Response to Editor and Referee #3

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

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

To Editor and Referee #3

We sincerely thank the Editor for the careful handling of our manuscript. We also greatly appreciate the constructive and insightful comments provided by the anonymous referee #3. These comments have been invaluable in helping us improve the quality and clarity of the manuscript. Below, we provide a point-by-point response to the referee's comments.

1.The authors state that changes in CCEs are primarily governed by temperature-driven physical processes, while precipitation remains stable. However, a stable mean precipitation does not preclude changes in precipitation intensity or timing (e.g., shorter, more intense rainy seasons). The authors should discuss whether the shift in "Hot-Wet" (HW) extremes is influenced by changes in precipitation distribution or atmospheric moisture capacity (Clausius-Clapeyron scaling).

-Answer: Thank you for this valuable suggestion. We fully agree and have expanded the discussion accordingly in the revised manuscript (lines 386–396).

However, it should be emphasized that precipitation responses are often manifested through pronounced changes in intensity and intermittency, rather than in long-term totals alone (Du et al., 2022; Maity and Maity, 2022). In particular, warming can lead to a redistribution of precipitation toward shorter duration but more intense events, even in regions where mean precipitation exhibits statistically insignificant trends (Fowler et al., 2021). For HW events, these changes are closely linked to both thermodynamic and moisture-related processes. As global and regional temperatures rise, the atmosphere's moisture holding capacity increases at an approximate rate of 6–7% per °C, consistent with Clausius–Clapeyron scaling (O'Gorman and Muller, 2010; Ali et al., 2021). Previous studies have demonstrated that such moistening effects can substantially intensify CCEs, even in regions where average precipitation remains relatively unchanged (Gimeno et al., 2022; Zhang et al., 2024).

Ali, H., Fowler, H. J., Lenderink, G., Lewis, E., and Pritchard, D.: Consistent Large-Scale Response of Hourly Extreme Precipitation to Temperature Variation Over Land, Geophys. Res. Lett., 48, e2020GL090317, https://doi.org/10.1029/2020GL090317, 2021.

Du, H., Donat, M. G., Zong, S., Alexander, L. V., Manzanas, R., Kruger, A., Choi, G., Salinger, J., He, H. S., Li, M.-H., Fujibe, F., Nandintsetseg, B., Rehman, S., Abbas, F., Rusticucci, M., Srivastava, A., Zhai, P., Lippmann, T., Yabi, I., Stambaugh, M. C., Wang, S., Batbold, A., Oliveira, P. T. D., Adrees, M., Hou, W., Silva, C. M. S. E., Lucio, P. S., and Wu, Z.: Extreme Precipitation on Consecutive Days Occurs More Often in a Warming Climate, B. Am. Meteorol. Soc., 103, E1130–E1145, https://doi.org/10.1175/BAMS-D-21-0140.1, 2022.

Fowler, H. J., Lenderink, G., Prein, A. F., Westra, S., Allan, R. P., Ban, N., Barbero, R., Berg, P., Blenkinsop, S., Do, H. X., Guerreiro, S., Haerter, J. O., Kendon, E. J., Lewis, E., Schaer, C., Sharma, A., Villarini, G., Wasko, C., and Zhang, X.: Anthropogenic intensification of short-duration rainfall extremes, Nat. Rev. Earth Environ., 2, 107–122, https://doi.org/10.1038/s43017-020-00128-6, 2021.

Gimeno, L., Sorí, R., Vázquez, M., Stojanovic, M., Algarra, I., Eiras-Barca, J., Gimeno-Sotelo, L., and Nieto, R.: Extreme precipitation events, WIREs Water, 9, e1611, https://doi.org/10.1002/wat2.1611, 2022.

Maity, S. S. and Maity, R.: Changing Pattern of Intensity–Duration–Frequency Relationship of Precipitation due to Climate Change, Water Resour. Manage., 36, 5371–5399, https://doi.org/10.1007/s11269-022-03313-y, 2022.

O’Gorman, P. A. and Muller, C. J.: How closely do changes in surface and column water vapor follow Clausius–Clapeyron scaling in climate change simulations, Environ. Res. Lett., 5, 025207, https://doi.org/10.1088/1748-9326/5/2/025207, 2010.

Zhang, W., Zhou, T., and Wu, P.: Anthropogenic amplification of precipitation variability over the past century, Science, 385, 427–432, https://doi.org/10.1126/science.adp0212, 2024.

2.The manuscript states that wet events are based on exceedance of the 90th percentile, while dry events are defined as seven consecutive days without rainfall. This mixes a daily-threshold event (wet) with a multi-day process definition (dry). It is currently unclear how HD/CD are counted in annual totals (e.g., whether each day within a 7-day dry spell is counted, or the spell is counted as one event; how overlap with hot/cold days is handled).

-Answer: We appreciate your concern regarding the apparent inconsistency between daily based wet extremes and spell based dry extremes. In our framework, compound climate extremes are quantified in units of days rather than spells. Although dry conditions are defined as a seven-day rain free spell, each day within such a spell is treated as a dry day. Accordingly, HD (CD) events are counted when a hot (cold) extreme occurs on any day during a dry spell. This approach is consistent with the methodology of Wang et al. (2024), and we have clarified the counting rule in Section 2.4 to avoid any ambiguity (lines 194–195).

For dry conditions defined as seven consecutive days without precipitation, each day within a dry spell is treated as a dry day in the counting of CCEs.

Wang, Y., Sun, W., Huai, B., Wang, Y., Ji, K., Yang, X., Du, W., Qin, X., and Wang, L.: Comparison and evaluation of the performance of reanalysis datasets for compound extreme temperature and precipitation events in the Qilian Mountains, Atmos. Res., 304, 107375, https://doi.org/10.1016/j.atmosres.2024.107375, 2024.

3.For a monsoon-dominated coastal basin like the MRB, how do shifts in the Western Pacific Subtropical High (WPSH) or typhoons contribute to the detected non-stationarity? Incorporating a brief discussion on these external drivers would strengthen the "Discussion" section.

-Answer: Thank you for this constructive suggestion. We have expanded the Discussion section accordingly in the revised manuscript (lines 459–479).

Furthermore, while statistically robust, our current non-stationary GAMLSS framework employs time merely as a proxy covariate for climate change. While this formulation is widely adopted and effective for detecting long-term trends, time itself serves only as an indirect proxy for the underlying physical processes driving changes in CCEs (Ragno et al., 2019). From a physical perspective, the evolution of compound hot–dry events are governed by a combination of *thermodynamic and dynamic mechanisms, including background warming, shifts in large-scale atmospheric circulation, and land–atmosphere feedbacks (Bevacqua et al., 2022; Zhang et al., 2021; Tian et al., 2024). For example, global mean surface temperature (GMST) can serve as a physically meaningful indicator of anthropogenic thermodynamic forcing, directly linking greenhouse gas increases to enhanced surface heat stress (Gillett et al., 2021). In this subtropical monsoon dominated basin, variations in the intensity, westward extension, and persistence of the Western Pacific Subtropical High (WPSH) can regulate subsidence strength, cloud cover, and surface radiative forcing, thereby favoring persistent hot conditions while suppressing precipitation (Li et al., 2024; An et al., 2025). Changes in the strength and variability of the East Asian summer monsoon (EASM) influence large-scale moisture transport and rainfall timing, affecting both the onset and persistence of dry spells (Park et al., 2020; Dou et al., 2025). In addition, antecedent soil moisture has been shown to influence the persistence and amplification of heat extremes through soil moisture–temperature feedbacks (Jiang and Wang, 2024), further highlighting the value of including land-surface states as covariates. Therefore, incorporating physically based covariates into the GAMLSS framework may therefore improve the interpretation of non-stationarity.*

Bevacqua, E., Zappa, G., Lehner, F., and Zscheischler, J.: Precipitation trends determine future occurrences of compound hot–dry events, Nat. Clim. Chang., 12, 350–355, https://doi.org/10.1038/s41558-022-01309-5, 2022.

Dou, Z., Liu, B., Henderson, M., Zhou, W., Ma, R., Chen, M., and Zhang, Z.: Changes in Timing and Precipitation of the East Asian Summer Monsoon over China Between 1960 and 2017, Earth, 6, 24, https://doi.org/10.3390/earth6020024, 2025.

Gillett, N. P., Kirchmeier-Young, M., Ribes, A., Shiogama, H., Hegerl, G. C., Knutti, R., Gastineau, G., John, J. G., Li, L., Nazarenko, L., Rosenbloom, N., Seland, Ø., Wu, T., Yukimoto, S., and Ziehn, T.: Constraining human contributions to observed warming since the pre-industrial period, Nat. Clim. Chang., 11, 207–212, https://doi.org/10.1038/s41558-020-00965-9, 2021.

Jiang, Y. and Wang, G.: Soil Moisture Dominates the Land Surface Feedback in the Development of Compound Drought–Heat Extremes in Tropical South America, J. Hydrometeorol., 25, 1649–1664, https://doi.org/10.1175/JHM-D-24-0005.1, 2024.

Li, Z., Ren, H.-L., Lu, M., and Zhou, F.: Interannual variations of westward extension area of western Pacific subtropical high and its relationship with precipitation in East Asia, Atmos. Res., 298, 107148, https://doi.org/10.1016/j.atmosres.2023.107148, 2024.

Park, J., Kim, H., Simon Wang, S.-Y., Jeong, J.-H., Lim, K.-S., LaPlante, M., and Yoon, J.-H.: Intensification of the East Asian summer monsoon lifecycle based on observation and CMIP6, Environ. Res. Lett., 15, 0940b9, https://doi.org/10.1088/1748-9326/ab9b3f, 2020.

Ragno, E., AghaKouchak, A., Cheng, L., and Sadegh, M.: A generalized framework for process-informed nonstationary extreme value analysis, Adv. Water Resour., 130, 270–282, https://doi.org/10.1016/j.advwatres.2019.06.007, 2019.

Tian, Y., Giaquinto, D., Di Capua, G., Claassen, J. N., Ali, J., Li, H., and De Michele, C.: Historical changes in the Causal Effect Networks of compound hot and dry extremes in central Europe, Commun. Earth Environ., 5, 764, https://doi.org/10.1038/s43247-024-01934-2, 2024.

Xuehua, A., Shanlei, S., Qianrong, M., Hao, W., Daiyuan, L., and Wei, W.: Elucidating the Varied Characteristics of Compound Hot–Drought from Two Distinctive Extreme Events in the Yangtze River Valley, Int. J. Climatol., 45, e8809, https://doi.org/10.1002/joc.8809, 2025.

Zhang, W., Luo, M., Gao, S., Chen, W., Hari, V., and Khouakhi, A.: Compound Hydrometeorological Extremes: Drivers, Mechanisms and Methods, Front. Earth Sci., 9, 673495, https://doi.org/10.3389/feart.2021.673495, 2021.

4.The study runs a 10-year historical simulation (2005–2014) using CMIP6bc and ERA5 forcing and uses 30 stations for validation. CMIP6bc is described as an 18-model ensemble mean and the paper argues that 10 years is “sufficient” given computational cost. For a paper focusing on extremes and return periods, readers will expect more targeted evaluation (especially for precipitation extremes and compound-event-relevant indices).

-Answer: Thank you for this thoughtful comment. We fully understand your concern that studies focusing on extremes and return periods typically require rigorous and targeted evaluation. We would like to clarify that the 2005–2014 historical period used in this study serves primarily as a data quality control and consistency check, rather than as a comprehensive evaluation of extreme events statistics. Additionally, many previous studies have extensively evaluated this dataset (Jamal et al., 2023; Huang et al., 2024; Wu and Zheng, 2023). Therefore, our validation over this 10-year period is not intended to re-establish the credibility of CMIP6bc, but rather to ensure the internal consistency of the boundary forcing used for the WRF simulations over the MRB. For this reason, the historical evaluation results are presented in the Supplementary Material, where they are used to demonstrate the basic realism of the WRF simulations in terms of spatial patterns and variability. In addition, we note that the capability of the WRF model to simulate extreme precipitation over the MRB has been examined in our previous work (Zhang et al., 2025), in which long-term simulations were evaluated using 12 extreme precipitation indices proposed by the Expert Team on Climate Change Detection and Indices (ETCCDMI). These studies have demonstrated the added value of WRF downscaling for representing extreme precipitation processes in this region, providing further confidence in the suitability of the model framework adopted here.

Nevertheless, we appreciate your constructive suggestion. A more targeted and long-term evaluation of precipitation extremes and CEEs-related indices represents an important direction for future work, and we plan to pursue this in subsequent studies.

Huang, Y., Xue, M., Hu, X., Martin, E., Novoa, H. M., McPherson, R. A., Liu, C., Chen, M., Hong, Y., Perez, A., Morales, I. Y., Ticona Jara, J. L., and Flores Luna, A. J.: Increasing frequency and precipitation intensity of convective storms in the Peruvian Central Andes: Projections from convection-permitting regional climate simulations, Quart. J Royal Meteoro. Soc., 150, 4371–4390, https://doi.org/10.1002/qj.4820, 2024.

Jamal, K., Li, X., Chen, Y., Rizwan, M., Khan, M. A., Syed, Z., and Mahmood, P.: Bias correction and projection of temperature over the altitudes of the Upper Indus Basin under CMIP6 climate scenarios from 1985 to 2100, J. Water Clim. Change, 14, 2490–2514, https://doi.org/10.2166/wcc.2023.180, 2023.

Wu, L. and Zheng, H.: Regional Climate Effects of Irrigation under Central Asia Warming by 2.0 °C, Remote Sens., 15, 3672, https://doi.org/10.3390/rs15143672, 2023.

Zhang, Y., Deng, C., Xu, W., Zhuang, Y., Jiang, L., Jiang, C., Guan, X., Wei, J., Ma, M., Chen, Y., Peng, J., and Gao, L.: Long-term variability of extreme precipitation with WRF model at a complex terrain River Basin, Sci. Rep., 15, 156, https://doi.org/10.1038/s41598-024-84076-x, 2025.

5.The study currently uses "time" as the sole covariate to represent non-stationarity. While common, time is a proxy for physical change. The authors should comment on the potential benefits of using physically-based covariates, such as Global Mean Surface Temperature (GMST) or regional circulation indices, to improve the causal link between forcing and response.

-Answer: Thank you for your comment. We have added a discussion in the revised manuscript following your suggestion (lines 459–479).

Furthermore, while statistically robust, our current non-stationary GAMLSS framework employs time merely as a proxy covariate for climate change. While this formulation is widely adopted and effective for detecting long-term trends, time itself serves only as an indirect proxy for the underlying physical processes driving changes in CCEs (Ragno et al., 2019). From a physical perspective, the evolution of compound hot–dry events are governed by a combination of thermodynamic and dynamic mechanisms, including background warming, shifts in large-scale atmospheric circulation, and land–atmosphere feedbacks (Bevacqua et al., 2022; Zhang et al., 2021; Tian et al., 2024). For example, global mean surface temperature (GMST) can serve as a physically meaningful indicator of anthropogenic thermodynamic forcing, directly linking greenhouse gas increases to enhanced surface heat stress (Gillett et al., 2021). Meanwhile, regional circulation indices, such as those characterizing the Western Pacific Subtropical High (WPSH) or East Asian summer monsoon (EASM), could help disentangle the dynamic contributions of circulation persistence, subsidence, and moisture transport anomalies that modulate the co-occurrence of heat and drought over China (Li et al., 2024; An et al., 2025; Ni et al., 2024). In addition, antecedent soil moisture has been shown to influence the persistence and amplification of heat extremes through soil moisture–temperature feedbacks (Jiang and Wang, 2024), further highlighting the value of including land-surface states as covariates. Therefore, incorporating physically based covariates into the GAMLSS framework may therefore improve the interpretation of non-stationarity.

Bevacqua, E., Zappa, G., Lehner, F., and Zscheischler, J.: Precipitation trends determine future occurrences of compound hot–dry events, Nat. Clim. Chang. 12, 350–355, https://doi.org/10.1038/s41558-022-01309-5, 2022.

Dou, Z., Liu, B., Henderson, M., Zhou, W., Ma, R., Chen, M., and Zhang, Z.: Changes in Timing and Precipitation of the East Asian Summer Monsoon over China Between 1960 and 2017, Earth 6, 24, https://doi.org/10.3390/earth6020024, 2025.

Gillett, N. P., Kirchmeier-Young, M., Ribes, A., Shiogama, H., Hegerl, G. C., Knutti, R., Gastineau, G., John, J. G., Li, L., Nazarenko, L., Rosenbloom, N., Seland, Ø., Wu, T., Yukimoto, S., and Ziehn, T.: Constraining human contributions to observed warming since the pre-industrial period, Nat. Clim. Chang. 11, 207–212, https://doi.org/10.1038/s41558-020-00965-9, 2021.

Li, Z., Ren, H.-L., Lu, M., and Zhou, F.: Interannual variations of westward extension area of western Pacific subtropical high and its relationship with precipitation in East Asia, Atmos. Res. 298, 107148, https://doi.org/10.1016/j.atmosres.2023.107148, 2024.

Park, J., Kim, H., Simon Wang, S.-Y., Jeong, J.-H., Lim, K.-S., LaPlante, M., and Yoon, J.-H.: Intensification of the East Asian summer monsoon lifecycle based on observation and CMIP6, Environ. Res. Lett. 15, 0940b9, https://doi.org/10.1088/1748-9326/ab9b3f, 2020.

Ragno, E., AghaKouchak, A., Cheng, L., and Sadegh, M.: A generalized framework for process-informed nonstationary extreme value analysis, Adv. Water Resour. 130, 270–282, https://doi.org/10.1016/j.advwatres.2019.06.007, 2019.

Tian, Y., Giaquinto, D., Di Capua, G., Claassen, J. N., Ali, J., Li, H., and De Michele, C.: Historical changes in the Causal Effect Networks of compound hot and dry extremes in central Europe, Commun. Earth Environ. 5, 764, https://doi.org/10.1038/s43247-024-01934-2, 2024.

Xuehua, A., Shanlei, S., Qianrong, M., Hao, W., Daiyuan, L., and Wei, W.: Elucidating the Varied Characteristics of Compound Hot–Drought from Two Distinctive Extreme Events in the Yangtze River Valley, Intl. J. Climatol. 45, e8809, https://doi.org/10.1002/joc.8809, 2025.

Zhang, W., Luo, M., Gao, S., Chen, W., Hari, V., and Khouakhi, A.: Compound Hydrometeorological Extremes: Drivers, Mechanisms and Methods, Front. Earth Sci. 9, 673495, https://doi.org/10.3389/feart.2021.673495, 2021.

6.The GAMLSS framework relies on selecting the best distribution using AIC. For discrete count data (number of days of CCEs), it is crucial to specify which distributions (e.g., Poisson, Negative Binomial) were tested and how the model handled "zero-inflation," as some grids may have many years with zero CCE events.

-Answer: We admitted that there are many distributions involved in GAMLSS models. In the previous studies, 3-7 distributions are usually selected for fitting in the GAMLSS models (Du et al., 2015; Faulkner et al., 2024; L. Slater et al., 2021). We chose some widely used distribution functions (e.g., Normal, Gamma, Weibull) (Supplement Table S2). Given that our research data pertains to extreme events, we have also considered distributions that account for skewness and heavy-tailed data structures in our modeling (e.g., Johnson's SU, Sinh-arcsinh). At each grid, we also retained the best-fitting distributions with the smallest Akaike Information Criterion (AIC). We evaluated the model fits by checking the Filliben coefficient. The Filliben coefficient results demonstrate that most model's fit is satisfactory (Supplement Figure S6). Regarding the zero-inflation issue you raised, we would like to clarify that when a specific CCE does not occur for many years at a given grid, the GAMLSS model returns NA for that grid. Consequently, these grids were excluded from the analysis and are displayed as blank areas in Figure 6. Once again, we thank you for this valuable feedback, which has helped improve the clarity of our manuscript.

Table S2 Distribution functions in this study.

Distribution function	Abbreviation	Number of parameters
Gamma	GA	2
Gumbel	GU	2
Inverse Gamma	IGAMMA	2
Inverse Gaussian	IG	2
Logistic	LO	2
Log-Normal	LOGNO	2
Reverse Gumbel	RG	2
Weibull	WEI3	2
Normal	NO	2
Exponential gen. beta 2	EGB2	4
Johnson's SU repar.	JSU	4
Johnson's original SU	JSUo	4
Generalised t	GT	4
SU	SU	4
NET	NET	4
Sinh-arcsinh	SHASH	4
Sinh-arcsinh original	SHASHo	4
Sinh-arcsinh original 2	SHASHo2	4

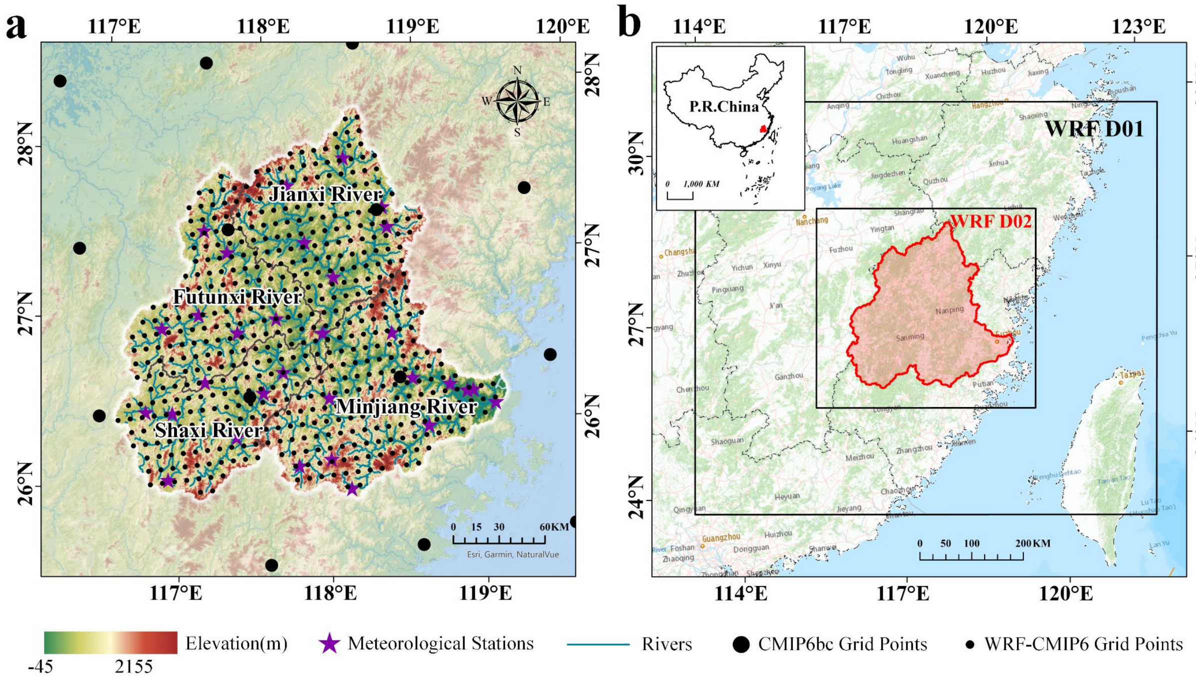
Du, T., Xiong, L., Xu, C. Y., Gippel, C. J., Guo, S., and Liu, P. Return period and risk analysis of nonstationary low-flow series under climate change. J. Hydrol. 527, 234–250. https://doi.org/10.1016/j.jhydrol.2015.04.041, 2015.

Faulkner, D. S., Longfield, S., Warren, S., & Tawn, J. A. Modelling non-stationary flood frequency in England and Wales using physical covariates. Hydrol. Earth Syst. Sci. 55(2), 205–220. https://doi.org/10.2166/nh.2024.134, 2024.

Slater, L. J., Anderson, B., Buechel, M., Dadson, S., Han, S., Harrigan, S., Kelder, T., Kowal, K., Lees, T., Matthews, T., Murphy, C., and Wilby, R. L.: Nonstationary weather and water extremes: a review of methods for their detection, attribution, and management, Hydrol. Earth Syst. Sci. 25, 3897–3935, https://doi.org/10.5194/hess-25-3897-2021, 2021.

7.The authors use a 3 km convection-permitting resolution to capture local convective precipitation and orographic effects. It would be highly beneficial to explicitly state the "added value" compared to the original 1.25° CMIP6 data. Are there specific sub-basins or high-elevation areas where the low-resolution GCMs completely fail to capture CCEs that the 3 km WRF model successfully identifies?

-Answer: Thank you for this insightful comment. The added value of using convection-permitting WRF downscaling relative to the original 1.25° CMIP6 data is particularly pronounced for a small, topographically complex basin such as the MRB. At 1.25°, the CMIP6bc resolution is far too coarse to resolve the hydroclimatic heterogeneity of the MRB. As shown in this figure below, the entire basin is covered by only about four CMIP6 grid cells, meaning that large portions of the upstream mountains, midstream valleys, and downstream plains are effectively averaged into a few coarse pixels. Under such resolution, localized extremes driven by orography, land–atmosphere feedbacks, and mesoscale convection cannot be physically represented. By contrast, the 3 km WRF simulations explicitly resolve deep convection and terrain-induced circulation, allowing precipitation and temperature extremes to be simulated at the scale of individual sub-basins. This added value is especially evident in high-elevation and headwater regions (e.g., the Shaxi River Basin), where steep topography produces sharp gradients in rainfall and temperature. It enables the detection of CCEs at sub-basin scales that are fundamentally unresolved in the original CMIP6, which is critical for risk assessment in mountainous river basins such as the MRB. Thank you again for this insightful question. In future work, we will further explore methods to reduce potential secondary biases introduced by the WRF model.



8.While the CMIP6bc dataset is bias-corrected, the WRF model can introduce secondary biases in orographic precipitation. How were these secondary biases validated against the 30 monitoring stations mentioned in Section 2.2?

-Answer: Thank you for your question. We used 30 observational stations in the MRB to evaluate the performance of the WRF model during the historical period (2005–2014). A grid-to-point approach was applied, in which precipitation and temperature were extracted from the WRF grid cell closest to each station, and their spatiotemporal characteristics were evaluated. The detailed results are presented in Supplementary Results S1.

We fully acknowledge your concern that WRF can introduce systematic secondary biases, particularly in orographic precipitation over complex terrain. Indeed, our previous work (Zhang et al., 2025) demonstrated that WRF tends to overestimate precipitation in high-elevation regions while underestimating it over lowland plains, a bias pattern that has also been widely reported in other convection-permitting regional climate model studies. These biases are mainly associated with uncertainties in microphysical parameterizations and land–atmosphere coupling over mountainous terrain. Correcting such secondary biases in regional climate model outputs remains a major challenge, especially for future projections. To address this limitation in future work, we plan to explore machine learning based post-processing approaches, in which the residuals between historical WRF simulations and station observations are learned and subsequently transferred to future simulations in a physically constrained manner. This approach offers a promising pathway to reduce systematic regional model biases while preserving the internally consistent climate change signal. We have added a discussion of this limitation and potential methodological improvements in the revised Discussion section (lines 444–459).

Nevertheless, certain limitations persist. Even at convection-permitting resolution (3 km), the WRF model exhibits systematic biases in simulating orographic precipitation, a well-documented challenge often stemming from uncertainties in microphysical parameterization schemes and the representation of land-atmosphere energy and moisture exchanges over mountainous regions (Talbot et al., 2012; Zhang et al., 2025). Specifically, the overestimation of precipitation in high-elevation regions by WRF may artificially enhance the frequency of wet-related compound extremes, whereas the underestimation of precipitation in lowland and downstream areas may bias the detection of dry-related compound extremes. Because the identification of CCEs relies on precipitation and temperature thresholds and their co-occurrence, systematic precipitation biases can further influence threshold estimation and event classification, thereby affecting the spatial distribution and frequency of detected CCEs. To address this limitation in future work, we plan to explore machine learning based post-processing approaches (Yin et al., 2021; Xie et al., 2023), in which the residuals between historical WRF simulations and station observations are learned and subsequently transferred to future simulations in a physically constrained method. This approach offers a promising pathway to reduce systematic regional model biases while preserving the internally consistent climate change signal.

Talbot, C., Bou-Zeid, E., and Smith, J.: Nested Mesoscale Large-Eddy Simulations with WRF: Performance in Real Test Cases, J. Hydrometeorol., 13, 1421–1441, https://doi.org/10.1175/JHM-D-11-048.1, 2012.

Xie, Y., Sun, W., Ren, M., Chen, S., Huang, Z., and Pan, X.: Stacking ensemble learning models for daily runoff prediction using 1D and 2D CNNs, Expert Sys. Appl., 217, 119469, https://doi.org/10.1016/j.eswa.2022.119469, 2023.

Yin, H., Zhang, X., Wang, F., Zhang, Y., Xia, R., and Jin, J.: Rainfall-runoff modeling using LSTM-based multi-state-vector sequence-to-sequence model, J Hydrol., 598, 126378, https://doi.org/10.1016/j.jhydrol.2021.126378, 2021.

Zhang, Y., Deng, C., Xu, W., Zhuang, Y., Jiang, L., Jiang, C., Guan, X., Wei, J., Ma, M., Chen, Y., Peng, J., and Gao, L.: Long-term variability of extreme precipitation with WRF model at a complex terrain River Basin, Sci. Rep., 15, 156, https://doi.org/10.1038/s41598-024-84076-x, 2025.

9.The finding that the 100-year return period frequency of CCEs increases significantly (3.12 days per decade) has profound implications for regional infrastructure. The authors should briefly discuss how these findings might impact reservoir operations or urban flood management in downstream cities like Fuzhou.

-Answer: Thank you for your comment. This issue has been addressed in the revised manuscript (lines 417–427).

The projected increase in the frequency of 100-year CCEs has important implications for flood control and water resources management in the MRB, particularly in the middle and lower reaches and densely populated urban centers such as Fuzhou. The basin's complex topography and highly heterogeneous land cover amplify the spatial variability of rainfall and runoff, while low-lying urban areas in Fuzhou are particularly vulnerable to both pluvial and fluvial flooding. More frequent HW events are likely to produce intense, concentrated rainfall, rapidly depleting reservoir flood control capacity and increasing the likelihood of spillway activation, while simultaneously exacerbating urban inundation in flood prone districts (He et al., 2024). HD events may reduce river storage, but if followed by subsequent heavy rainfall, they can increase uncertainty in peak flows and place additional stress on flood management systems (Hariharan Sudha et al., 2024).

10.You already note systematic WRF biases in orographic precipitation. Consider briefly indicating whether any bias correction/post-processing is applied before CCE detection; if none, state this clearly and discuss implications.

-Answer: Thank you for this comment. This issue is closely related to Comment 8, and we appreciate the opportunity to clarify it further. We acknowledge that the WRF model can exhibit systematic biases in simulating orographic precipitation over complex terrain, which may, to some extent, influence the subsequent identification of CCEs. In this study, no additional bias correction or statistical post-processing was applied to the WRF outputs prior to CCEs detection. This choice reflects the fact that applying bias correction to future projections involves additional methodological challenges, particularly the reliance on relationships trained from historical observations and simulations that must then be transferred to future climate conditions. Such an approach implicitly assumes stationarity of model errors, which may not hold under climate change and may risk distorting physically consistent climate signals, particularly for extremes and compound events. We therefore chose to retain the raw, physically based WRF projections and explicitly discuss the associated uncertainties. The potential implications of uncorrected WRF biases for CCE identification, as well as possible methodological solutions (e.g., physically constrained or machine learning based post-processing approaches), have been addressed in the Discussion section as part of the study's limitations and future research directions (lines 444–459).

Nevertheless, certain limitations persist. Even at convection-permitting resolution (3 km), the WRF model exhibits systematic biases in simulating orographic precipitation, a well-documented challenge often stemming from uncertainties in microphysical parameterization schemes and the representation of land-atmosphere energy and moisture exchanges over mountainous regions (Talbot et al., 2012; Zhang et al., 2025). Specifically, the overestimation of precipitation in high-elevation regions by WRF may artificially enhance the frequency of wet-related compound extremes, whereas the underestimation of precipitation in lowland and downstream areas may bias the detection of dry-related compound extremes. Because the identification of CCEs relies on precipitation and temperature thresholds and their co-occurrence, systematic precipitation biases can further influence threshold estimation and event classification, thereby affecting the spatial distribution and frequency of detected CCEs. To address this limitation in future work, we plan to explore machine learning based post-processing approaches (Yin et al., 2021; Xie et al., 2023), in which the residuals between historical WRF simulations and station observations are learned and subsequently transferred to future simulations in a physically constrained method. This approach offers a promising pathway to reduce systematic regional model biases while preserving the internally consistent climate change signal.

Talbot, C., Bou-Zeid, E., and Smith, J.: Nested Mesoscale Large-Eddy Simulations with WRF: Performance in Real Test Cases, J. Hydrometeorol., 13, 1421–1441, https://doi.org/10.1175/JHM-D-11-048.1, 2012.

Xie, Y., Sun, W., Ren, M., Chen, S., Huang, Z., and Pan, X.: Stacking ensemble learning models for daily runoff prediction using 1D and 2D CNNs, Expert Sys. Appl., 217, 119469, https://doi.org/10.1016/j.eswa.2022.119469, 2023.

Yin, H., Zhang, X., Wang, F., Zhang, Y., Xia, R., and Jin, J.: Rainfall-runoff modeling using LSTM-based multi-state-vector sequence-to-sequence model, J Hydrol., 598, 126378, https://doi.org/10.1016/j.jhydrol.2021.126378, 2021.

Zhang, Y., Deng, C., Xu, W., Zhuang, Y., Jiang, L., Jiang, C., Guan, X., Wei, J., Ma, M., Chen, Y., Peng, J., and Gao, L.: Long-term variability of extreme precipitation with WRF model at a complex terrain River Basin, Sci. Rep., 15, 156, https://doi.org/10.1038/s41598-024-84076-x, 2025.

11.Ensure the statistical significance levels (e.g., 90% and 99% confidence) are clearly visible in the spatial plots for the transition from stationary to non-stationary behavior.

-Answer: Thank you for this comment. We agree that clearly indicating statistical significance levels is important, and we appreciate you for pointing this out. We would like to clarify that the figures referred to represent two different types of information. Figure 6 illustrates the spatial distribution of stationary versus non-stationary states of CCEs under two emission scenarios. This figure is intended to depict the classification status of each grid, rather than a temporal transition process or trend. Therefore, statistical significance levels are not explicitly shown in Figure 6, as it represents a categorical state rather than a hypothesis test on trends. In contrast, Figure 8 (k–t panels) represent the temporal trends of 100-year CCEs over the period 2025–2065. For these figures, we explicitly performed a grid-wise t-test on the estimated trends, and only results that pass the 99% confidence level are highlighted. We have ensured that this significance level is clearly indicated in the figure legend and caption in the revised manuscript.

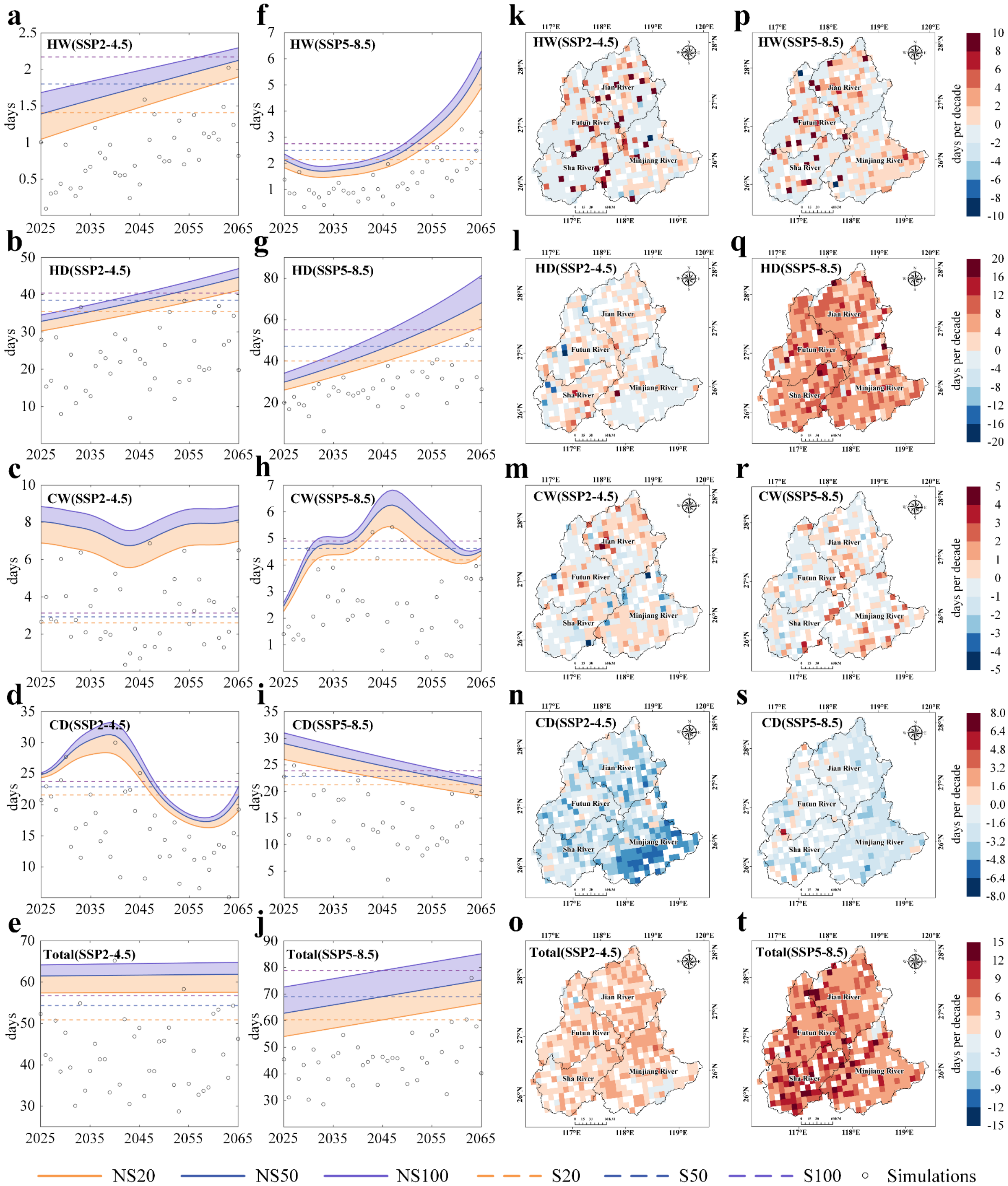


Figure 8. Comparison of non-stationary (NS) and stationary (S) characteristics for CCEs under 20-, 50-, and 100- year return periods (a-j). Spatial distributions of trends in CCEs under 100-year return periods (k-t), 20- and 50-year return period result are provided in Supplement Figure S7. Blank areas indicate grid points that failed to pass the 99% confidence test.

12.Ensure that recent studies regarding "compound hot-dry" events in China are consistently cited to contextualize the MRB findings.

-Answer: Thank you for your comment. We have added a discussion of this issue and cited relevant recent studies in the Discussion section (lines 417–426).

This pattern is consistent with studies highlighting the rising prevalence of hot-stagnation and hot-dry extremes in East Asia (Yin et al., 2025). In particular, across China, hot–dry extremes are projected to double by 2050 under high-emission scenarios (Yao et al., 2024). Guo et al. (2023) also revealed that under global warming, extreme hot conditions are projected to dominate most regions of China, with some areas experiencing more than 50 extreme hot days. Moreover, there is evidence suggesting that both compound hot–dry and compound hot–wet events are projected to increase significantly under future climate scenarios. Notably, compound hot–dry events exhibit substantially higher frequency, longer duration, and greater intensity than compound hot–wet events (Fang et al., 2025).

Fang, P., Wang, T., Yang, D., Tang, L., and Yang, Y.: Substantial increases in compound climate extremes and associated socio-economic exposure across China under future climate change, npj Clim. Atmos. Sci., 8, 17, https://doi.org/10.1038/s41612-025-00910-7, 2025.

Guo, J., Wang, X., Fan, Y., Liang, X., Jia, H., and Liu, L.: How Extreme Events in China Would Be Affected by Global Warming—Insights from a Bias-Corrected CMIP6 Ensemble, Earth's Future, 11, e2022EF003347, https://doi.org/10.1029/2022EF003347, 2023.

Yao, H., Zhao, L., He, Y., Dong, W., Shen, X., Wang, J., Hu, Y., Ling, J., Xiao, Z., and Huang, C.: Changes caused by human activities in the high health-risk hot-dry and hot-wet events in China, Commun. Earth Environ., 5, 464, https://doi.org/10.1038/s43247-024-01625-y, 2024.

Yin, C., Ting, M., Kornhuber, K., Horton, R. M., Yang, Y., and Jiang, Y.: CETD, a global compound events detection and visualisation toolbox and dataset, Sci. Data, 12, 356, https://doi.org/10.1038/s41597-025-04530-x, 2025.

13. “Generalized dditive Models…” should be “Generalized Additive Models…”.

-Answer: Thank you for pointing out this typo. The spelling has been corrected from “Generalized dditive Models” to “Generalized Additive Models” in the revised manuscript (line 749).