RESPONSE TO REFEREES

Ms. Ref. No.: Egusphere-2025-2438

Title: Non-Stationary Dynamics of Compound Climate Extremes: A WRF-CMIP6-GAMLSS Framework for Risk Reassessment in Southeastern China

To Anonymous Referee #1

Thank you for your thoughtful and detailed review of our manuscript. We greatly appreciate the time and effort you dedicated to providing feedback. Your constructive suggestions have been invaluable, and we will implement all changes in a revised version of the manuscript.

1.In the introduction, where you mention the need for fine-resolution models, you may need to add the reasons for the required high-resolution models for capturing compound extremes (e.g., local convective precipitation, spatial heterogeneity, …).

We thank the reviewer for this valuable comment. Following your suggestion, we will add in the revised manuscript the reasons why high-resolution models are necessary to capture compound climate extremes (CCEs), emphasizing factors such as local convective precipitation and spatial heterogeneity.

Compared to Global Climate Models (GCMs), Regional Climate Models (RCMs) offer higher spatial resolution, allowing for more precise simulations of local climate effects induced by topography, such as local convective precipitation, orographic effects, and regional climate heterogeneity (Gilbert et al., 2025). In regions with complex terrain, RCMs are particularly effective at capturing spatial variations of climate variables, such as the differences in wind patterns, precipitation, and their distribution caused by topography in mountainous or basin areas (Imran and Evans, 2025). For example, Byun et al. (2023) assessed the ability of RCMs and GCMs to simulate storm tracks in East Asia, revealing that RCMs are better able to capture high-resolution topography, thereby reducing the biases found in GCMs. Lin et al. (2022) showed that RCMs driven by ERA-Interim reanalysis data are capable of capturing small-scale processes, such as orographic effects, and outperform GCMs in reproducing the large-scale features of the Heat Wave Magnitude Index-daily (HWMId). Torrez-Rodriguez et al. (2023)

also demonstrated that RCMs are better at reproducing the main spatio-temporal characteristics of precipitation in subtropical complex terrain regions.

2.May you please check the following articles and discuss how you improve their work and what your innovation is compared to it? https://link.springer.com/article/10.1007/s00382-020-05538-2

Thank you for your insightful comment regarding the comparison of our work with the study by Singh et al. (2021) on non-stationary compound extreme events (CCEs). After reviewing their work alongside our own, we would like to point out the following key differences and innovations that distinguish our study. Additionally, we will include this comparison in the discussion section of the revised manuscript.:

Compared to the study by Singh et al. (2021), our research presents significant innovations in both spatial scale and methodology. First, while Singh et al. (2021) focus on large-scale ensemble simulations to analyze compound extreme events in Canada, our study targets the medium-to-small scale of the Minjiang River Basin (MRB), a region heavily influenced by complex monsoonal climates and topography. Through high-resolution WRF model dynamic downscaling, we are able to conduct a more fine-grained risk assessment of compound extreme events and their spatial heterogeneity, offering a more localized approach to climate risk evaluation. Second, in terms of methodology, Singh et al. (2021) employ a Bayesian Copula model to analyze the dependence structure between temperature and precipitation, whereas we introduce the GAMLSS model to capture the non-stationary changes and assess the risk of compound extremes. Through the GAMLSS model, we are able to simultaneously handle variations in both the mean and variance of climate variables, providing a more comprehensive and detailed framework for risk assessment.

3.May you make a list of the 18 climate models you applied for your study in the supplementary file?

Thank you for your suggestion. We will provide a list of the 18 models used in the bias-corrected CMIP6 dataset (Xu et al., 2021) in the supplementary file as requested.

Table S1 CMIP6 models used in CMIP6bc.

No.	Model	Institution	Approximate grid spacing
1	ACCESS-CM2	Commonwealth Scientific and Industrial Research Organisation (Australia)	1.875° × 1.25°
2	ACCESS-ESM1–5	Commonwealth Scientific and Industrial Research Organisation (Australia)	1.875° × 1.25°
3	CanESM5	Canadian Centre for Climate Modelling and Analysis (Canada)	2.81° × 2.81°
4	BCC-CSM2-MR	Beijing Climate Center (China)	1.125° × 1.125°
5	FGOALS-f3-L	Institute of Atmospheric Physics, Chinese Academy of Sciences (China)	1.25° × 1°
6	FGOALS-g3	Institute of Atmospheric Physics, Chinese Academy of Sciences (China)	2° × 2.25°
7	EC-Earth3	European EC-Earth Consortium (Europe)	0.70° × 0.70°
8	EC-Earth3-Veg	European EC-Earth Consortium (Europe)	0.70° × 0.70°
9	IPSL-CM6A-LR	Institute Pierre Simon Laplace (France)	2.5° × 1.26°
10	AWI-CM-1-1-MR	Alfred Wegener Institute, Helmholtz Centre for Polar and Marine Research (Germany)	0.94° × 0.94°
11	MPI-ESM1-2-HR	Max Planck Institute for Meteorology (Germany)	0.94° × 0.94°
12	MPI-ESM1-2-LR	Max Planck Institute for Meteorology (Germany)	1.875° × 1.875°
13	MIROC6	Japan Agency for Marine-Earth Science and Technology (Japan)	1.41° × 1.41°
14	MRI-ESM2-0	Meteorological Research Institute, Japan Meteorological Agency (Japan)	1.125° × 1.125°
15	NorESM2-LM	Norwegian Climate Center (Norway)	2.5° × 1.875°
16	CESM2	Climate and Global Dynamics Laboratory, National Center for Atmospheric Research (USA)	1.25° × 0.94°
17	CESM2-WACCM	Climate and Global Dynamics Laboratory, National Center for Atmospheric Research (USA)	1.25° × 0.94°
18	GFDL-ESM4	Geophysical Fluid Dynamics Laboratory, National Oceanic and Atmosphere Administration (USA)	1.25° × 1.0°

4.You mentioned that "The dataset used in this study covers the historical period (2005–2014)", why did you choose only 10 years as historical data?

Thank you very much for your insightful comment. We would like to clarify that the bias-corrected CMIP6 dataset (Xu et al., 2021) we used has already been extensively validated (Jamal et al., 2023; Huang et al., 2024; Wu and Zheng, 2023). Given that the focus of our study is on assessing the non-stationary changes of future compound climate extremes (CCEs), a comprehensive and detailed evaluation of the dataset was not conducted. Additionally, running WRF simulations requires substantial computational resources—for example, simulating one year over the MRB takes approximately 4 days on 80 CPU cores. Considering both the reliability of the dataset and the need to optimize computational resources, we select a 10-year historical period (2005–2014) as being sufficient to demonstrate the reliability of the bias-corrected data for our study purposes.

5.Why did you only use SSP2-4.5 and SSP5-8.5? Why not SSP1-2.6?

Thank you for your insightful comment. The reason we focused on SSP2-4.5 and SSP5-8.5 scenarios is that the bias-corrected dataset we used (Xu et al., 2021) only provides data for these two scenarios. This limitation is due to the specific selection of SSP scenarios made during the dataset development. We speculate that the dataset creators aimed to highlight the differences between the moderate and high-emission scenarios, particularly to emphasize the potential impacts of future climate changes under these contrasting pathways. By focusing on SSP2-4.5 (moderate emission scenario) and SSP5-8.5 (high-emission scenario), the dataset offers a clear comparison of how differing levels of greenhouse gas emissions can influence climate projections, especially in terms of temperature rise, extreme events, and other key climate variables. Although SSP1-2.6, which represents a low-emission scenario, is also highly relevant, it may not have been included to maintain the dataset's focus on the more critical scenarios that are likely to dominate future climate projections.

6.Please make clearer how the downscaling integrates with your GAMLSS framework.

We perform dynamical downscaling using the WRF model to downscale the bias-corrected CMIP6 data (1.25° × 1.25°) to a 3 km resolution. Subsequently, compound extreme climate events (CCEs) are calculated based on the high-resolution WRF outputs. These calculated CCEs are then used as input for the GAMLSS framework to analyze their non-stationary characteristics. This approach allows the integration of high-resolution dynamical downscaling with the statistical modeling of extremes, ensuring that both local-scale variability and non-stationarity are adequately captured. We will provide a more detailed description of this method in the revised manuscript.

7.Please make it clear what you mean by “enhanced” or “advanced” GAMLSS in the manuscript. Do you mean the GAMLSS, which considers non-stationary characteristics?

Thank you for your valuable comment. We apologize for the ambiguity in the description of “enhanced” or “advanced” GAMLSS. We clarify it as follows: Most existing studies apply the two-parameter GAMLSS that only models the mean and variance to constrain data fitting. In contrast, our “enhanced/advanced GAMLSS” extends this framework by incorporating four parameters—mean, variance, skewness, and kurtosis—to comprehensively characterize the data distribution (line 158-160). This extension enables the model to capture more complex distributional features (e.g., asymmetry and tail thickness) that cannot be fully described by the two-parameter setting. We will revise the relevant descriptions in the manuscript to explicitly define this parameter extension, ensuring clarity for readers.

8.In the supplementary file, please provide a table showing the validation results.

Thank you for your comment. We will provide several tables showing the validation results in the supplementary file.

Table S2 Meteorological stations information.

ID	Name	Longitude (°N)	Latitude (°E)	Elevation (m)
1	Jiuxianshan	118.1	25.72	1653.5
2	Gutian	118.73	26.58	361.5
3	Datian	117.83	25.7	400.1
4	Youxi	118.15	26.17	126.1
5	Dehua	118.23	25.48	521.4
6	Yongtai	118.93	25.87	85.6
7	Fuzhou	119.28	26.08	83.8
8	Changle	119.5	25.97	4.1
9	Minhou	119.15	26.15	57.8
10	Minqing	118.85	26.23	40.8
11	Sanming	117.62	26.27	215
12	Ninghua	116.63	26.23	358.9
13	Yong’an	117.35	25.97	206
14	Shaxian	117.8	26.4	120.6
15	Qingliu	116.85	26.2	310.6
16	Liancheng	116.75	25.72	380.0
17	Guangze	117.3	27.52	265.4
18	Nanping	118.17	26.65	125.6
19	Jiangle	117.47	26.73	154.7
20	Jianning	116.85	26.83	342.3
21	Shaxi	117.15	26.4	357.4
22	Taining	117.17	26.9	342.9
23	Shaowu	117.47	27.33	191.5
24	Shunchang	117.8	26.8	175.2
25	Jianou	118.31	27.05	154.9
26	Jianyang	118.12	27.33	196.9
27	Zhenghe	118.82	27.37	221.5
28	Songxi	118.8	27.52	205.4
29	Wuyishan	118.03	27.77	220.6
30	Pucheng	118.53	27.92	276.9

Table S3 Temperature simulation results based on ERA5

Station	STD	RMSE	CC
Jiuxianshan	1.14	0.59	0.99
Gutian	0.98	0.29	0.99
Datian	0.97	0.07	1.00
Youxi	0.99	0.23	0.99
Dehua	0.98	0.20	0.99
Yongtai	1.00	0.22	0.99
Fuzhou	0.97	0.26	0.98
Changle	0.92	0.20	0.98
Minhou	0.97	0.35	0.95
Minqing	0.98	0.16	0.99
Sanming	1.03	0.30	0.99
Ninghua	0.99	0.12	0.99
Yongan	1.01	0.32	0.99
Shaxian	1.03	0.36	0.99
Qingliu	0.96	0.14	0.99
Liancheng	1.01	0.27	0.99
Guangze	1.01	0.19	0.99
Nanping	1.02	0.29	0.99
Jiangle	1.02	0.29	0.99
Jianning	1.02	0.19	0.99
Shaxi	0.97	0.26	0.99
Taining	0.99	0.21	0.99
Shaowu	1.03	0.31	0.99
Shunchang	1.03	0.32	0.99
Jianou	0.78	0.25	0.99
Jianyang	0.75	0.36	0.99
Zhenghe	1.01	0.14	0.99
Songxi	0.99	0.14	0.99
Wuyishan	0.82	0.27	1.00
Pucheng	1.05	0.26	0.99

Table S4 Temperature simulation results based on CMIP6bc

Station	STD	RMSE	CC
Jiuxianshan	1.10	0.66	0.96
Gutian	0.96	0.37	0.97
Datian	0.94	0.29	0.96
Youxi	0.95	0.30	0.96
Dehua	0.97	0.30	0.96
Yongtai	0.96	0.29	0.96
Fuzhou	0.96	0.32	0.96
Changle	0.88	0.28	0.96
Minhou	0.53	0.68	0.96
Minqing	0.94	0.27	0.96
Sanming	0.97	0.37	0.96
Ninghua	0.93	0.25	0.97
Yongan	0.95	0.30	0.96
Shaxian	0.96	0.33	0.97
Qingliu	0.91	0.26	0.97
Liancheng	0.93	0.32	0.96
Guangze	0.96	0.28	0.98
Nanping	0.98	0.37	0.97
Jiangle	0.95	0.27	0.97
Jianning	0.96	0.28	0.98
Shaxi	0.92	0.33	0.97
Taining	0.94	0.28	0.97
Shaowu	0.95	0.27	0.97
Shunchang	0.95	0.30	0.97
Jianou	0.79	0.32	0.97
Jianyang	0.73	0.41	0.97
Zhenghe	0.95	0.25	0.97
Songxi	0.94	0.25	0.97
Wuyishan	0.81	0.35	0.97
Pucheng	0.95	0.24	0.98

Table S5 Precipitation simulation results based on ERA5

Station	STD	RMSE	CC
Jiuxianshan	1.20	0.71	0.80
Gutian	1.13	0.55	0.87
Datian	1.20	0.71	0.81
Youxi	1.35	0.72	0.86
Dehua	1.16	0.64	0.83
Yongtai	1.04	0.69	0.78
Fuzhou	0.94	0.75	0.74
Changle	0.76	0.89	0.62
Minhou	1.04	0.79	0.73
Minqing	1.10	0.65	0.81
Sanming	0.98	0.61	0.81
Ninghua	1.18	0.74	0.78
Yongan	1.12	0.61	0.84
Shaxian	0.97	0.56	0.84
Qingliu	1.16	0.72	0.79
Liancheng	1.36	0.89	0.75
Guangze	1.24	0.51	0.92
Nanping	0.97	0.53	0.85
Jiangle	1.07	0.45	0.91
Jianning	1.12	0.69	0.79
Shaxi	1.01	0.57	0.84
Taining	1.11	0.46	0.91
Shaowu	1.35	0.82	0.80
Shunchang	1.06	0.51	0.88
Jianou	0.96	0.54	0.85
Jianyang	0.99	0.46	0.89
Zhenghe	1.06	0.44	0.91
Songxi	1.17	0.55	0.89
Wuyishan	1.23	0.48	0.93
Pucheng	1.06	0.59	0.84

Table S6 Precipitation simulation results based on CMIP6bc

Station	STD	RMSE	CC
Jiuxianshan	1.19	0.98	0.61
Gutian	1.12	0.92	0.63
Datian	1.38	1.05	0.65
Youxi	1.11	0.85	0.68
Dehua	1.06	0.83	0.69
Yongtai	0.94	0.97	0.52
Fuzhou	0.94	0.94	0.57
Changle	0.82	0.70	0.73
Minhou	0.93	0.96	0.54
Minqing	1.16	0.97	0.60
Sanming	1.10	0.84	0.68
Ninghua	1.12	0.81	0.71
Yongan	1.26	1.04	0.59
Shaxian	0.97	0.82	0.66
Qingliu	1.23	0.98	0.63
Liancheng	1.31	1.11	0.56
Guangze	1.13	0.86	0.68
Nanping	0.98	0.75	0.71
Jiangle	1.13	0.84	0.69
Jianning	1.06	0.88	0.64
Shaxi	1.26	0.96	0.67
Taining	1.16	0.89	0.66
Shaowu	1.15	0.92	0.64
Shunchang	1.11	0.78	0.73
Jianou	1.01	0.80	0.68
Jianyang	1.13	0.89	0.65
Zhenghe	1.11	0.96	0.59
Songxi	1.15	0.90	0.66
Wuyishan	1.18	0.83	0.72
Pucheng	1.11	0.80	0.71

9.In the results and discussion, I could not find how the results show that considering the non-stationary characteristics leads to better or more reliable results. May you compare the results with previous studies in which the time series was assumed to be stationary?

Thank you for the constructive comment. We will enrich our results and add a discussion comparing them with previous studies in the revised manuscript.

Within the GAMLSS framework, we constructed both stationary and non-stationary models and evaluated their performance using the Akaike Information Criterion (AIC), adhering to the established principle that a smaller AIC value indicates a better model fit. The results show that, compared to the stationary model, the non-stationary model occupies more grid points (i.e., has a lower AIC value), indicating its stronger ability to adapt to the characteristics of the time series (Fig. 6). Furthermore, the comparative analysis of the return period results between the two models (Fig. 8) shows that the non-stationary model exhibits more extreme trends in compound extreme events (CEEs), reinforcing the importance of accounting for non-stationarity in such analyses. Additionally, the subsequent evaluation using the Filliben coefficient confirmed the goodness-of-fit of the selected models (Fig. S3), further validating our approach. We would like to clarify that the statement in the original manuscript claiming that the "non-stationary model is better than the stationary model" is misleading. A more accurate description is that the non-stationary model is more appropriate when accounting for temporal trends and mean-state changes, whereas the stationary model tends to underestimate the recurrence risk of CCEs based on the results.

Many previous studies have detected the non-stationary characteristics of hydro-meteorological variables (e.g., precipitation and runoff), indicating that their statistical properties are not constant over time (Shao et al., 2022; Awasthi et al., 2022; Slater et al., 2021). In a case study in Colombia (Gonzalez-Alvarez et al., 2018), the research compared return values under stationary and non-stationary conditions and found that rainfall estimates for the 10-year and 2-year return periods were significantly higher under non-stationary conditions, indicating that in extreme rainfall analysis, using a non-stationary model can better capture the increasing trend of rainfall than a stationary model. A low-flow frequency analysis study in Turkey indicated that non-stationary models outperform stationary models (Yılmaz and Muhammet, 2024), suggesting that when watershed hydrological relationships may change over time, relying solely on the stationary assumption could underestimate the associated risks. However, some studies have shown that in certain cases (De Luca and Galasso, 2018), stationary models are sufficient, while non-stationary frameworks perform slightly better during periods with trends or variability. In this study, we assessed changes in the recurrence risk of CCEs based on the WRF-CMIP6-GAMLSS framework. The results indicate that CCEs in most areas of the MRB exhibit non-stationarity, primarily driven by mean-state shifts induced by climate warming. Overall, over time, stationary models systematically underestimate the risk of CCEs, particularly after 2045. These findings underscore the importance of incorporating non-stationary approaches in future climate risk assessments to improve the accuracy of extreme event predictions.

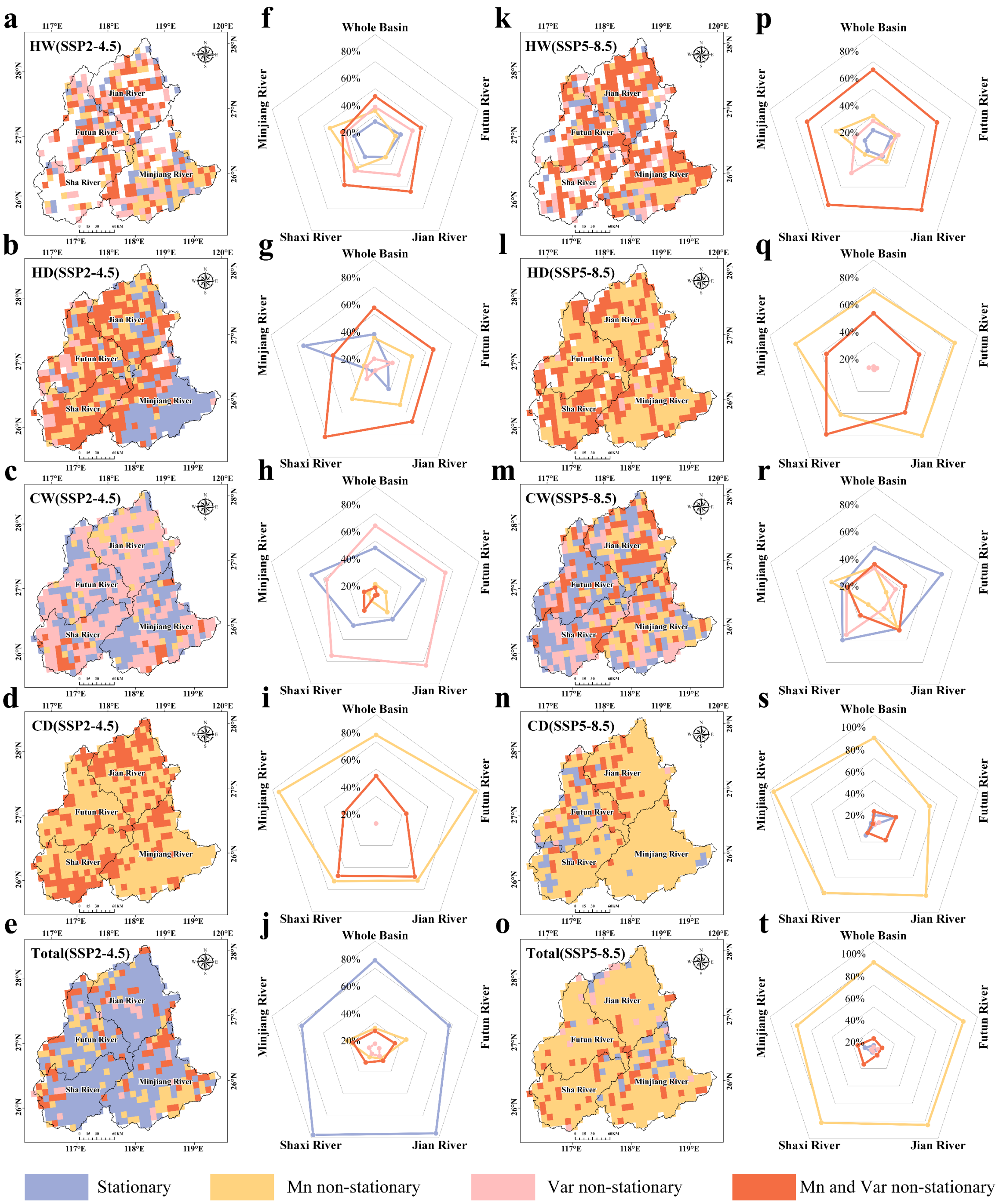

Fig. 6 Stationary and non-stationary characteristics for CCEs in the MRB (a-e and k-o), percentage 240 of non-stationary and stationary characteristics across five basins (f-j and p-t).

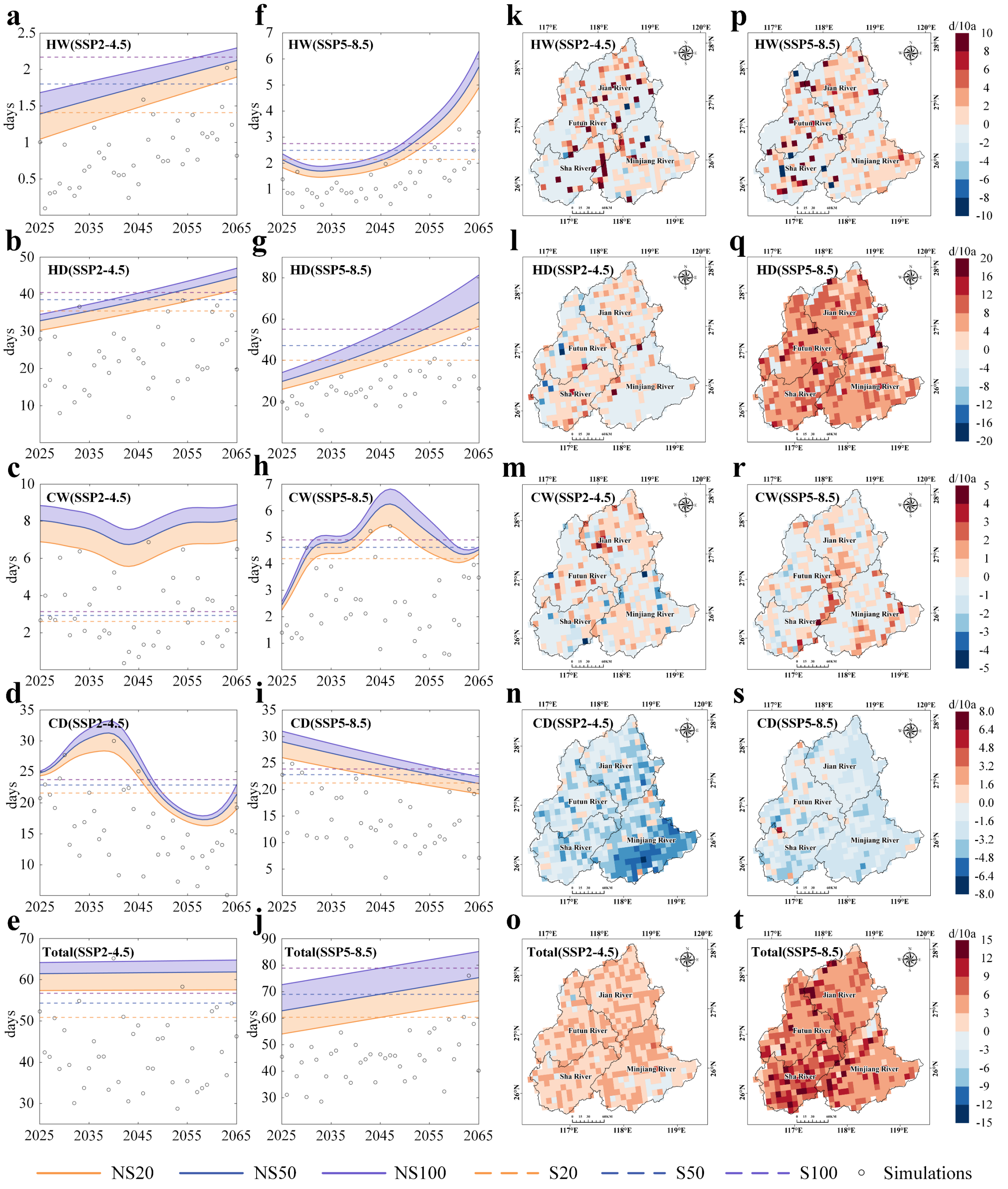

Fig. 8. Comparison of non-stationary (NS) and stationary (S) characteristics for CCEs under 20-, 50-, and 100- year return periods (a-j). Spatial distributions of trends in CCEs under 100-year return periods (k-t), 20- and 50-year return period result are provided in Supplement Fig. S4.

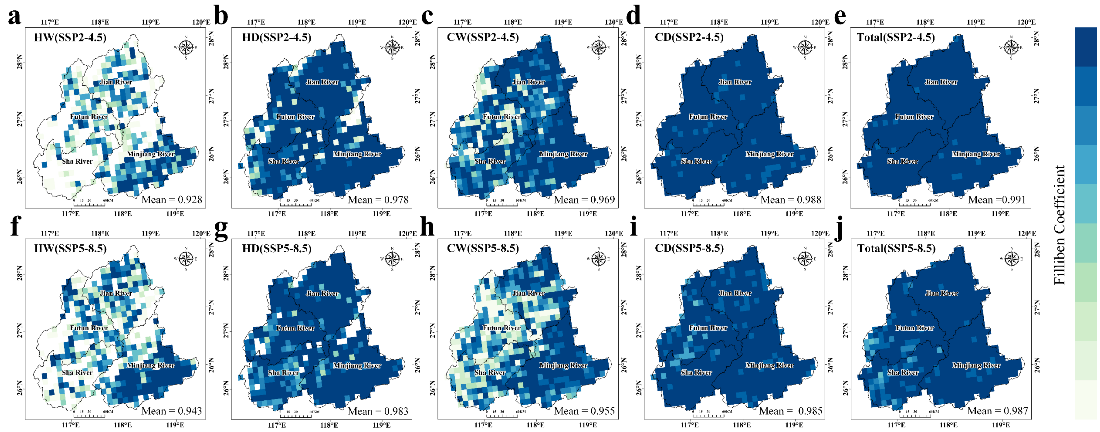

Fig. S3 Maps of the Filliben Coefficient for CCEs.

10.The English language also should be assessed more carefully.

Thank you for your suggestion. We will carefully revise the manuscript to further improve the clarity and quality of the English language.

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