AfriClimate AI
AI for a Climate-Resilient Africa

L'IA per il meteo

Scuola estiva CCAI

Shruti Nath | Rendani Mbuvha

Climate Change AI

UNIVERSITY OF THE WITWATERSRAND, JOHANNESBURG

1922 2022

UNIVERSITY OF OXFORD

Chi è AfriClimate AI

La nostra missione

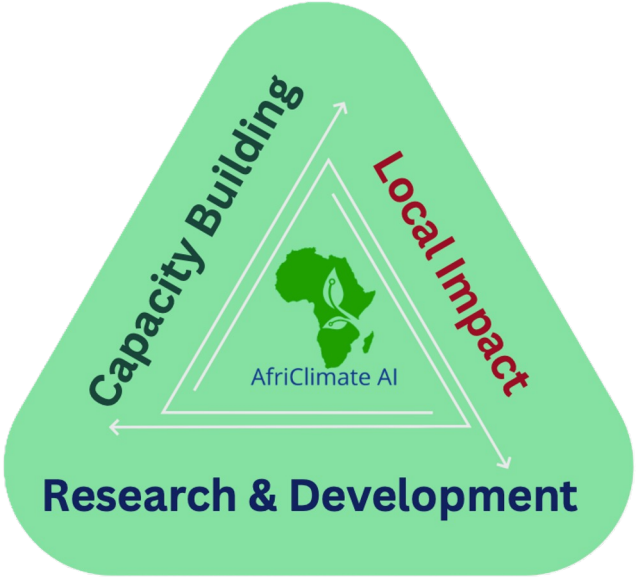
Far progredire la ricerca su clima e IA in Africa:

Sviluppando competenze locali
Formando ricercatori e professionisti in tutto il continente

R&S attenta al contesto
Ricerca radicata nelle realtà climatiche e socioeconomiche africane

Messa in opera di soluzioni di IA
Dal prototipo ai servizi climatici operativi

Dati locali
Migliorare l’accesso a dati osservativi africani di qualità



Le origini: il Deep Learning Indaba



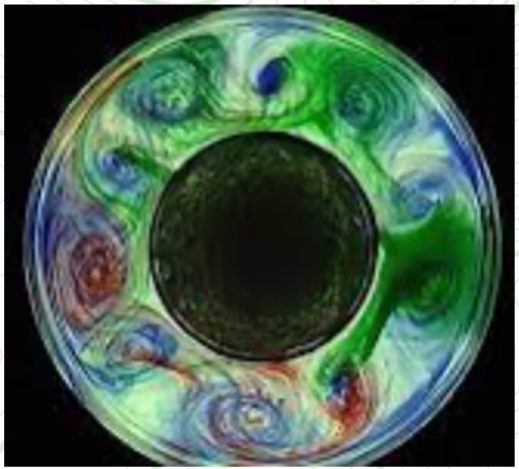
Deep Learning Indaba, Kigali 2025

Struttura della lezione

Parte A: previsione a breve termine («il meteo»)

Parte B: previsione a lungo termine («previsioni stagionali»)

Il meteo come problema ai valori iniziali: all'inizio del XX secolo





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

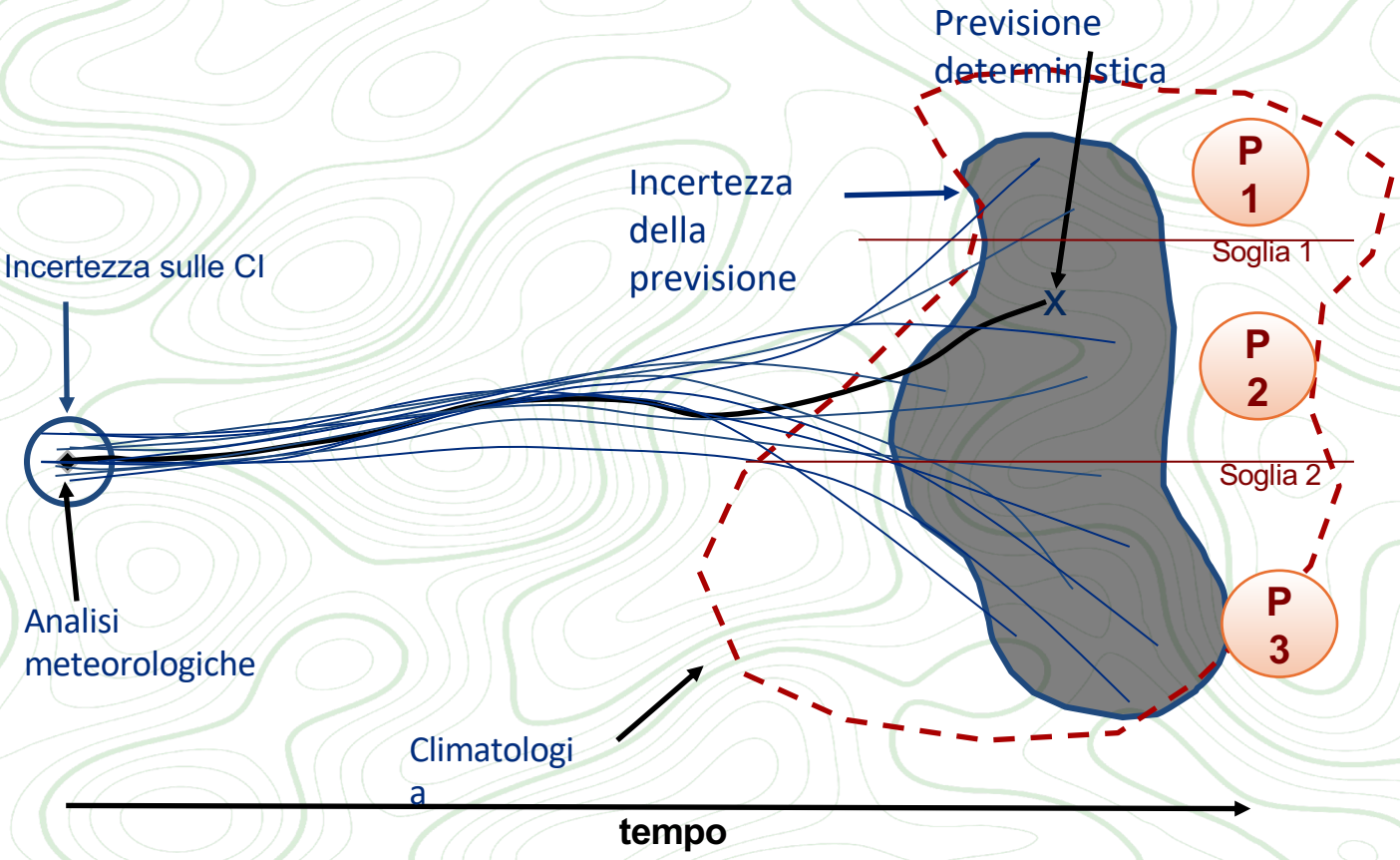
$$\frac{\delta \mathrm{v}}{\delta t} + (\mathrm{v} \cdot \nabla) \cdot \mathrm{v} = \frac{1}{\rho} \cdot \nabla p + v \cdot \Delta \mathrm{v} + \boldsymbol{f}$$

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

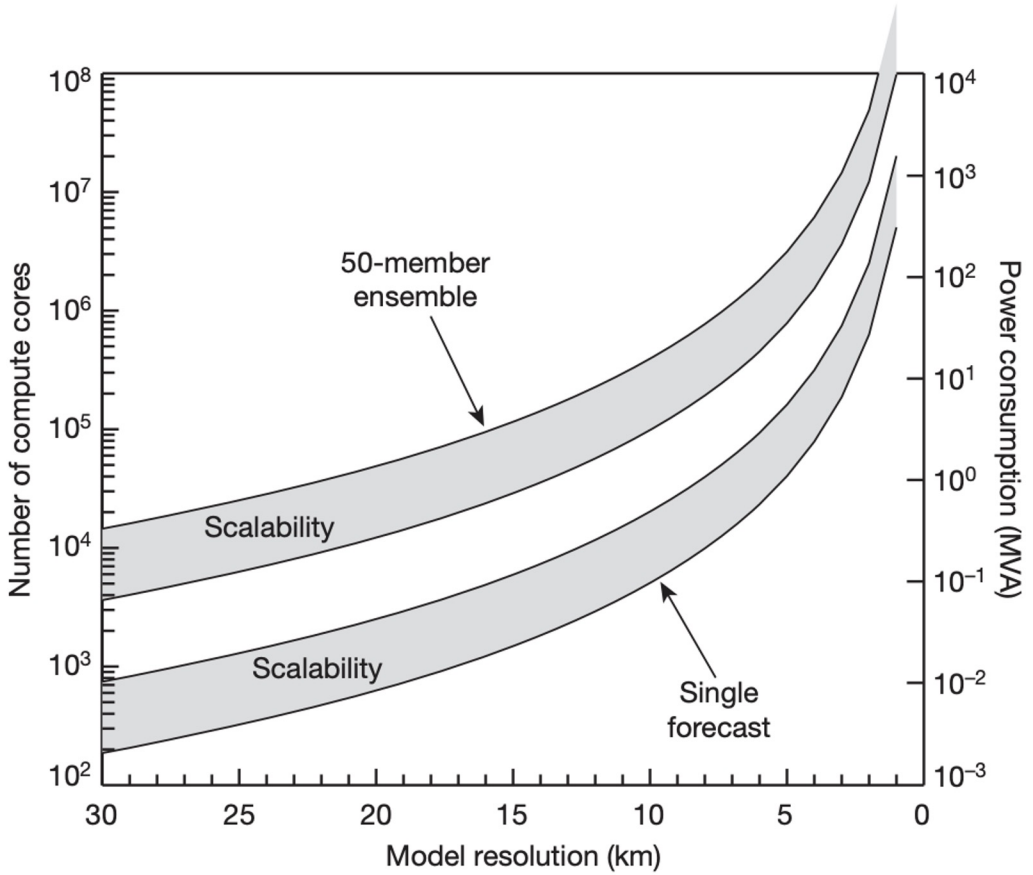
$$PV = nRT$$

Come sono le previsioni attuali?

Previsioni probabilistiche



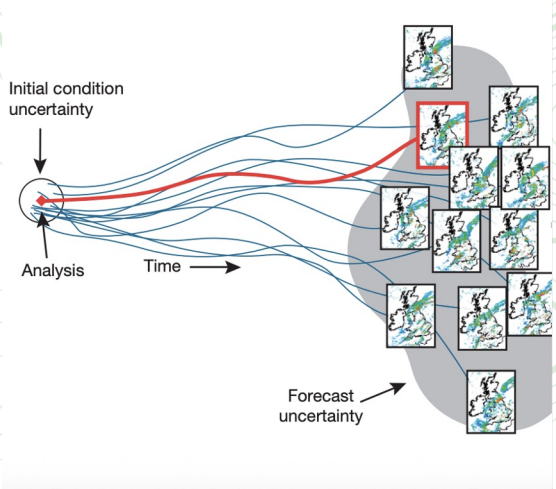
Capacità di supercalcolo dal 1970



REVIEW

The quiet revolution of numerical weather prediction

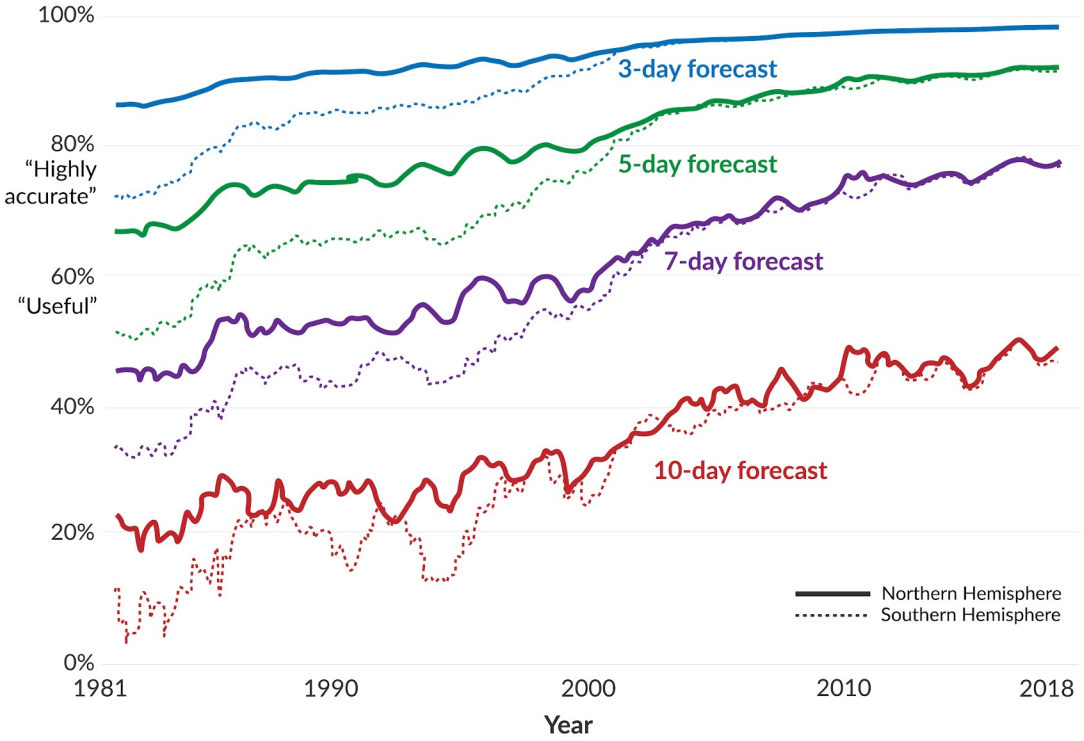
Peter Bauer[1], Alan Thorpe[1] & Gilbert Brunet[2]



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.

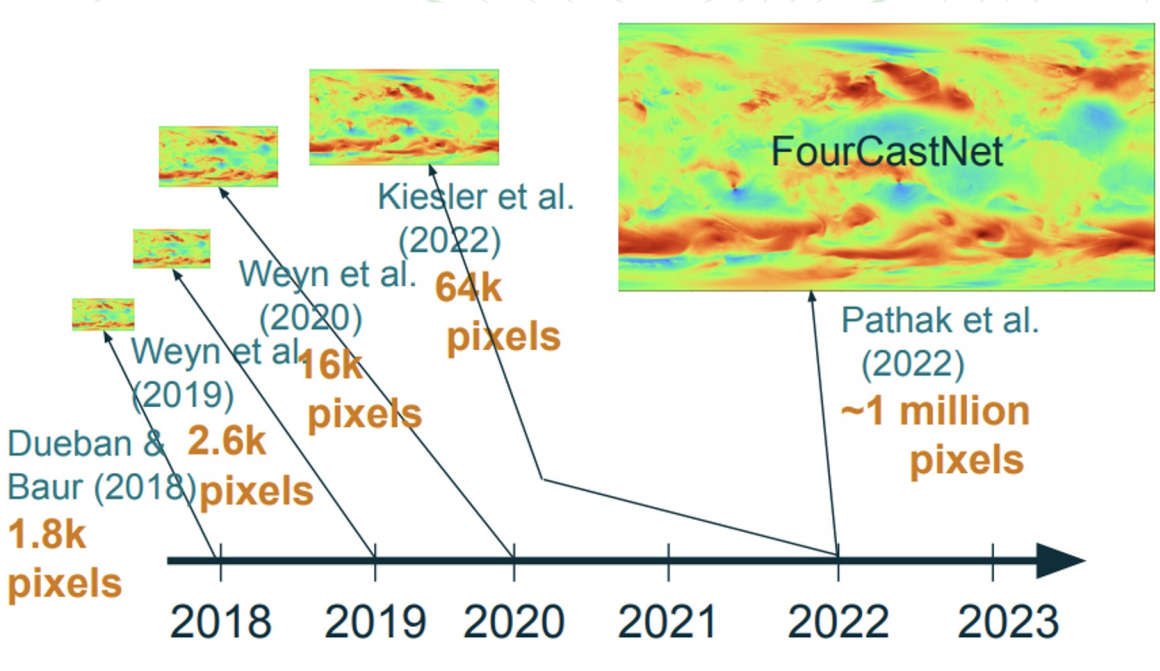
Our World in Data



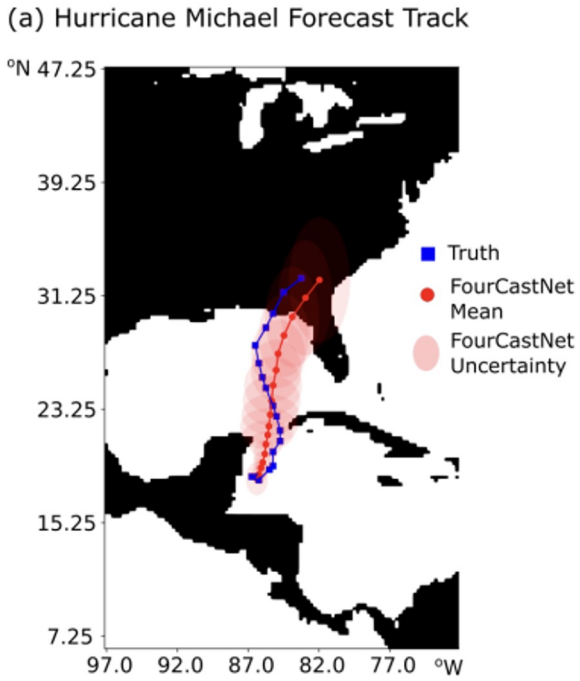
Source: European Centre for Medium-Range Weather Forecasts (ECMWF).

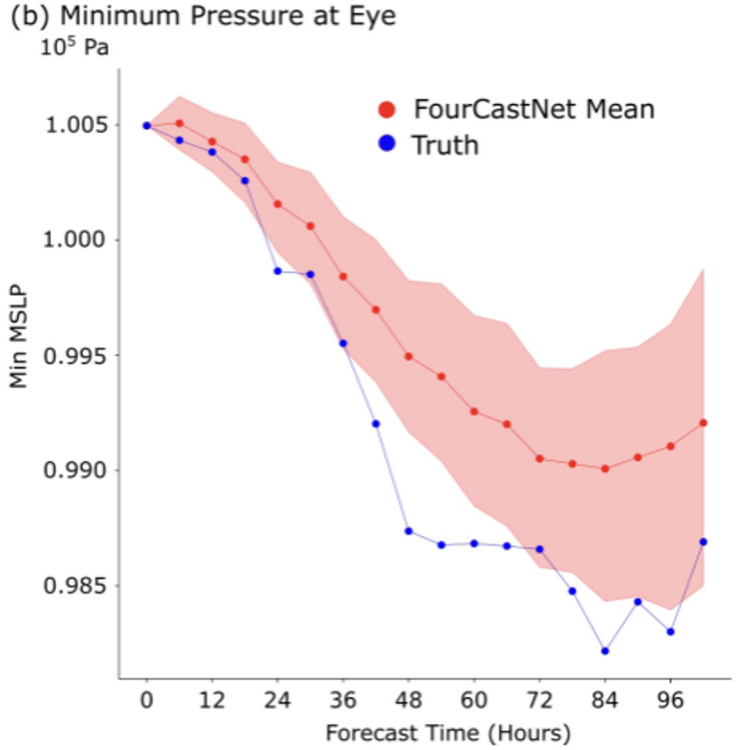
Licensed under CC-BY by the author Hannah Ritchie.

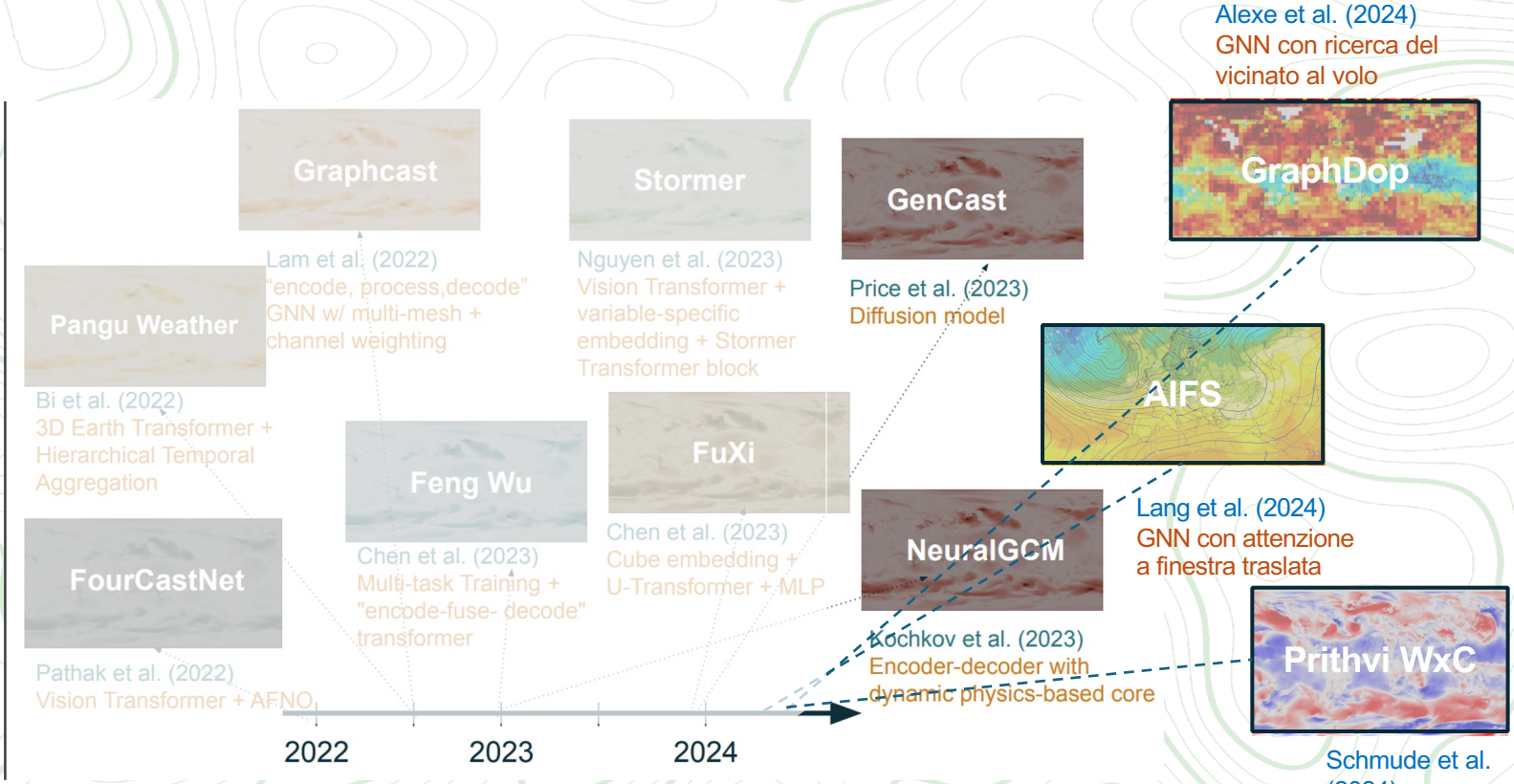
Portare il rumore: i modelli di IA



La prima prova di concetto: previsioni dell'uragano Michael

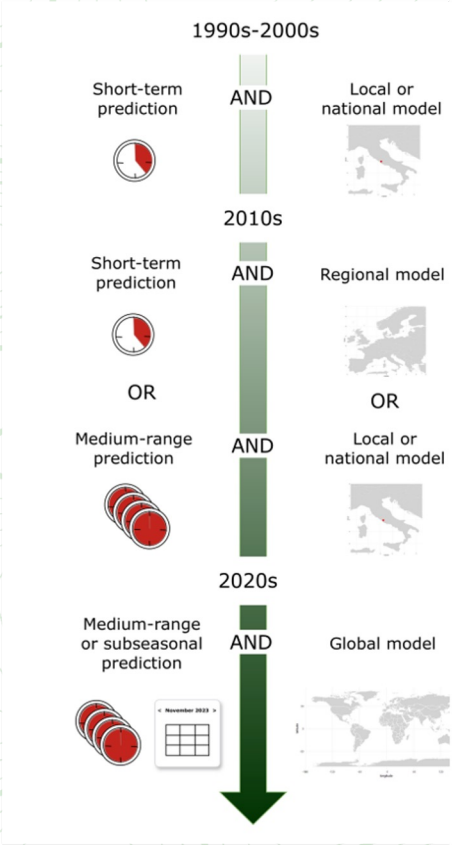


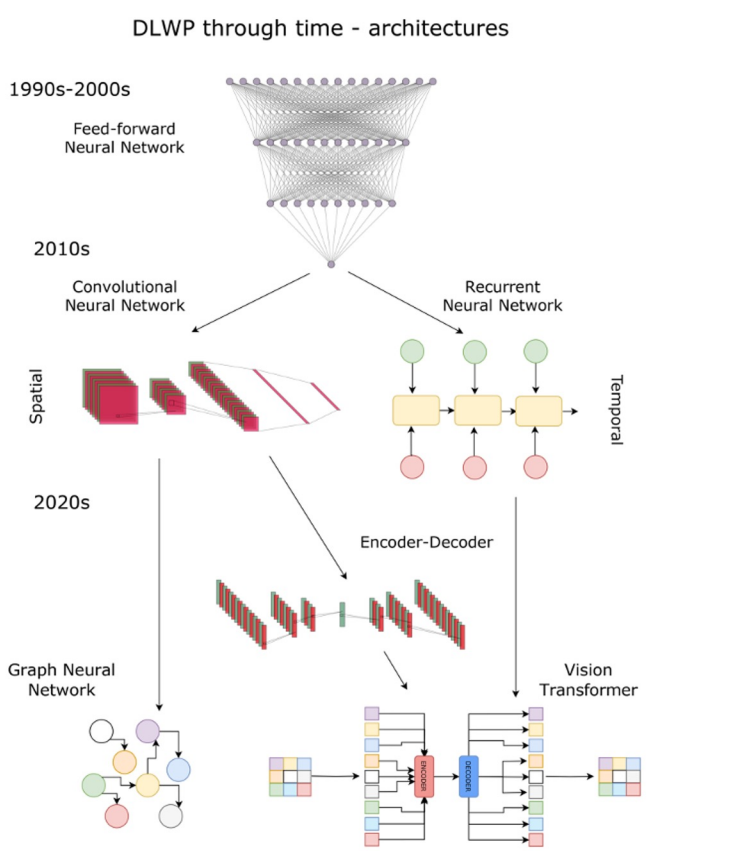




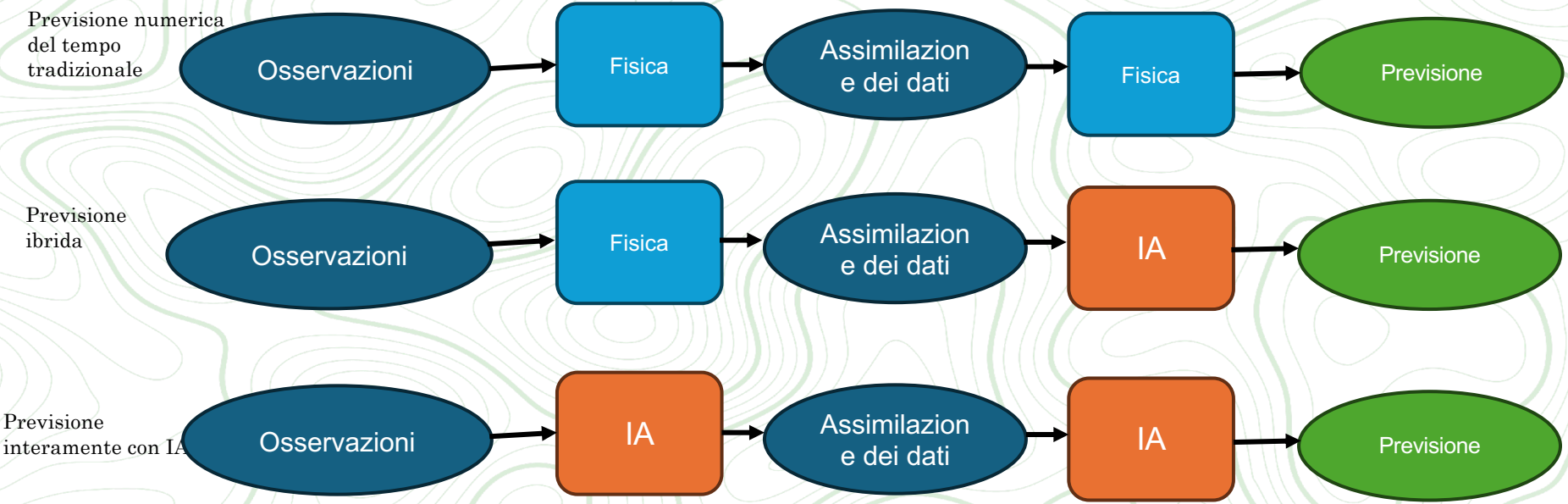
Lo sviluppo dei modelli di IA sembra autoalimentarsi, stimolando sempre nuovi sviluppi!

General timescales of developments

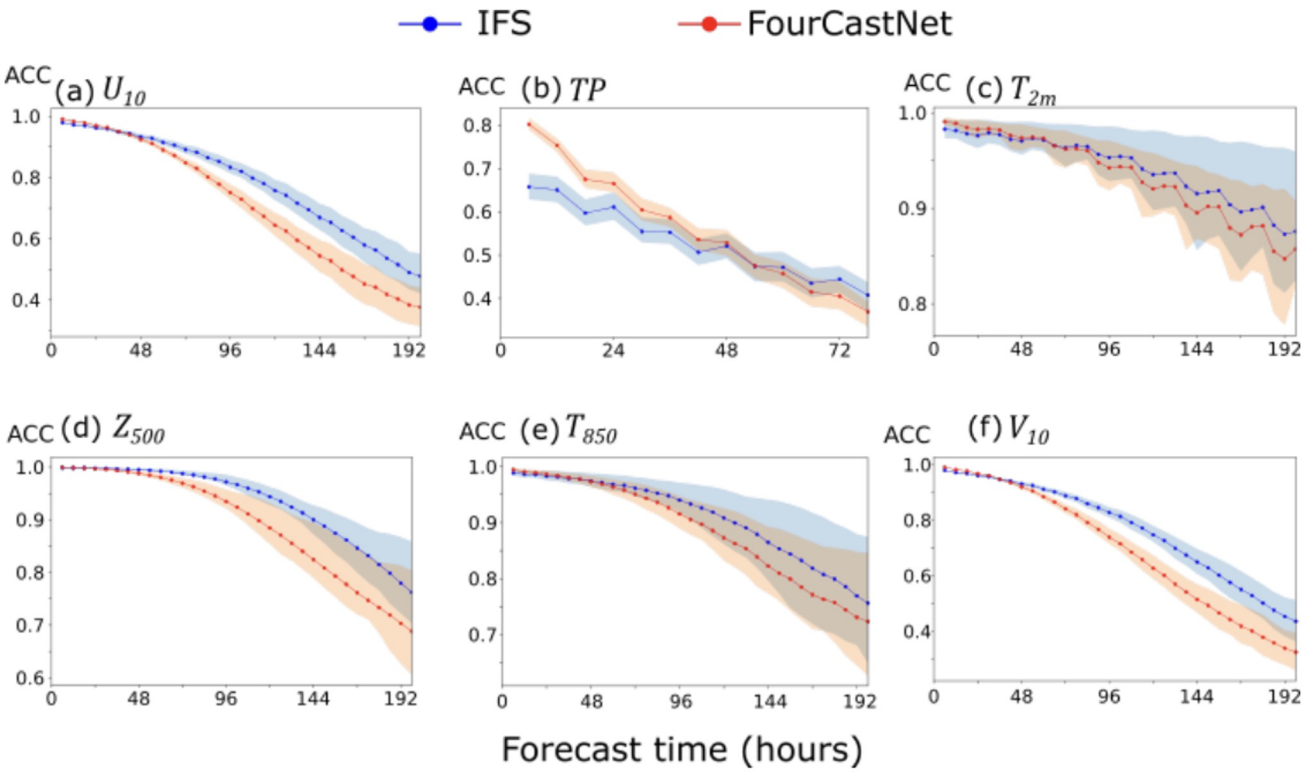




Il futuro dell'IA?

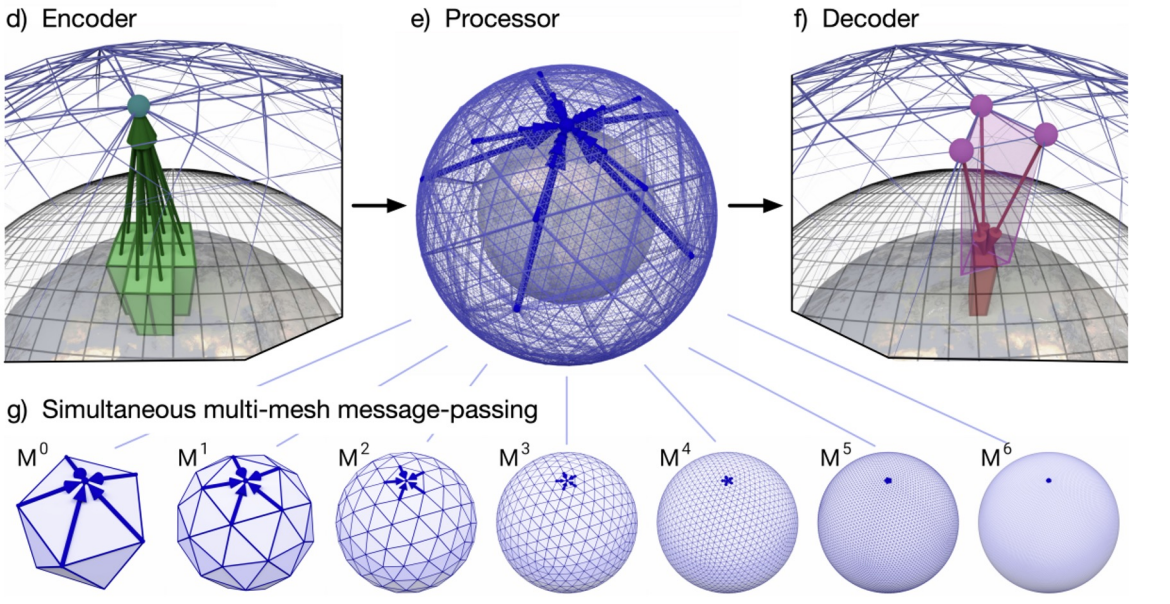


L’accuratezza era comparabile ma peggiorava con il tempo



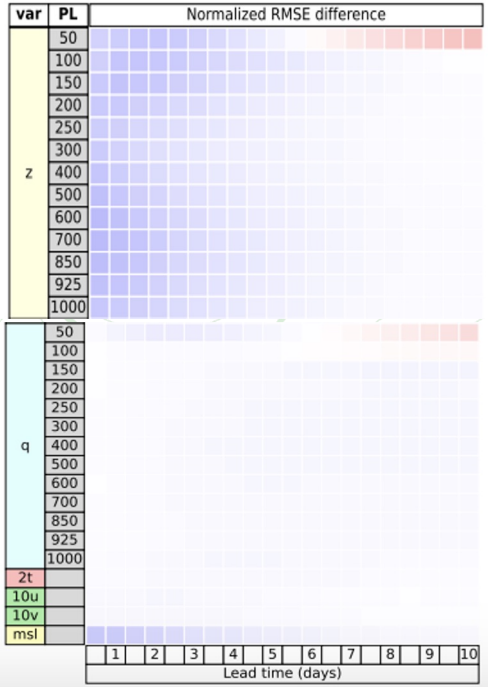
GraphCast

- L'encoder apprende gli attributi dei nodi trasferiti dalla griglia al multi-mesh
- Multi-mesh ottenuto per raffinamento iterativo: icosaedro regolare (12 nodi, 20 facce, 30 spigoli) raffinato sei volte
- Il processore esegue poi il message passing su 16 strati GNN non condivisi
- Rollout simile a FourCastNet

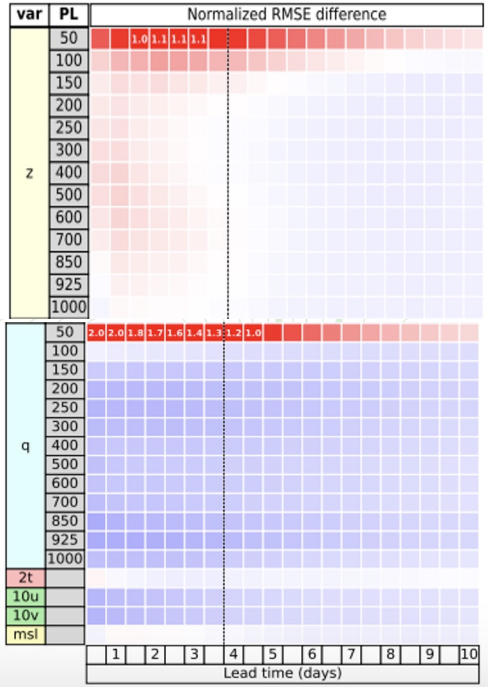


Studi di ablazione del multi-mesh

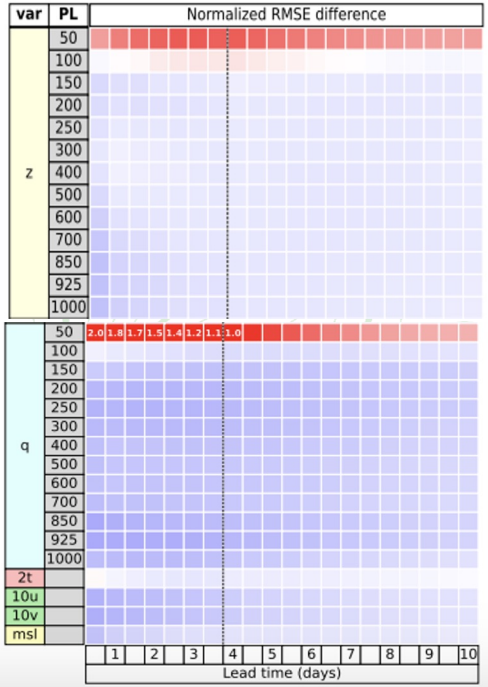
GraphCast – senza multi-mesh



Senza multi-mesh – HRES

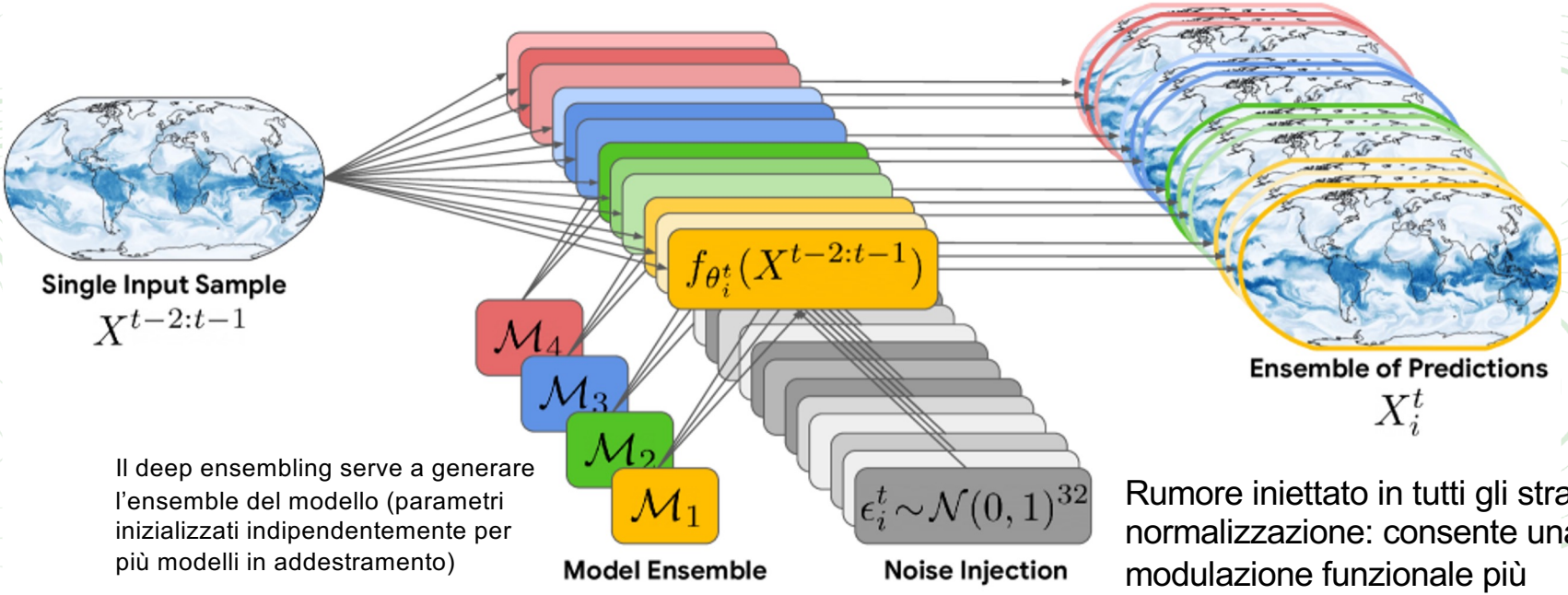


GraphCast – HRES



Il blu è migliore

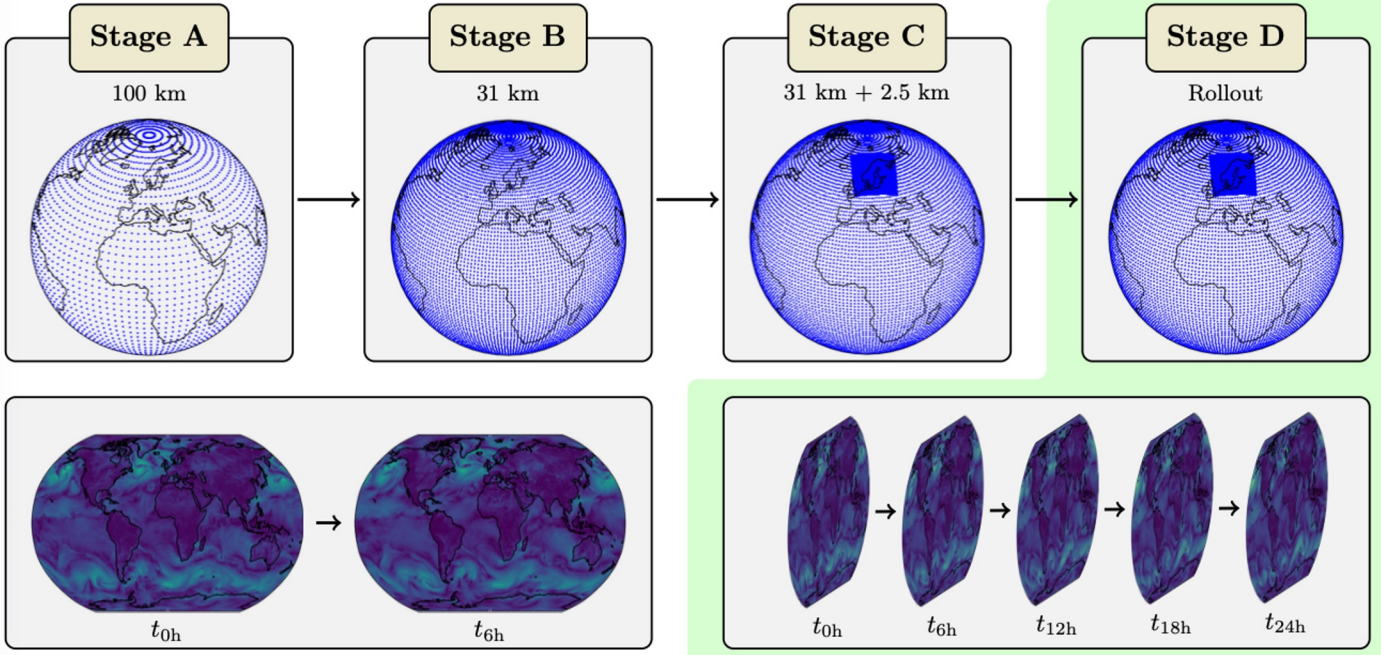
Tramite deep ensembling e normalizzazione condizionale a parametri condivisi



Il deep ensembling serve a generare l'ensemble del modello (parametri inizializzati indipendentemente per più modelli in addestramento)

Rumore iniettato in tutti gli strati di normalizzazione: consente una modulazione funzionale più strutturata tra strati mantenendo la coerenza spaziale

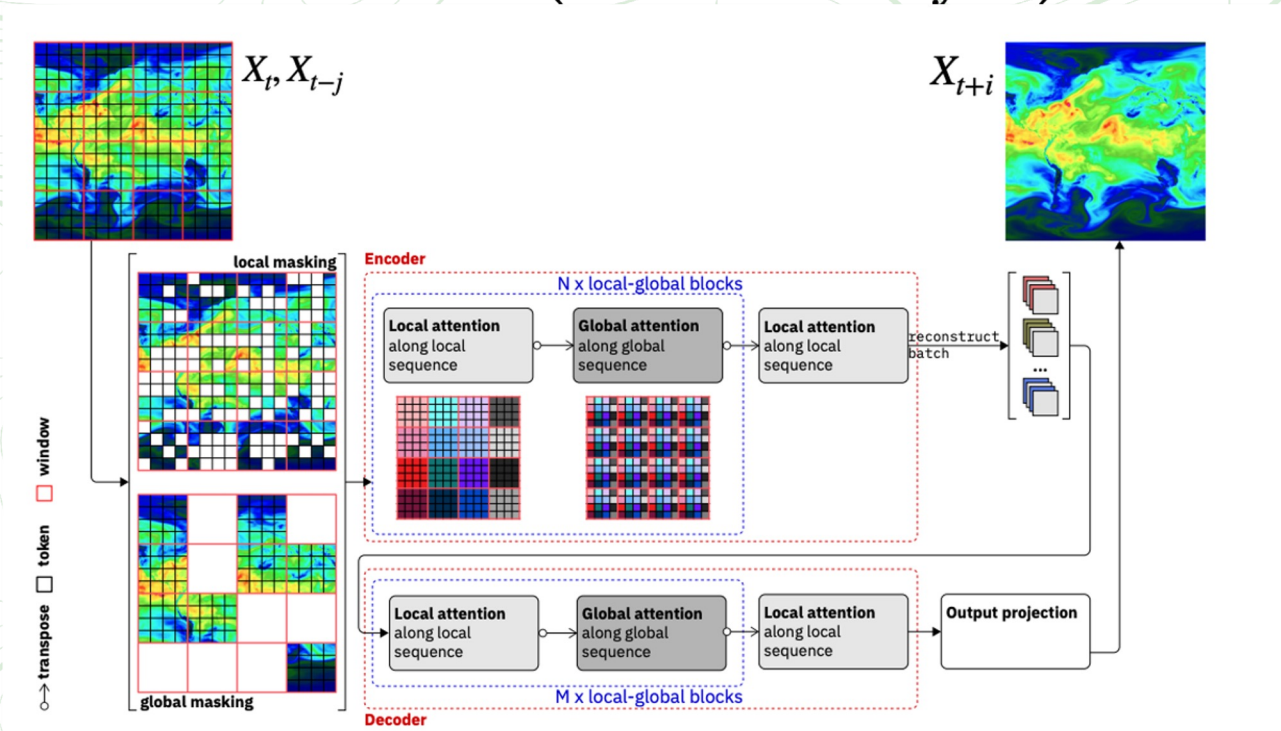
I graph transformer si adattano facilmente a modelli a risoluzione variabile



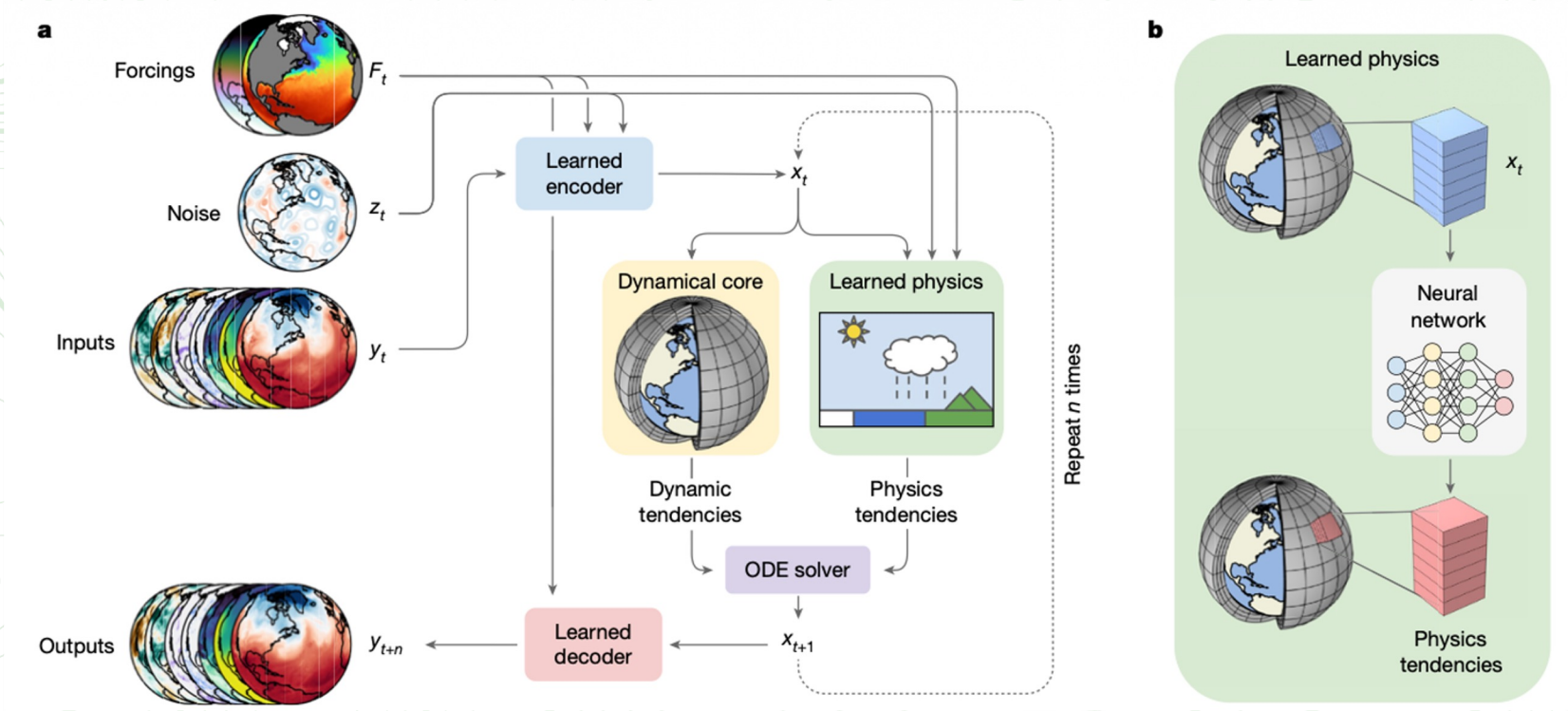
Prithvi WxC

https://arxiv.org/pdf/2409.13598

- Trained on MERRA-2 data (NASA reanalysis)



Hybrid approaches: fully learning all parameterizations



Questi modelli sono utili operativamente?

Fare confronti equi

- Per confronti equi, notiamo che esistono diversi tipi di previsione:
  - Deterministiche (cioè un solo membro dell'ensemble)
  - Probabilistiche
- I modelli di IA sono addestrati su ERA5; per le precipitazioni ciò non è sempre realistico e occorre correggere verso le stime satellitari
- Anche gli output della previsione numerica basata sulla fisica vanno corretti verso le stime satellitari

Come definire l'utilità di una previsione?

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

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

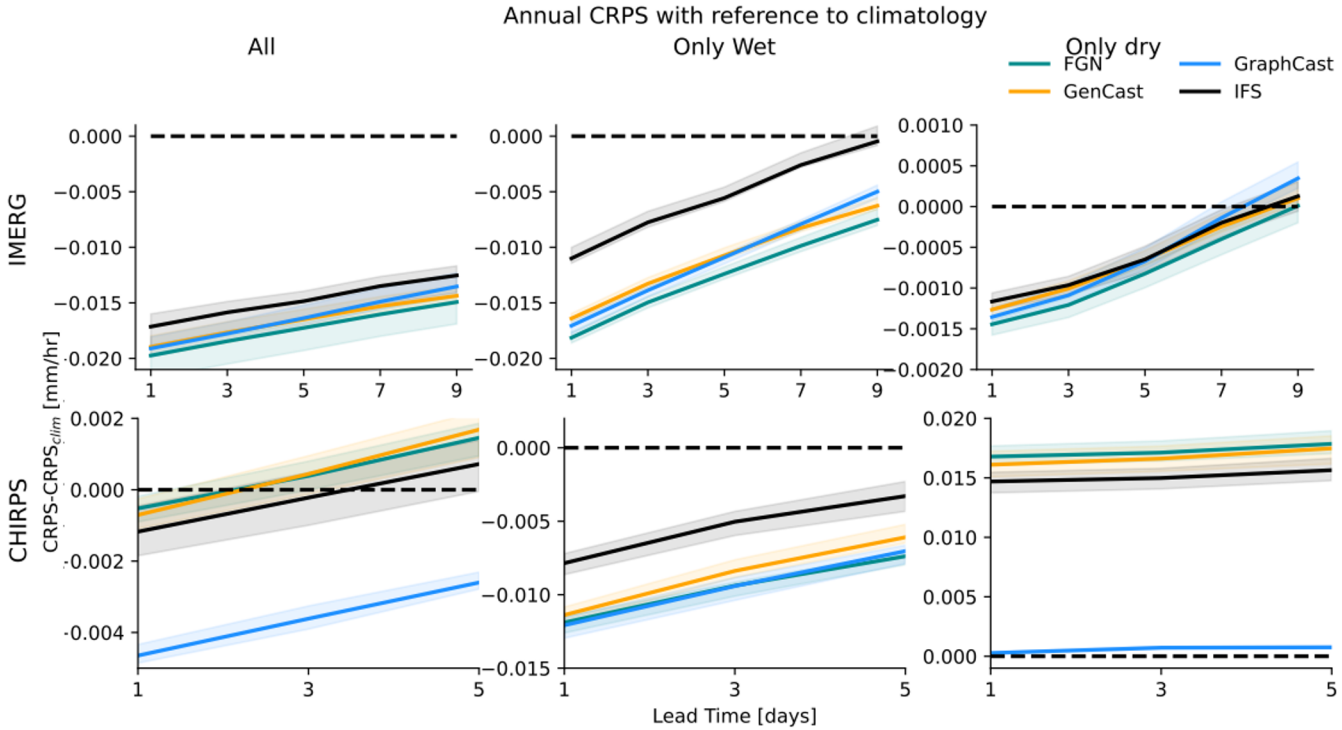
MAE, CRPS, Log-likelihood etc. are all proper scoring rules and can be broken down into

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

Calibrazione errata — Discriminazione — Incertezza

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

Lead time di 1 e 9 giorni

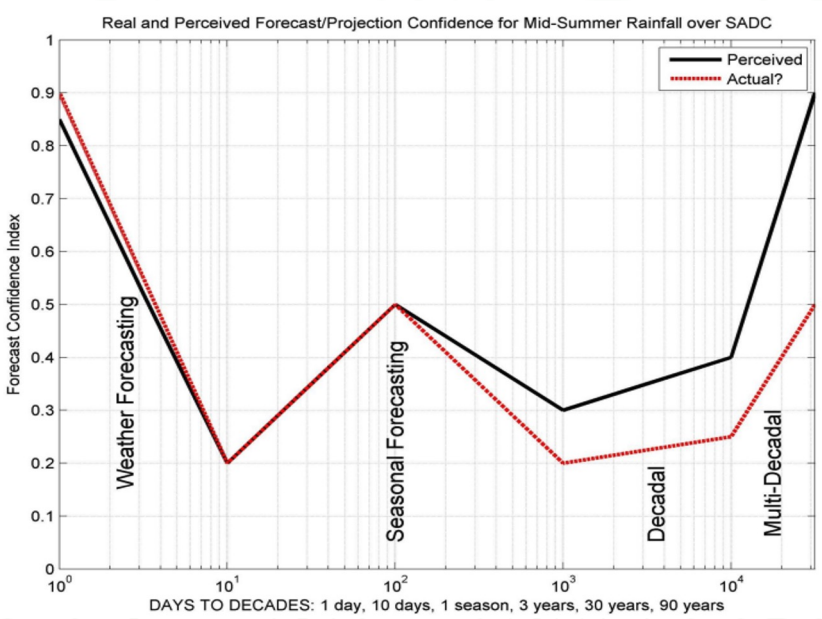


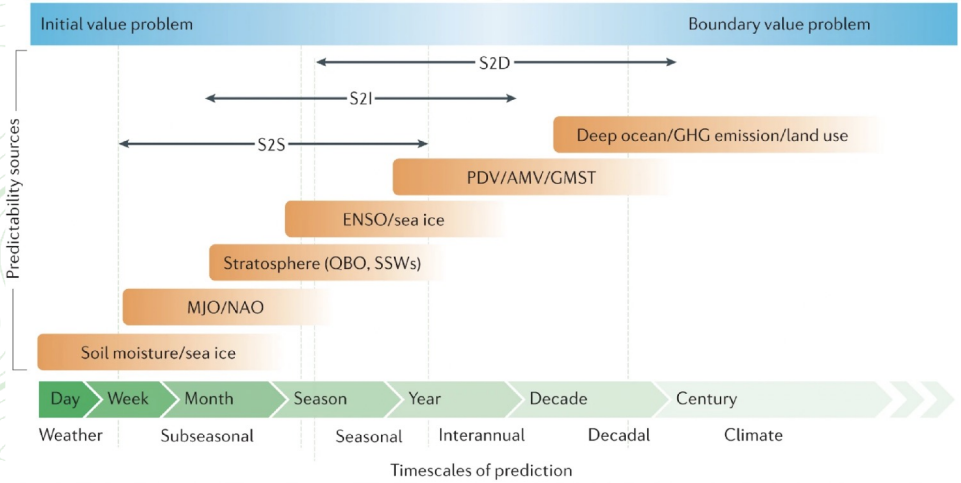
2024-2025 come anni di

Forecast 4Africa
by AfriClimate AI

Che cos'è la previsione stagionale?

Come saranno i prossimi 90 giorni?

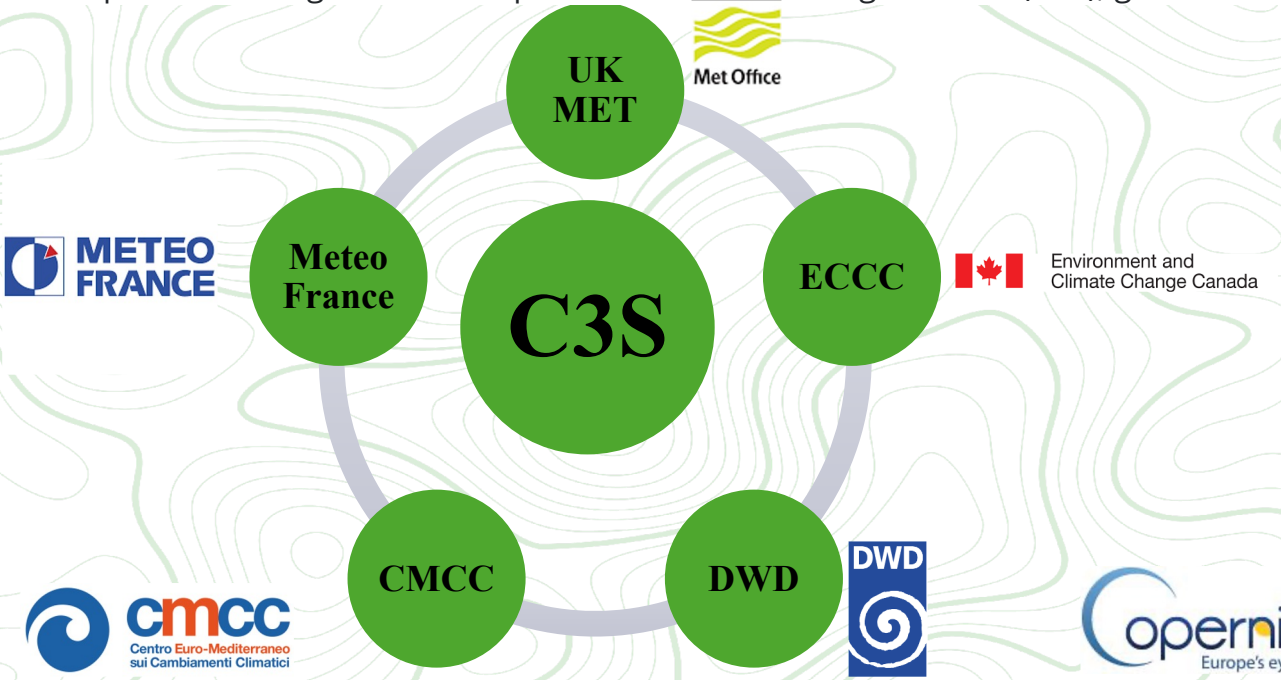




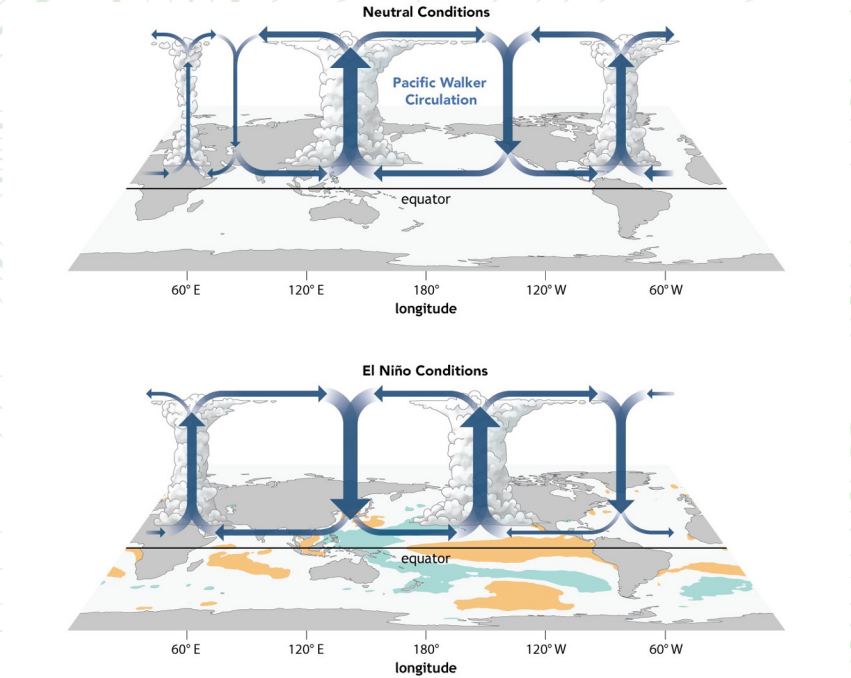
Fonte: Istituto meteorologico norvegese

Modelli di previsione stagionale

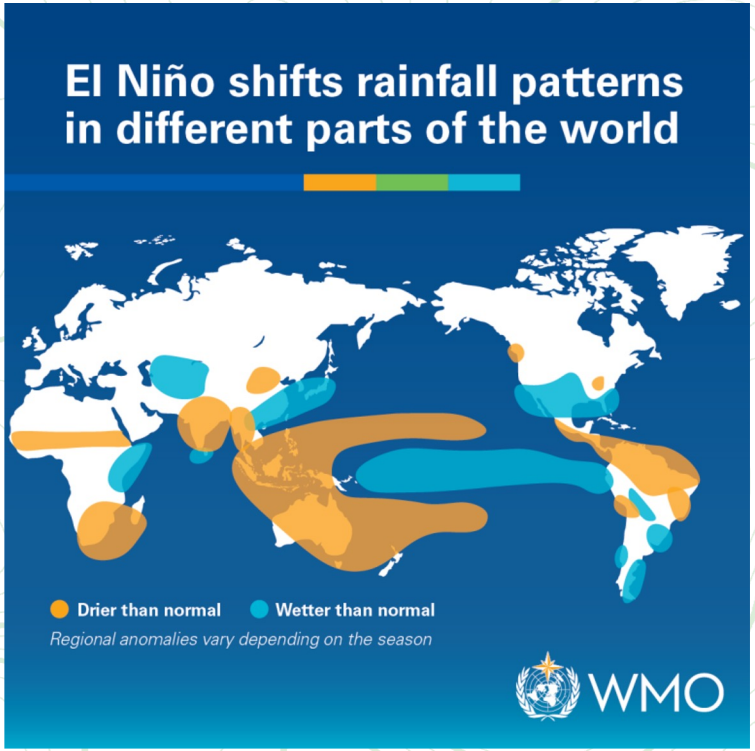
Servizio di previsioni stagionali del Copernicus Climate Change Service (C3S), gestito dall'ECMWF



L’ENSO e le fonti di skill delle previsioni stagionali



L’arrivo di El Niño. Illustrazione di 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

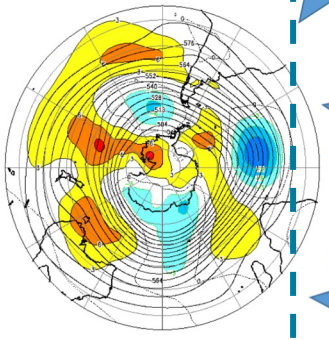
Importanza della previsione stagionale

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.

Una funzione di trasferimento



Riverflow



Malaria



Dry-land crop yield

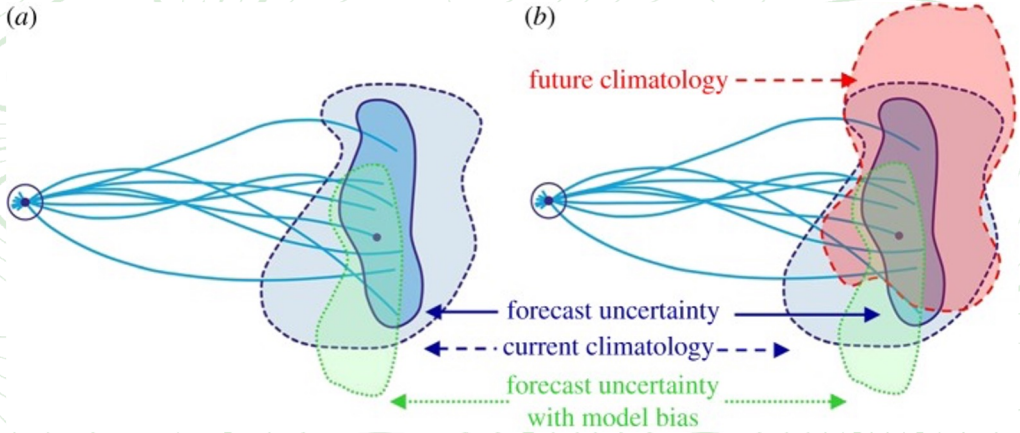
6 CLEAN WATER AND SANITATION

13 CLIMATE ACTION

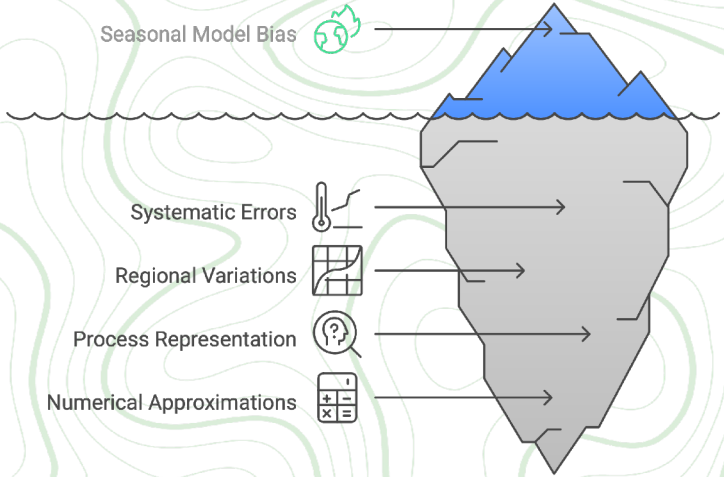
3 GOOD HEALTH AND WELL-BEING

2 ZERO HUNGER

Bias dei modelli stagionali e sue fonti

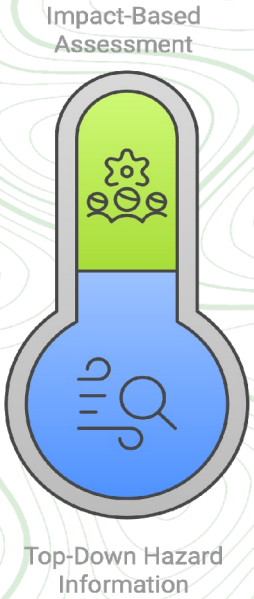


Bias dei modelli stagionali e sue fonti



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.

Valutazione basata sugli impatti vs valutazione tradizionale



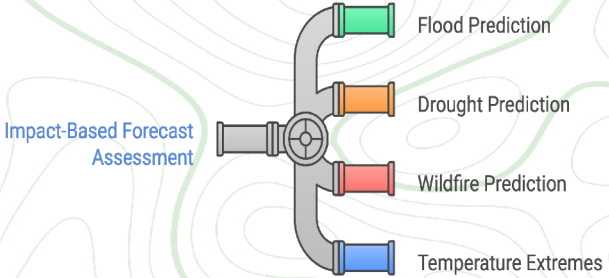
Impact-Based Assessment

Translates forecasts into meaningful information for decision-making

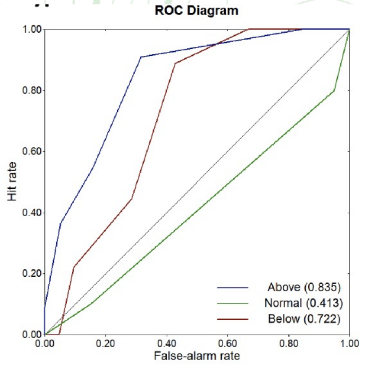
Traditional Assessment

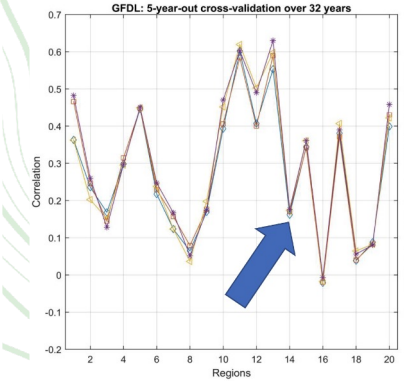
Captures weather patterns compared to reference data

Metriche basate su indici



Correlazioni, RMSE e misure probabilistiche





Quanto sono validi i modelli stagionali «così come sono» in termini di impatti?

AGU ADVANCING EARTH AND SPACE SCIENCES

Earth's Future

RESEARCH ARTICLE
10.1029/2024EF004936

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.

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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

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Data curation: Zahir Nikraftar
Formal analysis: Zahir Nikraftar
Investigation: Zahir Nikraftar

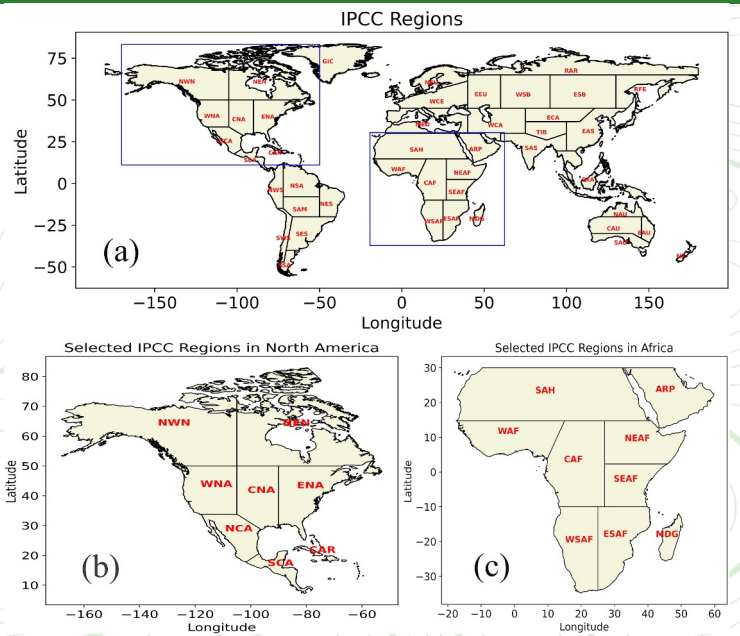
Impact-Based Skill Evaluation of Seasonal Precipitation Forecasts

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

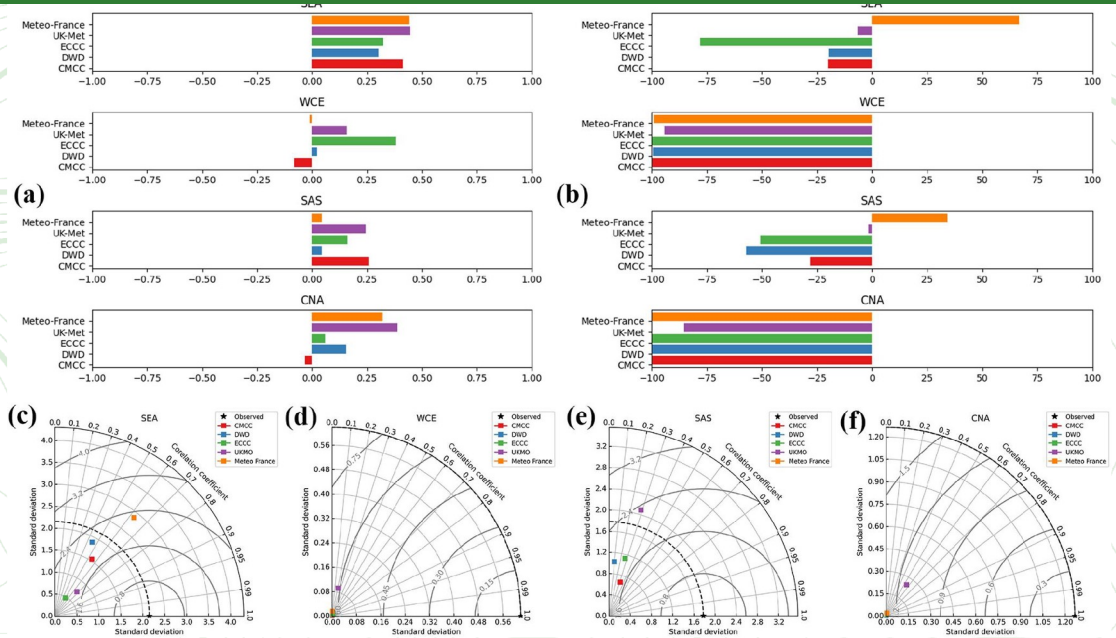
Abstract We introduce an impact-based framework to evaluate seasonal forecast model skill in capturing extreme weather and climate events over regions prone to natural disasters such as floods and wildfires. Forecasting hydroclimatic extremes holds significant importance in an era of increasing hazards 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

Valutazione basata sugli impatti – giorni di forte pioggia nelle regioni soggette ad alluvioni



Prestazioni dei modelli per il numero di giorni di forte precipitazione oltre 10 mm e il 75° percentile dei dati di riferimento (nwd10q75): a) coefficiente tau di Kendall, b) bias percentuale e diagramma di Taylor per c) SEA, d) WCE, e) SAS e f) CNA.

Correzione del bias dei modelli di previsione stagionale

Quantile mapping

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

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

Scalatura lineare

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

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



L’IA nella previsione stagionale

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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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

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.

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

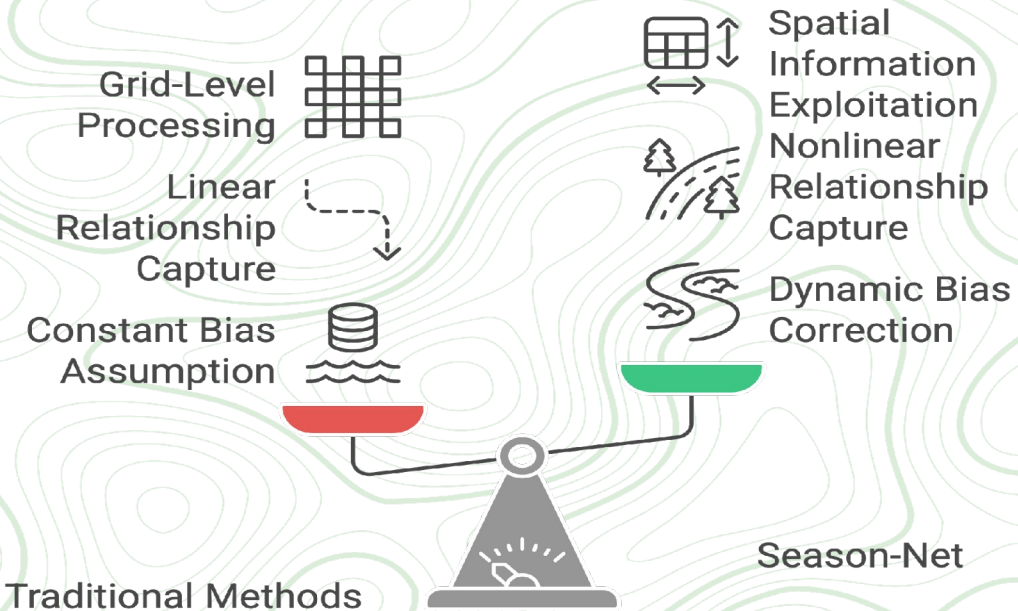
Bobby Antonio[1] · Kristian Strommen[1,2] · Hannah M. Christensen[1]

Received: 12 September 2025 / Accepted: 11 January 2026 / Published online: 16 March 2026
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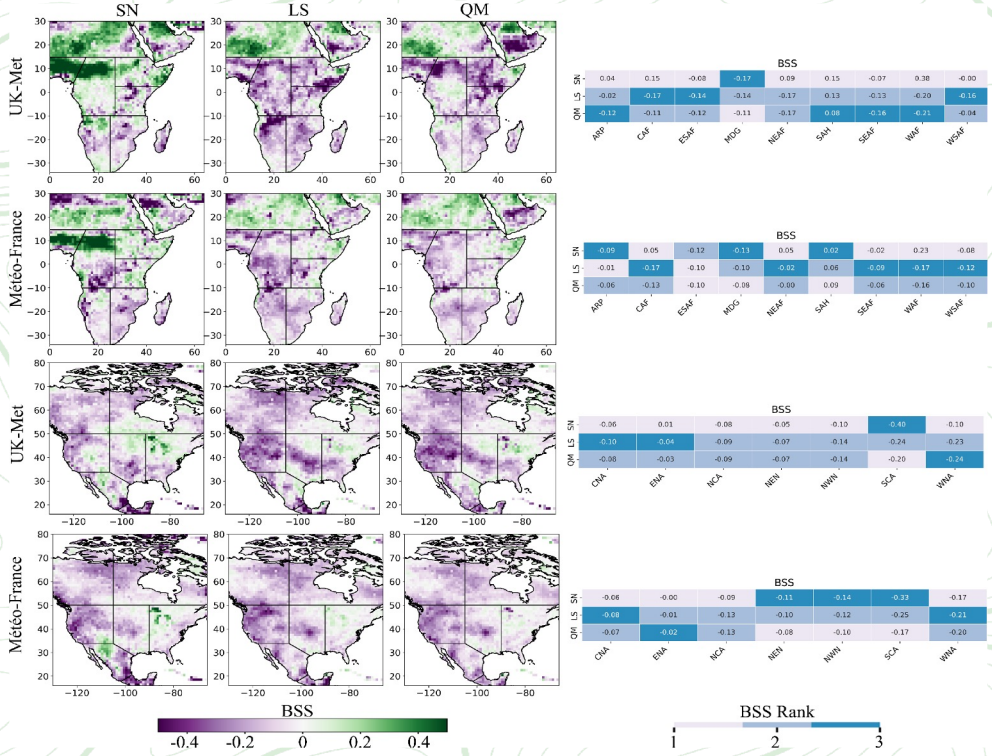
Abstract
Machine-learnt weather prediction (MLWP) models are now well established as being competitive with conventional numerical weather prediction (NWP) models in the medium range. However, there is still much uncertainty as to how this performance extends to longer timescales, where interactions 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

Perché i metodi di IA

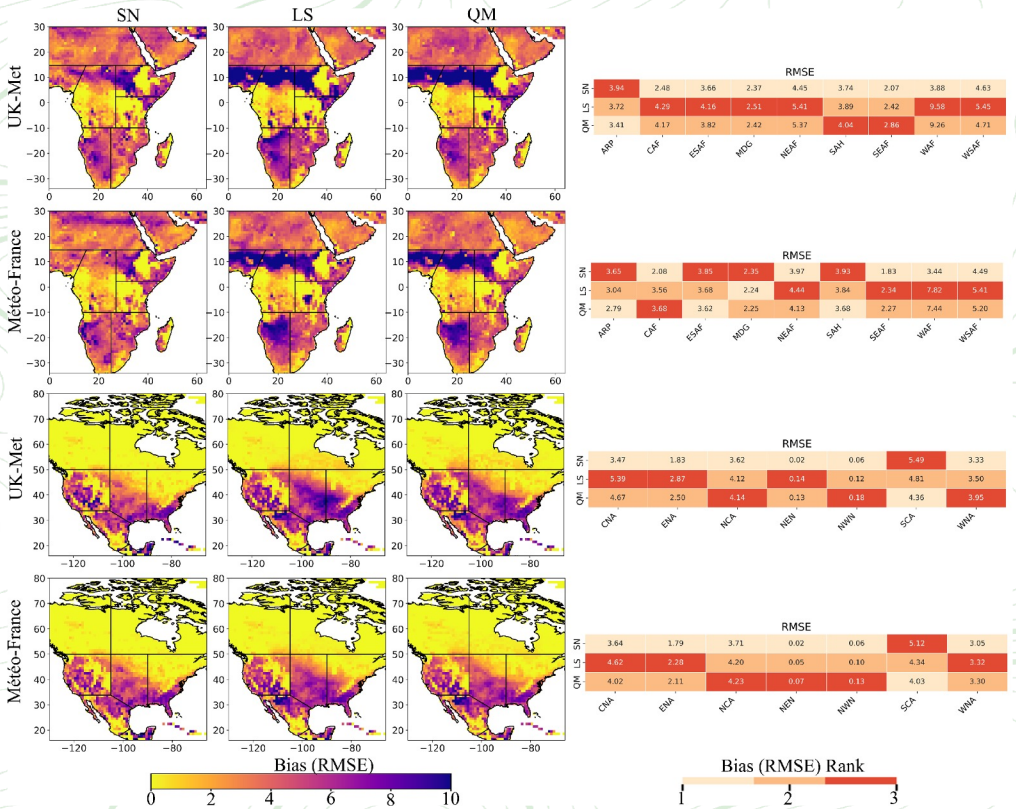


Risultati della correzione del bias – Brier Skill Score



Brier Skill Score (BSS) sull'Africa (righe 1 e 2) nella stagione SON e sul Nord America (righe 3 e 4) in JJA, per Season-Net (colonna 1), LS (colonna 2) e QM (colonna 3). La media per regione IPCC è riportata nella tabella a destra di ogni riga. La scala dei colori del bias è limitata a [-0,5, 0,5] per una visualizzazione coerente tra le mappe.

Valutazione basata sugli impatti – frequenza dei giorni caldi (WDF))



Frequenza dei giorni caldi (WDF): numero di giorni oltre i 35 °C

Mappe di RMSE dell'indice WDF nel periodo di test sull'Africa (righe 1 e 2) nella stagione SON e sul Nord America (righe 3 e 4) in JJA, per Season-Net (colonna 1), LS (colonna 2) e QM (colonna 3). La media per regione IPCC è riportata nella tabella a destra di ogni riga. La scala dei colori del bias è limitata a [0, 10] per una visualizzazione coerente tra le mappe

Risultati dei modelli meteo di IA estesi

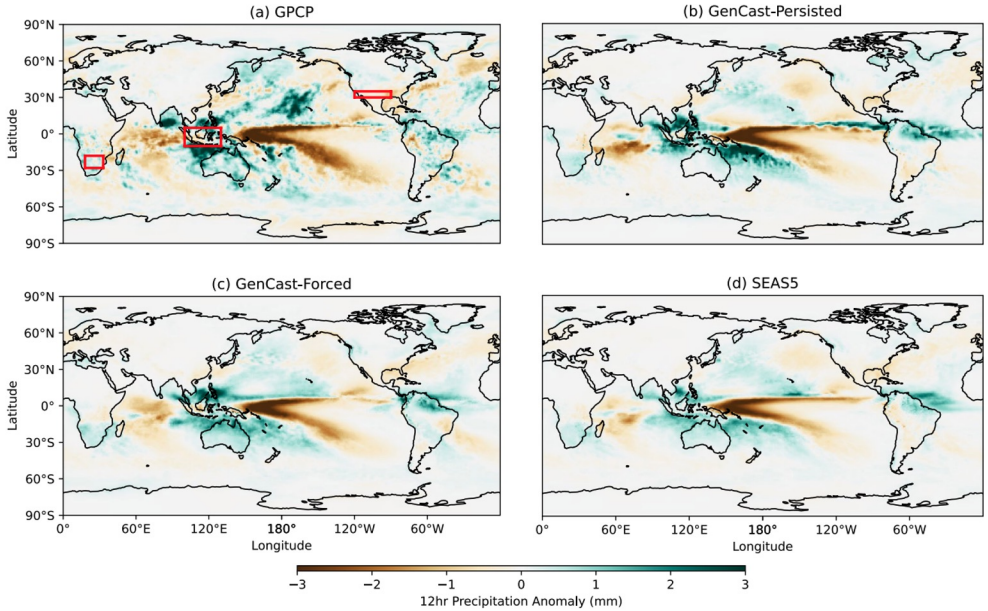


Fig. 1 Seasonal 12hr precipitation anomalies for December 2010–February 2011 (Strong La Niña). Red boxes indicate the subregions used in Fig. 3

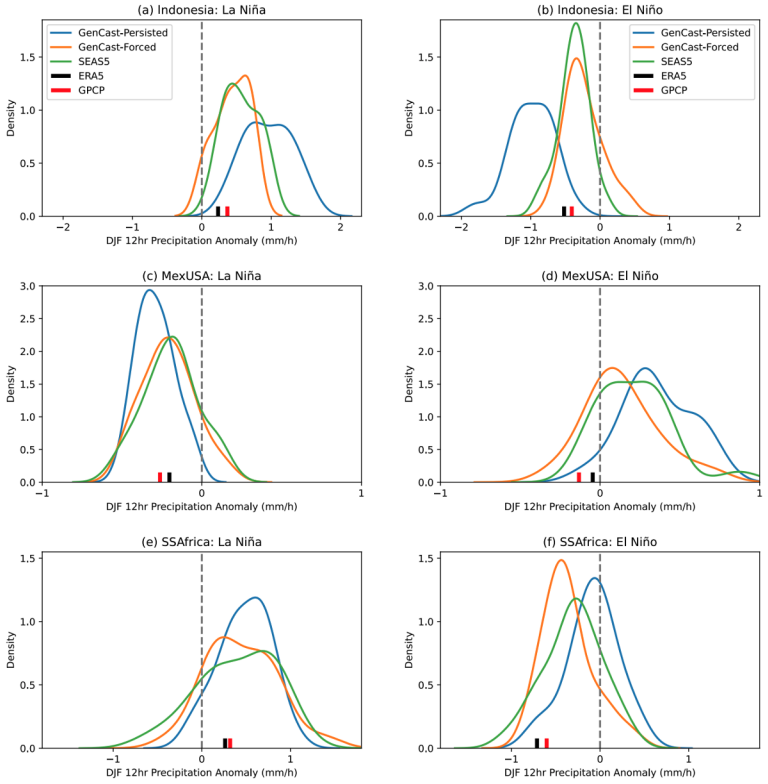


Fig. 3 Kernel density estimate for the distribution of DJF 12hr precipitation anomalies, averaged over each of the subregions shown in Figs. 1 and 2 (rows), and for each of the La Niña and El Niño case studies (columns). In each plot the ERA5 value is shown in black

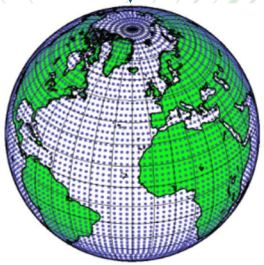
Antonio, B., Strommen, K. and Christensen, H.M., 2026. Seasonal forecasting using the GenCast probabilistic machine learning model. Climate Dynamics, 64(4), p.148.

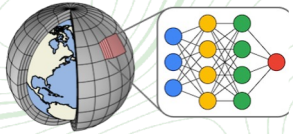
ImvulaNet: co-produzione delle previsioni per l'impatto locale

Piogge e rese locali fornite dagli agricoltori









NeuralGCM



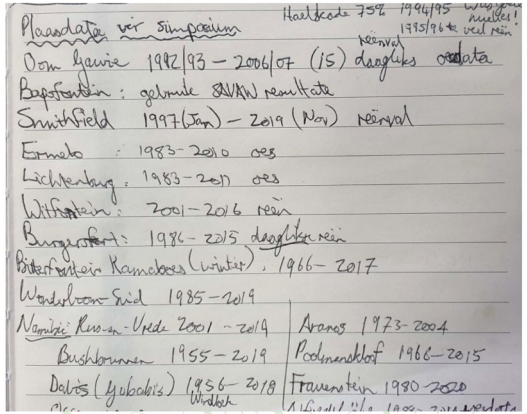
frontiers in Climate

ORIGINAL RESEARCH
published: 08 September 2020
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.

Strumento integrato di supporto alle decisioni per gli

AfriClimate AI
AI for a Climate-Resilient Africa

IDRC · CRDI
Canada

ARC · LNR

UK International Development
Partnership | Progress | Prosperity

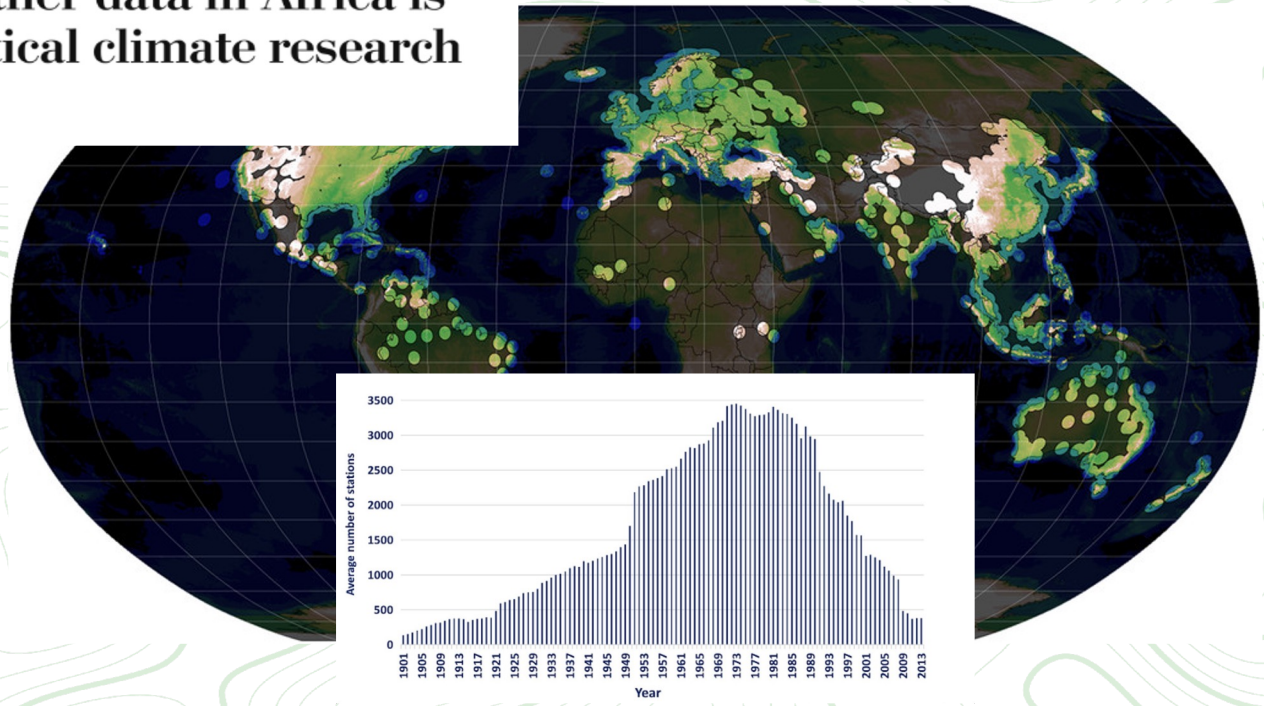
Avvertenza: l’ostacolo della scarsità di dati

The Washington Post
Democracy Dies in Darkness

AFRICA

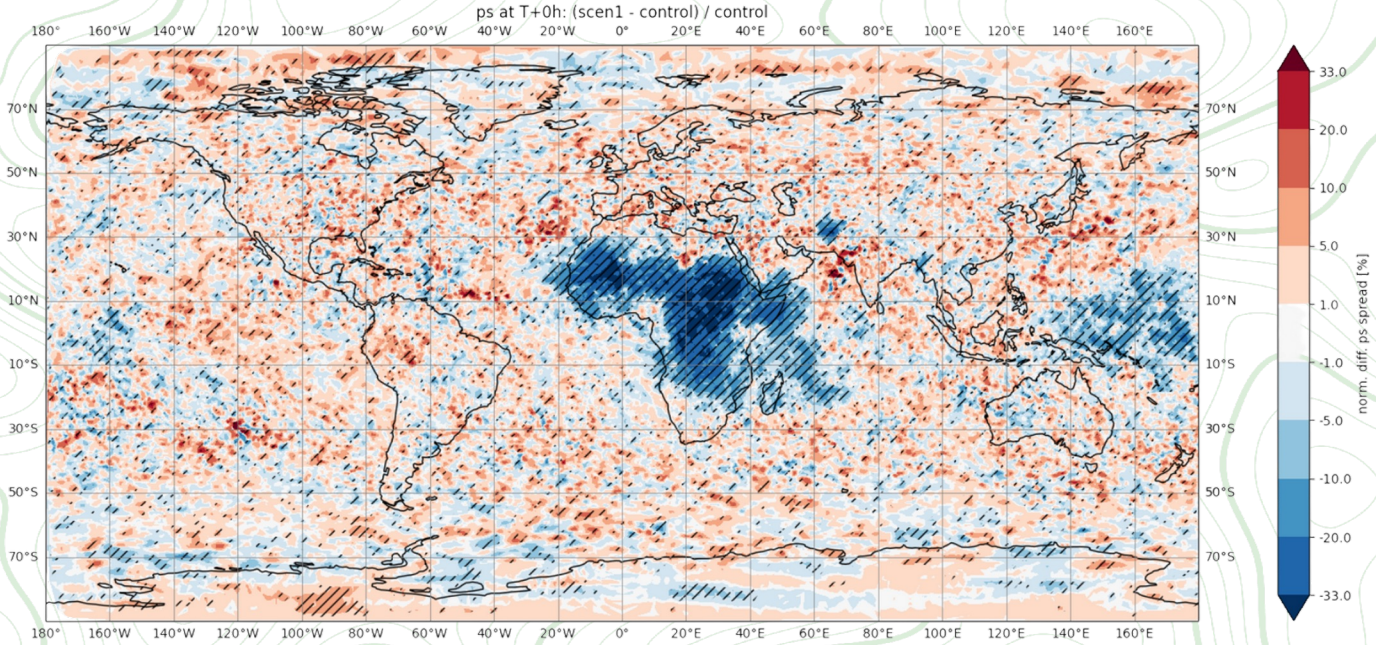
A lack of weather data in Africa is thwarting critical climate research

By Rachel Chason and Rael Ombuor
September 24, 2021 at 5:00 a.m. EDT



Evoluzione del numero di stazioni meteo usate nel prodotto GPCC completo sull’Africa (T. DINKU)

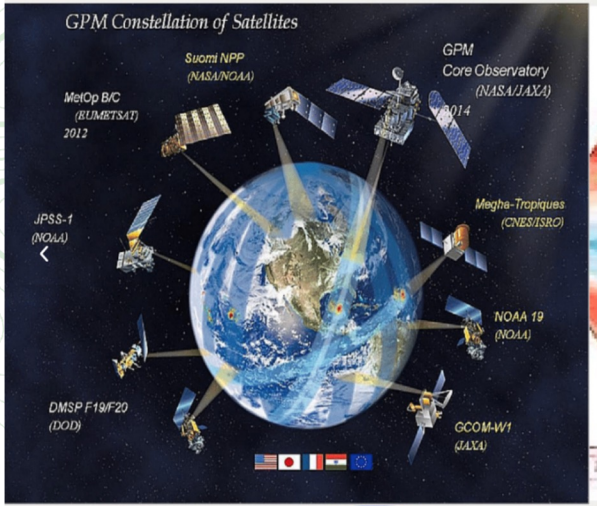
La scarsità di dati danneggia le previsioni meteo



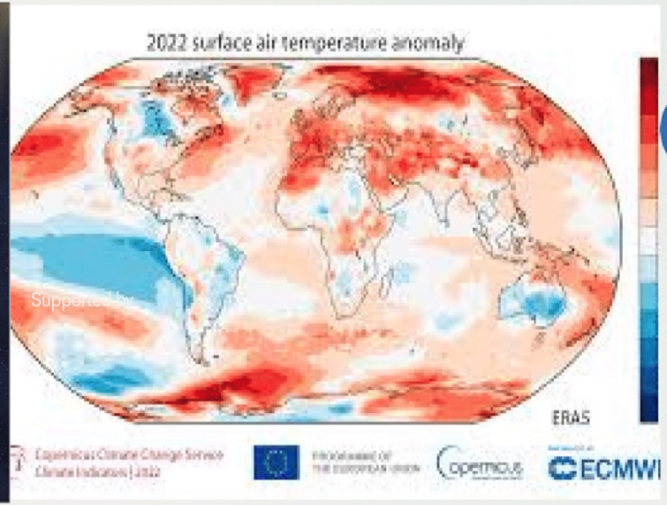
Riduzione percentuale dell'incertezza dell'analisi della pressione al suolo con osservazioni di superficie aggiuntive simulate sull'Africa (ECMWF, 2025)

Ricorrere a proxy globali?

Satellite Products



Renanalysis Products



Merged / Blended Products

MSWEP

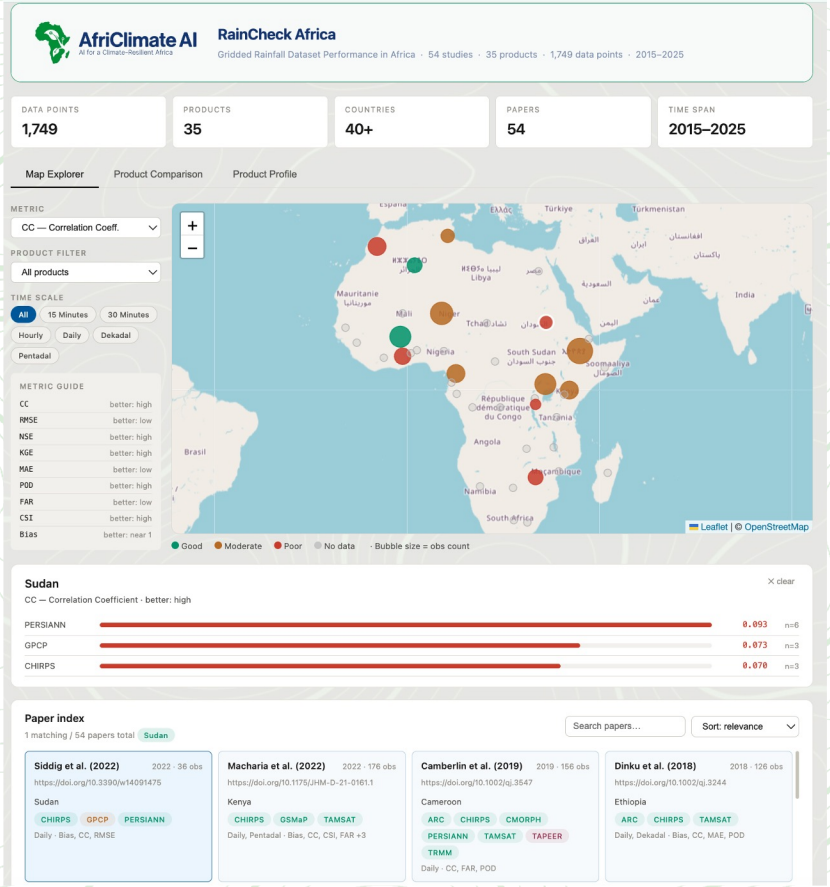
Climate Hazards Center
UC SANTA BAR

NASA

全球降水観測計画
GPM
GLOBAL PRECIPITATION MEASUREMENT

ECMWF

Ma quale proxy? …RainCheck Africa



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

Messaggi chiave

Parte A — previsione a breve termine

- I modelli di IA (GraphCast, GenCast, AIFS, Prithvi WxC) rivaleggiano ormai con la NWP fisica, a una frazione del costo di calcolo
- La skill probabilistica (calibrazione, discriminazione e incertezza, IDR) conta quanto l'accuratezza grezza
- I sistemi ibridi IA-fisica sono la realtà operativa nel breve periodo

Parte B — previsione stagionale

- Correlazione e RMSE possono mascherare una skill scarsa sugli impatti che contano: giorni di forte pioggia, ondate di caldo, siccità
- La correzione del bias (scalatura lineare, quantile mapping, Season-Net) è indispensabile perché le previsioni siano utilizzabili
- Emergenza di modelli meteo di IA estesi alle scale stagionale e sub-stagionale
- Anche qui l'IA riduce il divario, ma i guadagni restano disomogenei tra regioni

Dalla ricerca all'impatto

La skill di una previsione crea valore solo quando raggiunge chi agisce. La co-produzione con agricoltori e servizi meteorologici nazionali trasforma l'output dei modelli in informazioni affidabili e utili alle decisioni.

Quiz: partecipate su Slido



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

Letture chiave

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.

Grazie

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https://africlimate.ai/



Slide di riserva del quiz

Domanda 1 di 4

SCELTA MULTIPLA

Passando dalle previsioni a medio termine a scale più lunghe (stagionali, decennali), verso che cosa si sposta la fonte dominante di prevedibilità/incertezza, a partire da un problema ai valori iniziali?

A) Maggiore fabbisogno di potenza di calcolo

B) Un problema ai valori al contorno, guidato da componenti a variazione più lenta come l’ENSO, il contenuto di calore oceanico e il forzante dei gas serra

C) Disponibilità di dati satellitari

D) La sola risoluzione del modello

RISPOSTA

Risposta corretta: B

Il diagramma delle scale temporali mostra la prevedibilità che passa da fonti legate alle condizioni iniziali (umidità del suolo, MJO/NAO) a breve termine a fonti legate alle condizioni al contorno (ENSO, PDV/AMV/GMST, oceano profondo/emissioni di gas serra/uso del suolo) su scale più lunghe.

Domanda 2 di 4

VERO / FALSO

La maggior parte dei modelli NWP basati sull’IA finora (ad es. FourCastNet, GraphCast, Pangu-Weather) si basa su architetture encoder-processor-decoder e genera previsioni a più giorni tramite rollout autoregressivo, reinserendo ogni previsione come input del passo successivo.

Vero

Falso

RISPOSTA

Risposta corretta: Vero

Questa ossatura encoder-processor-decoder con rollout autoregressivo è l’architettura comune a FourCastNet, GraphCast, Pangu-Weather e modelli NWP basati sull’IA simili.

Domanda 3 di 4

SCELTA MULTIPLA

Quale delle seguenti descrive meglio il ruolo dell’ENSO come fonte di skill delle previsioni stagionali?

A) L’ENSO non ha effetti misurabili sui regimi regionali di pioggia

B) L’ENSO modifica i regimi di pioggia in modo diverso nelle varie regioni del mondo, fornendo un segnale climatico prevedibile che i modelli stagionali possono sfruttare

C) L’ENSO influisce sulla skill solo alla scala meteorologica (breve termine), non stagionale

D) L’ENSO è una tecnica di correzione del bias usata per regolare l’output dei modelli stagionali

RISPOSTA

Risposta corretta: B

El Niño modifica i regimi di pioggia (più umidi/secchi del normale) in modo diverso a seconda della regione: è proprio questa teleconnessione a rendere l’ENSO il segnale climatico che dà skill alla previsione stagionale.

Domanda 4 di 4

SCELTA MULTIPLA

I metodi di correzione del bias come scalatura lineare, quantile mapping e Season-Net sono considerati essenziali perché le previsioni stagionali siano utilizzabili per le decisioni.

Vero

Falso

RISPOSTA

Risposta corretta: Vero