PLOS Climate

RESEARCH ARTICLE

Regional heterogeneity and warming dominance in the United States

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Citation: Rivas MDG, Gonzalo J (2026) Regional heterogeneity and warming dominance in the United States. PLoS Clim 5(2): e0000808. https://doi.org/10.1371/journal.pclm.0000808

Editor: Ahmed Kenawy, Mansoura University, EGYPT

Received: July 30, 2025

Accepted: December 12, 2025

Published: February 4, 2026

Peer Review History: PLOS recognizes the benefits of transparency in the peer review process; therefore, we enable the publication of all of the content of peer review and author responses alongside final, published articles. The editorial history of this article is available here: https://doi.org/10.1371/journal.pclm.0000808

Abstract

Climate change exhibits substantial variability across both space and time, requiring mitigation and adaptation strategies that effectively address challenges at global and local scales. Accurately capturing this variability is essential for assessing climate impacts, attributing underlying causes, and formulating effective policies. This study introduces simple yet robust quantitative methods to detect local warming, distinguish among different types of warming, and compare warming trends across contiguous U.S. states using the concept of warming dominance. In contrast to traditional approaches that focus solely on average temperatures, our analysis rigorously and systematically examines the entire distribution of daily temperatures for the contiguous United States from 1950 to 2021. The results reveal that, while 44% of states show no statistically significant warming based on average temperature trends, a much larger proportion—84%—exhibit warming when assessing various quantiles of the distribution. Statistical significance is evaluated using HAC-robust *t*-tests at the 5% significance level (95% confidence), ensuring that detected warming reflects genuine shifts rather than random variability. These findings underscore the substantial heterogeneity in warming patterns: some states, such as those located in the so-called "Warming Hole," display no evidence of warming at any quantile; others experience more pronounced warming in either the lower or upper tails of the temperature distribution; and a few states show consistent warming across all quantiles. The study concludes by identifying which states exhibit warming dominance over others and which appear comparatively less affected. These insights are particularly important in the United States, where climate policy is formulated and implemented at both federal and state levels.

1 Introduction

Climate change is a complex and multifaceted phenomenon with impacts that vary widely across different regions. Although the climate system functions on a global scale, its effects are experienced locally, resulting in significant regional variability.

Data availability statement: All data used in this study are publicly available. The raw temperature data were obtained from publicly accessible sources as detailed in the manuscript. The full set of processed datasets used in the empirical analysis, including intermediate files required to reproduce the results, are provided as Supporting Information (S1 Data). The MATLAB codes used to clean, transform, and process the raw data, as well as the scripts used to generate all tables and figures, are available from the corresponding author upon reasonable request and will also be made available on the author's academic webpage. The MATLAB codes used to clean, transform, and process the raw data into the analytical datasets, as well as the scripts used to generate all tables and figures in the manuscript, are available upon reasonable request from the corresponding author and will also be made available on the author's personal academic webpage.

Funding: Gobierno de Aragón and European Regional Development Fund (ERDF, EU), grant LMP71-18 — received by MDG. Agencia Española de Investigación (MCIN/AEI/10.13039/501100011033) and ERDF, grants PID2020-114646RB-C44 (MDG), PID2023-147593NB-I00 (JG), PID2023-150095NB-C44 (MDG), RED2022-134122-T (LG, JG). MCIN/AEI and European Union NextGenerationEU/PRTR, grant TED2021-129784B-I00 — received by MDG and JG. MCIN/AEI, grant CEX2021-001181 (María de Maeztu) — received by JG. Comunidad de Madrid, grants EPUC3M11 and V PRICIT — received by JG. The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

Competing interests: The authors have declared that no competing interests exist.

These localized impacts affect numerous sectors such as real estate, agriculture, tourism, public health, income distribution, and the frequency of extreme weather events and natural disasters. Moreover, public perceptions and psychological responses to climate change are deeply influenced by these region-specific experiences. Despite the extensive body of climate change research, focused and systematic examination of its regional differences remains relatively recent, with a limited number of studies explicitly addressing this important heterogeneity.

This study introduces a quantitative methodology designed to describe and compare the warming processes experienced by different regions and states across the contiguous United States. For the purposes of this analysis, we use the terms Climate Change (CC) and Warming (W) interchangeably, defining warming as a positive trend in temperature data [1]. Focusing specifically on temperature trends—a key climate variable central to decision-making and a primary indicator of climate change—we produce robust results that remain valid even in the presence of common statistical misspecifications such as heteroskedasticity and serial correlation, provided these issues are less pronounced than the underlying trend.

From a physical-climate perspective, spatial differences in warming arise from well-documented mechanisms such as atmospheric circulation patterns, land–ocean thermal contrasts, and feedback processes involving snow and ice cover, precipitation and hydrological-cycle dynamics, and soil moisture e.g., [2–8]. Regional amplification effects, particularly in high-latitude regions and continental interiors, are closely linked to changes in atmospheric circulation regimes and surface-albedo feedbacks [9,10]. In the contiguous United States, these processes contribute to distinct regional responses, with the so-called "Warming Hole" in the Southeast often attributed to aerosol forcing, cloud feedbacks, and ocean–atmosphere interactions [11,12]. Integrating such physical insights with statistical methods enables a more comprehensive characterization of regional climate dynamics and provides a bridge between empirical detection and physical interpretation of observed trends.

Our novel methodology not only reproduces well-established findings, thereby confirming its validity, but also reveals previously hidden patterns by examining the full distribution of temperature data. This dual capability underscores both its reliability and added analytical value. Additionally, the method is easy to apply, robust under various data conditions, and yields interpretable outputs, making it a valuable tool for both researchers and policymakers. A critical aspect of our approach challenges the traditional focus of many climate change studies, which predominantly emphasize shifts in average temperature while overlooking important insights found within the entire warming process. By analyzing the full temperature distribution—including both lower (left-tail) and upper (right-tail) quantiles—we provide a broader and more comprehensive understanding of warming patterns. This distributional perspective aligns with methodologies commonly used in other fields, such as income distribution research, where analyzing the full distribution is standard practice.

This approach complements recent contributions that extend climate analysis beyond mean temperature and toward changes in the full distribution. For instance, [13] test for shifts in the entire probability density of temperature, while [14] apply quantile trend regression to identify heterogeneous slopes across the quantiles of the mean temperature process. The former requires relatively long temporal windows (e.g., 30 years) to estimate densities, which can be problematic when temperature records exhibit non-stationarity, whereas the latter focuses on the conditional mean process rather than the unconditional distribution assessed in our study. [15] conceptualize climate as a continuously evolving distribution and provide graphical assessments of relative changes across quantiles and geographical locations, but without formal statistical testing. Meanwhile, [16] use multidimensional ensemble empirical mode decomposition (MEEMD) to isolate oscillatory components from long-term warming trends in gridded temperature fields, enhancing regional comparisons of warming and its acceleration; however, MEEMD does not readily allow statistical comparison of full distributions or identification of distinct warming patterns within regions.

In line with this broader framework, we introduce the concept of Warming Dominance (WD), a tool for assessing and comparing the intensity and characteristics of warming across geographic areas. WD provides a complementary diagnostic structure that is informative for climate adaptation, mitigation, and compensation strategies, offering a refined basis for policy-relevant assessments. Related tools—such as the Synthetic Warming Dominance Index and the Pareto-dominance framework—further enhance interpretability and cross-regional comparability when there are many regions.

Our recommendation is to combine the numerical WD method with existing visual tools, such as the IPCC WGI Interactive Atlas [17], the Copernicus Climate Atlas (C3S) [18], and NOAA's Climate at a Glance platform [19]. These platforms offer spatially resolved visualizations of climate indicators, and integrating them with the WD approach strengthens both the interpretability and practical relevance of our findings.

The remainder of the paper is structured as follows: Sect 2 details the data and methodology, Sect 3 presents the empirical results for U.S. states, and Sect 4 discusses the methodological and policy implications. Sect 5 summarizes the main findings and outlines directions for future research. References and an appendix (S1 Appendix in complementary material) conclude the paper.

2 Data and methods

2.1 Data

We use a panel dataset of county-level daily mean temperatures for the 48 contiguous U.S. states over the period 1950–2021. (Alaska and Hawaii are excluded. Although the District of Columbia is included in the original dataset, it is excluded from the main analysis due to limited data availability. State-level data are constructed by aggregating county-level observations using land and water area weights. For 1950–2019, we rely on PRISM-based gridded temperature data compiled by Wolfram Schlenker (http://www.columbia.edu/~ws2162/links.html). For 2020–2021, we extend the series using recent PRISM data and land cover information from the NLCD 2019 dataset, constructing cropland-weighted county-level averages. We thank Seunghyun Lee and Aaron Smith (ARE Department, UC Davis) for assistance with data preparation.) After harmonizing data sources and aggregating to the state level, we obtain a balanced panel with 26,298 daily observations per state. Each state-level series is denoted by $Temp^{i}_{jd}$, where i indexes the state, j the year, and d the day. This structure allows us to compute time series of temperature distribution characteristics at the annual level for each state. (The dataset is publicly available and can be downloaded from https://www.aaronsmithagecon.com/download-us-weather-data (see [20]).)

The PRISM-based dataset ensures high spatial representativeness by combining dense station coverage in populated areas with robust interpolation algorithms in sparsely monitored regions. This design minimizes the potential bias arising from uneven spatial sampling, allowing for consistent state-level aggregation across the entire U.S. mainland. The resulting distributions capture genuine climatic heterogeneity rather than artifacts of data density or measurement coverage. This approach follows the principles established in [1], where an analogous methodology was applied to the Central England using a high-frequency station network to quantify changes in temperature distributions.

In addition, the quantile-based design of the analysis inherently enhances robustness by reducing sensitivity to data coverage and to changes in the number or spatial distribution of weather stations over time.

2.2 Statistical methods

In [1] (GG2020), we define Global Warming (GW) as the presence of an increasing trend in temperature data, expanding the analysis beyond the mean, as commonly done in the literature, to include the entire temperature distribution. The core of this methodology involves treating observed quantiles as representative of the temperature distribution for a given region or the globe. From cross-sectional data, we calculate annual unconditional quantiles and other distributional characteristics, which are then automatically transformed into time-series objects suitable for statistical analysis. We define $C_t = (C_{1t}, C_{2t}, ..., C_{pt})$ as a vector of p distributional characteristics (mean (m), interquartile range (iqr), and the following quantiles: $q05$, $q10$, $q20$, $q30$, $q40$, $q50$, $q60$, q70, $q80$, $q90$, and $q95$ estimated from D days (typically 365) for each state and year. Based on this framework, we test for the presence of a trend in any distributional characteristic of the temperature distribution.

Definition 1. *(Practical definition): A characteristic C_t of a functional stochastic process X_t contains a trend if in the least square regression,*

$$C_t = \alpha + \beta t + u_t,\ t = 1, ..., T, \tag{1}$$

$\beta = 0$ is rejected.

Several remarks are relevant with respect to this definition: (i) regression (1) has to be understood as the linear LS approximation of an unknown trend function $h(t)$ (see [21]); (ii) the parameter β is the *plim* of $\widehat{\beta}_{ols}$; (iii) if the regression (1) is the true data-generating process, with $u_t \sim I(0)$, then the OLS $\widehat{\beta}$ estimator is asymptotically equivalent to the GLS estimator (see [22]) and the $t-test(\beta = 0)$ is *N(0,1)*; (iv) in practice, in order to test $\beta = 0$, it is recommended to use a robust HAC version of $t_{\beta=0}$ (see [23]); and (v) this test only detects the existence of a trend but not the type of trend.

For all these reasons, in the empirical applications we implement definition 1 by estimating regression (1) using OLS and constructing a HAC version of $t_{\beta=0}$ ([24])).

It is important to emphasize that this test assesses only the presence or absence of a trend, without identifying its specific form. The procedure described in GG2020 is capable of detecting a wide range of trend types commonly discussed in the literature, including polynomial, logarithmic, and stochastic trends. To determine the precise nature of the trend, as outlined in [25], we recommend conducting an out-of-sample forecast competition among various trend specifications and selecting the model that demonstrates the best predictive performance. In this study, we adopt equation (1) as a linear approximation of the underlying, potentially unknown trend. This approach enables both comparisons of warming processes across states and a detailed analysis of the warming trajectory within individual states. (An alternative and noteworthy definition of trend is presented in [26]. This approach is primarily intended for detrending the data, rather than for comparing different warming processes.)

This approach has enormous strength and is the starting point for the development of powerful tools that allow us to approach a better understanding of key climate change issues such as causes, consequences and prediction in the long run. For instance, we can easily analyze the trend behavior of the different distributional characteristics and not only of the mean to detect and define different types of warming processes, establishing a typology:

Definition 2. *(Warming Typology): Applying least square regression 1 to each of the characteristics, define four types of warming processes:*

- **W0**: *There is no trend in any of the quantiles (No warming).*

- **W1**: *All the location distributional characteristics have the same positive trend (dispersion does not contain a trend)*
- **W2**: *The Lower quantiles have a larger positive trend than the Upper quantiles (dispersion has a negative trend)*
- **W3**: *The Upper quantiles have a larger positive trend than the Lower quantiles (dispersion has a positive trend).*

It should be noted that this classification has a dynamic nature: it is based on the evolution of the trend of the temperature quantiles, lower and upper [27]. It is a complement, therefore, to other classical classifications such as that of [28] and [29] or the proposal of [30] for the US.

In the previous definitions, we classify the warming process of different regions which is crucial in the design of local mitigation and adaptation policies. But we, also, need to compare the different climate change processes of two regions in order to characterize climate heterogeneity independently of the type of warming they are experimenting. For this purpose, we propose the following definitions that share the spirit of the stochastic dominance concept used in the economic-finance literature.

Definition 3. *(Warming Dominance in the mean (WDm): We say that the temperature distributions of **Region A** warming dominates (WD) the temperature distributions of **Region B** if in the following least square regression*

$$m_t(A) - m_t(B) = \alpha + \beta t + u \tag{2}$$

$\beta > 0$.

Warming dominance in mean is the standard approach to compare the warming processes of two regions. In many occasions this dominance does not offer a full comparison of both warming processes. It has the limitation that the average of a distribution has. Two regions could suffer an equivalent warming process in mean but one dominates the other in some of the quantiles. For this reason, we propose the following definition of warming dominance in distribution.

Definition 4. *(Warming Dominance (WD): We say that the temperature distributions of **Region A** warming dominates (WD) the temperature distributions of **Region B** if in the following regression*

$$q_{\tau t}(A) - q_{\tau t}(B) = \alpha_\tau + \beta_\tau t + u_{\tau t}, \tag{3}$$

$\beta_\tau \geq 0$ *for all* $0 < \tau < 100$ *and there is at least one value* τ^* *for which a strict inequality holds.*

Several remarks are relevant with respect to the two previous definitions: (i) In regression (3), under the null hypothesis of no dominance at quantile τ, the test statistic t-stat $= \widehat{\beta_\tau}/\sigma_{\text{HAC}}(\widehat{\beta_\tau})$ is asymptotically distributed as $\mathcal{N}(0, 1)$, where σ_{HAC} denotes the heteroskedasticity- and autocorrelation-consistent (HAC) standard error of $\widehat{\beta_\tau}$; (ii) The test is robust to any trend detectable under regression (1), for instance, the quantiles could contain a non-liner trend component; (iii) *Warming Dominance* (WD) can be classified as strong or weak depending on whether $\beta_\tau > 0$ for all τ, or only for some quantiles; (iv)*WD* can also be partial—for instance, present only in the lower or upper quantiles.

3 Quantitative results

As an initial exploration of climate characteristics by state, Fig 1 presents the U.S. climate regions as defined by the National Centers for Environmental Information (NCEI, Karl and Koss, 1984). This classification delineates up to nine distinct climate regions, which will later be compared to the typology derived from our methodology. Based on climatological analyses of the period 1895–1983, this classification considers the temporal and spatial distributions of temperature and precipitation across groups of contiguous states using principal component analysis techniques. Additionally, it provides

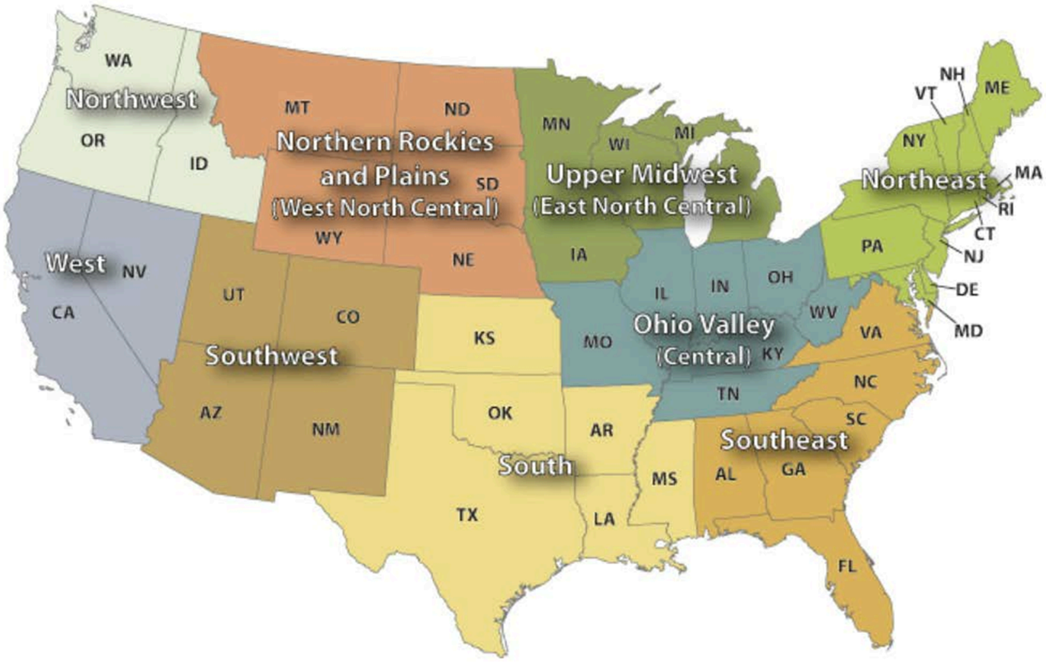

Fig 1. **Climate areas in the U.S. (NCEI, Karl and Koss, 1984).** Base layer: U.S. Census Bureau, Cartographic Boundary Files — States (public domain). *Source:* https://www.census.gov/geographies/mapping-files/time-series/geo/carto-boundary-file.html.

https://doi.org/10.1371/journal.pclm.0000808.g001

descriptive temporal data on maximum, minimum, mean, and standard deviation values, as well as the 5th and 95th quantiles and seasonal variations for each area. This classification is valuable for placing current climate anomalies in historical context and shares certain features with our approach, though the primary distinction lies in the dynamic components incorporated into the latter.

More recently, the National Commission for US National Climate Assessment has been considering and adjusting the regional boundaries in 4-year increments for at least a decade. Its most recent report identifies eight climate regions, as illustrated in Fig 2. This institution, through the US Global Change Research Program, assesses the science of climate change and its impacts across the United States, both in the present and throughout the century. It systematically documents the effects of climate change and the corresponding responses across various sectors and regions, aiming to enhance public and private decision-making at all levels. Our work contributes to this discussion by providing quantitative testable tools for analysis, offering a data-driven perspective to support informed policy development.

Next, we present the average temperature trends for each state over the period considered (Fig 3). This figure shows that some states exhibit a clear upward trend in temperature, such as California, while others, like Oklahoma, show little to no discernible trend.

Building on the preliminary descriptive analysis, we now implement the methodology outlined above. We test for the presence of statistically significant trends as evidence of climate change. These results then form the basis for constructing a typology of climate change across states and for evaluating the presence of Warming Dominance.

3.1 Warming existence

In this section, we apply the trend test defined in (1) to both the mean and selected quantiles to assess the presence of warming. (As a preliminary analysis, we test all quantiles for the presence of a unit root using the Augmented Dickey-Fuller test, [31], with a constant and trend, selecting lag length via the Schwartz Information Criterion (SBIC).

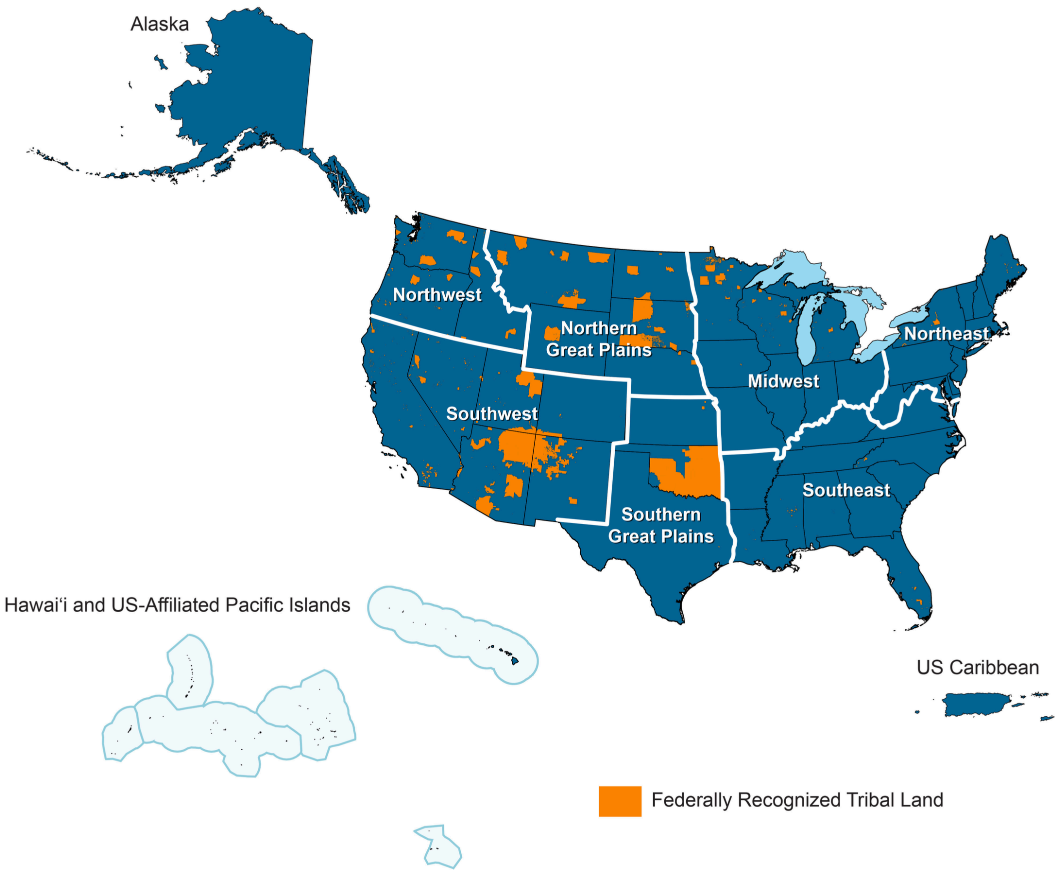

Fig 2. Climate areas in the U.S. (National Climate Assessment, 2023, Fifth Report). *Source*: Adapted from the Fifth U.S. National Climate Assessment (2023). Public-domain material (U.S. Government Work). No permission required. URL: https://nca2023.globalchange.gov/regions.

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Results—available upon request—consistently reject the null hypothesis of a unit root across all quantiles and states.) The results provide the empirical basis for the typology developed in the following section. Detailed estimates are reported in Table AI-1 in S1 Appendix, while Figs 4 and 5 display the estimated coefficients and corresponding *t*-ratios for four key distributional characteristics: the mean, interquartile range (*iqr*), and quantiles (*q05*) and (*q95*). In addition, maps (in Figs 6, 7 and 8) classify states according to the significance of warming trends for the three characteristics mentioned above.

The first conclusion is the significant heterogeneity in temperature distribution. For the most commonly studied characteristic—the average—we find positive, and widely significant, slopes ranging from 0.022 to 0.0007, and even a negative slope of –0.0006, although not significant, in the case of Oklahoma. The highest and significant slopes are observed in Rhode Island, Arizona, Connecticut, and California, while the lowest are in Wisconsin and Michigan. The heterogeneity is even more pronounced when we examine the *iqr*, which measures the dispersion of the temperature distribution although in most of the states it does no contain a significant trend. Here, we find both positive values (indicating a widening distribution) and negative values (indicating a shrinking distribution). For example, states like Nevada, Oregon, and California exhibit widening distributions, while shrinking distributions are not significant.

For *q05*, which measures trends in lower temperatures, values are always positive but exhibit a wide range of variation although is only significant in 10 of the 48 states analyzed. For instance, and focusing only on significant trends, values

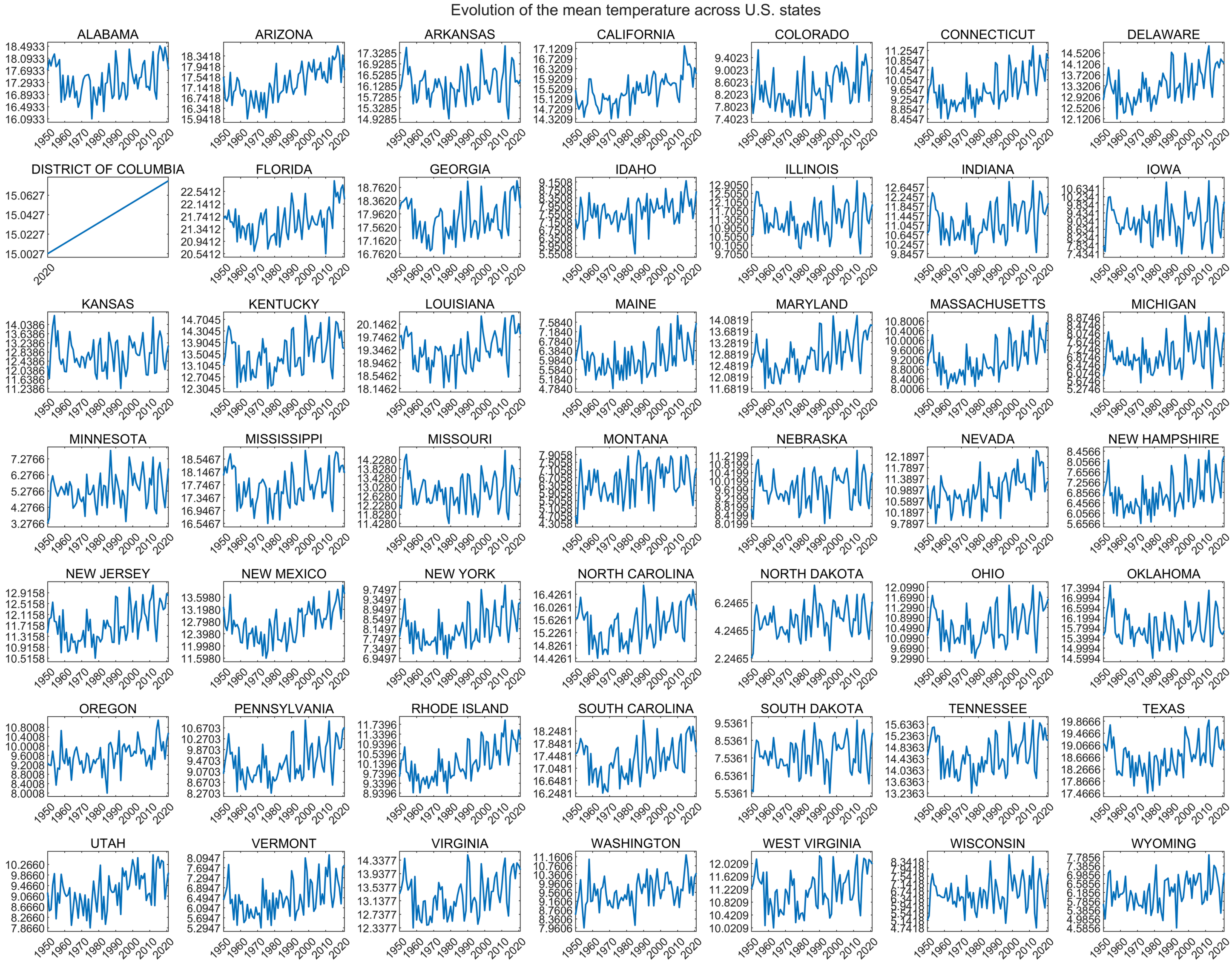

Fig 3. **Evolution of the mean temperature across contiguous U.S. states (1950–2021).** *Source*: Own elaboration from PRISM state-level temperature series (see Sect 2 for data description). Figure generated with MATLAB (R2024b). Each panel shows the annual mean temperature (°C) for one U.S. state, illustrating both the long-term upward trend and the regional heterogeneity of warming.

https://doi.org/10.1371/journal.pclm.0000808.g003

hover around 0.03 in North Dakota, Montana, Minnesota, and South Dakota, but are much lower in Nevada, Oregon and New Mexico. Regardless of the range, a consistent pattern emerges: lower temperatures exhibit a clear upward trend to varying degrees.

This pattern, however, does not hold for *q95*, which tracks trends in higher temperatures where significant trends are found in half of the states studied. In states like Rhode Island, Oregon, Washington, and Massachusetts, higher temperatures have increased by more than 0.02, while in other states, such as North and South Dakota, the trend is downward.

Beyond evaluating the coefficient values that indicate trend magnitudes, it is essential to assess their statistical significance as defined by the model equation. The table presents detailed results, including p-values for these tests. Notably, the most significant trends appear in *q95*, even in those cases where no warming is detected in the mean, indicating that

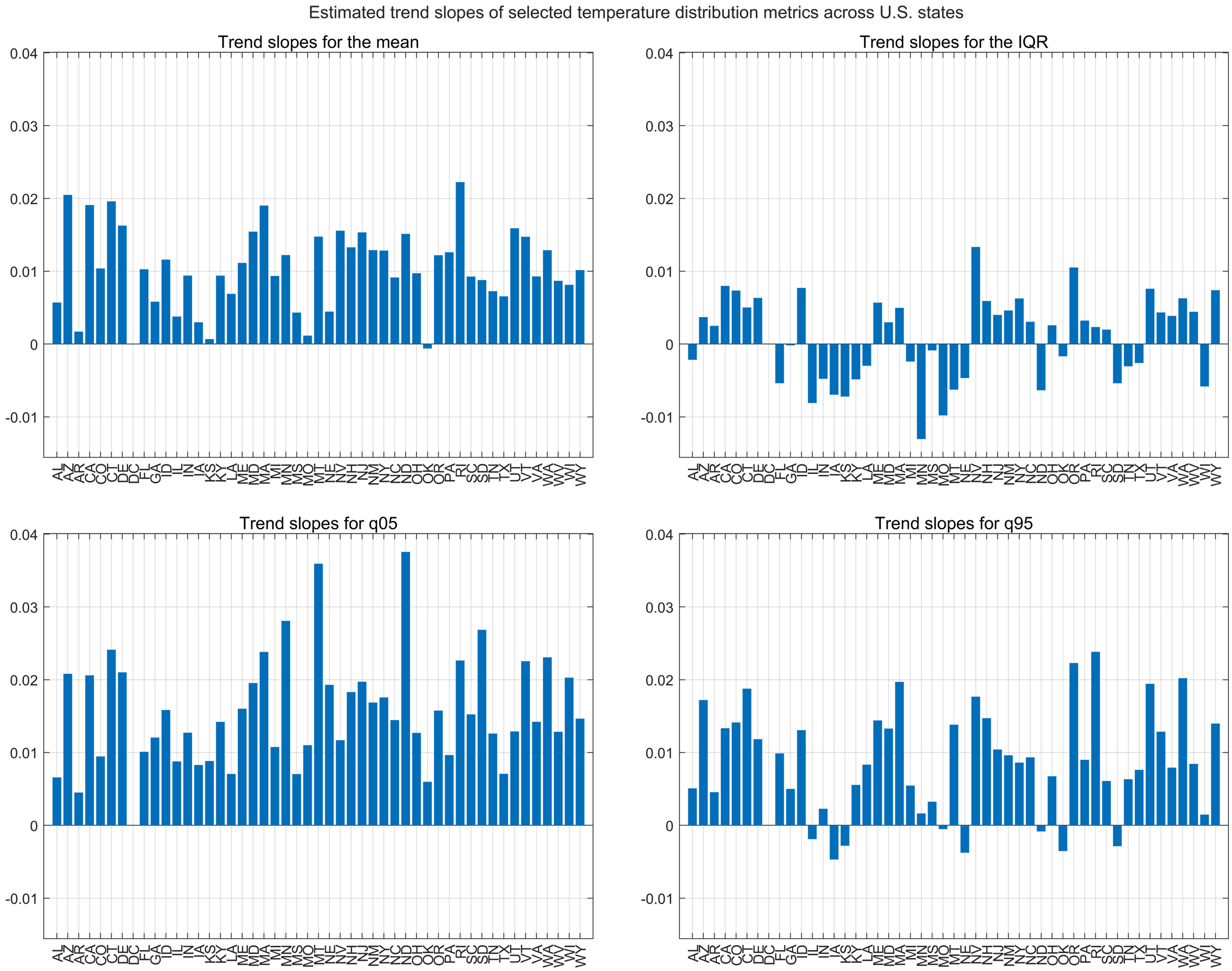

Fig 4. **Trend slopes of representative distributional characteristics across U.S. states (1950–2021).** *Sources*: Own elaboration from PRISM state-level temperature series (see Sect 2). Figure generated with MATLAB (R2024b). The panels show the estimated linear trend coefficients for the mean, the interquartile range (IQR), the lower tail (q_{05}), and the upper tail (q_{95}) of the temperature distribution across U.S. states.

https://doi.org/10.1371/journal.pclm.0000808.g004

the most intense warming occurs in the right tail of the distribution, corresponding to the highest temperatures. Additionally, the accompanying figures and maps visually summarize key characteristics, such as the *mean*, *q05*, and *q95*.

The importance of going beyond the average is clearly illustrated by the following figures which summarize the above information. The trend in the mean is significant in only 27 of the 49 states (55%). However, 41 of them (84%) show positive and significant trends in AT LEAST one of the quantiles of the distribution.

3.2 Typology of warming processes

Based on the previous results, we aim to establish a typology of climate change for different states. To achieve this, and following the definitions outlined in Sect 2.2, we developed an algorithm comprising the following steps:

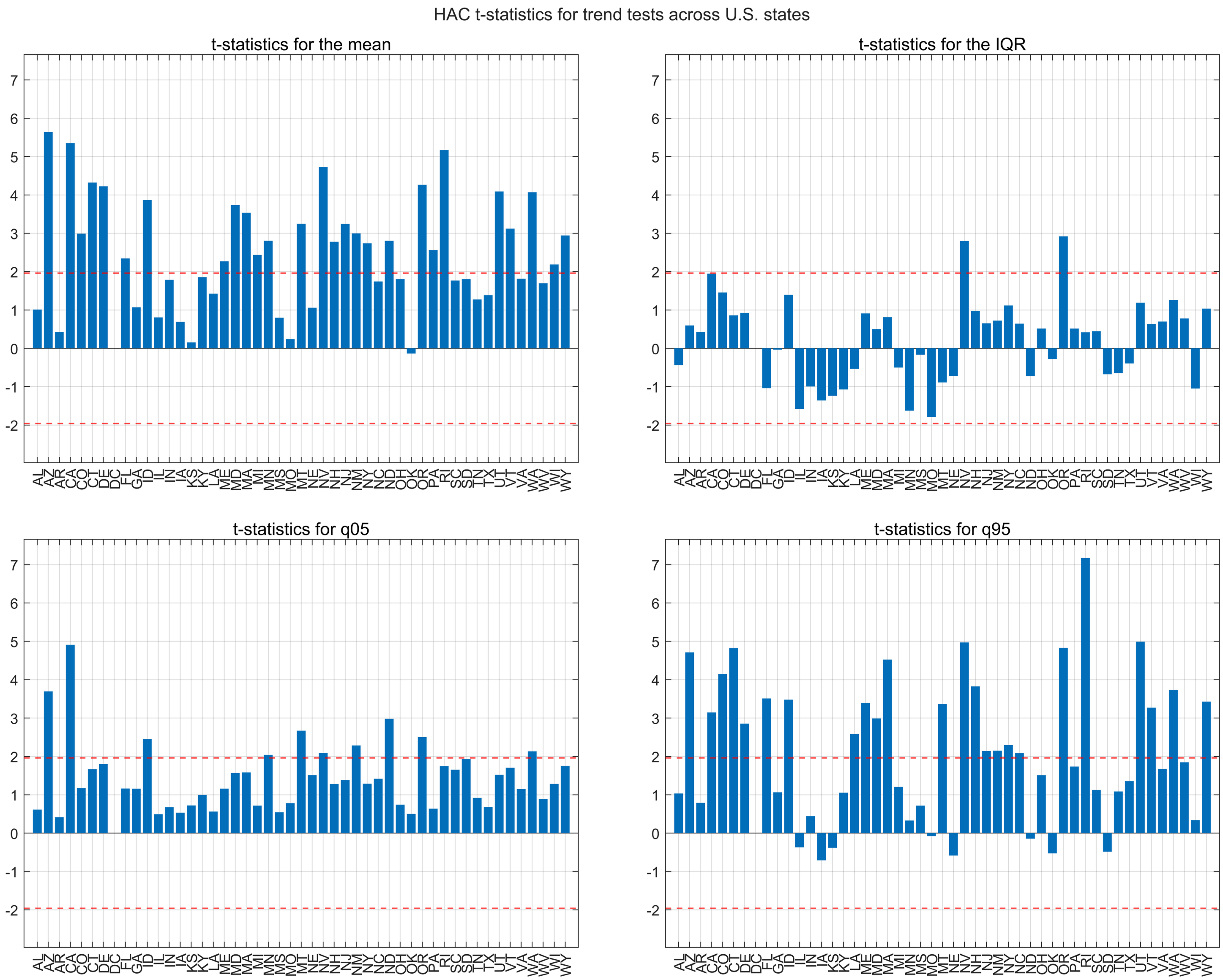

Fig 5. **T-statistics for trend tests of representative distributional characteristics.** *Sources*: Own elaboration from PRISM state-level temperature series (see Sect 2). Figure generated with MATLAB (R2024b). Red horizontal lines mark the 5% two-sided critical values (±1.96).

https://doi.org/10.1371/journal.pclm.0000808.g005

1. Test for the existence of warming: We employ a Wald test to evaluate the null hypothesis that no statistically significant trend exists in a panel consisting of quantiles from *q05* to *q95*. If this hypothesis cannot be rejected, the state is classified as type *W0* and the algorithm stops.
2. If the previous hypothesis is rejected, indicating warming at some quantile, we analyze the sign and significance of the difference between the lower and upper quantiles, along with the interquartile range (*iqr*):
   - We carry out the following tests for each state i:

     $$q05_{t,i} - q95_{t,i} = \alpha_1 + \beta_{1,i}t + u_{1,i,t}$$
     $$q10_{t,i} - q90_{t,i} = \alpha_2 + \beta_{2,i}t + u_{2,i,t}$$

     and check if $\beta_{1,i}$ or $\beta_{2,i}$ are significant and, in this case, positive or negative.

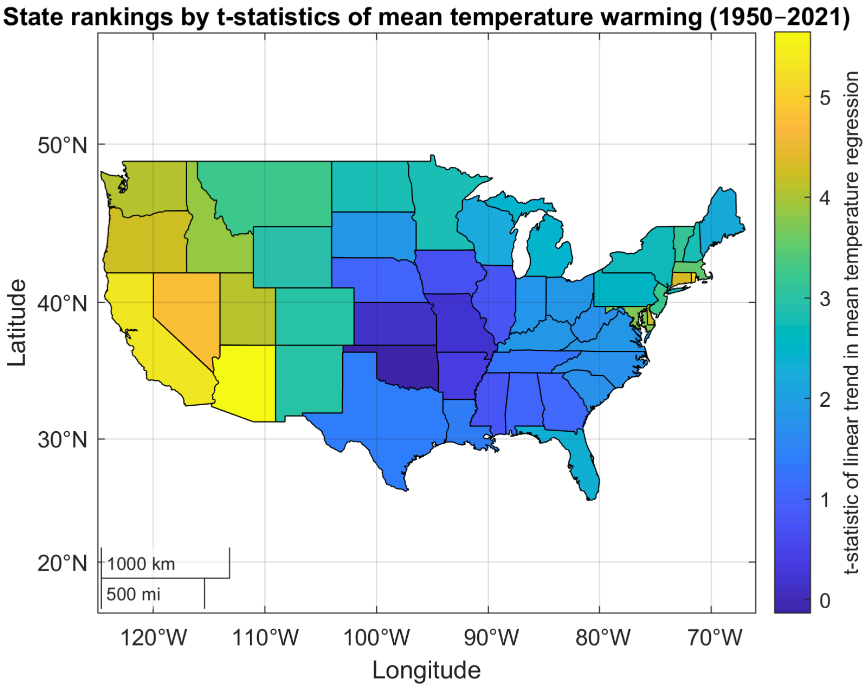

Fig 6. State rankings by HAC-based *t*-statistics of mean temperature warming across U.S. states (1950–2021). *Sources*: Own elaboration from PRISM state-level temperature series (see Sect 2). Map generated with MATLAB (R2024b, Mapping Toolbox); no additional permissions required beyond software citation. Colours represent the HAC-based *t*-statistic of the linear trend in mean temperature for each state. Cooler (bluer) shades indicate weaker or statistically insignificant warming signals (lower *t*-statistics), whereas warmer (green to yellow) shades indicate stronger statistical evidence of warming (higher *t*-statistics). Negative values, where present, correspond to cooling trends.

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- We study the sign significance of the trend coefficient of *iqr=q75-q25*.
- To establish typology, we use a conservative level of significance of 10%.

3. Based on the possible combinations of these results (a total of 27), the following typology is established. Note that some undefined cases can occur.

According to our analysis, climate change in mean is evident in 55% of contiguous U.S. states. However, the temperature distribution across these states is highly heterogeneous. When examining the distribution as a whole, we reject the null hypothesis of no warming ($W0$) in 84% of the states. This indicates that while almost half of the states do not exhibit global warming in the mean, they do show significant trends in specific parts of the temperature distribution. These findings underscore the importance of considering the entire distribution of temperatures rather than focusing solely on average values, and suggest the need for a typology that takes all aspects into account.

The results are presented in Figs 9 and 10. The first map shows the states in which no statistically significant trend is detected across the quantiles, leading to the assumption that no warming is present. These states include Alabama, Arkansas, Illinois, Kansas, Mississippi, Missouri, Oklahoma, and Texas. It is worth noting that most of these states are located within the Southern climate zone, which corresponds to a large extent to the so-called "Warming Hole" (see, for instance [32]. The warming hole over the Southern described by [33] is clear in our analysis. [34] and [35] noted that the Southern has experienced the smallest temperature increase in recent years. In our study, we do not find any trend in any of the quantiles of the temperature distribution of most of the states in the Southern, with the exception of Florida. [36] identified the Southern as one of the few places in the world displaying an overall cooling trend hence describing

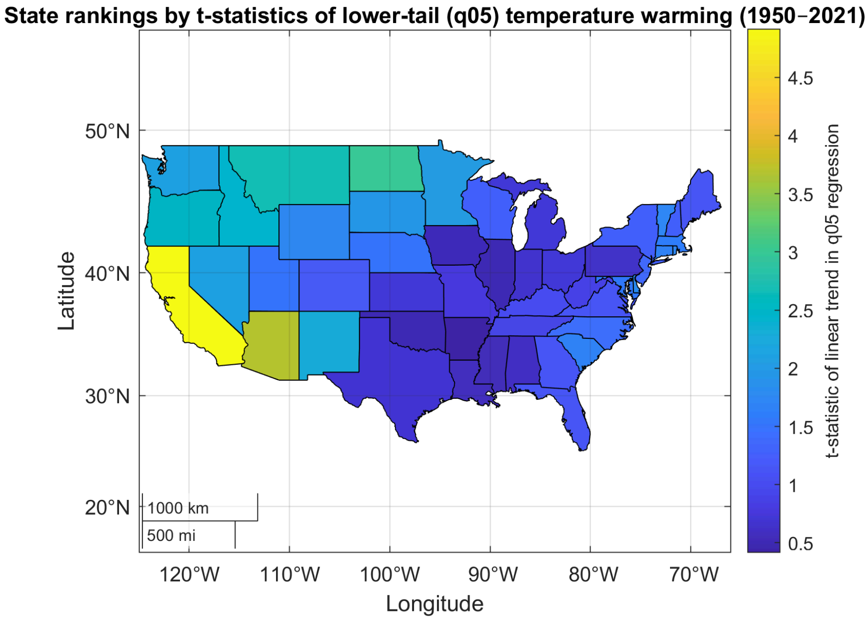

Fig 7. **State rankings by HAC-based *t*-statistics of lower-tail (q_{05}) temperature warming across U.S. states (1950–2021).** *Sources*: Own elaboration from PRISM state-level temperature series (see Sect 2). Map generated with MATLAB (R2024b, Mapping Toolbox); no additional permissions required beyond software citation. Colours represent the HAC-based *t*-statistic of the linear trend in the 5th percentile (q_{05}) of the temperature distribution for each state. Cooler (bluer) shades indicate weaker or statistically insignificant warming in the lower tail (lower *t*-statistics), whereas warmer (green to yellow) shades indicate stronger statistical evidence of lower-tail warming (higher *t*-statistics). Negative values, where present, correspond to cooling trends in the lower tail.

https://doi.org/10.1371/journal.pclm.0000808.g007

the Southern as a warming hole. They attributed the warming hole to land-atmosphere interaction. But [33] attributed it to the decadal and multidecadal variabilities linked to the Atlantic and Pacific Oceans.

The second figure presents the typology for all states and reveals some noteworthy patterns. The types are not uniformly distributed across the contiguous U.S., but rather concentrated in specific regions. For instance, **Type W3** states are located along the West Coast, including California, Idaho, Nevada, Oregon, Washington, and Wyoming. This type of warming is characterized by a greater increase in higher temperatures than in lower temperatures, resulting in a positive trend in the *iqr*. This pattern corresponds to the West and parts of the Northwest climate zones.

In contrast, **Type W2**, characterized by a larger increase in lower quantiles relative to higher quantiles and a negative trend in the *iqr*, is primarily found in the Central North region, roughly corresponding to the Northern Rockies and Plains West NW Central area. This includes states such as Iowa, Minnesota, Montana, Nebraska, and North and South Dakota.

Finally, states in the **Type W1** category, located in the Upper Midwest (East North Central), parts of the Northwest, and the Northeast, exhibit similar trends across all quantiles, with no statistically significant trend observed in the *iqr*.

Two final remarks. When aggregating data from all states, weighted by surface area, the overall trend for the contiguous U.S. can be classified as warming Type *W1*. (For the Globe as a whole, a *W2* type is obtained (see [27]).) This indicates that the trends across the quantiles of the distribution are similar, with no statistically significant trend observed in the interquartile range (*iqr*). Additionally, there is evidence of acceleration in these trends. For instance, an analysis of typology over the period 1990–2021 reveals that the proportion of states experiencing warming has increased to 87%, with a notable rise in Type *W3* states, which now represent 43% of the total. As regard to the average, it can also be seen that the number of states where it is significant increases as we approach the end of the sample.

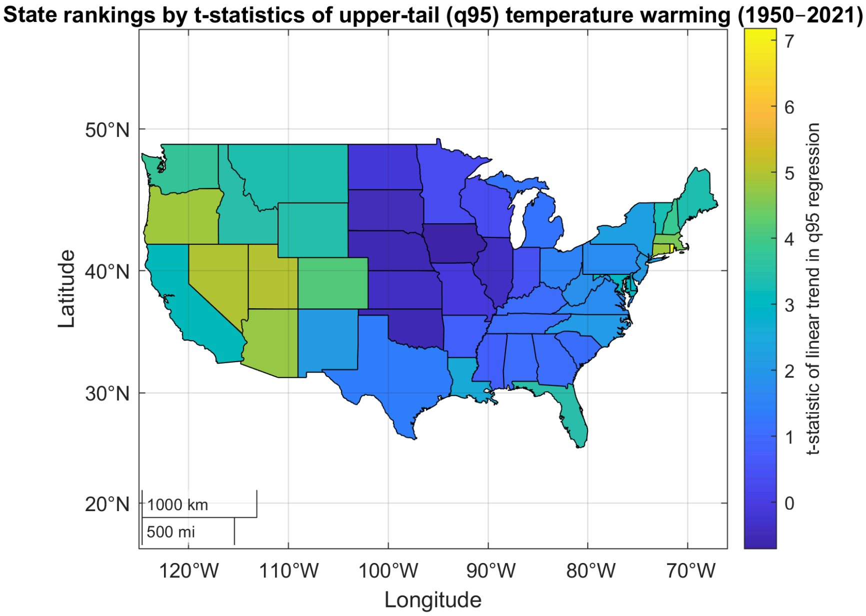

Fig 8. State rankings by HAC-based *t*-statistics of upper-tail (q_{95}) temperature warming across U.S. states (1950–2021). *Sources*: Own elaboration from PRISM state-level temperature series (see Sect 2). Map generated with MATLAB (R2024b, Mapping Toolbox); no additional permissions required beyond software citation. Colours represent the HAC-based *t*-statistic of the linear trend in the 95th percentile (q_{95}) of the temperature distribution for each state. Cooler (bluer) shades indicate weaker or statistically insignificant warming in the upper tail (lower *t*-statistics), whereas warmer (green to yellow) shades indicate stronger statistical evidence of upper-tail warming (higher *t*-statistics). Negative values, where present, correspond to cooling trends in the upper tail.

https://doi.org/10.1371/journal.pclm.0000808.g008

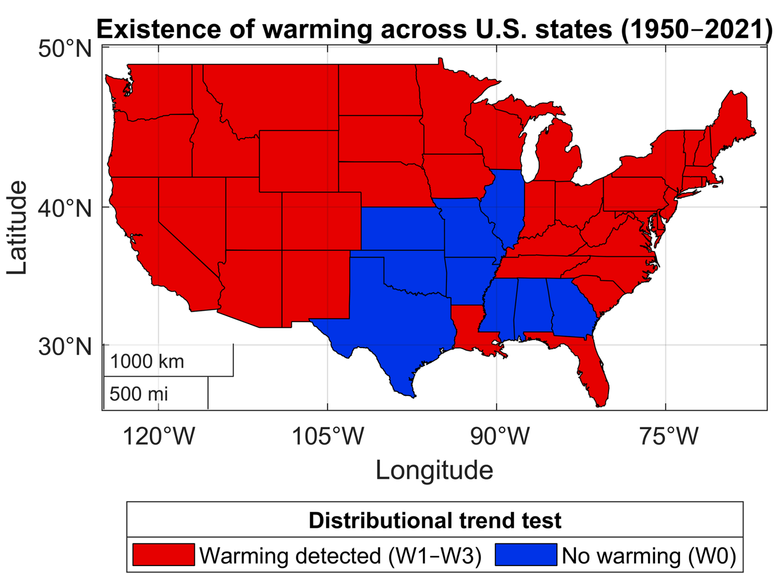

Fig 9. Test of warming existence across U.S. states (1950–2021). *Sources*: Own elaboration from PRISM state-level temperature series (see Sect 2). Map generated with MATLAB (R2024b, Mapping Toolbox); no additional permissions required beyond software citation. States coded as 0 correspond to cases in which the joint trend test fails to reject the null hypothesis of no warming (type W0), while states coded as 1 indicate warming detected in at least one part of the temperature distribution (types W1–W3).

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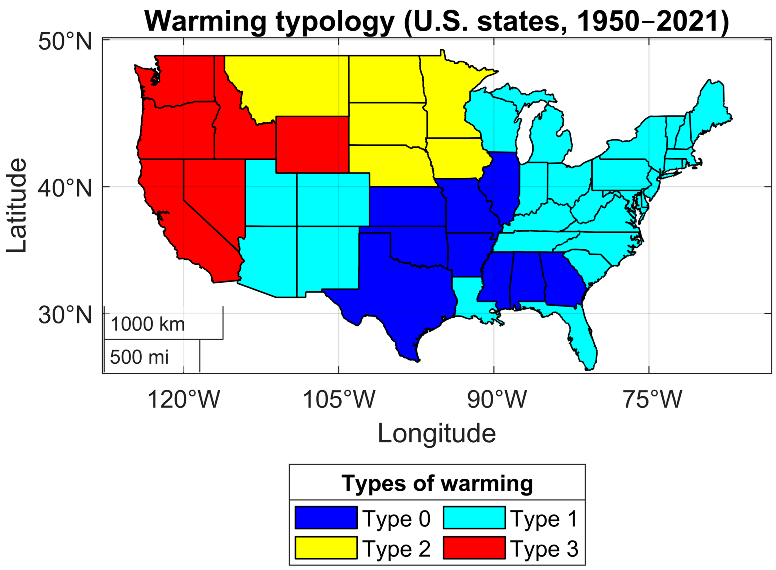

Fig 10. **Warming typology across U.S. states (1950–2021).** *Sources*: Own elaboration from PRISM state-level temperature series (see Sect 2). Map generated with MATLAB (R2024b, Mapping Toolbox); no additional permissions required beyond software citation. States are classified into four categories (W0–W3) according to the estimated warming pattern, distinguishing mean warming, dispersion changes, and tail-specific effects.

https://doi.org/10.1371/journal.pclm.0000808.g010

In summary, while the typology derived from our methodology shares many similarities with the climate zones proposed by NCEI, it provides an alternative lens for identifying and testing the nuances of warming patterns. This alternative perspective may offer valuable insights into specific characteristics that might not be fully captured by traditional classifications.

3.3 Warming dominance

The application of the Warming Dominance test, *WD*, yields a total of 1,176 possible state-pair comparisons for each characteristic. This large number complicates comprehensive presentation and makes individual result interpretation overly cumbersome. To streamline analysis, we propose three approaches:

1. Constructing a Synthetic Index: This index will summarize each state's warming dominance relative to others.
2. Identifying Pareto-Dominant States: These are states that dominate at least one other state without being dominated by any.
3. Focusing on Specific Case Studies: This approach allows for an in-depth analysis of selected states or regions.

The Synthetic Warming Dominance Index (SWDI) for all the quantiles is defined as follows:

$$SIWD_i = \frac{1}{q * (n-1)} \sum_{k=1}^{q} \sum_{j=1}^{n-1} WD_{ij}^{k} \tag{4}$$

where

- $WD_{ij}^{k} = 1$ if region *i* warming-dominates region *j* in quantile *k*
- $WD_{ij}^{k} = -1$ if region *j* warming-dominates region *i* in quantile *k*

- $WD_{ij}^k = 0$ if neither of the two regions significantly dominates the other.

The index ranges from [–1,1], and can be computed for individual quantiles k:

$$SWDI_i^k = \frac{1}{(n-1)} \sum_{j=1}^{n-1} WD_{ij}^k \tag{5}$$

Remarks on the ***WD***:

- The *WD* can initially be computed using only the mean before calculating it for the full distribution.
- *WD* may be classified as either strong or weak, depending on its significance across quantiles.
- Partial *WD* may also occur, for example, in only the lower or upper quantiles.
- The position of the *WD* in the distribution is not indifferent as it affects the perception of *CC*, especially if it occurs in the higher quantiles.
- A synthetic index $SWDI_i \in [-1, 1]$ of ***WD*** can be defined for each region $i = 1...n$ accounting for all quantiles $k = 1...q$.
- The use of the *SWDI* is an efficient way to quantify the warming dominance of each state relative to others when n is large. It condenses complex pairwise comparisons into a single index, facilitating easier interpretation.

The results of the *SWDI* calculation are displayed in Map, Fig 11 and presented by quantiles in Table 1. Additionally, for specific characteristics (*q05*, *mean*, *q95*), heat maps provide matrix-form t-ratio results from the *WD* test (Figs 12, 13 and 14). Notable observations include:

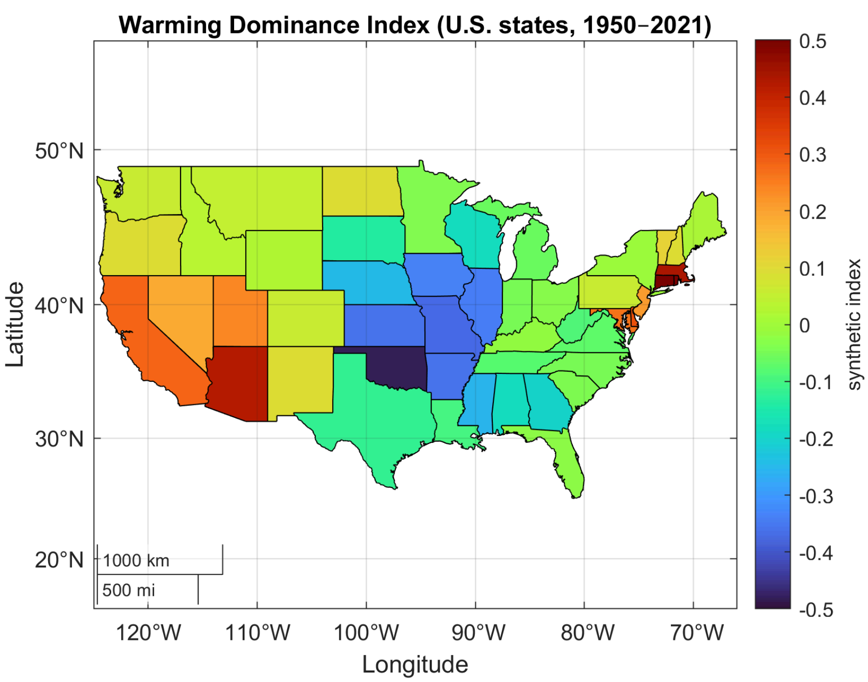

Fig 11. **Synthetic warming dominance index across U.S. states (1950–2021).** *Sources*: Own elaboration from PRISM state-level temperature series (see Sect 2). Map generated with MATLAB (R2024b, Mapping Toolbox); no additional permissions required beyond software citation. Colours represent the synthetic Warming Dominance Index (WD_{total}), which summarizes the relative strength of warming signals across the full set of distributional measures. Positive values indicate stronger and more pervasive warming dominance.

https://doi.org/10.1371/journal.pclm.0000808.g011

Table 1. Results of pareto warming dominance tests (1950-2021).

states/quantiles	mean	q05	q10	q20	q30	q40	q050	q60	q70	q80	q90	q95
AL	–1	–1	–1	–1	–1	–1	–1	–1	–1	–1	–1	–1
AZ	2	0	2	2	2	2	2	2	2	1	2	2
AR	–1	–1	–1	–1	–1	–1	–1	–1	–1	–1	–1	–1
CA	2	2	2	2	2	2	2	2	2	1	2	1
CO	1	–1	–1	–1	–1	1	–1	–1	1	1	1	1
CT	1	2	2	2	2	1	2	1	2	2	1	1
DE	1	2	1	2	2	1	1	1	2	1	1	1
DC	0	0	0	0	0	0	0	0	0	0	0	0
FL	1	–1	–1	0	2	1	–1	1	–1	–1	–1	0
GA	–1	0	–1	–1	–1	–1	–1	–1	–1	–1	–1	–1
ID	0	0	–1	–1	–1	1	1	–1	1	1	2	1
IL	–1	–1	–1	2	–1	–1	–1	–1	–1	–1	–1	–1
IN	–1	0	–1	2	2	2	0	0	1	–1	–1	–1
IA	–1	–1	–1	–1	2	–1	–1	–1	–1	–1	–1	–1
KS	–1	–1	–1	–1	–1	–1	–1	–1	–1	–1	–1	–1
KY	–1	–1	0	2	0	1	–1	–1	1	–1	–1	–1
LA	–1	–1	–1	0	–1	–1	–1	1	–1	–1	–1	–1
ME	–1	0	–1	–1	–1	–1	1	1	–1	1	1	1
MD	1	2	1	2	2	1	1	1	1	1	1	1
MA	1	2	2	2	1	1	1	1	2	2	1	1
MI	–1	–1	–1	2	2	0	–1	–1	–1	1	–1	–1
MN	2	2	1	2	2	2	1	–1	–1	–1	–1	–1
MS	–1	–1	–1	–1	–1	–1	–1	0	–1	–1	–1	–1
MO	–1	–1	–1	–1	0	–1	–1	–1	–1	–1	–1	–1
MT	2	2	1	2	2	2	1	–1	–1	–1	2	2
NE	–1	1	–1	2	–1	1	–1	–1	–1	–1	–1	–1
NV	1	–1	–1	–1	–1	1	1	1	2	2	2	2
NH	1	–1	–1	–1	–1	–1	1	1	1	1	1	1
NJ	1	1	2	0	1	1	1	1	1	1	1	1
NM	1	2	0	0	1	1	1	1	1	1	1	–1
NY	1	–1	–1	0	–1	–1	1	1	1	–1	–1	–1
NC	–1	1	1	–1	–1	–1	–1	1	–1	–1	–1	1
ND	2	2	2	2	2	0	2	–1	1	1	–1	–1
OH	–1	–1	–1	2	1	1	–1	–1	1	–1	–1	–1
OK	–1	–1	–1	–1	–1	–1	–1	–1	–1	–1	–1	–1
OR	1	0	–1	–1	–1	–1	1	–1	0	1	2	2
PA	1	–1	–1	2	2	1	1	1	1	1	–1	–1
RI	2	2	2	2	2	2	2	2	2	2	2	2
SC	0	1	–1	–1	0	–1	–1	–1	–1	–1	–1	–1
SD	–1	2	1	0	–1	2	–1	–1	–1	–1	–1	–1
TN	–1	–1	–1	0	1	–1	–1	–1	–1	–1	–1	–1
TX	–1	–1	–1	0	–1	–1	–1	–1	–1	–1	–1	–1
UT	1	0	–1	0	2	1	1	–1	1	2	2	2
VT	1	2	2	2	–1	–1	1	1	1	1	1	1
VA	–1	–1	1	–1	–1	–1	–1	1	1	–1	–1	–1
WA	1	0	–1	–1	–1	–1	2	0	–1	–1	2	2
WV	–1	–1	–1	–1	–1	0	–1	–1	–1	–1	–1	–1
WI	–1	2	–1	0	2	–1	–1	–1	–1	–1	–1	–1
WY	1	–1	–1	–1	2	1	–1	–1	1	0	2	1

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- In terms of average *WD*, certain states stand out: RI, AZ, CT, MA, DE, CA, NJ, and MD.
- Warming dominance is more pronounced in the upper quantiles than in the lower ones. This means that the warming process is more concentrated in the high quantiles, a result that is consistent with the higher percentage of significant trends in *q95* (Fig 15).

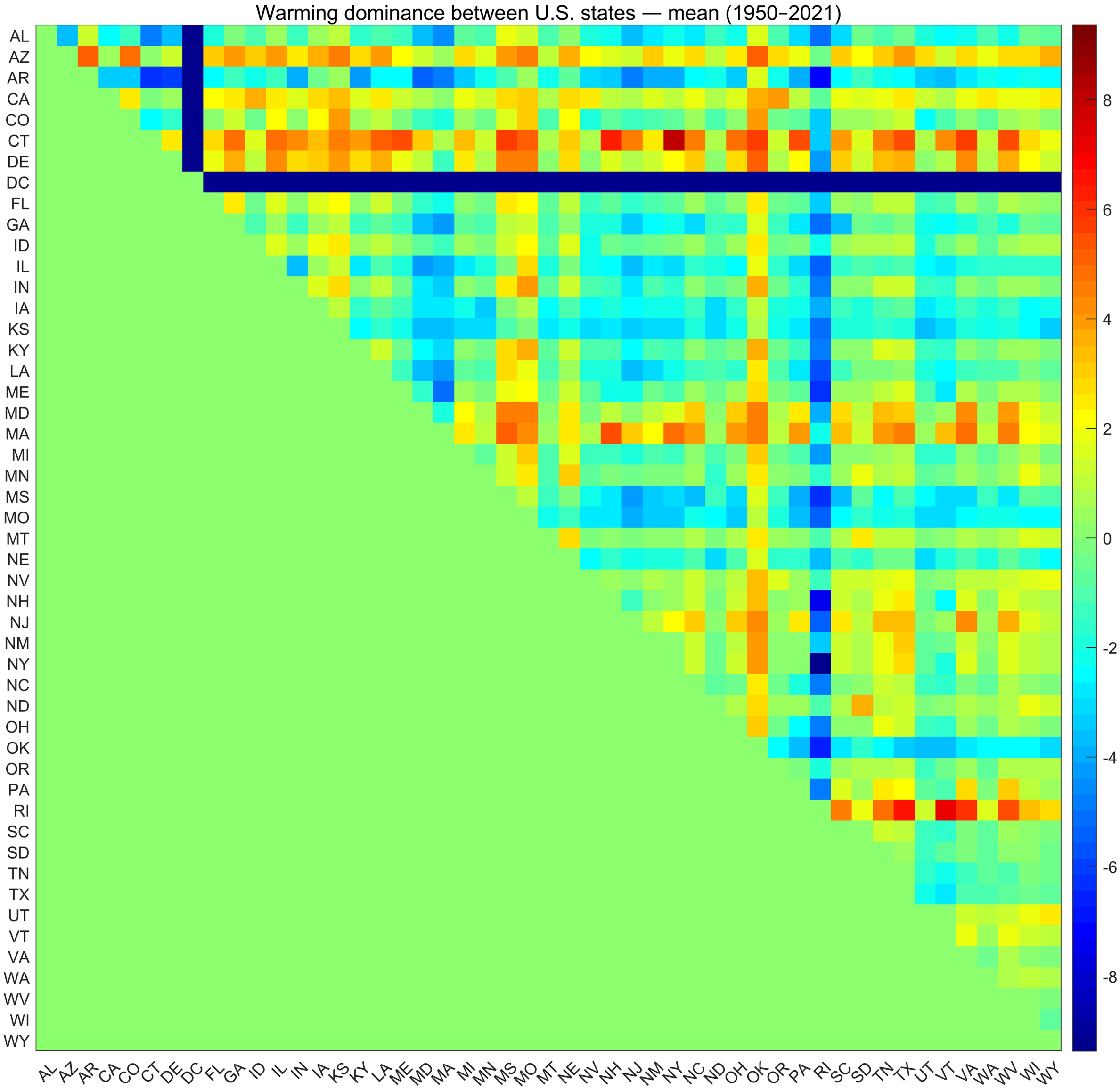

Fig 12. **Warming dominance between U.S. states based on mean temperatures (1950–2021).** *Sources*: Own elaboration from PRISM state-level temperature series (see Sect 2). Figure heatmap generated with MATLAB (R2024b) using pairwise HAC-based trend tests. Each cell shows the *t*-statistic for the dominance of the state in the row over the state in the column. Positive (negative) values indicate that the row (column) state exhibits stronger mean-temperature warming.

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- The synthetic index highlights the following states, in order: RI, CT, MA, AZ, DE, CA, and MD.
- Relying solely on the mean for analysis provides an incomplete perspective; a comprehensive examination of the entire distribution is essential. Fig 16 illustrates that certain states display non-uniform *WD* across quantiles, highlighting discrepancies that are not evident when considering only the mean.
- Map analysis reveals that warming dominance is primarily concentrated along the two coasts, specifically the southwest and northeast (climatic zones of the West, Southwest, and Northeast).

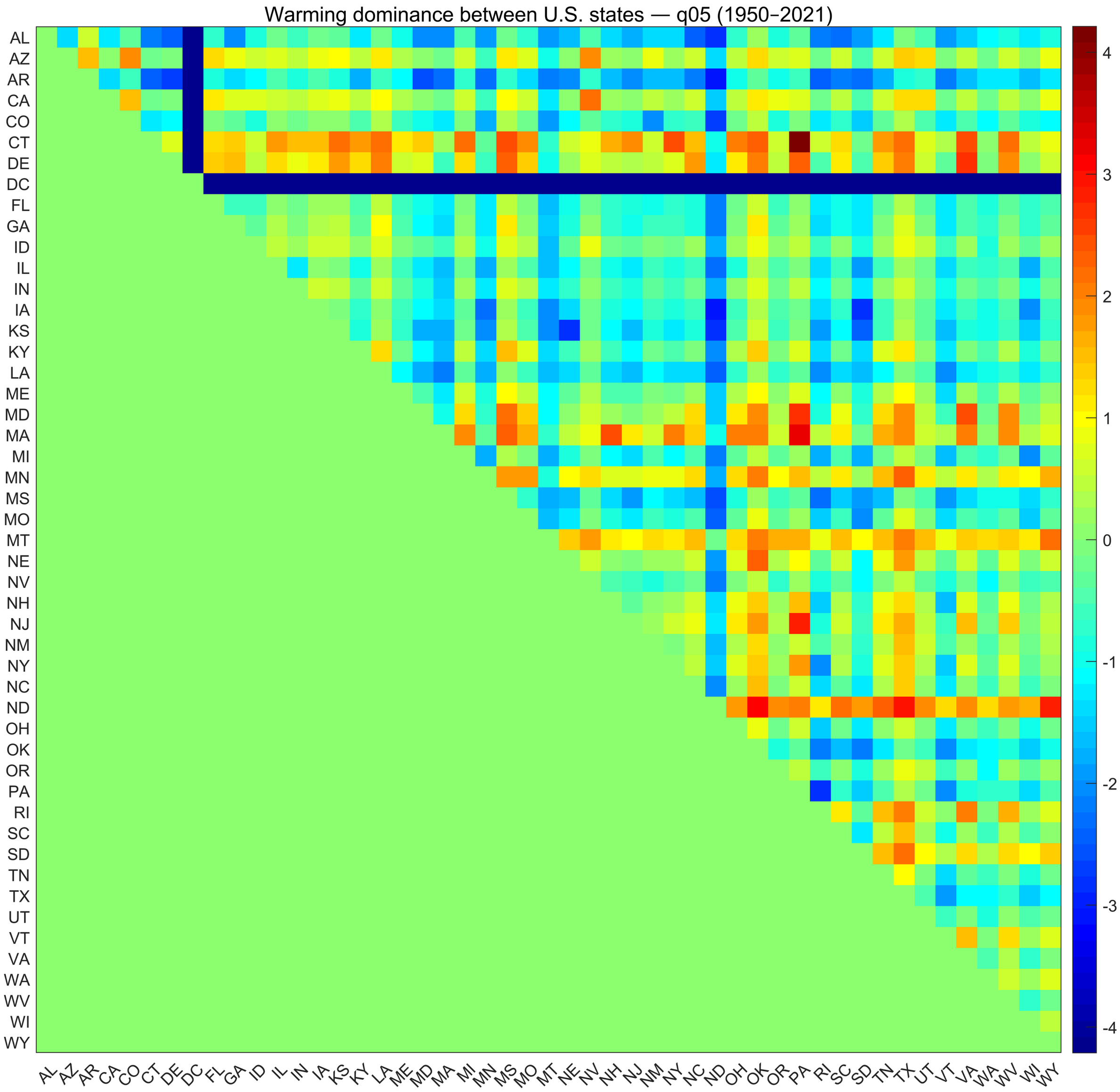

Fig 13. **Warming dominance between U.S. states based on lower-tail (q_{05}) temperatures (1950–2021).** *Sources*: Own elaboration from PRISM state-level temperature series (see Sect 2). Figure heatmap generated with MATLAB (R2024b) using pairwise HAC-based trend tests. Each cell shows the *t*-statistic for the dominance of the state in the row over the state in the column. Positive (negative) values indicate that the row (column) state exhibits stronger warming at the lower tail of the temperature distribution.

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- By converting the states that are either dominated or dominating into binary values (1 and 0), we obtain a concordance of 0.78 with political ideology based on historical voting patterns (where 1 represents Democratic and 0 Republican preferences).

The Pareto Warming Dominance Index (PWDI) takes values 2,1,0,–1,–2, with interpretations as follows:

- 2 = Strong Pareto dominance, where a state dominates at least one other state and is dominated by none.
- 1 = Weak dominance, where the state dominates more states than it is dominated by.

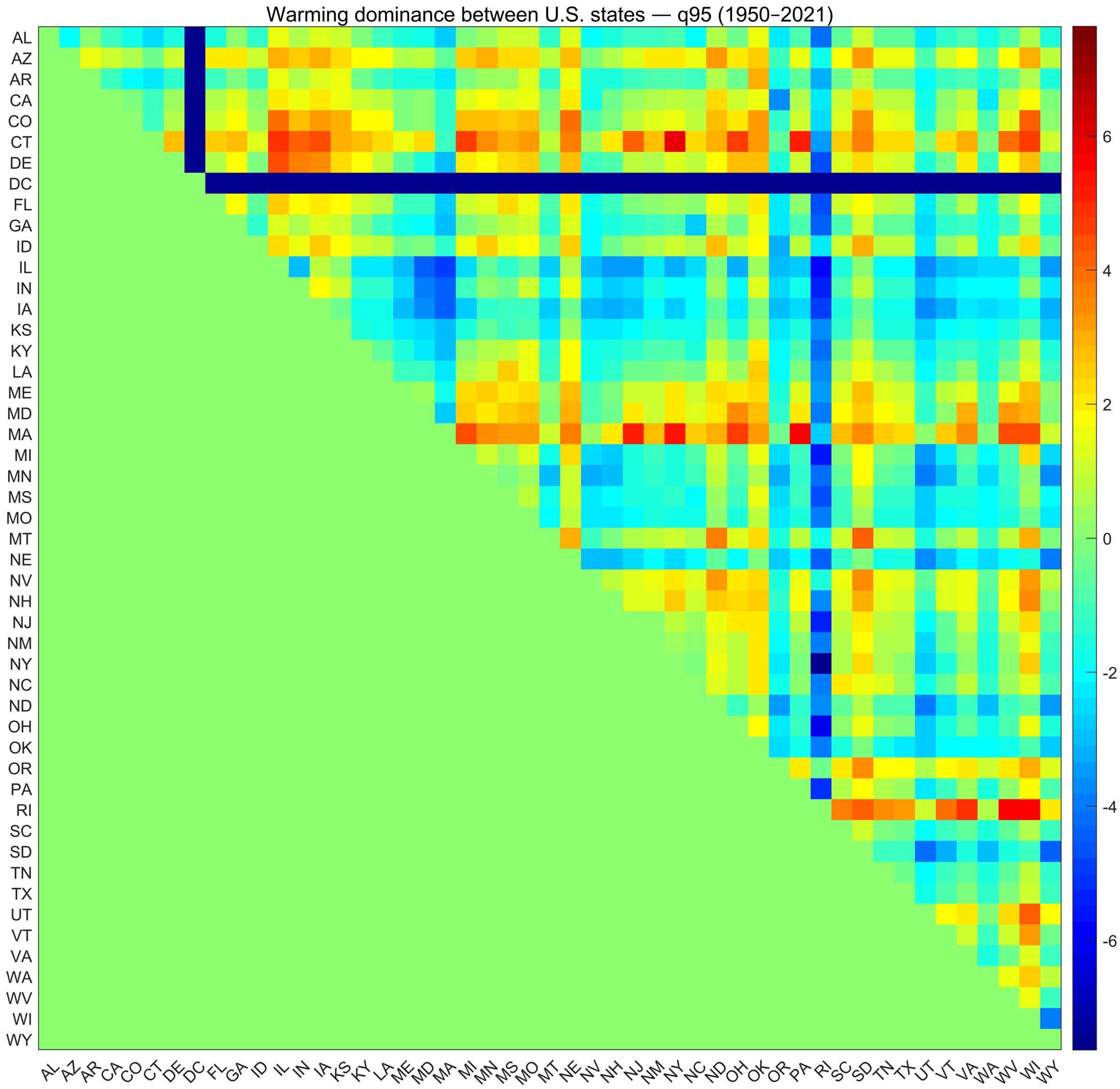

Fig 14. **Warming dominance between U.S. states based on upper-tail (q_{95}) temperatures (1950–2021).** *Sources*: Own elaboration from PRISM state-level temperature series (see Sect 2). Figure generated with MATLAB (R2024b) using pairwise HAC-based trend tests. Each cell shows the *t*-statistic for the dominance of the state in the row over the state in the column. Positive (negative) values indicate that the row (column) state exhibits stronger warming at the upper tail of the temperature distribution.

https://doi.org/10.1371/journal.pclm.0000808.g014

- 0 = Non-Pareto dominance, where the state neither dominates nor is dominated by others.
- –1 = Weakly dominated, where the state is dominated by more states than it dominates.
- –2 = Strong Pareto dominated, where the state does not dominate any other state but is dominated by at least one.

The *PWDI* is calculated for each quantile, and a synthetic indicator, *SPWDI*, can also be computed, which takes the value 1 if the state dominates in all quantiles except the mean, and 0 otherwise.

Regarding the Pareto *WD* analysis, Table 1 provides detailed information by states and quantiles, while Map, (Fig 17) shows the SPWDI calculation and its geographical representation. Here, it is clear that only the states of AZ, CA, MD, MA,

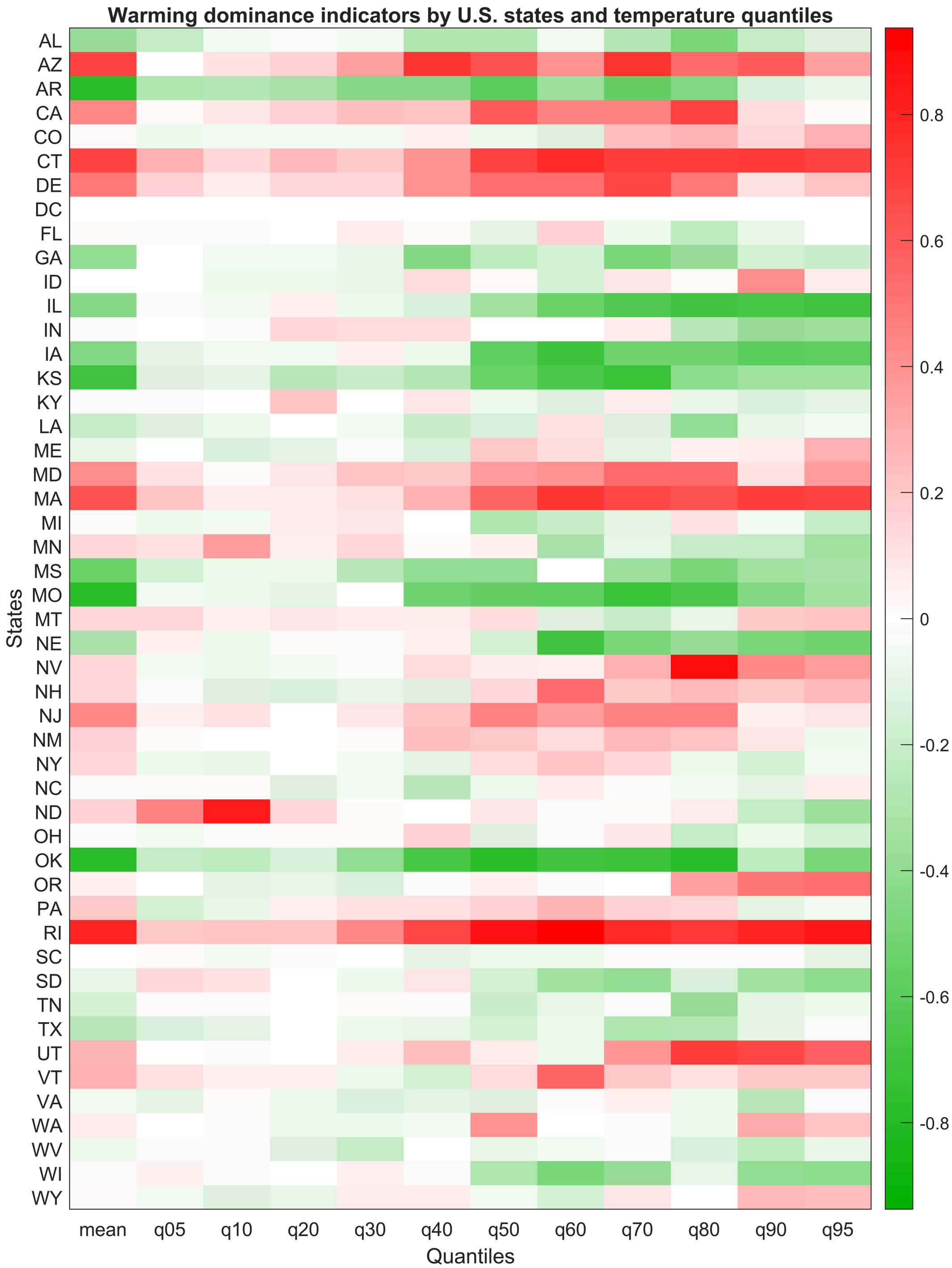

Fig 15. **Warming dominance indicators (WDI) by U.S. states and temperature quantiles.** *Sources*: Own elaboration from PRISM state-level temperature series (see Sect 2). Figure generated with MATLAB (R2024b) from the spreadsheet `WD_USA.xlsx`. Each cell shows the synthetic WDI for a given state and quantile (mean, q_{05}–q_{95}). Colours represent the magnitude of warming dominance, with green (red) shades indicating negative (positive) values. States are sorted alphabetically to enhance comparability.

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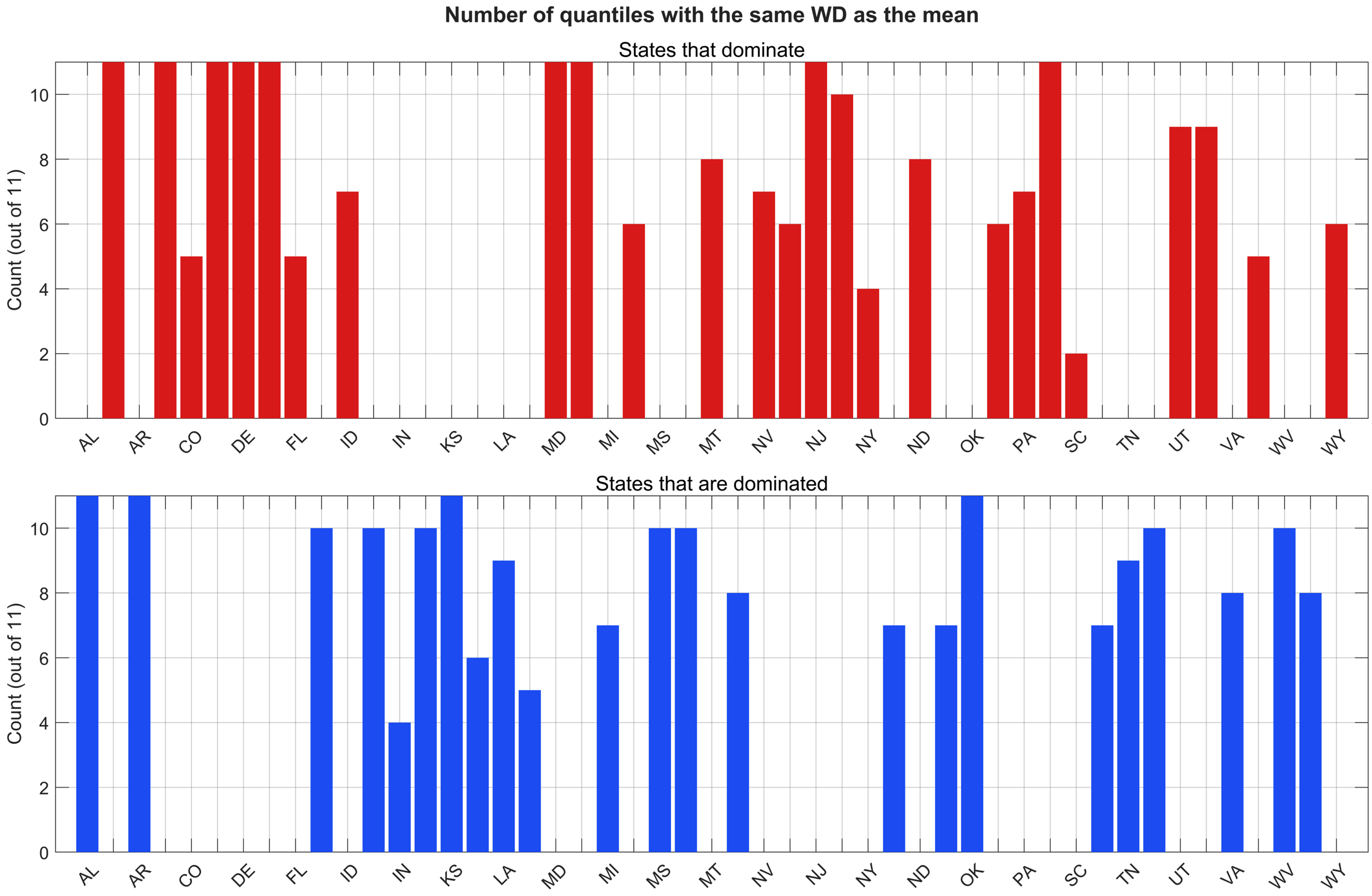

Fig 16. **Consistency of warming dominance across temperature quantiles for U.S. states (1950–2021).** *Sources*: Own elaboration from PRISM state-level temperature series (see Sect 2). Figure generated with MATLAB (R2024b) using pairwise HAC-based trend tests. The upper panel shows, for states with positive mean warming dominance, the number of temperature quantiles (q_{05}–q_{95}) that also exhibit positive dominance. The lower panel shows, for states with negative mean dominance, the number of quantiles that also display negative dominance. Red bars indicate dominant states, and blue bars indicate dominated states.

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NJ, and RI are Pareto dominant, all located in the Pacific and Atlantic regions. It is important to note that the PWDI is a more stringent measure than the SWDI, enabling the identification of states that exert a stricter dominance by considering their entire area of influence rather than focusing solely on peer relationships.

In summary, this section has enabled the calculation and statistical comparison of states with a dominant warming process relative to others, as well as the classification of their typology based on temperature distribution. However, this is not merely a quantitative exercise. The results provide valuable insights into which regions are more exposed to climatic risks and, consequently, offer crucial information for policymakers in designing more targeted and effective policies. These insights are particularly important in the United States, where climate policy is formulated and implemented at both federal and state levels.

3.4 Case study (CA)

The progression of the warming process in California is presented in Table AII-1 (S1 Appendix), which shows that all estimated trends are positive and statistically significant. (Detailed analyses for other states are available upon request.)

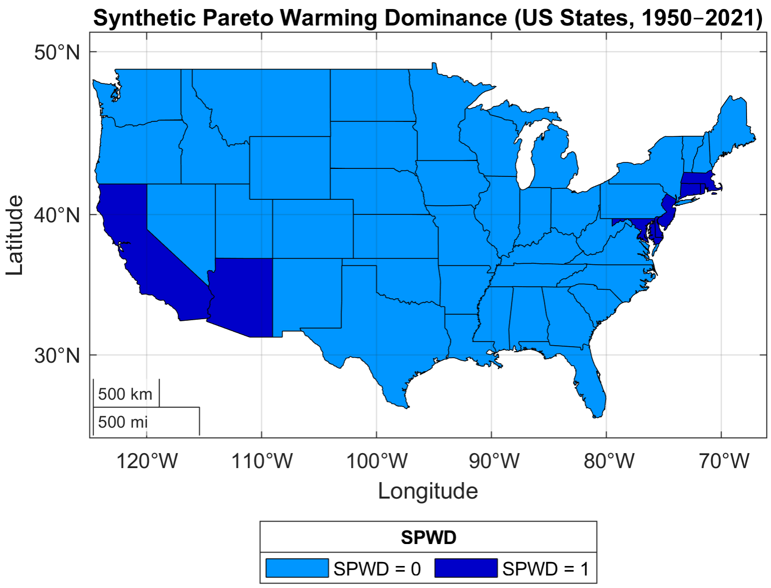

Fig 17. **Synthetic pareto warming dominance (SPWD) across U.S. states (1950–2021).** *Sources*: Own elaboration from PRISM state-level temperature series (see Sect 2). Map generated with MATLAB (R2024b, Mapping Toolbox); no additional permissions required beyond software citation. The figure shows the classification of states according to the Synthetic Pareto Warming Dominance indicator (SPWD): states in dark blue satisfy Pareto warming dominance, while those in light blue do not. The SPWD provides a summary measure of whether warming dominance holds jointly across all distributional dimensions.

https://doi.org/10.1371/journal.pclm.0000808.g017

Based on the typologies introduced in Sect 3.2, California is classified as type *W3*. The combination of a positive trend in the lower quantiles with an even steeper increase in the upper quantiles constitutes an ideal trigger for widespread summer wildfires. To design effective climate mitigation and adaptation policies at both federal and state levels, it is crucial to compare California's warming dynamics with those observed in other states. Fig AII-1 (S1 Appendix) summarizes the results of the Warming Dominance tests (Definitions 3 and 4) and highlights two key findings.

First, California exhibits a dominant warming pattern relative to most states—especially in the upper part of the temperature distribution. Out of 576 possible comparisons (48 states × 12 characteristics), California dominates in 172 cases (30%) and is dominated in only 4. This upward-skewed dominance suggests that the state is particularly vulnerable to warming at higher quantiles, potentially increasing public awareness of climate change. The table also reveals cases of strong and partial dominance.

Second, the comparison across quantiles reveals asymmetries not visible at the mean. For instance, while California clearly dominates Nevada, Oregon, and Washington on average, it is itself dominated by those states at the highest quantiles (*q80*, *q95*). The value of a full-distribution approach is illustrated through specific cases: (i) California dominates Kansas across most of the distribution (Fig AII-2, S1 Appendix); (ii) in Iowa, *WD* at the mean is driven by dominance in specific quantiles (Fig AII-2, S1 Appendix); (iii) in Minnesota, no*WD*is observed at the mean, but dominance emerges in the right tail (Fig AII-3, S1 Appendix). (These results must be interpreted in light of California's unique geography and climate: a large, climatically diverse state with coastal exposure and high susceptibility to droughts and wildfires. These factors, combined with the state's economic structure—particularly its reliance on agriculture, tourism, and technology—warrant deeper analysis of how warming affects both productivity and socio-economic outcomes such as housing and health.).

Such discrepancies between mean-based dominance and quantile-specific dominance are uncommon but noteworthy—occurring in only 5 out of 1,176 possible pairwise comparisons across all states. This indicates that distributional dominance is statistically more stable than mean dominance, although identifying which part of the distribution drives average dominance remains informative. The magnitude of dominance, particularly when assessed using synthetic indices, is a separate but equally important dimension. Fig AII-5 (S1 Appendix) illustrates sign reversals in *WD* across states, distinguishing dominant from dominated cases.

More commonly, however, *WD* arises only in the tails of the distribution even when absent at the mean. Fig AII-5 (S1 Appendix) maps the number of quantiles in which each state dominates or is dominated without exhibiting average-level *WD*. Out of 1,176 pairwise comparisons,*WD* appears at the mean in 445 cases, at *q05* in 107, and at *q95* in 382. Among the 731 cases with no *WD* at the mean, 32 show *WD* in *q05* and 152 in *q95*. In California's case, this phenomenon is observed in states such as IN, KY, MI, MT, NH, NC, ND, OH, PA, SC, SD, UT, VI, VA, and WV—states that are not dominated on average but are in specific quantiles, particularly in the right tail. These cases may heighten public perceptions of warming impacts.

4 Discussion

The proposed methodology and its application to the contiguous U.S. states raise important questions and open new avenues for policy-relevant debate. While it is widely recognized that climate change (*CC*) is a non-uniform phenomenon, its heterogeneity is seldom quantified in a systematic or comparative way across regions. This stands in contrast to fields such as income distribution, wage inequality, and health disparities, where comparative metrics are routinely employed and regarded as essential for informing policy decisions.

This study introduces robust quantitative tools to describe, measure, test, and compare climate change at the regional level, enabling more nuanced diagnostics and the design of targeted and effective mitigation and adaptation strategies. In the absence of such comparative analyses, the formulation of efficient climate policies becomes considerably more difficult. Although climate change is a global and complex process, its impacts are most acutely experienced at the local level. Regional variations in climate are particularly consequential for ecosystems and biodiversity, agriculture, water resources, energy, transportation, public health, and more—reinforcing the well-known principle: "think globally, act locally." While our empirical application focuses on U.S. states, the proposed methodology is flexible and can be readily extended to other regional contexts, including countries, states, or subnational areas.

Our approach not only replicates previously established findings—thereby confirming its empirical validity—but also reveals new patterns that emerge only when analyzing the full distribution of temperature data. This dual capacity highlights the method's reliability and its added analytical value. Furthermore, the methodology is easy to implement, robust to a range of data conditions, and yields interpretable results, making it a valuable tool for researchers and policymakers alike.

A central contribution of this paper is the introduction of the Warming Dominance (*WD*) concept, which enables quantitative comparisons of climate change intensity both across regions and across the entire temperature distribution. By analyzing warming dominance at different quantiles, this study recognizes that climate change impacts vary by region and differ throughout the distribution. Tools such as the Synthetic Warming Dominance Index (*SWDI*) and Pareto-dominance frameworks assist in summarizing and interpreting these complex results. For example, the *SWDI* condenses multidimensional comparisons into a single, interpretable metric that reflects each state's relative warming intensity. Similarly, identifying Pareto-dominant and -dominated states (using the *PWDI* and *SPWDI*) introduces a comparative dimension that highlights those states experiencing the most significant warming within their respective spheres of influence. Our WD numerical tools perfectly complement existing visual comparison tools, such as such as the IPCC WGI Interactive Atlas [17], the Copernicus Climate Atlas (C3S) [18], and NOAA's Climate at a Glance platform [19].

Beyond its direct climatological interpretation, the Pareto Warming Dominance Index (*PWDI*) also offers potential value for research on public perceptions, political ideology, and climate-related attitudes. Because the *PWDI* classifies each state into five ordered categories—from strongly dominant to strongly dominated—it provides a simple and interpretable mapping of how regions experience warming relative to one another. These ordinal categories may serve as meaningful predictors in sociological and political-economy analyses, helping to explain why citizens in some regions perceive climate change as an immediate threat while others view it as distant or less consequential. For example, states classified as strongly dominant (*PWDI* = 2) experience more intense and pervasive warming signals across the temperature distribution, which may foster higher public concern and stronger support for mitigation and adaptation policies. Conversely, states in strongly dominated positions (*PWDI* = −2) exhibit comparatively weaker warming signals, potentially contributing to lower perceived urgency, climate skepticism, or divergent policy preferences. Integrating *PWDI*-based diagnostics with survey data and behavioral indicators thus opens a promising avenue for future interdisciplinary work connecting climatic asymmetries with sociopolitical dynamics.

The concept of *WD* also prompts broader and more difficult questions. One key issue is whether climate change may generate both risks and benefits. Several important questions emerge: Could high-latitude regions benefit from milder temperatures, potentially reducing their perceived vulnerability to climate change and weakening their commitment to emission reductions? Might climate change alter global patterns of wealth distribution or shift geopolitical balances? Could it influence public attitudes and even reshape political ideologies?

A particularly salient challenge is whether climate change creates “winners” and “losers,” and whether it is feasible to design compensatory policies that account for these asymmetries. Our findings suggest that the most intense climate impacts are concentrated in U.S. coastal regions, which may not only reshape perceptions of climate risk but also affect political preferences and priorities. This raises further questions about how climate change interacts with regional levels of development and, in turn, with adaptive capacity. Historical emissions—another contentious issue—may also influence how responsibilities and compensations are framed. The feasibility of designing redistributive climate policies will depend heavily on the geopolitical context and may be more achievable in countries like the United States, where adaptation policies and interregional transfers are already part of the institutional framework. These considerations are particularly relevant in the U.S., where both federal and state governments play significant roles in shaping climate policy.

The methodology presented here offers a promising quantitative framework for assessing regional climate change impacts, and it may help address several of the critical questions outlined above. While the present analysis does not attempt to attribute regional warming dominance to specific anthropogenic mechanisms, the proposed framework may support future attribution studies linking observed asymmetries with emissions patterns, socioeconomic factors, and regional policy responses. Future research will expand this approach to incorporate other dimensions of climate change—such as precipitation variability and sea level rise—thus offering a more comprehensive assessment of warming dominance beyond temperature distributions. Moreover, the tools developed here are being applied in future work to explore issues of causality-attribution, and the economic and public health consequences of climate change. Future extensions of this research will also seek to connect the quantitative diagnostics of warming dominance with the physical mechanisms that generate regional variability, including changes in land use, atmospheric circulation, and urbanization. The proposed framework is also easily transferable to other climate dimensions, such as precipitation variability or sea-level rise, as long as sufficiently granular data are available. Extending the *WD* approach to these variables would allow a more comprehensive assessment of climate change heterogeneity across multiple environmental indicators. Taken together, these extensions highlight the versatility of the proposed approach and its potential to inform applied climate analysis.

Beyond its methodological contributions, the *WD* framework also provides actionable insights for policy design. Because warming intensity and typology vary substantially across regions, state-level diagnostics can guide differentiated adaptation and mitigation strategies. For instance, coastal and southern states exhibiting dominance in upper quantiles may prioritize resilience to extreme heat and energy infrastructure, whereas northern regions showing lower-tail dominance may focus on winter adaptation measures, agricultural planning, and ecosystem management. However, the interpretation of “warming dominance” should also consider differences in vulnerability, population density, and economic exposure, as these factors determine the real-world implications of regional warming asymmetries. Recognizing such spatial diversity ensures that climate policies are not only efficient but also equitable across the U.S. territory, reinforcing the need for regionally informed climate governance.

Ultimately, the findings of this study offer a quantitative foundation that can inform both federal and state-level climate strategies. By revealing where and how warming is most intense within the United States, the *WD* framework can help policymakers prioritize adaptation investments, anticipate regional vulnerabilities, and design mitigation efforts that reflect local climatic realities. Embedding such diagnostic tools into planning processes could improve the allocation of resources, enhance policy coordination across jurisdictions, and contribute to more effective and equitable climate governance.

5 Conclusions

This paper introduces the concept and methodology of *Warming Dominance*, providing a consistent statistical framework to measure and compare regional warming patterns across the United States. The results demonstrate that moving beyond mean-based analyses reveals substantial heterogeneity in climate change intensity. The proposed tools, including the *SWDI* and Pareto-dominance indicators, open the way for systematic regional assessments and policy-relevant applications. Future research will build upon this foundation to integrate physical mechanisms and socioeconomic dimensions, thereby advancing a more comprehensive understanding of regional climate change.

Acknowledgments

We are indebted to an Editor and the three referees for very helpful comments. We gratefully acknowledge the insightful feedback from seminar participants at the University of California, Davis; University of California, Riverside; University of Glasgow; Rimini Center for Economic Analysis; and the Carlos III reading group. The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

Supporting information

S1 Data.
(RAR)

S1 Appendix.
(PDF)

Fig All 1.
(TIFF)

Fig All 2.
(TIFF)

Fig All 3.
(TIFF)

Fig All 4.
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Fig All 5.
(TIFF)

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