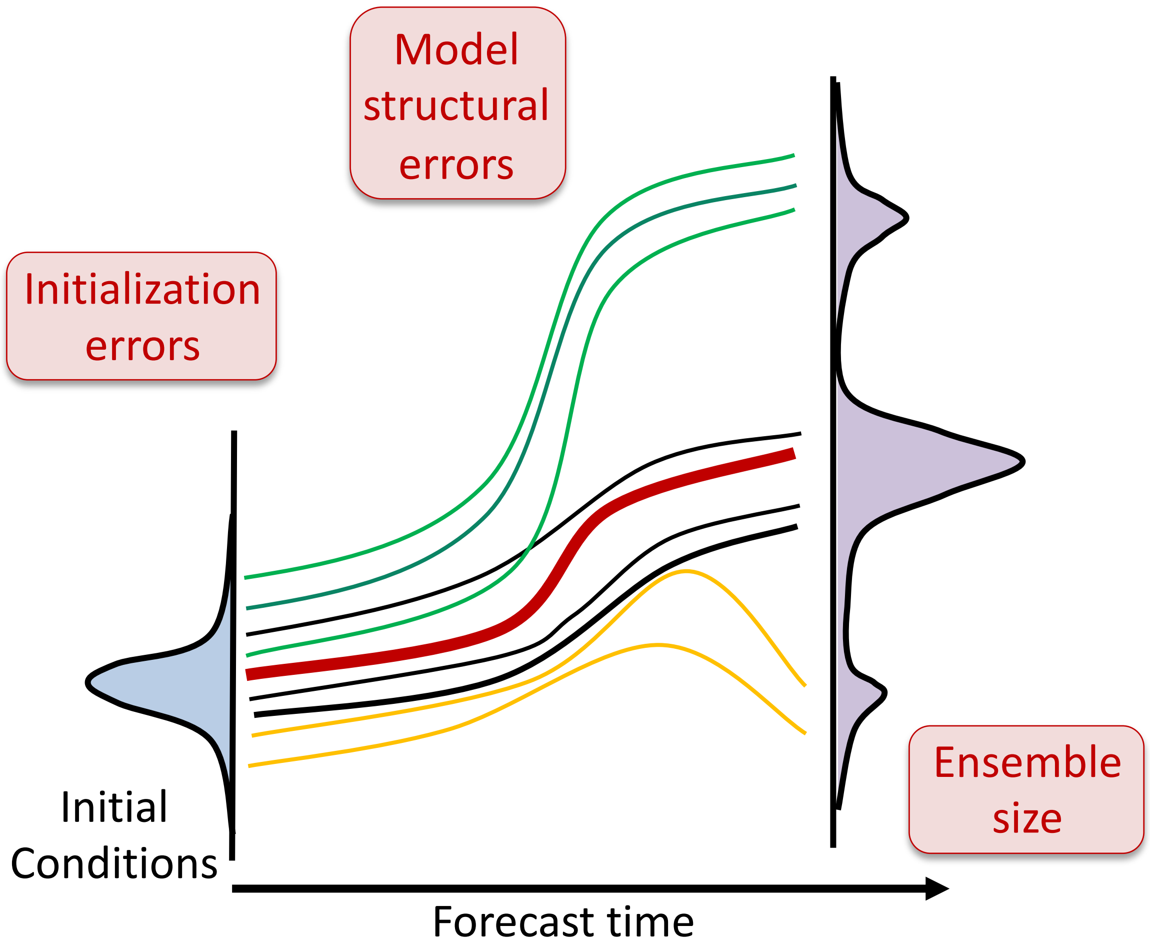
# Deep learning (DL) is a promising approach to help improve climate predictions

- ☑ Deep neural networks can discover patterns or "features" automatically that humans cannot
- ☑ Can keep memory effects and rich spatial structure
- ☑ Observational data can be used more effectively ("data-driven" approach)
- ☑ Can fully leverage pre-existing data
- ☑ Offers huge speed up in time and resources
- ☑ Complements traditional methods



# Probabilistic approaches are required for seasonal forecasts




## Dynamical forecasts

- Initialize from different states
- Incorporate multiple models
- Limited sample size due to computational costs

## Deep learning forecasts

- Initialize at different points in continuous runs to learn seasonal dependencies
- Train on multiple climate models
- Use generative/variational methods to represent distributions

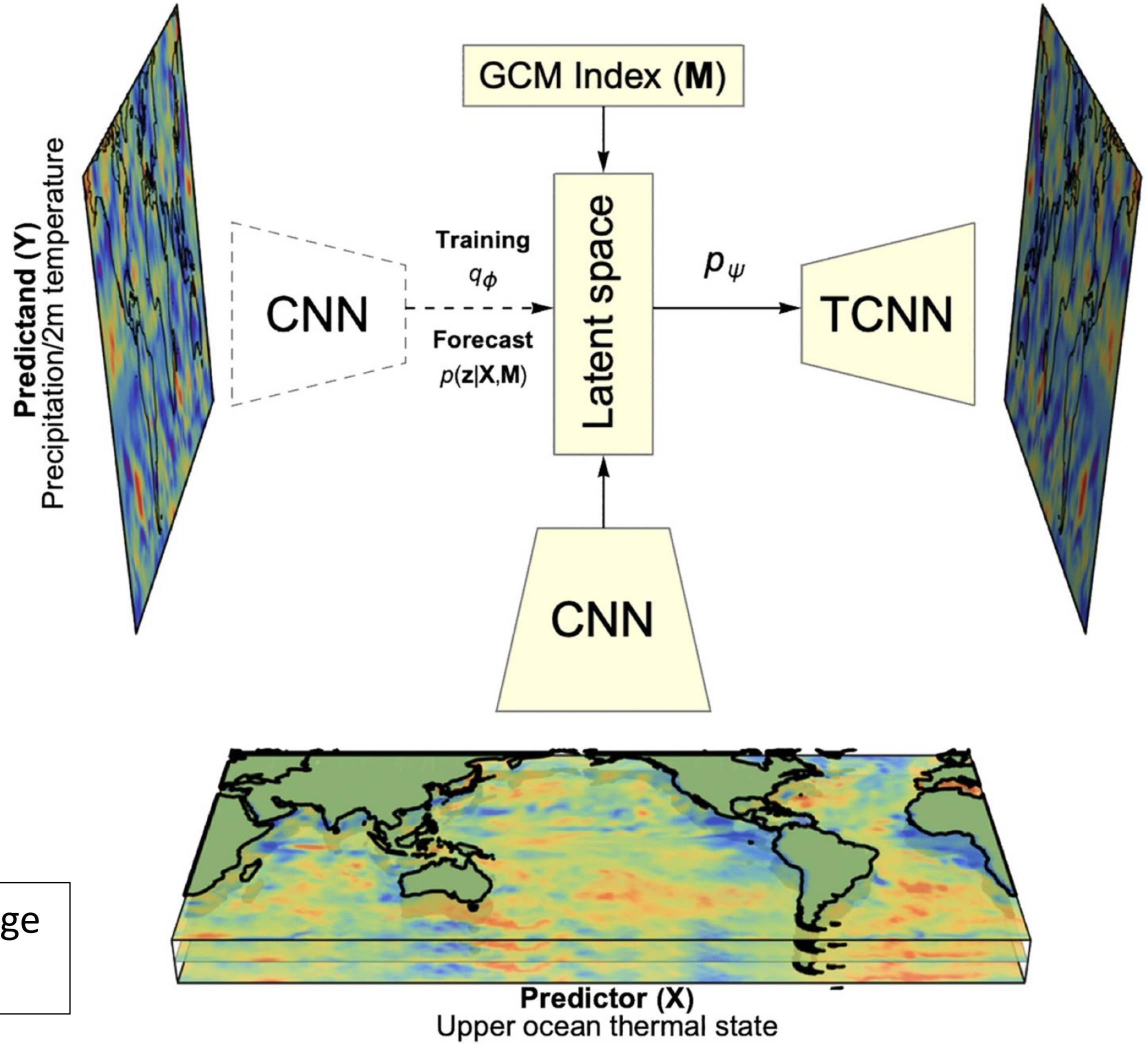
# We developed the *Conditional Generative Forecasting* (CGF) system for seasonal forecasts

## CGF is built using

*Convolutional neural networks (CNNs)*
- From computer vision
- Designed for maps and images

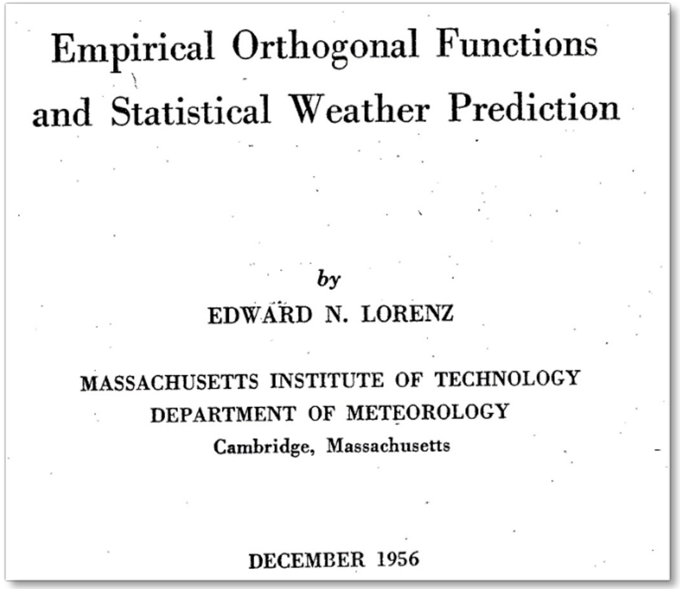
*Autoencoders / U-Nets*
- Effective at extracting low-dimensional patterns and features
- Non-linear generalization of Empirical Orthogonal Functions

*Conditional variational methods*
- Approximate probability distribution function (PDF) of the input / output data
- Enable drawing plausible samples from the PDF




| | |
|---|---|
| ***Inputs:*** maps of ocean heat content in July (8 layers, 5-100 m) | ***Outputs:*** maps of Oct-March average precipitation or air temperature |

# Autoencoders are related to Empirical Orthogonal Functions


Empirical Orthogonal Functions and Statistical Weather Prediction

by

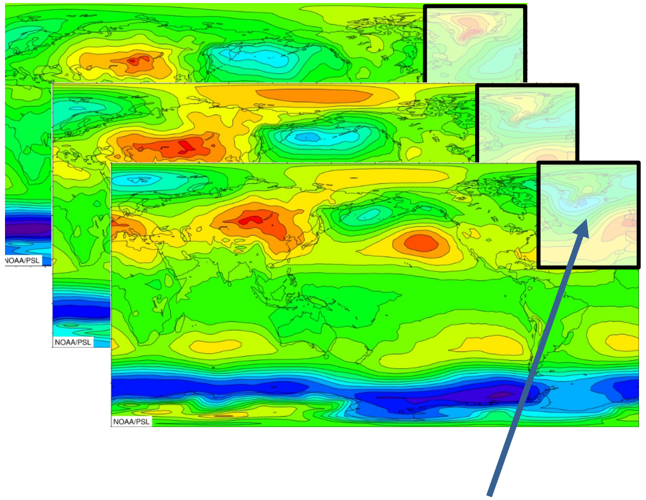
EDWARD N. LORENZ

MASSACHUSETTS INSTITUTE OF TECHNOLOGY
DEPARTMENT OF METEOROLOGY
Cambridge, Massachusetts

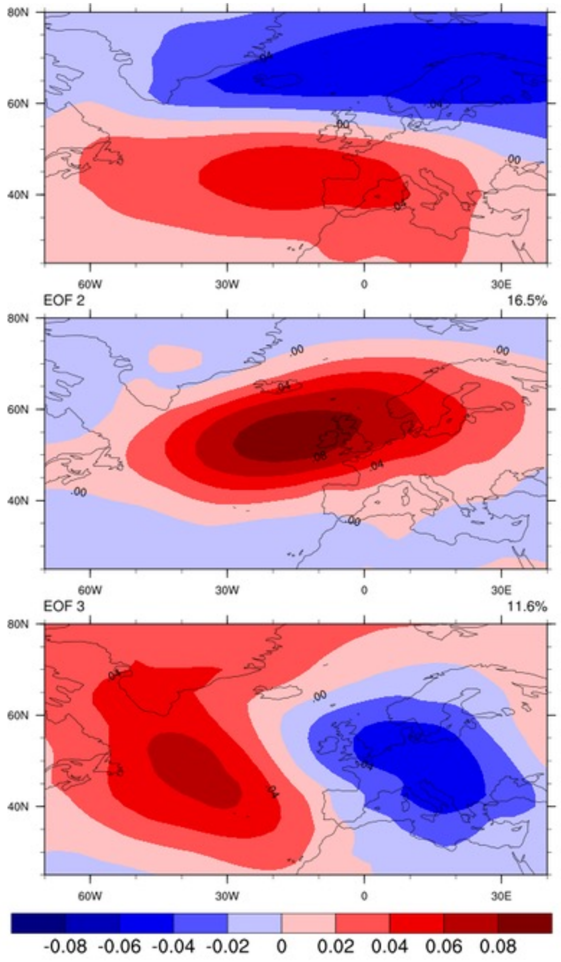
DECEMBER 1956

- EOFs are a technique used for extracting spatial and spatiotemporal patterns.
- EOFs are also known as Principal Component Analysis (PCA)

Consider a set of monthly mean sea level pressure (SLP) maps




EOFs characterize ~80% of the variability in the North Atlantic with 3 modes instead of 968 grid cells (22 lat by 44 lon)




North Atlantic Oscillation

EOF1 (53.3%)

EOF2 (16.5%)

EOF3 (11.6%)

# EOF analysis is a form of unsupervised learning

## Example EOF analysis

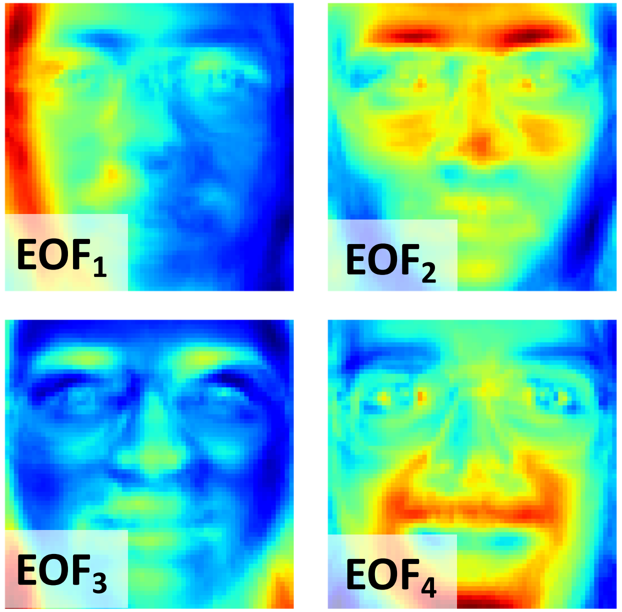
N_images, N_pixels per image

F(N_pixels) → N_EOFs

EOF transform

training

Reduced space




- Trained EOFs on 350 images from the Olivetti face database
- Each image has 64 x 64 pixels (4096 total pixels)
- Retained 100 EOFs (explain 57.7% of the variance)

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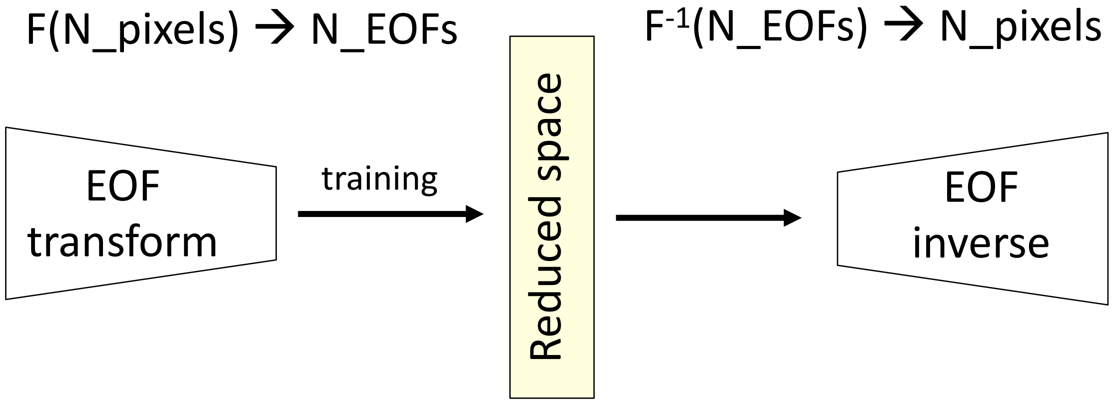


Reconstructed Actual

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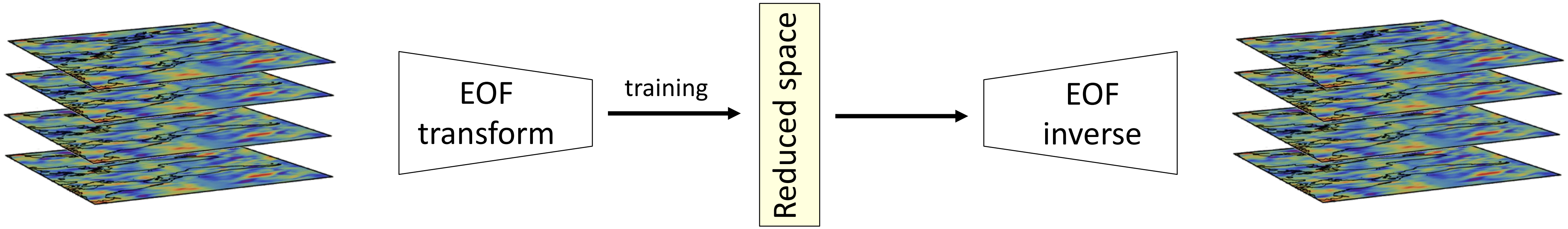
# Autoencoders are related to Empirical Orthogonal Functions

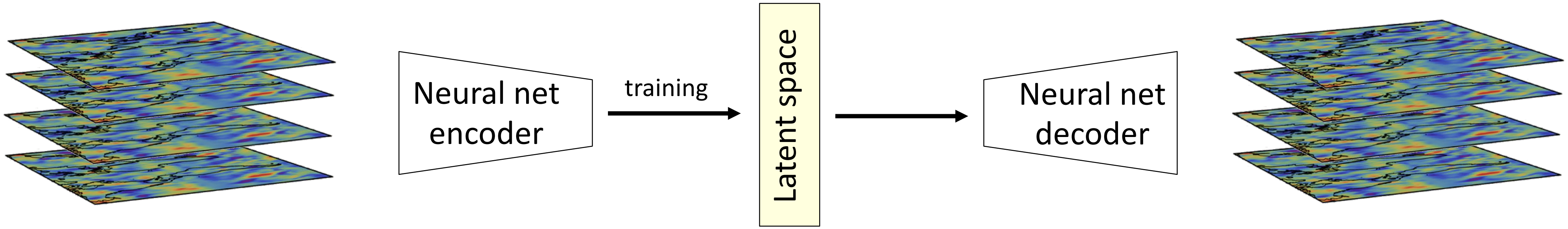
## EOFs




- The “O” in EOF implies the components in the reduced space are linearly related.
- Independent components are available for interpretation.
- Fast to train and relatively few samples needed, but many components may be needed for noisy data.

# Autoencoders are related to Empirical Orthogonal Functions

## Autoencoders




- Neural networks transform the data.
- Latent space features can be non-linearly related.
- Interpretability can be challenging.
- Many samples needed and slow to train.
- Easy to augment latent space with additional information.
- Autoencoders with linear activation functions == EOFs.

# *Conditional Generative Forecasting* (CGF) model

## Encoding

*Ocean heat (**X**)*
Input:  8 x 90 x 180  [~130,000]
Latent space: 128 x 6 x 12 [~9,000]

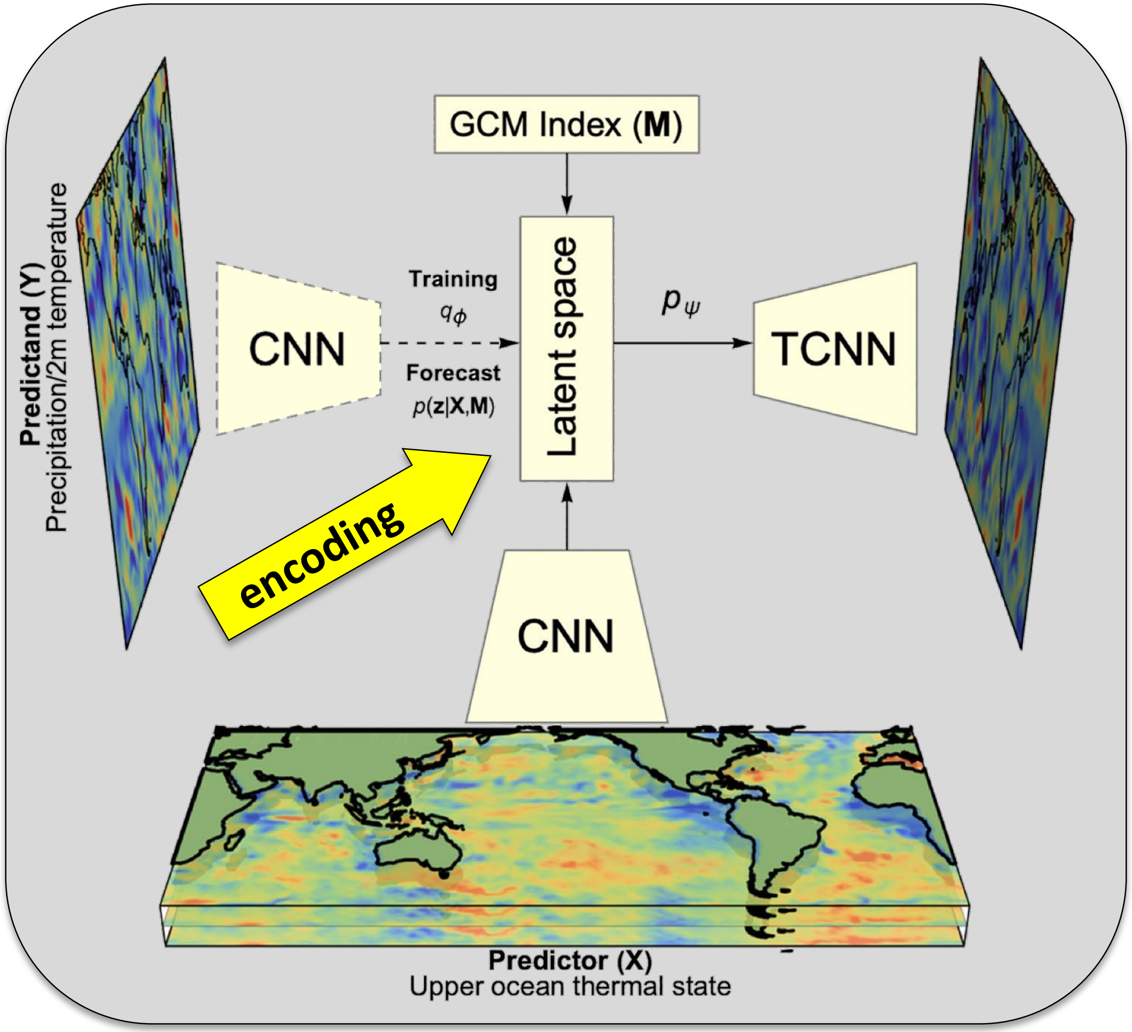
*Precipitation -or- Surface temperature (**Y**)*
Input: 1 x 90 x 180   [~16,000]
Latent space: 128 x 6 x 12  [~9,000]

## Embedding

GCM information (**M**) is concatenated into the latent space with a learned embedding vector

## Probabilistic Forecasts

The latent space **z** is represented by a Gaussian distribution that depends on **X** and **M**, and a mapping function that relates **Y** to **z**.



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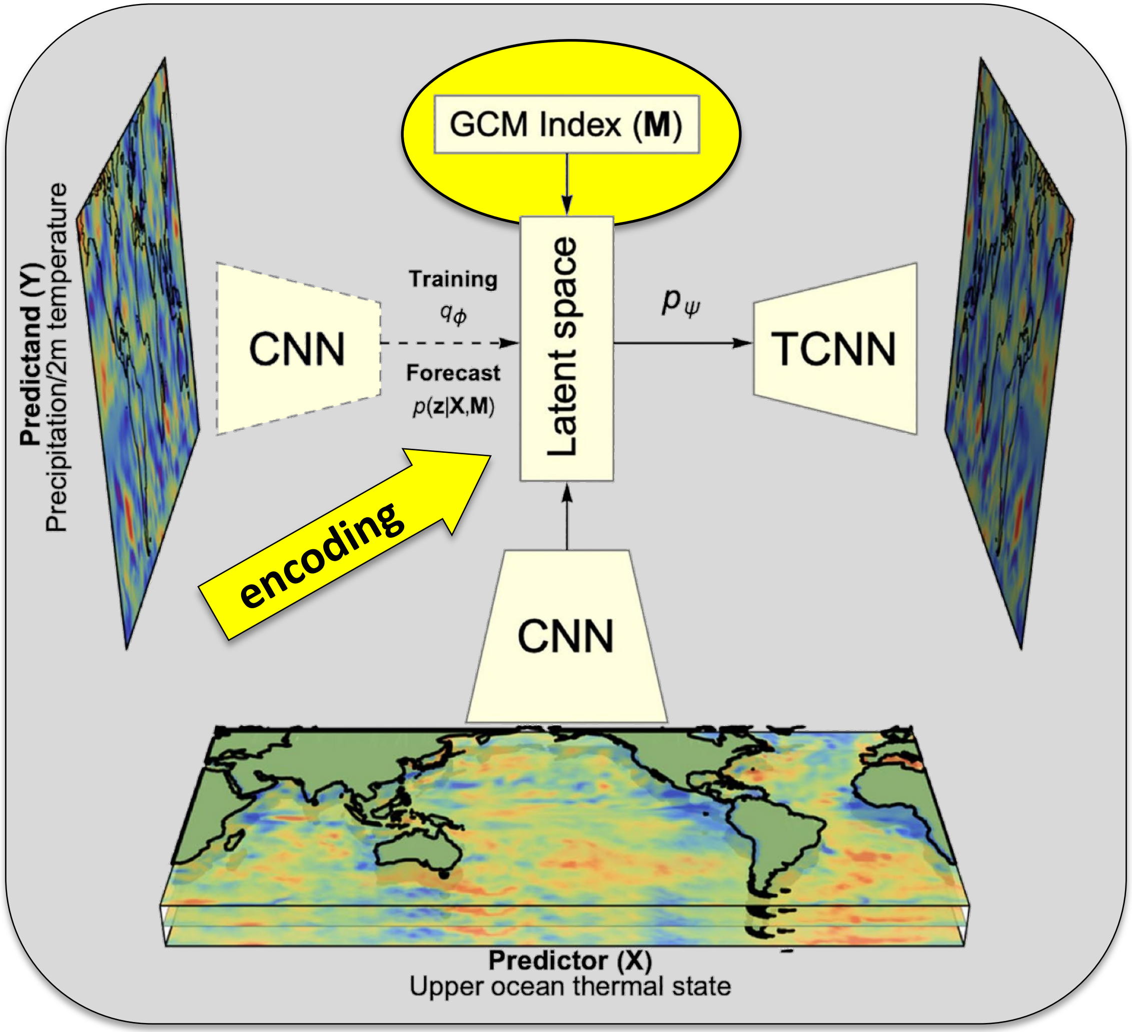

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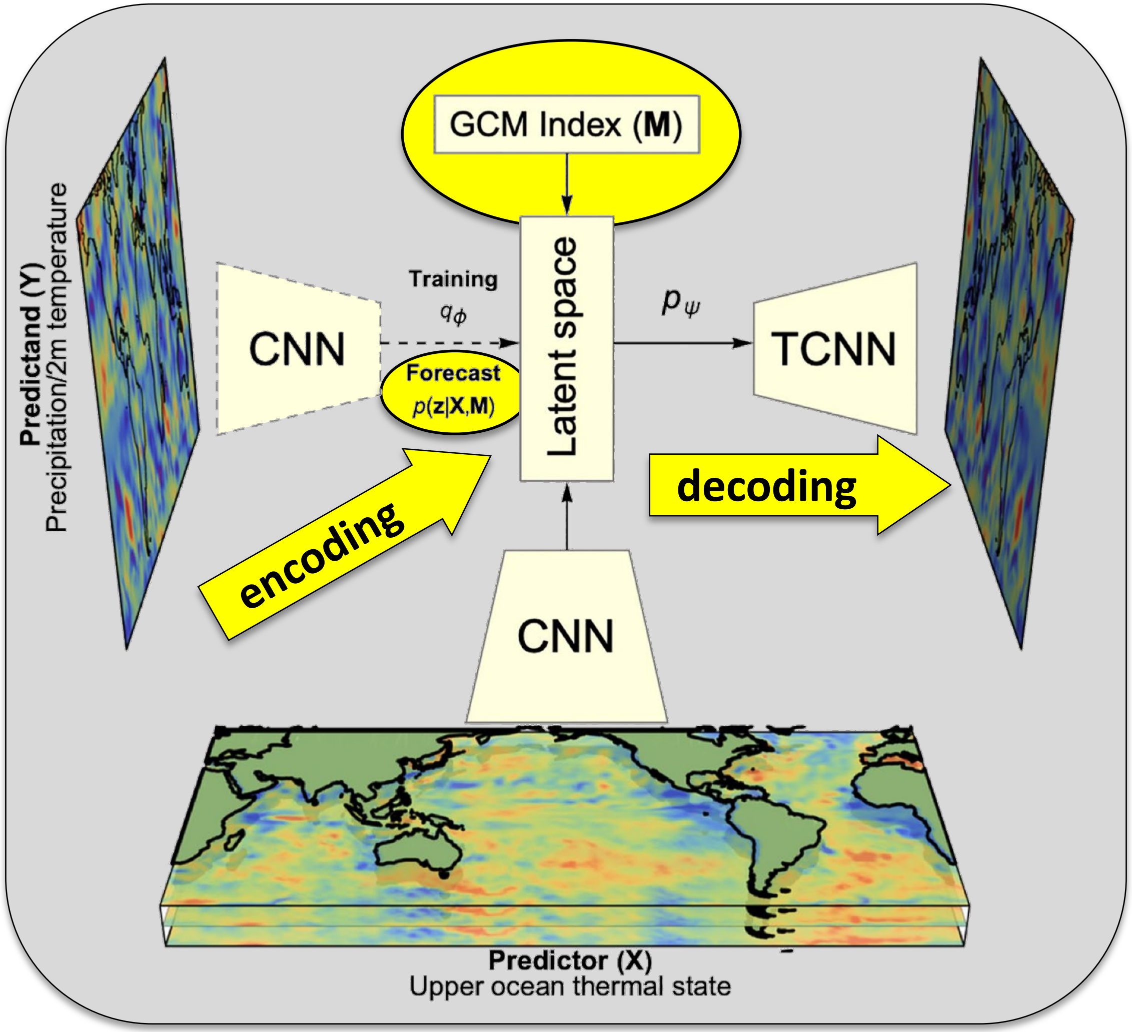
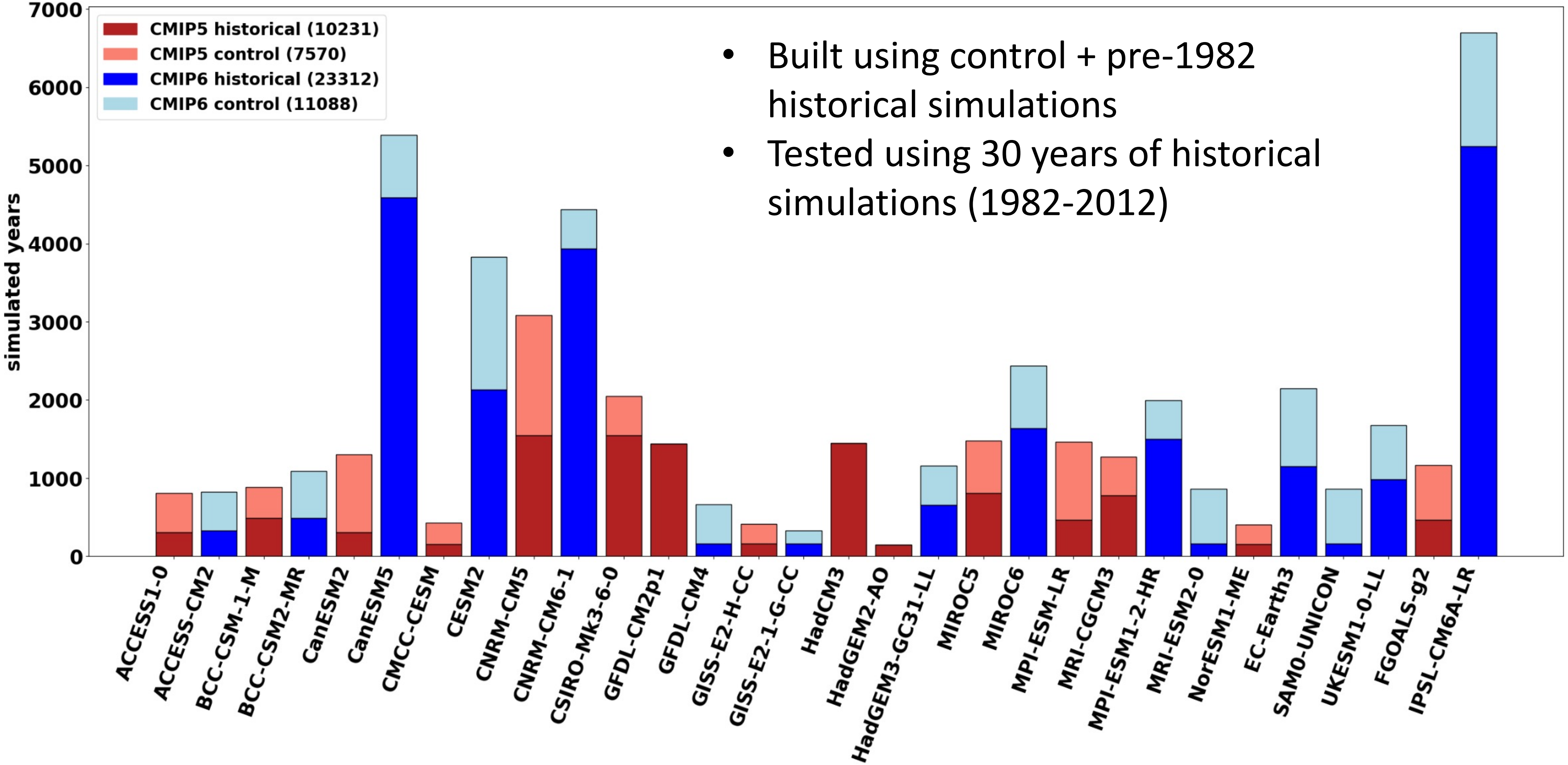


# CGF used 52,201 simulated years from 30 climate models




- Built using control + pre-1982 historical simulations
- Tested using 30 years of historical simulations (1982-2012)

# Evaluation Strategy

## Dynamical Forecasts

- North American Multi-Model Ensemble (NMME)
- Forecast anomalies of precipitation and 2-m temperature
- Four models, 10 ensemble members each (CCSM4, CESM1, CanCM4, GFDL CM2.5)

## "Observations"

- *For comparison:* precipitation from the Global Precipitation Climatology Project (GPCP)
- *For comparison:* temperature from ECMWF Reanalysis v5 (ERA5)
- *For CGF input:* ocean heat from ECMWF Ocean Reanalysis (ORAS5)

## Metrics to assess forecast skill

- *Deterministic:*

  1. anomaly correlation coefficient
  2. normalized root mean square skill

- *Probabilistic:*

  1. area under ROC curve
  2. continuous ranked probability score

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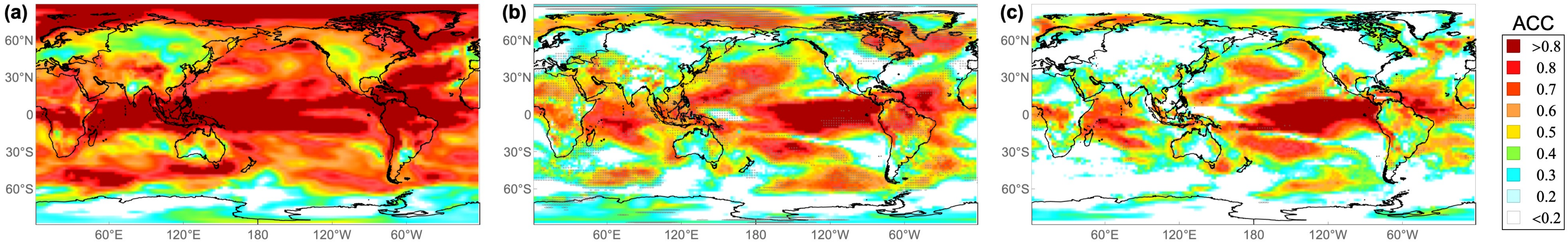
# CGF is competitive with dynamical seasonal forecast systems

**Forecast skill for 2-m temperature for $\text{CGF}_{\text{CanESM}}$**

- *Conditioned* on a single GCM (CanESM)
- Anomaly correlation coefficients for October-March average initialized from July ocean heat

$\text{CGF}_{\text{CanESM}}$ for CanESM simulations | $\text{CGF}_{\text{CanESM}}$ for observations | CanCM4 for observations




model simulations vs. observations

deep learning vs. dynamical system

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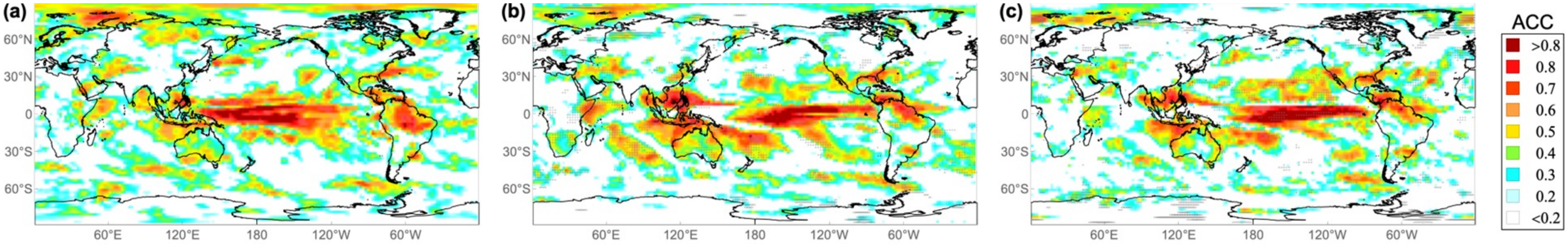


model simulations vs. observations

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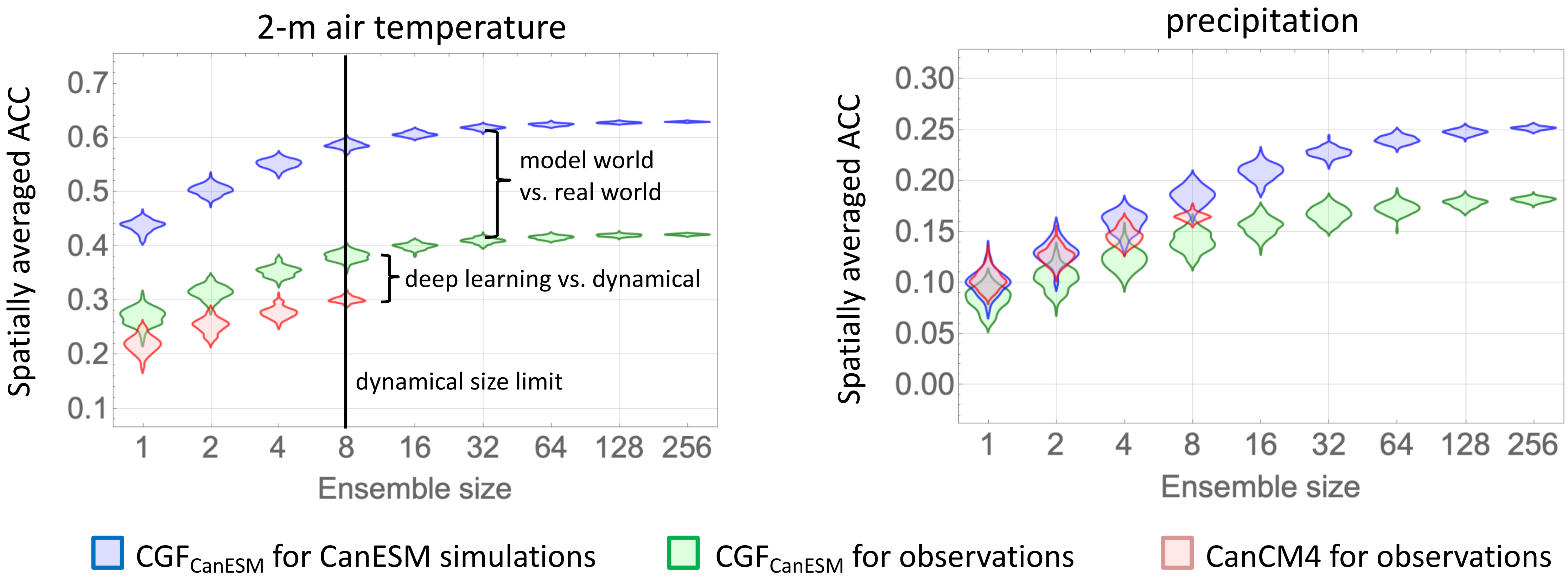
# CGF is competitive with dynamical seasonal forecast systems

## Single model ensemble forecasts for $CGF_{CanESM}$

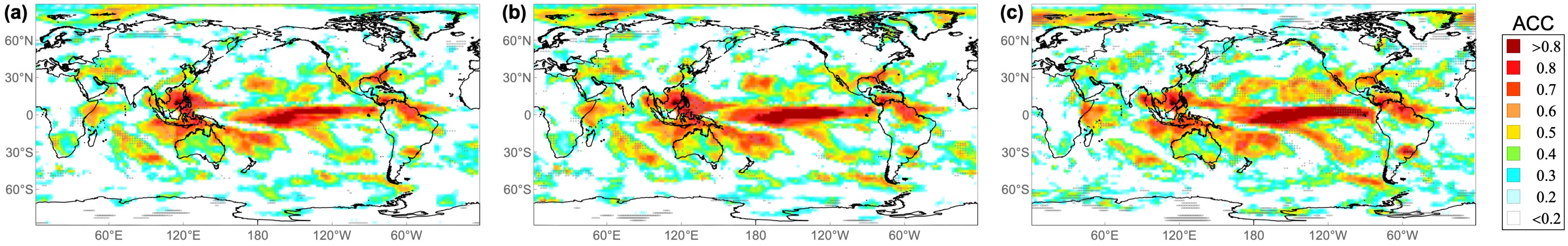


# CGF is competitive with *multi-model ensemble* dynamical seasonal forecast systems

## Forecast skill for precipitation for CGF ensemble

- Considers multiple models and multiple initializations per model
- Anomaly correlation coefficients for October-March average initialized from July ocean heat

$CGF_{Ens}$ for real-world forecast | $CGF_{\tilde{M}}$ for real-world forecast | NMME for real-world forecast



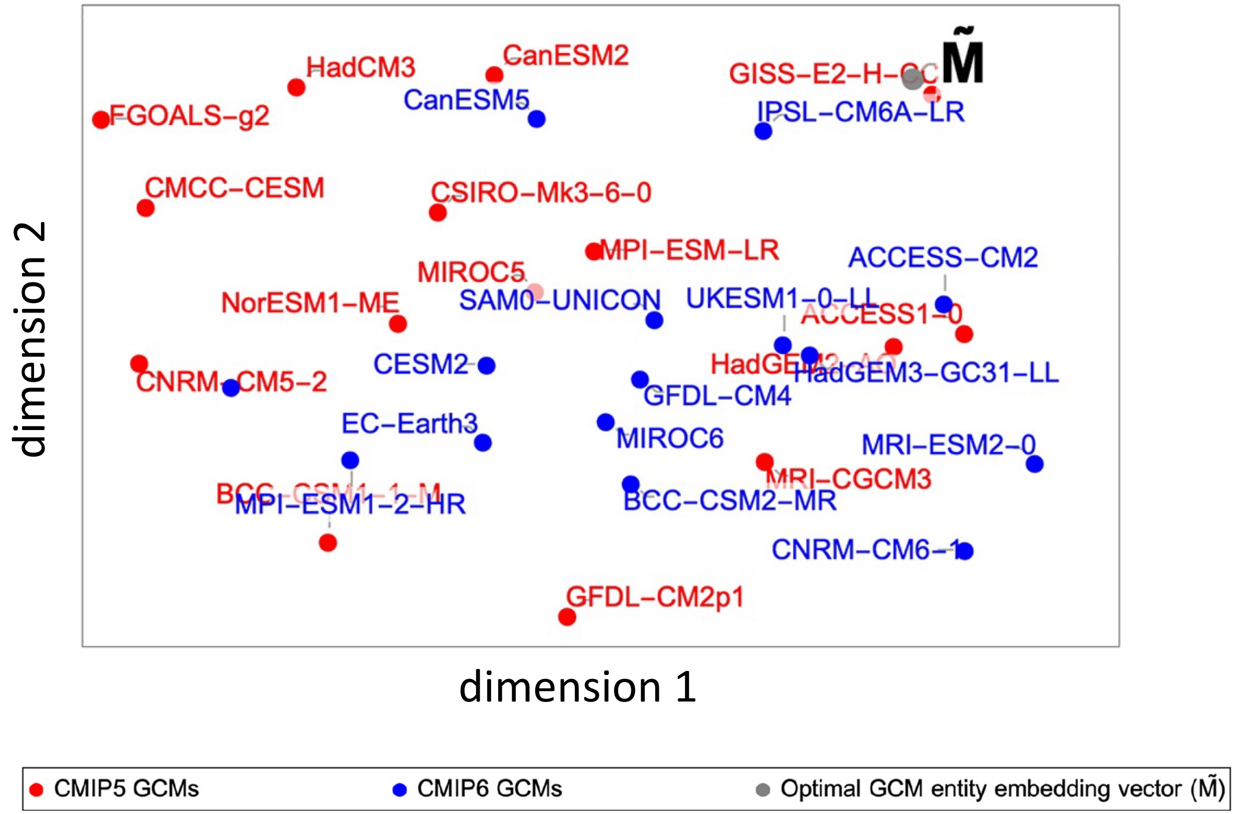

Thirty dynamical models, ten ensemble members each

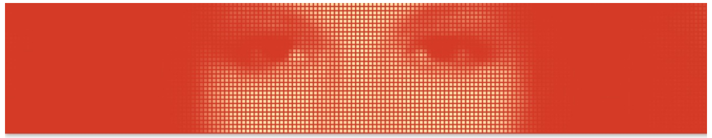
Optimal dynamical model ($\tilde{M}$) with 300 realizations

Four dynamical models, ten ensemble members each

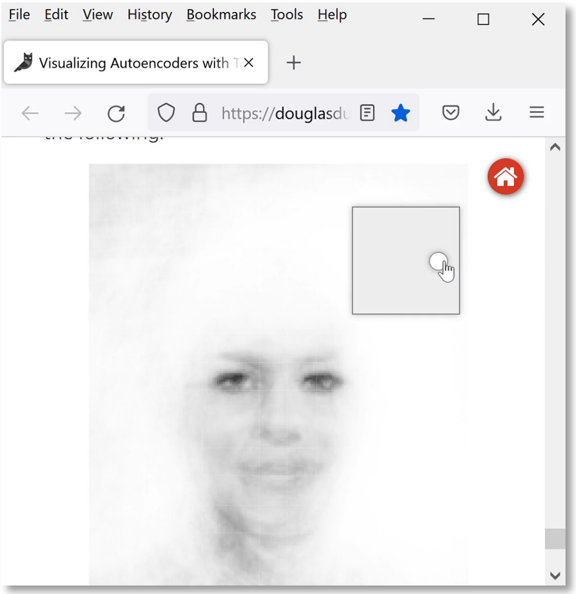
# CGF’s latent space can be interpolated, sampled, and explored

t-SNE for CGF precipitation
(t-distributed stochastic neighbor embedding)



Visualizing Autoencoders with Tensorflow.js




https://douglasduhaime.com/posts/visualizing-latent-spaces.html

# Summary and conclusions

- Deep learning can help with climate modeling and seasonal forecasting.
  - e.g., autoencoders are non-linear generalizations of Empirical Orthogonal Function analysis
  - *generative* models can capture distributions of data for probabilistic models and ensembles
- We built a deep learning-based *Conditional Generative Forecast* (CGF) model.
  - Uses conditional variational autoencoder technology.
  - Skillful in predicting Oct-Mar precipitation and temperature initialized from July ocean heat content (relative to dynamical ensemble forecasts).
  - Incorporates probability distributions of the initial state and multi-model ensembles.
- Work is on-going to better understand sources of predictability at the seasonal time scale using deep learning systems.
  - E.g., using saliency maps and analysis
- See Pan et al (2021) in JAMES for related work using Generative Adversarial Networks to bias correct climate projections.

# Architecture of CGF