

# Research papers

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## Evaluating the Performance of Selected Reanalysis Datasets over Vietnam

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## Evaluating the Performance of Selected Reanalysis Datasets over Vietnam

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### Abstract

Vietnam, a country highly exposed to extreme weather events, still struggles to fill in significant gaps in its historical meteorological records, limiting a comprehensive understanding of past climate dynamics. The emergence of long-term reanalysis datasets, such as 20CR, ERA5, ERA-20C, and CERA-20C, offers a promising alternative for exploring historical climate variability. However, their reliability in representing Vietnam's climate has not been thoroughly assessed. This study provides the first comprehensive evaluation of the four above-mentioned reanalysis datasets over Vietnam for the period 1961–2010, focusing on their ability to reproduce climatological means, spatial patterns, interannual variability, and extremes of temperature and precipitation. Using specific statistical metrics, including correlation, centered root mean square difference (RMSD), and the composite Discriminatory Skill Score (DISO) index, along with 22 extreme indices, the reanalysis products are compared against station-level observations. Results show that all datasets reasonably capture temperature climatology, with ERA5 consistently outperforming others across spatial and temporal scales. For precipitation, ERA5 again demonstrates superior performance, while 20CR and ERA-20C exhibit moderate skill. In contrast, CERA-20C, despite incorporating coupled atmosphere-ocean dynamics, performs poorly across most aspects, especially in representing precipitation and related extremes. Overall, despite inherent uncertainties, ERA5 stands out as a reliable long-term reanalysis dataset for climate studies in Vietnam.

Nonetheless, caution is needed when interpreting results derived solely from any single reanalysis product. A multi-dataset or index-specific approach remains essential, especially in regions with complex topography and limited observational coverage, such as Vietnam.

### Keywords

Reanalysis datasets, Vietnam, Evaluation, Extreme events

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## Résumé

Le Vietnam, pays particulièrement exposé aux événements météorologiques extrêmes, fait encore face à des difficultés pour combler les lacunes dans ses archives météorologiques historiques, ce qui limite la compréhension approfondie de la dynamique climatique passée. L'émergence des réanalyses climatiques à long terme, tels que 20CR, ERA5, ERA-20C et CERA-20C, constitue une alternative prometteuse pour explorer la variabilité climatique historique. Cependant, leur fiabilité dans la représentation du climat vietnamien n'a pas encore été évaluée de manière approfondie. Nous proposons ici la première évaluation complète des quatre jeux de réanalyses mentionnés ci-dessus sur le Vietnam pour la période 1961–2010. Cette étude se concentre sur leur capacité à reproduire les moyennes climatologiques, les structures spatiales, la variabilité interannuelle et les extrêmes de température et de précipitations. À l'aide d'indicateurs statistiques spécifiques, incluant la corrélation, RMSD et DISO, ainsi que 22 indices d'extrêmes climatiques, les réanalyse ont été comparées aux observations des stations. Les résultats montrent que l'ensemble des réanalyses reproduit de manière satisfaisante la climatologie de la température, ERA5 surpassant systématiquement les autres à toutes les échelles spatiales et temporelles. Pour les précipitations, ERA5 présente également de meilleures performances, tandis que celles de 20CR et ERA-20C sont modérées. En revanche, CERA-20C, malgré l'intégration de dynamiques atmosphère-océan couplées, se révèle globalement peu performant, notamment dans la représentation des précipitations et des extrêmes

associés. Dans l'ensemble, malgré des incertitudes inhérentes, ERA5 apparaît comme le jeu de réanalyses le plus fiable pour les études climatiques au Vietnam. Néanmoins, une certaine prudence reste nécessaire lors de l'interprétation de résultats reposant sur un seul produit de réanalyse. Une approche multi-jeux de données ou spécifique selon les indices choisis demeure essentielle, en particulier dans des régions à topographie complexe et à couverture observationnelle limitée, telles que le Vietnam.

## Mots-clés

Données de réanalyse, Vietnam, Évaluation, Événements extrêmes.

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# Introduction

Throughout human development, extreme weather and climate events have played a pivotal role in shaping ecosystems and societal resilience. These events, defined by the Intergovernmental Panel on Climate Change (IPCC) as phenomena that are rare relative to the historical distribution at a given place and time, are statistically inevitable due to the tail behaviour of meteorological variables (IPCC, 2021).

Recent scientific consensus supports the conclusion that anthropogenic global warming, caused by massive greenhouse gas emissions, has increased both the intensity and frequency of climate extremes (IPCC, 2021; Luo et al., 2024). Precipitation extremes have intensified within many regions, with significant trends evident in both in situ and gridded datasets (Madakumbura et al., 2021). Simulated historical and projected future rainfall extremes have been strongly linked to human-induced climate change, as natural variability alone cannot fully explain the observed change signals (Kusunoki et al., 2020). Drought represents another intensifying extreme, driven by heightened variability in evapotranspiration and precipitation deficits under a warming world (Yuan et al., 2023). Moreover, drought, when amplified or compounded by extreme temperatures, is drawing increasing attention for its profound impacts on

ecosystems, the economy, and human health (Adom, 2024; Gu et al., 2025; Tripathy et al., 2023).

Temperature-related extremes have also shown clear signals of anthropogenic influence (IPCC, 2021). This influence is argued to favour the increasing activity of wave resonance, which is consequently linked to enhanced boreal-summer heatwave events (Mann et al., 2017). Furthermore, recent studies tracking consecutive hot days over several decades have identified clear increasing trends in heatwave duration, frequency, and geographical spread, which correspond closely with global warming patterns (Luo et al., 2024). These increasing extremes, projected to continue under future climate scenarios (Kim et al., 2020), have already caused substantial socio-economic, ecological, and environmental impacts, and are expected to pose even greater threats in the future (Black, 2024; Callahan & Mankin, 2022; Zhang et al., 2024).

Vietnam is among the countries most exposed to climate-related natural disasters worldwide (Thanh et al., 2004). This characteristic has marked its existence from the pre-modern era. Historical documentation, such as the Complete History of Đại Việt (Đại Việt sử ký toàn thư), compiled by Hieu Phung (Phung, 2022), records a diverse array of extreme events, including droughts, floods, and typhoons, as early as the 15th century.



These events have often been implicated in the rise and fall of dynasties (Lieberman & Buckley, 2012). The country's central location within the Asian monsoon system, combined with the influences of the Pacific subtropical high, the Tibetan high, the Intertropical Convergence Zone (ITCZ), and tropical cyclone activities, among other factors, contributes to its climatic volatility (Nguyen et al., 2014; Pham–Thanh et al., 2010). Nevertheless, Vietnam's climate records remain incomplete within the pre-modern era. An organized meteorological network was not established in Vietnam until the early 20th century. Note that much of the data from that period remains undigitized (Thomas et al., 2021; Thomas et al., 2025).

Previous literature, to a certain extent, has also paid attention to such challenging periods, but rather on a broader study region. A notable example is the work of Kubota et al. (2016), which utilised historical in-situ data in several countries from the late 19th century to investigate the Pacific–Japan pattern over the Western North Pacific region during summer. Their study highlights the importance of historical data in understanding interdecadal variability, particularly in relation to the interaction between El Niño–Southern Oscillation (ENSO) and the Pacific–Japan pattern. In another study, the onset of the Philippine summer monsoon was examined using rescued monthly data from as early as 1891, revealing a strong connection between tropical cyclones

activity and the onset date in May and June (Kubota et al., 2017). However, such research typically targets a limited set of variables and phenomena and thus hinders the investigation of the evolution and mechanism of extreme events at local scales, such as in Vietnam.

The development of reanalysis datasets has marked a significant advancement in historical climate reconstruction. Unlike raw observations, which are irregular in time and space, reanalysis provides a consistent, long-term record of the Earth system components, including atmospheric and oceanic states. This is achieved by integrating diverse observational datasets, including satellite measurements, ground-based stations, radiosondes, and ship or aircraft reports, into a global framework using numerical models and data assimilation techniques. Although numerous reanalysis datasets have been produced by different climate centers worldwide, only a limited number extend far into the past, for example, to the early 20th century. In this regard, the 20th Century Reanalysis (20CR) dataset (Compo et al., 2011) was pioneering in that it assimilated surface-based observations spanning more than two centuries. Its accessibility has made it a foundational tool for studying historical climate, for example, in investigating large-scale atmospheric circulation patterns and extreme weather events (Laloyaux et al., 2016). Despite its strengths, the 20CR dataset has known limitations,

particularly in accurately representing vertical atmospheric structure in regions with sparse observational coverage (Jiang et al., 2021).

Another major 20th-century reanalysis product, the ERA-20C dataset, produced by the European Centre for Medium-Range Weather Forecasts (ECMWF), focuses on surface observations but does not account for ocean-atmosphere coupling (Poli et al., 2016). To address this, ECMWF developed CERA-20C (Laloyaux et al., 2017), a coupled dataset that incorporates ocean-atmosphere interactions. Although its spatial resolution remains coarse ( $\sim 1^\circ \times 1^\circ$ ), CERA-20C has demonstrated advantages in capturing decadal variability (Laloyaux et al., 2017). More recently, ERA5 has become one of the most widely used reanalysis products. Extending back to 1940, it offers higher spatial ( $\sim 31$  km) and temporal (hourly) resolution and has been commonly employed in climate and meteorological research across diverse disciplines.

Therefore, as a premise to facilitate further research on historical climate extremes in Vietnam, we aim to conduct an overview evaluation of the performance of the above-mentioned reanalysis datasets in capturing the climatology and extreme tendencies of temperature and precipitation. This is an aspect that has received little attention in previous literature. Understanding their

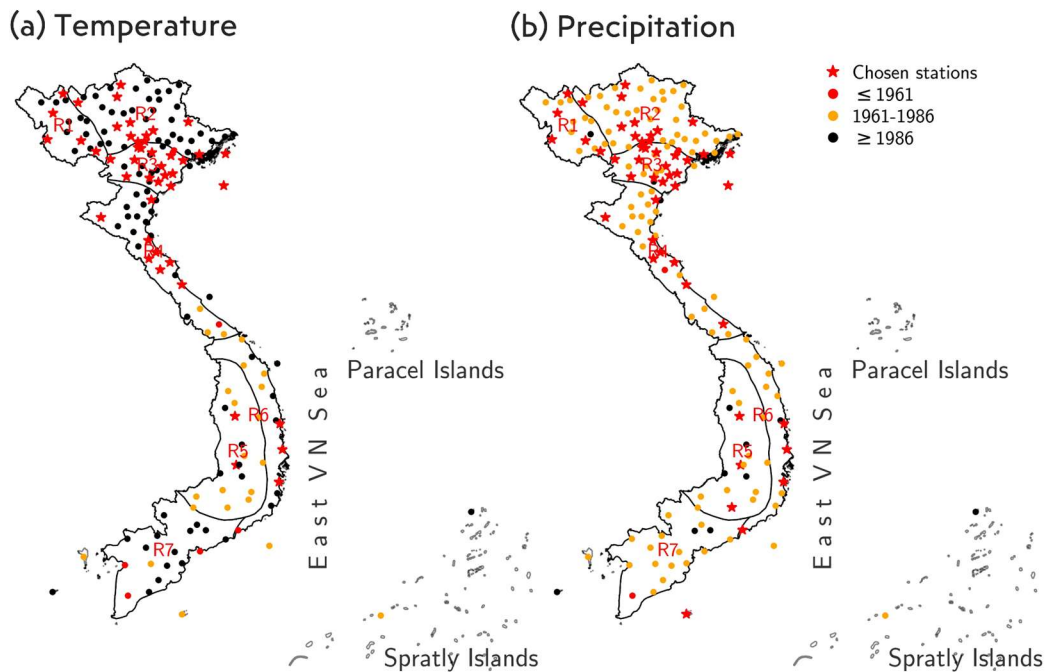
performance can help identify the most suitable datasets for future studies.

# 1. Methodology and data

## 1.1. Study region and observational data

This study focuses on the continental part of Vietnam, which is divided into 7 climatic regions: Northwest (R1), Northeast (R2), Red River Delta (R3), North Central (R4), Central South (R5), Central Highlands (R6), and Southern (R7) (Figure 1). These regions are categorised based on variations in radiation, temperature, and rainfall (Nguyen and Nguyen, 2004).

**Figure 1. Spatial distribution of meteorological stations in Vietnam used in this study for temperature (left) and precipitation (right).**



Note: The red dots and red stars indicate stations with data prior to or starting from 1961. Orange dots denote stations with data beginning after 1961 but before 1986, while black dots indicate stations with data from 1986 onward. The stations selected for this study (red stars) have less than 5% missing data during the period 1961–2010, while stations marked with red dots have more than 5% missing data over the same period. Source: Authors' own visualization. Original.

The observational data used as the reanalysis validation basis were collected from the meteorological network of over 160 stations, starting from 1961 to the present, operated by the Vietnam Meteorological and Hydrological Administration (VNMHA) (Figure 1). Due to historical context, the station density in the Central and Southern regions remains relatively modest compared to the Northern region. In particular, no long-term temperature records from the Southern (R7) region were available for this study. The number of temperature and

precipitation stations has increased over time, with a notable increase in temperature stations from 1986 (Figure 1a).

For both variables, the number of stations with long-term records (around 60 years) remains limited, accounting for only about one-third of the total. Among them, stations with less than 5% missing data during the period 1961–2010 (red star shown in Figure 1), i.e., 46 and 49 stations for temperature and precipitation, respectively, are selected as the main reference for the subsequent evaluation procedure. The final year, 2010, is chosen to align with the data availability period of certain reanalysis datasets described below.

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## 1.2. Reanalysis datasets

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As the catalog of high-resolution reanalysis datasets remains rather limited for the 20th century, we focus on four datasets that cover this specific period: 20CR, ERA-20C, CERA-20C, and ERA5. The details of the coverage period and resolution of each dataset are provided in Table 1. For comparison with station observations, the reanalysis values were extracted from the nearest grid point for the period 1961–2010.

**Table 1. Time coverage and spatial resolution of the reanalysis datasets used in this study.**

Dataset	Time span	Resolution
20CR	~1800s–present	~1°x1° (~111km x 111km)
ERA-20C	1900–2010	~1°x1° (~111km x 111km)
CERA-20C	1901–2010	~1°x1° (~111km x 111km)
ERA5	1940–present	~31 km

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## 1.3. Extreme indices

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Besides the evaluation of climatological performance, this study also investigates the ability of the four datasets to capture past extreme events. Extreme events are commonly represented using 27 indices recommended by the Joint World Meteorological Organization Commission for Climatology/WCRP Climate Variability and Predictability project's Expert Team on Climate Change Detection, Monitoring and Indices (ETCCDI) (Peterson et al., 2001).

In the context of Vietnam, some of the 27 indices mentioned above are unsuitable for tropical climates, e.g., frost days (FD) and icing days (ID), or rely on localized thresholds, e.g., growing season length (GSL). These indices were therefore excluded from our analysis. As a result, only 22 ETCCDI indices were retained for use in this study (Table 2). Note that the indices R10mm, R20mm, and R50mm, originally defined among the 27 ETCCDI indices, are included under index number 17 (Rxmm) in Table 2.

**Table 2. The 22 ETCCDI indices used in this study**

#	Index Name	Description	Units
1	TXx	Hottest day: Monthly and annual highest value of daily maximum temperature	°C
2	TNx	Warmest night: Monthly and annual highest value of daily minimum temperature	°C
3	TXn	Coldest day: Monthly and annual lowest value of daily maximum temperature	°C
4	TNn	Coldest night: Monthly and annual lowest value of daily minimum temperature	°C
5	TNI0p	Cool nights: Percentage of time when daily min temperature <10th percentile	%
6	TXI0p	Cool days: Percentage of time when daily max temperature <10th percentile	%
7	TN90p	Warm nights: Percentage of time when daily min temperature >90th percentile	%
8	TX90p	Warm days: Percentage of time when daily max temperature >90th percentile	%
9	DTR	Diurnal temperature range: Annual mean difference between daily max and min temperature	°C
10	SU25	Summer days: Annual count when daily max temperature > 25°C	days
11	TN20	Tropical nights: Annual count when daily min temperature > 20°C	days
12	WSDI	Warm spell duration index: Annual count when at least 6 consecutive days of max temperature >90th percentile	days
13	CSDI	Cold spell duration index: Annual count when at least 6 consecutive days of min temperature <10th percentile	days
14	Rx1day	Maximum 1-day precipitation amount: Monthly and annual maximum 1-day precipitation	mm
15	Rx5day	Maximum 5-day precipitation amount: Monthly and annual maximum consecutive 5-day precipitation	mm
16	SDII	Simple daily intensity index: The ratio of annual total precipitation to the number of wet days ( $\geq 1$ mm)	mm/day

17	Rxmm	Number of precipitation days above a specific threshold: Annual count when precipitation $\geq x$ mm, where x can be 1, 5, 10, 20, or 50mm	days
18	CDD	Consecutive dry days: Highest number of consecutive days when precipitation $< 1$ mm	days
19	CWD	Consecutive wet days: Highest number of consecutive days when precipitation $\geq 1$ mm	days
20	R95p	Very wet days: Annual total precipitation from days $> 95$ th percentile	mm
21	R99p	Extremely wet days: Annual total precipitation from days $> 99$ th percentile	mm
22	PRCPTOT	Annual total wet day precipitation: Annual total precipitation from days $\geq 1$ mm	mm

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#### 1.4. Trend analysis

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To assess trends in temperature and precipitation indices, we employ the non-parametric Mann-Kendall (MK) test (Mann, 1945; Kendall and Gibbons, 1990). As the test does not assume any specific data distribution, it is especially well-suited for identifying trends in extreme indices derived from daily or seasonal climate observations. The MK test evaluates whether there is a statistically significant upward or downward trend in a time series (typically at a 90% confidence level or higher). In this study, the MK test is applied in combination with Sen's slope estimator (Sen, 1968) to quantify the magnitude of detected trends.

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#### 1.5. Composite evaluation indices

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The accuracy and skill performance of each dataset are also assessed using the Discriminatory Skill Score (DISO) (Hu et al., 2019), a composite metric that incorporates correlation (R), normalized mean absolute error (NMAE), and normalized root mean square error (NRMSE). Recent adaptations of DISO also include mean absolute percentage error (MAPE) to enhance sensitivity to systematic bias (Jiang et al., 2021). By incorporating multiple bias indicators, this approach offers a more balanced and comprehensive evaluation, minimizing the dominance of any single metric, such as correlation.

If  $O_i$  represents the observation series and  $M_i$  the reanalysis series, the formulas for the component indicators and the DISO are as follows:

$$R = \frac{\sum_{i=1}^n (O_i - \bar{O})(M_i - \bar{M})}{\sqrt{\sum_{i=1}^n (O_i - \bar{O})^2} \sqrt{\sum_{i=1}^n (M_i - \bar{M})^2}} \quad (1)$$

$$NMAE = \frac{1}{n} \sum_{i=1}^n \frac{(O_i - M_i)}{|\bar{O}|} \quad (2)$$

$$NRMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n \frac{(O_i - M_i)^2}{|\bar{O}|}} \quad (3)$$

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{O_i - M_i}{O_i} \right| \quad (4)$$

$$DISO = \sqrt{(R-1)^2 + NMAE^2 + NRMSE^2 + MAPE^2} \quad (5)$$

A lower DISO score indicates higher performance relative to observational references.

## 2. Results and discussion

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### 2.1. Climatological means & seasonal cycles

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First, we assess the ability of the reanalysis datasets to represent the climatological mean of temperature and precipitation over the study period (1961–2010) (Figure 2). For temperature, the majority of stations show a close agreement in climatological averages between observations and the reanalysis datasets for both annual and seasonal scales, yet with a dominant tendency towards underestimation in the reanalysis compared to observations. This systematic underestimation is pronounced in all datasets. However, some large overestimations – up to 5°C – are found at a few stations in all reanalysis dataset across four seasons. Notably, stations with large biases, including Tam Dao in R1 (up to +5.6 °C) and Sapa in R2 (up to +3.31 °C), are generally located in mountainous areas, highlighting the limitations of coarse-resolution reanalysis in representing detailed topographical features.

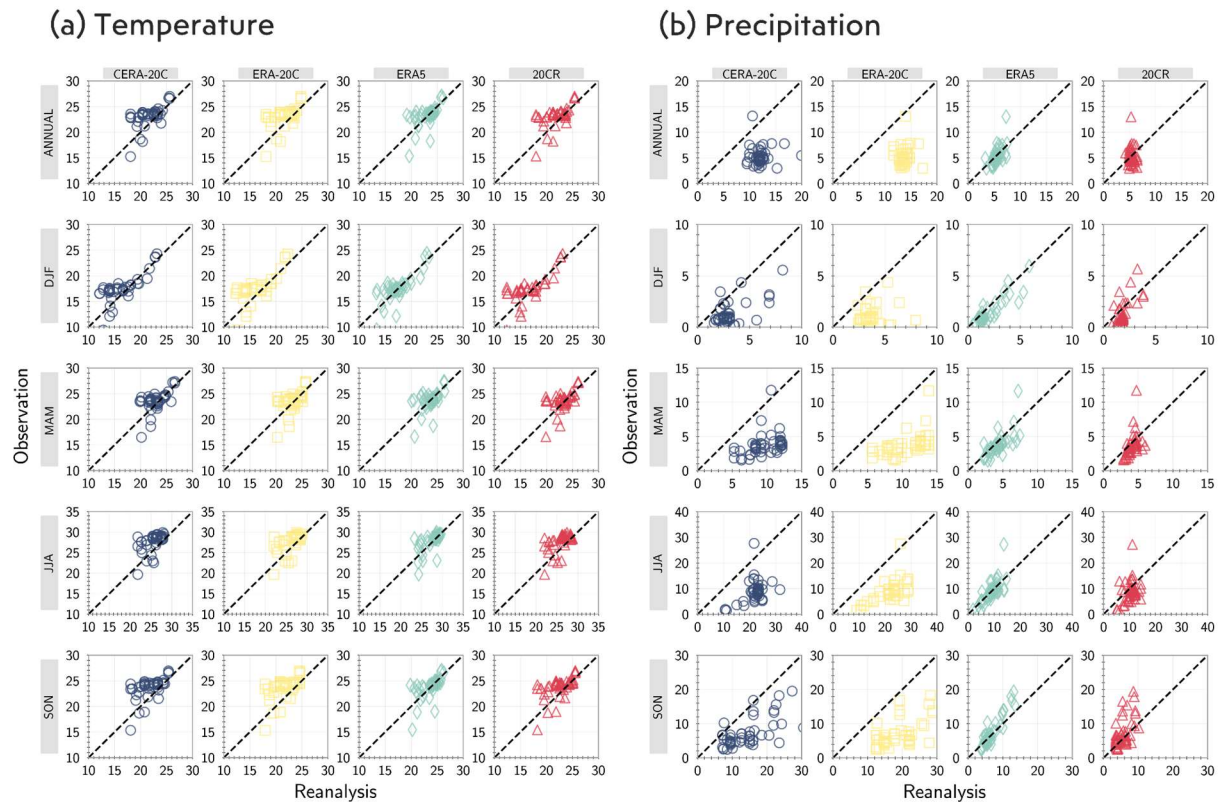
Regarding precipitation, the evaluation poses a considerably more complex challenge. A systematic overestimation is evident in both the CERA-20C and ERA-20C datasets. Notably, while the magnitude of the mean bias in ERA-20C closely aligns with that of CERA-20C, this similarity does not extend to the bias in interannual variability (later shown in Figures. 4 and 5). This suggests the presence of anomalously high precipitation values in multiple ERA-20C station grid points, potentially linked to temporal inhomogeneities or outlier events. Conversely, the 20CR dataset exhibits a tendency for rainfall values to converge within a narrower range, smaller than the range observed in station data. This, along with its lower RMSD values (to be discussed later), suggests a more homogeneous but less realistic climatological representation of 20CR's precipitation over Vietnam. Among the four datasets, ERA5 provides the best performance in representing station-level precipitation, for both annual and seasonal averages.

Given the limited number of stations, their uneven distribution, and the non-homogeneous geographical characteristics, we evaluate how the datasets represent the spatial distribution of temperature and precipitation averaged for the entire study period, considering both annual and seasonal averages. Figure 3 presents Taylor diagrams (Taylor, 2001), spatially comparing the reanalysis products with station observations. In these diagrams, the radial distance indicates the ratio of the standard deviation (STD) of the reanalysis products to that of the observations, while the polar angle reflects the spatial correlation with gauge data. Each symbol – dot, square, diamond, or triangle – represents the performance of a given dataset in capturing the spatial distribution of climatological



averages (annual or seasonal) for the period 1961–2010. The observations are represented by a point on the horizontal axis (correlation = 1) at unit distance from the origin, indicating no error in standard deviation. The linear distance between each symbol and this point is proportional to the centered root mean square difference (RMSD), the shorter the distance, the better the performance.

**Figure 2. Scatter plots comparing climatological averages from reanalysis and station observations at each station location for temperature and precipitation over 1961–2010.**

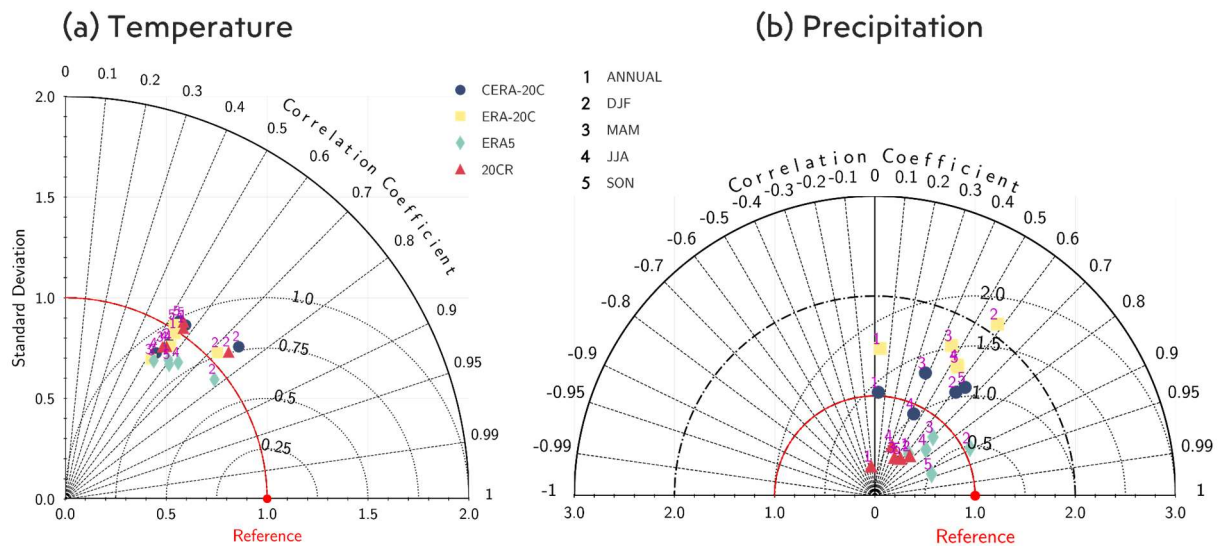


Note: Comparison of annual and seasonal averages over 1961–2010 between reanalysis (x-axis) and station observations (y-axis) at each station location for a) temperature (°C), and b) precipitation (mm/day). DJF: December–January–February; MAM: March–April–May; JJA: June–July–August; SON: September–October–November. Source: Authors' own visualization. Original.

For temperature, the boreal winter seasons (DJF) stand out most distinctly, with deviations from observations that are more pronounced than those of the annual mean and the transitional seasons. Conversely, other seasons exhibit relatively moderate correlations with the observational record. On a climatological scale, the four reanalysis datasets display only minor differences, suggesting a broadly homogeneous spatial representation. However, as shown in subsequent analyses, their performance diverges more substantially when examined in greater detail. Representing precipitation is more challenging for the reanalysis products (Figure 3b). ERA-20C and CERA-20C, in particular, show clear limitations in

capturing spatial distributions. Excessively strong spatial variability, i.e., high NSTD values, causes this dataset to perform poorly with respect to RMSDs. ERA-20C also exhibits significant bias, especially during the dry seasons (DJF). Although 20CR and ERA5 also show reduced spatial variability, their spatial correlations and RMSDs remain relatively closer to the reference point, indicating reasonable performance in representing spatial distributions. Among the four datasets, ERA5 performs the best, which may be partly attributed to its relatively higher resolution (31 km, compared to approximately 110 km for the other three datasets).

**Figure 3. Taylor diagrams showing the spatial comparison of 1961–2010 climatological averages for (a) temperature and (b) precipitation between the four reanalysis products and station observations.**



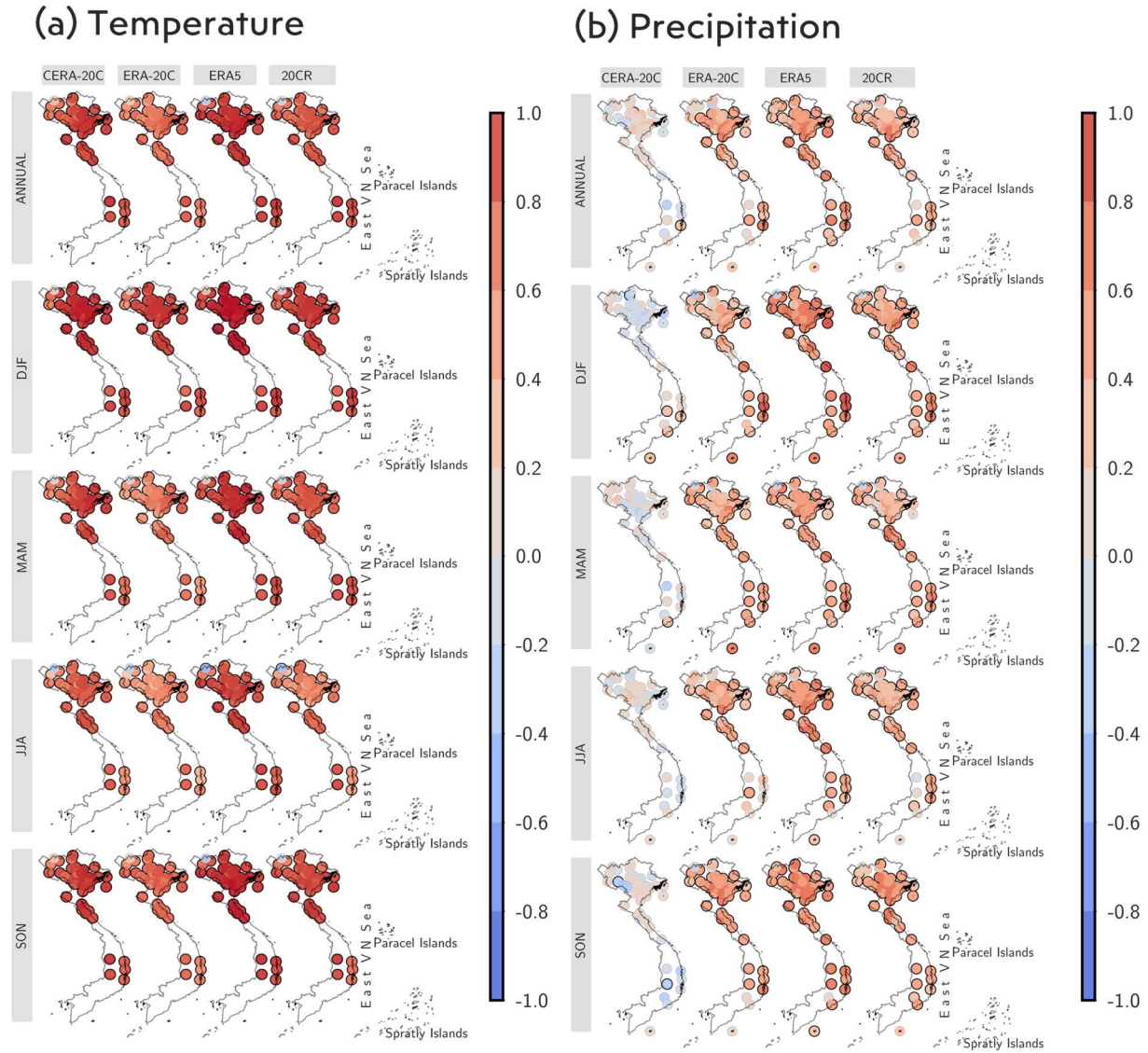
Source: Authors' own visualization. Original.

## 2.2. Interannual variability

Figures 4 and 5 illustrate the ability of the datasets to capture interannual variability at each station using correlations and RMSD values. Overall, stronger and statistically significant correlations are observed at all stations for temperature (Figure 4.a) compared to precipitation (Figure 4.b), for both annual values and seasonal averages. Notably, all four products fail to capture the interannual variability at Station Tuan Giao, located in the Northwest, with non-statistically significant and even negative correlations in JJA. Except for Station Tuan Giao, the correlation values for temperature are quite high, with many stations showing values above 0.7. This indicates a good capability of the reanalysis datasets to capture interannual variability. Overall, ERA5 outperforms the other datasets, followed by

CERA-20C, with relatively higher correlation values not only for annual averages but also for seasonal means.

**Figure 4. Correlations between reanalysis and observed interannual signals at each station for annual and seasonal averages during 1961–2010, for (a) temperature and (b) precipitation.**



Note: Circles with black contours indicate that the correlation is statistically significant at the 95% confidence level.  
Source: Authors' own visualization. Original.

Regarding precipitation, the ability of the datasets to reproduce interannual variability varies significantly. CERA-20C exhibits the weakest performance, with correlation values noticeably lower than those of the other datasets – some stations even show negative correlations when compared to observations. It is noteworthy that CERA-20C incorporates coupled ocean – atmosphere interactions, whereas ERA-20C, also developed by ECMWF, does not account for this coupling. While such coupling allows for a physically consistent

two-way exchange between two key components of the climate system, it may also be a contributing factor to the substantial degradation in the simulation of local precipitation in CERA-20C. Excluding CERA-20C, the correlation values for precipitation from the remaining reanalysis datasets are relatively similar, commonly above 0.4, with some stations exhibiting correlations greater than 0.8. This suggests that, overall, ERA-20C, ERA5, and 20CR are capable of capturing interannual variability in precipitation. Among them, ERA5 consistently outperforms the others by maintaining high correlations across both seasonal and annual timescales.

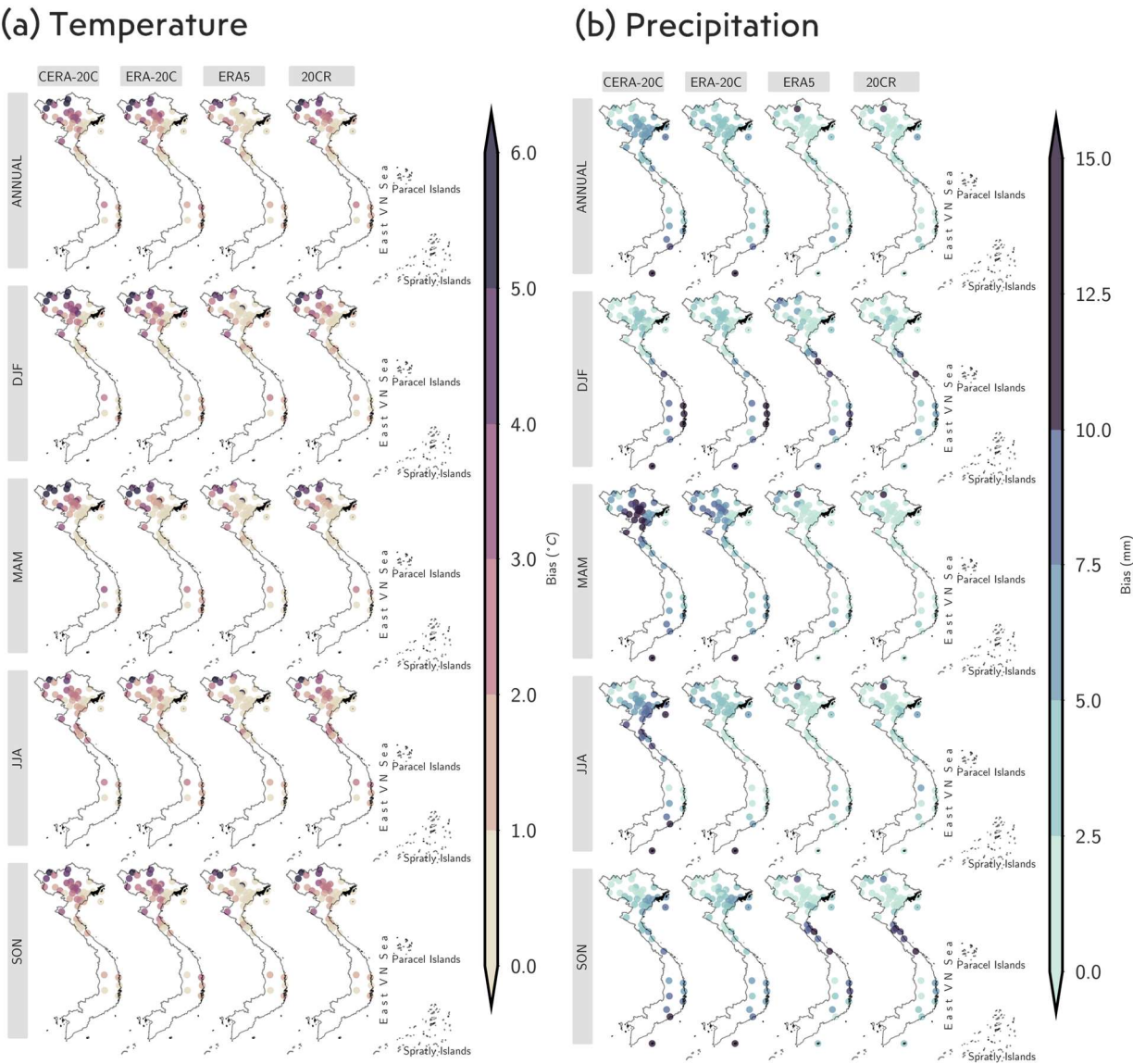
The bias, as indicated by RMSD values, showcases a similar picture, where smaller RMSD values suggest better capability in representing interannual variability (Figure 5).

For temperature, all four datasets show relatively low bias along the coastal regions but face greater challenges in the northwestern region, possibly due to the complex terrain. RMSD values are relatively consistent across different seasons and in the annual mean. Among the datasets, ERA5 demonstrates superior performance, particularly with relatively low bias at stations in the Central Northern region. While the other three datasets show RMSD values exceeding 3°C, ERA5 generally maintains its bias below 1°C. This advantage is likely attributed to its higher spatial resolution, which allows for a more accurate representation of local features. Furthermore, consistent with the correlation results, the Tuan Giao station near the northern border stands out with notably high RMSD values across all datasets.

Regarding precipitation, the poor performance of CERA-20C is further reflected in the RMSD values. In Figure 5b, biases exceeding 12 mm are recorded at several stations for CERA-20C, particularly over the Red River Delta during the MAM season, and over 6 mm at coastal stations in Northern and North Central Vietnam during summer (JJA). In contrast, ERA-20C, the reanalysis version without ocean-atmosphere coupling, generally exhibits smaller biases compared to CERA-20C over the same locations. However, in spite of offering improved representation and reduced bias, ERA5 and 20CR still face certain challenges in reproducing the interannual variability of precipitation in the Central coastal region during autumn (SON), whereas the two earlier datasets do not encounter the same issue. This region, characterized by complex coastal terrain and rainfall strongly influenced by tropical cyclone activity (Pham Thi Thanh et al., 2024), presents significant difficulties for models in accurately simulating precipitation patterns. This suggests that the development of datasets with higher data assimilation density or spatial resolution does not always guarantee better performance.



**Figure 5. Similar to Figure 4, but showing RMSD values instead of correlations.**



Source: Authors' own visualization. Original.

### 2.3. Extreme events

In this section, we focus on whether the reanalysis products can accurately capture extreme events via the ETCCDI indices listed in Table 2. We first compare trends in these extreme indices across the stations used and then evaluate the performance of the datasets using the DISO metric.

### 2.3.1. Trends in temperature-related extreme indices

Figure 6 indicates a wider range of slopes in the observational data compared to those of the reanalysis products, regardless of the metrics analysed. This broad distribution reflects the complex spatial variability of local station data. Moreover, caution is needed when comparing the slopes of different indices, as their value ranges can differ drastically.

ERA5 performs relatively better than the other datasets in reproducing the spread of trends derived from the observational data, although it still exhibits a narrower spread compared to the observations. This suggests that ERA5 still has limitations in capturing outliers or highly localized trends. ERA5's superior performance is most evident in the WSDI duration-related indices, where it effectively captures observed signals for consecutive days, allowing for the reproduction of the associated slopes. ERA5 also closely follows the observed trends in the warm night (Tn90p) and warm day (Tx90p) indices. On the contrary, CSDI and Tn10p pose a challenge for ERA5, as it fails to capture the observed trends. While ERA5 indicates a decrease in both the number of extreme cool nights (Tn10p) and persistent cold events, observations and other datasets consistently show the opposite behavior – except 20CR for CSDI. The latter suggests an increase in the occurrence of cool nights that are more isolated in time, rather than persistent enough to develop into prolonged cold spells.

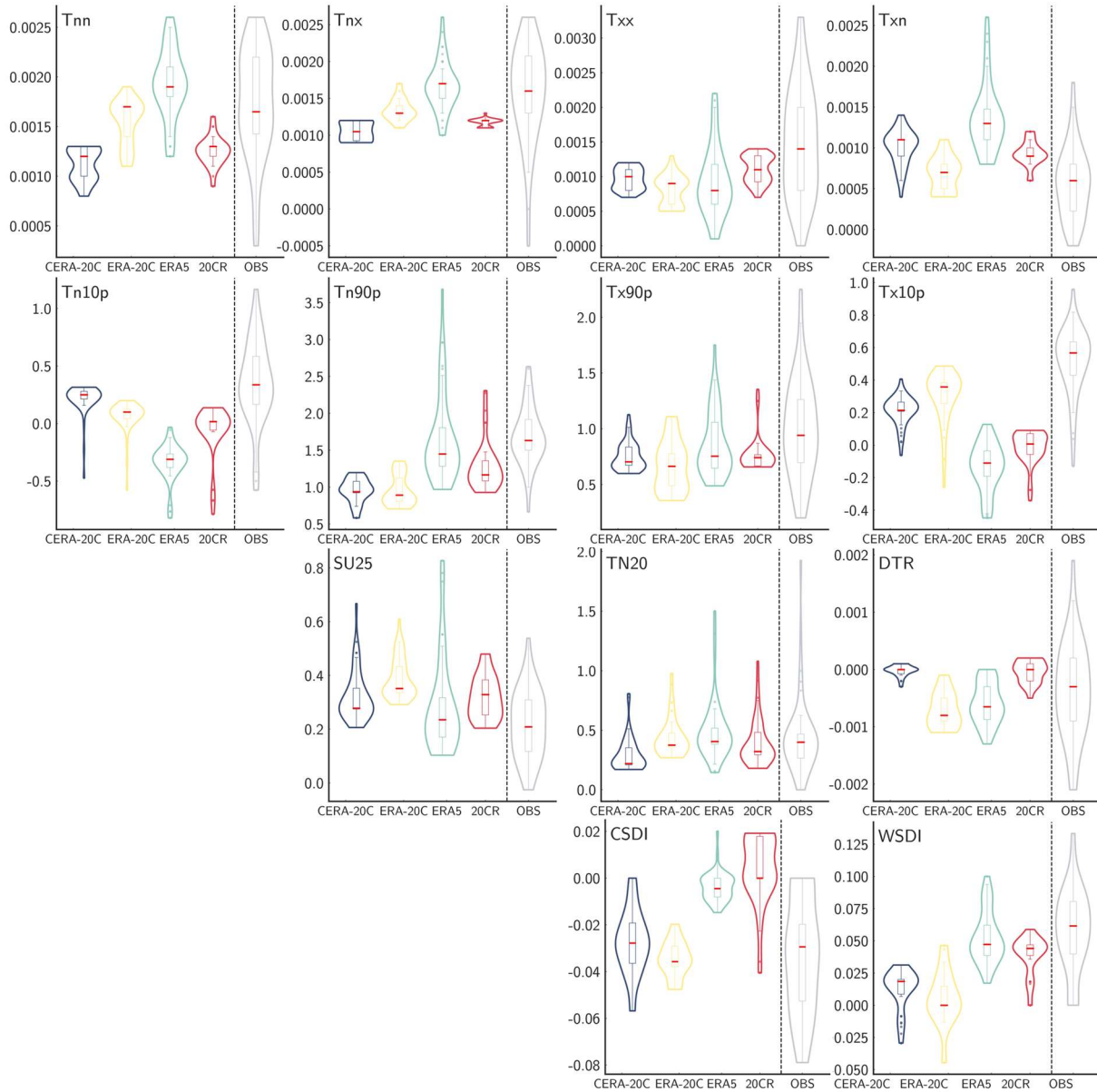
Both developed by ECMWF, neither ERA-20C nor CERA-20C shows a clear performance advantage over the other, despite CERA-20C being theoretically expected to perform better due to its ocean-atmosphere coupling. The much narrower distributions of ERA-20C and CERA-20C compared to the observations highlight their “smoothed” spatial and temporal variability, possibly due to their coarse resolution.

The 20CR dataset exhibits the weakest performance among all datasets. Characterized by narrow and noticeably skewed slope distributions, 20CR fails to capture the spatial variability of the observed trends. Its slope distribution is clearly detached from the observational data, with the mean of 20CR trends failing near or below the 25th percentile of the observational distribution for the majority of temperature-related indices.

Although there exist differences among the reanalysis products and the observations, Figure 6 exhibits general positive trends in temperature-related extreme indices across all products, indicating a shift toward hotter conditions, except for the two indices CSDI and DTR. For the Cold Spell Duration Index (CSDI), both the observation and reanalysis products exhibit generally no or negative trends following a decrease in persistent cold events in a warming climate. Regarding the Diurnal Temperature Range (DTR), the majority of stations display

negative trends, consistent with previous findings in many parts of the world, which indicate a narrowing DTR in the context of global warming (Sun et al., 2019).

**Figure 6. Violin plots and box plots of Sen's slopes for the temperature-related extreme indices across the stations used in the study during the period 1961–2010, for the four reanalysis datasets and the observations.**



Note: The unit for each sub-figure corresponds to the unit of the respective index (as shown in Table 2) expressed per year. Violin plots represent the distribution of values across stations. The width of the violin at a given value is proportional to the number of stations with similar trend values: thicker sections indicate more frequently occurring values, while narrow ends correspond to rarer values. Together, the violin plot and the embedded boxplot (showing the median and interquartile range) display the overall spread and the shape of the distribution, which cannot be inferred from the boxplot alone. Source: Authors' own visualization. Original.

### 2.3.2. Trends in precipitation-related extreme indices

Regarding precipitation-related indices (Figure 7), the median slope for all indices is approximately zero, indicating the absence of significant or systematic trends across stations. The observed trend patterns are generally well captured by ERA5, followed by 20CR, for the threshold-based precipitation indices ( $R_x$  mm). Meanwhile, CERA-20C strongly underestimates trends in the number of rainy days ( $R1mm$ ), whereas ERA-20C exhibits the opposite pattern, overestimating this metric. As thresholds increase – for instance, to 50 mm – the number of exceedance days in CERA-20C and ERA-20C becomes small, increasing the uncertainty in trend detection, as demonstrated by the wider spread in their violin plots.

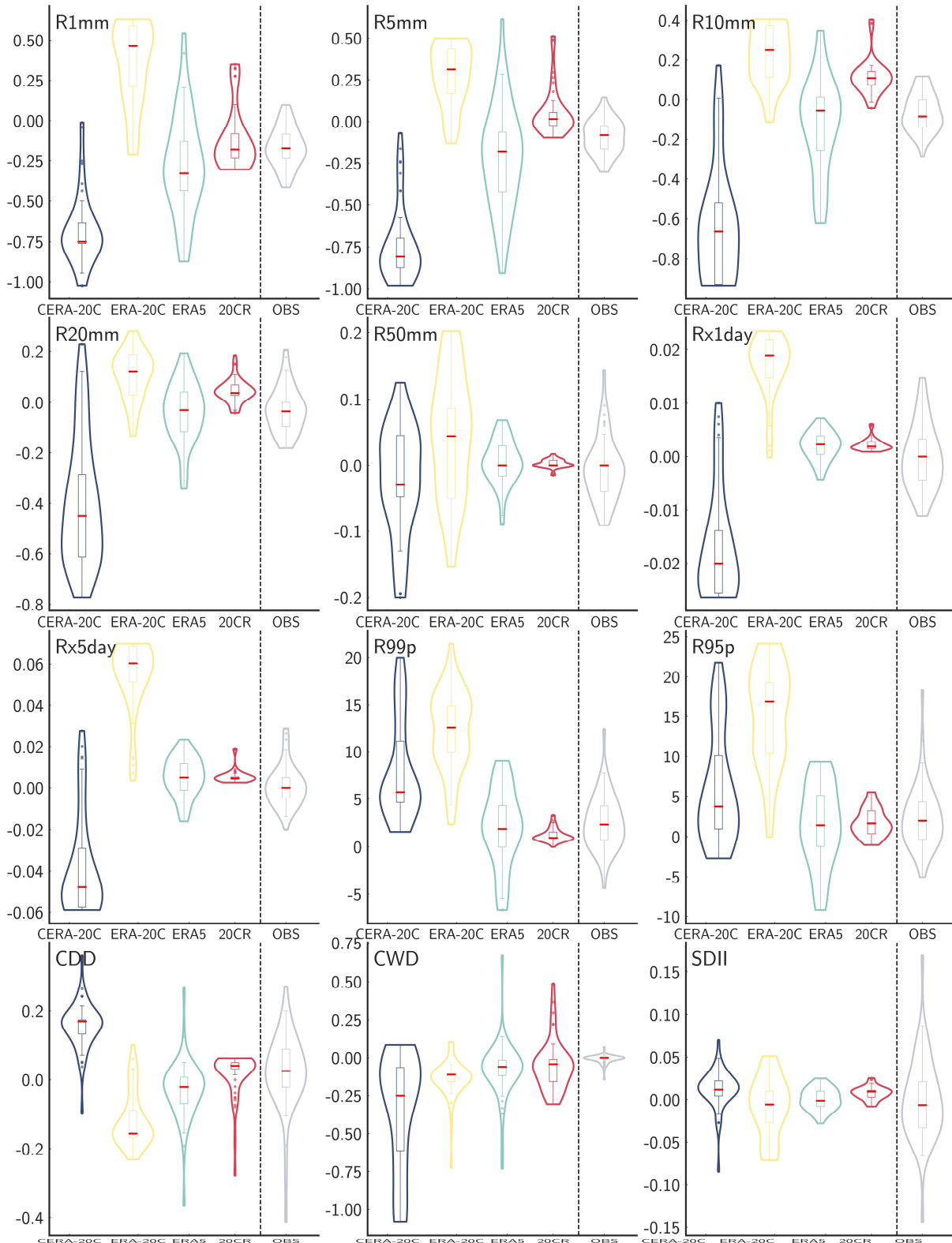
Furthermore, indices reflecting signal persistence (i.e., CDD, CWD) also exhibit substantial variability across datasets, with ERA5 and 20CR still being the closest to the observed values in terms of the median. For CWD, observations show little to no trend at almost all stations, which explains the narrow range of OBS values. Meanwhile, reanalysis products often overestimate the number of wet days (not shown) because the 1 mm threshold for wet days is more easily met, leading to an overestimation of CWD and poorer performance in representing this extreme index (see Figure 9). As a result, the variability in reanalysis trends is much larger than in the observations. Notably, CERA-20C stands out as an exception, as it underestimates trends in the number of consecutive wet days, highlighting its underperformance in capturing precipitation persistence.

For the remaining precipitation indices, CERA-20C continues to fail in reproducing the full distribution observed at stations, with long tails suggesting distinct trends at certain stations that deviate significantly from observational records. In contrast, ERA-20C tends to produce higher slope values than observations, implying that the increasing trends in extreme precipitation may be overestimated at many stations. 20CR, conversely, shows a closer resemblance to the observations, as the median of station trends remains near zero; nevertheless, it also exhibits a more limited variability in comparison to ERA5.

These findings highlight the need for great caution when using reanalysis datasets to assess past extreme events, as different datasets can yield markedly different results, often diverging from actual observations. Once again, among the reanalysis products considered, ERA5 demonstrates the best overall performance at most stations in Vietnam used in this study.



**Figure 7. Same as Figure 6, but for precipitation-related indices**



Source: Authors' own visualization. Original.

### 2.3.3. Performance assessment using DISO

In this sub-section, we assess the ability of the selected reanalysis datasets to represent extreme events using the composite DISO index, which allows for the simultaneous evaluation of variability and bias magnitude. Due to the nature of the DISO formulation, lower values indicate better agreement between the reanalysis outputs and the observational reference data.

Figure 8 presents the DISO values for temperature-related indices. Owing to their relatively stable variability, temperature-related variables are generally well represented across all datasets. Indices related to daily maximum and minimum temperatures (e.g., Txn, Txx, Tnn, Tnx) are reasonably well reproduced at most stations, as indicated by their low DISO scores.

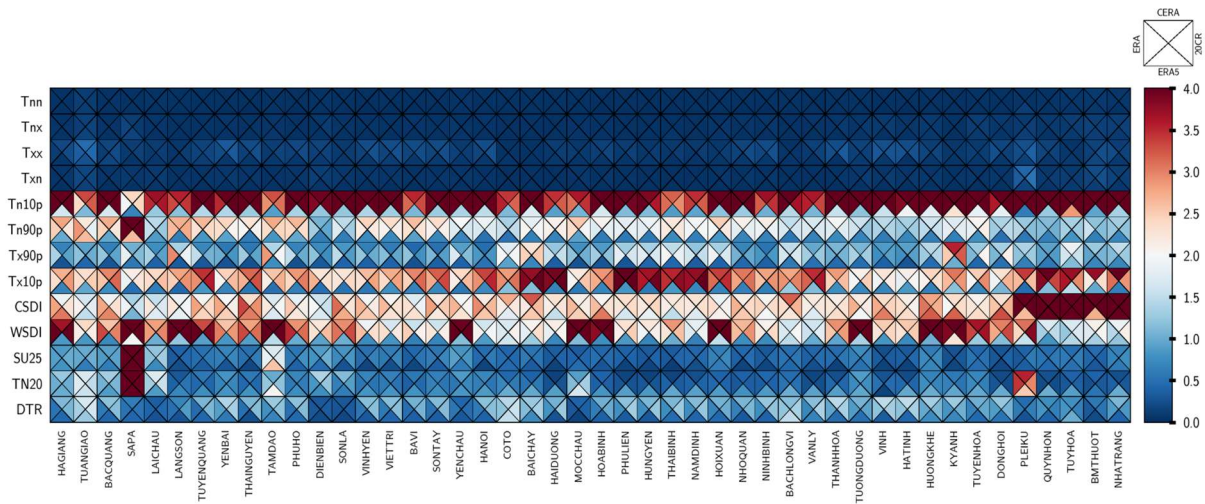
However, limitations begin to emerge when evaluating more sensitive cold-temperature extremes, such as Tn10p and Tx10p. Most reanalysis products tend to overestimate temperatures, which leads to inaccuracies in the determination of threshold values derived from the baseline period. This introduces systemic bias, especially evident in the Tn10p index, and also in the CSDI index, which is influenced by both threshold definitions and temporal continuity. Central Vietnam demonstrates the largest discrepancies, where none of the reanalysis products can adequately reproduce CSDI (not shown).

On the other hand, high-temperature indices such as Tx90p show considerably better agreement among datasets. Nevertheless, differences remain in the WSDI index, which reflects the number of consecutive hot days. The requirement for temporal continuity remains a challenge, with only four stations located in Central Vietnam showing reasonable agreement across the datasets. This pattern in WSDI, contrasted with CSDI, further highlights the regional sensitivity in the performance of the reanalysis datasets.

Among the four datasets, ERA5 generally exhibits much better performance, as demonstrated by lower DISO scores across most indices, such as Tn10p, Tn90p, Tx90p, Tx10p, and WSDI, at all stations used. Of the three remaining datasets, none systematically outperforms the others, though ERA-20C demonstrates certain advantages in many cases.

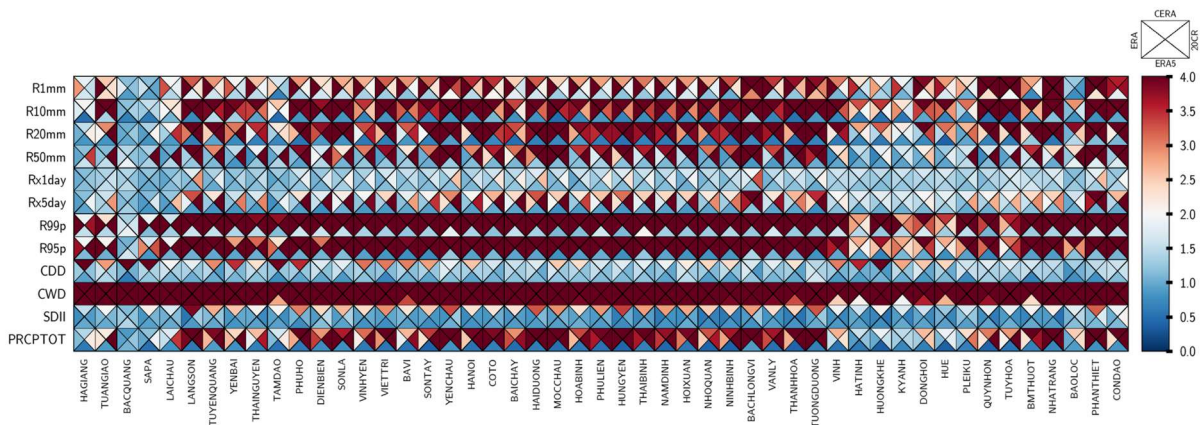
Similarly, for precipitation-related indices, ERA5 stands out as the most consistent dataset (Figure 9). This is particularly evident as ERA5 records the lowest DISO values for high-intensity precipitation events such as R95p and R99p. However, for the CWD index (consecutive wet days), all datasets, including ERA5, struggle to provide accurate representations.

**Figure 8. DISO values for temperature-related extreme indices from the reanalysis datasets.**



Note: ERA-20C, CERA-20C, 20CR, and ERA5 are represented clockwise as triangles within a square, starting with ERA-20C in the left triangle. Source: Authors' own visualization. Original.

**Figure 9. Same as Figure 8 but for precipitation-related indices**



Source: Authors' own visualization. Original.

Among the remaining three datasets, 20CR demonstrates certain advantages over CERA-20C and ERA-20C in threshold-based precipitation indices (e.g. Rxmm) but performs relatively poorly in intensity-based indices such as Rx5day and PRCPTOT. Notably, while both 20CR and ERA-20C are able to reasonably capture consecutive dry days (CDD) and precipitation intensity (SDII), as reflected by favorable DISO scores, CERA-20C, despite being a coupled mode, exhibits considerable limitations in representing both average precipitation characteristics (Figures 5 and 6) and extremes, particularly for CDD and SDII, compared to the other datasets.

### 3. Conclusions

This study is the first to provide a comprehensive evaluation of four major reanalysis datasets, including ERA5, 20CR, ERA-20C, and CERA-20C, over Vietnam for the period 1961–2010, assessing their performance in representing climatological means, spatial distributions, interannual variability, and extremes of temperature and precipitation.

Our results showed that all four datasets demonstrate reasonable capability in capturing the temperature climatology, with ERA5 consistently outperforming the others across most metrics and seasons. Its higher spatial resolution and improved data assimilation potentially contribute to lower biases, higher correlations, and more realistic spatial and temporal variability. In contrast, representing precipitation remains a much more challenging task. ERA5 again emerges as the most reliable product, exhibiting the lowest bias and strongest spatial and temporal agreement with station observations. While 20CR also performs relatively well in threshold-based indices and some aspects of interannual variability, its performance in capturing intensity-based extremes, such as RX5day and PRCPTOT, remains limited. ERA-20C shows moderate skill but suffers from high spatial variability and biases, particularly during the dry seasons. CERA-20C, despite incorporating coupled ocean–atmosphere dynamics, consistently underperforms across nearly all aspects, especially in representing precipitation and its related extremes.

Our evaluation using the composite DISO index further supports these findings: ERA5 consistently yields the lowest DISO values across both temperature- and precipitation-related extreme indices, highlighting its robustness for characterizing climate extremes in the region. However, no dataset performs optimally across all indices. Discrepancies, particularly in the representation of cold spell duration (CSDI), consecutive wet days (CWD), and high-intensity rainfall events, underscore the need for great caution in interpreting results derived solely from reanalysis products. Given the heterogeneity of Vietnam's topography and the limitations inherent in each dataset, a targeted, index-specific or multi-dataset approach remains essential, particularly for applications involving extreme event detection and long-term climate risk assessment.

Overall, ERA5 stands out as the most reliable long-term reanalysis dataset for climate studies in Vietnam, offering the most consistent performance across both spatial scales and temporal metrics. Consequently, within the framework of GEMMES, a new gridded dataset for Vietnam covering the period from 1940 to the near-present period is being developed, with ERA5 serving as the background dataset (Nguyen-Xuan et al., 2025). It should be noted, however, that the number of stations used in this study is limited in southern Vietnam;

therefore, the results obtained in this study primarily apply to the Central and Northern regions of the country. Furthermore, our study focuses only on the period 1961–2010. Future research will extend the evaluation to the recent period (2010–2025) as well as to the years prior to 1961. The latter assessment can be carried out through comparisons with digitized station data obtained from archival sources in France and Vietnam, collected within the framework of the GEMMES Vietnam project Phase 2 (Thomas et al., 2025).

# Bibliography

**ADOM, P. K. (2024).** The socioeconomic impact of climate change in developing countries over the next decades: A literature survey. *Heliyon*, 10(15), e35134.

**BLACK, E. (2024).** Global Change in Agricultural Flash Drought over the 21st Century. *Advances in Atmospheric Sciences*, 41(2), 209–220.

**CALLAHAN, C. W., & MANKIN, J. S. (2022).** Globally unequal effect of extreme heat on economic growth. *Science Advances*, 8(43), eadd3726.

**COMPO, G. P., WHITAKER, J. S., SARDESHMUKH, P. D., MATSUI, N., ALLAN, R. J., YIN, X., GLEASON, B. E., VOSE, R. S., RUTLEDGE, G., BESSEMOULIN, P., BRÖNNIMANN, S., BRUNET, M., CROUTHAMEL, R. I., GRANT, A. N., GROISMAN, P. Y., JONES, P. D., KRUK, M. C., KRUGER, A. C., MARSHALL, G. J., ... WORLEY, S. J. (2011).** The Twentieth Century Reanalysis Project. *Quarterly Journal of the Royal Meteorological Society*, 137(654), 1–28.

**THOMAS, F., VU, Đ. L., CULAS, C., & PANNIER, E. (2021).** Climate change and adaptation in Viet Nam: Contributions from environmental history. In E. Espagne (Ed.), *Climate change in Viet Nam: Impacts and adaptation* (pp. 81–114). Paris: Agence Française de Développement. <https://www.afd.fr/en/ressources>

/climate-change-viet-nam-impacts-and-adaptation

**GU, L., SCHUMACHER, D. L., FISCHER, E. M., SLATER, L. J., YIN, J., SIPPEL, S., CHEN, J., LIU, P., & KNUTTI, R. (2025).** Flash drought impacts on global ecosystems amplified by extreme heat. *Nature Geoscience*, 18(8), 709–715.

**HU, Z., CHEN, X., ZHOU, Q., CHEN, D., & LI, J. (2019).** DISO: A rethink of Taylor diagram. *International Journal of Climatology*, 39(5), 2825–2832.

**IPCC (2021).** Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Masson-Delmotte, V., P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M.I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T.K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, and B. Zhou (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 2391 pp. doi:10.1017/9781009157896.

**JIANG, J., ZHOU, T., CHEN, X., & WU, B. (2021).** Central Asian Precipitation Shaped by the Tropical Pacific Decadal Variability and the Atlantic Multidecadal Variability. *Journal of Climate*, 34, 7541–7553.

**KENDALL, M.G. & GIBBONS, J.D. (1990).** Rank Correlation Methods (5th edition). Oxford University Press, 260 pp.

**KIM, Y.-H., MIN, S.-K., ZHANG, X., SILLMANN, J., & SANDSTAD, M. (2020).** Evaluation of the CMIP6 multi-model ensemble for climate extreme indices. *Weather and Climate Extremes*, 29, 100269.

**KUBOTA, H., KOSAKA, Y., & XIE, S.-P. (2016).** A 117-year long index of the Pacific-Japan pattern with application to interdecadal variability. *International Journal of Climatology*, 36(4), 1575–1589.

**KUBOTA, H., SHIROOKA, R., MATSUMOTO, J., CAYANAN, E. O., & HILARIO, F. D. (2017).** Tropical cyclone influence on the long-term variability of Philippine summer monsoon onset. *Progress in Earth and Planetary Science*, 4(1), 27.

**KUSUNOKI, S., OSE, T., & HOSAKA, M. (2020).** Emergence of unprecedented climate change in projected future precipitation. *Scientific Reports*, 10(1), 4802.

**LALOYLAUX, P., BALMASEDA, M., DEE, D., MOGENSEN, K., & JANSSEN, P. (2016).** A coupled data assimilation system for climate reanalysis. *Quarterly Journal of the Royal Meteorological Society*, 142(694), 65–78.

**LALOYLAUX, P., DE BOISSESON, E., & DAHLGREN, P. (2017).** CERA-20C: An

Earth system approach to climate reanalysis. *ECMWF newsletter*, 150, 25–30.

**LIEBERMAN, V., & BUCKLEY, B. (2012).** The impact of climate on Southeast Asia, circa 950–1820: New findings. *Modern Asian Studies*, 46(5), 1049–1096.

**LUO, M., WU, S., LAU, G. N. C., PEI, T., LIU, Z., WANG, X., ... & ZHANG, W. (2024).** Anthropogenic forcing has increased the risk of longer-traveling and slower-moving large contiguous heatwaves. *Science Advances*, 10(13), ead11598.

**MADAKUMBURA, G. D., THACKERAY, C. W., NORRIS, J., GOLDENSON, N., & HALL, A. (2021).** Anthropogenic influence on extreme precipitation over global land areas seen in multiple observational datasets. *Nature Communications*, 12(1), 3944.

**MANN, H.B. (1945).** Nonparametric tests against trend. *Econometrica*, 13, 245–259

**MANN, M. E., RAHMSTORF, S., KORNHUBER, K., STEINMAN, B. A., MILLER, S. K., & COUMOU, D. (2017).** Influence of Anthropogenic Climate Change on Planetary Wave Resonance and Extreme Weather Events. *Scientific Reports*, 7(1), 45242.

**NGUYEN, D.N. & NGUYEN, T.H. (2004).** Vietnamese climate and climatic resources, Hanoi Agriculture Press, Hanoi (in Vietnamese).

**NGUYEN, D. Q., RENWICK, J., & MCGREGOR, J. (2014).** Variations of surface temperature and rainfall in Vietnam from 1971 to 2010. *International Journal of Climatology*, 34(1), 249–264.

**NGUYEN-XUAN, T. ET AL. (2025).** Developing Gridded Datasets for Vietnam Using Reanalysis Data and Historical Station Observations Since the 1940s. *AFD Research Papers*, n°395.

**PETERSON, T., FOLLAND, C., GRUZA, G., HOGG, W., MOKSIT, A., & PLUMMER, N. (2001).** Report on the activities of the working group on climate change detection and related rapporteurs 1998–2001. WMO, WCDMP-47, WMO-TD 1071, Geneva, Switzerland, 143 pp.

**PHAM-THANH, H., NGO-DUC, T., MATSUMOTO, J., PHAN-VAN, T., & VO-VAN, H. (2020).** Rainfall Trends in Vietnam and Their Associations with Tropical Cyclones during 1979–2019. *Sola*, 16, 169–174.

**PHAM THI THANH, N., THI, T. D., DUUY, T. T., BA, K. T., THI PHUONG, H. N., VU-THANH, H., ... & TRINH-TUAN, L. (2024).** Characteristics of rainfall distribution induced by tropical cyclones using GSMaP data over the Vietnam region. *Journal of Water and Climate Change*, 15(8), 4001–4015.

**PHUNG, H. (2022).** Meteorology in Vietnam, Pre-1850. In Oxford Research Encyclopedia of Climate Science. <https://doi.org/10.1093/acrefore/9780190228620.013.835>

**POLI, P., HERSBACH, H., DEE, D. P., BERRISFORD, P., SIMMONS, A. J., VITART, F., ... & FISHER, M. (2016).** ERA-20C: An atmospheric reanalysis of the twentieth century. *Journal of Climate*, 29(11), 4083–4097.

**SEN, P. K. (1968).** Estimates of the Regression Coefficient Based on Kendall's Tau. *Journal of the American Statistical Association*, 63(324), 1379–1389.

**SUN, X., REN, G., YOU, Q., REN, Y., XU, W., XUE, X., ... & ZHANG, P. (2019).** Global diurnal temperature range (DTR) changes since 1901. *Climate Dynamics*, 52(5), 3343–3356.

**TAYLOR, K. E. (2001).** Summarizing multiple aspects of model performance in a single diagram. *Journal of geophysical research: atmospheres*, 106(D7), 7183–7192.

**THANH, T. D., SAITO, Y., HUY, D. V., NGUYEN, V. L., TA, T. K. O., & TATEISHI, M. (2004).** Regimes of human and climate impacts on coastal changes in Vietnam. *Regional Environmental Change*, 4(1), 49–62.

**THOMAS, F., NGO-DUC, T. & NGUYEN-NGOC-MINH, T. (2025).** The climate archives of Indochina – Insights for understanding climate change in Vietnam and Southeast Asia. *AFD Research Papers*, n°394.

**TRIPATHY, K. P., MUKHERJEE, S., MISHRA, A. K., MANN, M. E., & WILLIAMS, A. P. (2023).** Climate change will accelerate the high-end risk of compound drought

and heatwave events.

*Proceedings of the National Academy of Sciences*, 120(28), e2219825120.

**YUAN, X., WANG, Y., JI, P., WU, P., SHEFFIELD, J., & OTKIN, J. A. (2023).** A global transition to flash droughts under climate change. *Science*, 380(6641), 187–191.

**ZHANG, G., ZHANG, S., WANG, H., GAN, T. Y., FANG, H., SU, X., SONG, S., FENG, K., JIANG, T., HUANG, J., XU, P., & FU, X. (2024).** Biodiversity and Wetting of Climate Alleviate Vegetation Vulnerability Under Compound Drought–Hot Extremes. *Geophysical Research Letters*, 51(10), e2024GL108396.



# List of acronyms and abbreviations

## Reanalysis Datasets

<b>20CR</b>	20th Century Reanalysis
<b>CERA-20C</b>	Coupled ECMWF Reanalysis of the 20th Century
<b>ERA-20C</b>	ECMWF Reanalysis of the 20th Century
<b>ERA5</b>	ECMWF Reanalysis v5

## Meteorological Agencies & Programs

<b>AFD</b>	Agence française de développement
<b>ETCCDI</b>	Expert Team on Climate Change Detection and Indices
<b>VNHMA</b>	Vietnam National Hydro-Meteorological Administration
<b>WNP</b>	Western North Pacific

## Statistical & Skill Metrics

<b>DISO</b>	Discriminatory Skill Score Index
<b>MAPE</b>	Mean Absolute Percentage Error
<b>NMAE</b>	Normalized Mean Absolute Error
<b>NSTD</b>	Normalized Standard Deviation
<b>NRMSE</b>	Normalized Root Mean Square Error
<b>RSTD</b>	Relative Standard Deviation



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