

Reply to Reviewer 2 - Anonymous reviewer

Reviewer's general comments

The manuscript presents a assessment of low flow freq analysis using non-stationary extension of Weibull and copula based dependence framework. The framework is used for evaluating around 700 European catchments from the ROBIN dataset and demonstrates the implications of non-stationarity on low-flow frequency estimates, particularly for rare events. The study addresses an important topic given increasing concerns regarding climate-change induced nonstationary impacts on hydrological droughts and low-flow conditions. The manuscript is generally well structured and methodologically rigorous. However, some aspects require a bit of attention and explanation before publication. Here are some points to consider by the authors:

Response to Reviewer's general comments

Dear Reviewer, thank you very much for your careful evaluation of our manuscript, "Non-stationary low-flow frequency analysis with mixed Weibull components and Copula-based dependence framework" (<https://doi.org/10.5194/egusphere-2026-1820>), and for your constructive and encouraging feedback. We appreciate your positive assessment of the relevance, structure, and methodological rigour of our study.

We have carefully considered all of your comments and suggestions and have revised the manuscript accordingly to improve the clarity of the methodological choices, assumptions, interpretation, and limitations of the proposed framework. Please find below our point-by-point responses to each comment in italic, followed by the corresponding revisions made to the manuscript. In the revised text, additions and modifications are shown in blue.

Sincerely yours,

Farhana Sweeta Fitriana, Svenja Fischer, Gabriele Weigelhofer, Johannes Laimighofer and Gregor Laaha

Reviewer's specific comments

(1) The introduction provides a good overview of non-stationary frequency analysis literature, however authors should more clearly explain why existing approaches (e.g. GAMLSS-based low-flow frequency analysis) are insufficient and specifically why the proposed extension of LFAmix and LFAmixC is necessary in the set up which they have used.

Response to comment 1:

We thank the reviewer for this helpful comment. We agree that the distinction between the proposed framework and existing approaches to non-stationary low-flow frequency analysis should be stated more clearly. GAMLSS-based approaches provide a flexible framework for representing temporal variation in distribution parameters through time or other covariates. However, in seasonal climates, non-stationarity is only one part of the modelling problem, because annual low-flow minima may originate from either summer or winter processes that differ substantially in their physical controls and statistical distributions, and these seasonal components may also be dependent. The stationary LFA_{mixC} framework was developed specifically to represent this seasonal process heterogeneity and the dependence between summer and winter low flows (Laaha, 2023b). However, it does not allow the seasonal marginal distributions or their dependence structure to change over time. The contribution of the proposed NSLFA_{mixC} framework is therefore not simply to introduce time-varying distribution parameters, but to extend the established process-based seasonal mixture framework to non-stationary conditions. In this way, seasonal heterogeneity, inter-seasonal dependence, and temporal change can be represented consistently within the same low-flow frequency-analysis framework. The consideration of covariates, which makes the GAMLSS a frequently applied model, can also be realised for

the $NSLFA_{mixC}$ model by simply replacing the time parameter by any other covariate. A further practical distinction concerns the Weibull formulation.

We have revised the Introduction accordingly and added the following clarification (Lines 58-61):

GAMLSS-based approaches provide a flexible framework for representing temporal variation in the distribution. However, they do not address the additional process heterogeneity that arises when annual low flows originate from distinct seasonal generating processes, nor the dependence that may exist between these seasonal components.

(2) The manuscript adopts WEI3 throughout, but should the justification or advantages/disadvantages of using alternative distributions be included. Since low-flow frequency analysis often employs Lognormal, Generalized Logistic, Pearson Type III or GEV formulations, authors should discuss why WEI3 is uniquely suitable and whether results are sensitive to this choice.

Response to comment 2:

We appreciate the reviewer's thoughtful comment on the choice of marginal distribution. In the present study, we deliberately retain the WEI3 formulation because of its theoretical basis for lower extremes and its consistency with the established LFA_{mixC} framework. We nevertheless agree that examining alternative marginal distributions would be useful for assessing the broader applicability of the framework in future work. In response to a related comment from Reviewer 1, we also analyse an L-moment ratio diagram for the stationary summer and winter low-flow samples (Fig. 1). The empirical L-skewness and L-kurtosis values show reasonable agreement with the theoretical Weibull relationship, further supporting the use of WEI3 for the seasonal margins. At the same time, apparent departures from a fitted Weibull distribution at individual catchments may not necessarily reflect the choice of distribution alone, but may also indicate sample properties such as process heterogeneity. In particular, annual low-flow minima may be generated by different summer and winter mechanisms, so that a single annual distribution may be less appropriate than a framework that explicitly represents the seasonal components. This is one of the main motivations for the $NSLFA_{mixC}$ approach, and previous studies by Laaha (2023a, b) have shown the benefit of explicitly accounting for seasonal process heterogeneity in low-flow frequency analysis. For this reason, the present study focuses on extending the theoretically motivated WEI3-based seasonal mixture and copula framework to non-stationary conditions, rather than conducting a catchment-specific comparison of alternative marginal distributions. We therefore retain WEI3 as the theoretically motivated marginal distribution in the present study. Extending the framework to other marginal distributions in future work would provide a useful test of the generality of the proposed modelling approach.

We have revised the manuscript accordingly. In Lines 341-343, we added: *Alternative low-flow distributions may also provide suitable representations at individual catchments. However, the present study retains WEI3 because of its theoretical basis for lower extremes and its consistency with the established LFA_{mixC} framework.*

We also added the following statement to the limitations and future work section (Lines 551-554): *In addition, the present framework is developed using WEI3, supported by its theoretical basis for lower extremes and its established use in low-flow frequency analysis. Extending the framework to alternative marginal distributions to consider local deviations from this assumption would provide a useful assessment of its broader applicability.*

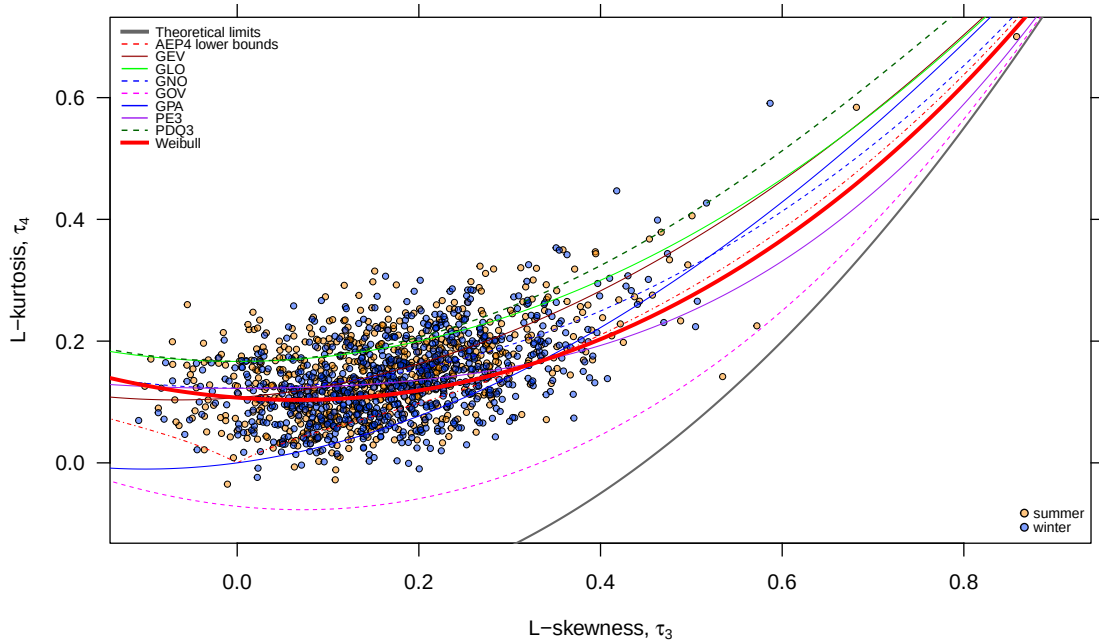


Figure 1. L-moment ratio diagram for summer and winter low-flow series. Points represent empirical L-skewness (τ_3) and L-kurtosis (τ_4) of the seasonal low-flow samples, while the curves show theoretical L-moment relationships for candidate distributions, including the Weibull distribution.

(3) Non-stationarity is only introduced through the location parameter. While the authors justify this using parsimony arguments, climate change can influence both variability and shape of low-flow distributions. Understandable that this will make the model very more sensitive and risky. . . .some discussion or such probabilistic sensitivity analysis is recommended.

Response to comment 3:

Thank you for highlighting this point. We appreciate the reviewer's thoughtful comment on how we represent non-stationarity. We agree that climate change may affect not only the location of low-flow distributions, but also their variability and potentially their tail behaviour. In the present study, however, we deliberately restrict non-stationarity to the location parameter as a parsimonious first-order formulation. This choice is motivated by both statistical and hydrological considerations. Allowing additional distribution parameters to vary independently over time would substantially increase model complexity and estimation uncertainty, particularly given the limited length of the annual seasonal low-flow series, as also noted by the reviewer. Moreover, previous scaling analyses have shown strong relationships among the moments of streamflow series (Vogel and Sankarasubramanian, 2000), suggesting that changes in variability may not necessarily occur independently of changes in the mean (Serago and Vogel, 2018). Allowing the scale parameter to vary independently with time could therefore introduce additional flexibility without accounting for these structural relationships. Particular caution is also required for the shape parameter, since temporal variation in shape would imply changes in tail behaviour. Such changes are more difficult to estimate robustly and to relate directly to physical climatic drivers, particularly when inference concerns rare low-flow events.

Introducing an independently time-varying shape parameter would therefore further increase parameter uncertainty and the risk of overfitting. We therefore fully agree with the reviewer that such extensions of the model would affect uncertainty and sensitivity of the model. At the same time, we agree that changes in variability deserve further investigation. An important next step is therefore to examine whether temporal changes in variability can be represented more parsimoniously as consequential changes associated with shifts in the mean, rather than by introducing an independently time-varying scale parameter. Such an approach could account for changing variability while preserving the structural relationships among streamflow moments and limiting unnecessary parameterisation. We have clarified this point further in the Discussion and Limitations sections by emphasising the parsimonious rationale for the location-only formulation and by identifying the investigation of variability changes associated with shifts in the mean as an important next step.

We have revised the manuscript accordingly. In Lines 545-548, we added: [An important next step is to investigate whether temporal changes in low-flow variability can be represented parsimoniously as consequential changes associated with shifts in the mean, rather than by independently varying additional distribution parameters, while remaining consistent with the underlying physical processes driving change.](#)

(4) The framework assumes a linear temporal evolution in location and dependence parameters. However, low-flow behaviour often exhibits regime shifts, accelerations, thresholds, or oscillatory behaviour linked to climatic variability. If not nonlinear relationships related analysis is done, at least this should be discussed in detail.

Response to comment 4:

We appreciate the reviewer's thoughtful comment on the assumed temporal form of non-stationarity. We agree that low-flow behaviour may exhibit more complex dynamics, including regime shifts, accelerations, thresholds, or oscillatory variability. The reason for limiting the model to a linear trend was already motivated in the manuscript and has now been clarified further. In brief, the linear formulation provides a simple and parsimonious representation of gradual temporal change while avoiding unnecessary model complexity. Given the limited record length, more flexible nonlinear formulations, or additional time-varying distribution parameters, would require stronger empirical support and could substantially increase estimation uncertainty and the risk of overfitting. The linear temporal component is also supported by the preceding trend analysis, in which monotonic change in the seasonal low-flow series was assessed using the block-bootstrap Mann-Kendall test. We then evaluated the non-stationary formulation directly against the simpler stationary model using a likelihood-ratio test, and the results were generally consistent. The linear formulation should therefore be interpreted as a parsimonious first-order representation of historical change rather than as an assumption that low-flow behaviour is intrinsically linear. We have expanded the discussion to clarify that more complex temporal dynamics may occur and that nonlinear formulations, change-point approaches, or climatic covariates could be considered where sufficiently long records and supporting evidence are available.

We have now added a discussion of the model's motivation. [\(Lines 383-393\) Its value lies not in universally replacing stationary models, but in identifying and representing catchments where seasonal low-flow regimes exhibit temporal change. In this case, the stationarity assumption may be violated and should not be ignored in the frequency analysis. To keep the framework parsimonious, non-stationarity was introduced as a linear trend in the location parameter and was evaluated formally by comparing the non-stationary and stationary models using a likelihood-ratio test. The linear formulation was chosen as a simple and parsimonious way to represent gradual temporal change. Given the limited record length, more flexible non-linear formulations or time-varying scale and shape parameters would require stronger empirical support and could substantially increase estimation uncertainty and the risk of overfitting. More complex temporal dynamics, including regime shifts, accelerations, thresholds, or oscillatory behaviour linked to climatic variability, may also occur. Nonlinear formulations, change-point approaches, or climatic covariates could therefore be considered where sufficiently long records and supporting evidence are available.](#)

(5) The use of PAM clustering and seasonality histograms is interesting, but the physical interpretation of the resulting clusters needs stronger discussion. For example, how sensitive are the results to the chosen clustering approach, silhouette threshold (0.2), or seasonal definitions (April–October and November–March)?

Response to comment 5:

Thank you for pointing this out, and we appreciate the suggestion. We have strengthened the discussion of the physical interpretation of the seasonality clusters and added sensitivity analyses in the Appendix. The PAM analysis identified two dominant seasonal patterns, with medoid peaks in February (winter-type) and August (summer-type). Catchments with silhouette widths below 0.2 were classified as mixed, resulting in 82.50% summer-type, 14.44% winter-type, and 3.06% mixed catchments. The classification was only weakly sensitive to the silhouette threshold, using 0.15 and 0.25 instead of 0.20 retained 98.47% and 98.89% agreement with the baseline, respectively, with differences mainly affecting the mixed class (Table. 1). As an additional robustness check, hierarchical clustering was applied. Agreement with PAM was high (96.67% agreement in the summer, winter, and mixed classifications), and both approaches yielded the same physical interpretation, with representative cluster profiles peaking in February and August. Differences were confined to weakly affiliated or mixed catchments, with no direct switches between summer- and winter-type regimes. The April-October and November-March seasonal definition follows the established continental-scale European convention of Laaha et al. (2017), as already stated in the manuscript Lines 116-118. This definition does not determine the PAM clusters, which are based on the complete 12-month seasonality histograms, but is used for their physical interpretation. Shifting either seasonal boundary by one month did not change the cluster interpretation, resulting in 100% agreement with the baseline (Table 2). Overall, the dominant summer-winter seasonality structure is robust to the methodological choices considered, while the small differences are limited to catchments with weak or transitional seasonality. We have added the following text to the Results and Discussion section: *Lines 310-313: The classification is robust to the choice of silhouette-width threshold, with thresholds of 0.15 and 0.25 retaining 98.47% and 98.89% agreement, respectively, with the baseline threshold of 0.2. Changes primarily affect the proportion of catchments classified as mixed domain. Additional sensitivity analyses of the clustering approach and seasonal definition similarly support the robustness of the dominant summer-winter structure, with detailed results provided in Appendix B.*

We have also added the detailed sensitivity results in Appendix B:

Table 1. Sensitivity of the low-flow seasonality classification to the silhouette-width threshold used to identify catchments with mixed seasonality. The baseline threshold is $s < 0.20$. Agreement refers to the percentage of catchments retaining the same classification as under the baseline threshold.

	Threshold	Winter (n)	Winter (%)	Summer (n)	Summer (%)	Mixed (n)	Mixed (%)	Agreement (%)
1	0.10	109	15.14	605	84.03	6	0.83	97.78
2	0.15	106	14.72	603	83.75	11	1.53	98.47
3	0.20	104	14.44	594	82.50	22	3.06	100.00
4	0.25	102	14.17	588	81.67	30	4.17	98.89
5	0.30	94	13.06	575	79.86	51	7.08	95.97

Table 2. Sensitivity of the physical interpretation of the PAM clusters to the seasonal definition. The baseline defines summer as April-October and winter as November-March.

	Seasonal Definition	Cluster 1	Cluster 2	Agreement (%)
1	Apr-Oct / Nov-Mar	Winter	Summer	100.00
2	May-Oct / Nov-Apr	Winter	Summer	100.00
3	Apr-Sep / Oct-Mar	Winter	Summer	100.00

(6) WEI3 fitting was successful in only 76.1% of catchments. This implies nearly one-quarter of stations could not be fitted successfully. May be the characteristics of these excluded catchments should be analysed and discussed, as this may introduce regional bias into the results.

Response to comment 6:

Thank you for this valuable suggestion. We further examined the catchments for which WEI3 fitting was unsuccessful to determine whether they show any clear spatial or hydrological pattern. Of the 721 catchments, WEI3 fitting was successful for 549 catchments (76.1%) and unsuccessful for 172 catchments (23.9%). The unsuccessful fits were distributed across the study domain rather than being concentrated in one particular region, while the successfully fitted catchments still provide broad spatial coverage across Europe (Fig. 2). We also compared catchment area, mean elevation, and low-flow characteristics, and distributional shape between the two groups (Table 3). Mean catchment elevation was similar, whereas unsuccessfully fitted catchments tended to be smaller, with a median area of 91.5 km² compared to 163.6 km² for successfully fitted catchments. These catchments also generally had lower specific low flows in the annual, summer, and winter series and less year-to-year variability. For example, median annual M7Q was 1.69 L s⁻¹ km⁻² for unsuccessful fits compared to 2.80 L s⁻¹ km⁻² for successful fits. We also examined which low-flow series were affected by fitting failures. The most common pattern was a winter-only failure, occurring in 54 catchments (31.4% of unsuccessful fits), followed by combined annual and summer failures in 49 catchments (28.5%). The remaining failures were distributed across the other seasonal combinations, indicating that the fitting difficulties were not limited to one particular series. The unsuccessful catchments also showed differences in distributional shape. Their low-flow series exhibited consistently higher positive L-skewness, compared with successfully fitted catchments. To further investigate whether distributional shape is related to fitting difficulties, we separately examined individual stationary WEI3 fits and estimated the Weibull shape parameter independently using L-moments. Among the series for which maximum-likelihood fitting was unsuccessful, 39-59% had an L-moment shape estimate below one, compared with approximately 3% of successfully fitted series. A shape parameter below one is relevant for the three-parameter Weibull because the likelihood can become increasingly difficult to optimise as the estimated location parameter approaches the lower endpoint of the observations. These results therefore suggest that the fitting difficulties occur more frequently for low-flow series with higher skewness and lower Weibull shape parameters. More generally, likelihood-based estimation can become non-regular when a distribution's support depends on estimated parameters (Coles et al., 2001). This issue is relevant to the three-parameter Weibull because its lower endpoint depends on the location parameter. Overall, the additional analysis shows that unsuccessful fits are spatially dispersed and do not indicate a clear regional concentration. They occur more frequently, however, in smaller catchments with lower low flows and more positively skewed low-flow distributions. The distributional-shape analysis provides a plausible explanation for the numerical difficulties encountered when estimating the three-parameter Weibull via maximum likelihood. Earlier low-flow studies have reported similar convergence issues (Vogel and Kroll, 1989). Although these results help explain the observed fitting difficulties, a more detailed investigation of the numerical behaviour of the WEI3 likelihood is beyond the scope of this study and would be an interesting topic for further methodological research.

We have added this discussion to the revised manuscript: Lines 345-355: The remaining optimisation failures are likely related to the constrained parameter space, which may yield infeasible parameter combinations. The unsuccessful fits were distributed throughout the study domain rather than being concentrated in a single geographical region, while the successfully fitted catchments retained broad spatial coverage across Europe. Unsuccessfully fitted catchments tended to be smaller and generally had lower low-flow values relative to catchment area in the annual, summer, and winter series, with less year-to-year variability. Mean catchment elevation was similar between the two groups. The unsuccessful catchments also showed consistently higher positive L-skewness, indicating differences in the distributional shape of their low-flow series. These characteristics may contribute to the greater difficulty in estimating the WEI3 parameters within the constrained parameter space. Similar convergence issues have been reported in earlier low-flow studies (Vogel and Kroll, 1989), suggesting that they arise from the estimation procedure rather than a general limitation of the WEI3 distribution itself. We also provide the corresponding spatial comparison and detailed catchment, low-flow, and distributional characteristics in Appendix D.

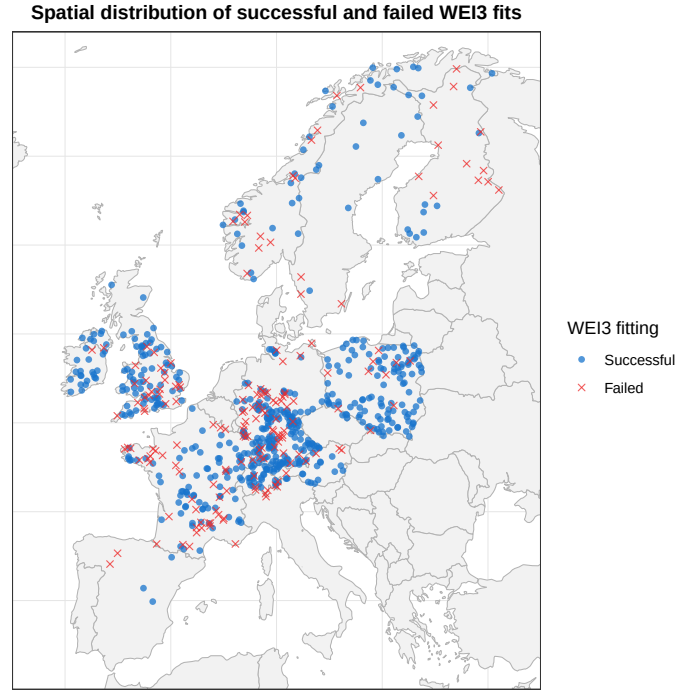


Figure 2. Spatial distribution of catchments with successful and unsuccessful WEI3 fits across the European study domain.

Table 3. Comparison of catchment characteristics, low-flow characteristics and distributional shape between catchments with successful and unsuccessful WEI3 fits. Values are reported as median [Q1-Q3]. Low-flow values are normalized by catchment area. p -values are based on Wilcoxon rank-sum tests.

Characteristic	Successful	Unsuccessful	p -value
Catchment area (km ²)	163.63 [83.60-494.50]	91.50 [44.15-247.21]	< 0.001
Mean catchment elevation (m)	349.82 [172.39-599.30]	350.00 [125.28-587.44]	0.291
<i>Low-flow magnitude and variability</i>			
Median annual M7Q (L s ⁻¹ km ⁻²)	2.80 [1.60-4.21]	1.69 [0.85-3.31]	< 0.001
Median summer M7Q (L s ⁻¹ km ⁻²)	2.97 [1.64-4.62]	1.93 [0.87-3.76]	< 0.001
Median winter M7Q (L s ⁻¹ km ⁻²)	4.86 [2.96-7.71]	3.27 [2.06-5.83]	< 0.001
IQR annual M7Q (L s ⁻¹ km ⁻²)	1.26 [0.86-2.00]	0.87 [0.51-1.39]	< 0.001
<i>Distributional shape</i>			
Annual L-skewness	0.13 [0.06-0.19]	0.22 [0.12-0.32]	< 0.001
Summer L-skewness	0.14 [0.08-0.20]	0.23 [0.13-0.32]	< 0.001
Winter L-skewness	0.16 [0.09-0.22]	0.26 [0.17-0.34]	< 0.001

(7) The paper focuses heavily on one Austrian catchment. Authors should consider presenting at least one additional example, preferably from a different characteristics dominated regime, to demonstrate framework performance across contrasting hydro-climatic conditions.

Response to comment 7:

Thank you for this suggestion. To complement the Austrian example and demonstrate the application of the $NSLFA_{mixC}$ framework under contrasting hydro-climatic conditions, we added a second example using Oksfjordvatn in Norway (Fig. 3). Stauf Vöckla at Traun represents a mixed seasonal low-flow regime (mixture rate = 0.52) with moderate inter-seasonal dependence (Kendall's $\tau = 0.48$). At this catchment, non-stationarity is mainly associated with the summer component, while the winter component remains stationary. Oksfjordvatn provides a contrasting case: it is winter-dominated (mixture rate = 0.40), has weaker inter-seasonal dependence (Kendall's $\tau = 0.26$), and both the summer and winter components were identified as non-stationary. The two catchments also show contrasting temporal behaviour. At Stauf Vöckla, summer low-flow magnitudes decrease over time and the non-stationary Q_{100} estimates decline, indicating increasingly severe low-flow conditions. At Oksfjordvatn, both summer and winter low-flow magnitudes increase over the observation period, and the corresponding Q_{100} estimates also increase, indicating less severe low-flow conditions toward the end of the record. These two examples therefore illustrate how the framework can represent different seasonal regimes, dependence structures, and directions of temporal change.

We have added the following text to the manuscript:

Lines 452-463: To further illustrate the framework under contrasting hydro-climatic conditions, we analysed the catchment Oksfjordvatn in Norway as a second example. Unlike Stauf Vöckla, which represents a mixed seasonal regime (mixture rate = 0.52), Oksfjordvatn is winter-dominated (mixture rate = 0.40) and exhibits weaker inter-seasonal dependence (Kendall's $\tau = 0.26$, compared with 0.48 at Stauf Vöckla). The temporal behaviour also differs between the two catchments. At Stauf Vöckla, non-stationarity is mainly associated with declining summer low flows, whereas at Oksfjordvatn both summer and winter components were identified as non-stationary and low-flow magnitudes increase over time. Consequently, the non-stationary Q_{100} estimates decrease through time at Stauf Vöckla, indicating increasingly severe low-flow conditions, but increase at Oksfjordvatn, indicating less severe low-flow conditions toward the end of the observation period. The corresponding four-panel analysis for Oksfjordvatn is provided in Appendix E. Overall, both examples demonstrate how the $NSLFA_{mixC}$ framework captures seasonal contrasts, temporal shifts, and dependence effects within a single coherent analysis. It also illustrates that non-stationarity may alter not only the magnitude of design low flows, but also the relative importance of summer and winter contributions to the annual low-flow regime.

(8) Statements such as a 100-year event becoming a 43-year event are powerful but may be misinterpreted by readers. It should be clarified that these changes are statistical diagnostics based on the fitted non-stationary model and should not be interpreted directly as future projections.

Response to comment 8:

We appreciate the reviewer for highlighting this point. We agree that the comparison between the 100-year return period in 1976 and the approximately 43-year return period in 2020 should be interpreted carefully. This comparison is based on the fitted non-stationary model and describes how the estimated return period of the same event changes between two points within the historical observation period. It is not intended as a projection of future event frequency. We have therefore clarified this interpretation in the manuscript by explicitly stating that the comparison represents a statistical diagnostic of historical change and should not be interpreted as a future projection.

We have revised the manuscript accordingly. In Lines 448-451, we added: *In particular, an event corresponding to a 100-year return period in 1976 is associated with a return period of about 43 years by 2020, indicating that such an event became approximately on average 2.3 times as frequent according to the fitted non-stationary model. This comparison is a statistical diagnostic of change within the historical observation period and should not be interpreted as a projection of future event frequency.*

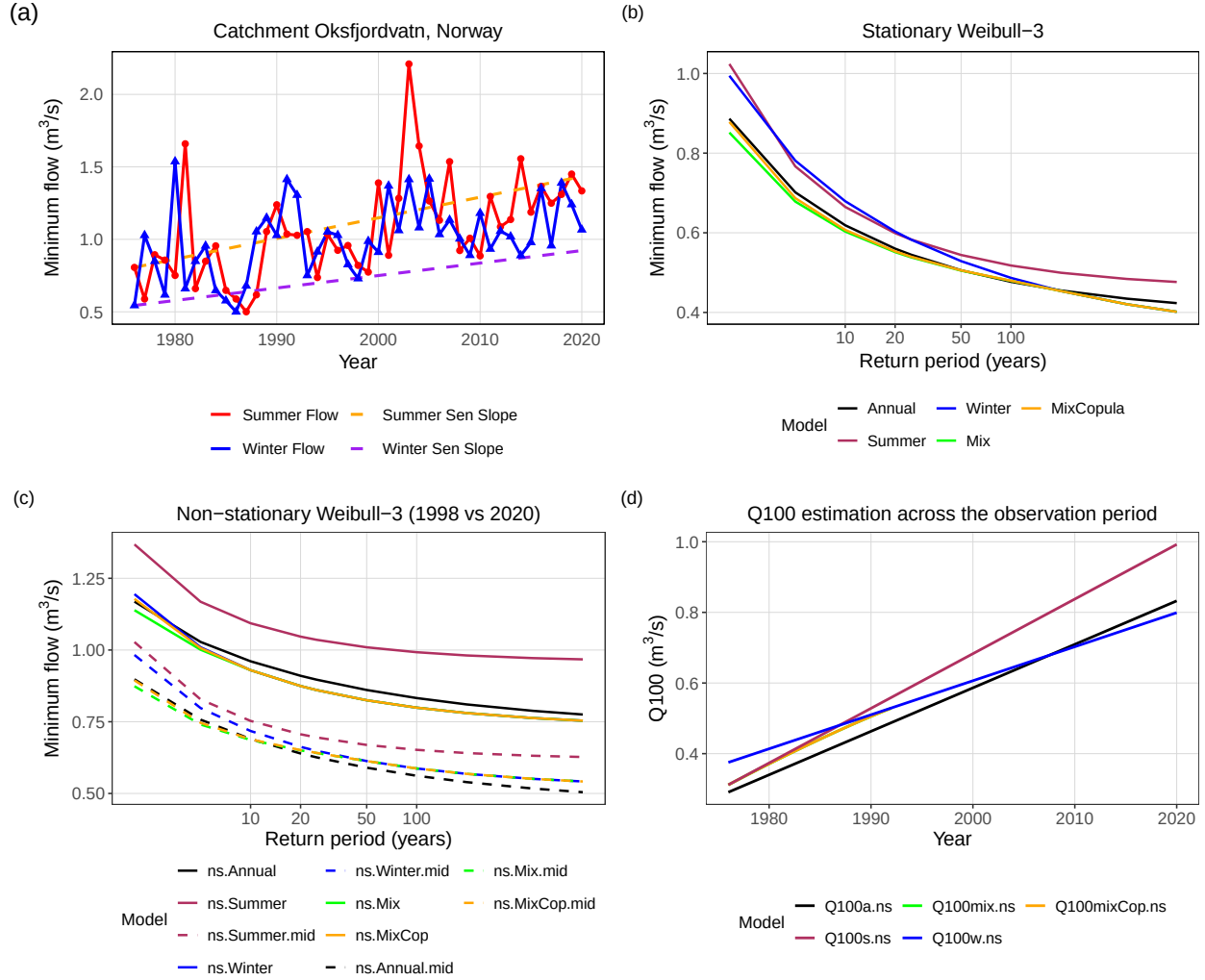


Figure 3. Application of the NSLFA_{mxC} framework to Oksfjordvatn, Norway. (a) Observed summer and winter minimum flows with corresponding Sen's slope trends. (b) Stationary WEI3 low-flow frequency estimates for the annual, summer, winter, mixture, and mixture-copula models. (c) Non-stationary low-flow frequency estimates evaluated at the midpoint (1998) and end (2020) of the observation period. (d) Evolution of the estimated 100-year low-flow quantile (Q_{100}) over the observation period.

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