Response to comments from reviewer 2

Manuscript: Coastal upwelling and tropical warm water intrusions are key drivers of interannual fog variability along the southwestern African coast # EGUSPHERE-2026-1208

First of all, we would like to thank the reviewer for the positive comments and for providing very helpful and constructive feedback. We thank the four anontymous reviewers in the acknowledgments of the updated version of the manuscript. The comments and suggestions from reviewer 2 are incorporated in italics and addressed by the authors in blue.

1 Specific Comments

Methods –The differences between the winds is an interesting result! Figure B2 highlights the lack of the diurnal cycle tracking for DJF, but it seems that previous papers indicate log-fog season in April-June and high-fog season September-November? Any reason the cycle isn't grouped by fog-season?

We thank the reviewer for this comment. The motivation for this figure was to check whether the reanalyses reproduce the diurnal cycle of the wind field and its pronounced summer/winter differences, which are described for the central Namib by Lindesay and Tyson (1990). In response to a related comment from Reviewer 1, we have already expanded Fig. B2 to include all four seasons (DJF, MAM, JJA, SON; Fig. B2 panels a–f) and added seasonal wind roses (Fig. B3) showing the joint distribution of wind direction and speed. We also examined the diurnal wind direction cycle grouped specifically by fog season rather than by calendar season, and found the results to be really similar to those obtained with the calendar-season grouping already shown. We therefore retain the standard calendar-season grouping (DJF/MAM/JJA/SON) throughout, as this is more general and allows for direct, consistent comparison across seasons rather than being tied to a fog-specific definition.

From Figure 4, also related to the winds– Since the bars are the contribution from each component, and SST data is the same, is the MERRA2 AN linear model therefore more sensitive to SST than its ERA5 counterpart? Could this mean that when constructing historical interannual variability, that ERA5 is more sensitive to low-level winds, and therefore has a higher correlation to El Niño if the primary mechanism is indeed strengthened northwesterly winds (sort of apparent in higher r values in line 289). Would it be possible to make the weight of the SST sensitivity the same between ERA5 and MERRA2, and might that indicate which reanalysis wind is more sensitive to the significant land warming (`https://wires.onlinelibrary.wiley.com/doi/full/10.1002/wcc.70025`), or would that excessively disrupt the construction of the model? Are there any previous cases from higher-temporal scales (diurnal, synoptic) that point to more fidelity in a particular reanalysis?

The SST data (NOAA OI SST) is indeed identical between the ERA5 and MERRA-2 configurations. The SST bar in Fig. 4 shows the linear trend of the partial reconstruction obtained by applying the estimated SST sensitivities to the SST anomaly field; since that anomaly field is identical in both configurations, any difference in the resulting trend contribution must originate in the estimated sensitivities themselves. However, we do not think this reflects a genuinely stronger physical sensitivity to SST in the AN-MERRA-2 model. In ridge regression, each predictor's coefficient is estimated jointly with all others under a shared regularization penalty, so its value depends on the collinearity structure among them. Because the SST predictor is identical in both configurations, differences in its attributed contribution arise from differences in its covariance with the other predictors, which do differ between the ERA5 and MERRA-2 configurations (e.g., winds, EIS, R700).

Regarding the proposed experiment: while equalizing the SST weight between the two configurations could in principle be performed, its interpretation would be difficult. The remaining coefficients would still depend on the differing covariance structures among predictors in the two reanalysis configurations, so the "leftover" wind coefficient would not isolate a clean, physically-interpretable wind sensitivity. We have therefore not pursued this experiment, though we recognize it as a interesting idea in principle.

Regarding the possible ENSO–wind–FLC link: as noted in the manuscript (Sect. 3.3), we consider this connection suggestive but not firmly established. Rouault and Tomety (2022) report weak, positive correlations between ENSO and coastal upwelling, attributed to weaker-than-normal upwelling-favorable southeasterly winds during ENSO events, and Li et al. (2025) find that more frequent, stronger northwesterly winds during ENSO years intensified fog over the past decade, though at annual rather than monthly resolution. We agree the higher ENSO correlation in the ERA5 configuration is plausibly related to differences in simulated wind sensitivity between the reanalyses, but given the current evidence we would rather flag this as an open question than overstate what the current evidence supports.

Regarding reanalysis fidelity for winds at higher temporal resolution: we are not aware of a study that directly evaluates diurnal- or synoptic-scale wind fidelity between ERA5 and MERRA-2 specifically for the Benguela/Namib coastal region. More broadly, Gruber et al. (2022) report that ERA5-based wind power simulations correlate better with observed generation than MERRA-2 across several countries, including South Africa, though the difference in error (RMSE) between the two reanalyses was not statistically significant for South Africa specifically. Patricola and Chang (2017) further show that coarse-resolution reanalyses generally struggle to represent the structure of the Benguela low-level coastal jet itself, missing its characteristic near-shore velocity maxima. Taken together, we do not think the existing literature supports a clean, region-specific conclusion that one reanalysis's winds are simply "more faithful" for this setting.

-Added in Section 3.2: "Note that the relative magnitude of each predictor's contribution shown in Fig. 4 depends on the ridge-regression sensitivities, which are estimated jointly across all predictors under the shared l^2-norm regularization term and are therefore shaped by the collinearity structure among predictors. Consequently, a difference between reanalyses in a given predictor's contribution should not, on its own, be taken as evidence of a difference in that variable's underlying physical importance."

Section 3.2, line 220 – Any further information on the annual FLC anomalies would be a great addition for the reader. Such as, do annual anomalies follow the seasonal cycle for the AN, so a positive anomaly means more fog in the peak season, or a slightly longer season (to the extent it's tractable in monthly data)? Similarly for the CN, do any months consistently appear from the historical reconstruction in years with strong reductions?

We thank the reviewer for this suggestion. We address this using the satellite-observed FLC record (2004–2019) rather than the 1982–2019 model-based reconstructions, as the satellite observations provide a direct record and are not subject to uncertainties associated with the reconstruction model. To investigate this, we correlated each calendar month's FLC anomaly with the annual mean anomaly across all years. This quantifies the association between monthly variability and the overall annual signal across the full record (Fig. 1, in this document).

In AN, the fog season exhibits a strong and well-defined seasonal cycle. Significant positive correlations are found in several months, indicating that annual anomalies are associated with variability occurring during different parts of the year. Within the fog season, the strongest correlations occur in June and July, when the season is still developing toward its maximum, whereas August and September, despite having the highest climatological fog occurrence, show weaker relationships with the annual anomaly. This suggests that interannual variability in AN is primarily associated with changes during the early development of the fog season, which may reflect variations in the strength and/or timing of the seasonal build-up.

We further examined whether strong and weak anomaly years are associated with changes in season length and found only minor differences, suggesting that substantial changes in season duration do not dominate the annual anomalies.
In CN, fog occurs throughout the year with a weaker seasonal cycle. The annual anomaly is most strongly associated with variability outside the climatological peak season, particularly in January, March, and April. In contrast, the peak season shows little relationship with the annual anomaly, suggesting that interannual variability in CN is primarily linked to changes in fog occurrence during non-peak months rather than variability during the climatological maximum.
-Added in Section 3.2: "To better characterize these annual anomalies, we examine which months they are primarily associated with and whether they reflect changes in the intensity of the fog season or shifts in its timing or duration. Using the satellite-observed FLC record (2004–2019), we correlated each calendar month's FLC anomaly with the annual mean anomaly across all years to identify which months' variability is most closely linked to the overall annual signal (Fig.B2. In AN, significant positive correlations occur in several months, with the strongest relationships found in June and July, when the fog season is still developing toward its maximum. In contrast, August and September, despite having the highest climatological fog occurrence, show weaker relationships with the annual anomaly. This indicates that AN annual anomalies are primarily associated with variability during the early development of the fog season, potentially reflecting changes in the strength and/or timing of seasonal build-up rather than substantial changes in season duration. In CN, where fog occurs throughout the year with a weaker seasonal cycle, annual anomalies are most strongly associated with variability outside the climatological peak season, particularly in January, March, and April, while the peak period contributes comparatively little to interannual variability."
-Added figure B2

Section 3.3 – As a suggestion, I would restructure section 3.3 to lead with the BNI influence (lines 303-335) and Figure 7, as it ties into the regional climate more directly than ENSO (and reflects the title of the manuscript).

We thank the reviewer for this suggestion and appreciate the rationale for leading with the BNI influence, as it is more directly connected to the regional climate context and the focus of the manuscript. However, we prefer to retain the current structure and introduce the ONI influence first. This is because the BNI is defined in a similar way to the ONI, and the ONI is a more widely recognized climate index. Presenting the ONI first therefore provides a more accessible introduction and allows us to place our results within the literature before discussing the more regionally specific BNI influence. In addition, we find that this structure provides a more progressive narrative, introducing the established large-scale climate mode first and then concluding the section with the stronger and more regionally relevant BNI/LUCI results.

2 Technical Comments

Abstract, Line 12: I would start the conclusions of the interannual variability section with the last conclusion, "..half of the variability in Angolan Namib comes from Benguela Niño events..". I would also include the % increase/reduction in FLC occurrence during El Niño years for reader context.

We agree that Benguela Niño events represent the stronger and more regionally relevant control on interannual FLC variability and have therefore revised the abstract to highlight this result before discussing ENSO. Specifically, we now introduce Benguela Niño events first . We also clarified that the ENSO-related enhancement is associated with El Niño con-

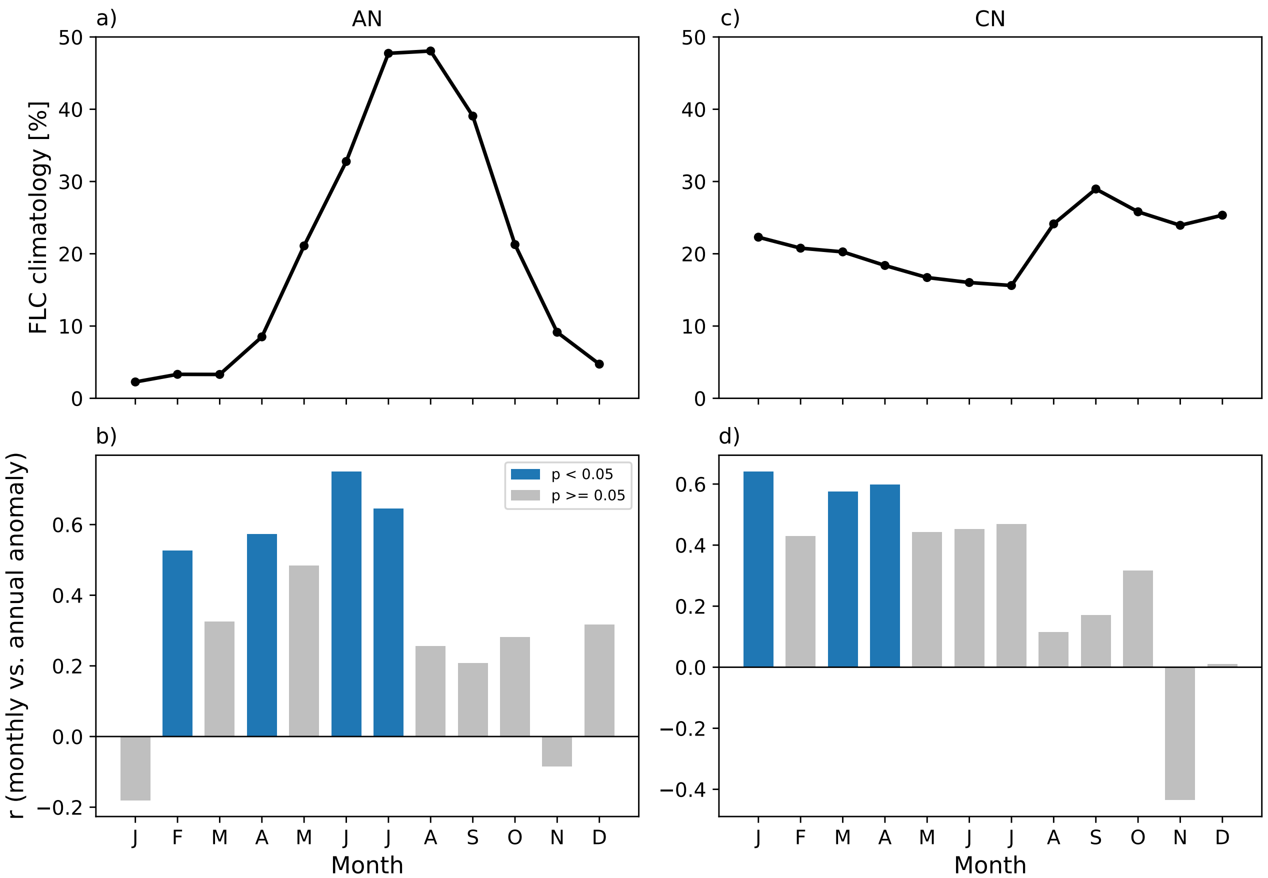

Figure 1: Based on the satellite-observed FLC record (2004–2019). (a, c) Average monthly cycle of FLC cover for AN and CN. (b, d) Correlation (r) between each month's FLC anomaly and the annual mean anomaly, for AN and CN; blue bars indicate $p < 0.05$.

ditions. We decided not to include the exact percentage change in FLC occurrence during El Niño years in the abstract because the ENSO influence is comparatively weak and not consistently significant across the different reconstruction datasets.

-Modified in the abstract: "Finally, the reconstructions are used to assess interannual variability and its links to climate modes. Benguela Niño events, associated with tropical water intrusion and SST warming, explain up to half of the interannual FLC variability in the Angolan Namib. El Niño conditions also enhance FLC occurrence, but their influence is much weaker."

Ln 190: Introduction, Line 50: It seems the Li (2025) reference sets up your study analyzing spatial drivers of interannual variability as a next step nicely (decrease in fog water since 1996, some discrepancies in El Nino periods before and after this period with in-situ observations, although only in one location). If desired, one could add another sentence here to *supply some of those motivations to the reader? Or maybe just the mechanism they supply that increases fog occurrence, and potential limitations? Some results later in this work reference the Li paper, so a bit more context would strengthen the impact of this study's results.*

We agree that additional context on the Li et al. (2025) study helps motivate the analysis of interannual variability presented here. We have added a sentence in the Introduction describing the proposed mechanisms linking El Niño to enhanced fog occurrence, namely increased moisture advection associated with stronger northwesterly winds and enhanced local moisture availability through vegetation transpiration. We also highlight the limitation that the reported El Niño signal is based on a single in-situ location and is mainly evident during the most recent decade of the record, motivating our spatially resolved analysis of FLC variability across the Namib region using satellite observations and reanalysis-based reconstructions.
-Added in the Introduction: "Additionally, teleconnections to El Niño-Southern Oscillation (ENSO) have been suggested to enhance fog occurrence in the Central Namib through increased moisture advection associated with more frequent northwesterly winds and enhanced local moisture availability via vegetation transpiration during El Niño conditions (Li et al., 2025). However, this relationship is based on observations from a single location and is mainly evident during the most recent decade of the record, motivating further investigation of the spatial extent and robustness of ENSO-related FLC variability across the Namib desert."

2.2, Line 102: Long term warming trend removed from BNI? Maybe mention the value in the case the reader is curious?

We agree that providing the magnitude of the removed long-term trend improves transparency. We have added that the linear trend removed from the BNI time series corresponds to $0.33°\mathrm{C} \cdot \mathrm{decade}^{-1}$.

3.1, Figure 2, Line 192: Add titles to subplots, even if small text, just makes looking at them together easier.

We have added predictor titles to Figure 2 and the corresponding figures in Appendix A.

3., Line 194: Add parentheses in Table 1 after SST (NOAA OI) so reader can't mistake reanalysis SST being used.

Done.

Figure 3 – Is there a time series of predicted vs observed FLC occurrence for 2003-2020 using the network? Maybe add in dots to both panels to show spread in observed fog anomalies. It would be nice to see observations next to what the network predicts. Any additional context to the 1996 divide posited by Li et al (2025) that you can add would be great, since the CN region includes Gobabeb research station, correct?

As noted in the manuscript, the final reconstruction (Fig. 3) uses fold-averaged sensitivities, in which each month from 2004–2019 contributes to the training data in all but one of the six cross-validation folds, making the resulting reconstruction non-independent. A fully out-of-sample reconstruction can instead be obtained by combining the predictions from all test folds, yielding correlations with the observations of $r = 0.64$ for AN-ERA5, $r = 0.62$ for AN-MERRA-2, $r = 0.61$ for CN-ERA5, and $r = 0.63$ for CN-MERRA-2. Using fold-averaged sensitivities ensures a continuous time series from 1982

to 2019, which allows the analysis of interannual variability and long-term trends, but as these fold-averaged values are not fully independent, we consider it potentially misleading to overlay the observations directly on Fig. 3.
To address the reviewer's request while keeping this distinction clear, we have added Fig. B1(Appendix), showing the observations against both the fully out-of-sample prediction ($\hat{y}$) and the fold-averaged reconstruction, at annual resolution, for both regions and reanalyses. As expected, the fold-averaged reconstruction correlates much more closely with the observations ($r = 0.88$–0.94) than the genuinely out-of-sample prediction does ($r = 0.61$–0.64).
Regarding the potential additional context related to the post-1996 changes reported by Li et al. (2025): although Gobabeb falls within the latitudinal band of our CN region, it lies some 60 km inland and therefore outside our study domain, which is restricted to the coastal strip within 24 km of the coastline. We have chosen not to directly compare our reconstruction with the specific pre-/post-1996 breakpoint identified in that study. As discussed in the manuscript, the reconstructed long-term trends are subject to substantial uncertainty, both due to differences between reanalysis products and the general lack of statistically significant trends. Even accounting for this uncertainty, we find no indication of a break point in our reconstructed time series corresponding to the one reported by Li et al. (2025), and we do not consider the reconstruction sufficiently robust for assessing a specific historical breakpoint on its own. Furthermore, the breakpoint identified by Li et al. (2025) is derived from a single long-term in-situ fog record at Gobabeb, whereas our CN reconstruction represents a regional-average FLC signal over the coastal domain; a change observed at an inland site outside this domain would not necessarily be expected to emerge in our reconstruction. Rather, our statistical framework is designed to quantify the sensitivities of FLC variability to large-scale cloud-controlling factors (SST, EIS, wind, and atmospheric moisture) and to investigate their role in interannual variability and long-term tendencies.
-Added Figure B1

References

Gruber, K., Regner, P., Wehrle, S., Zeyringer, M., and Schmidt, J.: Towards global validation of wind power simulations: A multi-country assessment of wind power simulation from MERRA-2 and ERA-5 reanalyses bias-corrected with the global wind atlas, Energy, 238, 121 520, https://doi.org/10.1016/j.energy.2021.121520, 2022.

Li, Y., Wang, L., Diersing, C. J., Qiao, N., Liu, Y., Maggs-Kölling, G., and Marais, E.: El Niño intensified fog formation in the Namib Desert, Earth's Future, 13, e2024EF005 725, https://doi.org/10.1029/2024EF005725, 2025.

Lindesay, J. A. and Tyson, P. D.: Thermo-topographically induced boundary layer oscillations over the central Namib, southern Africa, International Journal of Climatology, 10, 63–77, https://doi.org/10.1002/joc.3370100108, 1990.

Patricola, C. M. and Chang, P.: Structure and dynamics of the Benguela low-level coastal jet, Climate Dynamics, 49, 2765–2788, https://doi.org/10.1007/s00382-016-3479-7, 2017.

Rouault, M. and Tomety, F.: Impact of El Niño–Southern oscillation on the Benguela upwelling, Journal of Physical Oceanography, 52, 2573–2587, https://doi.org/10.1175/JPO-D-21-0219.1, 2022.

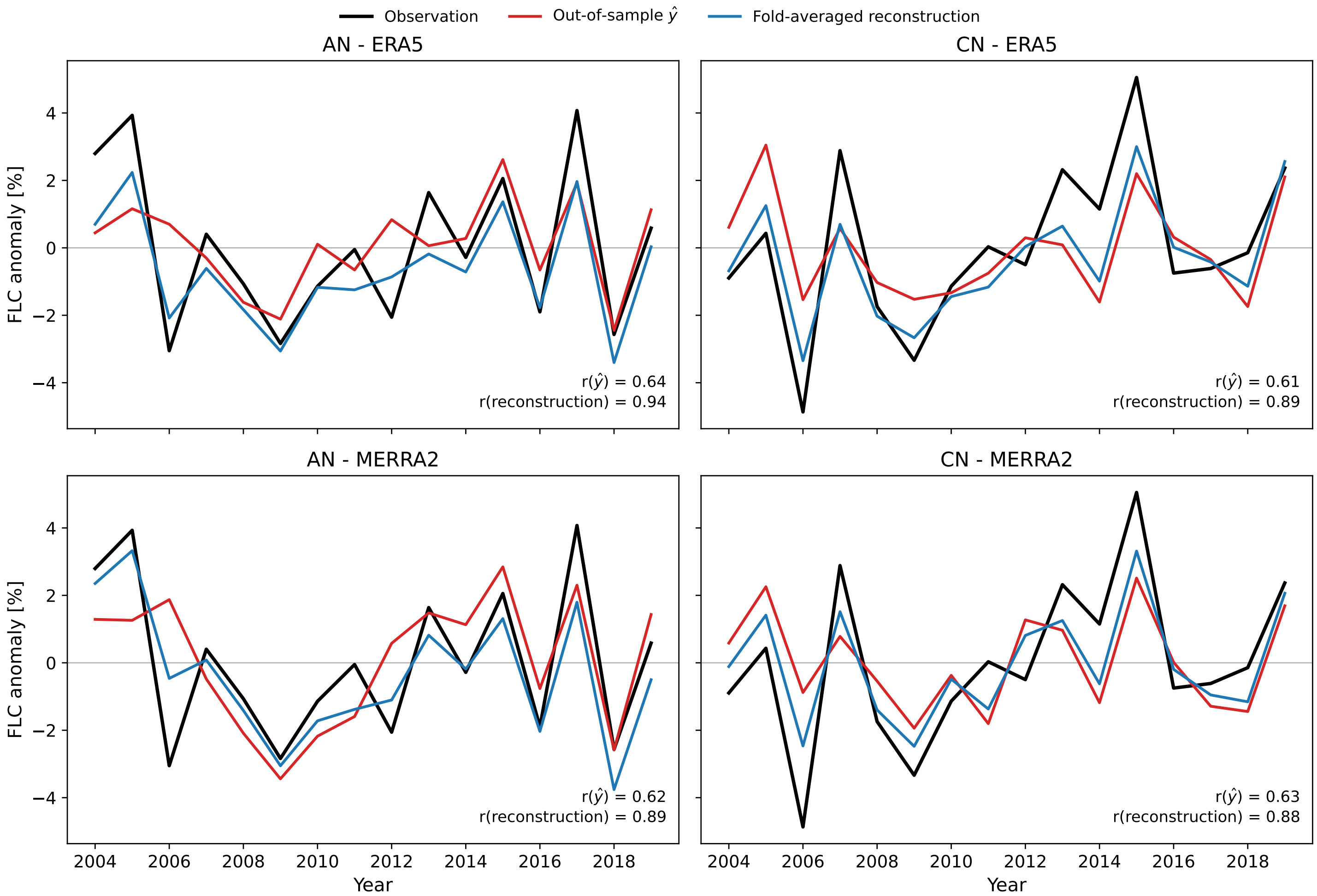

Figure 2: Comparison of observed annual FLC anomalies against the fully out-of-sample prediction ($\hat{y}$, red) and the fold-averaged reconstruction used in Fig. 3 (blue), for each region and reanalysis. The fold-averaged reconstruction is not independent of the observations and correlates more closely with them than the genuinely out-of-sample prediction, illustrating why Fig. 3 does not overlay observations directly.