



1 A causality-based perspective on Atlantic and tropical Pacific 2 teleconnections to Northeast Brazil in seasonal forecast systems

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12 13 Abstract

14 Seasonal forecast systems are routinely evaluated with skill metrics, which quantify forecast
 15 performance without revealing through which physical pathways it is achieved. In this study, we use
 16 the Liang–Kleeman (LK) causality formalism to evaluate how the Copernicus Climate Change Service
 17 (C3S) seasonal multi-system represents the causal influence of large-scale drivers from the tropical
 18 Atlantic, tropical Pacific and South Atlantic on surface wind and precipitation over Northeast Brazil
 19 (NEB), a region of strategic importance for renewable energy production where climate variability is
 20 strongly shaped by these drivers. The hindcast skill assessment, performed through the anomaly
 21 correlation coefficient (ACC) and mean squared error skill score (MSSS), reveals that for both variables
 22 the highest and most consistent predictive skill is concentrated around the February–May rainy season.
 23 In ERA5, the causal influences diagnosed with the LK formalism recover the known seasonality of the
 24 most prominent drivers, namely the Atlantic Meridional Mode, El Niño–Southern Oscillation (ENSO)
 25 and the South Atlantic Subtropical High, as well as their global teleconnection patterns. The C3S
 26 systems generally capture the emergence and disappearance of the causal links, although differing
 27 substantially in their strength, with no system performing consistently across drivers and initialisation
 28 months, and none capturing the austral winter ENSO influence on precipitation. Relating each system's
 29 fidelity in capturing the ERA5 causal strengths to its average skill shows that, for surface wind, systems
 30 with higher fidelity achieve higher MSSS, whereas no robust relationship is found for the ACC.
 31 Decomposing the MSSS reveals that this link, which is not explained by driver skill or ensemble size,
 32 arises from amplitude errors, where systems with less realistic teleconnections overestimate the
 33 amplitude of their forecast signal more strongly. Overall, this study shows that causality-based
 34 evaluation can complement conventional verification by identifying which forecast systems better
 35 reproduce the teleconnections underlying regional predictability, and positions the LK formalism as a
 36 diagnostic tool for process-oriented inter-model comparison across regions and timescales.

37 38 1. Introduction

39 Seasonal forecast systems have undergone substantial developments in recent decades (Goddard et al.
 40 2001; Doblas-Reyes et al. 2013; Merryfield et al. 2020), with current state-of-the-art models now capable
 41 of skilfully predicting some large-scale modes of variability, most notably the El Niño–Southern
 42 Oscillation (ENSO; Barnston et al. 2012; Ehsan et al. 2024). Even where large-scale predictability exists,
 43 translating it into reliable regional forecasts remains challenging. This is partly due to complex
 44 (non)linear interactions among drivers, often occurring across timescales (Muñoz et al. 2015; Arcodia et
 45 al. 2020; Pineda et al. 2023), but also due to the imperfect representation of dynamical processes



46 governing regional climate variability (Miller and Wang 2019; Meehl et al. 2021). Misrepresenting the
47 mechanisms linking large-scale modes of variability to regional climate responses can reduce predictive
48 skill (Misra and Zhang 2007; Williams et al. 2023), with systematic model errors often developing even
49 at short lead times (Vannière et al. 2013; Beverley et al. 2023).

50

51 In seasonal prediction, forecast quality is routinely assessed using deterministic and probabilistic
52 metrics that quantify different aspects of the agreement between forecasts and observations (Murphy
53 and Epstein 1989; Wilks 2019). While these metrics are valuable to assess model performance, they offer
54 limited insight into the physical processes and conditions underlying forecast success or failure, and
55 are therefore unable to diagnose the sources of model error. This shortcoming naturally leads to the
56 concept of *windows of opportunity* (Mariotti et al. 2020; Dunstone et al. 2023), whereby particular
57 dynamical conditions may favour enhanced forecast skill. Identifying such windows requires process-
58 based approaches that assess whether models capture dynamical processes (Eyring et al. 2019; Maloney
59 et al. 2019; Garfinkel et al. 2025), and causality-based approaches that evaluate whether models
60 reproduce causal relationships between large-scale climate drivers and their regional impacts (i.e.,
61 teleconnections; Nowack et al. 2020; Kretschmer et al. 2021; Kolstad 2026). Together, these approaches
62 can help bridge the gap between statistical forecast performance and physical understanding.

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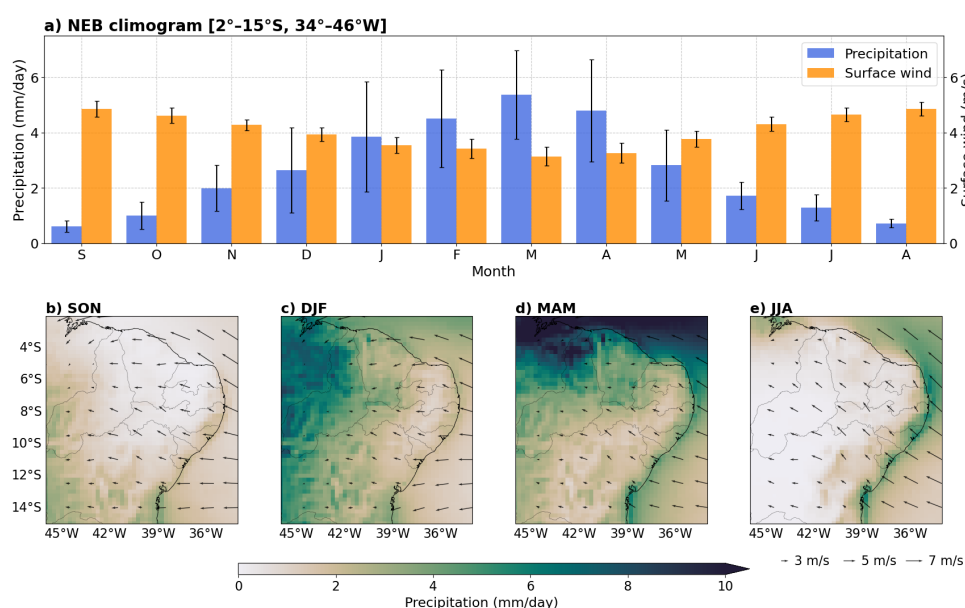
64 In climate variability studies, causal relationships between variables are often inferred using (lagged)
65 correlation analyses. While this approach is valuable for identifying statistical associations and
66 plausible teleconnections, it does not indicate the direction of influence and can sometimes reflect
67 spurious relationships rather than real causal links (Runge et al. 2019a), particularly in systems
68 characterised by strong coupling and feedbacks. To overcome these limitations, recent studies have
69 increasingly adopted causality-based frameworks grounded in dynamical systems and information
70 theory (Runge et al. 2019b; Runge et al. 2023). Among these, the Liang–Kleeman (henceforth, LK)
71 causality formalism (Liang and Kleeman 2005) introduces a measure of the magnitude and direction of
72 information flow (or information transfer) between time series, enabling the identification of causal
73 links in complex climate systems. The LK causality framework has been applied to study causal
74 influences between climate indices related to large-scale modes of climate variability (Vannitsem and
75 Liang 2022; Docquier et al. 2024a; Vannitsem et al. 2025), between snow cover and air temperature
76 (Komatsu et al. 2023; Takaya et al. 2024), between soil moisture and air temperature (Takaya et al. 2025),
77 and for the identification of Arctic (Docquier et al. 2024b) and Antarctic (Docquier et al. 2025) sea ice
78 drivers, demonstrating its potential to uncover physically meaningful causal relationships beyond
79 conventional correlation analyses. However, the LK framework has not yet been used to evaluate how
80 operational seasonal forecast systems represent teleconnections, nor whether this representation
81 relates to their forecast skill.

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83 In this study, we address this gap by using the LK causality framework to evaluate how state-of-the-art
84 seasonal forecast systems represent the teleconnections affecting Northeast Brazil (NEB), or Nordeste,
85 where the regional climate is strongly shaped by large-scale drivers from the Atlantic and tropical
86 Pacific. The region is also strategically important for Brazil’s energy and water security, concentrating
87 around 91% of the country’s installed wind power capacity (Lucena and Lucena 2019), particularly in the
88 Rio Grande do Norte state, and hosting major water supply and hydropower reservoirs along the
89 Parnaíba and São Francisco river basins (Souza Júnior et al. 2024; World Bank 2025). However, this
90 strategic importance is accompanied by considerable climate vulnerability. NEB is characterised by a



101 warm, semi-arid climate, with rainfall concentrated in a relatively narrow rainy season from February
 102 to May (Fig. 1a), particularly over northern NEB (Fig. 1d). The rainy season is associated with the
 103 southward migration of the Intertropical Convergence Zone (ITCZ; Cai et al. 2020), with rainfall
 104 peaking in early to mid-austral autumn (i.e., March–April), when the ITCZ typically reaches its
 105 southernmost position. Given the strong dependence of the Nordeste’s climate on this seasonal
 migration, anomalous displacements of the ITCZ often lead to severe droughts (Moura and Shukla 1981;
 Hastenrath 2006) and anomalous wind patterns (Hastenrath and Greischar 1993), with significant socio-
 economic consequences including water scarcity (Marengo et al. 2017), crop failures (Anderson et al.
 2019; Marengo et al. 2022), and impacts on wind and hydropower generation (Hastenrath 2012; dos
 Santos Gomes et al. 2025; Duque-Gardeazabal et al. 2026). Beyond the main wet season, a pre-wet season
 extends from mid-spring to mid-austral summer (i.e., October–January), partially visible in Fig. 1c, and
 more concentrated over western NEB (Hastenrath 2006; Vasconcelos Junior et al. 2018). The rest of the
 year, roughly covering austral winter (i.e., JJA) and spring (i.e., SON), is considerably drier, with JJA
 rainfall confined to a narrow strip along the eastern coast (Fig. 1e; Tedeschi et al. 2016).



106 Figure 1. a) Climogram including surface wind and precipitation in NEB over the period 1980–2025 in the ERA5
 107 reanalysis (Hersbach et al. 2020). Seasonal climatologies of precipitation (coloured shading) and surface wind (black
 108 arrows) over NEB for b) austral spring or SON, c) austral summer or DJF, d) austral autumn or MAM and e) austral
 109 winter or JJA. Top and bottom whiskers in a) represent one standard deviation from the climatological mean. Note
 110 that the months in a) go from September to August.
 111

112
 113 Timely access to reliable climate information is critical for stakeholders across climate-dependent
 114 sectors (Hewitt et al. 2012; Torralba et al. 2017; Lledó et al. 2019), and of particular relevance in the
 115 Nordeste, where large-scale climate variability drives month-to-month fluctuations in surface wind and
 116 precipitation. Anticipating these fluctuations with sufficient lead time is important for both the
 117 operation of an increasingly wind-dependent energy system (Souza Júnior et al. 2024) and water resource
 118 management. Seasonal climate predictions, which typically provide information as monthly and
 119 seasonal averages (White et al. 2022), therefore offer a pathway to inform decision-making in the



region's climate-sensitive sectors (Lima and Lall 2010; Marengo et al. 2022). This pathway is underpinned by the sustained developments in seasonal forecasting outlined earlier and by coordinated initiatives such as the Copernicus Climate Change Service (C3S) seasonal multi-system, which provides operational forecasts of key climate variables up to 6 months ahead. Over NEB, seasonal precipitation predictability has been demonstrated through dynamical models (Folland et al. 2001; Sun et al. 2006; Hounsou-Gbo et al. 2025; Vasconcelos Junior et al. 2025), statistical methods (Ward and Folland 1991; Hounsou-Gbo et al. 2019), and machine learning approaches (Silva and Mendes 2013; Pinheiro and Ouarda 2023), with skill generally concentrated around the rainy season. In contrast, surface wind prediction has received comparatively little systematic assessment, an uneven evidence base that may limit seasonal forecast usability across sectors. In addition, predictive skill for tropical Atlantic sea surface temperature (SST) variability, a key source of predictability for the region, remains more limited and seasonally dependent (Stockdale et al. 2006), although recent studies report notable advances over the northern tropical (Liu et al. 2025) and equatorial Atlantic (Nnamchi and Latif 2025).

In NEB, intra-annual climate variability is modulated by complex interactions among large-scale ocean and atmospheric drivers (Uvo et al. 1998; Torralba et al. 2015; Mao et al. 2022; dos Santos et al. 2023; Vitorio et al. 2025), including the Atlantic Meridional Mode (AMM; Utida et al. 2019; dos Santos Gomes and Lima 2021), ENSO (Rodrigues et al. 2011; Cai et al. 2020) and the South Atlantic Subtropical High (SASH; Kayano et al. 2018; Reboita et al. 2021). The AMM, which is most active during austral autumn (i.e., MAM; Chiang and Vimont 2004), modulates the interhemispheric (i.e., meridional) SST gradient, controlling the migration of the ITCZ. During its positive (negative) phase, the tropical North Atlantic (TNA) region is warmer (cooler) than the tropical South Atlantic (TSA), contributing to anomalous northward (southward) ITCZ displacements. Other Atlantic modes, including the Atlantic Zonal Mode (AZM; Zebiak 1993; Lübbecke et al. 2018) and the South Atlantic subtropical/oceanic dipole (SASD/SAOD; Venegas et al. 1997; Nnamchi et al. 2011), also modulate convection and regional circulation in the tropical Atlantic. Despite being localised within different regions in the Atlantic basin, both modes can affect atmospheric circulation patterns relevant for NEB climate, including ITCZ and southeasterly trade wind variability (Haarsma et al. 2003). In parallel, several mechanisms explain how ENSO influences tropical Atlantic variability (García-Serrano et al. 2017; Cai et al. 2019), with the tropical and extratropical pathways being the most prominent ones. In the former, ENSO-driven changes in the Walker circulation alter the Atlantic Hadley cell (Klein et al. 1999; Wang 2004), leading to anomalous ascending motions over TNA and a reduction in the strength of the low-level northeasterly trades. In the latter, during the positive phase of ENSO (i.e., El Niño), enhanced convection in the central tropical Pacific can trigger a Rossby wave train that reduces subsidence over TNA, weakening sea level pressure (SLP) and the northeasterly trades, thus reducing evaporative cooling and upwelling. During El Niño, both pathways favour warmer SSTs in TNA and a strengthened interhemispheric gradient, preventing the southward migration of the ITCZ and thus leading to rainfall deficits over NEB (Hastenrath 2012), with broadly opposite effects during La Niña. Because ENSO typically peaks in boreal winter and its influence on TNA lags by a few months, its impact on NEB is strongest during the following boreal spring, in the decay phase of the event (García-Serrano et al. 2017). Lastly, the SASH controls the strength of the southeasterly trades affecting the Nordeste coastline, which peak during austral winter (i.e., JJA), when the SASH is strongest (Sun et al. 2017; Reboita et al. 2019). The combined influence of these drivers, which can reinforce or offset one another, modulates the regional climate response over NEB, partially governing the seasonal distribution of rainfall and wind over the Nordeste.



Building on this background, here we extend the application of the LK causality formalism to the evaluation of teleconnections in state-of-the-art seasonal forecast systems, examining how they represent the influence of relevant modes of climate variability on surface wind and precipitation over NEB. While previous studies have applied the method at interannual and intra-monthly timescales in the context of climate projections and subseasonal predictions, respectively, here we quantify causality at the intra-annual scale, focusing on month-to-month variations in the context of seasonal predictions. This allows us to move beyond conventional skill-based evaluation and directly compare how different forecast systems represent the causal pathways, here diagnosed through information transfer, underlying regional predictability. Specifically, we assess whether the models participating in the C3S seasonal multi-system capture the causal influence of large-scale drivers, namely tropical Pacific and tropical Atlantic SST variability, together with South Atlantic SST and SLP variability, on NEB's surface wind and precipitation. Although the evaluation focuses on NEB, we also verify that the approach recovers the global teleconnection patterns of each driver, supporting its transferability to other regions. By combining conventional forecast verification with causality-based inter-model comparison, we assess not only when the systems are skilful, but also whether they reproduce the teleconnections associated with that skill.

2. Methods

In this section, we introduce the seasonal forecast systems and reanalysis datasets used in this study and, where relevant, describe the post-processing techniques applied to the data. We then describe how the large-scale drivers of NEB climate are characterised, outline the verification metrics used to assess hindcast skill, and present the Liang-Kleeman causality formalism.

2.1 Data

The data consist of hindcasts (i.e., retrospective forecasts) from the C3S seasonal multi-system (<https://climate.copernicus.eu/seasonal-forecasts>) and the ERA5 reanalysis (Hersbach et al. 2020), used as the observation-based reference. Essential information about the different forecast systems is included in Table 1. For systems with variable ensemble sizes across initialisation months (e.g., CFSv2), we retain the minimum ensemble size so that all initialisations contain the same number of members. The January 1993 initialisation of GloSea6 is not available in the C3S Climate Data Store (CDS).

Producing center	System	Hindcast period	Ensemble size	Horizontal resolution (atmosphere)	Horizontal resolution (ocean)	Reference
ECMWF	SEAS5.1	1981–2016	25	0.278° (Tco319)	0.25°	Johnson et al. 2019
Météo-France	System9	1993–2024	31	0.5° (TL359)	0.25°	Specq et al. 2026
DWD	GCFS2.2	1993–2023	30	~0.9° (T127)	0.4°	Fröhlich et al. 2021
CMCC	SPS4	1993–2024	30	~0.5° x 0.5°	0.25°	Sanna et al. 2025
ECCC	GEM5.2-NEMO	1993–2023	20	~1.1° x 1.1°	1°	Diro et al. 2024



NCEP	CFSv2	1993–2016	20	$\sim 1^\circ \times 1^\circ$ (T128)	$0.5^\circ \times 0.25^\circ$	Saha et al. 2014
JMA	MRI-CPS3	1993–2020	10	0.563° (TL319)	0.25°	Hirahara et al. 2023
BoM	ACCESS-S2	1993–2018	27	$\sim 0.83^\circ \times 0.56^\circ$ (N216)	0.25°	Wedd et al. 2022
UK Met Office	GloSea6	1993–2016	28	$\sim 0.83^\circ \times 0.56^\circ$ (N216)	0.25°	Kettleborough et al. 2026

Table 1. C3S seasonal forecast systems used in this work. From left to right, the table includes: producing center, system acronym, full hindcast period available, ensemble size, original horizontal atmospheric resolution, original horizontal oceanic resolution, and reference describing the system. For extensive information on the C3S seasonal multi-system, we refer the reader to:

<https://confluence.ecmwf.int/display/CKB/Description+of+the+C3S+seasonal+multi-system> (last access: 1st July 2026).

We use the common hindcast period, 1993–2016, across all C3S systems. Monthly anomalies are computed for our reference and hindcast datasets relative to this period using leave-one-out cross-validation (i.e., the climatological mean used to calculate anomalies for a given year is estimated from all years except the year being evaluated; Elsner and Schmertmann 1994; Hagedorn et al. 2006), which avoids artificially inflating the skill and emulates real-time forecast conditions. For ERA5, we additionally consider the 1980–2025 period, which broadly corresponds to the satellite era and provides a more reliable observation-based basis for characterising the causal relationships between large-scale climate drivers and NEB climate. Hence, ERA5-only analyses are computed over 1980–2025, whereas model evaluation is performed over 1993–2016, with the corresponding causality estimates compared against ERA5 over both periods. This dual approach allows us to assess the robustness of the inferred causal relationships while ensuring a fair comparison between the reanalysis and the forecast systems. The seasonal hindcasts were retrieved on the common 1° horizontal grid available in the CDS, while the ERA5 reference data were regridded to the same resolution, using bilinear interpolation for surface wind, 2-metre air temperature, SST, and SLP, and conservative interpolation for precipitation. Analyses involving only ERA5 are performed at the original 0.25° resolution.

Hindcast anomalies are computed through the SUBseasonal to decadal climate forecast post-processing and assessment suite (SUNSET; Agudetse et al. 2026). The ERA5 and C3S anomalies are detrended through a regression-based method (Greene et al. 2011), in which the anomaly field is regressed against a LOWESS-smoothed (Cleveland 1979) global mean surface temperature (GMST) time series to remove the forced climate change signal. The approach is analogous to pattern scaling (Tebaldi and Arblaster 2014), but uses a nonlinear reference trend (i.e., LOWESS-smoothed GMST), thereby not assuming that the temporal evolution of the forced signal remains linear. The rationale behind the detrending is twofold: first, to isolate internal variability to the greatest extent possible, and second, to enforce stationarity, a condition required by the LK causality formalism. The detrended field is not decomposed into its decadal and interannual components, as decadal variability influences interannual signals through changes in the background state, thereby impacting seasonal predictability (Kirtman and Schopf 1998). Further technical details are provided in the Supplementary Information (SI; Sect. S1).



2.2 Large-scale drivers of Northeast Brazil climate

To characterise the dominant large-scale drivers of climate variability affecting NEB, we use principal component analysis (PCA; Hannachi et al. 2007) to compute the empirical orthogonal functions (EOFs) and principal components (PCs) of SST over the tropical Pacific (TPAC; first mode), the tropical Atlantic (TATL; first three modes) and the South Atlantic (SATL; first two modes), and of SLP over the SATL (first three modes). The drivers and retained modes are selected based on their established relevance to NEB climate (Sect. 1), and by the physical interpretability of their EOF patterns and PC time series (Fig. 2). EOF1 of TATL SSTs correspond to a basin-wide mode of variability, EOF2 to the tropical Atlantic dipole (TAD; Enfield et al. 1999), which represents the interhemispheric SST gradient associated with the AMM, and EOF3 to the AZM. EOF1 of TPAC SSTs represents the canonical form of ENSO.

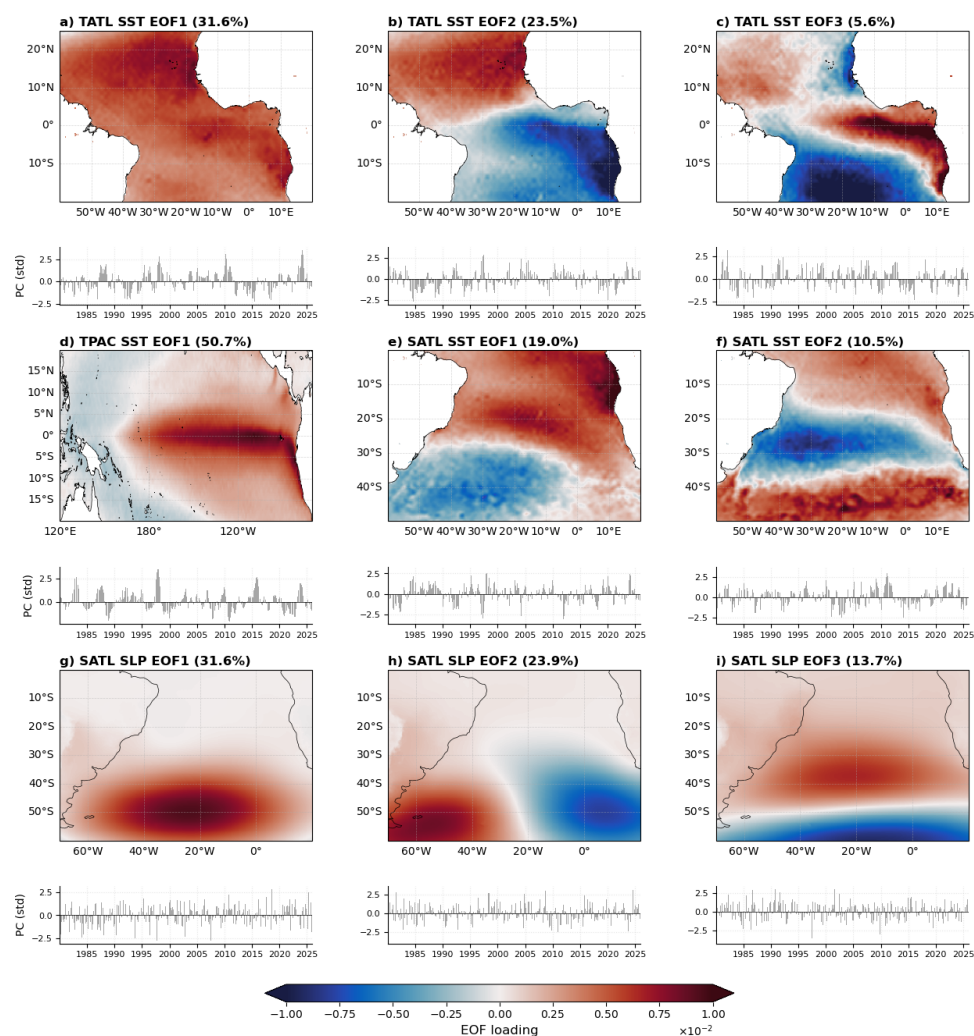


Figure 2. EOF spatial patterns, PC time series and explained variance for the first three modes of tropical Atlantic SST, a), b) and c), the first mode of tropical Pacific SST, d), the first two modes of South Atlantic SST, e) and f), and the first three modes of South Atlantic SLP, g), h) and i) over 1980–2025 in the ERA5 reanalysis. The EOF spatial



representations (i.e., EOF loadings) are dimensionless. The PC time series are normalised by the standard deviation over the full period.

For South Atlantic SSTs, EOF1 corresponds to a dipole mode, which represents the structure of the SASD/SAOD (Nnamchi et al. 2017), whereas EOF2 exhibits a tripole structure (Sterl and Hazeleger 2003). Lastly, EOF1, EOF2, and EOF3 of South Atlantic SLP represent different characteristics of the SASH, specifically, variations in its strength and zonal and meridional displacements (Venegas et al. 1997), respectively. Indian Ocean SST drivers are not considered because their variability is largely coupled to variability in the Pacific basin (Cai et al. 2019).

All EOFs are computed from detrended ERA5 monthly anomalies over the period 1980–2025 (Sect. 2.1). The drivers are represented by their respective PCs, rather than by conventional box-averaged indices (e.g., Niño3.4, TNA). This choice reduces sensitivity to spatial biases, as a model may misplace the centres of action of a particular mode (e.g., zonally shifted ENSO pattern) and thus penalise such spatial displacements as amplitude errors. Because each model has its own systematic biases, computing EOFs separately for each model would result in model-dependent spatial patterns and hence PCs that are not directly comparable. To ensure comparability across models and against the reanalysis, all hindcast anomalies are therefore projected onto ERA5 EOF patterns (Fig. 2). Reassuringly, the PCs closely track the corresponding conventional indices: the PC of TPAC SST EOF1 and the Niño3.4 index (Barnston et al. 1997) correlate at $r = 0.95$, and the PC of TATL SST EOF2 and the TAD index at $r = 0.97$ (Fig. S1). The PCA-based drivers therefore retain the physical interpretation of the established indices while providing a common basis for inter-model comparison. Applying the same projection to ERA5 recovers the original ERA5 PCs. Further technical details are provided in the SI (Sect. S2).

2.3 Hindcast skill metrics

Hindcast skill is evaluated for the ensemble mean of each C3S system (Table 1) through the Spearman formulation of the anomaly correlation coefficient (ACC):

$$ACC_{\rho} = 1 - \frac{6 \sum_{t=1}^n (r_{h'_t} - r_{o'_t})^2}{n(n^2 - 1)} \quad (1)$$

where $r_{h'_t}$ is the rank of the hindcast anomalies, h'_t , $r_{o'_t}$ is the rank of the reference anomalies, o'_t , n is the number of samples. For the ACC, statistical significance is computed through a one-tailed Student's t-test at the 95 % confidence level ($\alpha = 0.05$; Zar 1972). Although the ACC is commonly computed through its Pearson formulation, here we use the Spearman version because its nonparametric nature makes it less sensitive to outliers and does not require normally distributed data. This alternative version of the ACC indicates how well the relationship between the hindcast and reference anomalies can be described through a monotonic function, where $ACC = 1$ indicates a perfect monotonic increasing relationship. The ACC measures to what degree the hindcast and reference anomalies are in phase, but it is insensitive to systematic errors in amplitude (i.e., over- or underestimation of variability). Therefore, to offer a more comprehensive view, we also evaluate the mean squared error skill score (MSSS; Murphy and Epstein 1989):



$$MSSS = 1 - \frac{MSE_{hindcast}}{MSE_{clim}} = 1 - \frac{\sum_{t=1}^n (h'_t - o'_t)^2}{\sum_{t=1}^n o_t'^2} \quad (2)$$

where the climatological forecast corresponds to zero anomaly. MSSS = 1 indicates a perfect forecast, MSSS = 0 implies no improvement over a climatological forecast, and MSSS < 0 indicates worse performance than climatology. For the MSSS, statistical significance is assessed through a one-tailed permutation test at the 95% confidence level ($\alpha = 0.05$) with 1000 random permutations (Wilks 2019). Overall, these metrics are selected because they provide complementary perspectives on forecast performance (Barnston et al. 2019).

297

2.4 Liang–Kleeman causality formalism

The LK causality formalism (Liang 2014, 2021) is a method based on dynamical systems and information theory that quantifies the rate of information transfer between time series. In particular, it allows determining whether a causal relationship exists between a target variable (e.g., NEB precipitation) and its potential driver(s) (e.g., ENSO), including the magnitude and direction of the interaction. For a single target-driver pair, following Liang (2014), the rate of information transfer is given by:

304

$$T_{2 \rightarrow 1} = \frac{C_{11}C_{12}C_{2,1}' - C_{12}^2C_{1,1}'}{C_{11}^2C_{22} - C_{11}C_{12}^2} \quad (3)$$

306

where C is the sample covariance between variables (i.e., the sample covariance of a variable with itself is the sample variance). In the multivariate case, a generalisation of Eq. (3), the rate of information transfer between variables, following Liang (2021), is given by:

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$$T_{x_j \rightarrow x_i} = \frac{1}{|C|} \sum_{v=1}^n \Delta_{jv} C_{v,i'} \frac{C_{ij}}{C_{ii}} \quad (4)$$

312

where x_j is the driver, x_i is the target, C is the covariance matrix between all drivers and targets, $|C|$ is the determinant of C , n is the total number of variables, Δ_{jv} are the cofactors of C , $C_{v,i'}$ is the sample covariance between variable v and the time derivative of x_i , C_{ij} is the sample covariance between target and driver, and C_{ii} is the sample covariance of the target with itself (i.e., the variance of the target). The time derivative of x_i is approximated through the Euler forward difference scheme:

318

$$\frac{dx_i}{dt} = \frac{x_{i,t+k} - x_{i,t}}{k\Delta t} \quad (5)$$

320

where t represents any point in the time series, Δt represents the time step between consecutive points, and k is a parameter that controls the scale of the forward-difference approximation. In our case, we have $\Delta t = 1$ (i.e., 1 month) and $k = 1$. A nonzero rate of information transfer (i.e., $T_{x_j \rightarrow x_i} \neq 0$) implies that x_j is causal to x_i . Positive causality values indicate that the driver tends to make the target more uncertain, amplifying its variability, while negative values imply that the driver tends to stabilise the target, dampening its variability. The rate of information transfer is normalised as follows (Liang 2015, 2021):

328

$$\tau_{x_j \rightarrow x_i} = \frac{T_{x_j \rightarrow x_i}}{Z_i} \quad (6)$$

329



330

331 where τ is expressed in %. Z_i is the normaliser, which is expressed as follows:

332

$$333 \quad Z_i = \sum_{v=1}^n |T_{x_v \rightarrow x_i}| + \left| \frac{dH_i}{dt} \right| \quad (7)$$

334

335 where the terms on the right represent the information flow from all drivers to the target, including the
 336 self-influence of the target variable and the noise. Statistical significance is assessed using a bootstrap-
 337 based two-tailed Wald z-test (Wald 1943; Wilks 2019), in which the terms in the equations above are
 338 resampled with replacement, at the 95% confidence level ($\alpha = 0.05$). Resampling is performed over years, so
 339 that all (x, dx) pairs sharing a common trajectory are drawn together. The standard error of τ , σ_τ , is
 340 estimated as the standard deviation across all τ values obtained from 1000 bootstrap samples. The 95%
 341 confidence interval is then calculated as $\tau \pm 1.96\sigma_\tau$, and τ is considered statistically significant when
 342 this interval does not contain the zero value. Throughout this work, we use the normalised rate of
 343 information flow, τ , expressed in % and ranging in absolute value from 0 to 100. A value of $\tau \simeq 0$ %
 344 indicates no causal influence between target and driver, whereas $\tau = 100$ % implies that the driver fully
 345 accounts for the uncertainty in the target. Following Docquier et al. (2025), we consider a causal
 346 influence between target and driver to be strong when $|\tau| > 5\%$, weak when $1\% < |\tau| < 5\%$ and
 347 negligible when $|\tau| < 1\%$.

348

349 The normalised rate of information transfer, τ , as expressed in Eq. (6), is computed through application
 350 of Eqs. (3) and (4) to monthly detrended anomalies at the intra-annual scale, thereby quantifying month-
 351 to-month information flow. Specifically, we first compute univariate LK causality, Eq. (3), between the
 352 large-scale drivers introduced in Sect. 2.2 and surface wind and precipitation in NEB. For this, we use
 353 the complete time series from ERA5, spanning 1980–2025, which we consider as our most stable
 354 estimate of the causal relationship magnitude and direction. For each driver-target pair, the sample size
 355 is then $n = 552$ (12 months $\times$ 46 years). We then examine how these causal relationships vary throughout
 356 the year for the drivers with the strongest and most significant τ values over NEB. In this second case,
 357 causality is computed for four distinct periods over 1980–2025, which aim to represent seasonal
 358 variations: February to May (F-M-A-M), May to August (M-J-J-A), August to November (A-S-O-N), and
 359 November to February (N-D-J-F), where the hyphen indicates that τ values are computed month-to-
 360 month (i.e., using monthly anomalies). Each of these periods comprises four consecutive months, rather
 361 than the three of the standard climatological seasons, because Eq. (5) requires both month t and month
 362 $t + 1$ to lie within the period. As such, including the preceding month before each standard season
 363 retains the transition into its first month (e.g., November to December in the case of N-D-J-F) and
 364 increases the number of month-to-month transitions from two to three per year. Lastly, we quantify
 365 multivariate LK causality, Eq. (4), for the most important drivers of surface wind and precipitation in
 366 NEB and examine whether the seasonal forecast systems from the C3S multi-system capture the
 367 strength and direction of τ throughout the common hindcast period (1993–2016), by comparing against
 368 the same period in ERA5 and against 1980–2025. The extended period is included because its nearly
 369 doubled sample size and wider sampling of low-frequency variability provide a more stable τ estimate.
 370 Causal influences are computed for each model initialisation (i.e., 12 init dates) up to lead time 3, as
 371 longer lead times have reduced value in terms of forecast performance and usability. In the case of the
 372 hindcasts, the ensemble members are concatenated into a single time series following Komatsu et al.
 373 (2023), which allows us to maximise the sample size ($n = 3$ lead time transitions $\times$ 1 init date $\times$ 24 years $\times$
 374 n_{members}). For each initialisation, the same number of months is selected in the reanalysis (e.g., January



init: J-F-M-A, February init: F-M-A-M, etc.). The reanalysis sample size is $n = 72$ (3-month transitions $\times$ 24 years) and $n = 138$ (3-month transitions $\times$ 46 years) for the 1993–2016 and 1980–2025 periods, respectively. Transitions that would span discontinuities between consecutive windows in the concatenated series (e.g. February 1981 to November 1981) are excluded, so that only real month-to-month transitions within each period contribute to the covariances in Eqs. (3) and (4).

3. Results

In this section, we first assess C3S hindcast skill for surface wind and precipitation over NEB. We then use the LK framework to examine whether known causal pathways are recovered in ERA5, how they are represented across the C3S systems, and how predictive skill relates to causal fidelity. Skill over the corresponding driver domains is provided in the SI for both the ACC (Fig. S2–S5) and MSSS (Fig. S8–S11). For the tropical Pacific, skill is evaluated over the Niño3.4 region rather than the full EOF domain, as the former better characterises the canonical ENSO signal.

3.1 Hindcast skill assessment

The ACC scorecards (i.e., verification matrices of ACC values) for surface wind in NEB (Fig. 3) reveal a consistent seasonal distribution of skill across the C3S systems, with statistically significant values largely confined from December to April up to lead 2, broadly overlapping with NEB’s rainy season. At lead 1, skill is most consistent from February to April, with ACC values of 0.6–0.8 in all systems except CFSv2 (Fig. 3f). At longer leads (3–5), skill is overall lower and more heterogeneous, although several systems retain skill, particularly for October to December initialisations.

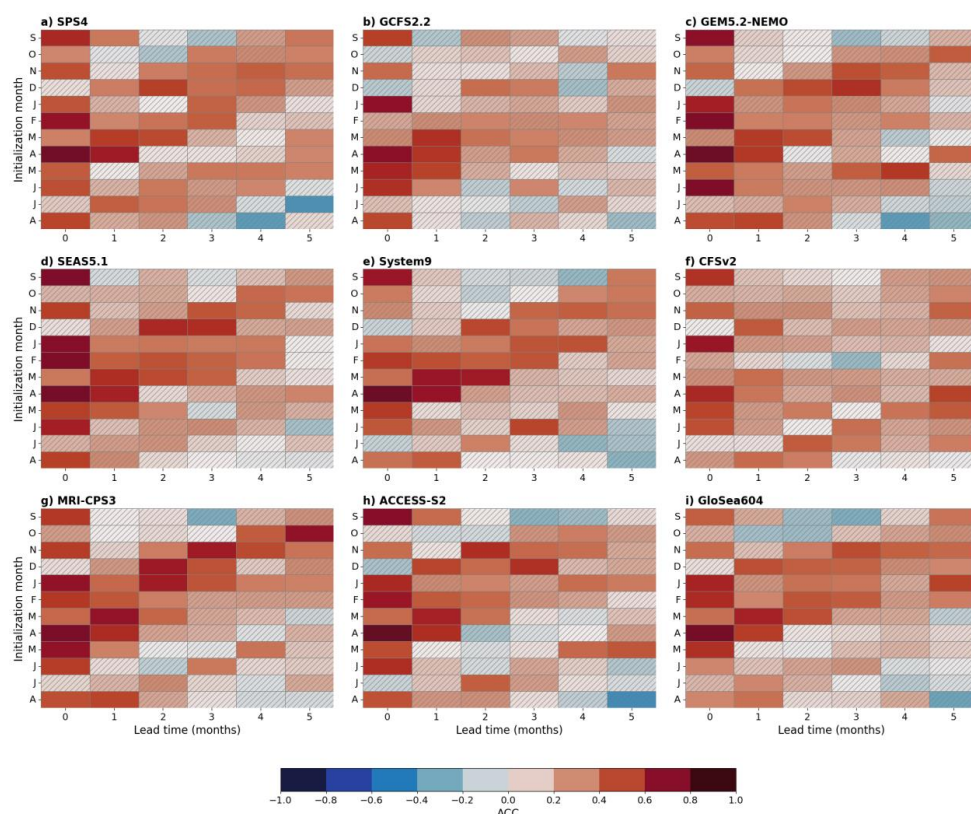


Figure 3. ACC scorecards of surface wind in NEB for all initialisation months and lead times for a) SPS4, b) GCM2.2, c) GEM5.2-NEMO, d) SEAS5.1, e) System9, f) CFSv2, g) MRI-CPS3, h) ACCESS-S2, and i) GloSea6. Non-hatched cells indicate statistically significant ACC at the 95 % confidence level ($\alpha = 0.05$), obtained through a standard one-tailed Student's t-test. Note that the initialisation months go from September to August.

In contrast, May to November initialisations generally show low or non-significant ACC values beyond lead 0, which has limited practical relevance for decision-making given part of the target month has already elapsed when the forecast becomes available. Overall, MRI-CPS3 (Fig. 3g), SEAS5.1 (Fig. 3d) and GEM5.2-NEMO (Fig. 3c) show the highest ACC for surface wind, with SPS4 (Fig. 3a), System9 (Fig. 3e), GloSea6 (Fig. 3i), and ACCESS-S2 (Fig. 3h) also performing comparatively well, whereas CFSv2 (Fig. 3f) and GCM2.2 (Fig. 3b) display the lowest skill.

Precipitation displays a similar but more persistent seasonal window of skill (Fig. 4), with significant ACC values for December to May initialisations extending to leads 2–3, coinciding with the Nordeste pre-wet and wet seasons, and with several systems remaining skilful at lead 1 in June. For several systems, skill at leads 1–2 for February to May initialisations is comparable to or greater than at lead 0. At longer leads (4–5), skill is more persistent than for surface wind, particularly for September to December initialisations, although with substantial differences across C3S systems.

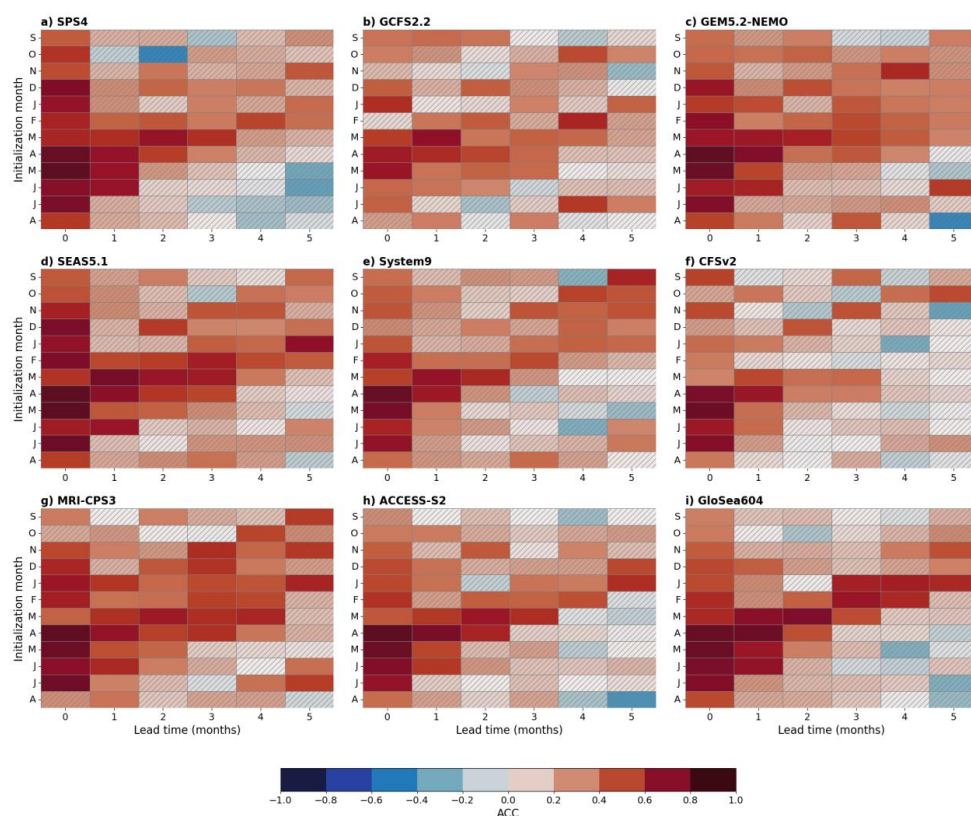


Figure 4. Same as Fig. 3 but for precipitation.

The July to November initialisations otherwise show predominantly low or non-significant skill, apart from lead 0 and some longer-lead hindcasts issued from September to November, which retain skill at leads 3–5 in some systems. Overall, MRI-CPS3 (Fig. 4g), SEAS5.1 (Fig. 4d) and GEM5.2-NEMO (Fig. 4c) again show the most consistent performance, with SPS4 (Fig. 4a), System9 (Fig. 4e), GloSea6 (Fig. 4i), and ACCESS-S2 (Fig. 4h) also performing relatively well. CFSv2 (Fig. 4f) displays again the lowest skill, whereas GCFS2.2 (Fig. 4b) shows skill up to lead 2, but deteriorates at longer horizons.

The MSSS scorecards (Fig. S6–S7) show a broadly similar seasonal distribution. For surface wind (Fig. S6), positive skill beyond lead 0 is concentrated from December to April at leads 1–2, narrowly concentrated around the rainy season, with more heterogeneous skill at longer leads (3–5). For precipitation (Fig. S7), and focusing again beyond lead 0, positive MSSS generally extends from December to May, and to June in some systems. GEM5.2-NEMO, SEAS5.1 and MRI-CPS3 retain the most consistent positive skill up to lead 3 and are the only systems to show positive values at longer leads during the rainy season forecast window. In general, both variables exhibit a marked skill degradation across systems during JJA, originating at long leads (3–5) in the MAM initialisations, with a smooth transition for surface wind and a sharper one for precipitation, the latter being particularly pronounced in System9, CFSv2, ACCESS-S2, and GloSea6. The window of reduced skill extends up to SON, where predictive skill re-emerges at long leads (3–5).



438 Considering both metrics and variables jointly, MRI-CPS3, SEAS5.1 and GEM5.2-NEMO show the
 439 most consistent performance across initialisations. SPS4, System9, GloSea6 and ACCESS-S2 generally
 440 perform better in terms of ACC than MSSS, whereas GCFS2.2 shows limited skill in terms of both
 441 metrics and CFSv2 exhibits the weakest overall performance.

442

443 3.2 Causal influences in ERA5 and the C3S multi-system

444 The univariate rate of information transfer is computed between the large-scale drivers (Fig. 2) and
 445 surface wind and precipitation in NEB through Eqs. (3) and (6). For conciseness, the EOF modes are
 446 hereafter referred to by the climate modes they represent (Sect. 2.2). We first examine the causal
 447 relationships in ERA5 over 1980–2025, which provides our most stable τ estimate (Sect. 2.4). For surface
 448 wind, the AMM (i.e., TATL SST EOF2) represents the dominant TATL driver (Fig. 5b), with significant
 449 influence over more than half of the region, whereas the AZM (i.e., TATL SST EOF3) displays only a
 450 limited influence over the eastern coast (Fig. 5c) and TATL SST EOF1 shows no noticeable causal effect
 451 (Fig. 5a), highlighting that a larger explained SST variance does not necessarily imply relevance to the
 452 regional climate response over NEB. The causal effect from ENSO (i.e., TPAC SST EOF1) is strong,
 453 although, in contrast with the AMM, spatially confined to northern NEB (Fig. 5d). The SASD/SAOD
 454 (i.e., SATL SST EOF1) also exerts a notable causal influence, although its pattern resembles the AMM
 455 one (Fig. 5e), suggesting that the two modes partly capture the same Atlantic SST variability. This is
 456 plausible because the SATL and TATL EOF domains substantially overlap (Fig. 2), so the corresponding
 457 modes cannot be deemed fully independent. A similar result is obtained with box-averaged indices, for
 458 which the AMM and SASD/SAOD produce broadly similar causal patterns over NEB. In this case, the
 459 TSA box of the AMM overlaps with the northern SASD/SAOD boxes, while also correlating with SATL
 460 SST EOF1 ($r = 0.86$, Fig. S1). For SATL SST EOF2, τ is overall stronger and exhibits a more spatially
 461 extensive influence (Fig. 5f), although this tripolar SST pattern has mainly been linked to anomalous
 462 anticyclonic circulation transporting moisture to southern Brazil (Pampuch et al. 2016). Lastly, among
 463 the SLP modes, only the mode representing meridional displacements of the SASH (i.e., SATL SLP
 464 EOF3) exerts a significant causal influence on Nordeste surface wind (Fig. 5i), with negative τ values,
 465 in contrast to the positive values found for SST modes, concentrated over southern NEB.

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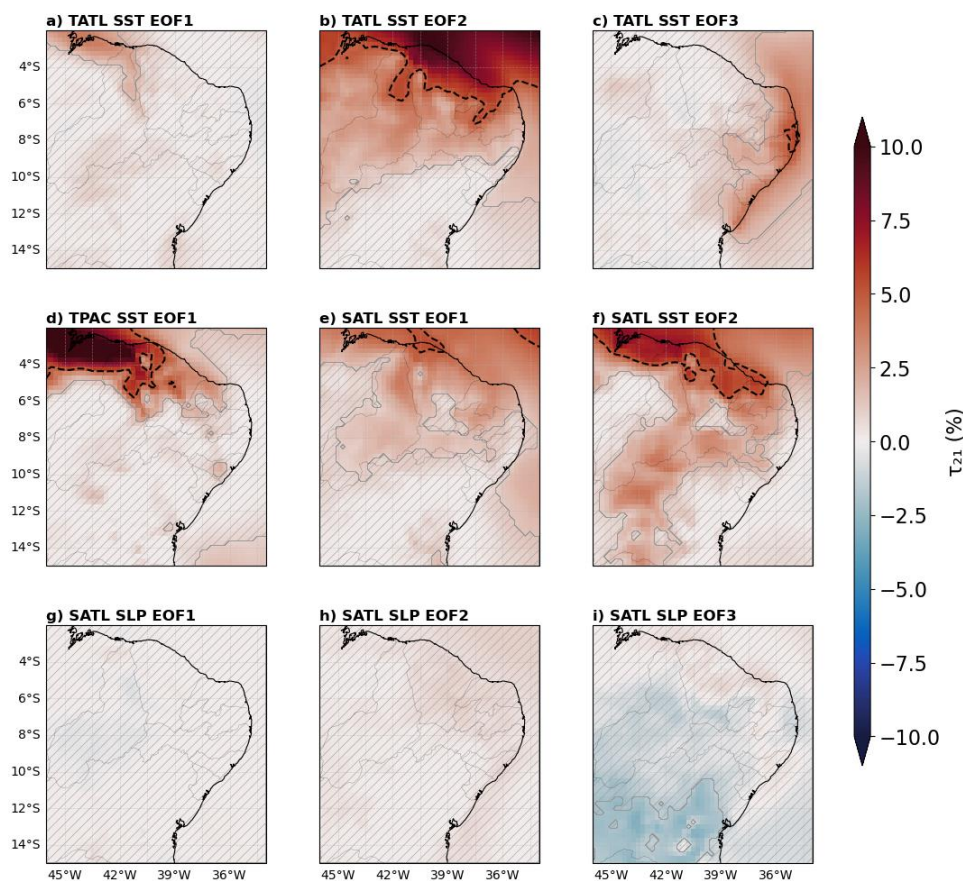


Figure 5. Normalised univariate information transfer, τ_{21} , between large-scale modes of climate variability (i.e., drivers) and surface wind in NEB (i.e., target) for all months over 1980–2025 in the ERA5 reanalysis. The drivers are the first three modes of tropical Atlantic SST, a)–c), the first mode of tropical Pacific SST, d), the first two modes of South Atlantic SST, e) and f), and the first three modes of South Atlantic SLP, g)–i). Hatching indicates where τ_{21} is not statistically significant at the 95% confidence level ($\alpha = 0.05$), obtained through a bootstrap-based two-tailed Wald z-test. The black dashed line marks where $|\tau_{21}| = 5\%$. The thin grey solid line marks the limit of the hatched area.

Precipitation displays broadly similar causal patterns (Fig. 6). The AMM again represents the dominant TATL driver (Fig. 6b), although its spatial influence is smaller than for surface wind, while the AZM influence remains confined mainly to eastern NEB (Fig. 6c). TATL SST EOF1 again shows no causal effect (Fig. 6a). This spatial heterogeneity is consistent with Hounsou-Gbo et al. (2015), who linked rainfall variability in northern and eastern NEB to distinct tropical Atlantic mechanisms. ENSO exhibits a weaker causal effect than for surface wind (Fig. 6d), although affecting a larger fraction of the region. Both SATL SST modes also display notable causal influences, with the SASD/SAOD again resembling the AMM pattern (Fig. 6e), albeit weaker, and SATL SST EOF2 affecting a larger area than the AMM (Fig. 6f). Lastly, none of the SATL SLP modes (Fig. 6g–i) show a significant causal effect on precipitation.

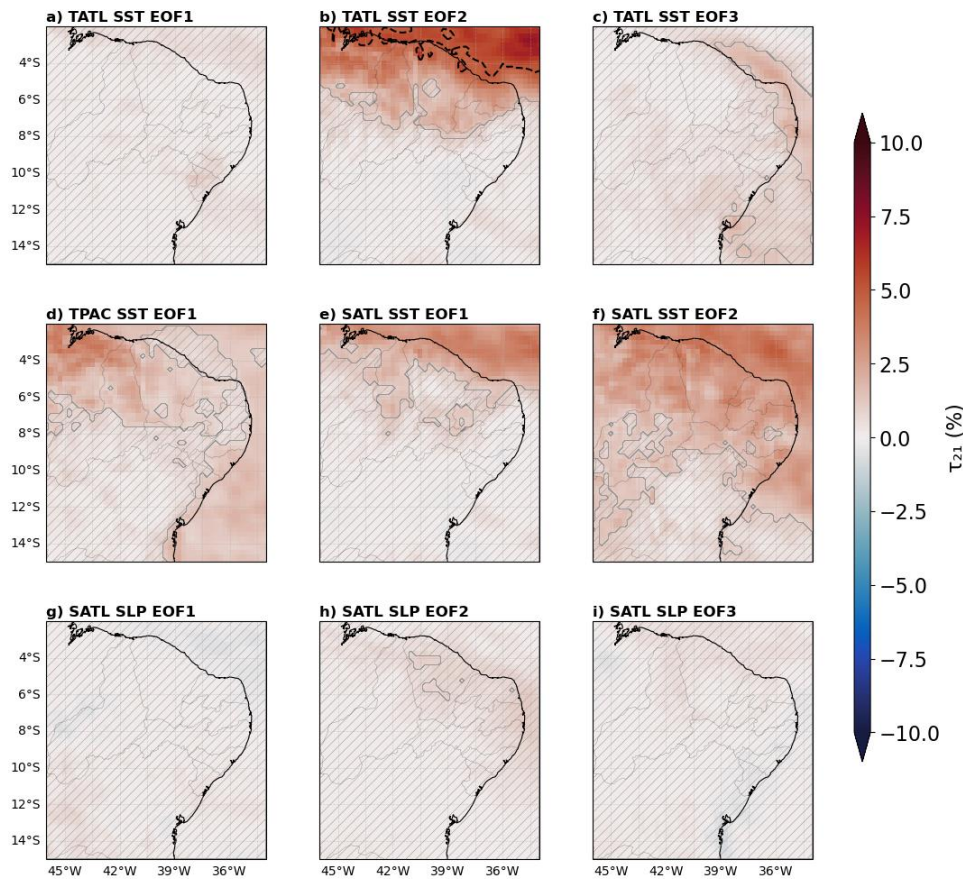


Figure 6. Same as Fig. 5 but for precipitation.

Considering the results above (Fig. 5–6), we now focus on the modes with prominent causal influences and well-established links to NEB climate. Specifically, we focus on the AMM, ENSO and SASH meridional displacements and examine the intra-annual evolution of their causal influences. The AZM is not considered due to its limited spatial influence, while the SASD/SAOD is excluded because its causal pattern largely overlaps with that of the AMM (Fig. S17–S18). SATL SST EOF2 is also not considered because, despite its notable τ values and extensive influence (Fig. S19–S20), its relationship with NEB climate remains less established.

For surface wind (Fig. 7), all three drivers exhibit marked seasonality. The AMM causal influence peaks during F-M-A-M (Fig. 7c), at the height of NEB’s rainy season, when the ITCZ typically reaches its southernmost position, with τ well over 15 % across much of the region. The influence is also notable during N-D-J-F, particularly over the ocean (Fig. 7b), but negligible during A-S-O-N and M-J-J-A (Fig. 7a,d), when the ITCZ is near its northernmost position.

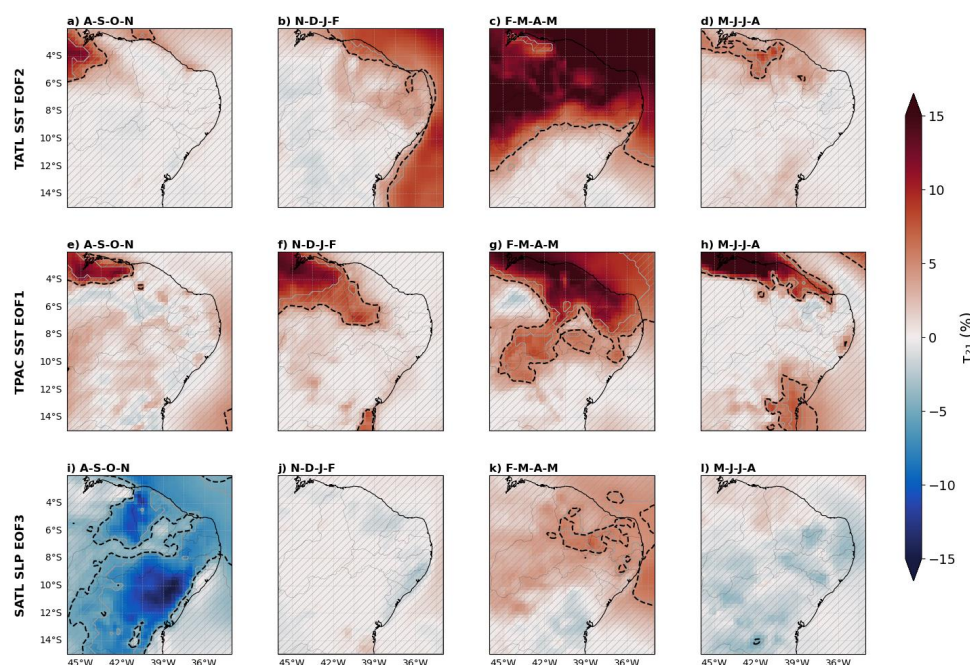


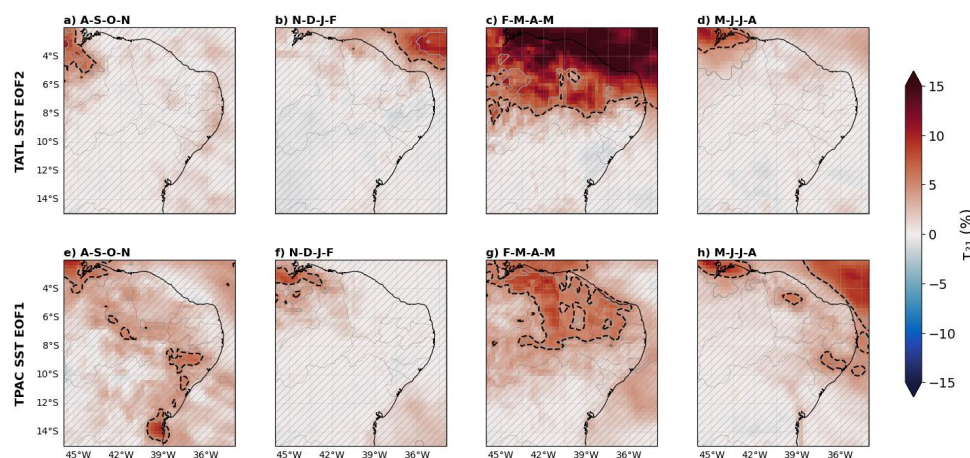
Figure 7. Normalised univariate information transfer, τ_{21} , between large-scale modes of climate variability (i.e., drivers) and surface wind in NEB (i.e., target) for the periods A-S-O-N, N-D-J-F, F-M-A-M, and M-J-J-A over 1980–2025 in the ERA5 reanalysis. The drivers are the second mode of tropical Atlantic SST, a)–d), the first mode of tropical Pacific SST, e)–h), and the third mode of South Atlantic SLP, i)–l). Hatching indicates where τ_{21} is not statistically significant at the 95 % confidence level ($\alpha = 0.05$), obtained through a bootstrap-based two-tailed Wald z-test. The black dashed line marks where $|\tau_{21}| = 5\%$. The thin grey solid line marks the limit of the hatched area.

ENSO also displays its strongest influence during F-M-A-M, concentrated over northern NEB (Fig. 7g). This period normally coincides with ENSO's demise, although it is also when its teleconnection to the TATL is strongest (García-Serrano et al. 2017). More moderate and spatially narrow influences occur in N-D-J-F and M-J-J-A (Fig. 7f,h), during the peak and development phase of ENSO, respectively, while in A-S-O-N the influence is essentially negligible (Fig. 7e). Lastly, SASH meridional displacements exert a strong negative causal influence during A-S-O-N, which falls within the period of most intense winds over NEB (Fig. 1a,b), when the SASH contracts from its late austral winter maximum extent to its early austral summer minimum (Sun et al. 2017). The other periods show no significant causal influence, apart from some weak and heterogeneous signals in F-M-A-M.

For precipitation (Fig. 8), a marked seasonal evolution is also observed. The AMM again exhibits the strongest causal influence during F-M-A-M (Fig. 8c), although over a smaller fraction of northern NEB than for surface wind, with negligible influence during the remaining periods (Fig. 8a–b,d). ENSO influence is also greatest during the F-M-A-M rainy season (Fig. 8g), while it is essentially negligible during the ENSO peak (N-D-J-F; Fig. 8f). The causal influence is heterogeneous and spatially limited during the dry season (A-S-O-N; Fig. 8e), whereas in M-J-J-A it is narrowly concentrated along the northeastern coast (Fig. 8h), which may contribute to the austral winter coastal precipitation observed in Fig. 1e (Tedeschi et al. 2016).



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Figure 8. Normalised univariate information transfer, τ_{21} , between large-scale modes of climate variability (i.e., drivers) and precipitation in NEB for the periods A-S-O-N, N-D-J-F, F-M-A-M, and M-J-J-A over 1980–2025 in the ERA5 reanalysis. The drivers are the second mode of tropical Atlantic SST, a)–d), and the first mode of tropical Pacific SST, e)–h). Hatching indicates where τ_{21} is not statistically significant at the 95 % confidence level ($\alpha = 0.05$), obtained through a bootstrap-based two-tailed Wald z-test. The black dashed line marks where $|\tau_{21}| = 5\%$. The thin grey solid line marks the limit of the hatched area.

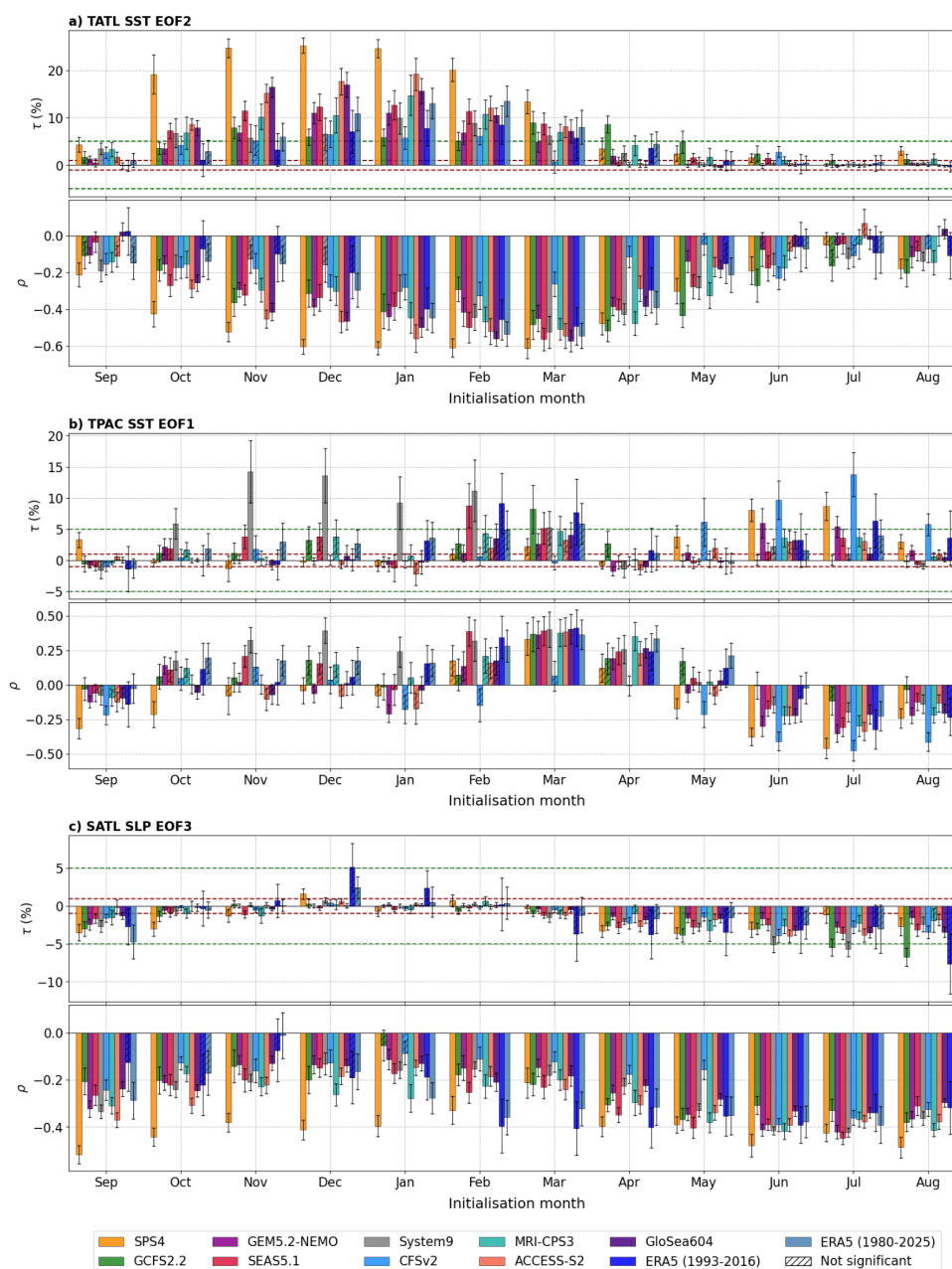
Overall, the causality analysis performed on ERA5 recovers causal patterns consistent with established teleconnections affecting NEB. This physical consistency extends beyond the Nordeste, as regions of strong information transfer in the corresponding global analyses (Fig. S12–S20) broadly coincide with the known teleconnection patterns of each mode (e.g., Fig. S15 for ENSO, Fig. S13 for the AMM). This indicates that the framework recovers teleconnections at the global scale rather than only region-specific causal relationships.

Lastly, we examine how the C3S seasonal forecast systems represent the normalised multivariate information transfer (τ) and the Spearman correlation (ρ) from the most prominent drivers of NEB climate variability to surface wind and precipitation across all initialisations. Fig. 9 shows the relationships between surface wind and the three drivers identified in Fig. 7 (i.e., AMM, ENSO, and SASH), whereas an alternative version arranged by initialisation month is provided in Fig. S21.

The strongest information transfer to surface wind originates from the AMM (Fig. 9a). In ERA5, the signal emerges weakly in November, peaks around January, and disappears by May, remaining negligible from June to September. This evolution is consistent with the ITCZ migration, which begins its southward displacement in mid-to-late October, reaches its southernmost position around January–February, and retreats northward during austral autumn, strongly affecting wind patterns in the process (Torres Silva dos Santos and Santos e Silva 2013). The extended ERA5 period (1980–2025) consistently yields stronger τ and narrower confidence intervals than the hindcast-matched period. Most systems reproduce the broad seasonal evolution and magnitude of the AMM causal influence, although with systematic model discrepancies following a number of recurring patterns. SPS4 strongly overestimates τ in every initialisation from October to March, with values often above 20 %, suggesting too strong coupling with tropical Atlantic variability. All systems overestimate τ in October, with GCFS2.2 and



562 GEM5.2-NEMO being closest to the reference. From November to January, ACCESS-S2 and GloSea6
563 substantially overestimate τ , and to a lesser extent also SEAS5.1 and MRI-CPS3, whereas GCFS2.2 and
564 CFSv2 underestimate it, particularly against the extended period. Agreement improves in February–
565 March, when almost all systems fall within the hindcast-matched or extended reference range, although
566 CFSv2 shows virtually no causal influence from the AMM in March, while the SPS4 bias becomes more
567 moderate. In April and May, the systems diverge, with GCFS2.2 overestimating τ while most others
568 show weak or negligible influence. From June to September, most systems correctly reproduce the
569 absence of information transfer in ERA5, although SPS4, System9, CFSv2 and MRI-CPS3 produce
570 spurious positive signals in September.
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573 Figure 9. Normalised multivariate information transfer, τ (top panels), and Spearman correlation coefficient, ρ (bottom
 574 panels), between the dominant large-scale modes of NEB's climate variability (i.e., drivers) and surface wind in NEB
 575 (i.e., target) for each initialisation month, over the common hindcast period (1993–2016) in the C3S multi-system,
 576 compared to ERA5 reanalysis over the periods 1993–2016 and 1980–2025. The drivers are a) the second mode of
 577 tropical Atlantic SST, b) the first mode of tropical Pacific SST, and c) the third mode of South Atlantic SLP.
 578 Hatching indicates where τ or ρ are not statistically significant at the 95 % confidence level ($\alpha = 0.05$), obtained



579 through a bootstrap-based two-tailed Wald z-test. Error bars indicate bootstrap standard errors, calculated as the
580 standard deviation across 1000 bootstrap resamples over independent years. The red and green dashed horizontal
581 lines indicate where $\tau = \pm 1\%$ and $\tau = \pm 5\%$, respectively. Note that the initialisation months go from September to August.

582 In ERA5, the causal influence from ENSO (Fig. 9b) emerges in January and peaks in March before
583 rapidly disappearing, although it remains non-significant across initialisations. A weaker secondary
584 maximum, also non-significant, appears between June and August, although with larger uncertainty.
585 The hindcast-matched (1993–2016) causal link exhibits a larger magnitude than the extended (1980–
586 2025) one, although the differences are less marked if the confidence intervals are considered, with
587 February being the only notable exception. No system captures the January signal, and System9
588 markedly overestimates it. In February, only System9 and SEAS5.1 reproduce its strength, albeit with
589 large uncertainty, while the other systems underestimate it. Agreement is better in March, although
590 SPS4, GEM5.2-NEMO, ACCESS-S2 and, most notably, CFSv2, underestimate τ , with the latter unable to
591 represent any information transfer from ENSO. During the austral winter re-emergence, SPS4 and CFSv2
592 overestimate τ in June and July, while GCF5.2 underestimates it in both months, as do System9 and
593 GloSea6 in July. Elsewhere in the year, System9 (October–December), SPS4 (May, August–September)
594 and CFSv2 (May, August) show causal links absent in the reanalysis.

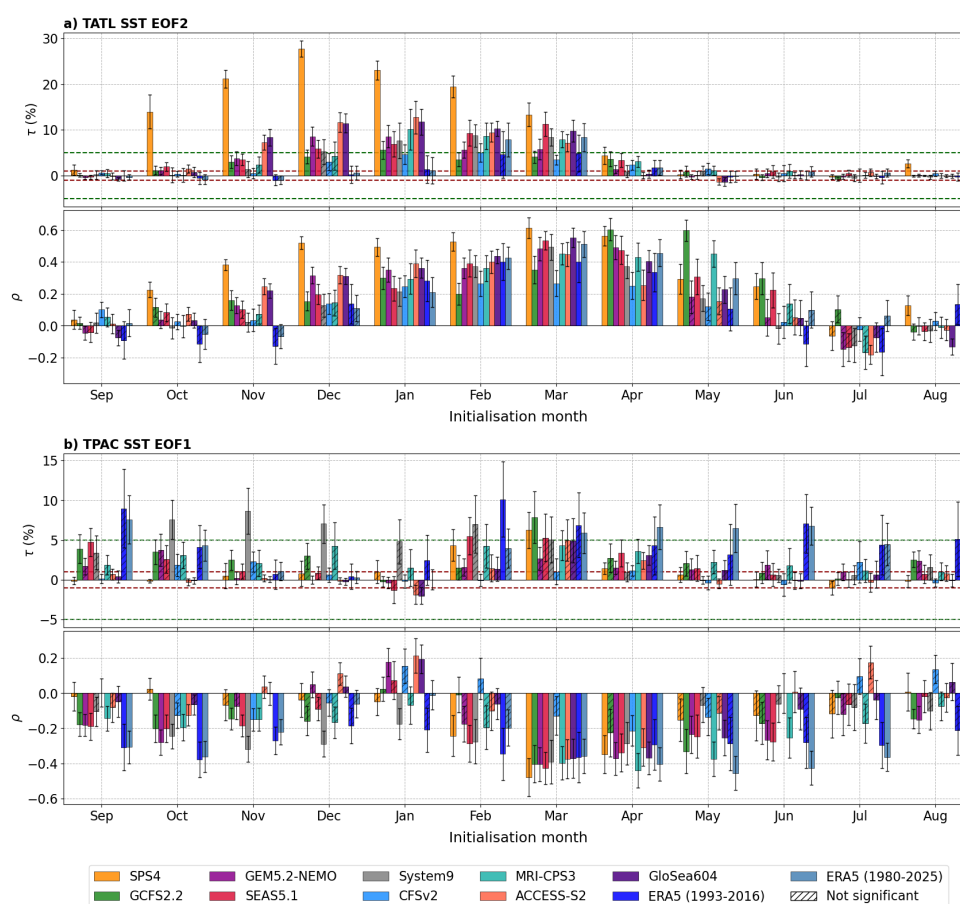
595 In the reanalysis, the causal influence from meridional displacements of the SASH (Fig. 9c) emerges
596 weakly in March and extends to September, with the largest τ values, negative for this mode,
597 concentrated from June to September. Over this period, the SASH intensifies and expands northward,
598 directly affecting the Nordeste (Sun et al. 2017). The hindcast-matched period shows wide confidence
599 intervals in all months and a stronger τ magnitude, except from July to September. No system reproduces
600 the March causal influence, underestimating τ against the hindcast-matched period but agreeing with the
601 extended one, which illustrates the value of the extended period as a more stable estimate. From April to
602 July, most systems capture a causal link, although the wide confidence intervals make it difficult to
603 compare against the reference. Weak or non-significant values appear in GEM5.2-NEMO (April–June),
604 MRI-CPS3 (April, June–July), CFSv2 (May), ACCESS-S2 (May), GloSea6 (May) and SPS4 (July), while
605 System9 (June–July) and GCF5.2 (July) overestimate τ . August shows the strongest SASH influence in both
606 ERA5 estimates, being significant in the extended one, and all systems underestimate it except for
607 GCF5.2. In September, only SPS4, GCF5.2 and, to a lesser extent, System9 and GEM5.2-NEMO
608 reproduce its magnitude. From October to February, when the SASH weakens, contracts and shifts
609 southward (Sun et al. 2017), neither ERA5 nor the systems show significant causal influences.

610 Overall, correlation strength tends to follow the magnitude of τ across initialisations for each driver,
611 although the two metrics can have opposing signs, as for the AMM (Fig. 9a). This alignment is expected,
612 since in the LK framework causation necessarily implies correlation (Liang 2014). Nonetheless, there
613 are instances where weak-to-moderate, although significant correlations ($0.25 < |\rho| < 0.5$) are not
614 accompanied by information transfer, as in some systems for the AMM (April–May; Fig. 9a) and SASH
615 displacements (October–February; Fig. 9c), suggesting that statistical association arises without an
616 underlying causal link. For the AMM, the peak in τ (January) precedes the peak in ρ (February–March) by
617 one to two months, an offset not apparent for other drivers, where the metrics track each other closely
618 when both are present. For ENSO (Fig. 9b), correlation shifts from positive in April to negative in June
619 and back to positive in October, while τ remains positive throughout, illustrating that the sign of ρ
620 indicates the direction of the association whereas the sign of τ indicates whether the driver amplifies
621 or dampens variability in the target.



622 An equivalent analysis for NEB precipitation is shown in Fig. 10, with the normalised multivariate
 623 information transfer between the target and the two drivers of Fig. 8. An alternative version of Fig. 10
 624 is provided in the SI (Fig. S22). As for surface wind, the strongest causal influence comes from the AMM
 625 (Fig. 10a), although for precipitation it is narrowly concentrated from February to April, coinciding with
 626 the peak of the rainy season and with the southernmost position of the ITCZ, the region's main rain-
 627 bearing system. From May to January, the AMM influence in ERA5 is negligible, even where
 628 correlations exceed 0.5. As for the AMM influence on surface wind, τ is stronger and its confidence
 629 intervals narrower in the extended period (1980–2025).

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632 Figure 10. Normalised multivariate information transfer, τ (top panels), and Spearman correlation coefficient, ρ (bottom
 633 panels), between the dominant large-scale modes of NEB's climate variability (i.e., drivers) and precipitation in NEB
 634 (i.e., target) as a function of initialisation month, over the common hindcast period (1993–2016) in the C3S multi-
 635 system, compared to ERA5 reanalysis over the periods 1993–2016 and 1980–2025. The drivers are a) the second
 636 mode of tropical Atlantic SST and b) the first mode of tropical Pacific SST. Hatching indicates where τ or ρ are not
 637 statistically significant at the 95 % confidence level ($\alpha = 0.05$), obtained through a bootstrap-based two-tailed Wald z-
 638 test. Error bars indicate bootstrap standard errors, calculated as the standard deviation across 1000 bootstrap



639 resamples over independent years. The red and green dashed horizontal lines indicate where $\tau = \pm 1\%$ and $\tau = \pm 5\%$,
 640 respectively. Note that the initialisation months go from September to August.

641
 642 Most systems capture the magnitude of the information transfer from this mode, with some notable
 643 exceptions. In February, most fall within the reanalysis confidence intervals, although GCFS2.2,
 644 GEM5.2-NEMO and CFSv2 underestimate τ against the extended period. As for surface wind, SPS4
 645 shows by far the largest error, with τ at nearly 20 % in every initialisation from October to March,
 646 although more moderate at the end of the period. In March, almost all systems perform well, with some
 647 underestimation in GCFS2.2 and CFSv2 and a slight overestimation in SEAS5.1. In April, the reanalysis
 648 signal is weak and its confidence intervals wide, and most systems produce larger τ values than both
 649 reference periods, making it difficult to establish whether the causal relationship is well represented.
 650 From May to September, all systems correctly reproduce the absence of a causal influence. From
 651 October to January, they increasingly display τ magnitudes absent in ERA5, most notably SPS4 but also
 652 ACCESS-S2 and GloSea6. By December and especially January, every system shows an AMM influence
 653 not observed in ERA5.

654
 655 In ERA5, the causal influence from ENSO (Fig. 10b) emerges in February, peaks in March, and weakens
 656 through April and May, particularly in the hindcast-matched period. Unlike for surface wind, it does
 657 not disappear in austral autumn but persists through the season, strengthens in June, and is maintained
 658 until October. Although these months span the typical decay, transition and development phases of
 659 ENSO, this persistence may partly reflect long-lasting events that do not dissipate during boreal spring.
 660 The hindcast-matched (1993–2016) and extended (1980–2025) periods give similar τ magnitudes in all
 661 initialisations except February. Most systems miss the emerging signal in February, apart from SPS4,
 662 SEAS5.1, System9 and MRI-CPS3, whereas in March all reproduce its strength except GEM5.2-NEMO
 663 and CFSv2. In April and May, most systems underestimate the causal influence, with larger errors in
 664 SPS4, GEM5.2-NEMO, System9 and CFSv2 in April and poor performance across systems in May,
 665 where MRI-CPS3 performs best. From June to August, no system reproduces the magnitude of τ , with
 666 most showing no causal influence and a few only a weaker signal (MRI-CPS3, GCFS2.2, GEM5.2-
 667 NEMO). Although localised over northeastern NEB, this ERA5 influence from ENSO is also apparent
 668 in Fig. 8h and may relate to coastal precipitation during austral winter (Fig. 1e; Tedeschi et al. 2016). In
 669 September, only GCFS2.2, SEAS5.1 and System9 capture it, with substantial underestimation, and in
 670 October only GCFS2.2, GEM5.2-NEMO and MRI-CPS3 match τ , with System9 overestimating and the
 671 rest underestimating it. In the remaining months, ERA5 shows weak or negligible ENSO influence, yet
 672 System9 (November–January), MRI-CPS3 (December) and GCFS2.2 (November–December) detect links
 673 that are not observed.

674
 675 As for surface wind, correlation strength generally follows the magnitude of τ across initialisations,
 676 although here the two metrics have opposing signs for ENSO. Again, weak-to-moderate but significant
 677 correlations ($0.25 < |\rho| < 0.5$), even exceeding 0.5, are not always accompanied by information transfer,
 678 as in some systems for the AMM (April–May; Fig. 10a) and ENSO (March–April; Fig. 10b), again
 679 suggesting that statistical association arises here without an underlying causal link. The same offset
 680 between the AMM peaks in τ and ρ is apparent, whereas the ENSO correlation does not show the sign
 681 reversals found for surface wind.

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3.3 Causal fidelity and predictive skill

Lastly, we examine the relationship between information transfer and predictive skill by analysing whether model deviations in representing the strength of the ERA5 causal influence, $\Delta\tau = \tau_{\text{model}} - \tau_{\text{ref}}$, can be linked to average forecast skill, which is computed here over leads 0–3 in terms of the ACC (Fig. 3–4), and the MSSS (Fig. S6–S7). For each forecast system, causal fidelity, $|\Delta\tau|$, is calculated as the mean absolute departure of its information transfer from the ERA5 reference by averaging across initialisation months and drivers (e.g., AMM, ENSO). Fig. 11 shows this analysis for surface wind across the C3S multi-system, while corresponding results for precipitation are provided in the SI (Fig. S23). The analysis contrasts results based on all initialisations (Fig. 11a–d) with those retaining only cases where the ERA5 causal link is either significant at the 95 % confidence level (Fig. 11e–h) or where its magnitude satisfies $|\tau| \geq 5\%$ (Sect. 2.4). The magnitude criterion is included because ERA5 provides a single realisation, so each causal link rests on only 24 (1993–2016) or 46 (1980–2025) years, and significance alone would discard links that are strong but unresolved due to the limited sample size. These criteria act here as a filter determining which cases enter the causal fidelity average, since excluding a genuine link may distort that average more than retaining a marginal one. This is more relevant for the hindcast-matched period, as there every retained causal link satisfies the magnitude criterion, whereas only one initialisation-driver combination for precipitation and two for surface wind are also significant at $\alpha = 0.05$. Over 1980–2025, the two criteria nearly coincide, each retaining all but one case, which suggests that the longer record resolves the causal links more robustly and supports its use as the more stable reference for our τ estimates (Sect. 2.4). Since the correlations, both Pearson, r , and Spearman, ρ , are evaluated across only the nine systems of the C3S multi-system, statistical power is rather limited.

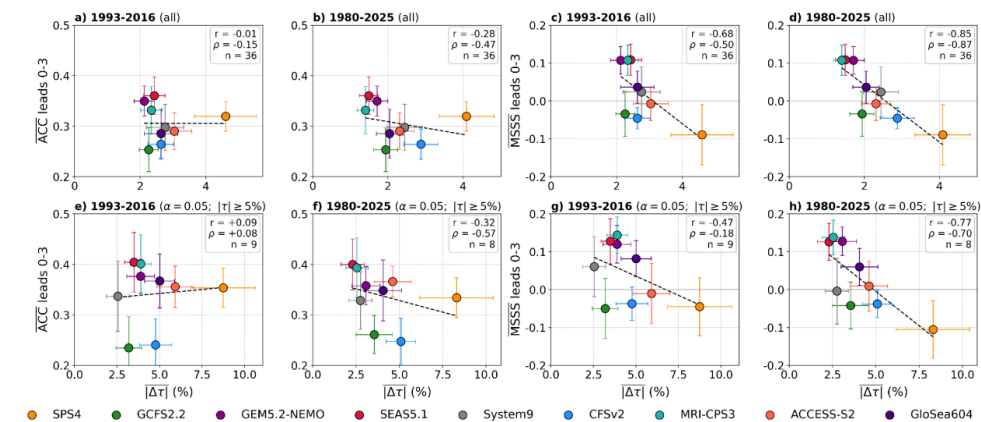


Figure 11. Relationship between causal fidelity, $|\Delta\tau|$, and average forecast skill over lead times 0–3, in terms of ACC, a)–b), e)–f), and MSSS, c)–d), g)–h), for surface wind in NEB across the C3S multi-system. For each metric, the left column uses ERA5 over 1993–2016 as the causal reference and the right column ERA5 over 1980–2025. For each system, $|\Delta\tau|$ is averaged over all initialisation months and drivers (i.e., AMM, ENSO, SASH meridional displacements). The top panels, a)–d), use all initialisation months, whereas the bottom panels, e)–h), retain only those for which the ERA5 causal link is either significant at the 95 % confidence level ($\alpha = 0.05$), obtained through a bootstrap-based two-tailed Wald z-test, or for which $|\tau| \geq 5\%$. The black dashed line is the ordinary least-squares fit across systems. The legend boxes include the Pearson, r , and Spearman, ρ , correlation coefficients, and the number of init-month $\times$ driver samples, n , entering the $|\Delta\tau|$ average. Error bars show the standard error of the mean, taken over n for $|\Delta\tau|$ and over the retained initialisation months for the corresponding skill metric.



718

719 A negative relationship emerges for the MSSS (Fig. 11c–d,g–h), where models that, on average, better
 720 reproduce the observed causal links attain higher MSSS. The association is strong and significant
 721 against the extended period (1980–2025), both across all cases ($r = -0.85$, $\rho = -0.87$; Fig. 11d) and when
 722 restricting to retained causal links ($r = -0.77$, $\rho = -0.70$; Fig. 11h), and consistent, though weaker, against
 723 the shorter hindcast-matched period for all cases ($r = -0.68$; Fig. 11c). Where both correlation
 724 coefficients are similar, this signals the relationship is less likely to be driven by an outlier system. In
 725 other instances, as for the hindcast-matched period (Fig. 11g), the correlation coefficients diverge ($r =$
 726 -0.47 , $\rho = -0.18$), pointing to greater sensitivity to individual systems. Similar results were found by
 727 Nowack et al. (2020) for precipitation, where climate models whose causal networks more closely
 728 matched observations better reproduced its regional patterns. In contrast, the ACC panels show neither
 729 robust nor significant relationships ($|r| \leq 0.32$; Fig. 11a–b,e–f), with only a moderate ρ coefficient across
 730 models against the extended period ($|\rho| \approx 0.6$; Fig. 11b,f). This divergence suggests that causal fidelity
 731 relates more clearly to forecast performance when evaluated with the MSSS, which penalises the full
 732 mean-squared error, than with the ACC, which measures phase agreement but is insensitive to
 733 systematic amplitude differences. The equivalent analysis for precipitation (Fig. S23) shows a similar
 734 pattern, where the association between $|\Delta\tau|$ and predictive skill is essentially absent when all
 735 initialisations are considered ($|r| \leq 0.2$), but strengthens to $r \approx -0.5$ once restricted to initialisations
 736 where the ERA5 causal link satisfies either of the aforementioned conditions. With only nine forecast
 737 systems, it does not reach significance in any configuration. The divergence between ACC and MSSS
 738 is less evident for precipitation than for surface wind.

739

740 To identify which aspect of forecast quality explains this relationship, we decompose the MSSS into its
 741 contributions from phase agreement, amplitude and mean bias (Sect. S3; Murphy 1988, 1996). All terms
 742 are computed for each system, initialisation month and lead time, and averaged in the same way as the
 743 MSSS in Fig. 11. For surface wind, causal fidelity is strongly related to the amplitude term ($r = 0.67$ to
 744 0.94), but not to the phase ($r = -0.26$ to 0.20) or mean-bias ($r = -0.03$ to 0.13) terms (Table S1). Spearman
 745 correlations yield the same pattern for the 1980–2025 reference, indicating that the relationship is not
 746 driven by a single system. In all nine C3S systems, the ensemble-mean amplitude exceeds the level
 747 justified by its correlation with the reference, and this excess increases with the causal fidelity error
 748 (Table S2). We also verified that the relationship is not explained by driver skill or ensemble size, as it
 749 persists after controlling for each system's average driver skill ($r = -0.70$ to -0.94 against 1980–2025;
 750 Table S3) and for ensemble size, which ranges from 10 to 31 members ($r = -0.76$ to -0.81 ; Table S3). For
 751 precipitation, the amplitude term shows the same tendency ($r = 0.31$ to 0.45 ; Table S1), but none of the
 752 relationships is significant. In addition, for the retained initialisations with an active ERA5 causal link
 753 $|\Delta\tau|$ cannot be separated from driver skill when estimated from EOF-domain averages.

754

755 4. Discussion and Conclusions

756 This study provides a causality-based perspective on seasonal predictability over Northeast Brazil. The
 757 hindcast skill assessment (Sect. 3.1) shows that the C3S seasonal forecast systems are able to reproduce
 758 part of the observed month-to-month variability of surface wind and precipitation over NEB,
 759 particularly from mid-to-late austral summer (i.e., January–February) through austral autumn (i.e.,
 760 MAM). This window of enhanced skill is consistent with the seasonal evolution of the main climate
 761 drivers affecting the Nordeste, including the southward migration of the ITCZ, the AMM and ENSO,
 762 suggesting that predictive skill is not merely a consequence of initial conditions but also reflects the



763 representation of relevant sources of predictability. Previous studies have similarly identified tropical
764 Atlantic and Pacific SST variability as major sources of rainy season predictability over NEB (Folland
765 et al. 2001; Sun et al. 2006; Vasconcelos Junior et al. 2025). For precipitation, skill is generally more
766 persistent than for surface wind and extends to longer lead times in some systems, further supporting
767 a contribution from slowly evolving large-scale SST drivers. In contrast, skill is markedly reduced
768 during austral mid-to-late winter (i.e., July–August) and spring (i.e., SON). This lack of realised skill
769 should not necessarily be interpreted as an absence of intrinsic predictability, but may instead indicate
770 that current forecast systems do not adequately translate processes, their timing, or their
771 teleconnections into regional forecast skill. For instance, the C3S systems are generally skilful in
772 predicting tropical Pacific (Fig. S3, S9) and tropical Atlantic SST anomalies (Fig. S2, S8), even at long
773 leads, whereas skill is more limited for South Atlantic SST (Fig. S4, S10) and particularly poor for South
774 Atlantic SLP (Fig. S5, S11). Given the contribution of tropical South Atlantic variability to NEB rainy-
775 season predictability (Hounsou-Gbo et al. 2019), and that tropical Atlantic biases have been linked to
776 reduced seasonal forecast skill over the region (Nobre et al. 2006; Misra and Zhang 2007), these
777 limitations may constrain the ability of current systems to reproduce relevant regional teleconnections.

778
779 The LK causality analysis (Sect. 3.2) provides a physically interpretable framework to examine this
780 window of skill. In ERA5, the AMM exerts the strongest causal influence on both surface wind and
781 precipitation, with maximum information transfer preceding and extending into the rainy season (i.e.,
782 December–April), broadly coinciding with the southward migration of the ITCZ. ENSO also exerts a
783 notable influence, particularly from February to April, a timing consistent with its delayed influence on
784 the tropical Atlantic and the strengthening of the interhemispheric SST gradient during the decay
785 phase of ENSO events (García-Serrano et al. 2017). For surface wind, meridional displacements of the
786 SASH also emerge as an important driver from June to September, within the period when winds over
787 NEB are strongest. Together, these results show that LK causality recovers established physical
788 pathways linking large-scale modes of variability to regional climate impacts, reveals their pronounced
789 seasonality, and distinguishes between drivers with strong, weak, or negligible influence (Docquier et
790 al. 2024b; Docquier et al. 2025). The same framework reproduces known global teleconnection patterns
791 of each driver (Fig. S12–S20), supporting its application to other regions. The C3S systems generally
792 reproduce the seasonal emergence and disappearance of the main causal links, but differ substantially
793 in their magnitude. No system performs consistently across drivers and initialisations. For surface
794 wind, SPS4, GloSea6 and ACCESS-S2 tend to overestimate the AMM influence, CFSv2 frequently
795 underestimates or misses important AMM and ENSO links, and the SASH influence remains uncertain
796 across systems. For precipitation, the most notable discrepancy is the austral winter ENSO influence.
797 From June to August, ERA5 shows a persistent information transfer that no system reproduces, with
798 most showing no causal influence at all. This signal is concentrated over northeastern NEB, where
799 austral winter rainfall is largely coastal (Fig. 1e; Tedeschi et al. 2016), a regime that current seasonal
800 forecast systems may struggle to represent. All these differences occur alongside clear contrasts in
801 conventional forecast performance. The fact that systems are generally most skilful when the main
802 causal pathways are strongest, while differing considerably in how accurately they represent these links,
803 highlights the value of LK causality for complementing conventional verification with a process-based
804 assessment of seasonal forecast performance.

805 The comparison between causal fidelity, $|\overline{\Delta\tau}|$, and average predictive skill (Sect. 3.3) further suggests
806 that representation of these physical pathways relates to forecast quality, although with a relationship
807 that depends on the metric considered. Models that more closely reproduce the strength of the ERA5



causal links (e.g., MRI-CPS3) attain higher MSSS, particularly when causal fidelity is evaluated against the extended 1980–2025 ERA5 period. In contrast, the relationship with the ACC is weaker. This divergence is physically interpretable, as the ACC measures the phase correspondence between model and reference anomalies but is insensitive to systematic amplitude error, whereas the MSSS penalises both (Murphy 1988). The MSSS decomposition confirms that the relationship with causal fidelity arises from the amplitude term rather than from phase agreement (Sect. 3.3). All systems overestimate the amplitude of the predictable signal over NEB, an error that is larger in systems that reproduce the causal links less accurately, suggesting that systems with less realistic teleconnections also tend to be overconfident in how predictable the regional response is. One possible explanation is that mean-state biases over the tropical Atlantic (e.g., in ITCZ location) affect both driver teleconnections to NEB and the variance of the regional response, so that errors in causal strength and in forecast amplitude share a common origin rather than one causing the other. The overestimated amplitude found here contrasts with the underestimated amplitude of ENSO teleconnections found over the North Atlantic in several of the same forecast systems (Williams et al. 2023), suggesting that the sign of teleconnection amplitude errors may be region-dependent. The association between causal fidelity and skill should nevertheless be interpreted cautiously. First, causal fidelity is evaluated relative to ERA5, which, although used here as the observation-based reference, contains systematic biases in both wind (Ramon et al. 2019) and precipitation (Lavers et al. 2022), as well as broader uncertainty (Ramon et al. 2024). In addition, the finite length of the reanalysis record introduces sampling uncertainty into the estimated causal relationships (Docquier et al. 2025). Second, skill reflects the total quality of the predicted field (e.g., precipitation), whereas causal fidelity captures only the examined large-scale pathways. A perfect correspondence between them is therefore not expected. The relationship should therefore be interpreted as a diagnostic of whether physically meaningful causal pathways contribute to forecast skill, rather than as a comprehensive attribution of model performance.

The inferred causal relationships should also be interpreted in light of the methodological assumptions and experimental design. In the univariate framework, Eq. (3), LK causality quantifies the total information transfer between a driver-target pair, without accounting for interactions from other drivers. In contrast, in the multivariate framework, Eq. (4), the causal links are conditioned on the set of drivers included in the analysis. Large-scale drivers such as ENSO, tropical Atlantic variability, and South Atlantic circulation are not independent (Cai et al. 2019; Keenlyside et al. 2020), and their inferred influences may reinforce, offset, or redistribute when considered simultaneously. The causal strength attributed to a given driver in the multivariate framework should therefore be interpreted as conditional on the chosen predictor set (Liang 2021), rather than as an absolute measure of its total influence on NEB climate. Similarly, weak but significant causal links should not necessarily be dismissed, as drivers with limited direct influence may still contribute indirectly through interactions with other modes (Docquier et al. 2025). The method is therefore most informative when interpreted alongside established dynamical mechanisms (Kretschmer et al. 2021).

The LK causality formalism also presents limitations, most notably its assumptions of linear stochastic dynamics (Liang 2016) and stationary time series. Although linearity may be a reasonable approximation for large-scale climate relationships, nonlinear interactions and feedbacks, inherent to the climate system, may not be fully captured. Recent extensions of the formalism to nonlinear systems (Pires et al. 2024) could therefore be explored in future work. To satisfy the stationarity requirement, we applied regression-based detrending (Sect. 2.1), which also isolates internal variability to the greatest extent possible. Consequently, the inferred causal relationships primarily reflect variability around a stable



mean state rather than externally forced signals. The magnitude and significance of information transfer are also sensitive to the temporal scale considered (Komatsu et al. 2023; Takaya et al. 2025; Docquier et al. 2025). Here, we analyse intra-annual (i.e., month-to-month) information transfer within four-month windows, consistent with the seasonal prediction problem addressed. However, alternative window lengths could lead to different results. For instance, shorter windows would provide greater temporal specificity but fewer monthly transitions for each causal estimate, whereas longer windows would increase the number of transitions while potentially combining distinct seasonal processes and obscuring changes in the causal relationships throughout the year. Sample size represents an additional limitation, particularly for the hindcast-matched analysis. Although our sample size is broadly comparable to previous LK causality studies (Komatsu et al. 2023; Takaya et al. 2024; Takaya et al. 2025; Docquier et al. 2025), direct comparison is complicated by differences in timescale and sampling strategy. This limitation affects both the reanalysis, for which the ERA5 dataset used here provides a single realisation, and the models, where the relatively short common hindcast period (1993–2016) is required to ensure a fair comparison across forecast systems. In the models, concatenating ensemble members increases the number of samples, but not the number of independent years, thereby leading to substantial uncertainty in the inferred causal links. In ERA5, the longer 1980–2025 period provides a more stable causal estimate, although not temporally matched to the hindcasts, whereas the shorter 1993–2016 period ensures temporal consistency at the cost of wider confidence intervals, a smaller sample, and reduced statistical significance. Future work could therefore revisit this analysis as longer hindcast and reanalysis records become available. Larger ensembles could reduce the uncertainty of model estimates, although they would not overcome the limited number of independent temporal samples. Finally, several analytical choices can also affect the interpretation of the results. In the main analysis, we focus on normalised information transfer, τ , use a 5 % threshold to identify strong causal links, and compare model estimates against two ERA5 periods. These choices are relevant because τ is a relative quantity and can be affected by changes in the normalisation terms in Eq. (7). As a robustness check, we also reproduced some of the key analyses, based on the multivariate version of τ , using instead the absolute information transfer, T , from Eq. (4), obtaining broadly consistent conclusions.

The present work focuses on the seasonal drivers previously introduced, but other modes of variability operating at different timescales may also contribute to NEB predictability. At interannual timescales, the Quasi-Biennial Oscillation (Baldwin et al. 2001) can modulate the large-scale drivers relevant to NEB climate (Sena et al. 2022; Rodrigo et al. 2025). At subseasonal timescales, the Madden–Julian Oscillation (MJO; Madden and Julian 1971) is known to influence the October–January pre-wet season over NEB (Valadão et al. 2017; Vasconcelos Junior et al. 2018; Vasconcelos Junior et al. 2021), to modulate regional circulation and trade-wind patterns (Valadão et al. 2017; Lombardi 2024), and interact with both ENSO (Hendon et al. 2007; Zhang et al. 2025) and tropical Atlantic air–sea variability (Barreiro et al. 2019). Given the seasonal scope of the study and its focus on month-to-month information transfer, the MJO was not included here. However, it remains an important candidate for future work, especially at subseasonal timescales and within seamless prediction frameworks that constrain longer-term predictions based on available shorter-term forecasts (Wetterhall and Di Giuseppe 2018; Delgado-Torres et al. 2026). Given the demonstrated subseasonal predictability over NEB at lead times of several weeks, and evidence that large-scale tropical variability contributes to this skill (Sapucci et al. 2025; Pegion et al. 2026; Coelho et al. 2026), future work could explore whether shorter-range information on the evolution of the ITCZ can help constrain seasonal predictions over the region. Recent work by Kretschmer et al. (2026), combining causal networks and information theory-based diagnostics to



898 jointly analyse the influence of subseasonal and seasonal drivers on regional extremes while accounting
 899 for the modulation of subseasonal teleconnections by seasonal-to-interannual background conditions,
 900 further illustrates the potential of extending causality-based analyses across timescales.

901
 902 From a forecasting perspective, the results highlight the rainy season as the main window of
 903 opportunity for seasonal prediction of both surface wind and precipitation, suggesting that improving
 904 seasonal predictions over NEB will require a better representation of the teleconnections linking
 905 tropical Pacific, tropical Atlantic, and South Atlantic climate variability to the Nordeste. The processes
 906 controlling predictability outside this period, which may operate at timescales not examined here, also
 907 need to be better understood. The results also have implications for the joint interpretation of wind and
 908 precipitation predictability over the region. Surface wind and precipitation in NEB are notably anti-
 909 correlated (Fig. 1a, S24), with rainier (drier) periods generally associated with weaker (stronger) winds
 910 (Barros et al. 2021). This relationship reflects underlying large-scale circulation changes affecting both
 911 variables, whereby conditions favouring a southward-displaced ITCZ and enhanced convection tend to
 912 suppress near-surface winds. From an applied perspective, this anti-correlation suggests a degree of
 913 complementarity between wind and hydrological resources. While this does not remove the need for
 914 reliable forecasts of both variables, seasonal climate information could support more integrated energy
 915 and water management in a region where both wind generation and reservoir operations are highly
 916 sensitive to climate variability (dos Santos Gomes et al. 2025; Duque-Gardeazabal et al. 2026).

917
 918 More broadly, this study shows that causality-based diagnostics can complement traditional forecast
 919 verification by assessing whether models reproduce the processes underlying regional predictability.
 920 While conventional skill metrics quantify different aspects of forecast quality, the LK framework
 921 explicitly evaluates the direction and magnitude of information transfer from large-scale drivers to
 922 regional climate variables, providing a process-oriented basis for inter-model comparison (Maloney et
 923 al. 2019). It also complements conventional correlation analyses, as significant correlations are not
 924 always accompanied by information transfer (Sect. 3.2), helping separate statistical associations from
 925 causal links and thereby reducing the risk of overinterpreting teleconnections (Kretschmer et al. 2026).
 926 For NEB, three main conclusions emerge. First, forecast skill for both surface wind and precipitation
 927 is concentrated around the rainy season, when the examined causal pathways are strongest. Second, the
 928 C3S seasonal forecast systems generally reproduce when these causal links emerge and vanish, but have
 929 difficulty reproducing their strength, with none reproducing the austral winter ENSO influence on
 930 precipitation. Third, for surface wind, systems that better represent the observed causal strengths
 931 achieve higher MSSS but not higher ACC, as errors in the amplitude of the regional response limit
 932 forecast quality. Since the framework also recovers the known global teleconnection patterns of each
 933 driver, future work could assess whether differences in predictive skill across forecast systems can be
 934 systematically related to the representation of relevant causal pathways in other regions, variables and
 935 prediction horizons. Overall, the causal evaluation framework presented here is transferable beyond
 936 NEB and across prediction timescales. By identifying which seasonal forecast systems better reproduce
 937 key teleconnections, it illustrates how causality-based diagnostics may help bridge the gap between
 938 statistical forecast performance and physical understanding.

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943 **Code availability**

944 SUNSET is publicly available via <https://gitlab.earth.bsc.es/es/sunset>. The code used to compute the
 945 Liang-Kleeman causality results has been adapted from
 946 https://github.com/Climdyn/Liang_Index_climdyn (Docquier et al. 2022). The code used for data post-
 947 processing and analysis and for reproducing the figures will be made publicly available upon
 948 publication and is available from the corresponding author upon request in the meantime.

949

950 **Data availability**

951 Data from the C3S seasonal forecast systems and the ERA5 reanalysis are publicly available and can be
 952 downloaded from the C3S Climate Data Store (CDS; <https://cds.climate.copernicus.eu/>).

953 **Author contributions**

954 **ALN, VT, RMM, ACA, AMS** and **DC** conceptualised the research idea. **ALN** designed and performed
 955 the analysis, developed the code, produced the figures, and wrote the original manuscript. **ALN, VT,**
 956 **RMM, ACA, PTC, CDT, AMS,** and **DC** contributed to the discussion and interpretation of the results.
 957 **PTC** contributed to the dissemination of the study. **VAR** assisted with the software use and data
 958 download and curation. **PAB** contributed to data download and curation. **VT, RMM** and **AS** supervised
 959 the project. **AS** secured the funding and led stakeholder engagement. All authors contributed to the
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969

970 **Competing interests**

971 The authors declare that they have no conflict of interest.

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