AfriClimate AI
AI for a Climate-Resilient Africa

IA para o tempo

Escola de verão CCAI

Shruti Nath | Rendani Mbuvha

Climate Change AI

UNIVERSITY OF THE WITWATERSRAND, JOHANNESBURG

1922 2022

UNIVERSITY OF OXFORD

Sobre a AfriClimate AI

Nossa missão

Promover a pesquisa em clima e IA na África:

Desenvolvendo competências locais

Formando pesquisadores e profissionais em todo o continente

P&D adaptado ao contexto

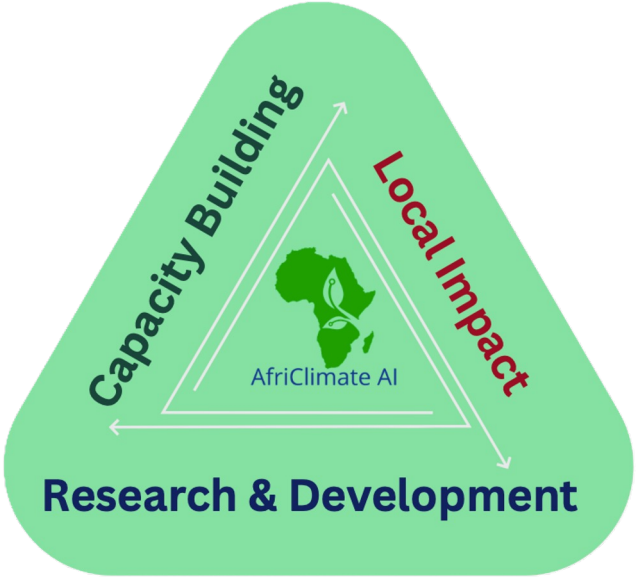
Pesquisa baseada nas realidades climáticas e socioeconômicas africanas

Implantação de soluções de IA

Do protótipo aos serviços climáticos operacionais

Dados locais

Melhorar o acesso a dados observacionais africanos de qualidade



Origens: o Deep Learning Indaba



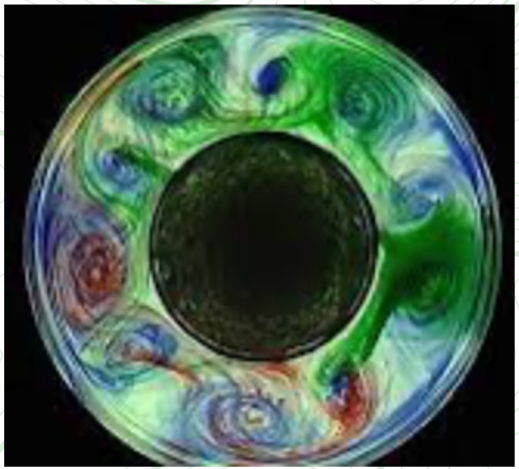
Deep Learning Indaba, Kigali 2025

Estrutura da aula

Parte A: previsão de curto prazo (“o tempo”)

Parte B: previsão de longo prazo (“previsões sazonais”)

O tempo como problema de valor inicial: na virada do século XX





Meteorologische Zeitschrift, Januar 1904.

Das Problem der Wettervorhersage, betrachtet vom Standpunkte der Mechanik und der Physik.

Von V. Bjerknes, Universität Stockholm.

Wenn es sich so verhält, wie jeder naturwissenschaftlich denkende Mann glaubt, daß sich die späteren atmosphärischen Zustände gesetzmäßig aus den vorhergehenden entwickeln, so erkennt man, daß die notwendigen und hinreichenden Bedingungen für eine rationelle Lösung des Prognoseproblems der Meteorologie die folgenden sind:

1. Man muß mit hinreichender Genauigkeit den Zustand der Atmosphäre zu einer gewissen Zeit kennen.

2. Man muß mit hinreichender Genauigkeit die Gesetze kennen, nach den sich der eine atmosphärische Zustand aus dem anderen entwickelt.

I.

Die Kenntnis des Zustandes der Atmosphäre zu passenden, übereingekommenen Zeiten zu schaffen, ist die Aufgabe der beobachtenden Meteorologie. In genügendem Umfange für eine rationelle Wettervorhersage ist diese

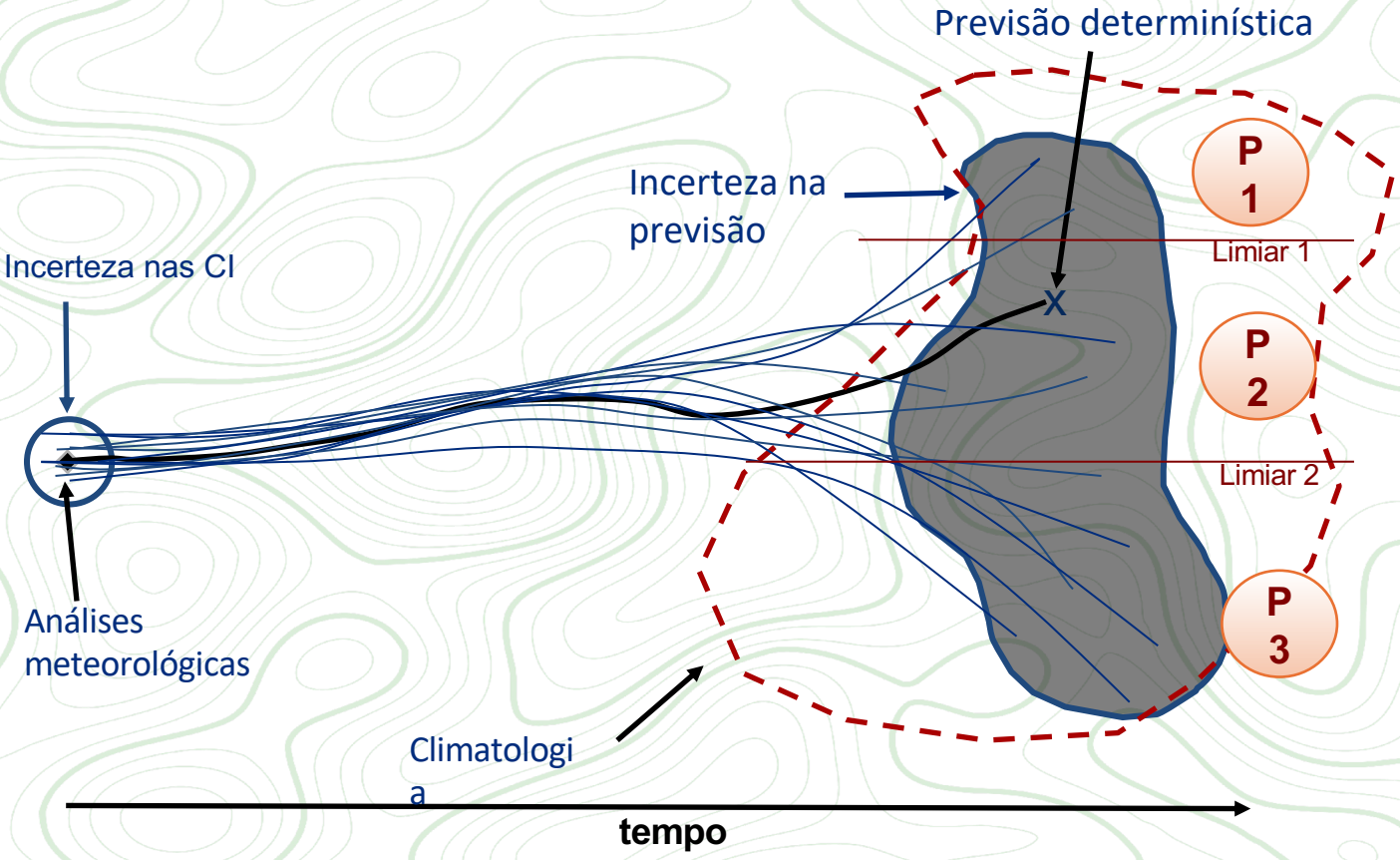
$$\frac{\delta \mathrm{v}}{\delta t} + (\mathrm{v} \cdot \nabla) \cdot \mathrm{v} = \frac{1}{\rho} \cdot \nabla p + v \cdot \Delta \mathrm{v} + \boldsymbol{f}$$

$$\Delta \mathrm{U} = \mathrm{Q} - \mathrm{W}$$

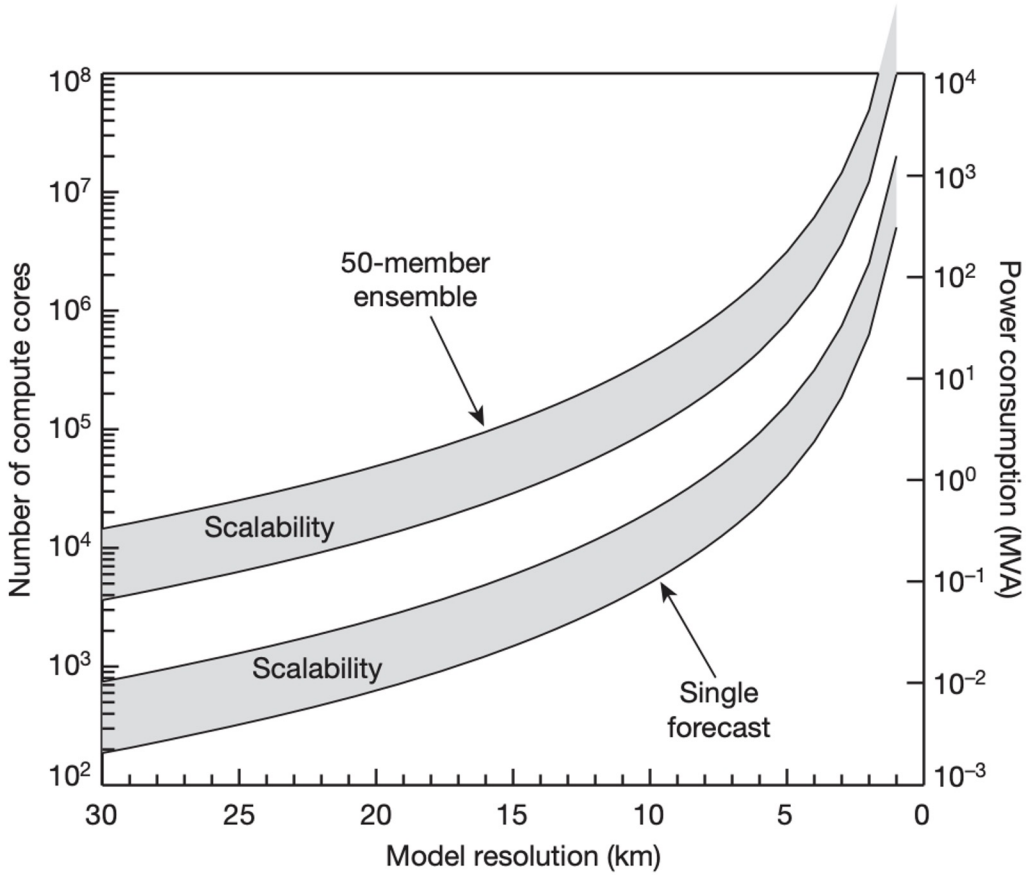
$$PV = nRT$$

Como são as previsões atuais?

Previsões probabilísticas



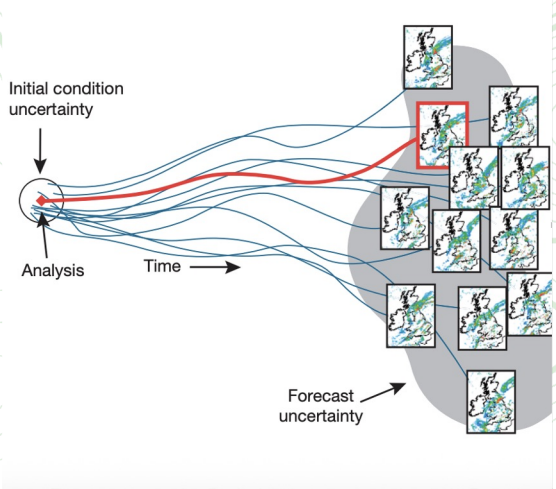
Capacidade de supercomputação desde 1970



REVIEW

The quiet revolution of numerical weather prediction

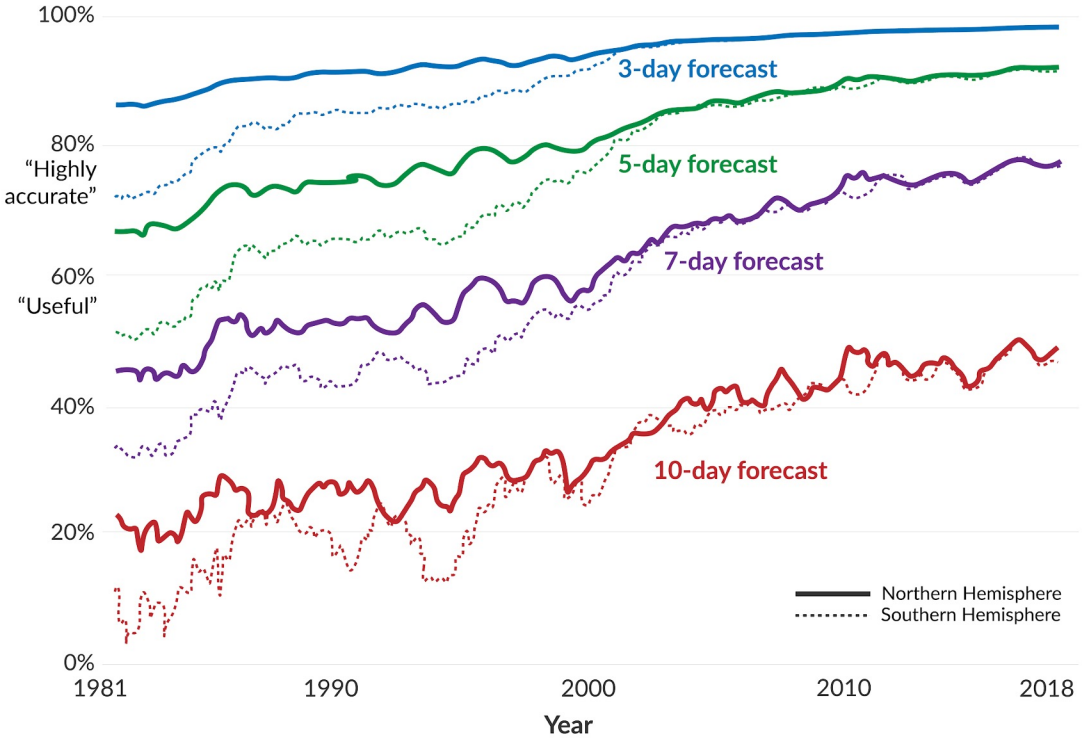
Peter Bauer[1], Alan Thorpe[1] & Gilbert Brunet[2]



The accuracy of weather forecasts has improved

Accuracy is measured as the difference between the forecast and subsequent weather. This is based on the '500 hPa geopotential height' which is a common meteorological metric used to measure air pressure.

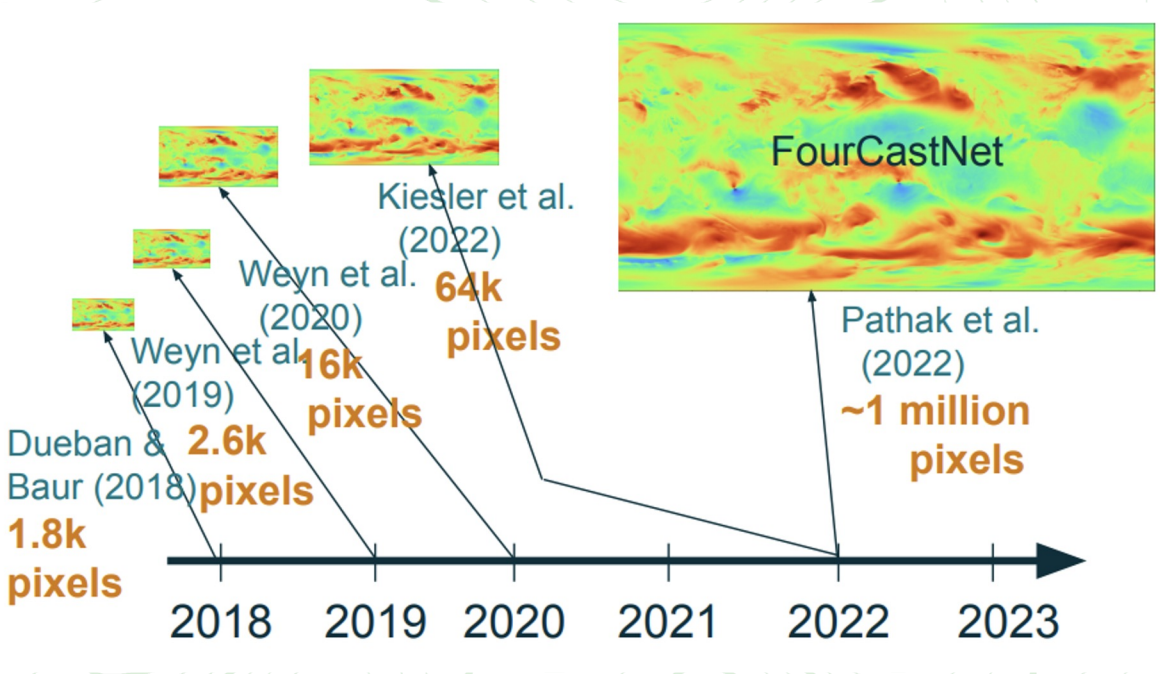
Our World in Data



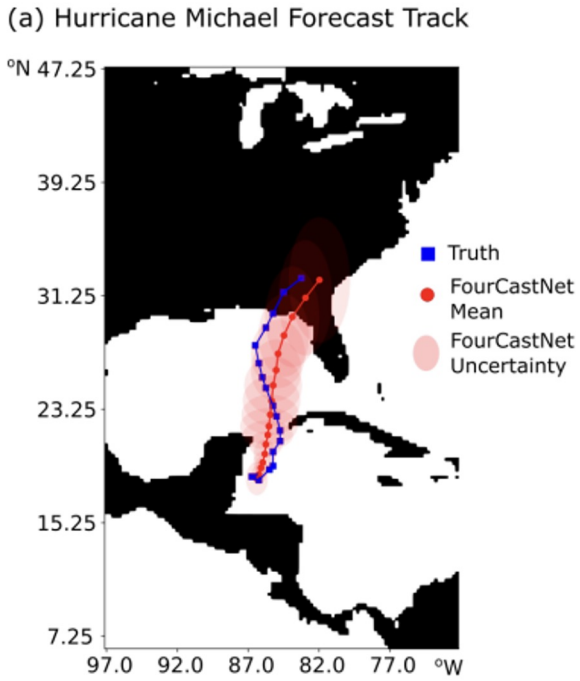
Source: European Centre for Medium-Range Weather Forecasts (ECMWF).

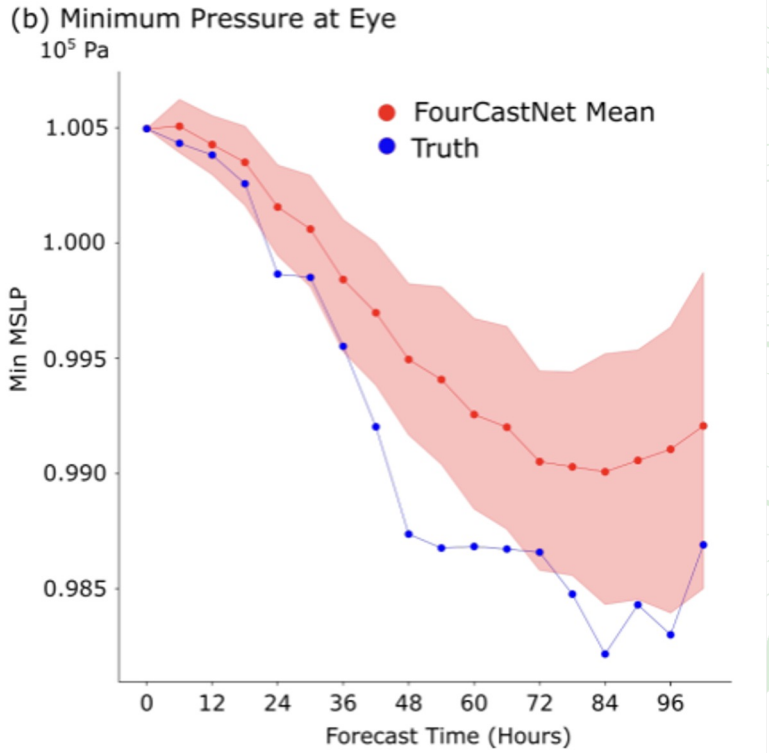
Licensed under CC-BY by the author Hannah Ritchie.

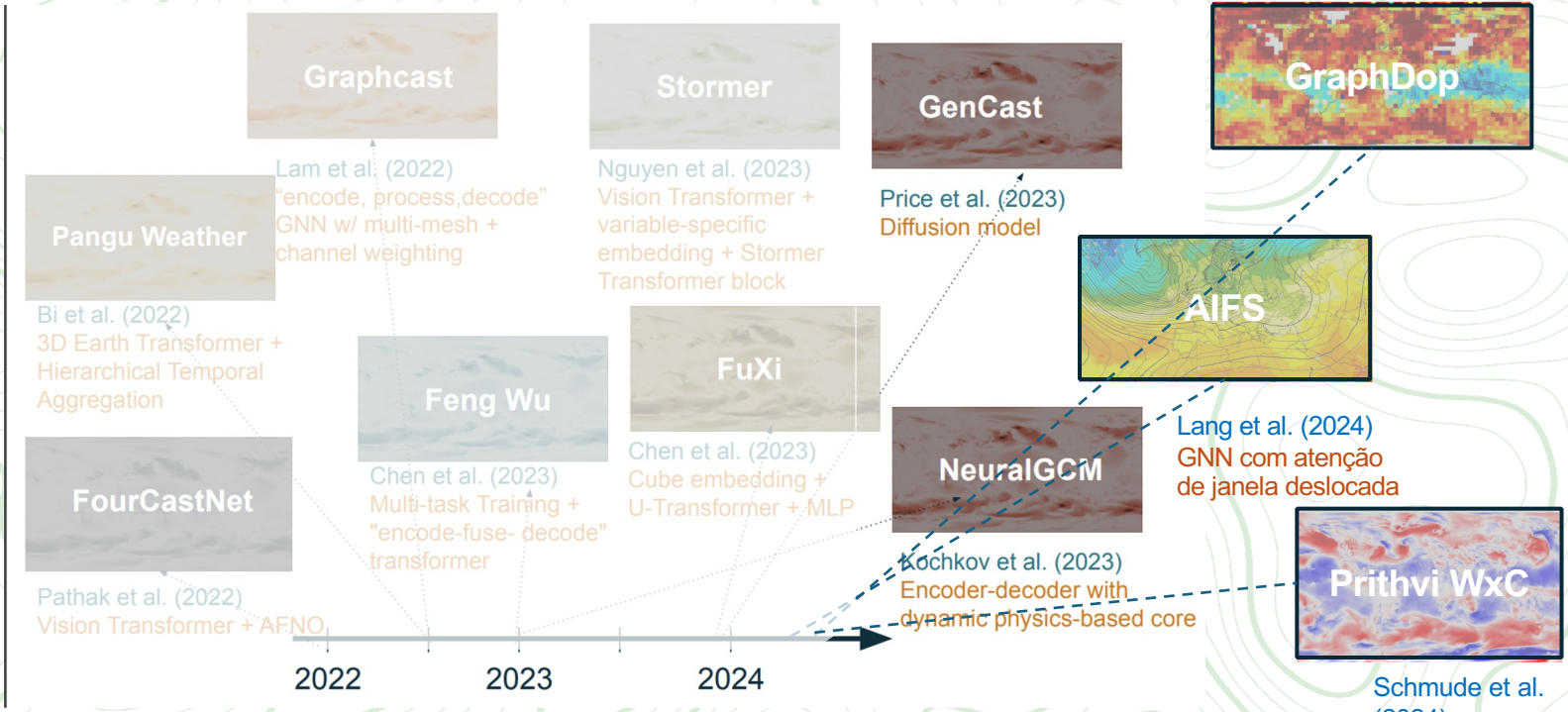
Trazendo o ruído: modelos de IA



A primeira prova de conceito: previsões do furacão Michael

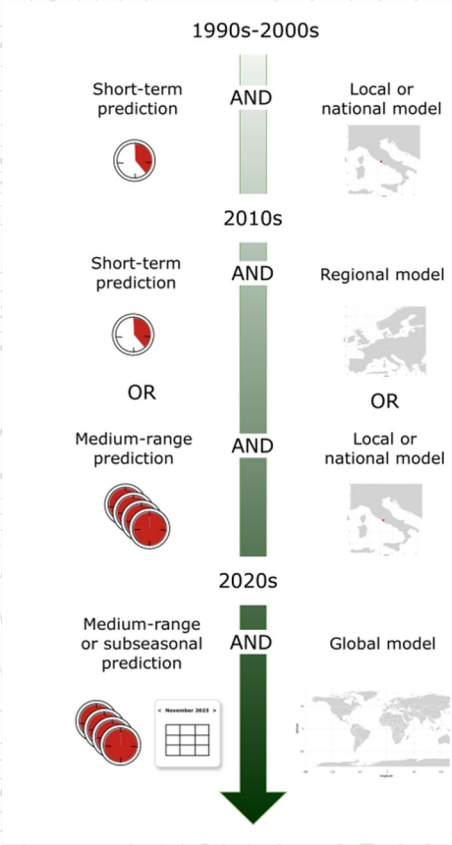


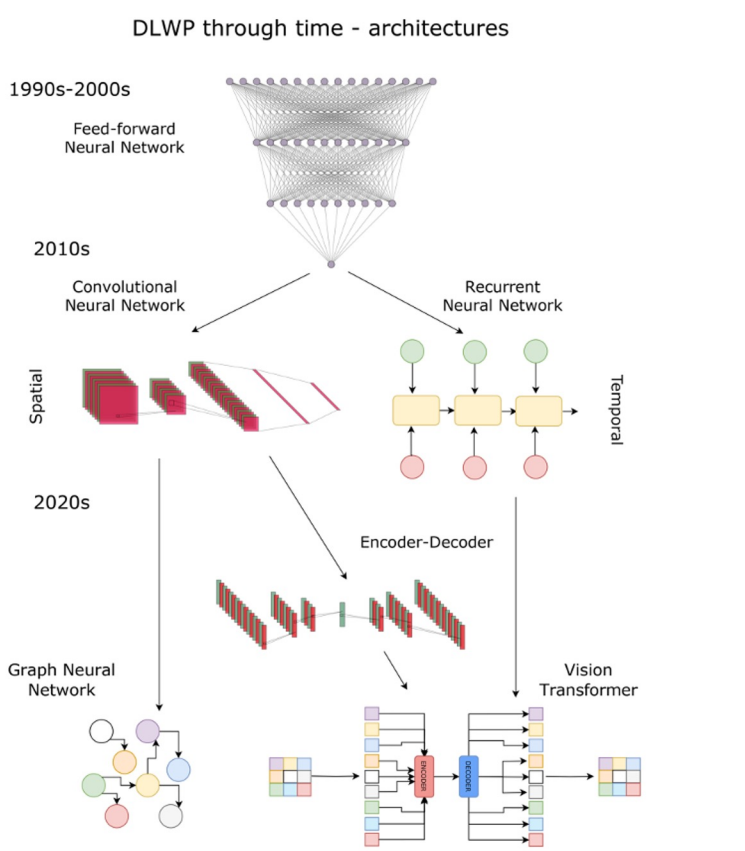




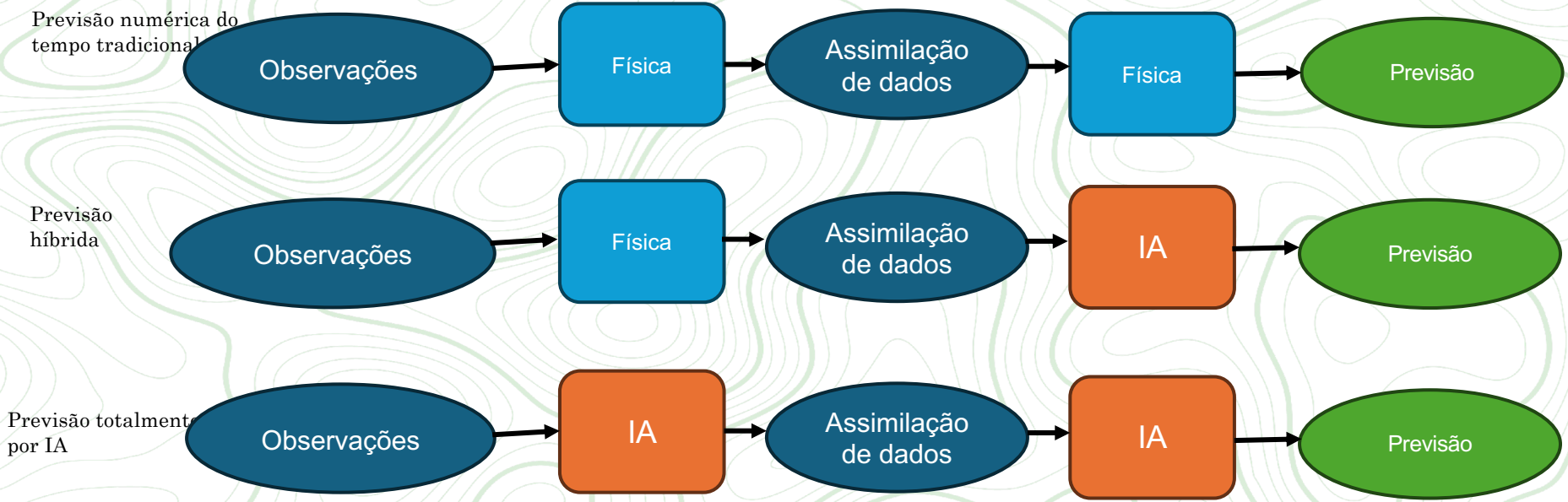
O desenvolvimento de modelos de IA parece se autoalimentar, estimulando cada vez mais avanços!

General timescales of developments

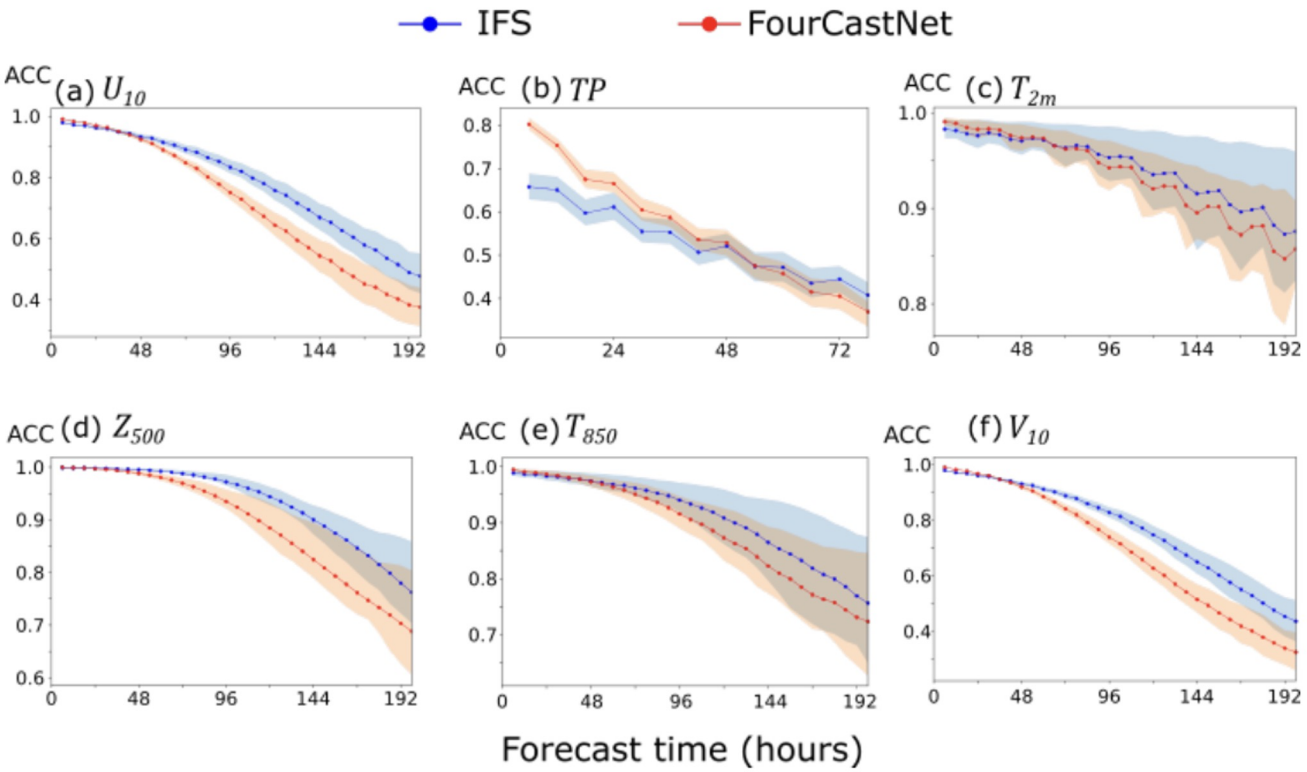




O futuro da IA?

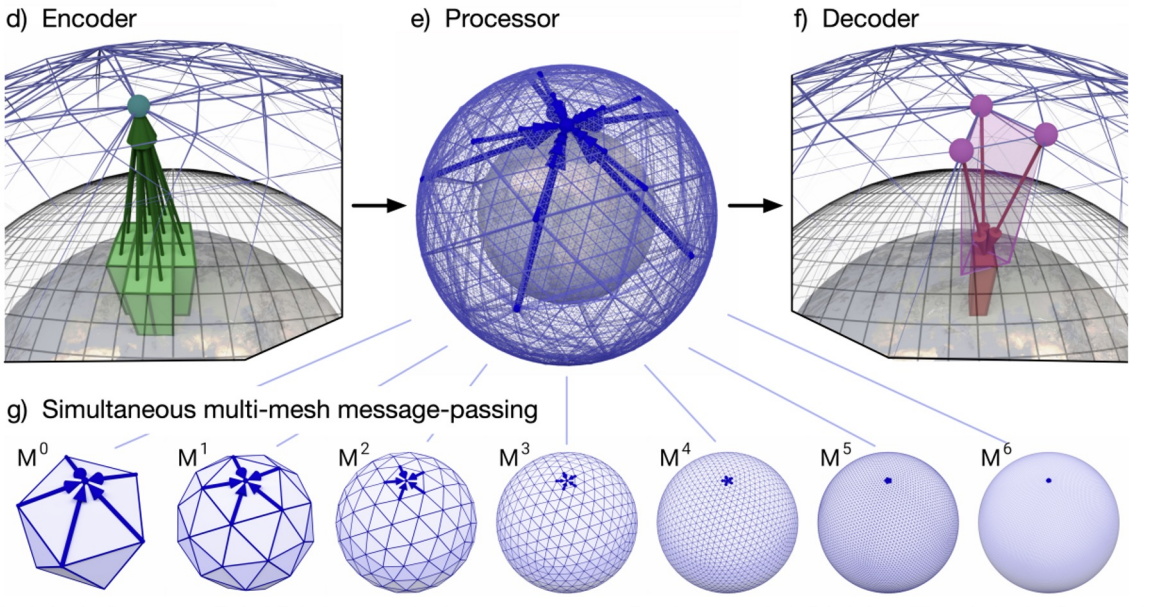


A precisão era comparável, mas se degradava com o tempo



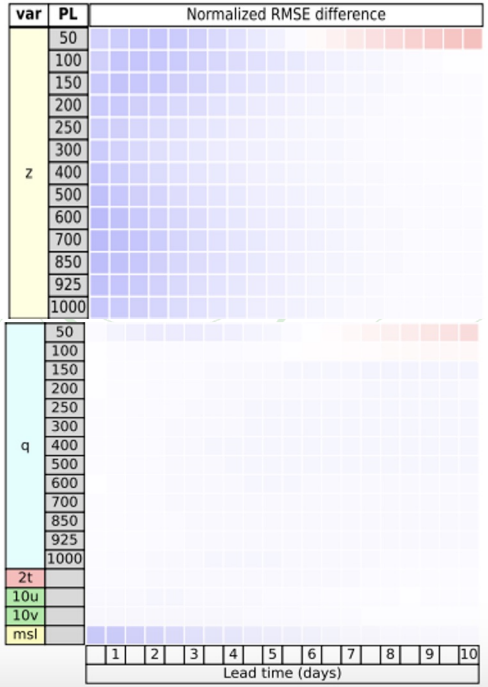
GraphCast

- O codificador aprende atributos dos nós transpostos da grade para a multimalha
- Multimalha feita por refinamento iterativo: icosaedro regular (12 nós, 20 faces, 30 arestas) refinado seis vezes
- O processador então faz a passagem de mensagens em 16 camadas GNN não compartilhadas
- Desdobramento semelhante ao do FourCastNet

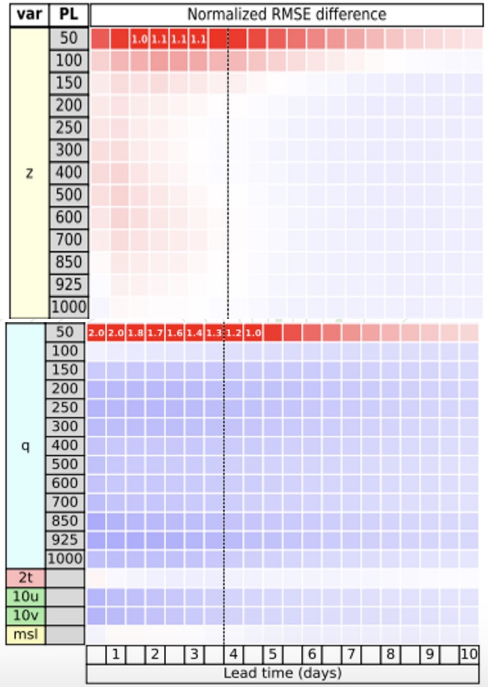


Estudos de ablação da multimalha

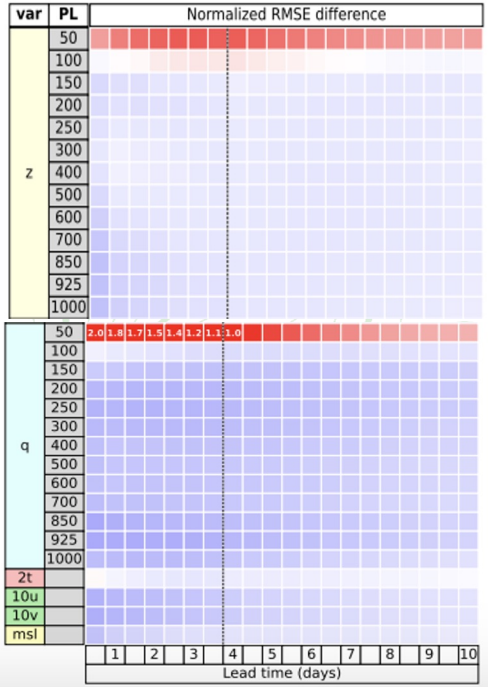
GraphCast – sem multimalha



Sem multimalha – HRES

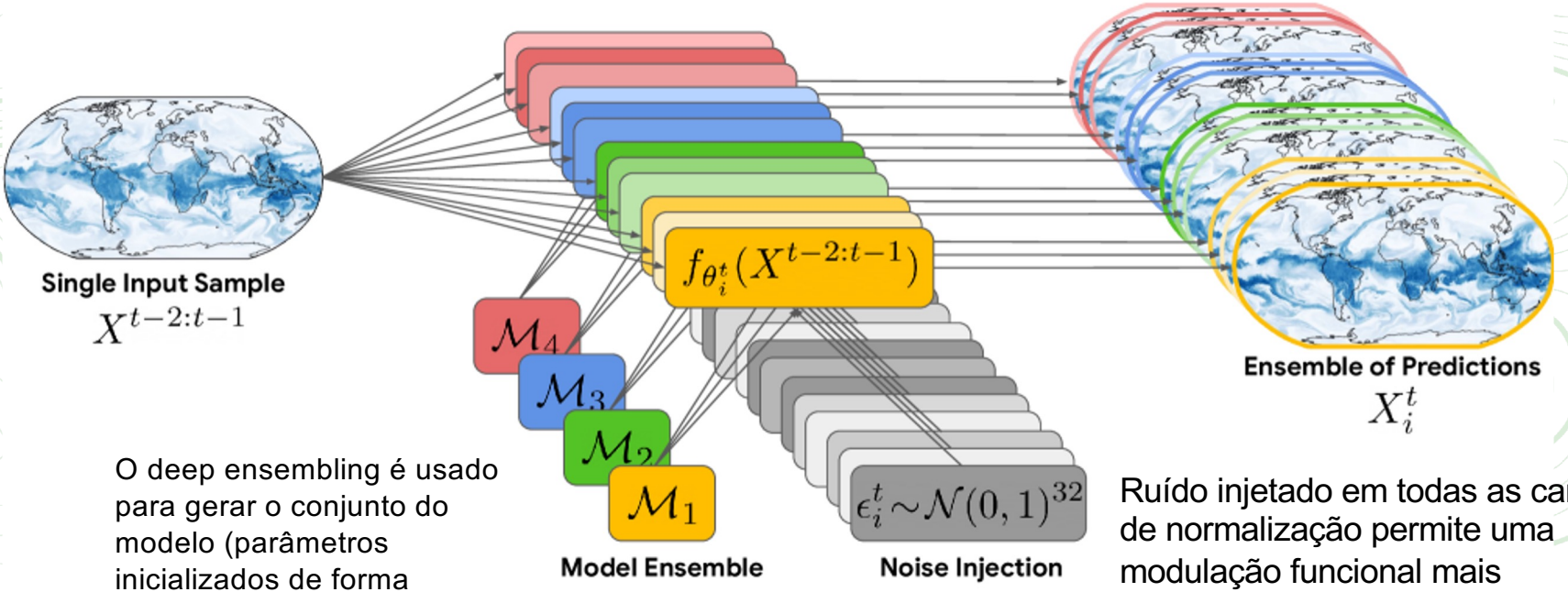


GraphCast – HRES



Azul é melhor

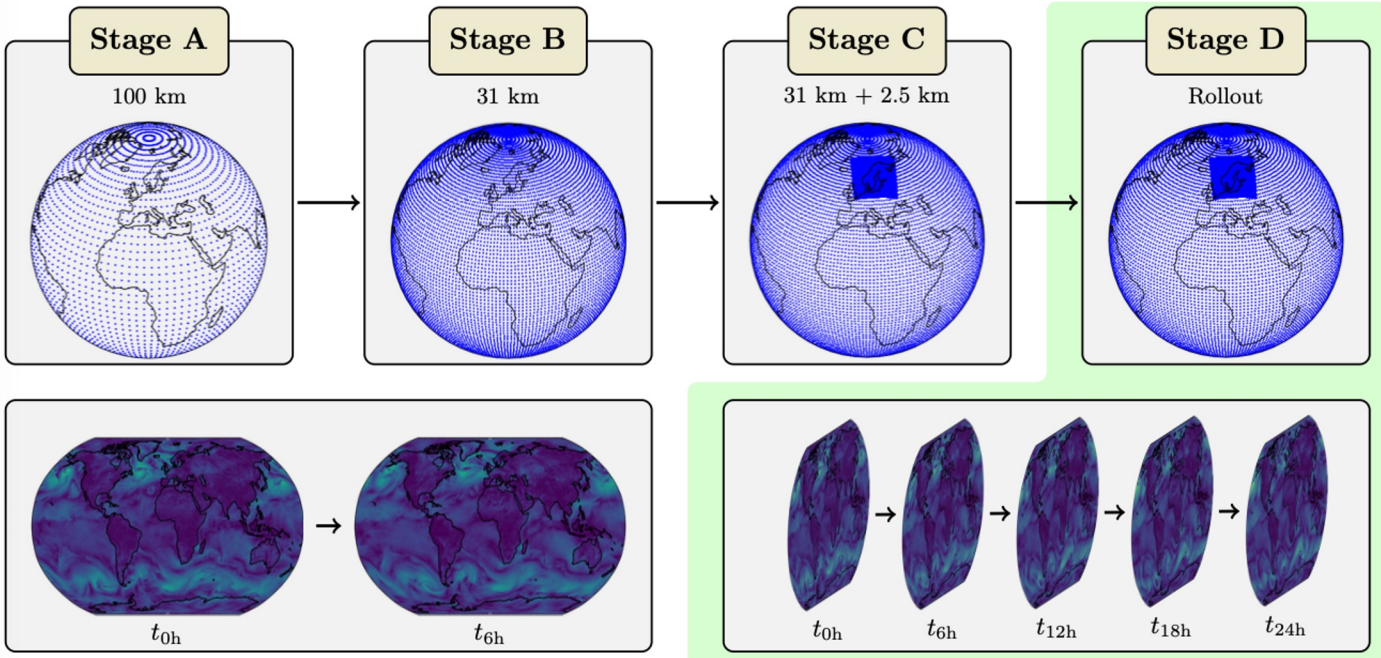
Por meio de deep ensembling e normalização condicional com parâmetros compartilhados



O deep ensembling é usado para gerar o conjunto do modelo (parâmetros inicializados de forma independente para vários modelos no treinamento)

Ruído injetado em todas as camadas de normalização permite uma modulação funcional mais estruturada entre camadas, mantendo a coerência espacial

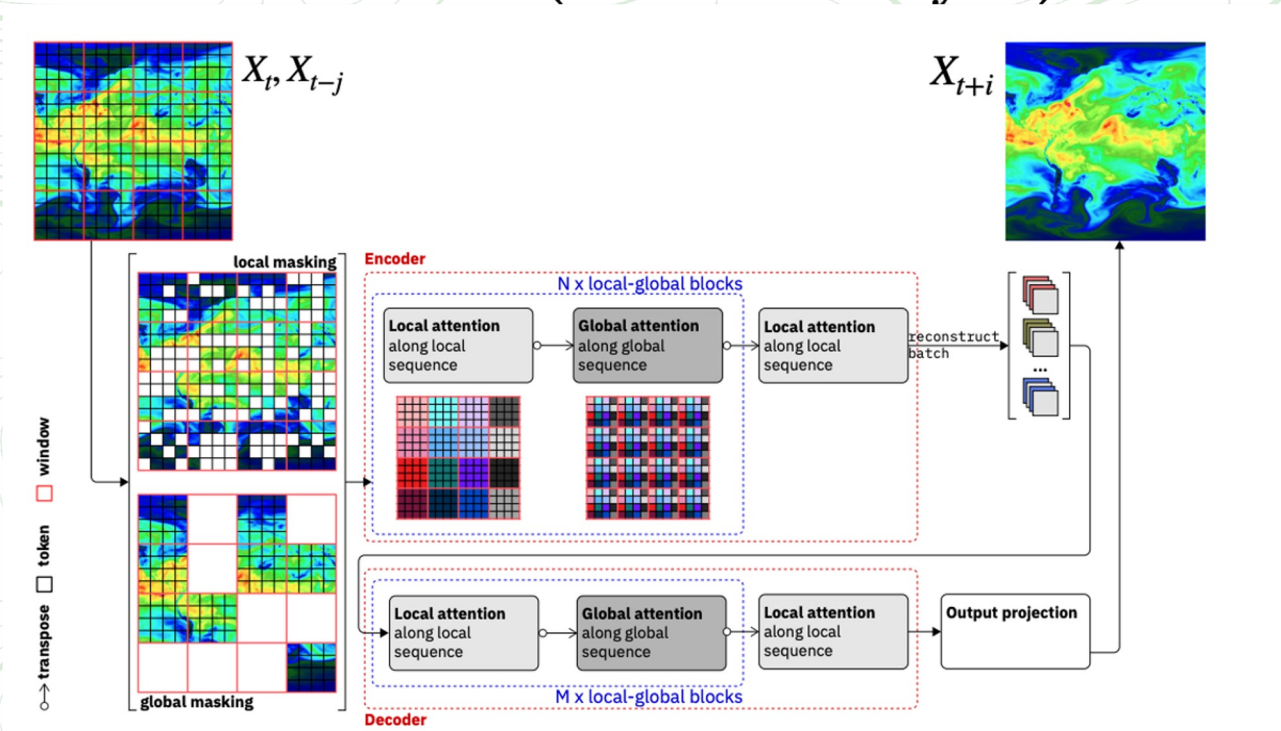
Graph transformers se adaptam facilmente a modelos de resolução variável



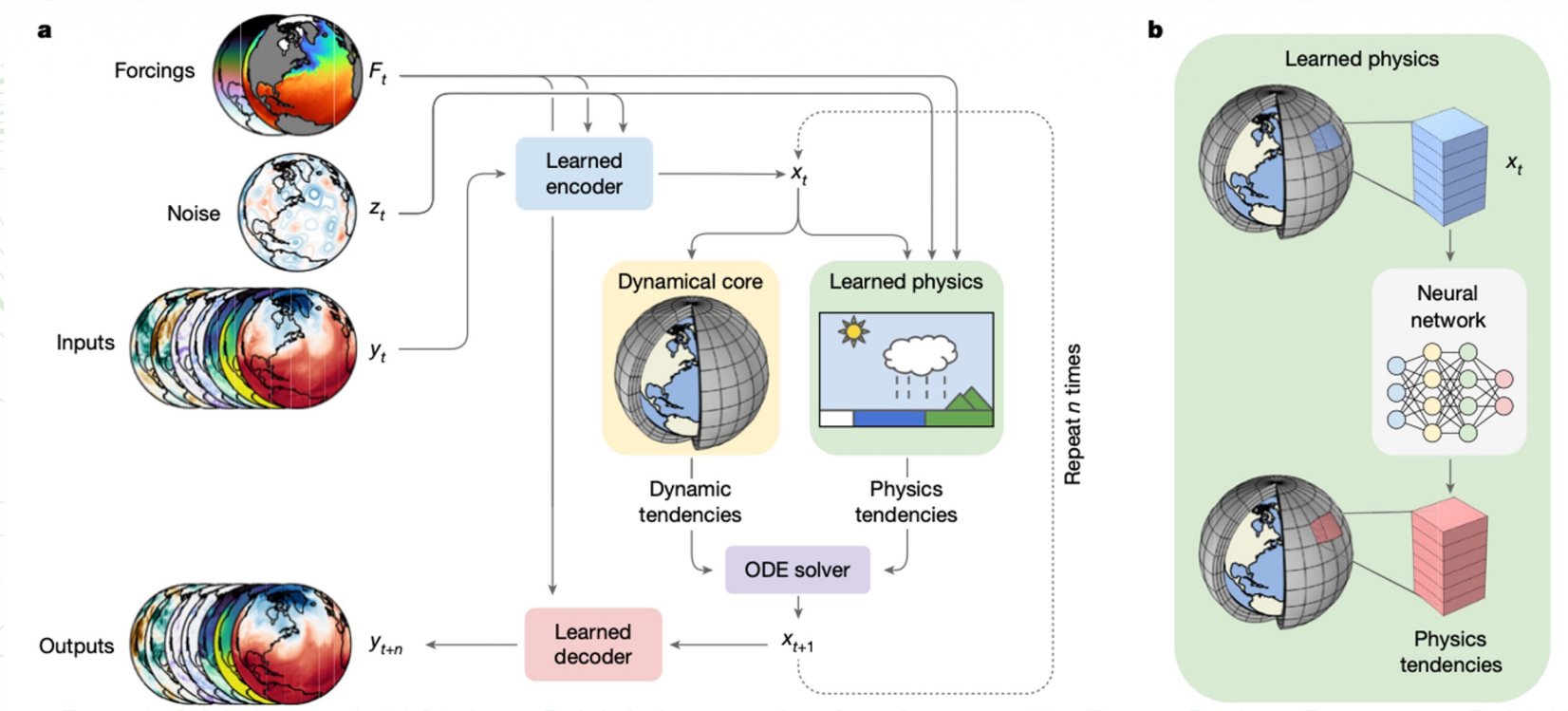
Prithvi WxC

https://arxiv.org/pdf/2409.13598

- Trained on MERRA-2 data (NASA reanalysis)



Hybrid approaches: fully learning all parameterizations



Esses modelos são úteis operacionalmente?

Fazendo comparações justas

- Para comparações justas, observamos que há diferentes tipos de previsão:
  - Determinísticas (ou seja, um único membro do conjunto)
  - Probabilísticas

- Os modelos de IA são treinados com ERA5; para a chuva isso nem sempre é realista, e é preciso corrigir em direção às estimativas de satélite

- A saída da previsão numérica baseada em física também deve ser corrigida em direção às estimativas de satélite

Como definir a utilidade de uma previsão?

- Any scoring rule $S(x, o)$ used to define the skill of a model's predicted outcomes $x \sim X$ against actual observations $o \sim Y$ is proper if

$$E[S(y, o)] \leq E[S(x, o)] \text{ for } y \sim Y$$

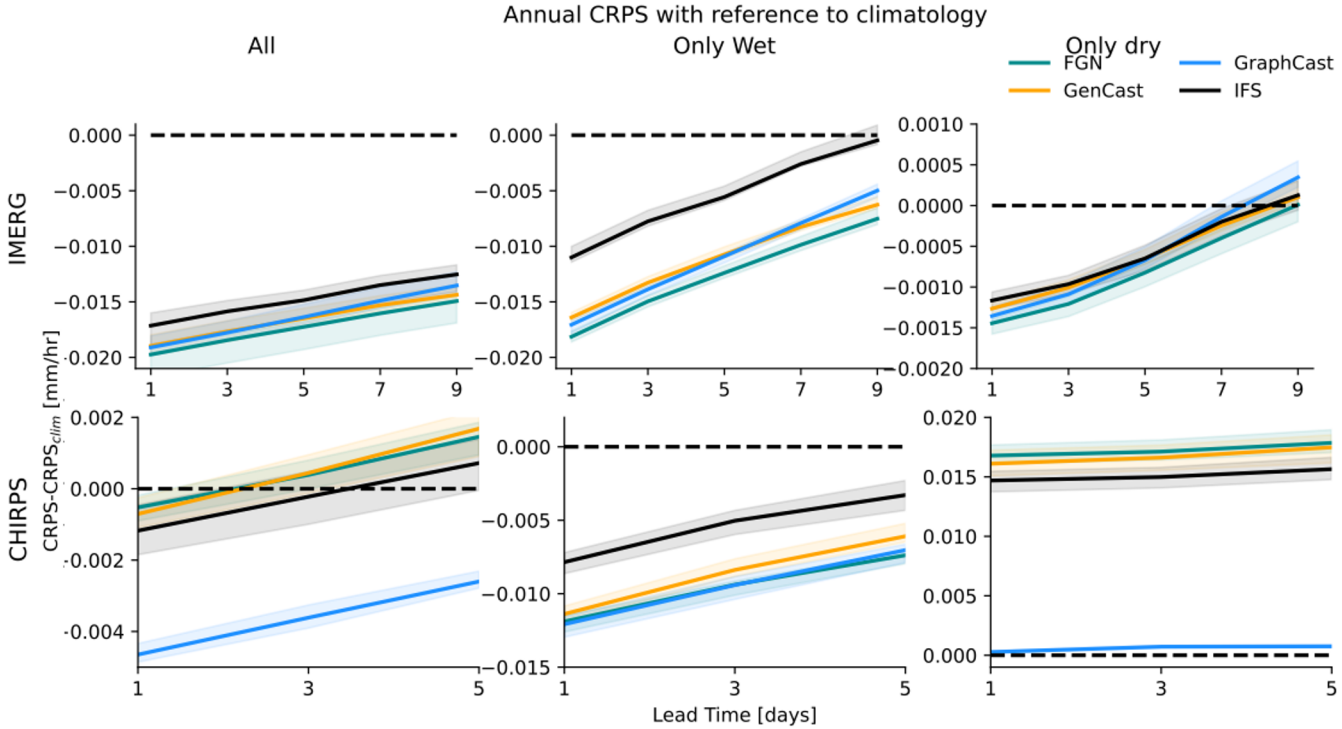
MAE, CRPS, Log-likelihood etc. are all proper scoring rules and can be broken down into

$$S_x = (S_x - S_{cal}) - (S_{ref} - S_{cal}) + S_{ref}$$

Descalibração | Discriminação | Incerteza

[1]Gneiting et al. (2025). https://doi.org/10.48550/arXiv.2506.03744

Antecedência de 1 e 9 dias

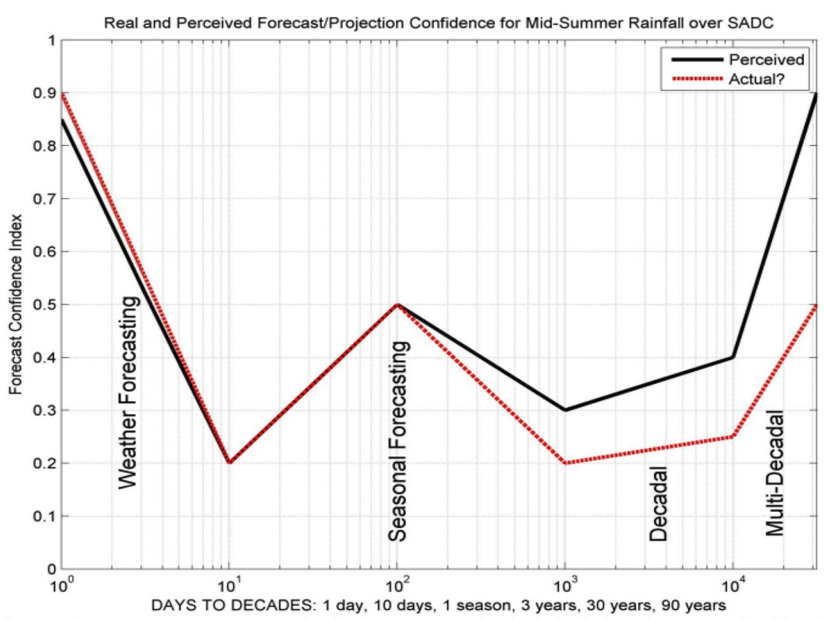


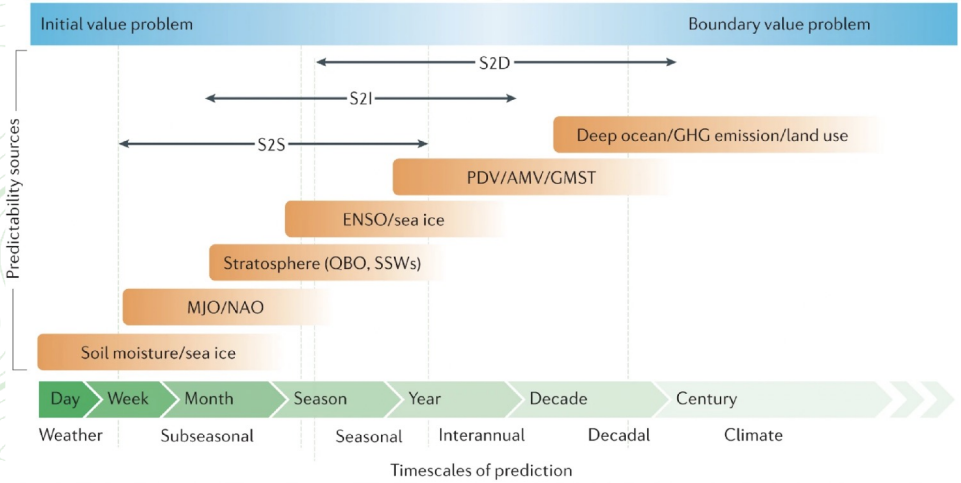
2024-2025 usados

Forecast 4Africa
by AfriClimate AI

O que é previsão sazonal?

Como serão os próximos 90 dias?

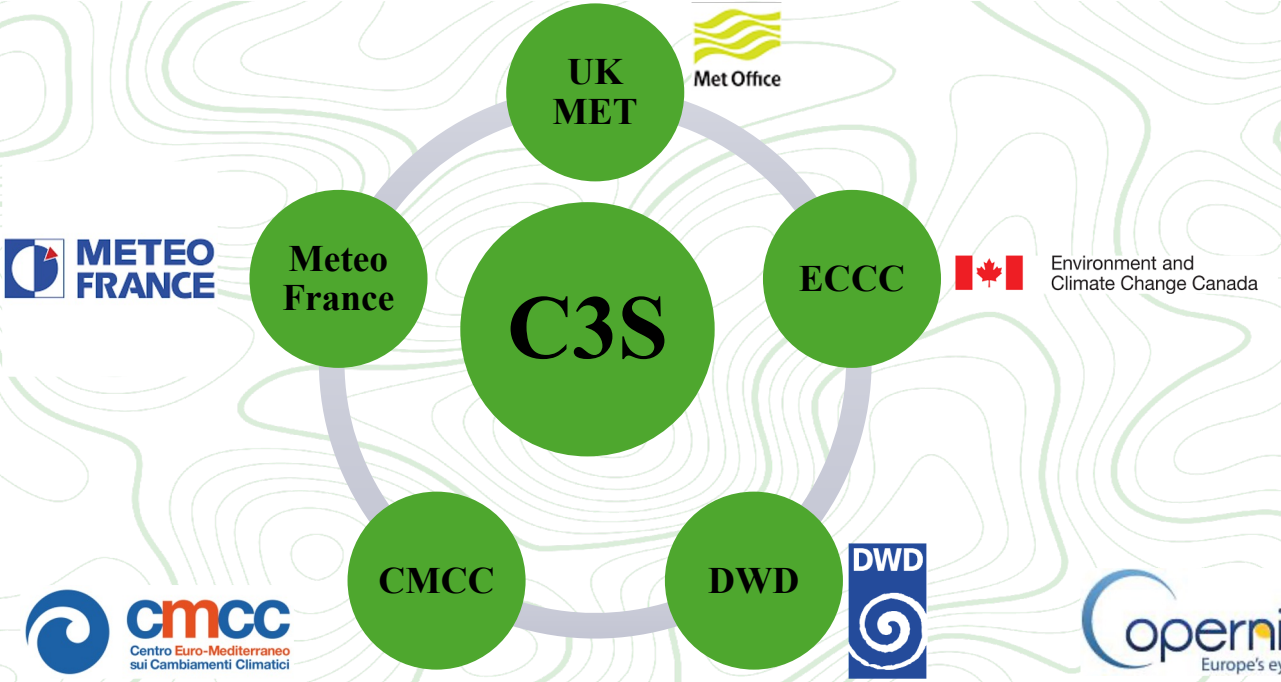




Fonte: Instituto Meteorológico Norueguês

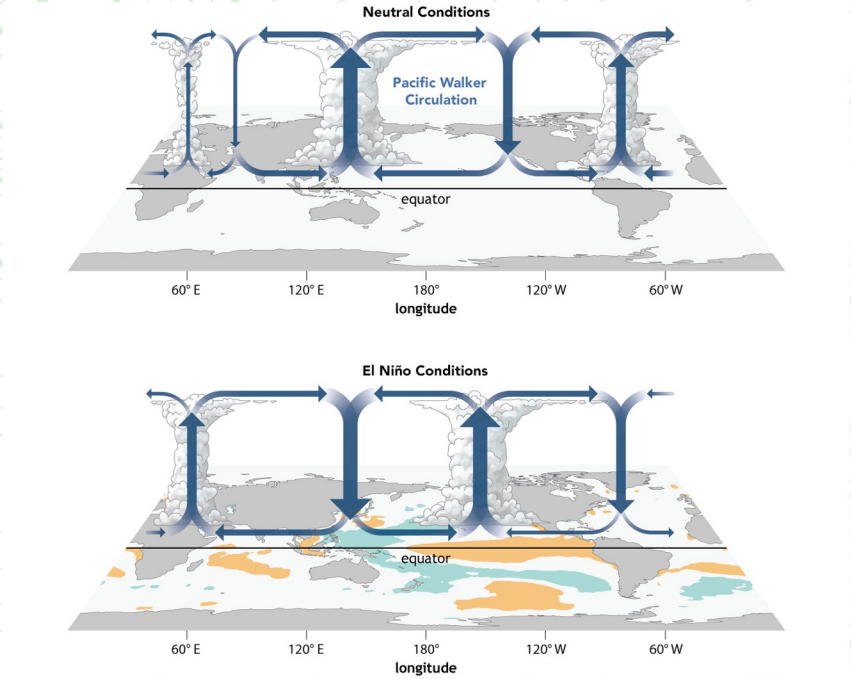
Modelos de previsão sazonal

Serviço de previsão sazonal do Serviço Copernicus para as Alterações Climáticas (C3S), operado pelo ECMWF

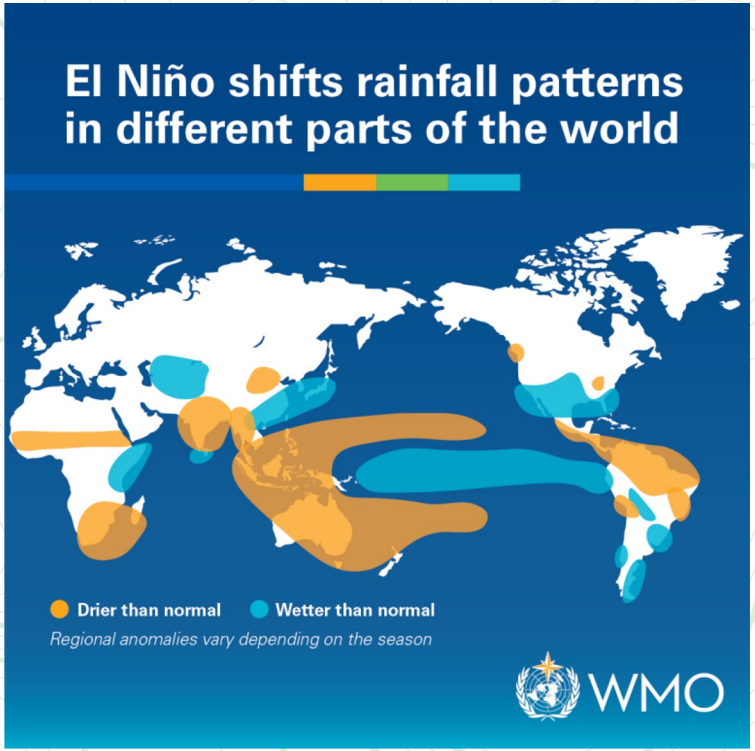




ENSO e as fontes de habilidade da previsão sazonal



A chegada do El Niño. Ilustração da NOAA/Climate.gov



Fonte: OMM e Lenssen, N. J. L., L. Goddard, and S. Mason, 2020: Seasonal Forec Skill of ENSO Teleconnection Maps. Wea. Forecasting, 35, 2387–2406

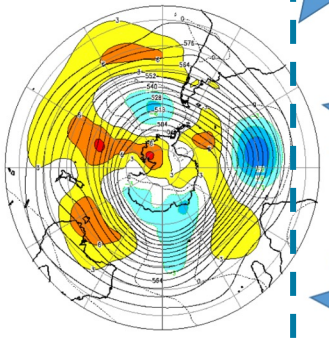
Importância da previsão sazonal

The prediction scheme

1. Phenomena to be predicted should contain a climate signal (e.g. ENSO) in the data; 2. Observed and model time series must be over sufficiently long enough periods so that robust statistical relationship can be developed; 3. and some form of quality control of the observed data had taken place.



ECHAM4.5-MOM3-DC2 ocean-atmosphere GCM



Geopotential heights/ rainfall, etc.

Alguma função de transferência



Riverflow



Malaria



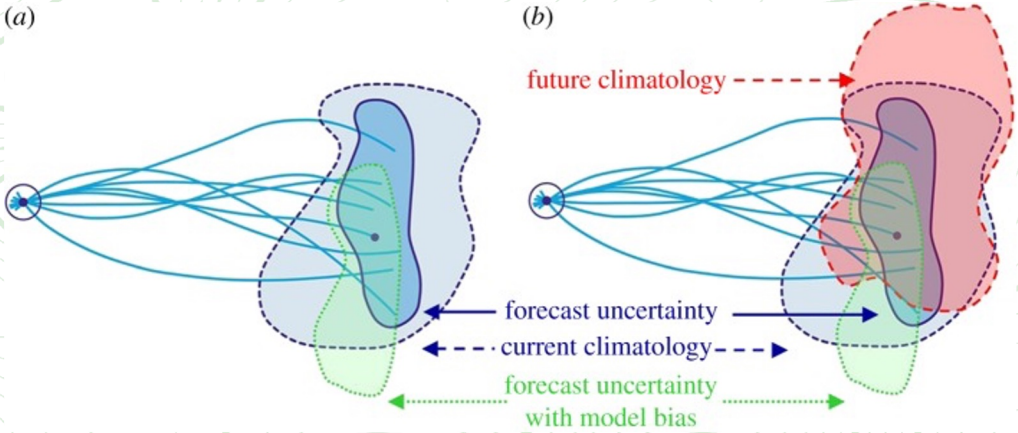
Dry-land crop yield

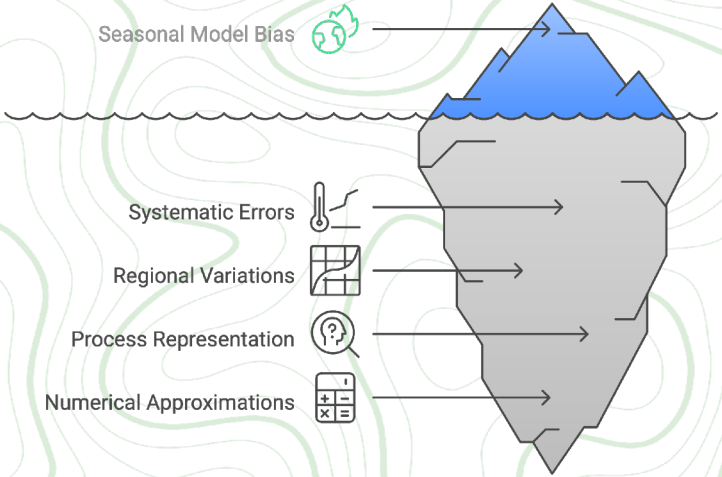






Viés dos modelos sazonais e suas fontes

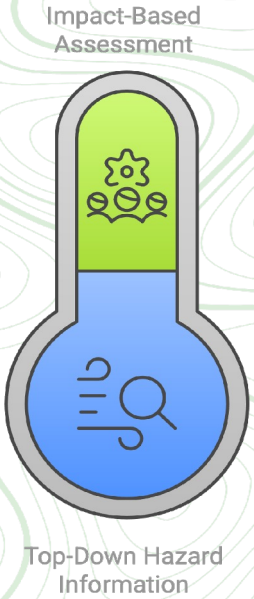




Viés dos modelos sazonais e suas fontes

Slingo J, Palmer T. Uncertainty in weather and climate prediction. Philos Trans A Math Phys Eng Sci. 2011 Dec 13;369(1956):4751-67. doi: 10.1098/rsta.2011.0161. PMID: 22042896; PMCID: PMC3270390.

Avaliação baseada em impactos vs. tradicional



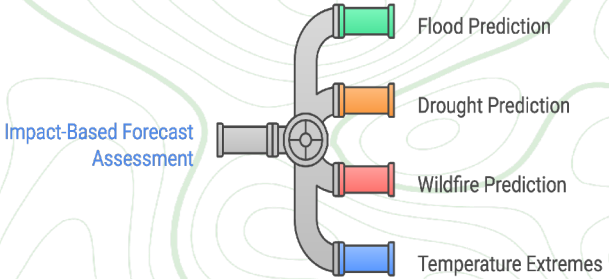
Impact-Based Assessment

Translates forecasts into meaningful information for decision-making

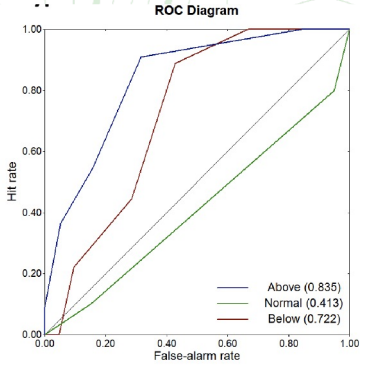
Traditional Assessment

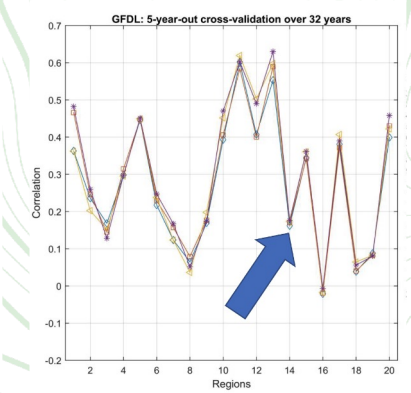
Captures weather patterns compared to reference data

Métricas baseadas em índices



Correlações, RMSE e medidas probabilísticas





Quão bons são os modelos sazonais “de fábrica” em termos de impacto?

AGU ADVANCING EARTH AND SPACE SCIENCES

Earth's Future

RESEARCH ARTICLE
10.1029/2024EF004936

Impact-Based Skill Evaluation of Seasonal Precipitation Forecasts

Zahir Nikraftar[1], Rendani Mbuvha[1,2], Mojtaba Sadegh[3,4], and Willem A. Landman[5]

[1]Machine Intelligence and Decision Systems (MInDS) Research Group, School of Electronic Engineering and Computer Science, Queen Mary University of London (QMUL), London, UK, [2]School of Statistics and Actuarial Science, University of Witwatersrand, Johannesburg, South Africa, [3]Department of Civil Engineering, Boise State University, Boise, ID, USA, [4]United Nations University Institute for Water, Environment and Health, Hamilton, ON, Canada, [5]Department of Geography, Geoinformatics and Meteorology, University of Pretoria, Pretoria, South Africa

Key Points:

- C3S models demonstrate notable skill in forecasting seasonal variability of precipitation, particularly in the tropical and sub-tropical regions
- UK-Met and Météo-France consistently outperform other models, demonstrating superior accuracy and reliability in various regions and seasons
- Our Impact-Based Framework offers valuable insights for targeted risk assessments, particularly in wildfire- and flood-prone regions using seasonal forecast models

Supporting Information:

Supporting Information may be found in the online version of this article.

Correspondence to:

R. Mbuvha,
r.mbuvha@qmul.ac.uk

Citation:

Nikraftar, Z., Mbuvha, R., Sadegh, M., & Landman, W. A. (2024). Impact-based skill evaluation of seasonal precipitation forecasts. *Earth's Future*, *12*, e2024EF004936. https://doi.org/10.1029/2024EF004936

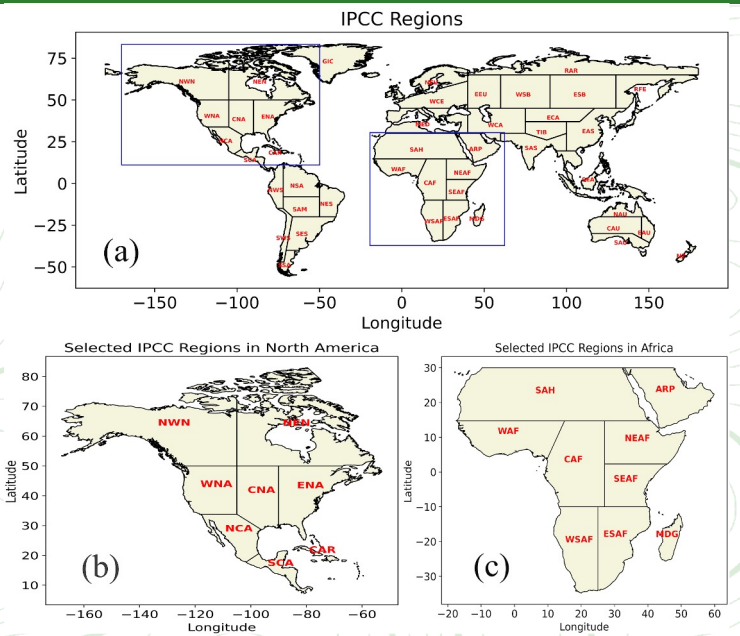
Received 3 JUN 2024
Accepted 16 OCT 2024

Author Contributions:

Conceptualization: Zahir Nikraftar, Rendani Mbuvha, Mojtaba Sadegh, Willem A. Landman
Data curation: Zahir Nikraftar
Formal analysis: Zahir Nikraftar
Investigation: Zahir Nikraftar

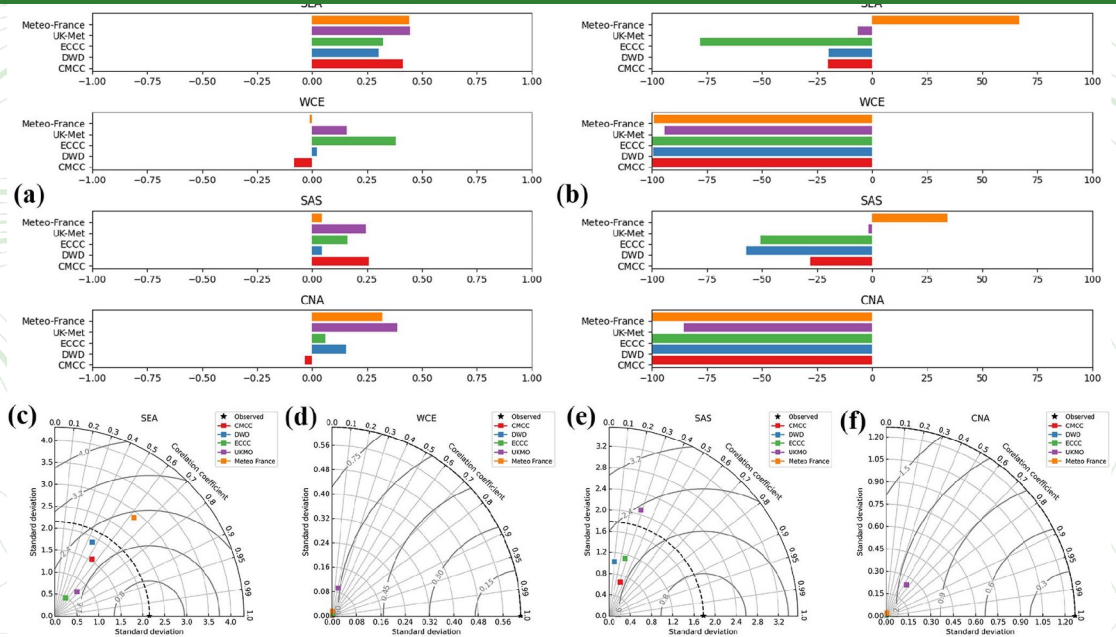
Abstract We introduce an impact-based framework to evaluate seasonal forecast model skill in capturing extreme weather and climate events over regions prone to natural disasters such as floods and wildfires. Forecasting hydroclimatic extremes holds significant importance in an era of increasing hazards such as wildfires, floods, and droughts. We evaluate the performance of five Copernicus Climate Change Service (C3S) seasonal forecast models (CMCC, DWD, ECCC, UK-Met, and Météo-France) in predicting extreme precipitation events from 1993 to 2016 using 14 indices reflecting timing and intensity (using absolute and locally defined thresholds) of precipitation at a seasonal timescale. Performance metrics, including Percent Bias, Kendall Tau Rank Correlation Score, and models' discrimination capacity, are used for skill evaluation. Our findings indicate that the performance of models varies markedly across regions and seasons. While models generally show good skill in the tropical regions, their skill in extra-tropical regions is markedly lower. Elevated precipitation thresholds (i.e., higher intensity indices) correlate with heightened model biases, indicating deficiencies in modeling severe precipitation events. Our analysis using an impact-based framework highlights the superior predictive capabilities of the UK-Met and Météo-France models in capturing the underlying processes that drive precipitation events, or lack thereof, across many regions and seasons. Other models exhibit strong performance in specific regions and/or seasons, but not globally. These results advance our understanding of an impact-based framework in capturing a broad spectrum of extreme weather and climatic events, and inform strategic amalgamation of diverse models across different regions and seasons, thereby offering valuable insights for disaster management and risk analysis.

Plain Language Summary We introduce a novel model assessment framework by investigating the impact of extreme events in areas prone to disasters such as floods and wildfires. We investigate how well five seasonal forecast models predict extreme precipitation, and related events such as floods and droughts. We assess the performance of models through 14 indices that assess the timing and intensity of precipitation during different seasons and in various regions globally. Our results show that some models outperform others in certain regions and seasons. We find that two models, UK-Met and Météo-France, are particularly skillful at predicting extreme events in various regions and seasons. This information is important for improved management and understanding of the risks of natural disasters.



Z., Mbuvha, R., Sadegh, M., & Landman, W. A. (2024). Impact-based skill evaluation of seasonal precipitation forecasts. *Earth's Future*, 12, e2024EF004936. https://doi.org/10.1029/2024EF004936

Avaliação baseada em impactos – dias de chuva forte em regiões sujeitas a inundações



Desempenho dos modelos para o número de dias de precipitação forte acima de 10 mm e do percentil 75 dos dados de referência (nwd10q75): a) coeficiente tau de Kendall, b) viés percentual e diagrama de Taylor para c) SEA, d) WCE, e) SAS e f) CNA, respectivamente.

Correção de viés dos modelos de previsão sazonal

Quantile mapping

$$F_{\text{obs}}(x_{\text{corrected}}) = F_{\text{model}}(x_{\text{model}})$$

- F_{obs}: Observed cumulative distribution.
- F_{model}: Model cumulative distribution.

Escalonamento linear

$$x_{\text{corrected}} = a \cdot x_{\text{model}} + b$$

- $a = \frac{\sigma_{\text{obs}}}{\sigma_{\text{model}}}$: Scaling factor for variability (standard deviation).
- $b = \mu_{\text{obs}} - a \cdot \mu_{\text{model}}$: Bias adjustment for the mean.



IA na previsão sazonal

JGR | Machine Learning and Computation

RESEARCH ARTICLE
10.1029/2025JH000957

Season-Net: A Deep Learning Framework for Bias Correction of Seasonal Forecasting Models

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Abstract Seasonal climate forecasts play a crucial role in decision-making across sectors like agriculture, energy, and disaster management. However, these forecasts often exhibit spatially structured biases that undermine their reliability, but this structure also enables more effective bias correction, particularly improving performance in predicting temperature extremes. Traditional bias correction methods such as quantile mapping (QM) and linear scaling (LS) are limited by assumptions of stationarity and their inability to capture complex spatiotemporal patterns. To address these challenges, we introduce Season-Net, a hybrid deep learning framework combining U-Net and ConvLSTM architectures. Season-Net is used to perform bias correction on seasonal daily temperature forecasts from the Met Office (GloSea6) and Météo-France (System 8) by learning season-specific spatial and temporal dependencies in a unified architecture. The model is trained with a novel sliding-window quantile mapping loss function that introduces temporal awareness into the quantile mapping process, enhancing its ability to capture temperature distribution and evolution. Evaluations across North America and Africa show that Season-Net consistently outperforms QM and LS in both deterministic (e.g., RMSE and Kendall's Tau) and probabilistic (e.g., Brier skill score and CRPSS) metrics. Furthermore, Season-Net excels in impact-based evaluations, significantly improving the prediction of extreme temperature events. These results highlight the superior capability of deep learning methods in correcting spatially structured seasonal forecast biases and enhancing the utility of climate predictions for climate-sensitive applications. Season-Net offers a promising pathway for advancing seasonal forecast postprocessing with high accuracy and impact relevance.

Key Points:

- Season-Net combines U-Net and ConvLSTM to correct spatial and temporal biases in seasonal temperature forecasts
- A temporal sliding-window QM loss enforces window-local CDF calibration, boosting extreme accuracy while preserving temporal awareness
- Across regions, Season-Net outperforms QM and LS on MAE and Kendall's tau, with the most notable gains in CRPSS and the Brier skill score (BSS)

Supporting Information:

Supporting Information may be found in the online version of this article.

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Citation:

Nikraftar, Z., Mbuvha, R., Sadegh, M., & Landman, W. A. (2025). Season-net: A deep learning framework for bias correction of seasonal forecasting models. *Journal of Geophysical Research: Machine Learning and Computation*, *2*, e2025JH000957. https://doi.org/10.1029/2025JH000957

Climate Dynamics (2026) 64:148
https://doi.org/10.1007/s00382-026-08077-4

ORIGINAL ARTICLE

Seasonal forecasting using the GenCast probabilistic machine learning model

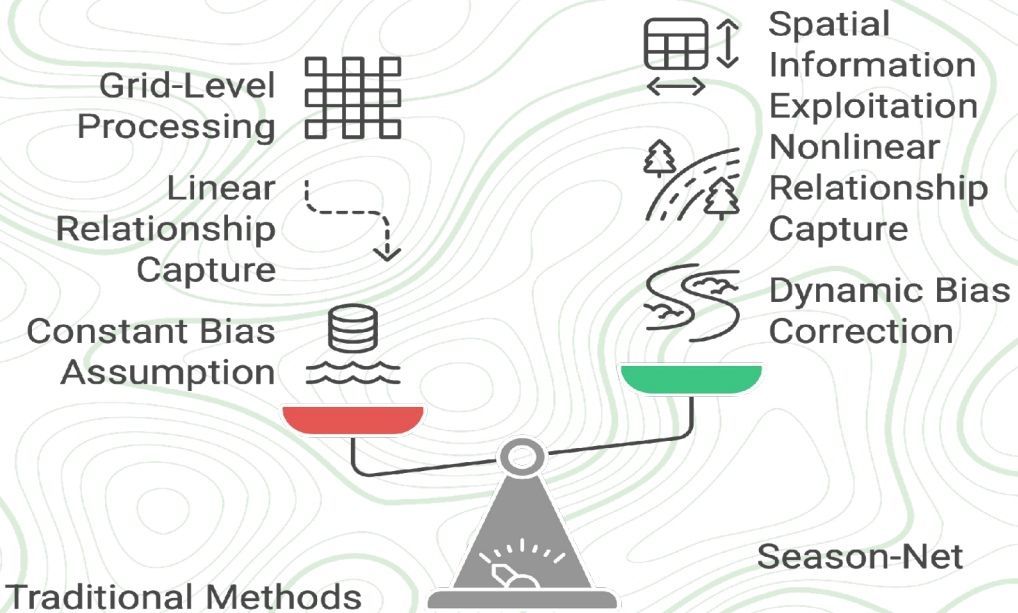
Bobby Antonio[1] · Kristian Strommen[1,2] · Hannah M. Christensen[1]

Received: 12 September 2025 / Accepted: 11 January 2026 / Published online: 16 March 2026
© The Author(s) 2026, modified publication 2026

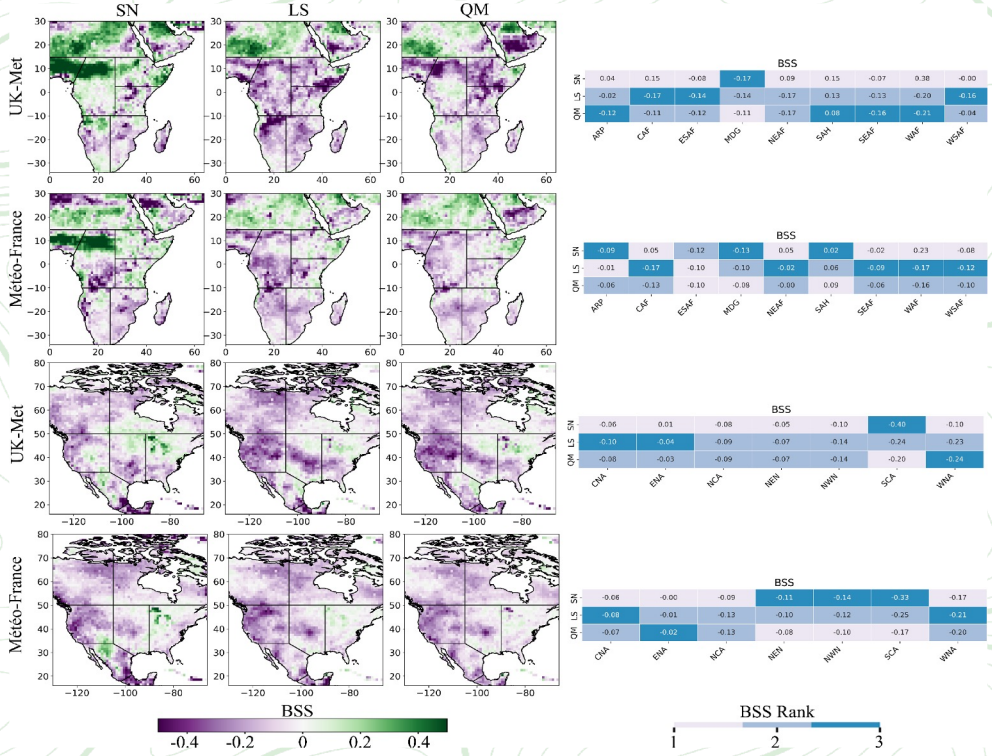
Abstract
Machine-learnt weather prediction (MLWP) models are now well established as being competitive with conventional numerical weather prediction (NWP) models in the medium range. However, there is still much uncertainty as to how this performance extends to longer timescales, where interactions with slower components of the earth system become important. We take GenCast, a state-of-the-art probabilistic MLWP model, and apply it to the task of seasonal forecasting with prescribed sea surface temperature (SST), by providing anomalies persisted over climatology (GenCast-Persisted) or forcing with observed SSTs (GenCast-Forced). The forecasts are compared to the European Centre for Medium-Range Weather Forecasts seasonal forecasting system, SEAS5. Our results indicate that, despite being trained at short timescales, GenCast-Persisted produces much of the correct precipitation patterns in response to El Niño and La Niña events, with several erroneous patterns in GenCast-Persisted corrected with GenCast-Forced. The uncertainty in precipitation response, as represented by the ensemble, compares favourably to SEAS5. Whilst SEAS5 achieves superior skill in the tropics for 2-metre temperature and mean sea level pressure (MSLP), GenCast-Persisted achieves higher skill in some areas in higher latitudes, including mountainous areas, with notable improvements for MSLP in particular; this is reflected in a slightly higher correlation with the observed NAO index. Reliability diagrams indicate that GenCast-Persisted has little skill relative to climatology, whilst GenCast-Forced produces forecasts with reliability comparable to SEAS5. These results provide an indication of the potential of MLWP models similar to GenCast for the 'full' seasonal forecasting problem, where the atmospheric model is coupled to ocean, land and cryosphere models.

Keywords Seasonal forecasting · Machine learning · Numerical weather prediction

Motivação para métodos de IA

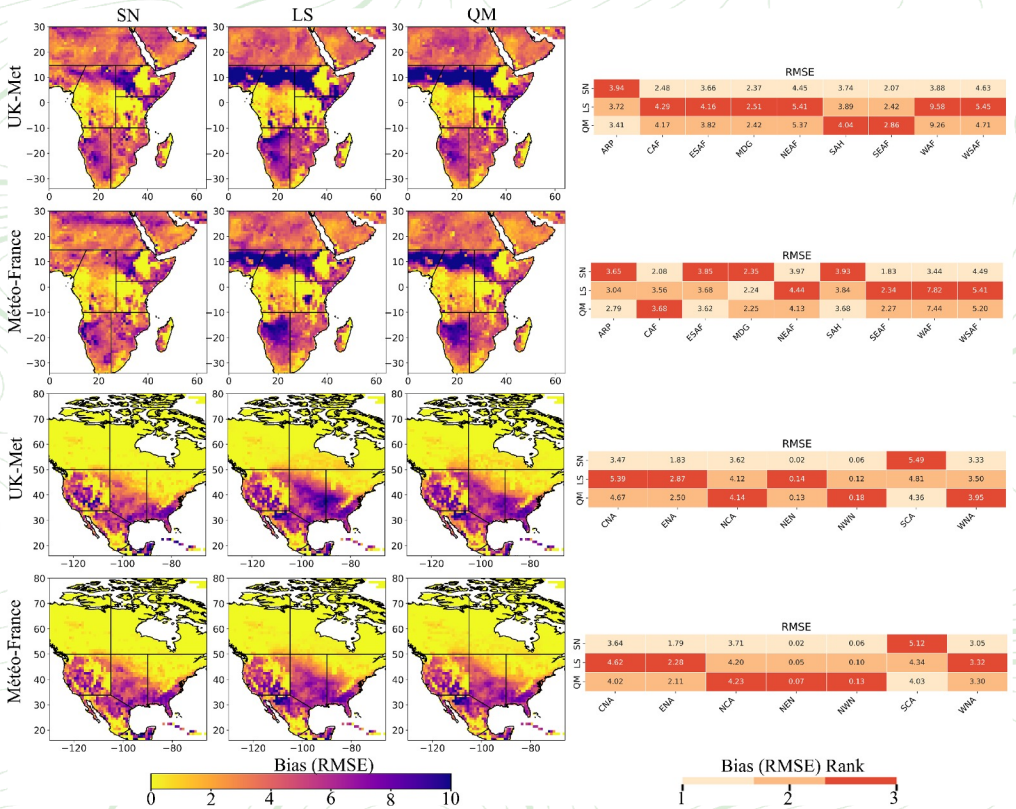


Resultados da correção de viés – Brier Skill Score



Brier Skill Score (BSS) sobre a África (linhas 1 e 2) na estação SON e a América do Norte (linhas 3 e 4) na estação JJA, para Season-Net (coluna 1), LS (coluna 2) e QM (coluna 3). A média por região do IPCC aparece na tabela à direita de cada linha. A escala de cores do viés é limitada a [-0,5, 0,5] para visualização consistente entre mapas.

Avaliação baseada em impactos – frequência de dias quentes (WDF))



Frequência de dias quentes (WDF): número de dias acima de 35 °C

Mapas de RMSE do índice WDF no período de teste sobre a África (linhas 1 e 2) na estação SON e a América do Norte (linhas 3 e 4) na estação JJA, para Season-Net (coluna 1), LS (coluna 2) e QM (coluna 3). A média por região do IPCC aparece na tabela à direita de cada linha. A escala de cores do viés é limitada a [0, 10] para visualização consistente entre mapas

Resultados de modelos meteorológicos de IA persistidos

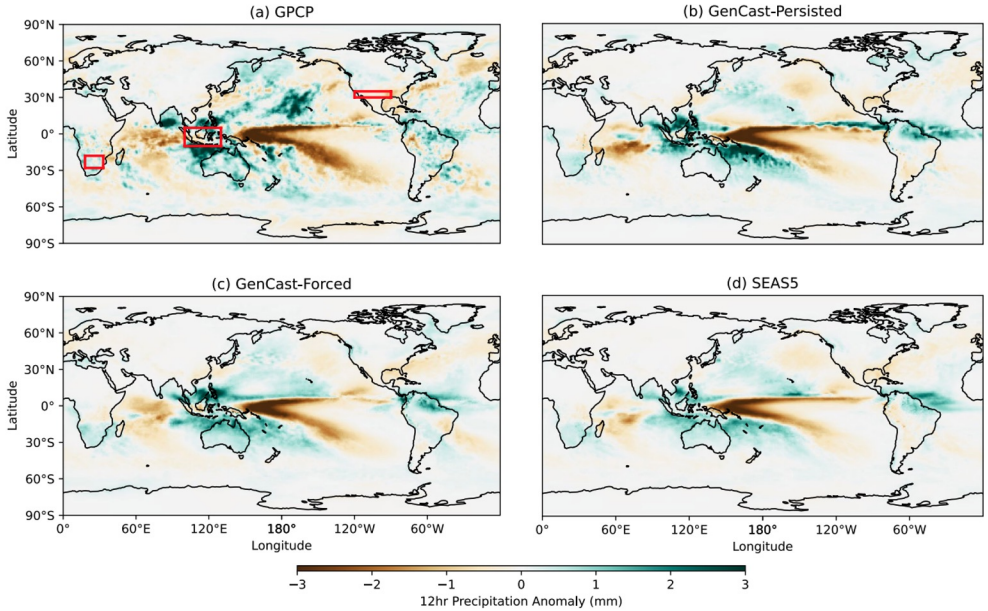


Fig. 1 Seasonal 12hr precipitation anomalies for December 2010–February 2011 (Strong La Niña). Red boxes indicate the subregions used in Fig. 3

Antonio, B., Strommen, K. and Christensen, H.M., 2026. Seasonal forecasting using the GenCast probabilistic machine learning model. Climate Dynamics, 64(4), p.148.

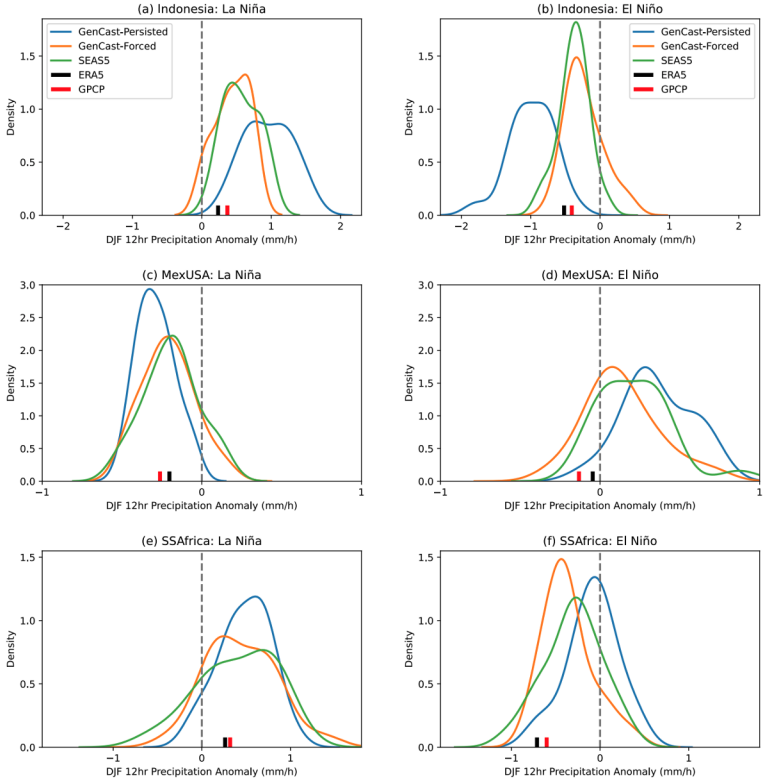


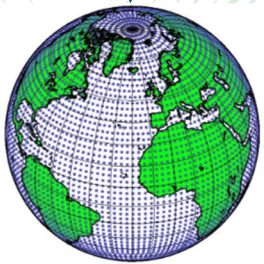
Fig. 3 Kernel density estimate for the distribution of DJF 12hr precipitation anomalies, averaged over each of the subregions shown in Figs. 1 and 2 (rows), and for each of the La Niña and El Niño case studies (columns). In each plot the ERA5 value is shown in black

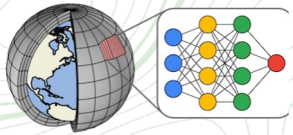
ImvulaNet: coprodução de previsões para impacto local

Chuva e produtividade locais informadas pelos agricultores









NeuralGCM



Ferramenta integrada de apoio à decisão para agricultores

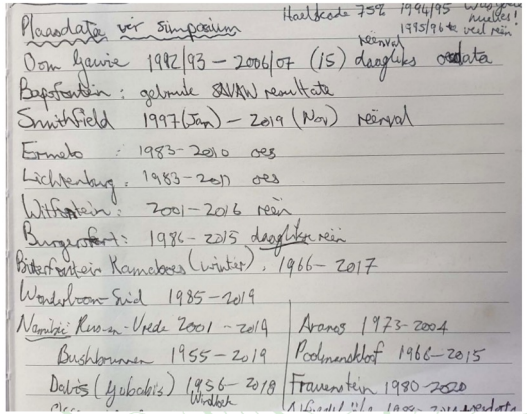
frontiers in Climate

ORIGINAL RESEARCH
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doi: 10.3389/fclim.2020.00005

Citizen Science for the Prediction of Climate Extremes in South Africa and Namibia

Willem A. Landman[1,2], Emma R. M. Archer[1] and Mark A. Tadross[3]*

[1] Department of Geography, Geoinformatics and Meteorology, University of Pretoria, Pretoria, South Africa, [2] International Research Institute for Climate and Society, The Earth Institute of Columbia University, New York, NY, United States, [3] Climate Systems Analysis Group, University of Cape Town, Cape Town, South Africa



Fonte: Landman, W. A., Archer, E. R., & Tadross, M. A. (2020). Citizen science for the prediction of climate extremes in South Africa and Namibia. Frontiers in Climate, 2, 5.

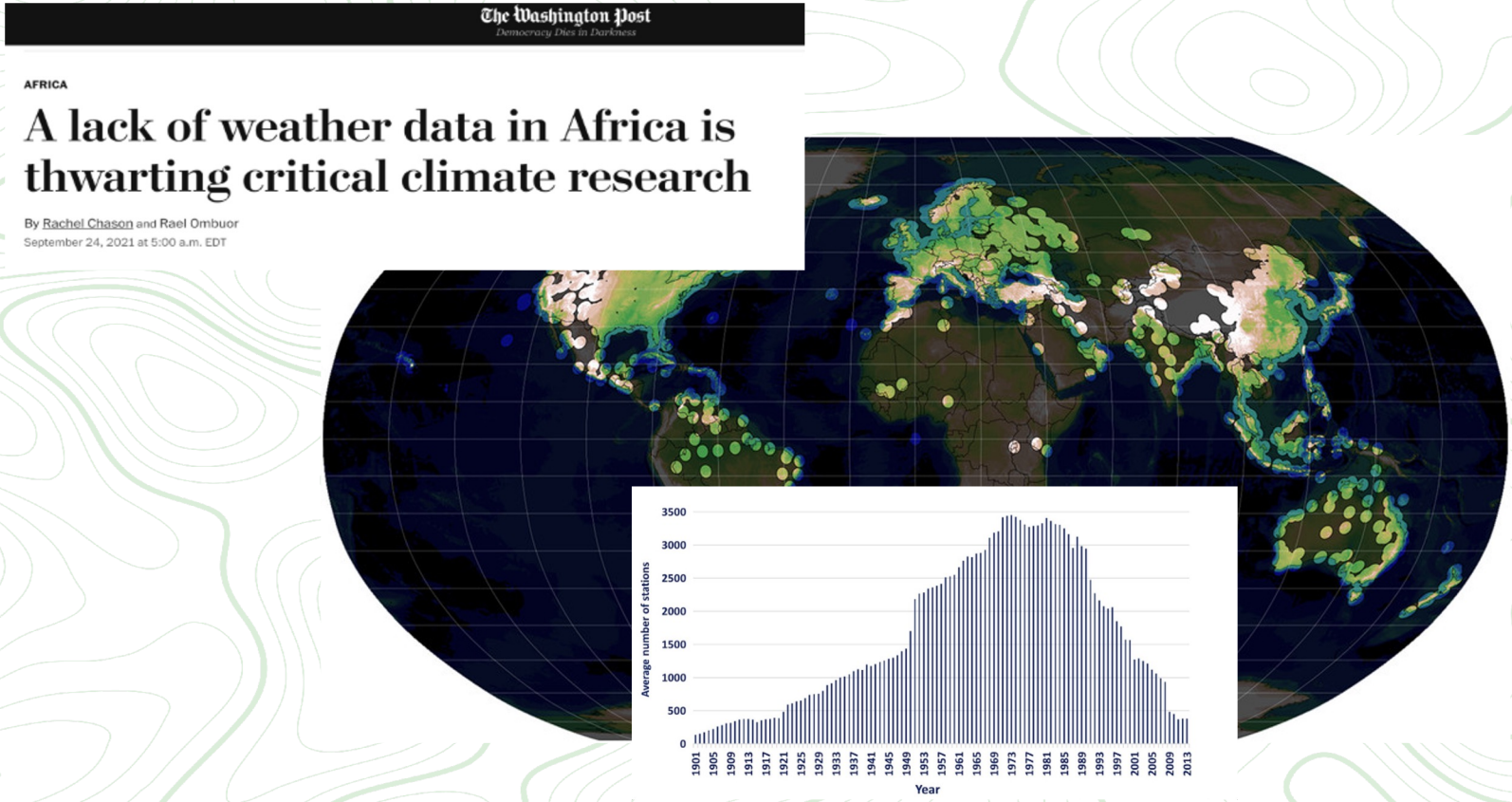
AfriClimate AI
AI for a Climate-Resilient Africa

IDRC · CRDI
Canada

ARC · LNR

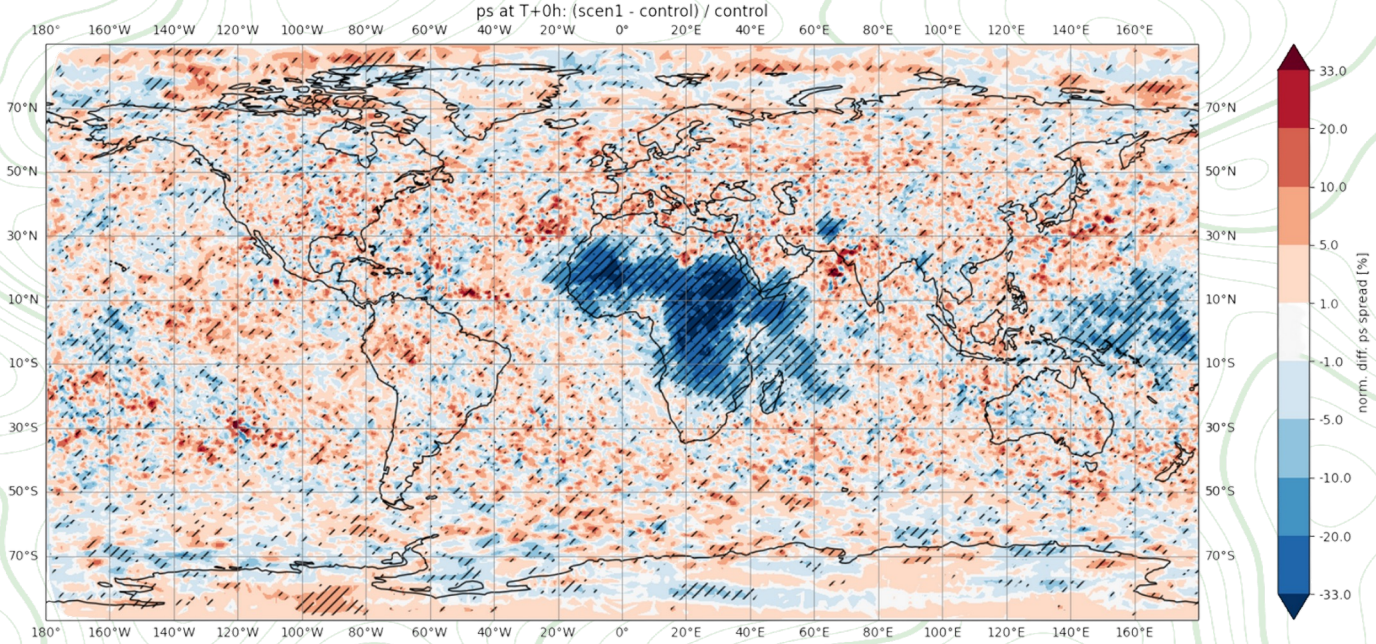
UK International Development
Partnership | Progress | Prosperity

Ressalva: o obstáculo da escassez de dados



Evolução do número de estações meteorológicas usadas no produto GPCC completo sobre a África (T. DINKU)

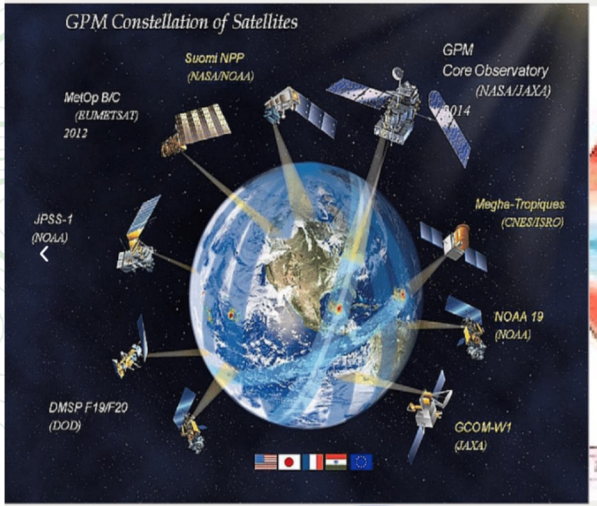
A escassez de dados prejudica a previsão do tempo



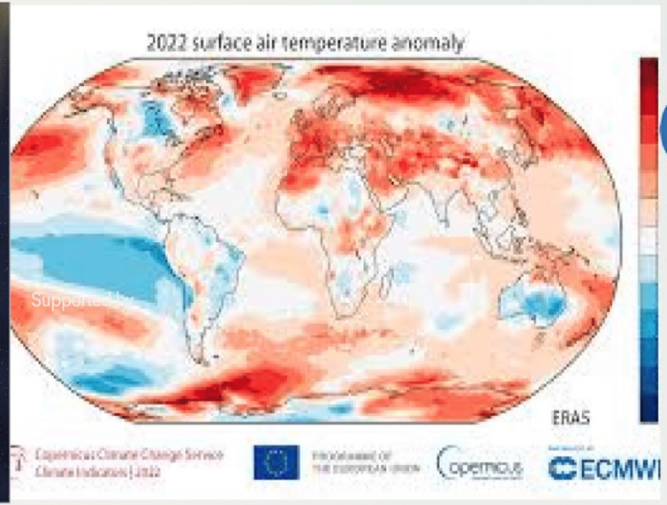
Redução percentual da incerteza da análise de pressão em superfície com observações de superfície adicionais simuladas sobre a África (ECMWF, 2025)

Recorrer a proxies globais?

Satellite Products



Renanalysis Products



Merged / Blended Products

MSWEP

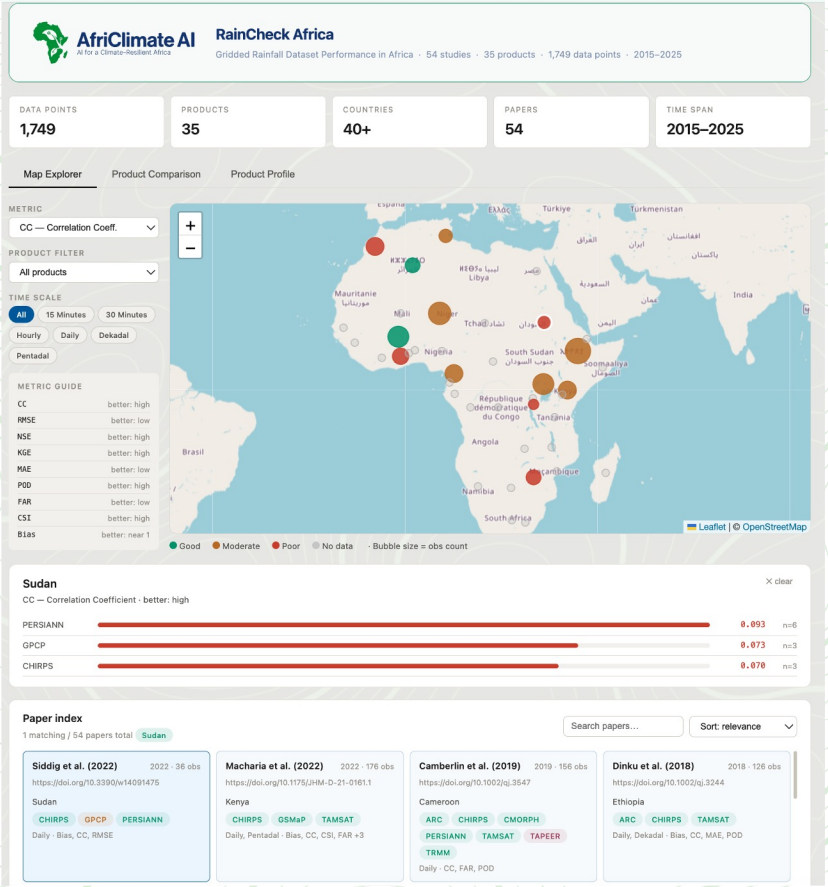
Climate Hazards Center
UC SANTA BAR

NASA

全球降水観測計画
GPM
GLOBAL PRECIPITATION MEASUREMENT

ECMWF

Mas qual proxy? …RainCheck Africa



https://africlimate-research.github.io/RainCheckAfrica/

Principais mensagens

Parte A — previsão de curto prazo

- Os modelos de IA (GraphCast, GenCast, AIFS, Prithvi WxC) já rivalizam com a PNT física, com uma fração da computação
- A habilidade probabilística (calibração, discriminação e incerteza, IDR) importa tanto quanto a precisão bruta
- Sistemas híbridos IA-física são a realidade operacional de curto prazo

Parte B — previsão sazonal

- Correlação e RMSE podem mascarar baixa habilidade nos impactos que importam: dias de chuva forte, ondas de calor, seca
- A correção de viés (escalonamento linear, quantile mapping, Season-Net) é essencial para que as previsões sejam utilizáveis
- Surgimento de modelos meteorológicos de IA persistidos para escalas sazonal e subsazonal
- A IA também reduz a lacuna aqui, mas os ganhos ainda são desiguais entre regiões

Da pesquisa ao impacto

A habilidade da previsão só gera valor quando chega a quem age. A coprodução com agricultores e serviços meteorológicos nacionais transforma a saída dos modelos em informação confiável e relevante para a decisão.

Hora do quiz: participe pelo Slido



https://app.sli.do/event/nCP9ZbfHnNTq9N8scZjmjV

Leituras principais

1. **Bauer, P., Thorpe, A., & Brunet, G.** (2015). *The quiet revolution of numerical weather prediction.* Nature, 525(7567), 47-55.
2. **Lam, R., Sanchez-Gonzalez, A., Willson, M., Wirnsberger, P., Fortunato, M., Alet, F., ... & Battaglia, P. (2023).** Learning skillful medium-range global weather forecasting. Science, 382(6677), 1416-1421.
3. **Nikraftar, Z., Mbuvha, R., Sadegh, M., & Landman, W. A. (2024).** *Impact-based skill evaluation of seasonal precipitation forecasts.* Earth's Future, 12, e2024EF004936.
4. **Antonio, B., Strommen, K., & Christensen, H.M. (2026).** *Seasonal forecasting using the GenCast probabilistic machine learning model.* Climate Dynamics, 64(4), p.148.

Obrigado

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https://africlimate.ai/



Slides reserva do quiz

Pergunta 1 de 4

MÚLTIPLA ESCOLHA

À medida que as previsões passam do médio prazo para escalas mais longas (sazonal, decenal), a fonte dominante de previsibilidade/incerteza deixa de ser um problema de valor inicial e passa a ser o quê?

A) Maior necessidade de poder computacional

B) Um problema de valor de contorno, impulsionado por componentes de variação mais lenta como o ENSO, o conteúdo de calor do oceano e a forçante dos gases de efeito estufa

C) Disponibilidade de dados de satélite

D) Apenas a resolução do modelo

RESPOSTA

Resposta correta: B

O diagrama de escalas de tempo mostra a previsibilidade passando de fontes ligadas às condições iniciais (umidade do solo, MJO/NAO) no curto prazo para fontes ligadas às condições de contorno (ENSO, PDV/AMV/GMST, oceano profundo/emissões de GEE/uso da terra) no longo prazo.

Pergunta 2 de 4

VERDADEIRO / FALSO

A maioria dos modelos de PNT por IA até hoje (p. ex. FourCastNet, GraphCast, Pangu-Weather) usa arquiteturas codificador-processador-decodificador e gera previsões de vários dias por desdobramento autorregressivo, reinserindo cada previsão como entrada do passo seguinte.

Verdadeiro

Falso

RESPOSTA

Resposta correta: Verdadeiro

Essa espinha dorsal codificador-processador-decodificador com desdobramento autorregressivo é a arquitetura comum ao FourCastNet, GraphCast, Pangu-Weather e modelos de PNT por IA semelhantes.

Pergunta 3 de 4

MÚLTIPLA ESCOLHA

Qual das opções a seguir descreve melhor o papel do ENSO como fonte de habilidade da previsão sazonal?

A) O ENSO não tem efeito mensurável nos padrões regionais de chuva

B) O ENSO altera os padrões de chuva de forma diferente em diferentes regiões do mundo, fornecendo um sinal climático previsível que os modelos sazonais podem explorar

C) O ENSO só afeta a habilidade de previsão na escala do tempo (curto prazo), não na sazonal

D) O ENSO é uma técnica de correção de viés usada para ajustar a saída dos modelos sazonais

RESPOSTA

Resposta correta: B

O El Niño altera os padrões de chuva (mais úmidos/secos que o normal) de forma diferente conforme a região: é justamente essa teleconexão que faz do ENSO o sinal climático que dá habilidade à previsão sazonal.

Pergunta 4 de 4

MÚLTIPLA ESCOLHA

Métodos de correção de viés como escalonamento linear, quantile mapping e Season-Net são considerados essenciais para que as previsões sazonais sejam utilizáveis na tomada de decisão.

Verdadeiro

Falso

RESPOSTA

Resposta correta: Verdadeiro