Frontiers in subseasonal to decadal prediction: A WCRP perspective

Bill Merryfield

Canadian Centre for Climate Modelling and Analysis

Environment and Climate Change Canada

WCRP
World Climate Research Programme

ECMWF Annual Seminar
Bonn, Germany
7-11 April 2025

WORLD METEOROLOGICAL ORGANIZATION
unesco Intergovernmental Oceanographic Commission
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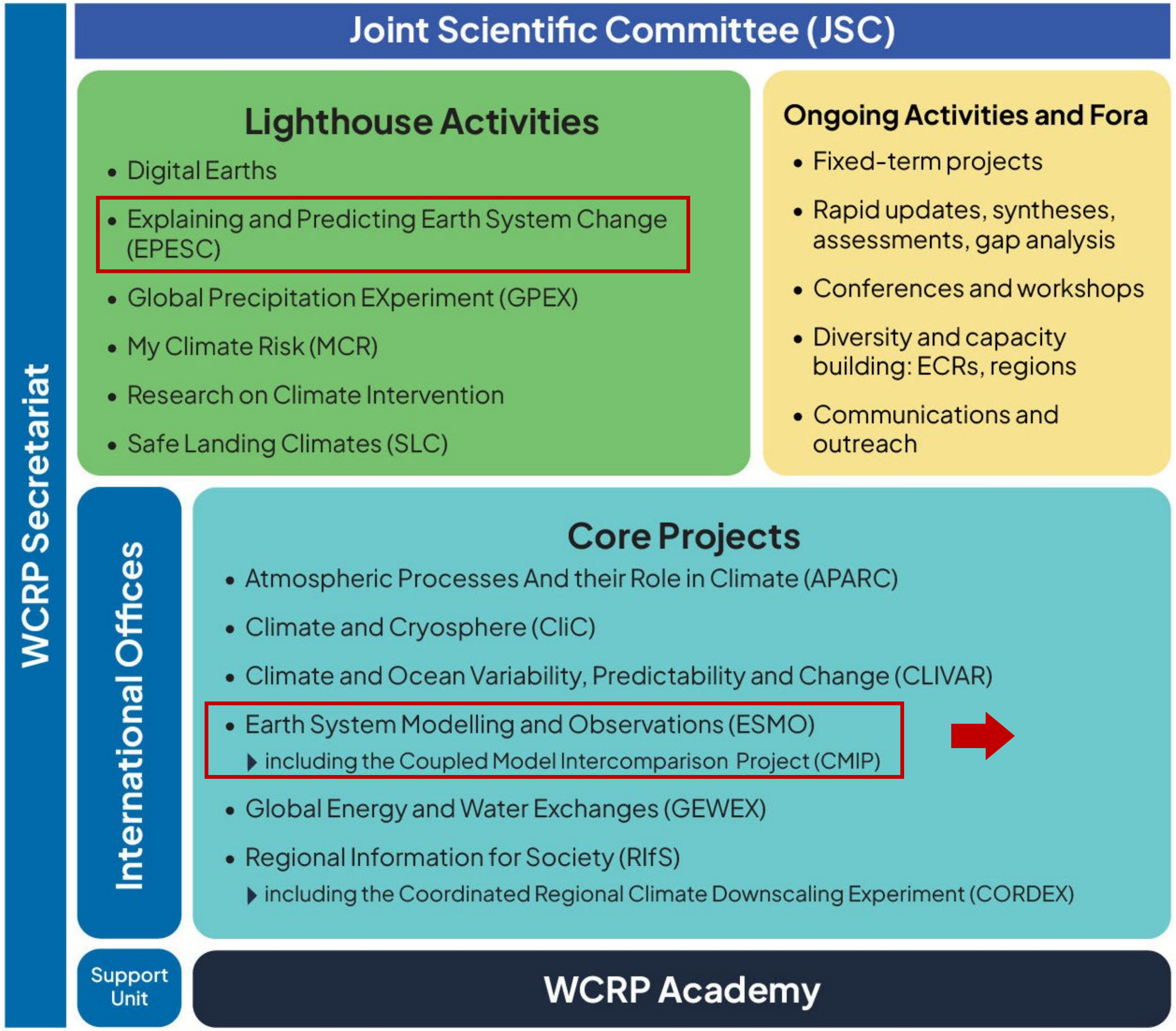
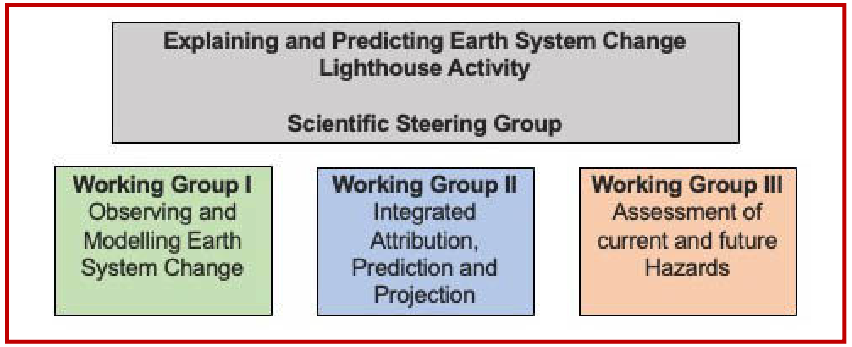
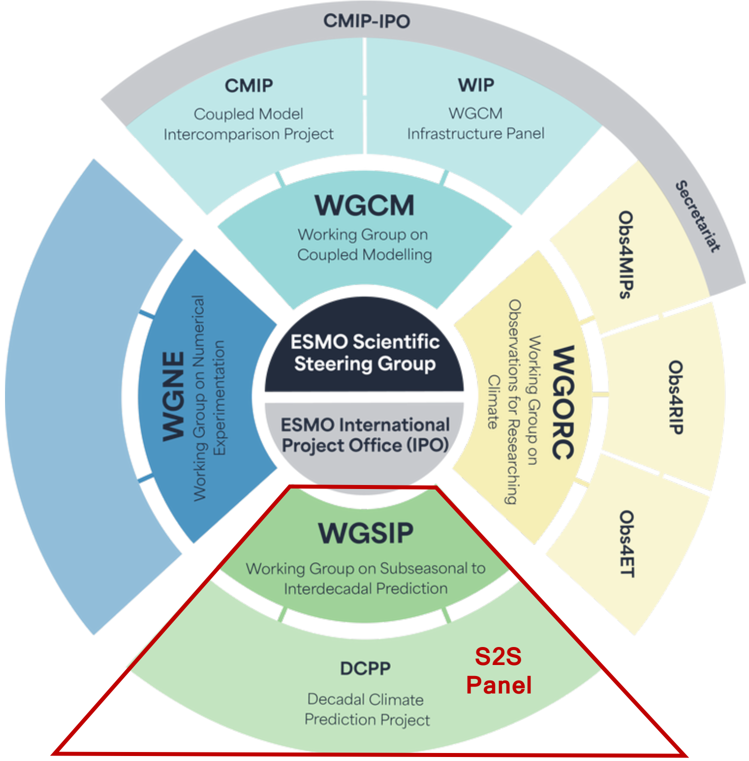
WCRP climate prediction landscape



WCRP
World Climate Research Programme
LIGHTHOUSE ACTIVITIES



ESMO
Earth System Modelling and Observations



Explaining and Predicting Earth System Change

WG 1

Observing and Modelling Earth System Change

- Apply modelling and observation in effective ways to quantify and improve understanding of observed variability and model strengths/deficiencies in representing
  - Earth's energy imbalance
  - Snow and its role in modelled/ observed trends & variability

WG 2

Integrated Attribution, Prediction and Projection

- Explain multi-annual to decadal changes e.g. through single/ multiple forcing experiments
- Build attribution capability for changes observed and predicted by WMO Annual to Decadal Lead Centre

WG 3

Assessment of Current and Future Hazards

- Understanding and predicting how changes on multi-annual-to-decadal timescales affect risks from weather and climate hazards

Activities under ESMO

WGSIP

Ongoing 2019-2024 Research Foci

- Long-range forecasts of monsoons
- Influences of temperature trends*
- Information for decision making

2025-2029 Research Foci

- ML/AI*
- Sources of predictability
- Ensemble information across time scales
- Land-atmosphere interactions

Climate-system Historical Forecast Project (CHFP)

- Long-term project to collect and archive seasonal hindcasts, enabling science & assessment of skill evolution as advocated by TPOS 2020
- Ingesting previous-generation hindcasts from WMO Global Producing Centres
- Data centre migrating to APCC/Busan

DCPP Panel

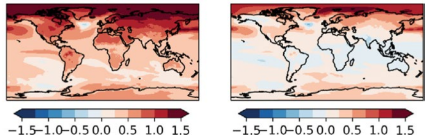
Formulation of decadal prediction experiments for CMIP7

- New emphasis on multi-year prediction to 28 months
- Fast track 10-year prediction from for AR7
- High-resolution experiments

Volcanic Response Readiness Exercise

- 8 centres re-ran predictions from 2022 incorporating forcing from hypothetical large eruption
- BAMS 2024

2022-2026 temperature anomalies without (left) and with (right) eruption



S2S Panel

- Currently spinning up to further S2S prediction science under WCRP, complementing WWRP SAGE
- Initial research foci under science plan:
  - S2S predictability and prediction of the Earth system across scales
  - Initialization and observation impacts

S2S2D 2026

International Conferences on Subseasonal to Decadal Prediction

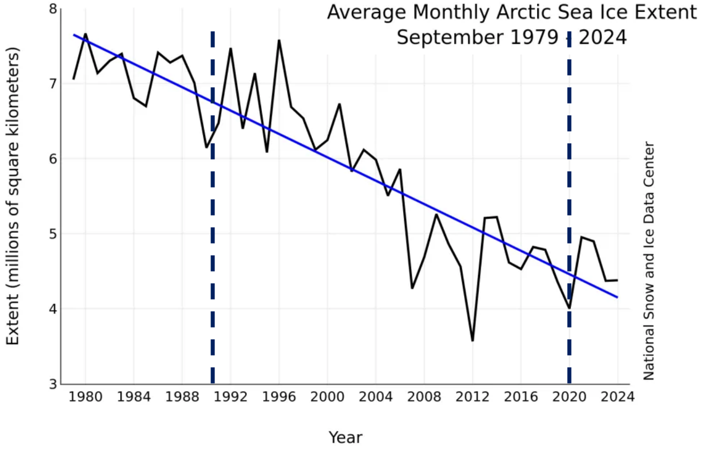
Third International Conference on Subseasonal to Seasonal Prediction (S2S)
Third International Conference on Seasonal to Decadal Prediction (S2D)

- 7-11 September 2026, University of Reading, UK
- Parallel conferences + plenary sessions on cross-cutting themes and synthesis
- Organization led by WCRP with WWRP involvement
- S2S leads: Cristiana Stan, Steve Woolnough S2D leads: Magdalena Balmaseda, Adam Scaife
- Save the date announcement + web site coming soon
- Contacts: Anca Brookshaw anca.brookshaw@ecmwf.int, Bill Merryfield bill.merryfield@ec.gc.ca

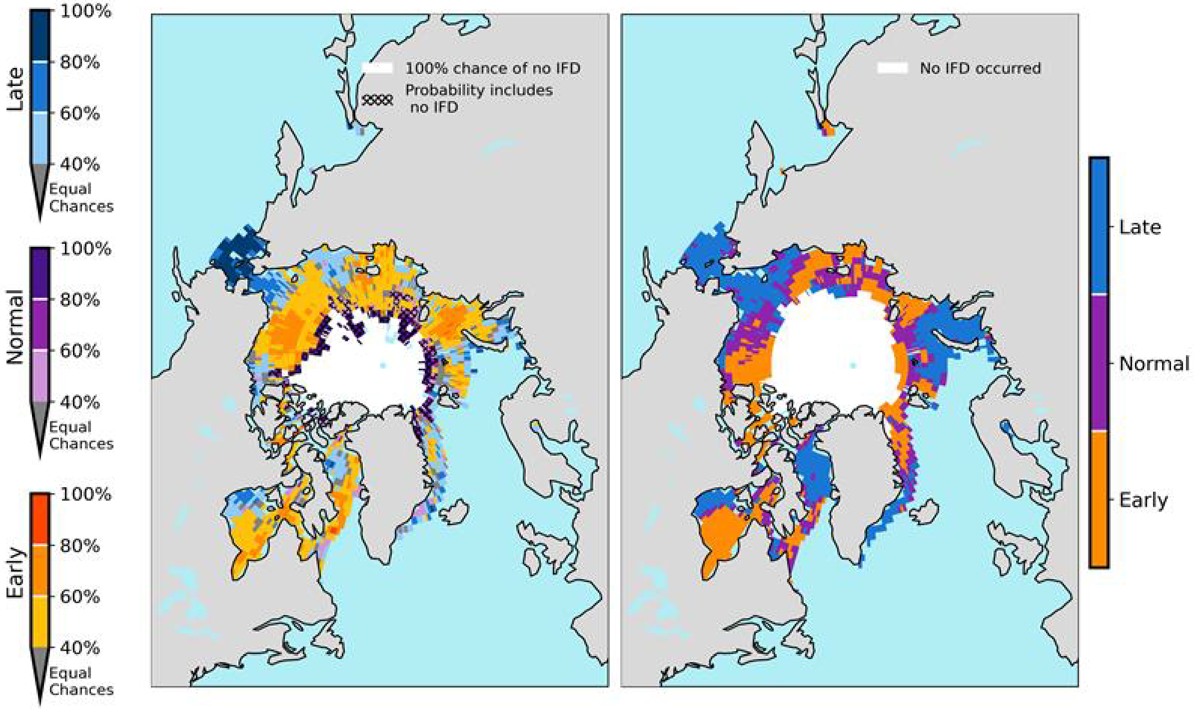
Predicting a rapidly changing Earth system

Example: Arctic sea ice prediction

- Arctic sea ice is one of the most rapidly changing components of the Earth system
- Conventional reference periods e.g. 1991-2020 are not suitable →
- ECCC provides calibrated probabilistic forecasts of Arctic ice-free up dates to the WMO
- Sliding 9-year reference period chosen as relevant to users



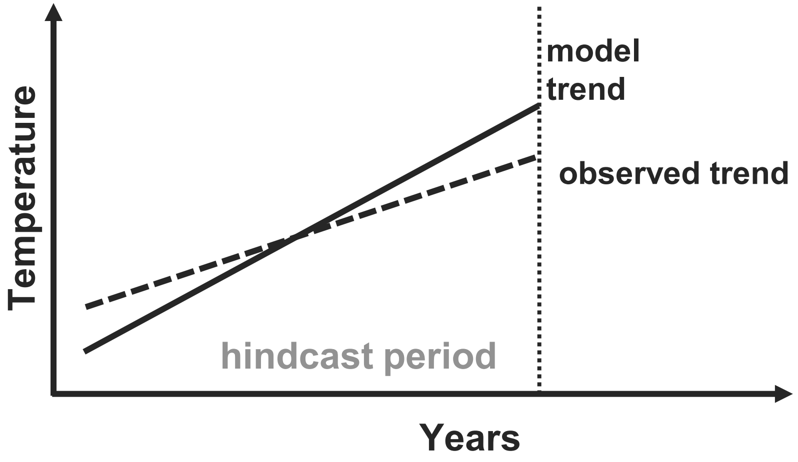
2024 early, near-normal or late **ice-free dates** relative to 2015-2023



ACF
Arctic Climate Forum

Methodology:
[Dirkson et al. *Wea. Forecasting* 2021]

Impacts of trends and trend errors



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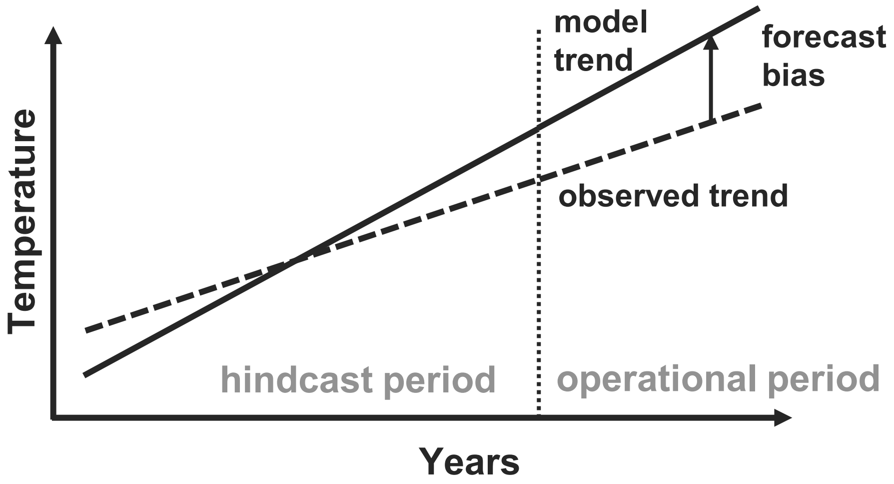

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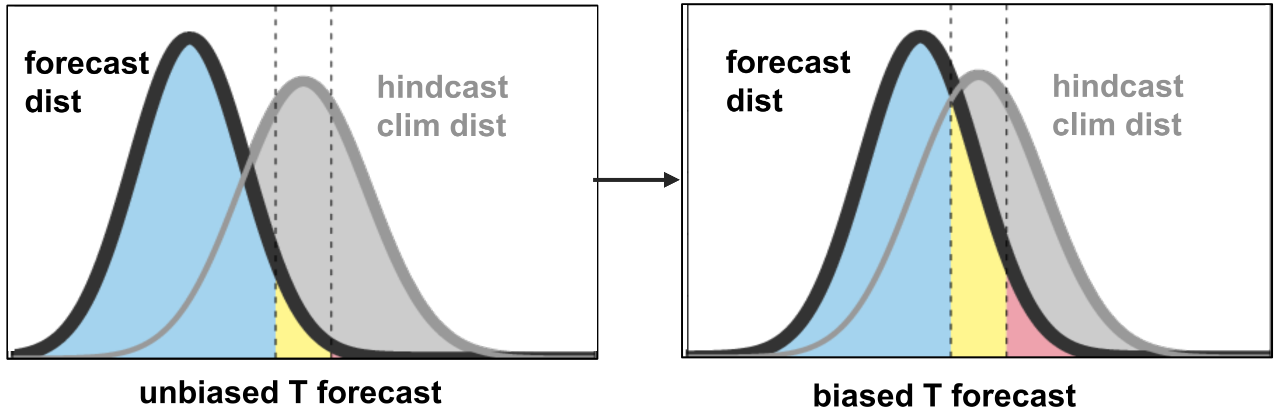

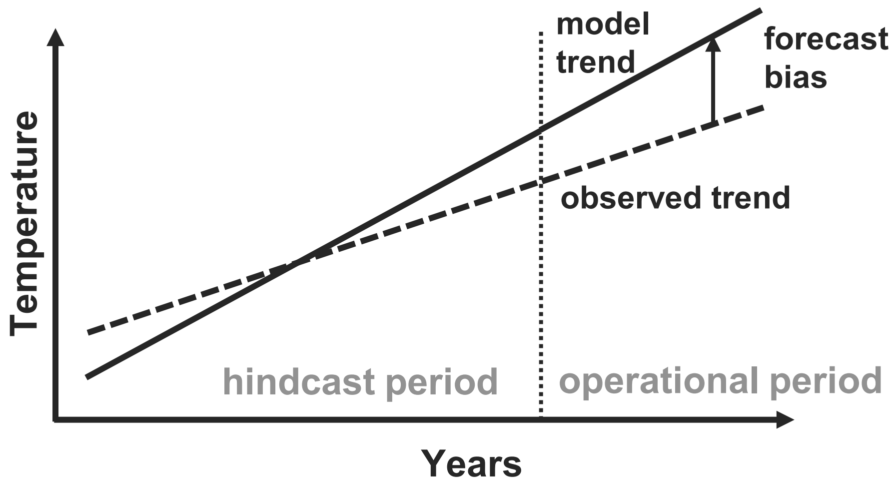

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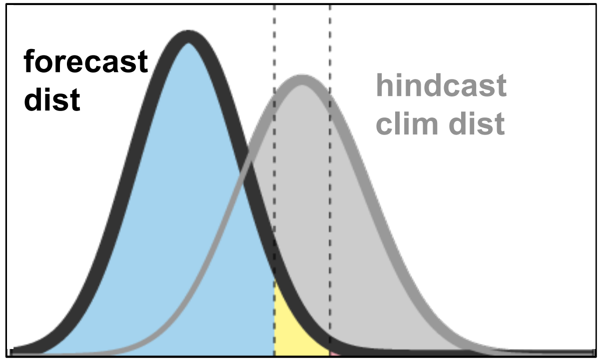
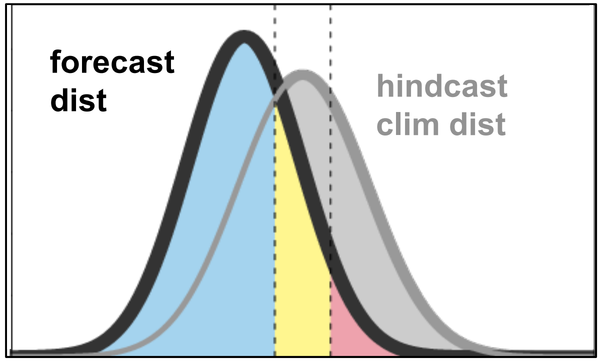


unbiased T forecast



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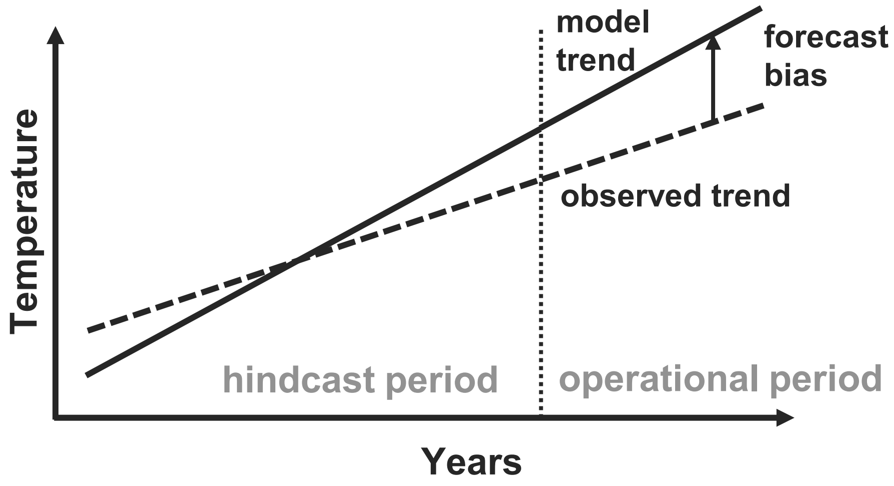

σ_{clim}=1 $\sigma_{forecast}$=0.86 $T'_{unbiased}$= -1.7 ΔT_{bias}= +0.8

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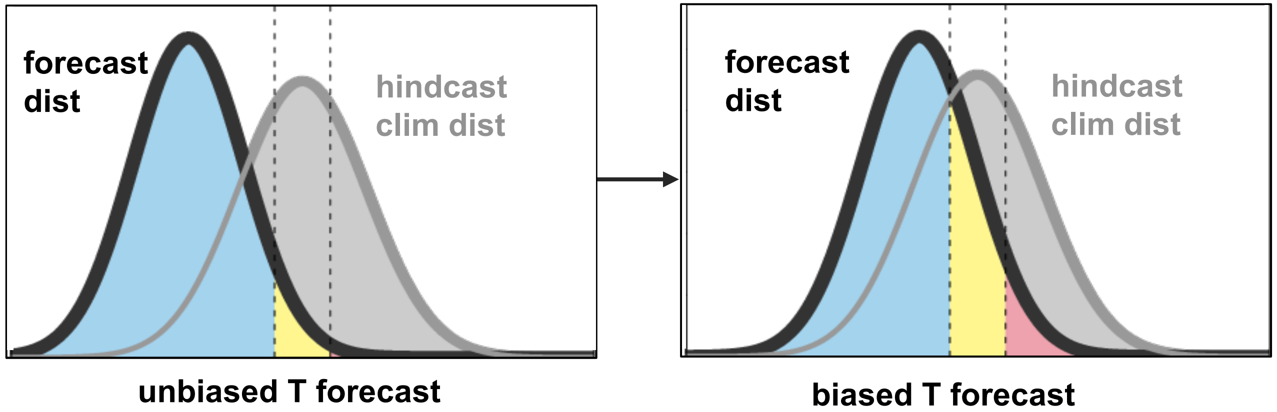

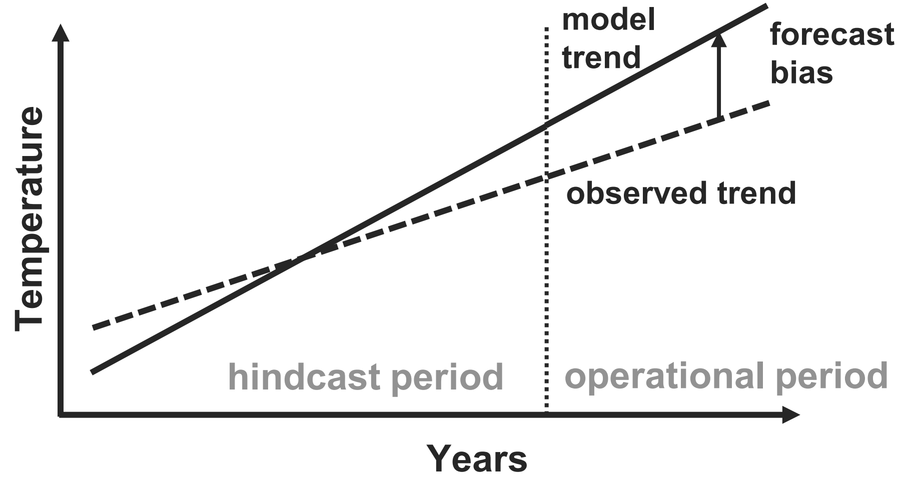

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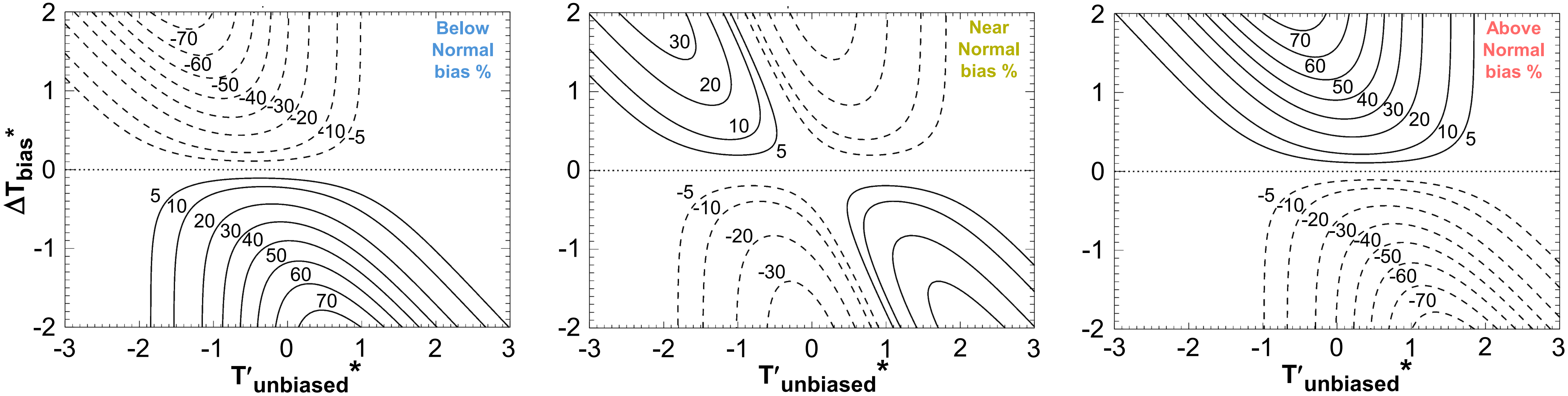

*units of σ_{clim}

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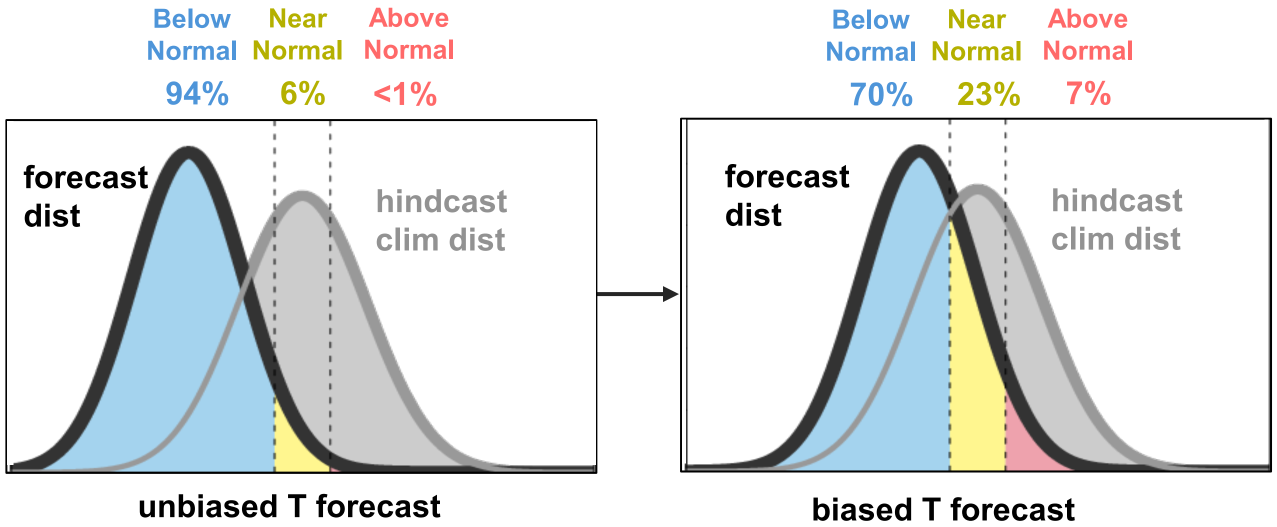

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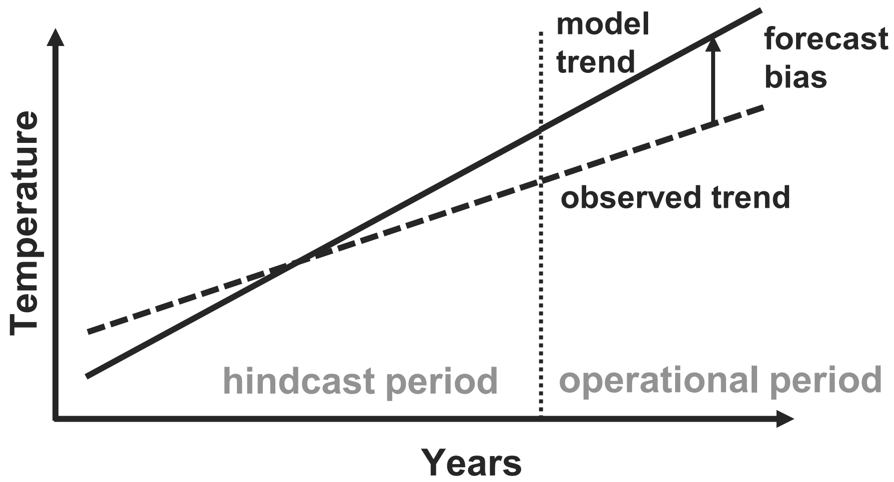
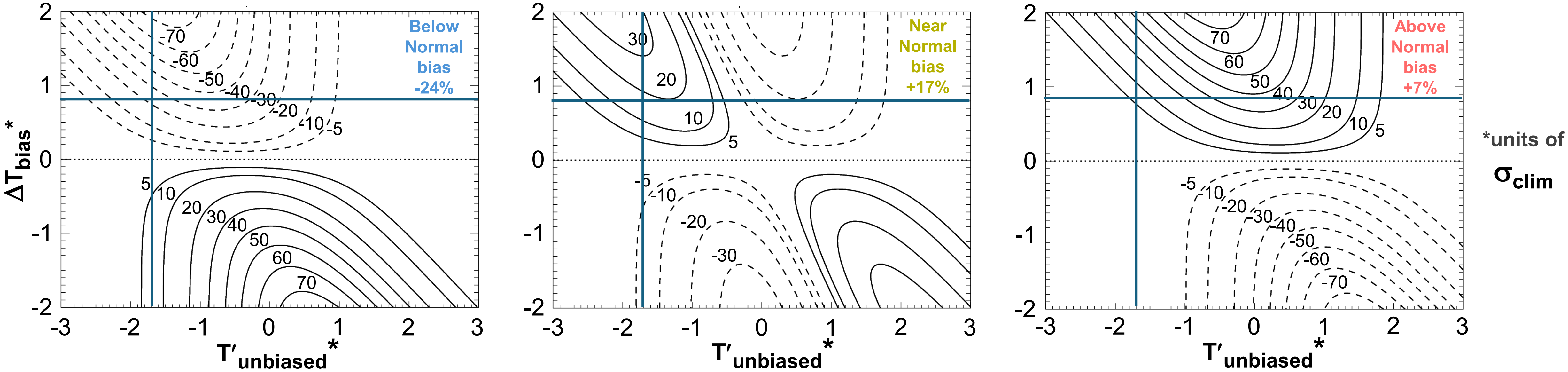
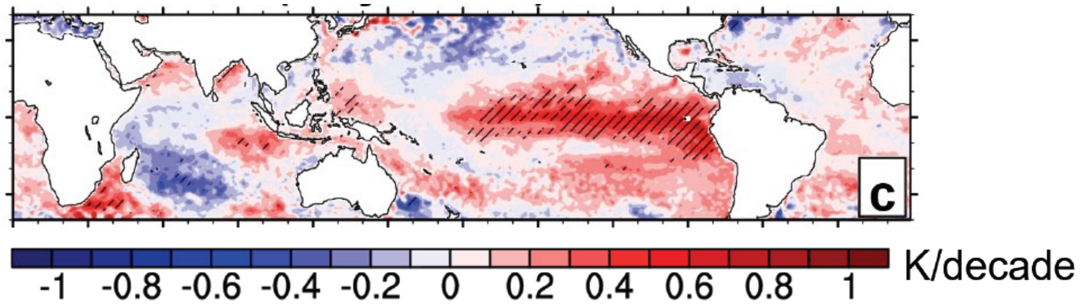


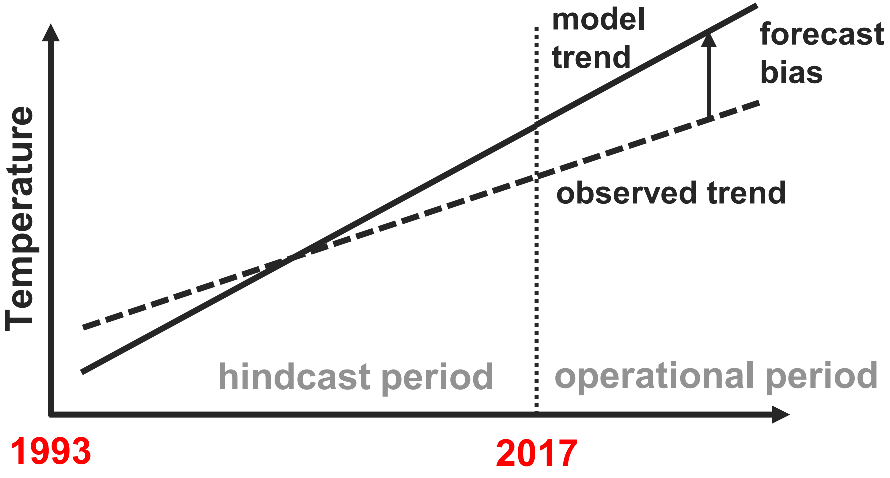


Impacts of trends and trend errors: seasonal

Tietsche et al., Workshop on Diagnostics for Global Weather Prediction, 9-12 September 2024

SEAS5 Nov 1993-2019 SST trend error from May start





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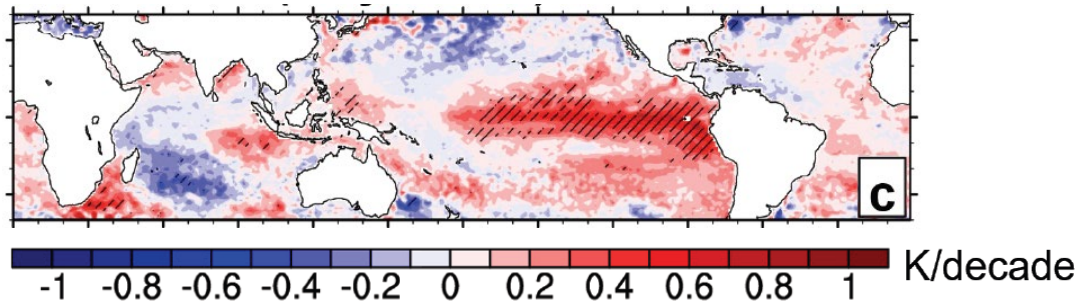

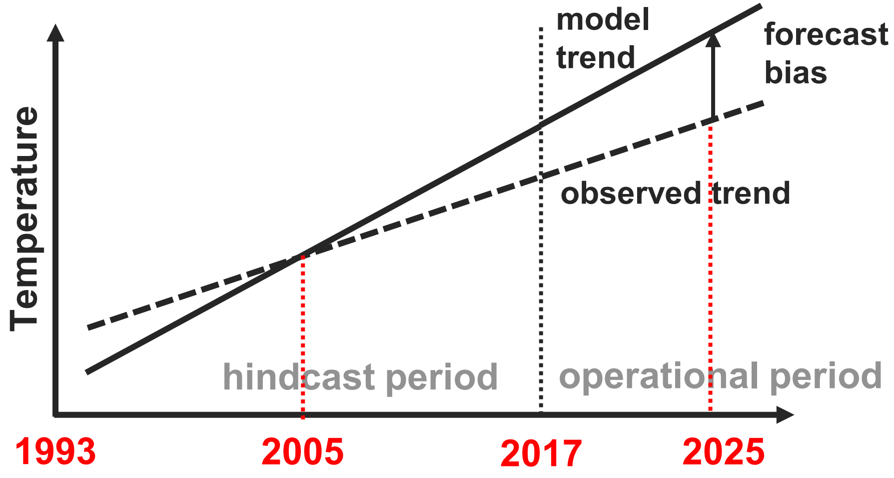

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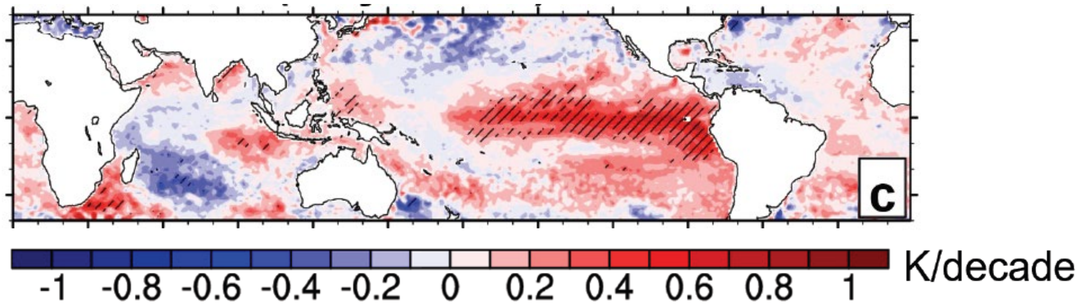
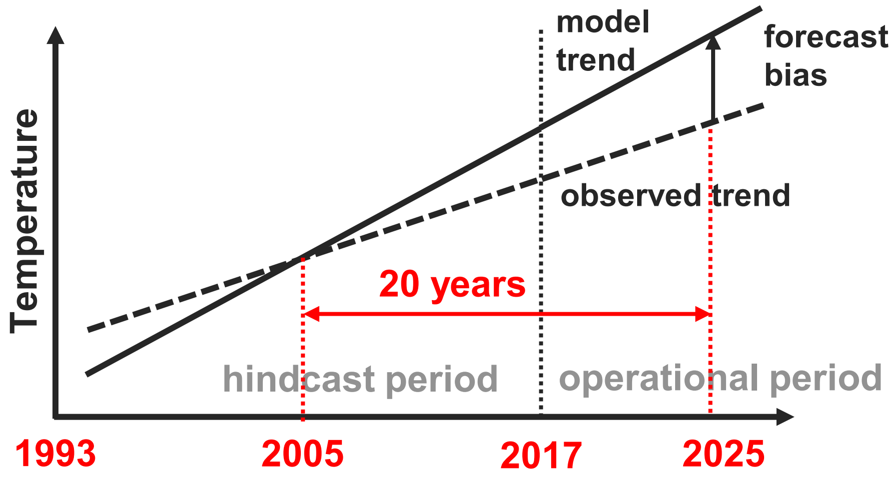


Nino3.4 trend bias ≈ 0.4K/decade → $\Delta T_{bias} \approx +0.8$ in 2025 → **consider**

$\sigma_{clim} \approx 1$	$\sigma_{forecast} \approx 0.5$	$T'_{unbiased} = 0$	$\Delta T_{bias} = +0.8$



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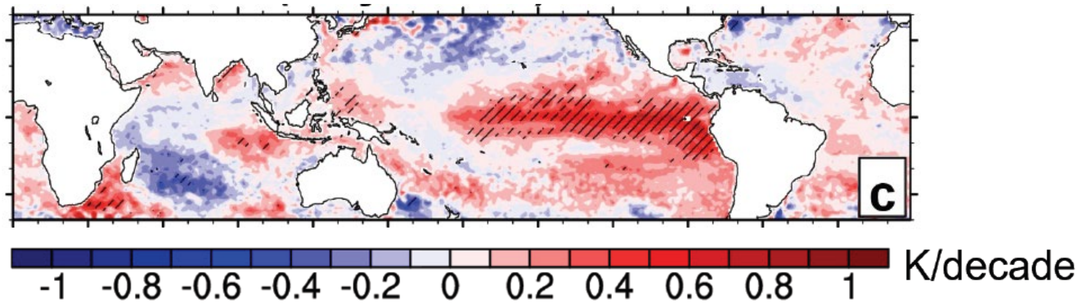

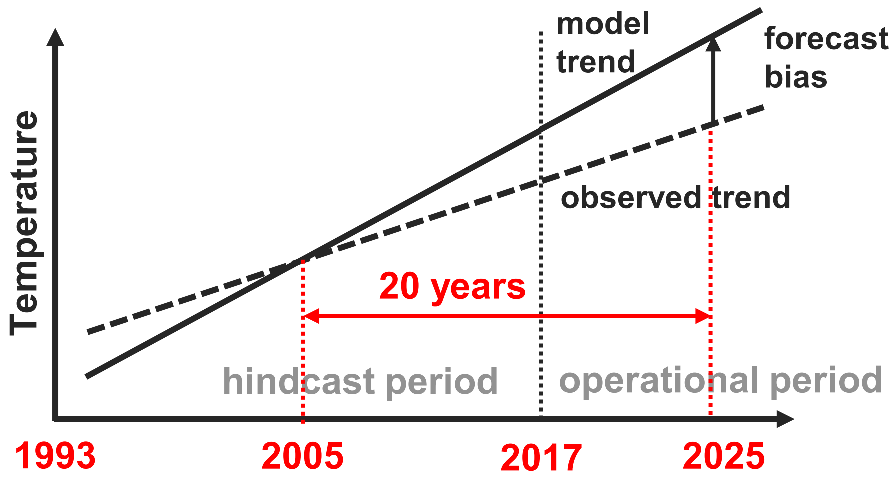

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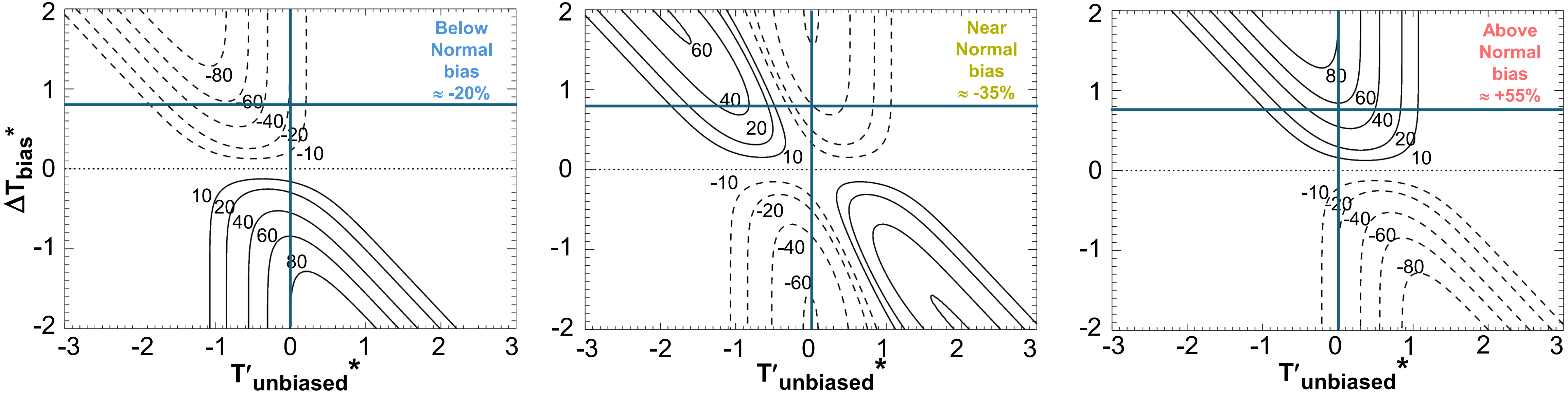

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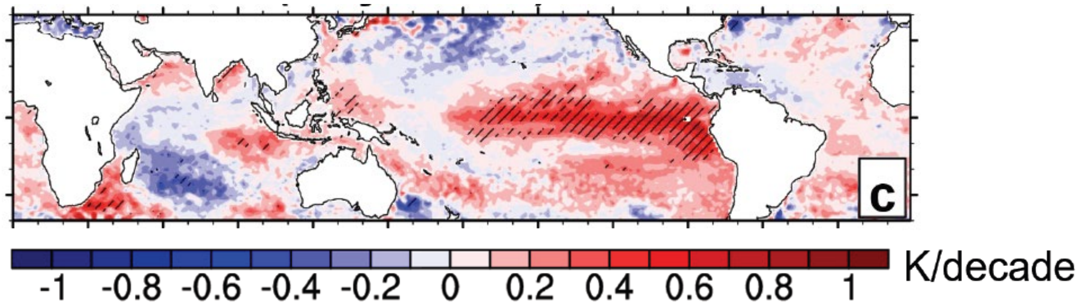

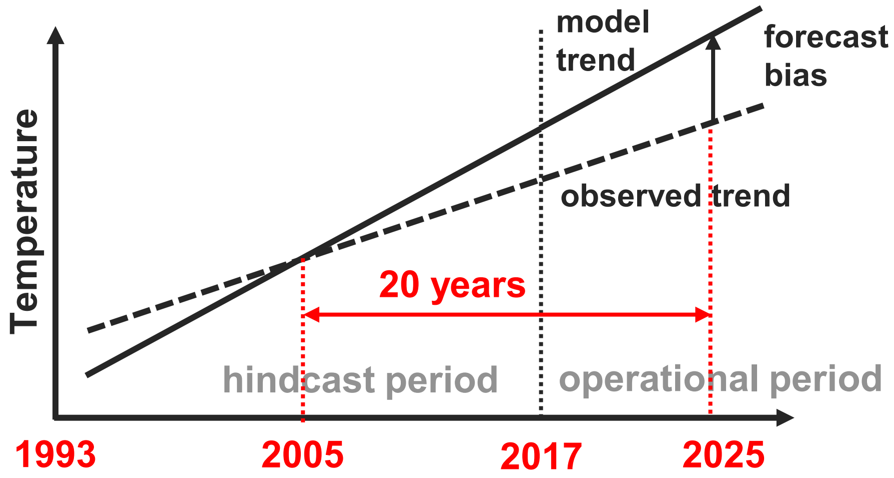

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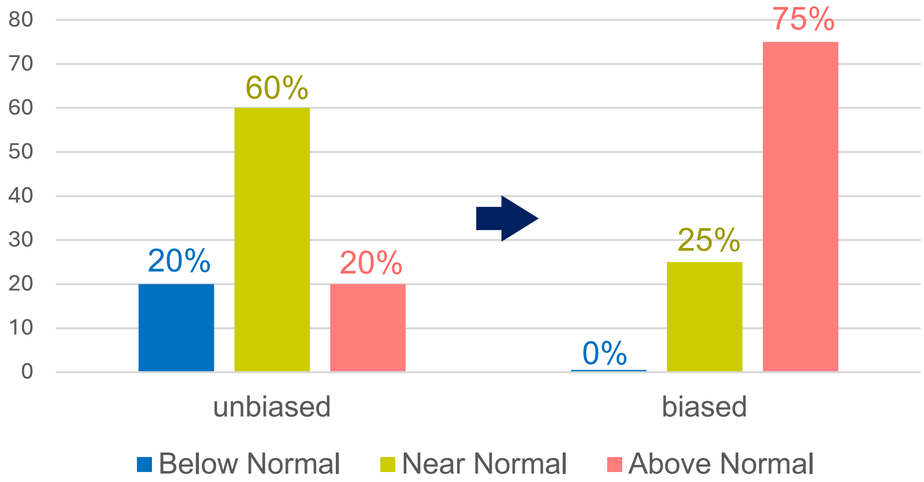
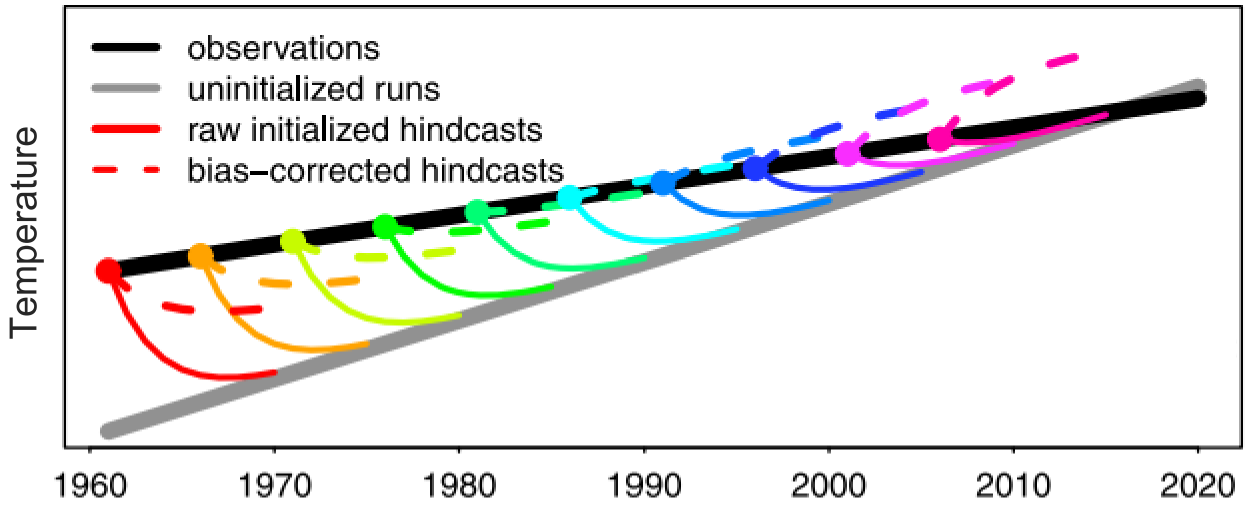
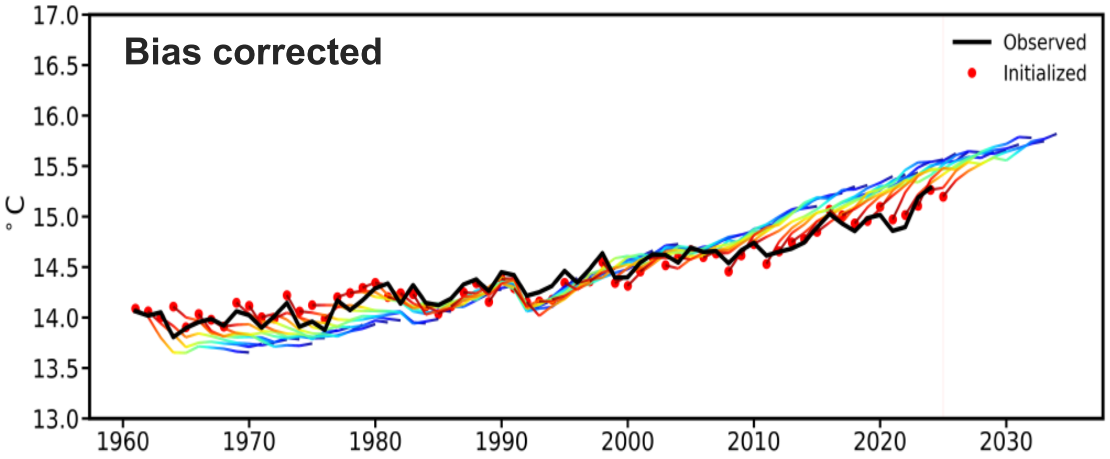


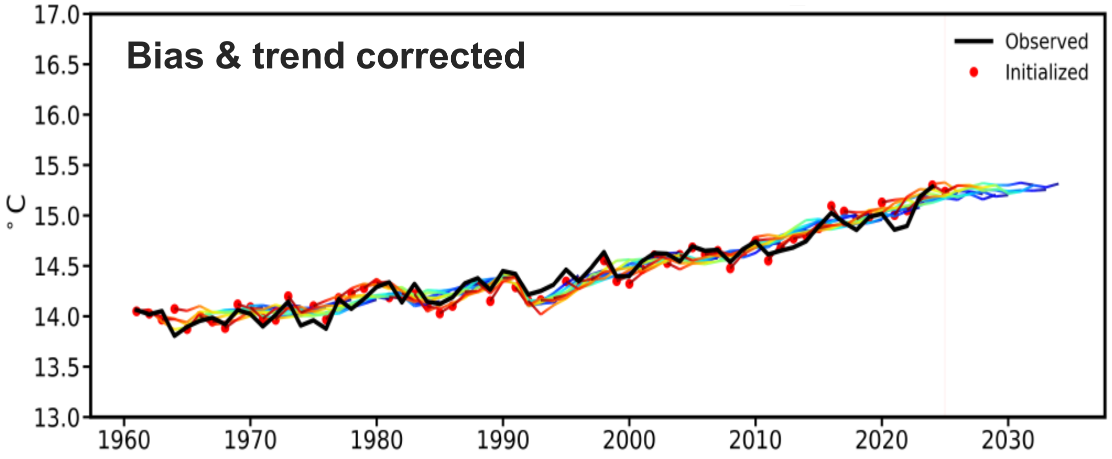
Impacts of trends and trend errors: decadal



Kharin et al. GRL 2012

CanESM5 global temperature decadal predictions initialized 1961-2025





Are seasonal forecast models biased “warm”?

Several years of operation provides an opportunity to assess various strengths and weaknesses of the system, as well as its performance in real time, and to explore the NMME representation of some observed features from the past four decades. The NMME team and seasonal forecasters, in paying close attention to the NMME forecasts every month for 10 years, have observed that the real-time NMME rarely accurately predicts below-average winter temperatures in North America (CPC staff 2019, personal communication). In fact, we suspected that the real-time NMME simply rarely predicts below-average North American winter temperatures at all. In a warming world, below-average winter months are rarer than above average, but do still occur, and can be very consequential for energy use, health, and many other factors (e.g., Trenary et al. 2015; Wolter et al. 1999).

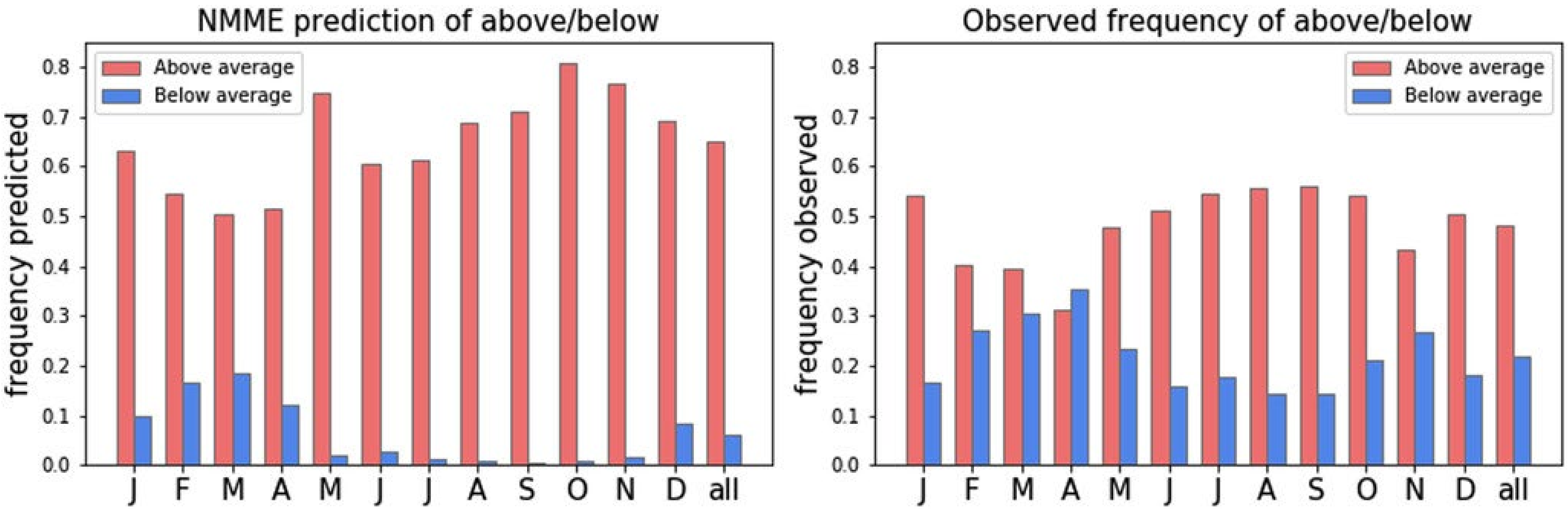
BAMS

A Decade of the North American Multimodel Ensemble (NMME)

Research, Application, and Future Directions

Emily J. Becker, Ben P. Kirtman, Michelle L’Heureux, Ángel G. Muñoz, and Kathy Pegion

Are seasonal forecast models biased “warm”?

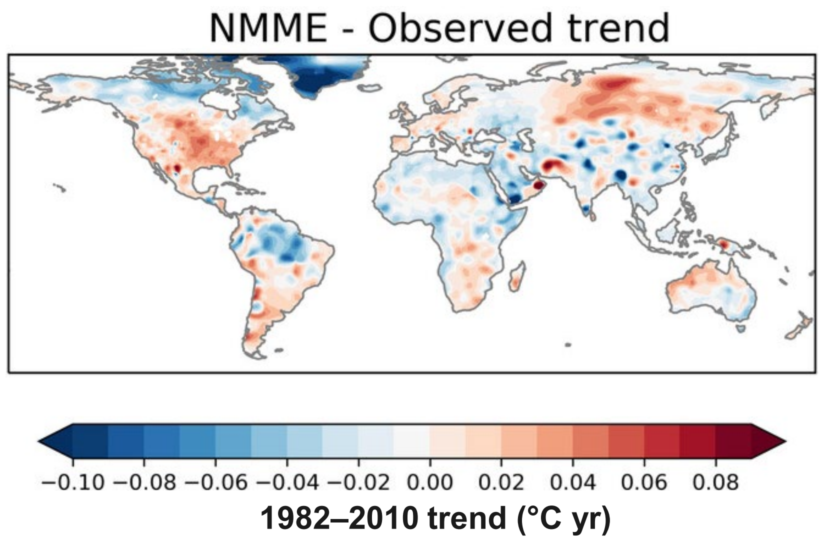


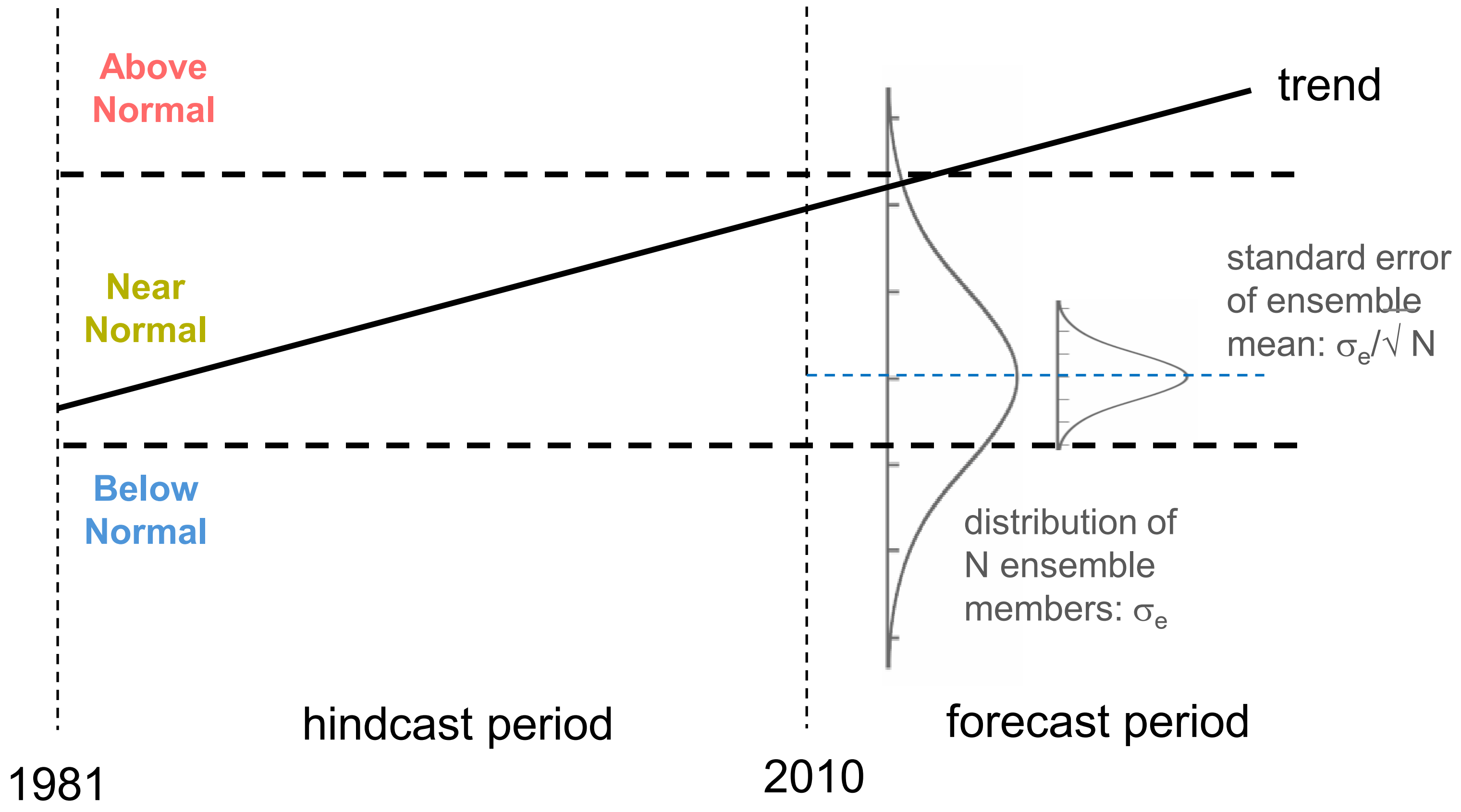
Frequency of prediction of above-average (upper tercile) and below-average (lower tercile) monthly mean land surface temperature anomaly in North America during the NMME real-time period of 2011–20. NMME prediction is shown for a 1.5-month lead and is the multimodel ensemble-mean anomaly of eight equally weighted models…

Becker et al. *BAMS* 2022

Are seasonal forecast models biased "warm"?

- A suggested possible contributor to apparent too-frequent NMME prediction of above normal is excessive NMME temperature trend over much of the US →
- However, this is based on consideration of ensemble means rather than individual ensemble members:





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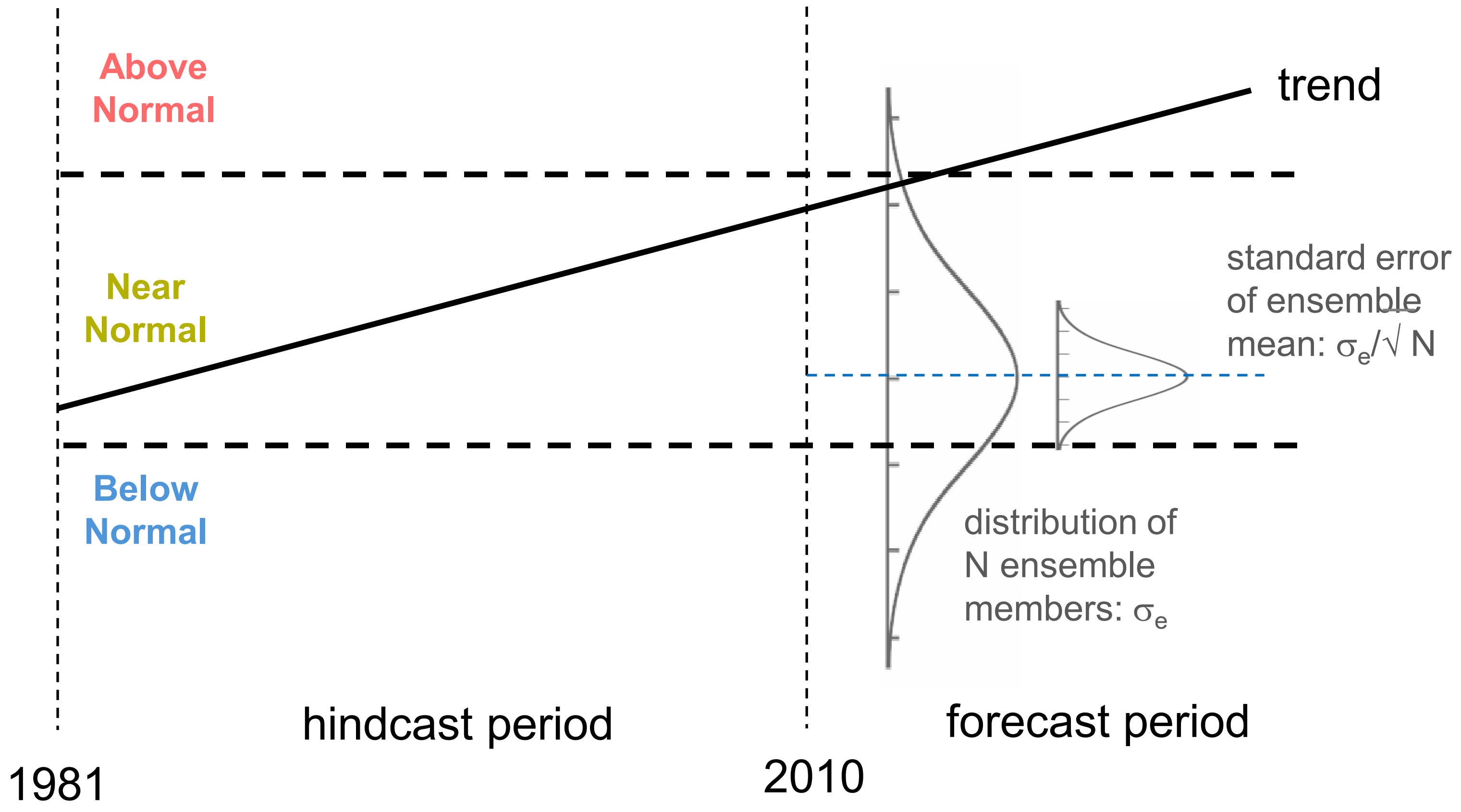
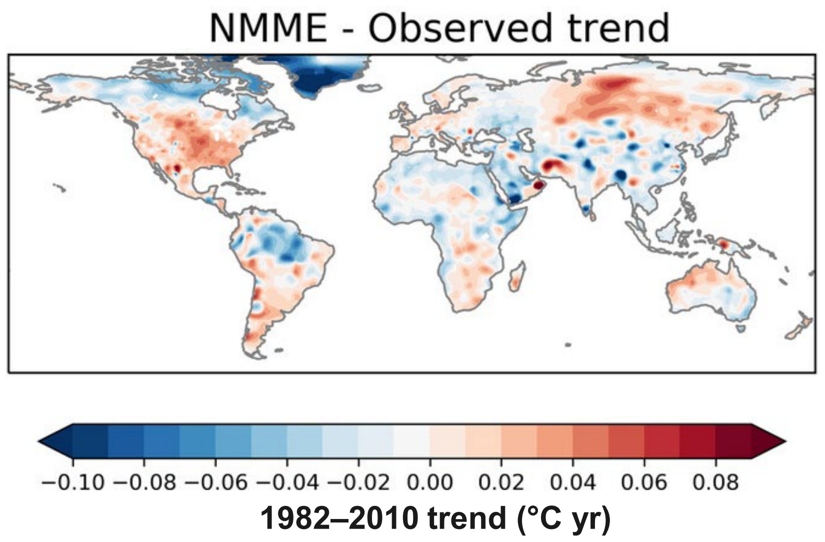
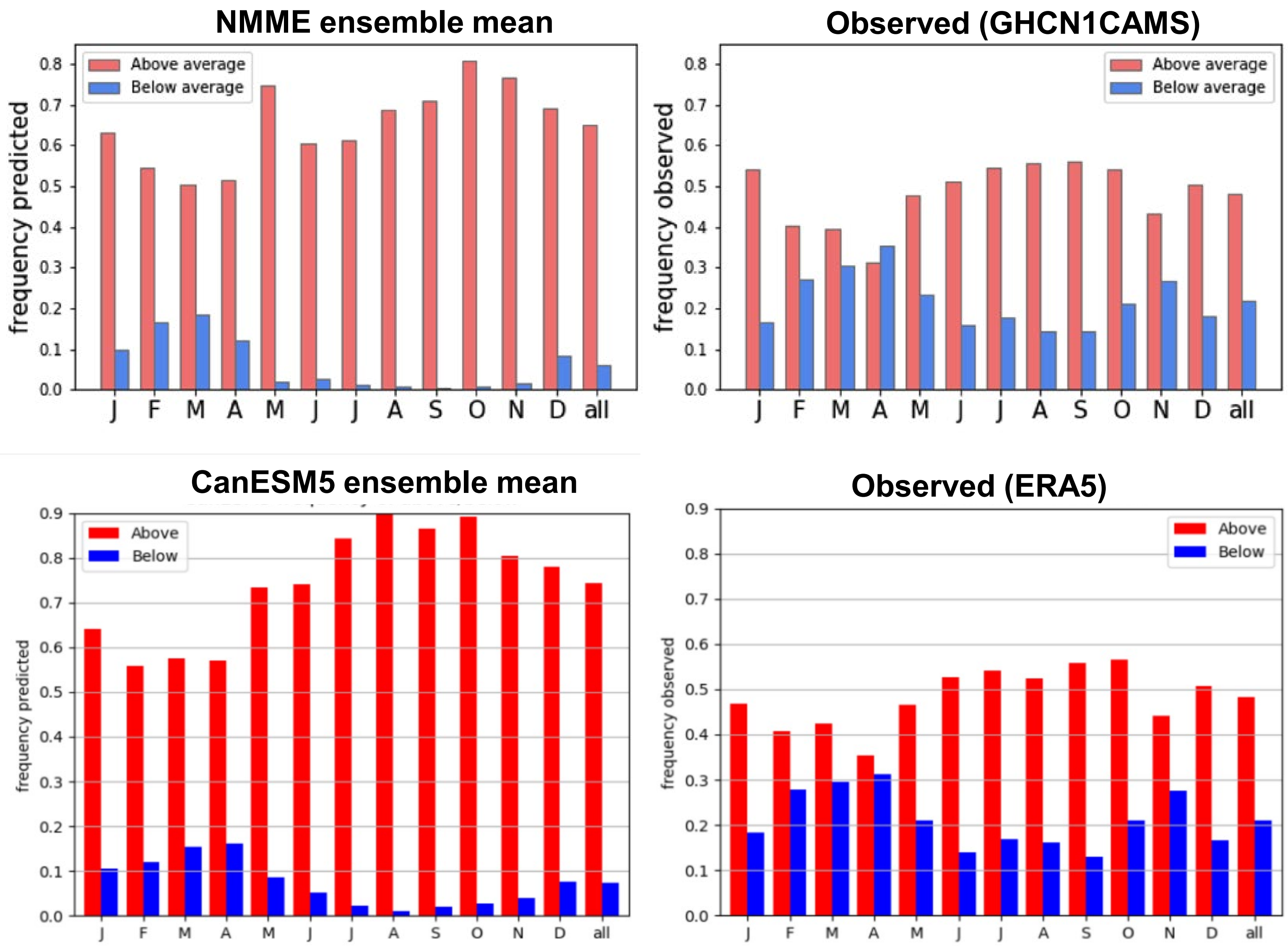




→ test this hypothesis using an independent model (CanESM5)

Are seasonal forecast models biased “warm”?



Frequency of prediction of monthly mean temperature anomaly in North America during 2011–20

Are seasonal forecast models biased “warm”?

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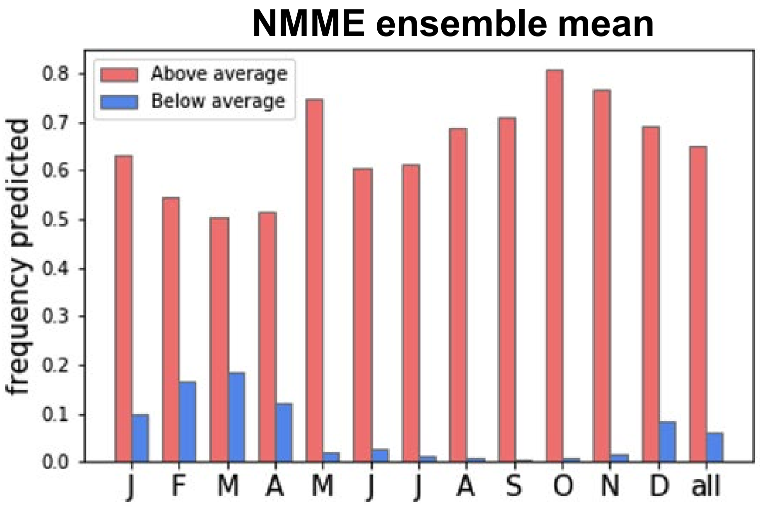

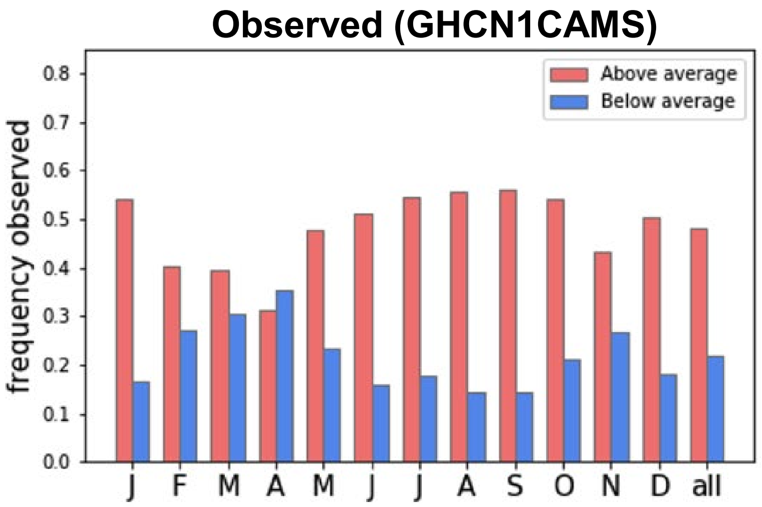

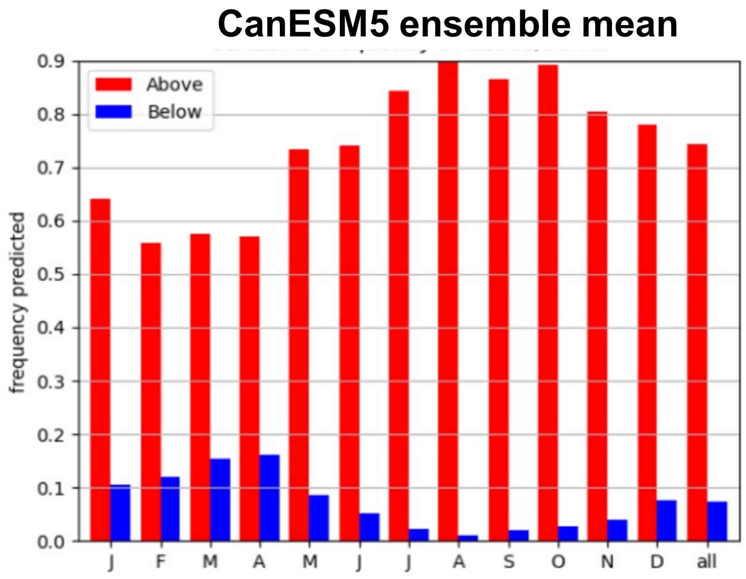

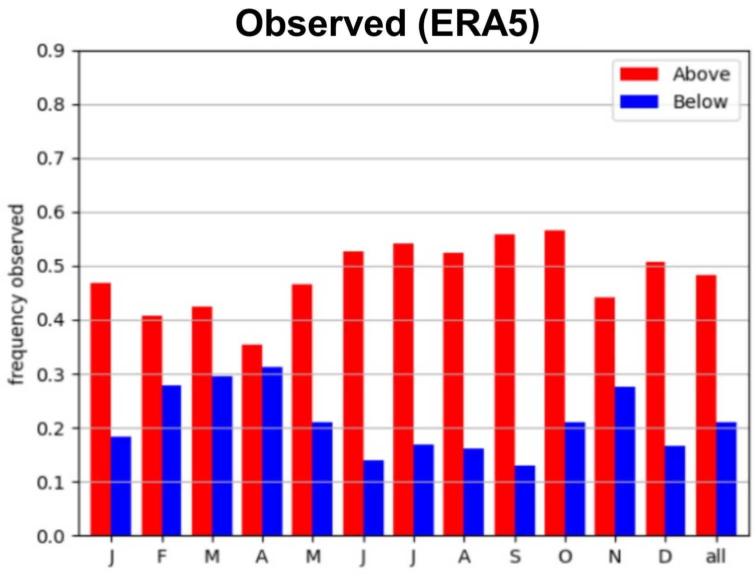

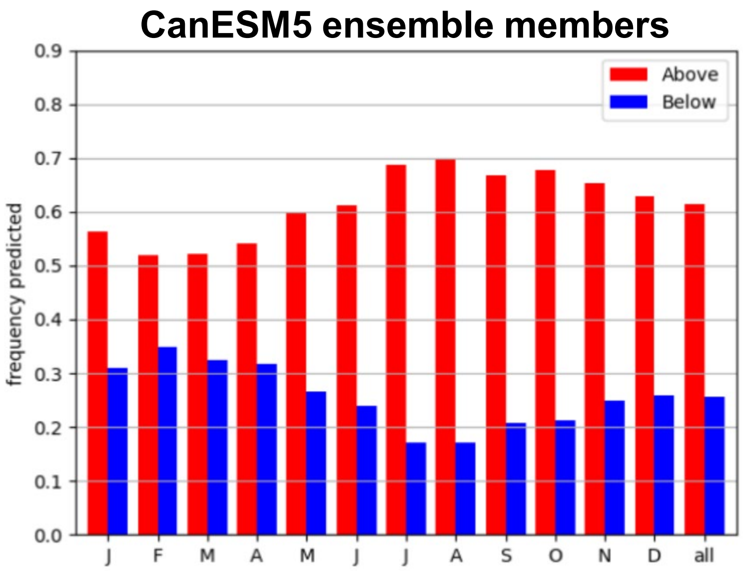

The AI/ML revolution: Where will it lead?

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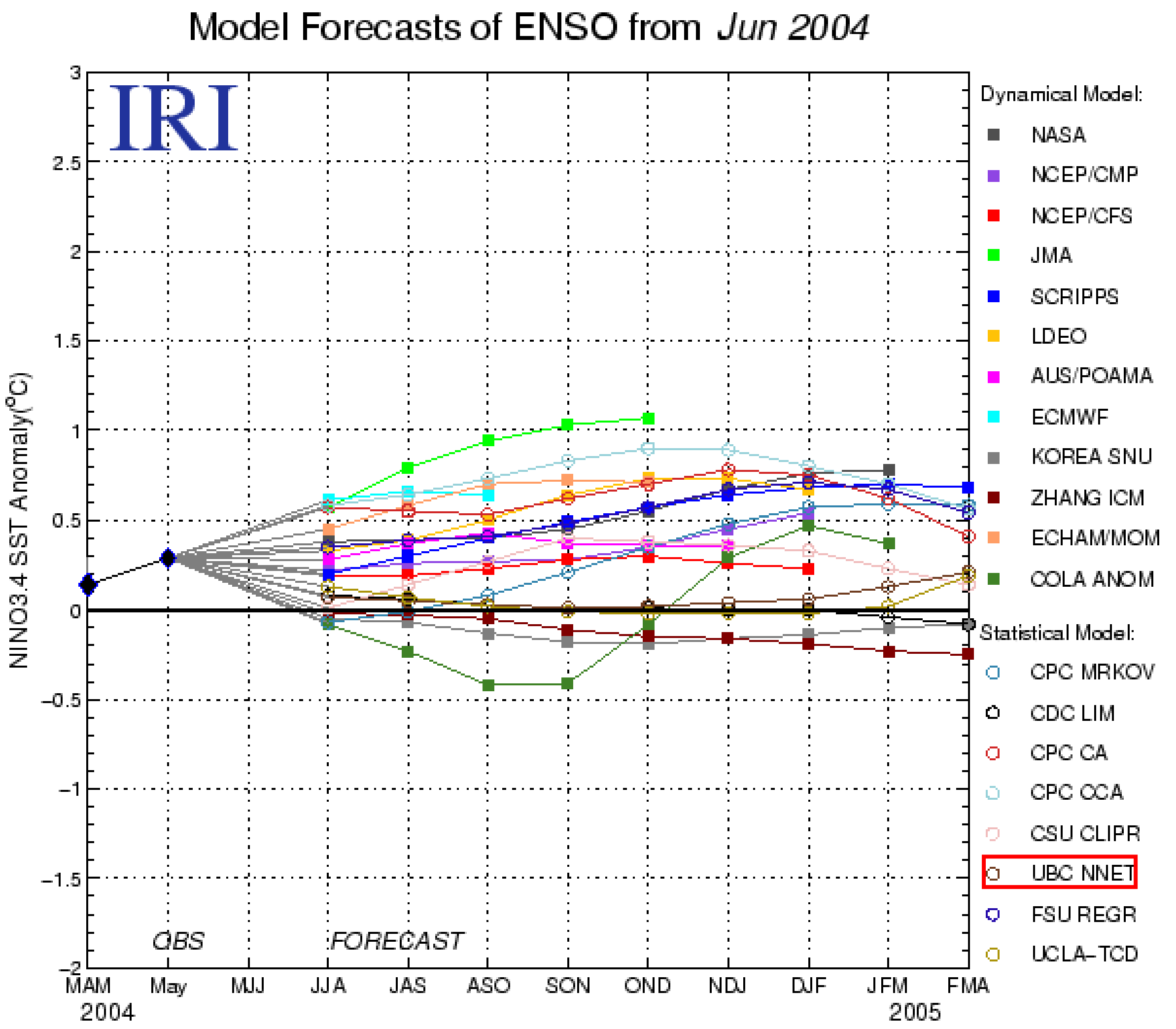
International Science Council

Early NN-based ENSO predictions

W. Hsieh et al. CPC outlooks from Mar 1996, IRI from Jun 2004:



	Seasons (2004-05)								
Model	**JJA**	**JAS**	**ASO**	**SON**	**OND**	**NDJ**	**DJF**	**JFM**	**FMA**
Dynamical models									
NASA/NSIPP model	0.3	0.3	0.3	0.4	0.5	0.6	0.7	0.8	0.8
NCEP Coupled model	0.2	0.3	0.3	0.3	0.4	0.4	0.5		
NCEP Coupled Fcst Sys	0.2	0.2	0.2	0.3	0.3	0.3	0.2		
Japan Met. Agency model	0.6	0.8	0.9	1.0	1.1				
Scripps Inst. HCM	0.2	0.3	0.4	0.5	0.6	0.6	0.7	0.7	0.7
Lamont-Doherty model	0.3	0.4	0.5	0.6	0.7	0.7	0.7		
POAMA (Austr) model	0.3	0.4	0.4	0.4	0.4	0.4			
ECMWF model	0.6	0.7	0.6						
SNU (Korea) model	-0.0	-0.1	-0.1	-0.2	-0.2	-0.2	-0.1	-0.1	-0.1
ZHANG ICM model	-0.0	-0.0	-0.1	-0.1	-0.1	-0.2	-0.2	-0.2	-0.2
ECHAM/MOM	0.5	0.6	0.7	0.7	0.7				
COLA Anomaly model	-0.1	-0.2	-0.4	-0.4	-0.1	0.3	0.5	0.4	
Average, dynamical models	*0.3*	*0.3*	*0.3*	*0.3*	*0.4*	*0.3*	*0.4*		
Statistical models									
NCEP/CPC Markov model	-0.2	-0.1	-0.1	-0.0	0.1	0.2	0.3	0.5	0.6
NOAA/CDC Linear Inverse	0.1	0.1	0.0	0.0	0.0	0.0	0.0	-0.0	-0.1
Dool Constructed Analog	0.6	0.5	0.5	0.6	0.7	0.8	0.7	0.6	0.4
NCEP/CPC Can Cor Anal	0.6	0.6	0.7	0.8	0.9	0.9	0.8	0.7	0.6
Landsea/Knaff CLIPER	0.1	0.1	0.3	0.4	0.4	0.4	0.3	0.2	0.1
Univ. BC Neural Network	0.1	0.1	0.0	0.0	0.0	0.0	0.1	0.1	0.2
FSU Regression	0.4	0.4	0.4	0.5	0.6	0.7	0.7	0.7	0.5
TDC - UCLA	0.1	0.1	0.0	-0.0	-0.0	-0.0	-0.0	0.0	0.2
Average, statistical models	*0.2*	*0.2*	*0.2*	*0.3*	*0.3*	*0.4*	*0.4*	*0.4*	*0.3*
Average, all models	**0.2**	**0.3**	**0.3**	**0.3**	**0.4**	**0.3**	**0.4**	**0.3**	**0.3**

CNN-based ENSO predictions

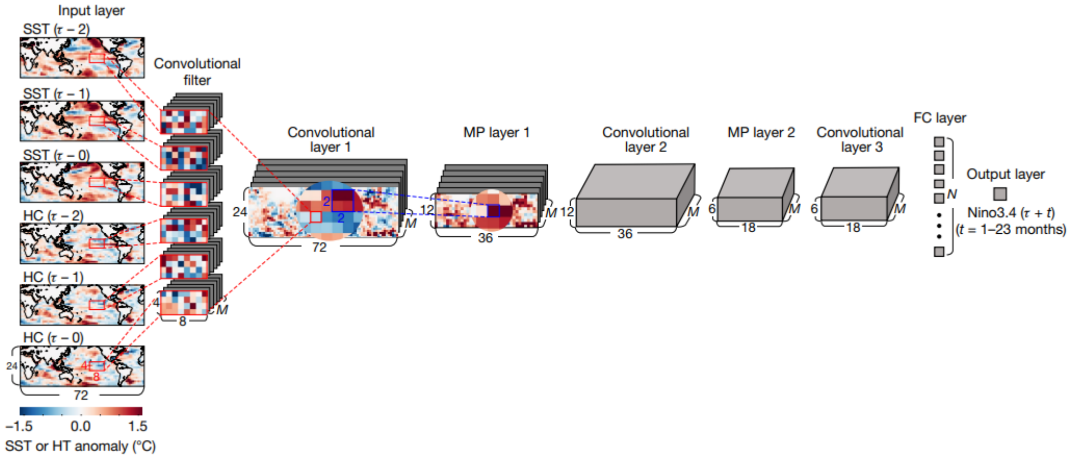
nature

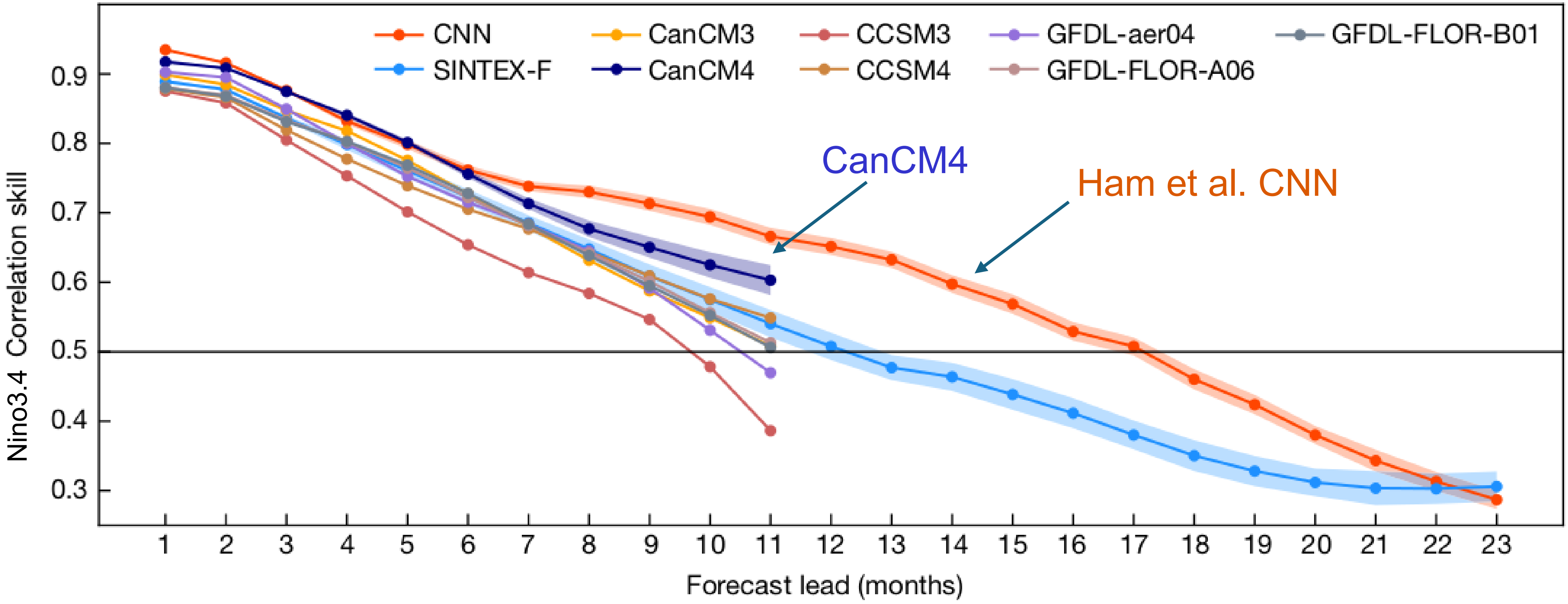
Letter | Published: 18 September 2019

Deep learning for multi-year ENSO forecasts

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

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





Followed by…

Table 1. The classification of ML methods used in ENSO prediction.

Author	Model	Input	Forecast Lead (month)
Ham et al. (2019)	CNN	SST, HC	17
Mu et al. (2021)	ENSO-ASC	SST, wind, rain, cloud, vapor	18
Hu et al. (2021)	Res-CNN	SSTA, HCA	20
Mu et al. (2022)	ENSO-GTC	SST, wind, rain, cloud, vapor	20
Wang et al. (2023b)	STIEF	SST, OHC	22
Zhou and Zhang (2023)	3D-Geoformer	SST, wind stress	18
Patil et al. (2023b)	CNN	SSTA, VATA	18
Lyu et al. (2023)	ResoNet	SST	21
Chibuike and Richman (2024)	AE+LSTM	SST	18

Shen et al. Appl. Computing Geosci. 2024

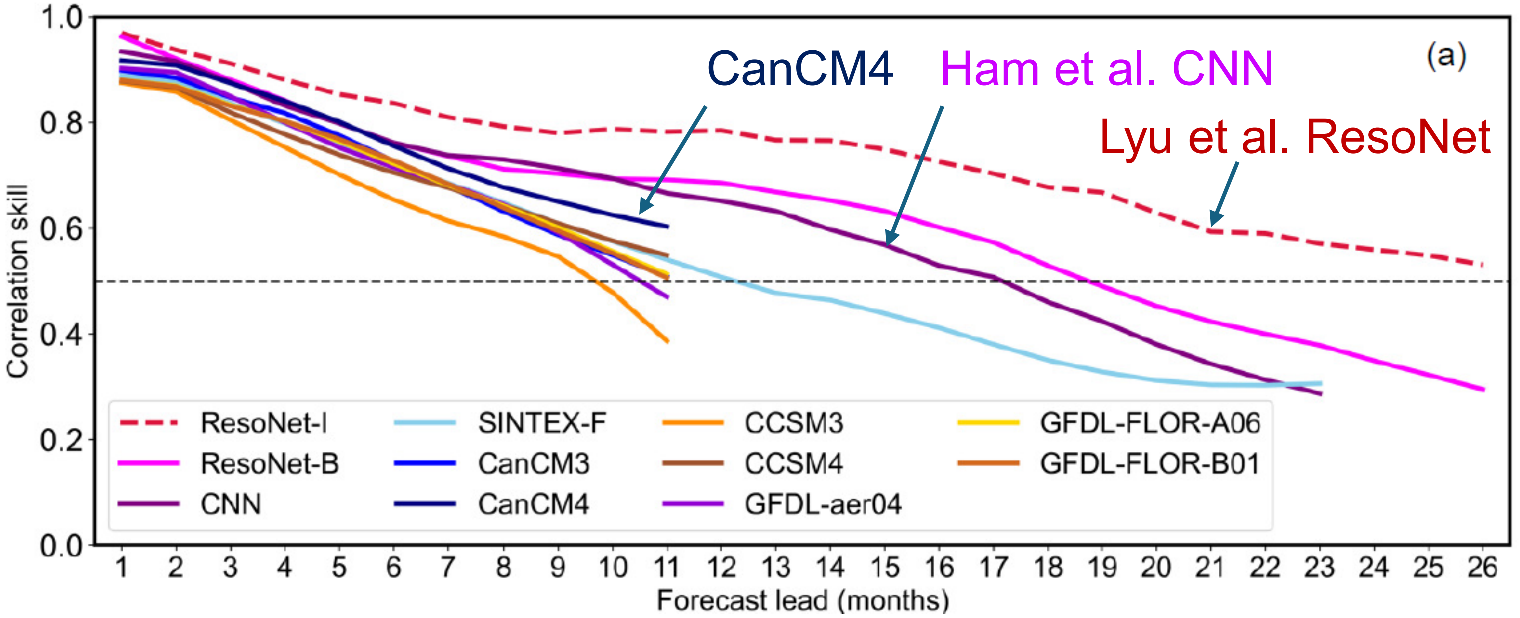
Home › Advances in Atmospheric Sciences › Article

ResoNet: Robust and Explainable ENSO Forecasts with Hybrid Convolution and Transformer Networks

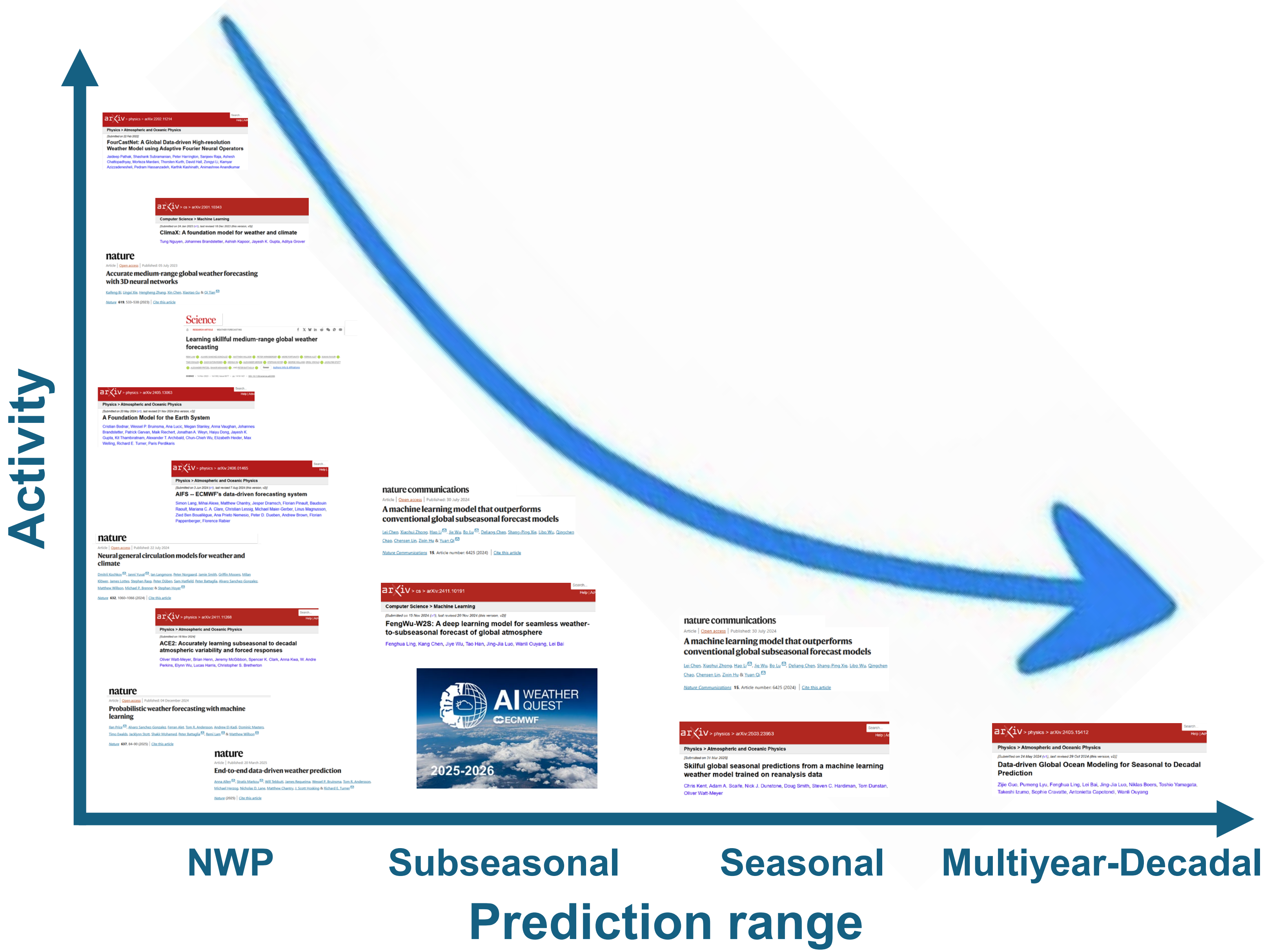
Original Paper | Published: 22 June 2024

Volume 41, pages 1289–1298, (2024) Cite this article

Pumeng Lyu, Tao Tang, Fenghua Ling, Jing-Jia Luo,
Niklas Boers, Wanli Ouyang & Lei Bai



AI driven GCM-based predictions



Astonishing pace of emergence of AI-based GCMs and weather prediction

Science

RESEARCH ARTICLE | WEATHER FORECASTING

Google DeepMind

Learning skillful medium-range global weather forecasting

REMI LAM, ALVARO SANCHEZ-GONZALEZ, MATTHEW WILLSON, PETER WIRNSBERGER, MEIRE FORTUNATO, FERRAN ALET, SUMAN RAVURI, TIMO EWALDS, ZACH EATON-ROSEN, WEIHUA HU, ALEXANDER MEROSE, STEPHAN HOYER, GEORGE HOLLAND, ORIOL VINYALS, JACKLYNN STOTT, ALEXANDER PRITZEL, SHAKIR MOHAMED, AND PETER BATTAGLIA fewer Authors Info & Affiliations

SCIENCE • 14 Nov 2023 • Vol 382, Issue 6677 • pp.

2023/11 GraphCast: deterministic

arXiv > physics > arXiv:2411.11268 Search... Help | Adv

Physics > Atmospheric and Oceanic Physics

Ai2

[Submitted on 18 Nov 2024]

ACE2: Accurately learning subseasonal to decadal atmospheric variability and forced responses

Oliver Watt-Meyer, Brian Henn, Jeremy McGibbon, Spencer K. Clark, Anna Kwa, W. Andre Perkins, Elynn Wu, Lucas Harris, Christopher S. Bretherton

2024/11 ACE2: accurate forced response

arXiv > physics > arXiv:2202.11214 Search... Help | Adv

Physics > Atmospheric and Oceanic Physics

NVIDIA

[Submitted on 22 Feb 2022]

FourCastNet: A Global Data-driven High-resolution Weather Model using Adaptive Fourier Neural Operators

Jaideep Pathak, Shashank Subramanian, Peter Harrington, Sanjeev Raja, Ashesh Chattopadhyay, Morteza Mardani, Thorsten Kurth, David Hall, Zongyi Li, Kamyar Azizzadenesheli, Pedram Hassanzadeh, Karthik Kashinath, Animashree Anandkumar

2022/02 FourCastNet: deterministic

arXiv > physics > arXiv:2405.13063 Search... Help | Adva

Physics > Atmospheric and Oceanic Physics

[Submitted on 20 May 2024 (v1), last revised 21 Nov 2024 (this version, v3)]

A Foundation Model for the Earth System

Microsoft

Cristian Bodnar, Wessel P. Bruinsma, Ana Lucic, Megan Stanley, Anna Vaughan, Johannes Brandstetter, Patrick Garvan, Maik Riechert, Jonathan A. Weyn, Haiyu Dong, Jayesh K. Gupta, Kit Thambiratnam, Alexander T. Archibald, Chun-Chieh Wu, Elizabeth Heider, Max Welling, Richard E. Turner, Paris Perdikaris

2024/05 Aurora: includes air pollution, ocn waves

nature

Article | Open access | Published: 04 December 2024

Google DeepMind

Probabilistic weather forecasting with machine learning

Ilan Price, Alvaro Sanchez-Gonzalez, Ferran Alet, Tom R. Andersson, Andrew El-Kadi, Dominic Masters, Timo Ewalds, Jacklynn Stott, Shakir Mohamed, Peter Battaglia, Remi Lam & Matthew Willson

Nature 637, 84–90 (2025) | 2024/12 GenCast: ensemble to 15 days

arXiv > cs > arXiv:2301.10343

Computer Science > Machine Learning

Microsoft

[Submitted on 24 Jan 2023 (v1), last revised 18 Dec 2023 (this version, v5)]

ClimaX: A foundation model for weather and climate

Tung Nguyen, Johannes Brandstetter, Ashish Kapoor, Jayesh K. Gupta, Aditya Grover

2023/01 ClimaX: NWP+climate

arXiv > physics > arXiv:2406.01465 Search... Help |

Physics > Atmospheric and Oceanic Physics

ECMWF

[Submitted on 3 Jun 2024 (v1), last revised 7 Aug 2024 (this version, v2)]

AIFS -- ECMWF's data-driven forecasting system

Simon Lang, Mihai Alexe, Matthew Chantry, Jesper Dramsch, Florian Pinault, Baudouin Raoult, Mariana C. A. Clare, Christian Lessig, Michael Maier-Gerber, Linus Magnusson, Zied Ben Bouallègue, Ana Prieto Nemesio, Peter D. Dueben, Andrew Brown, Florian Pappenberger, Florence Rabier

2024/06 AIFS: operational 2025/02

nature

Article | Published: 20 March 2025

UNIVERSITY OF CAMBRIDGE

End-to-end data-driven weather prediction

Anna Allen, Stratis Markou, Will Tebbutt, James Requeima, Wessel P. Bruinsma, Tom R. Andersson, Michael Herzog, Nicholas D. Lane, Matthew Chantry, J. Scott Hosking & Richard E. Turner

Nature (2025) | 2025/03 Aardvark: ingests raw observations

nature

Article | Open access | Published: 05 July 2023

HUAWEI HUAWEI CLOUD

Accurate medium-range global weather forecasting with 3D neural networks

Kaifeng Bi, Lingxi Xie, Hengheng Zhang, Xin Chen, Xiaotao Gu & Qi Tian

Nature 619, 533–538 (2023) 2023/07 Pangu: higher deterministic skill

nature

Article | Open access | Published: 22 July 2024

Google Research

Neural general circulation models for weather and climate

Dmitrii Kochkov, Janni Yuval, Ian Langmore, Peter Norgaard, Jamie Smith, Griffin Mooers, Milan Klöwer, James Lottes, Stephan Rasp, Peter Düben, Sam Hatfield, Peter Battaglia, Alvaro Sanchez-Gonzalez, Matthew Willson, Michael P. Brenner & Stephan Hoyer

Nature 632, 1060–1066 (2024) | 2024/07 NeuralGCM: hybrid GCM

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AI-driven global subseasonal predictions

nature communications

Article | Open access | Published: 30 July 2024

FUDAN UNIVERSITY

A machine learning model that outperforms conventional global subseasonal forecast models

Lei Chen, Xiaohui Zhong, Hao Li, Jie Wu, Bo Lu, Deliang Chen, Shang-Ping Xie, Libo Wu, Qingchen Chao, Chensen Lin, Zixin Hu & Yuan Qi

Nature Communications **15**, Article number: 6425 (2024) | 2024/07 FuXi-S2S: 42 days

arXiv > cs > arXiv:2411.10191

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Computer Science > Machine Learning

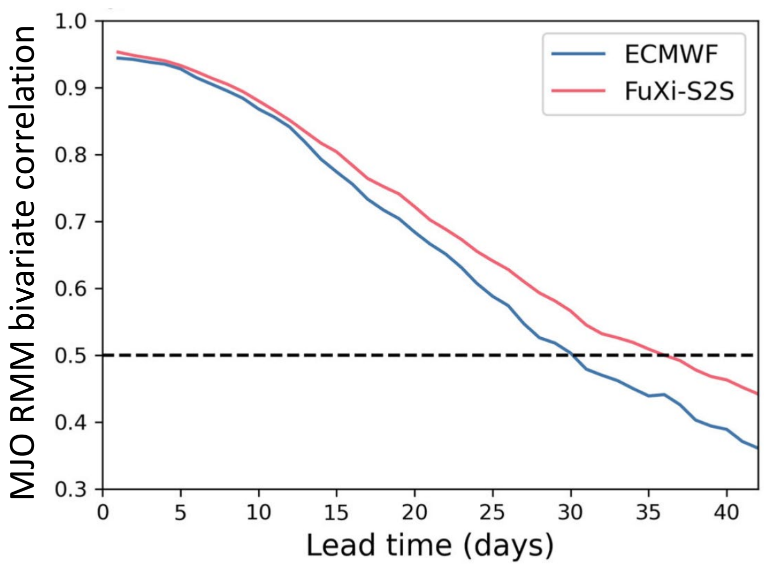
上海人工智能实验室 Shanghai Artificial Intelligence Laboratory

[Submitted on 15 Nov 2024 (v1), last revised 20 Nov 2024 (this version, v2)]

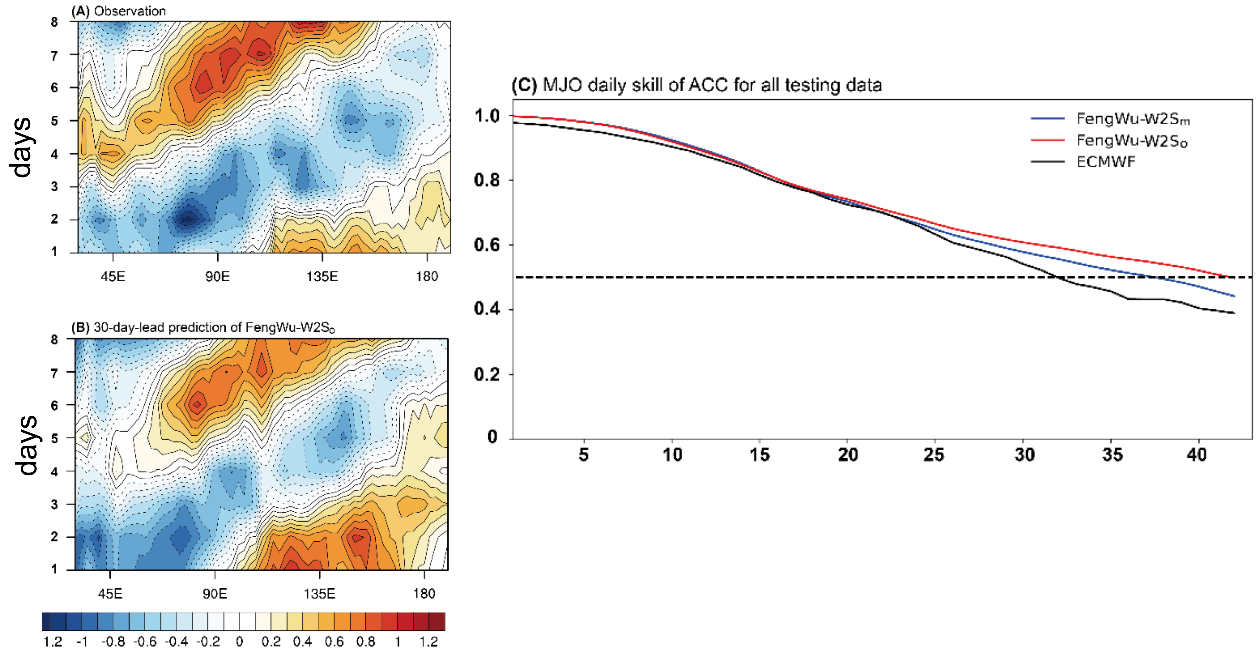
FengWu-W2S: A deep learning model for seamless weather-to-subseasonal forecast of global atmosphere

Fenghua Ling, Kang Chen, Jiye Wu, Tao Han, Jing-Jia Luo, Wanli Ouyang, Lei Bai

2024/11 FengWu-W2S: 42 days, attention to surface coupling



Composite OLR anomalies 15°N-15°S



AI-driven global seasonal predictions

JAMES Journal of Advances in Modeling Earth Systems

Lawrence Livermore National Laboratory

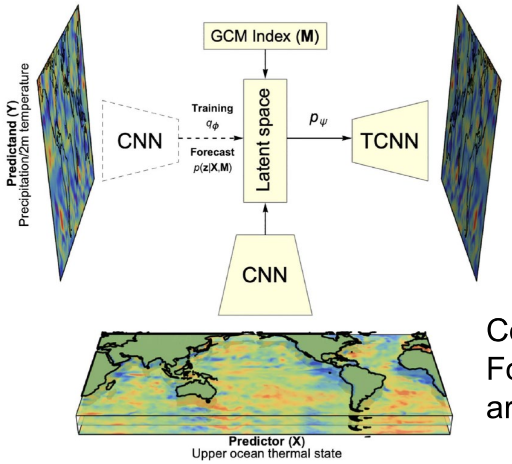
Research Article | Open Access

Improving Seasonal Forecast Using Probabilistic Deep Learning

Baoxiang Pan, Gemma J. Anderson, André Goncalves, Donald D. Lucas, Céline J. W. Bonfils, Jiwoo Lee

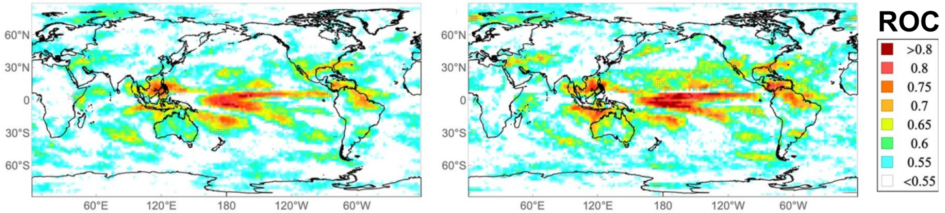
First published: 12 February 2022 | https://doi.org/10.1029/2021MS002766 | Citations: 7

2022/02 CMIP-based analogues



Conditional Generative Forecasting (CGF) architecture

ONDJFM precipitation from July



arXiv > physics > arXiv:2503.23953

Physics > Atmospheric and Oceanic Physics

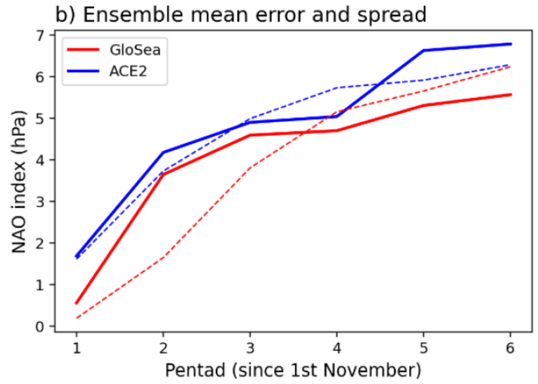
Met Office | Ai2

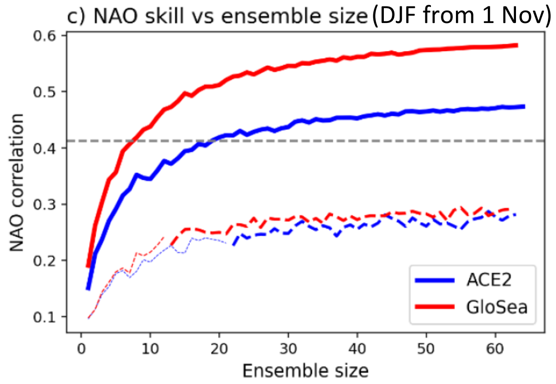
[Submitted on 31 Mar 2025]

Skilful global seasonal predictions from a machine learning weather model trained on reanalysis data

Chris Kent, Adam A. Scaife, Nick J. Dunstone, Doug Smith, Steven C. Hardiman, Tom Dunstan, Oliver Watt-Meyer

2025/03 ACE2: 4 months (2-tier)





Toward AI-driven global multi-year to decadal predictions

arXiv > physics > arXiv:2405.15412

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Physics > Atmospheric and Oceanic Physics

復旦大學 FUDAN UNIVERSITY

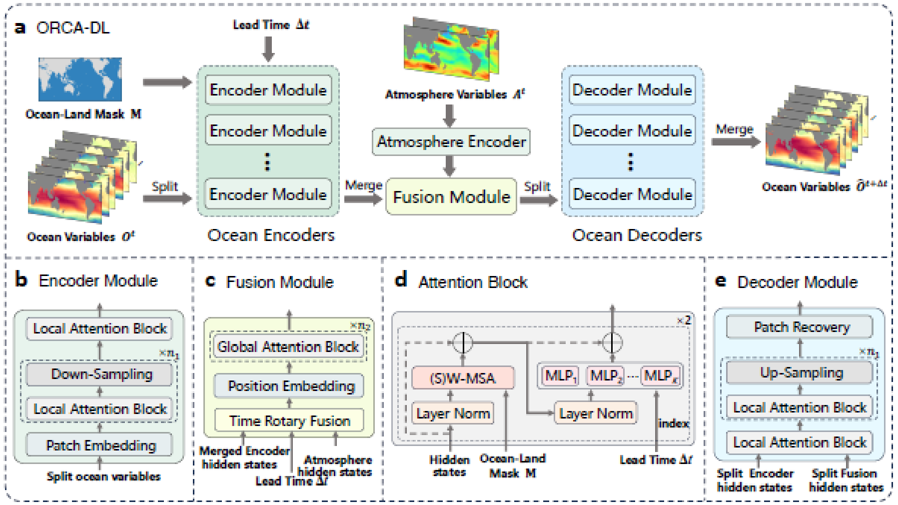
上海人工智能实验室 Shanghai Artificial Intelligence Laboratory

[Submitted on 24 May 2024 (v1), last revised 29 Oct 2024 (this version, v2)]

Data-driven Global Ocean Modeling for Seasonal to Decadal Prediction

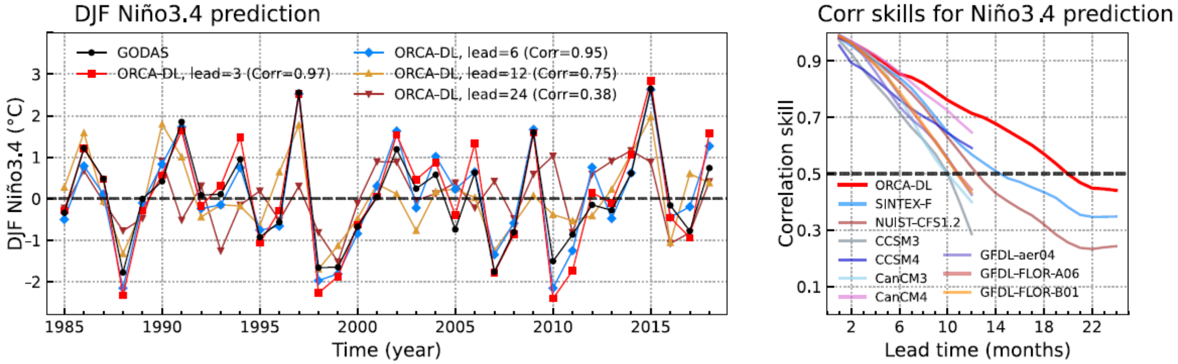
Zijie Guo, Pumeng Lyu, Fenghua Ling, Lei Bai, Jing-Jia Luo, Niklas Boers, Toshio Yamagata, Takeshi Izumo, Sophie Cravatte, Antonietta Capotondi, Wanli Ouyang

2024/05 ORCA-DL: data-driven 3D ocean model for S2D prediction

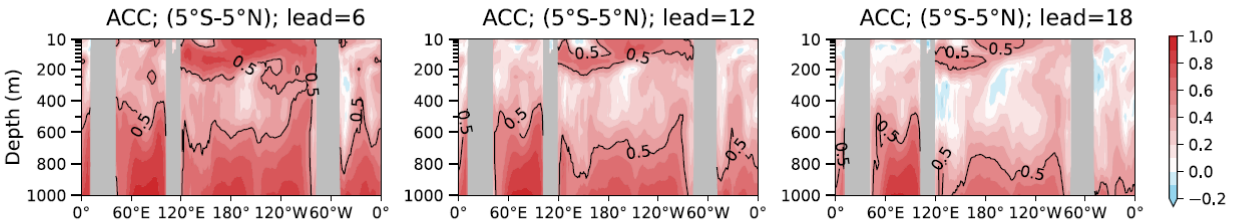


- Trained on 20 CMIP6 models
- SODA/ORAS5 pre-1980 for parameter tuning
- GODAS post-1980 for verification
- Does not yet treat changes in radiative forcing

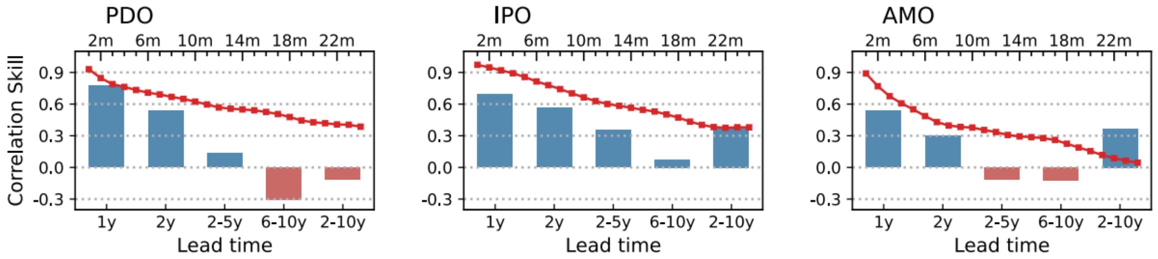
Multi-year ENSO skill



Near equatorial subsurface temperature skill



Multi-year to decadal climate mode skill



AI for km-scale downscaling

arXiv > physics > arXiv:2410.01776

Physics > Atmospheric and Oceanic Physics

Google Research

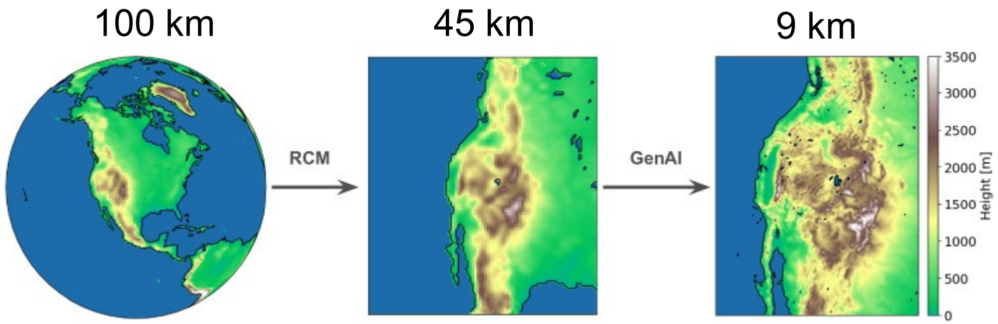
[Submitted on 2 Oct 2024]

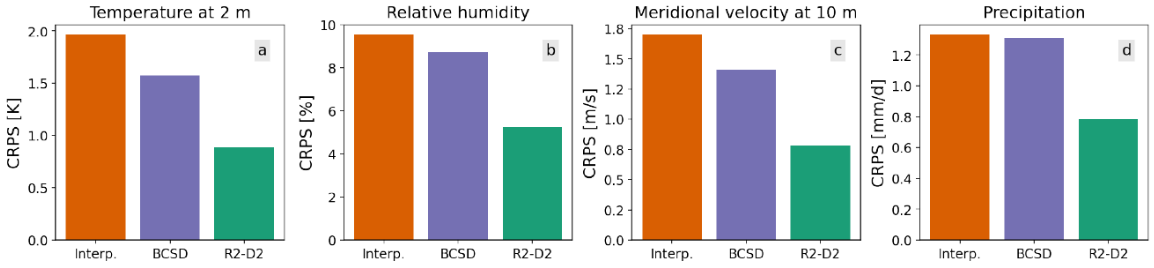
Dynamical-generative downscaling of climate model ensembles

Ignacio Lopez-Gomez, Zhong Yi Wan, Leonardo Zepeda-Núñez, Tapio Schneider, John Anderson, Fei Sha

2024/10 ESM→RCM→generative diffusion

- Trained on 45km→9km WRF differences
- CRPS greatly improved vs interpolated 45km and BCSD





communications earth & environment

NVIDIA

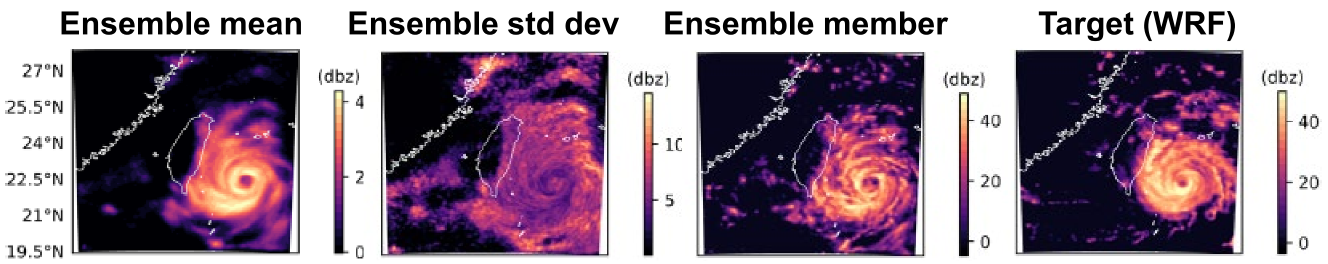
Article | Open access | Published: 24 February 2025

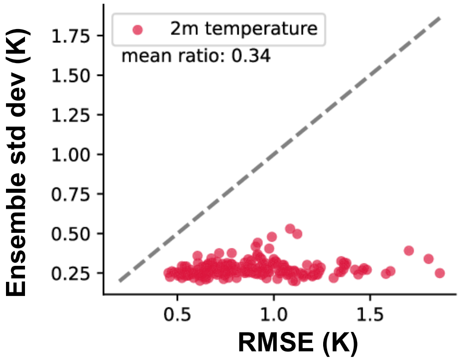
Residual corrective diffusion modeling for km-scale atmospheric downscaling

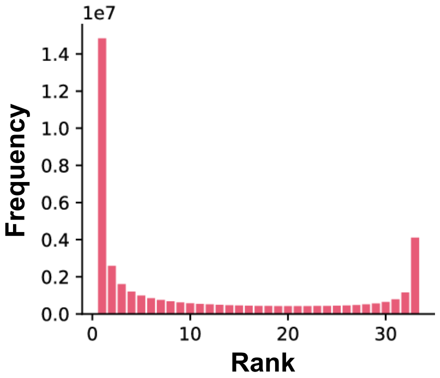
Morteza Mardani, Noah Brenowitz, Yair Cohen, Jaideep Pathak, Chieh-Yu Chen, Cheng-Chin Liu, Arash Vahdat, Mohammad Amin Nabian, Tao Ge, Akshay Subramaniam, Karthik Kashinath, Jan Kautz & Mike Pritchard

2025/02 25km→generative diffusion→2km

- Input: 25km reanalysis or dynamical/AI model data
- Training & verification data: input downscaled to 2km by WRF
- WRF spectra & PDFs reproduced well
- 32-member ensembles → overconfident, calibration remains a challenge





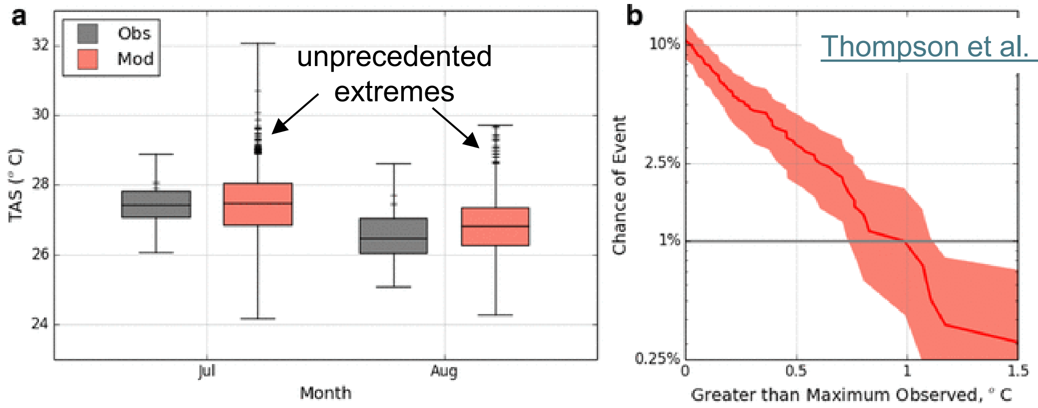


AI to probe realizable extremes

Non-AI approaches

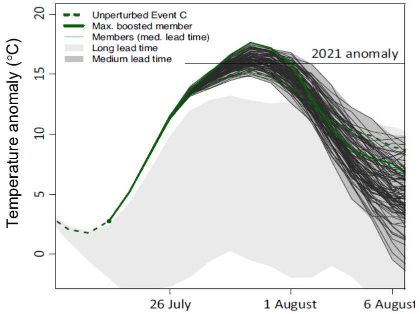
UNSEEN

- 1000s of validated seasonal/decadal hindcasts as independent realizations
- Example: chances of unprecedented hot months in South East China



Rare event algorithms/Ensemble boosting

- New ensembles successively bred from ensemble members trending toward extremes



Geophysical Research Letters

Research Letter | Free Access

Rare Event Algorithm Study of Extreme Warm Summers and Heatwaves Over Europe

F. Ragone, F. Bouchet

First published: 08 June 2021 | https://doi.org/10.1029/2020GL091197 | Citations: 19

nature communications

Perspective | Open access | Published: 22 August 2023

Storylines for unprecedented heatwaves based on ensemble boosting

E. M. Fischer, U. Beyerle, L. Bloin-Wibe, C. Gessner, V. Humphrey, F. Lehner, A. G. Pendergrass, S. Sippel, J. Zeder & R. Knutti

arXiv > cs > arXiv:2408.01581

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Computer Science > Machine Learning

Lawrence Berkeley National Laboratory

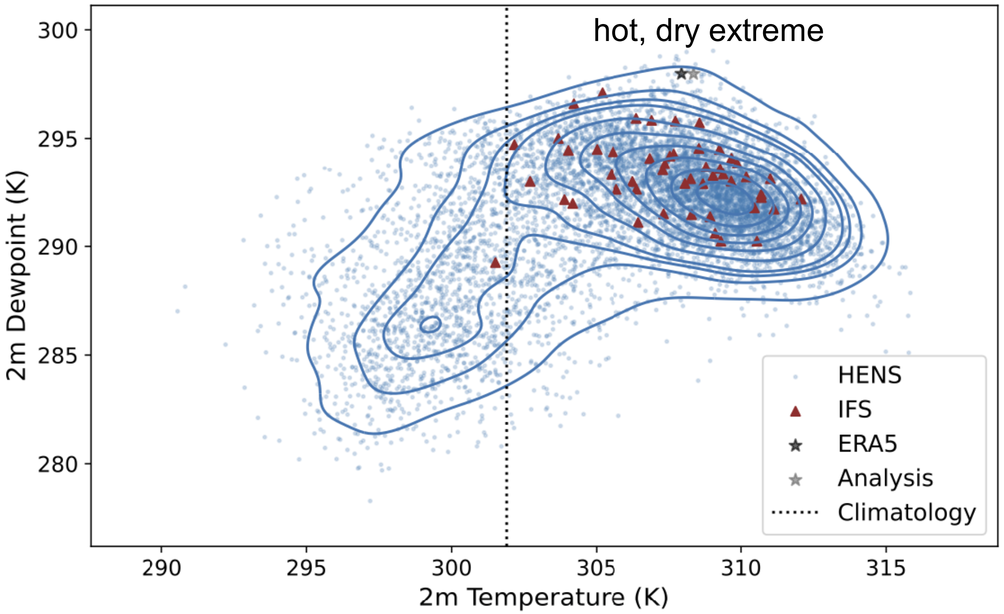
[Submitted on 2 Aug 2024 (v1), last revised 18 Feb 2025 (this version, v2)]

Huge Ensembles Part II: Properties of a Huge Ensemble of Hindcasts Generated with Spherical Fourier Neural Operators

Ankur Mahesh, William Collins, Boris Bonev, Noah Brenowitz, Yair Cohen, Peter Harrington, Karthik Kashinath, Thorsten Kurth, Joshua North, Travis OBrien, Michael Pritchard, David Pruitt, Mark Risser, Shashank Subramanian, Jared Willard

2024/08 Spherical Fourier Neural Operators→7424-member ensemble

- 15-day hindcasts initialized on each day of summer 2023
- Improved characterization of extreme quantiles (if reliable)



Large language models as a source of climate prediction information

Current utility of LLM: A test

Chatbot A

Are there any seasonal forecasts of heating and cooling degree days?

Yes, there are seasonal forecasts of heating and cooling degree days. Here's a breakdown of what they are and where you can find them:

Degree Days Outlook – Climate Prediction Center – NOAA

https://www.cpc.ncep.noaa.gov/pacdir/DDdir/N1.html

- **Understanding Heating and Cooling Degree Days: …**
- **Seasonal Forecasts: …**
- **Where to find information: …**

✓

Large language models as a source of climate prediction information

Current utility of LLM: A test

Chatbot B*

Are there any seasonal forecasts of heating and cooling degree days?

…

- **Heating Degree Days (HDD):**
- HDD are calculated by subtracting average daily temperature from a base temperature, typically 18°C…HDD data is available through various sources:
  - **Historical Data: …**
  - **Seasonal Climate Forecasts:** While specific HDD forecasts are rare, general seasonal climate forecasts indicate temperature trends. For instance, the Old Farmer's Almanac provides a 60-day extended weather forecast for Victoria, which includes temperature predictions that can help estimate HDD.

*ca. Feb 2025

Large language models as a source of climate prediction information

Crop-specific general information

When is the best time to plant my corn crop?

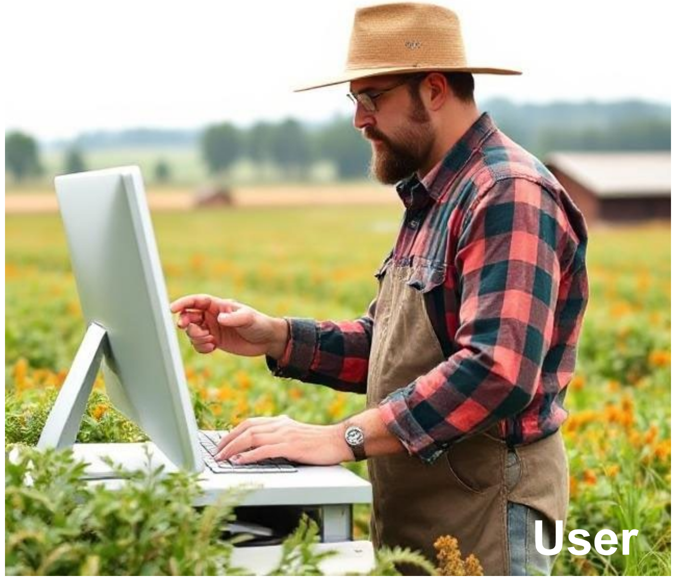
Determining the best time to plant corn involves considering several factors, primarily soil temperature and the risk of frost. Here's a breakdown of key considerations:

- **Soil Temperature:**
  - Corn seeds germinate best when soil temperatures are consistently between 50°F to 65°F (10°C to 18°C). For "super sweet" corn varieties, even warmer soil temperatures are preferred.
  - Planting in soil that's too cold can lead to poor germination and increased risk of seed rot.
- **Frost Risk:**
  - Corn is highly susceptible to frost damage, so it's crucial to wait until after the last expected spring frost in your area.
  - Paying attention to local frost dates and weather forecasts is essential.
- **…**
- "Plant after all danger of frost has passed" is a very common and very accurate rule of thumb.

In summary, prioritize waiting for consistently warm soil temperatures and ensuring the risk of frost has passed before planting your corn crop.

Toward individualized user-driven services

When is the best time to plant my corn crop?



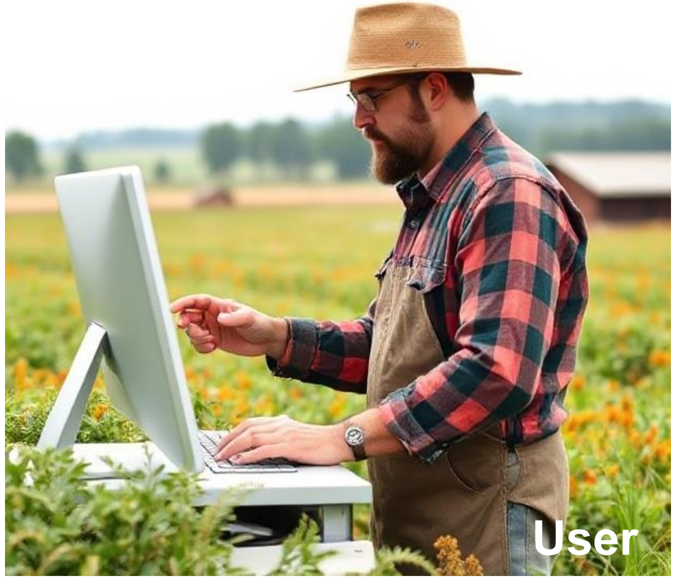
Toward individualized user-driven services

Antecedent soil moisture

Probability distribution of last frost

Probabilities of hot and dry spells

…



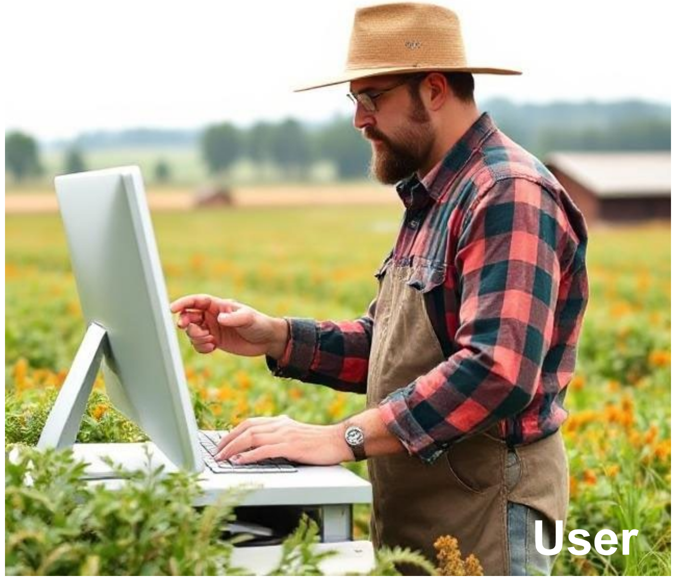
What is your exact location?

What is your tolerance for risk?

What is your capacity to irrigate?

…

Toward individualized user-driven services



Recommended courses of action

Decisions

Coming soon?

- AI-driven coupled Earth system models producing

  - seamless forecasts from weeks to a decade+

  - at km-scale resolution

  - including detailed assessment of low-probability high-impact event risks

- Integration of prediction data and chatbots to support user-specific applications (happening already with DestinE?)

- This will be a reality by _____________

Summary

- WCRP continues to facilitate advancements in subseasonal to decadal prediction in alignment with its strategic plan objective “Prediction of the near-term evolution of the climate system”

- Subseasonal to decadal prediction in a warming climate presents challenges due to
  - Evolution of climatic reference points
  - Model misrepresentation of regional and global trends
  - Potential for misinterpretation of forecast information such as deterministic ensemble means

- AI/ML is propelling extraordinarily rapid advancements
  - Advancements in weather prediction and climate modelling have begun to penetrate into subseasonal into decadal prediction
  - Services appear on the brink of being revolutionized by merging of Large Language Models and climate data
  - Assessments of AI/ML advances in weather and climate modelling and prediction are snapshots of a rapidly moving target