Virtual Seminar on Climate Economics

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Climate Change Heterogeneity: A New Quantitative Approach

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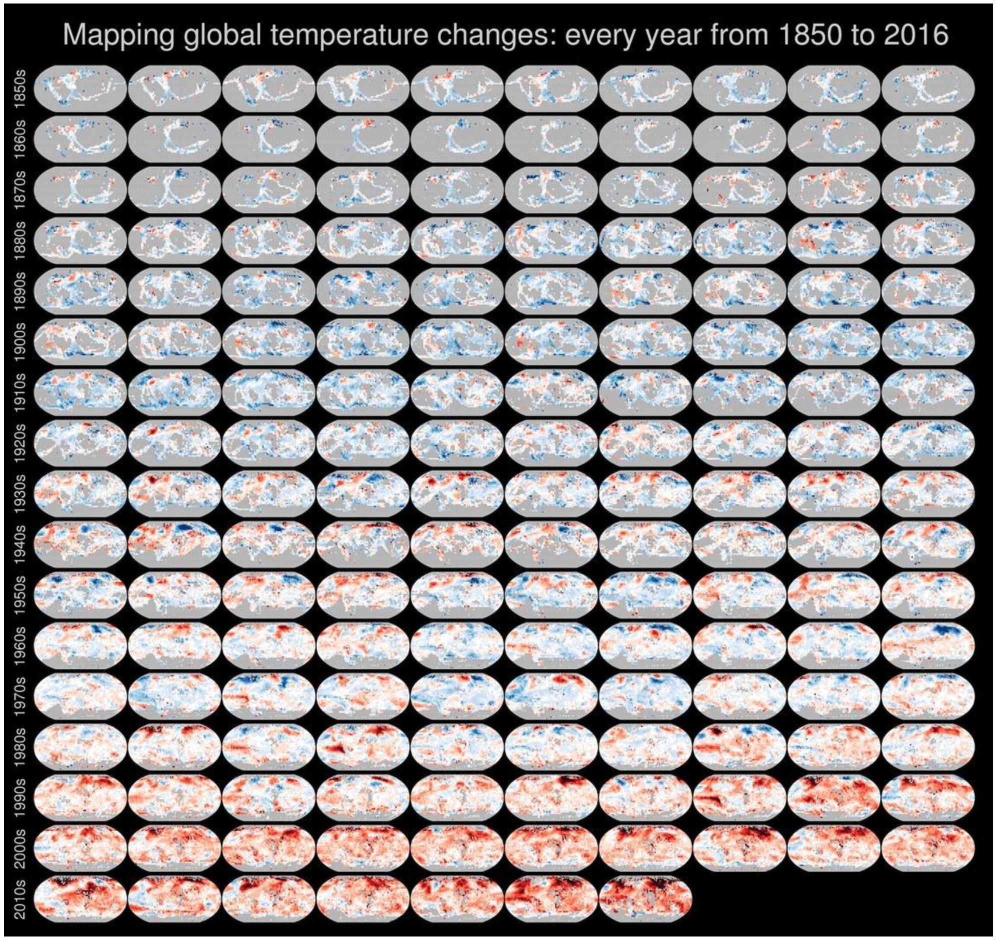
7th July, 2022

Some animations

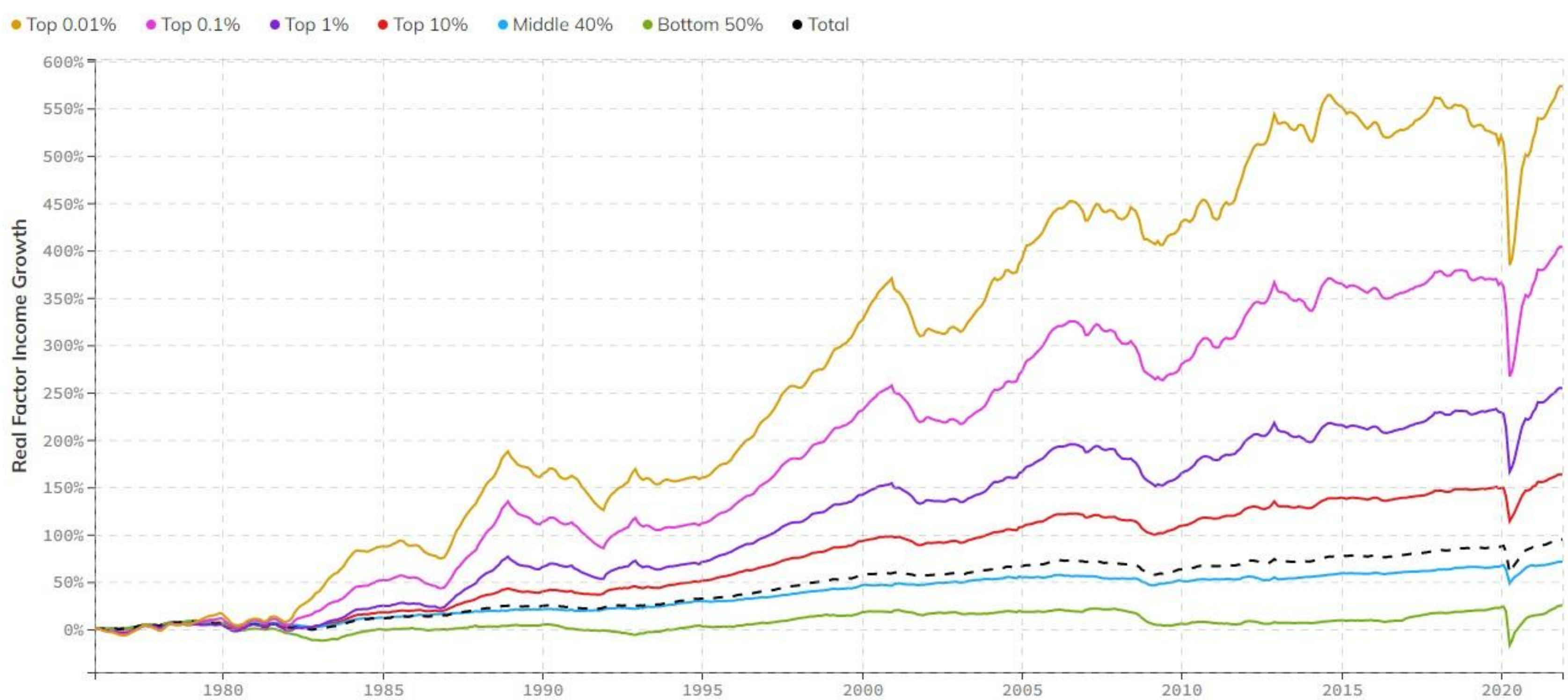
How quickly climate change is **accelerating**, in 168 maps (Ed Hawkins, U. Reading):



`https://climate.nasa.gov/climate_resources/139/video-global-warming-from-1880-to-2021/`

Some animations

An example sharing the same spirit: Real Time US Income Inequality
(Thomas Blanchet, Emmanuel Saez, Gabriel Zucman (UC. Berkeley))



https://realtimeinequality.org/

Some preliminaries

Three preliminary issues that help to follow this presentation:

1. In this presentation, we will consider **Climate Change** (CC) and **Warming** (W) equivalent.
2. We define **Warming** as the existence of an **increasing trend** in the temperature data. Temperature data is not only the **mean**; but the **whole temperature distribution**. Similar idea to income distribution versus average income.
3. The study of CC conveys, according to the intergovernmental panel on climate change (IPCC) reports four steps: (1) **Existence**, (2) **Causes**, (3) **Effects**, and (4) **Mitigation policies**. The analysis is incomplete if we study one of them without having analyzed the previous ones.

Why this paper can be important?

The importance of this paper rests on the following pillars:

1. **A Testable Definition of Warming, Warming acceleration and Warming amplification**.
2. A new **Warming typology** to characterize climate change heterogeneity (CCH).
3. Introduction of the new testable concept of **Warming Dominance (WD)**.
4. The existence of **CCH** opens the following doors:
   - The need to develop a NEW NON-UNIFORM causal-effect analysis that incorporates CCH (see Tol *ANYAS* 2021).
   - The mitigation-adaptation policies should be designed following a factor structure: common-global and idiosyncratic-local policies (see D ' Autume et al. *JPET* 2016, Brock and Xepapadeas *EER* 2020, and Peng et al. *NCC* 2021).
   - **Psychological effect**. Climate change public awareness increases when global warming is perceived not only as a global problem but as a local one too (see Malmendier *JEEA* 2020, Nowakowski and Oswald *IZA WP* 2020, and Maiella et al. *FP* 2020).

Why Spain?

Relevance of **CCH**, reflected in the last **IPCC AR6 report (2021, 2022)**, by the large space dedicated to regional warming.

Why Spain?

- We have chosen as benchmark geographical location Spain, because as the AR6 report says *"... Spain is fully included in the Mediterranean (MED) Reference Region, but is* ***one of the most climatically diverse countries in the world****"*.
- The most relevant European institutions (European Commission, Parliament, ECB, ...) highlight the special vulnerability of Spain to the effects of the Climate Change.
- This research builds on the methodology introduced in Gadea and Gonzalo (JoE 2020) (GG2020) to **quantitatively study(test) the existence of such climate change heterogeneity**.

Results Preview

- We find that Spain and the Globe not only present a **clear warming process**; but their warming evolves differently.
- Spain goes from a warming process where lower and upper temperatures share the same trend behavior (IQR is maintained constant through time, warming type ***W1*** to one characterized by a larger increase in the upper temperatures (IQR increases in time, warming type ***W3***).
- On the contrary, the whole Globe maintains a stable warming type process characterized by lower temperatures that increase more than the upper ones (IQR decreases in time). In our typology, this constitutes a case of warming type ***W2***.
- Spain and the Globe suffer similar **warming acceleration**. There is a clear asymmetric **warming amplification**: upper quantiles in Spain and lower quantiles in the Globe.
- Spain **warming dominates** the Globe in the whole temperature distribution but the lower quantiles (q05).

Outline

GG 2020 Methodology

Summary of the methodology introduced in Gadea and Gonzalo (JoE, 2020)

- For the purpose of this research, temperatures are seen as a stochastic process, $X = (X_t(\omega), t \in T)$, where T is an interval in $\Re$, defined on a probability space $(\Omega, \Im, P)$ and such that $t \to X_t(\omega)$ belongs to some function space **G** for all $\omega \in \Omega$. X defines a **G-valued stochastic process**. This function space **G** is equipped with a scalar product $< .,. >$, and or a norm $\| \ . \ \|$ and a *Borel* σ *-algebra*, B_G. It is separable and complete.
- **G** can be a Hilbert space as in Bosq (2000) (AR-H model for sequences of random Hilbert functions $X_1(\omega), X_2(\omega), ..., X_T(\omega)$), as in Chang, Park and co-autors (2012, 2015) (regression models for sequences of random state densities $f_1(\omega), f_2(\omega), ..., f_T(\omega)$) or a Banach space for sequence of random state distributions $(F_1(\omega), F_2(\omega), ..., F_T(\omega))$, etc.
- A convenient EXAMPLE of an infinite-dimensional discrete-time process consists on associating with $\xi = (\xi_n, n \in \Re_+)$ a sequence of random variables with values in an appropriated function space. This may be obtained by setting

$$X_t(n) = \xi_{tN+n}, 0 \leq n \leq N, t = 0, 1, 2, ..., T,$$

so $X = (X_t, t = 0, 1, 2, ..., T)$. If the sample paths of ξ are continuous, then we have a sequence $X_0, X_1, ...$ of random variables in $C[0, N]$.

GG 2020 Methodology

Using a distributional characteristic approach, we move from Ω to $\mathbb{R}^T$, as in a standard stochastic process, passing through a **G** functional space:

$$\underset{(\omega)}{\Omega} \xrightarrow{X} \underset{X_t(\omega)}{\mathbf{G}} \xrightarrow{C} \underset{C_t(\omega)}{\mathbb{R}}$$

Returning to the convenient example and abusing the notation, the stochastic structure can be summarized in the following array:

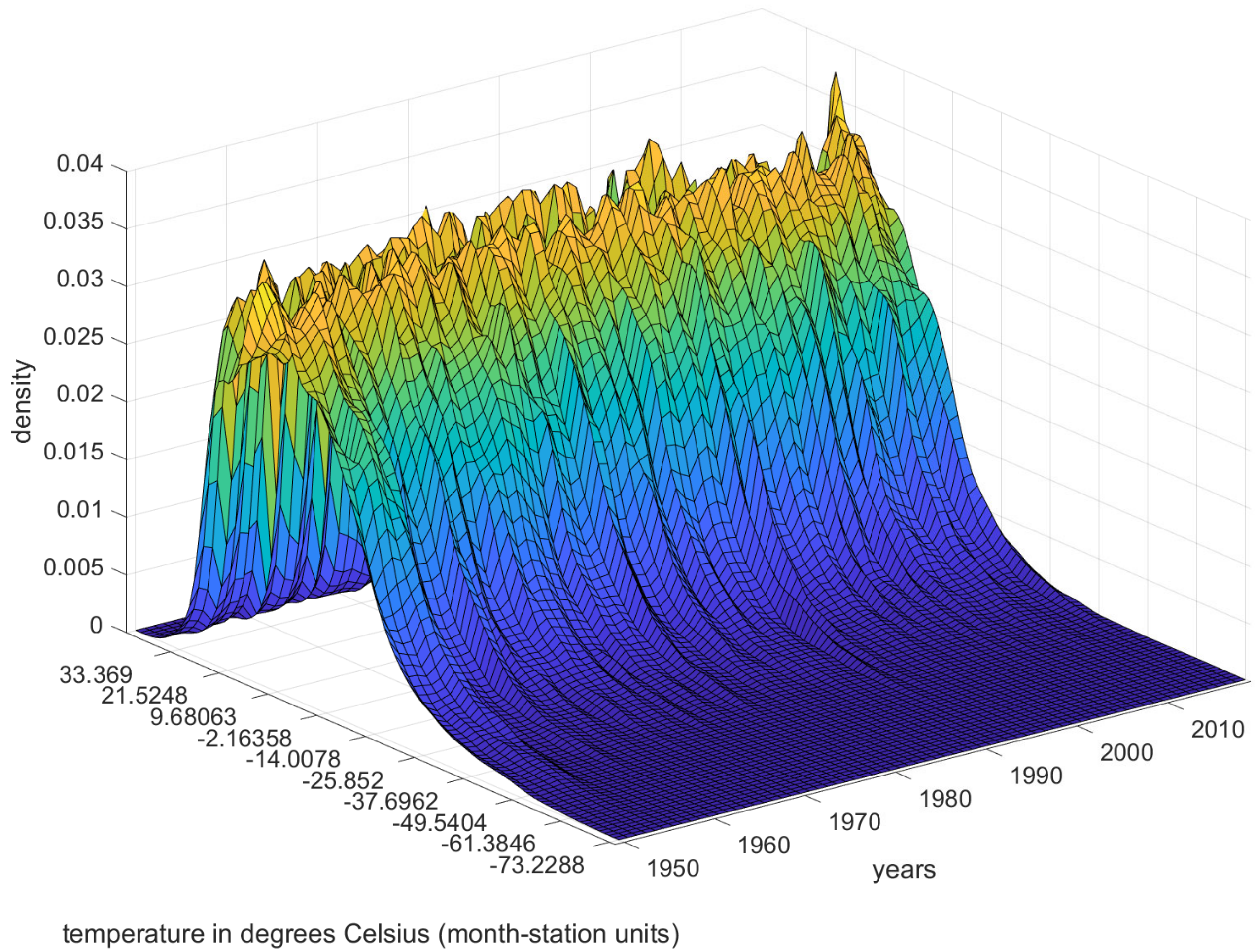
$X_{10}(\omega) = \xi_0(\omega)$	$X_{11}(\omega) = \xi_1(\omega)$	$\dots$	$X_{1N}(\omega) = \xi_N(\omega)$	$C_1(\omega)$
$X_{20}(\omega) = \xi_{N+1}(\omega)$	$X_{21}(\omega) = \xi_{N+2}(\omega)$	$\dots$	$X_{2N}(\omega) = \xi_{2N}(\omega)$	$C_2(\omega)$
$\vdots$	$\vdots$	$\dots$	$\vdots$	$\vdots$
$X_{T0}(\omega) = \xi_{(T-1)N+1}(\omega)$	$X_{T1}(\omega) = \xi_{(T-1)N+2}(\omega)$	$\dots$	$X_{TN}(\omega) = \xi_{TN}(\omega)$	$C_T(\omega)$

▸ GG method

Related literature: **(i) (with *N* higher time frequency)** Draghicescu, Guillas and Wu (*JCGS*, 2009), Zhou and Wu (*Ann. Stat*, 2009) and Zhou (*Ann. Stat*, 2010).
(ii) **(with *N* cross-section units)** Chang, Y., C. S. Kim, and J. Y. Park (*JoE*, 2016), and Chang, Y., R. K. Kaufmann, C. S. Kim, I. J. Miller, J. Y. Park, and S. Park (*JoE*, 2020).

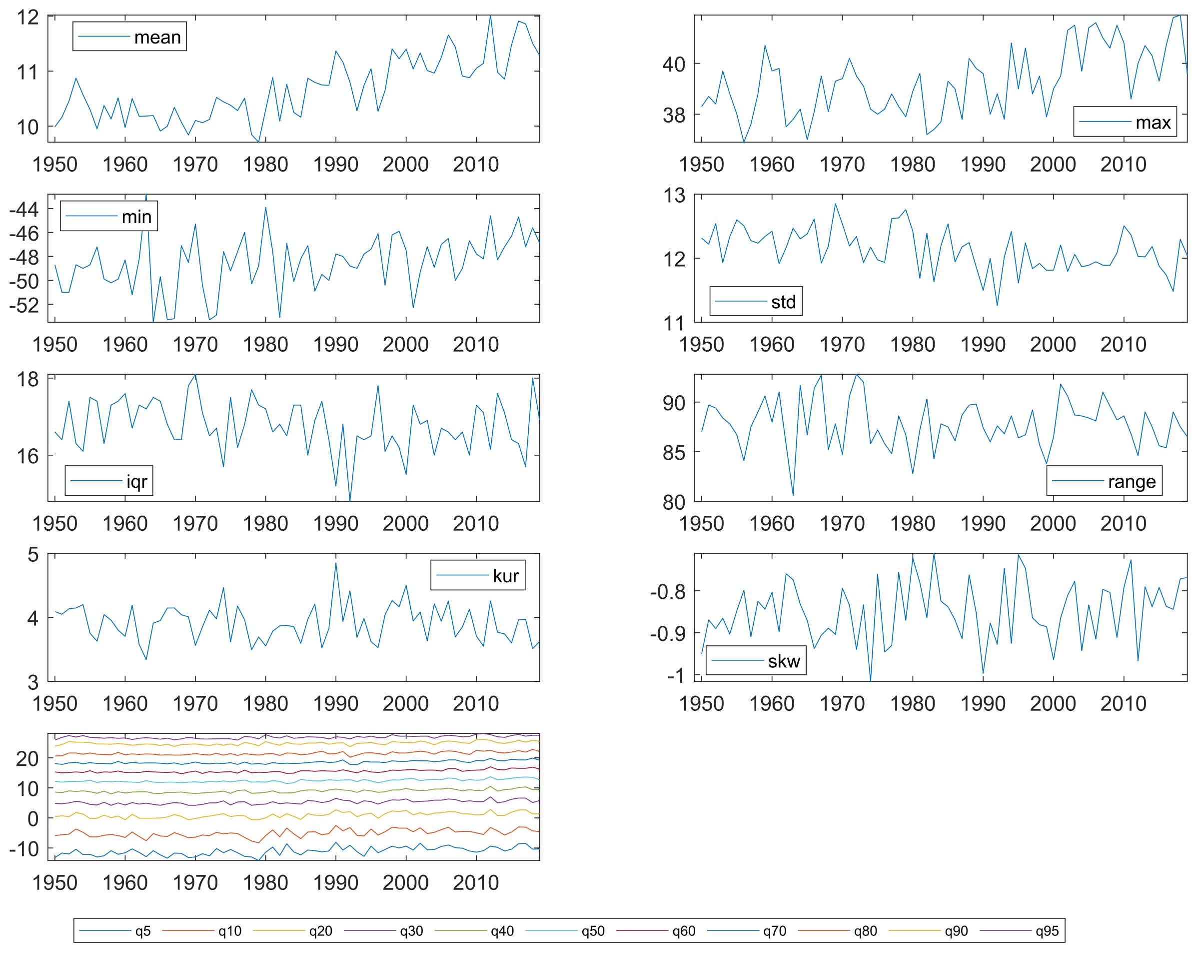
An example: The Globe

Global annual temperature density calculated with monthly data across stations



An example: The Globe

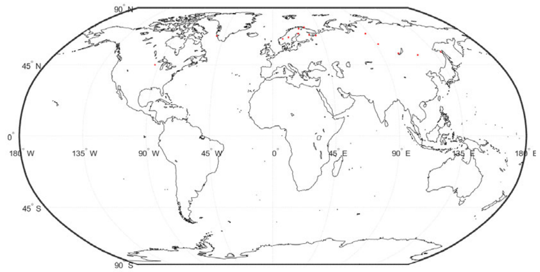
Distributional Characteristics of temperature data in the Globe (monthly data across stations, CRU, 1950-2019)



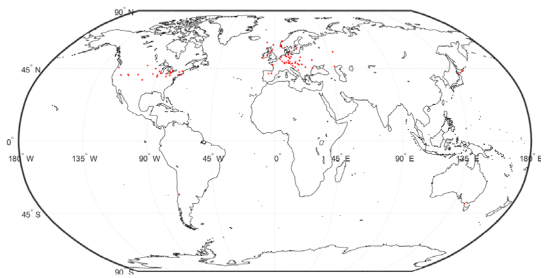
Where are located the QUANTILES?

Figure 1: The Globe: Quantile locations

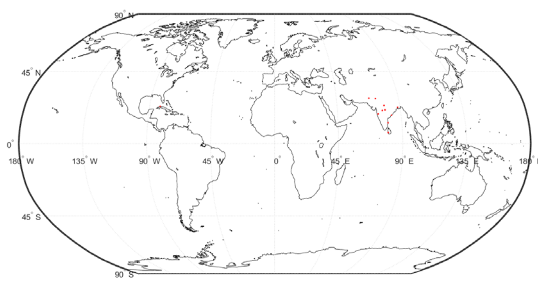
(The average latitude is 60.76, 46.21 and 20.33 for q05,q50 and q95, respectively)



(a) Panel A. q05



(b) Panel B. q50

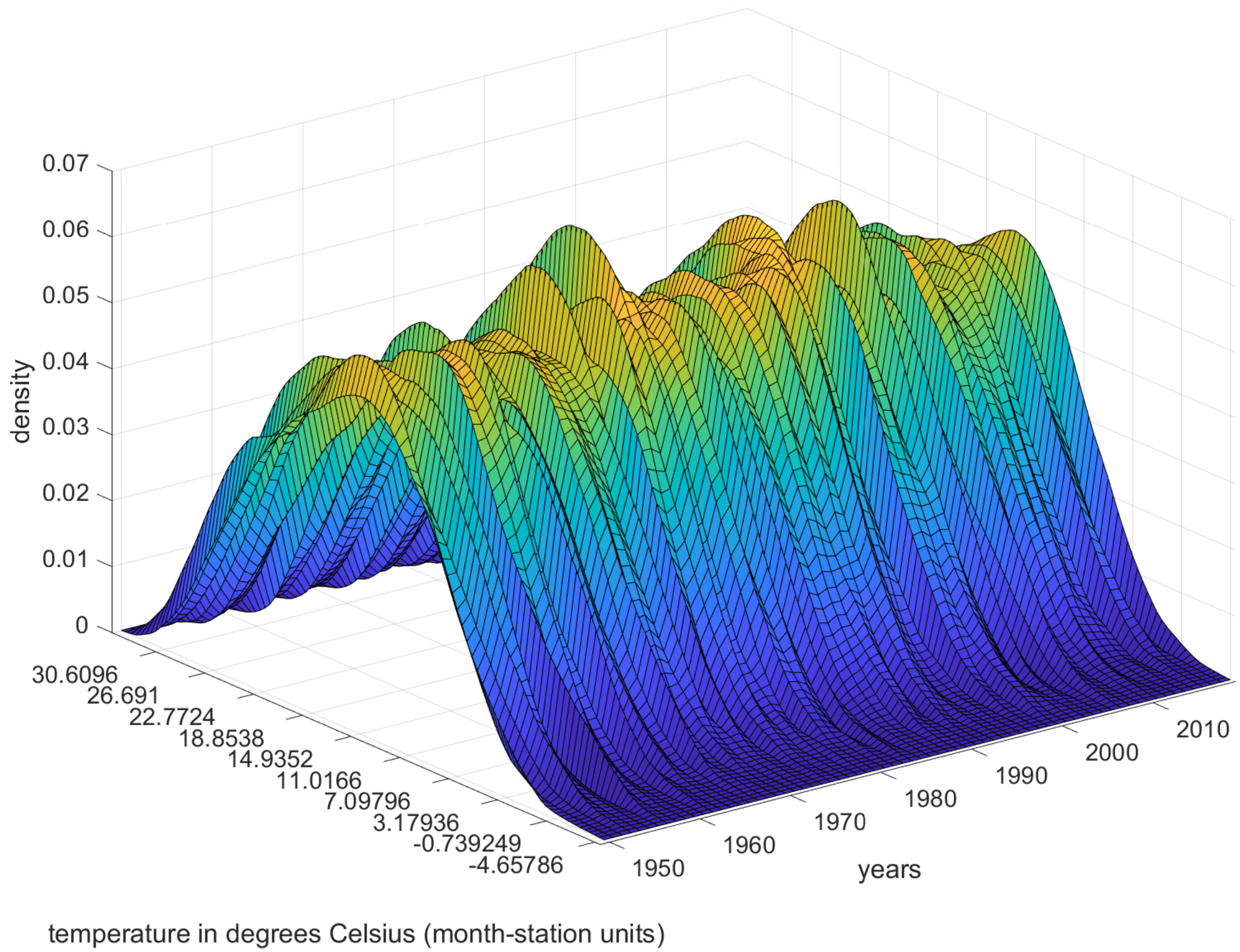


(c) Panel C. q95

Think on Zero dimension Energy Balance Models **versus** One dimension EBM.

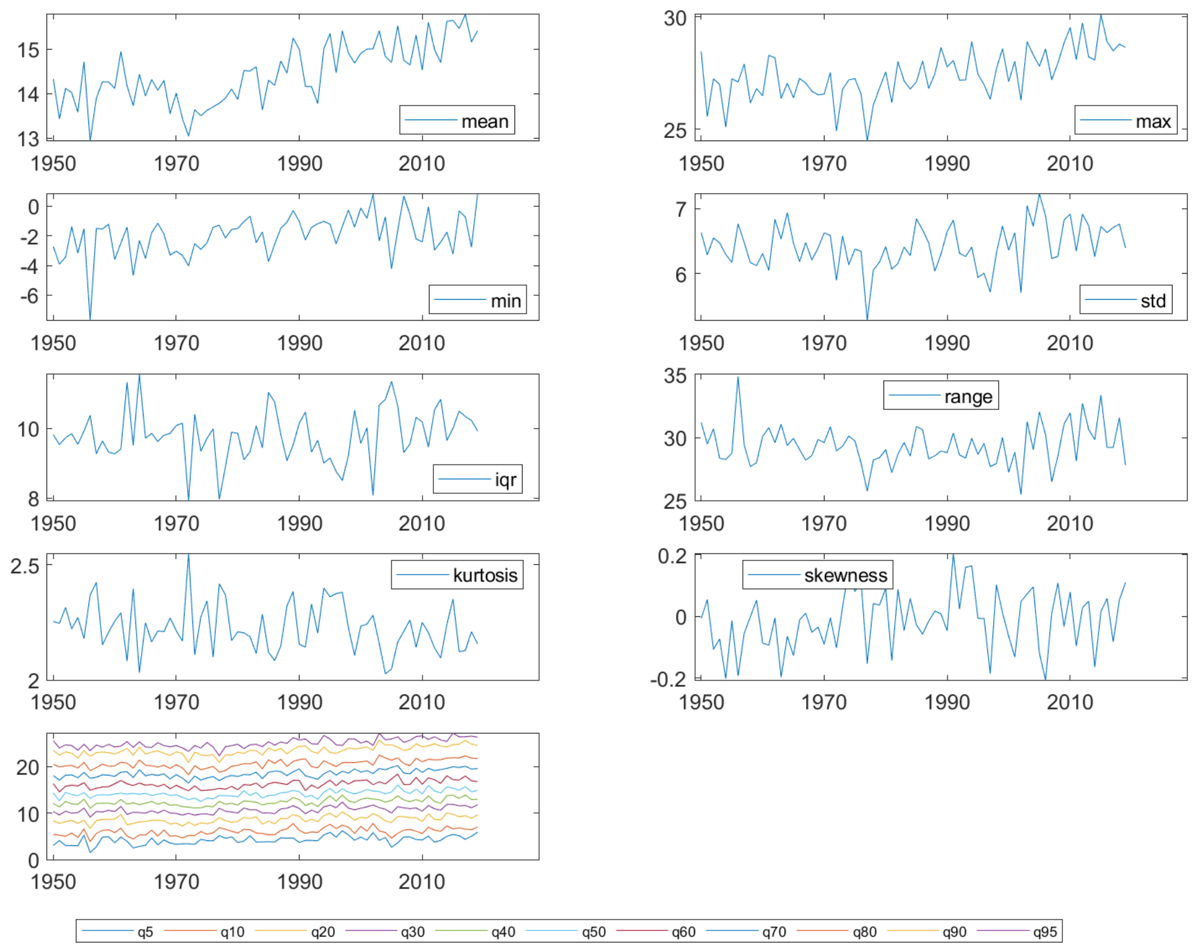
An example: Spain

Spain annual temperature density calculated with monthly data across stations



An example: Spain

Characteristics of temperature data in Spain with selected stations since 1950 (monthly data across stations, AEMET, 1950-2019)



Definition of Global (local) Warming

Definition of Glogal (local) Warming

Global (local) Warming is defined as the existence of an increasing trend in some of the characteristics measuring the central tendency or position (quantiles) of the global (local) temperature distribution.

BUT what is a **trend**?

We follow the intuitive definition given in White and Granger (2011) (WG): (i) a trend should have a direction; (ii) a trend should be basically smooth; (iii) a trend does not have to be monotonic throughout; and (iv) a trend can be a local behavior (observed trends can be related to a particular section of data).

A **trend** has a **deterministic** "flavour".

Empirical tools: definitions and tests

***(Practical Warming definition)*:**

A characteristic C_t of a functional stochastic process X_t contains a trend if in the LS regression,

$$C_t = \alpha + \beta t + u_t, \; t = 1, ..., T, \qquad (1)$$

$\beta = 0$ is rejected.

GG2020 shows that the $t_{\beta=0} - stat$ detects a trend even if it is not a linear one.
For example, $C_t \sim (\sqrt{t}, log(t), t^2, I(1), I(d, d > 1/2), ...) + I(0)$.

Empirical tools: definitions and tests

***(Co-trending)*:**

A set of m distributional characteristics (C_{1t},C_{2t},...,C_{mt}) do linearly co-trend if in the multivariate regression

$$\begin{pmatrix} C_{1t} \\ \dots \\ C_{mt} \end{pmatrix} = \begin{pmatrix} \alpha_1 \\ \dots \\ \alpha_m \end{pmatrix} + \begin{pmatrix} \beta_1 \\ \dots \\ \beta_m \end{pmatrix} t + \begin{pmatrix} u_{1t} \\ \dots \\ u_{mt} \end{pmatrix} \quad (2)$$

all the slopes are equal, $\beta_1 = \beta_2 = ... = \beta_m$.

This co-trending hypothesis can be tested by a standard Wald test.

Alternately, for any given pair of characteristics C_{it} and C_{jt} we can test $\beta = 0$ in the following regression:

$$C_{it} - C_{jt} = \alpha + \beta t + u_t. \quad (3)$$

The co-trending results are the base for our proposed dynamic **Warming Typology**.

Empirical tools: definitions and tests

This typology is based on the evolution of the different distributional characteristics, especially the lower and upper quantiles.

***(Warming typology)*:**

We define four types of Warming processes:

- *W0*: There is no trend in any of the quantiles (No Warming).
- ***W1***: All the quantiles share the same positive trend (*IQR* does not contain a trend)
- ***W2***: The Lower quantiles have a larger positive trend than the Upper quantiles (*IQR* has a negative trend)
- ***W3***: The Upper quantiles have a larger positive trend than the Lower quantiles (*IQR* has a positive trend).

▸ Simulations

- Most of the literature on Global or Local Warming only considers the trend behavior of the central part of the distribution (mean or median).
- The existing climate typologies are very static compared to the new one. ▸ Koppen
- This typology does not say anything about the intensity of the warming process. Part of this intensity is captured by the **warming acceleration** and **warming amplification**, and finally by **Warming Dominance**.

Empirical tools: definitions and tests

***(Warming acceleration)*:**

We say that there is warming acceleration in a distributional temperature characteristic C_t between the time periods $t_1 = (1, ..., s)$ and $t_2 = (s + 1, ..., T)$ if in the following two regressions:

$$C_t = \alpha_1 + \beta_1 t + u_t, \ t = 1, ..., s, ..., T, \tag{4}$$

$$C_t = \alpha_2 + \beta_2 t + u_t, \ t = s + 1, ..., T, \tag{5}$$

the second trend slope is larger than the first one: $\beta_2 > \beta_1$.

In practice, we implement this definition by testing in the previous system the null hypothesis $\beta_2 = \beta_1$ against the alternative $\beta_2 > \beta_1$.

Empirical tools: definitions and tests

***(Warming amplification with respect to the mean)*:**

We say that there is a warming amplification in distributional characteristic C_t with respect the *mean* if in the following regression:

$$C_t = \beta_0 + \beta_1 mean_t + \epsilon_t \quad (6)$$

the mean slope is greater than one: $\beta_1 > 1$.

When the mean $mean_t$ and C_t come from the same distribution we name this "**inner**" warming amplification. Otherwise, the mean may come from an external environment and, in that case, we call it "**outer**" warming amplification.

Empirical tools: definitions and tests

(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

$$q_{\tau t}(A) - q_{\tau t}(B) = \alpha_\tau + \beta_\tau t + u_{\tau t}, \tag{7}$$

$\beta_\tau \geq 0$ for all $0 < \tau < 1$ and there is at least one value τ^* for which a strict inequality holds.

See **Arctic** Dominance w.r.t the **Globe**.

▸ WD-Polar

It is also possible to have only *partial WD*. For instance, in the lower or upper quantiles.

The data

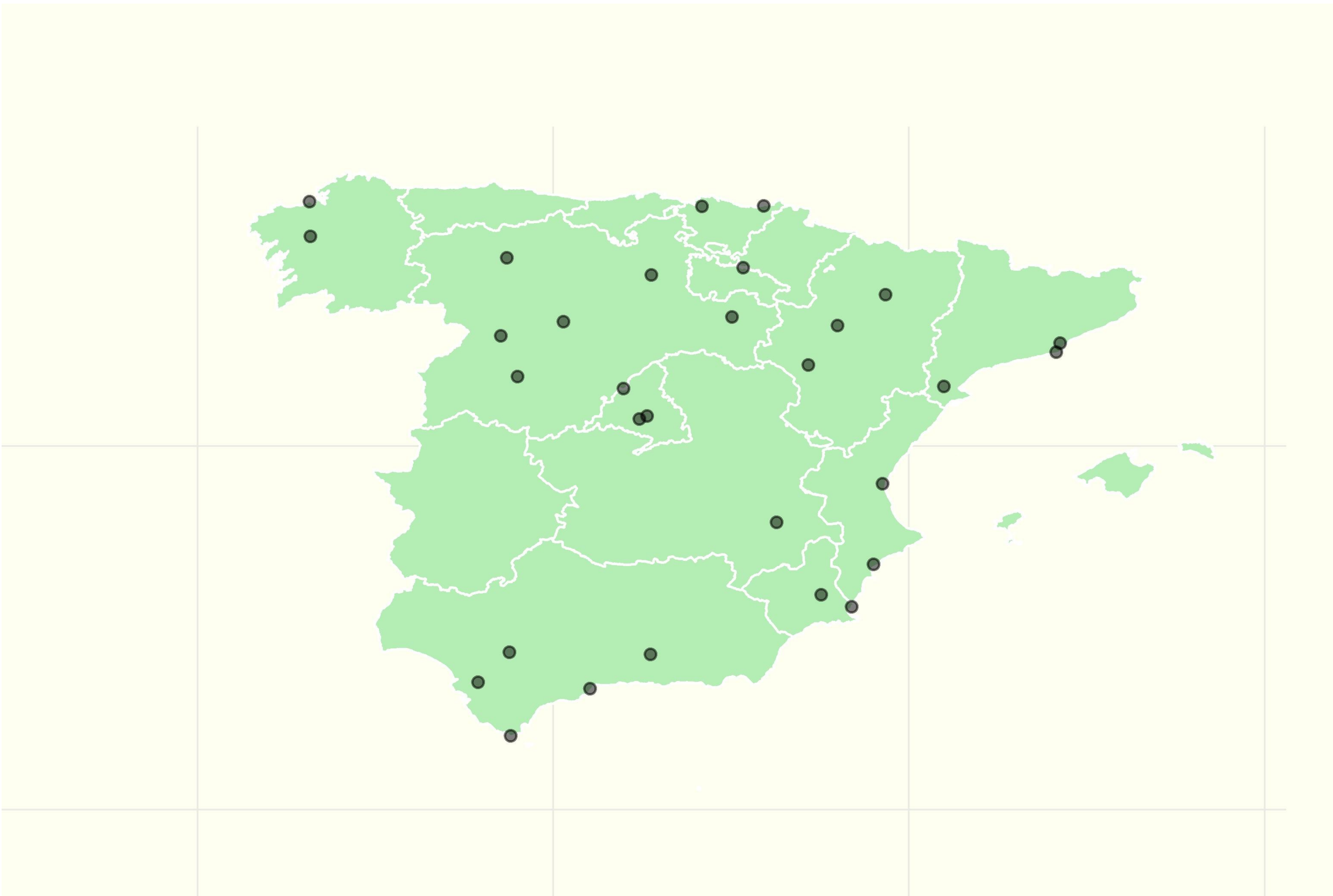
Sources:

- Agencia Española de Meterología (AEMET) for Spain, Madrid and Barcelona
- Climate Research Unit (CRU) for the Globe

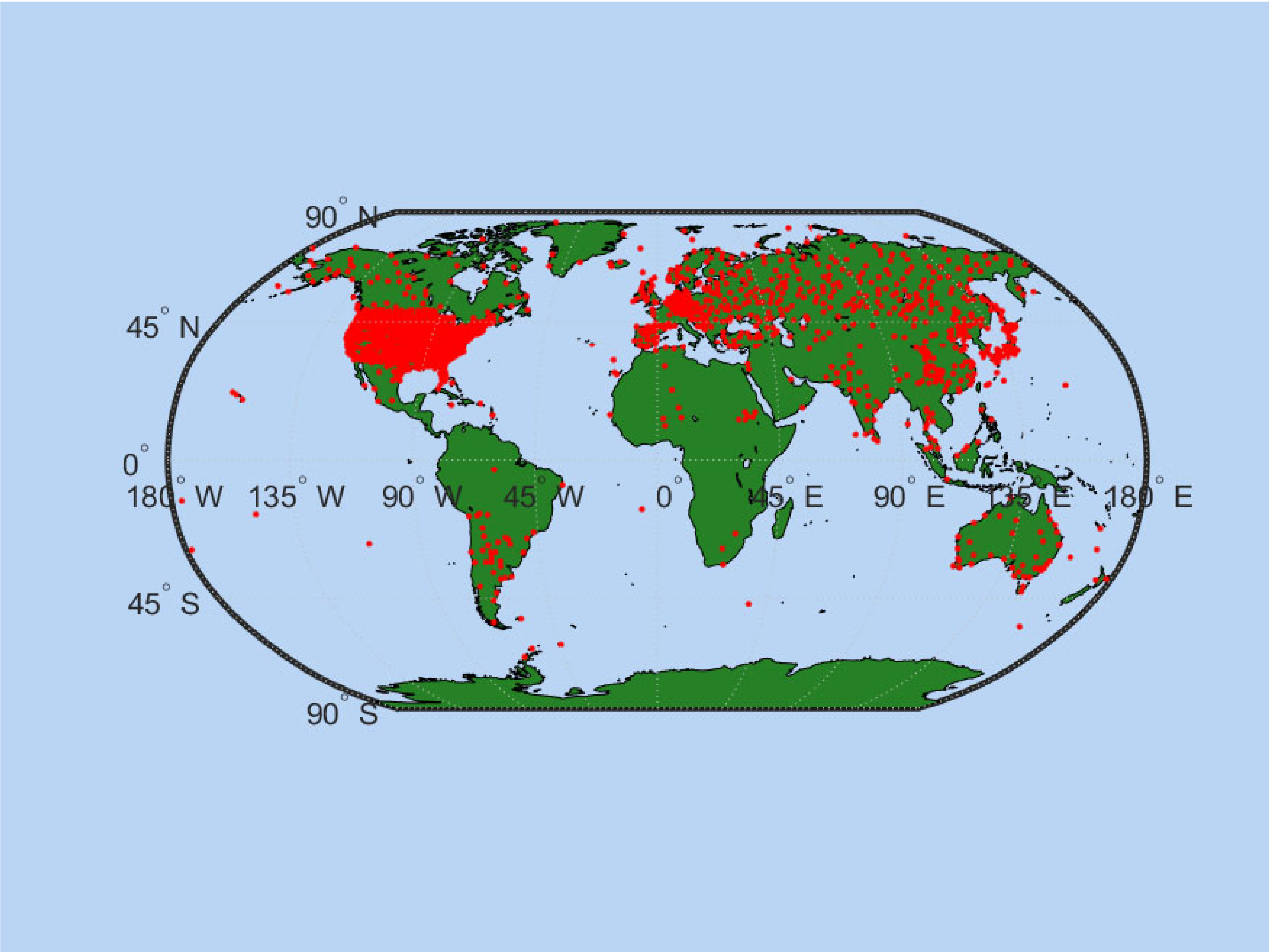
Sample, 1950-2019:

- For **Spain**, we select the longest span of time that guarantees a wide ans continuous sample of stations (30*12 station-month units) so that all the geographical areas of peninsular Spain are represented.
- For the **Globe**, we have selected the stations (2192*12 station-month units) that are permanently present in the period 1950-2019.

Spain. Selected stations, AEMET data 1950-2019



The Globe. Selected stations, CRU data 1950-2019



Distributional characteristics

- X is the local or global temperature,
- T (number of periods) is measured in years,
- N refers to monthly-stations units
- and $C_t = (C_{1t}, C_{2t}, ..., C_{pt})$ is a vector of p distributional characteristics
    - mean (*mean*),
    - maximum (*max*),
    - minimum (*min*),
    - standard deviation (*std*),
    - interquartile range (*iqr*),
    - total range (*range*),
    - kurtosis (*kur*),
    - skewness (*skw*),
    - and the following quantiles: $q05$, $q10$, $q20$, $q30$, $q40$, $q50$, $q60$, $q70$, $q80$, $q90$, and $q95$

estimated from N observations in each region.

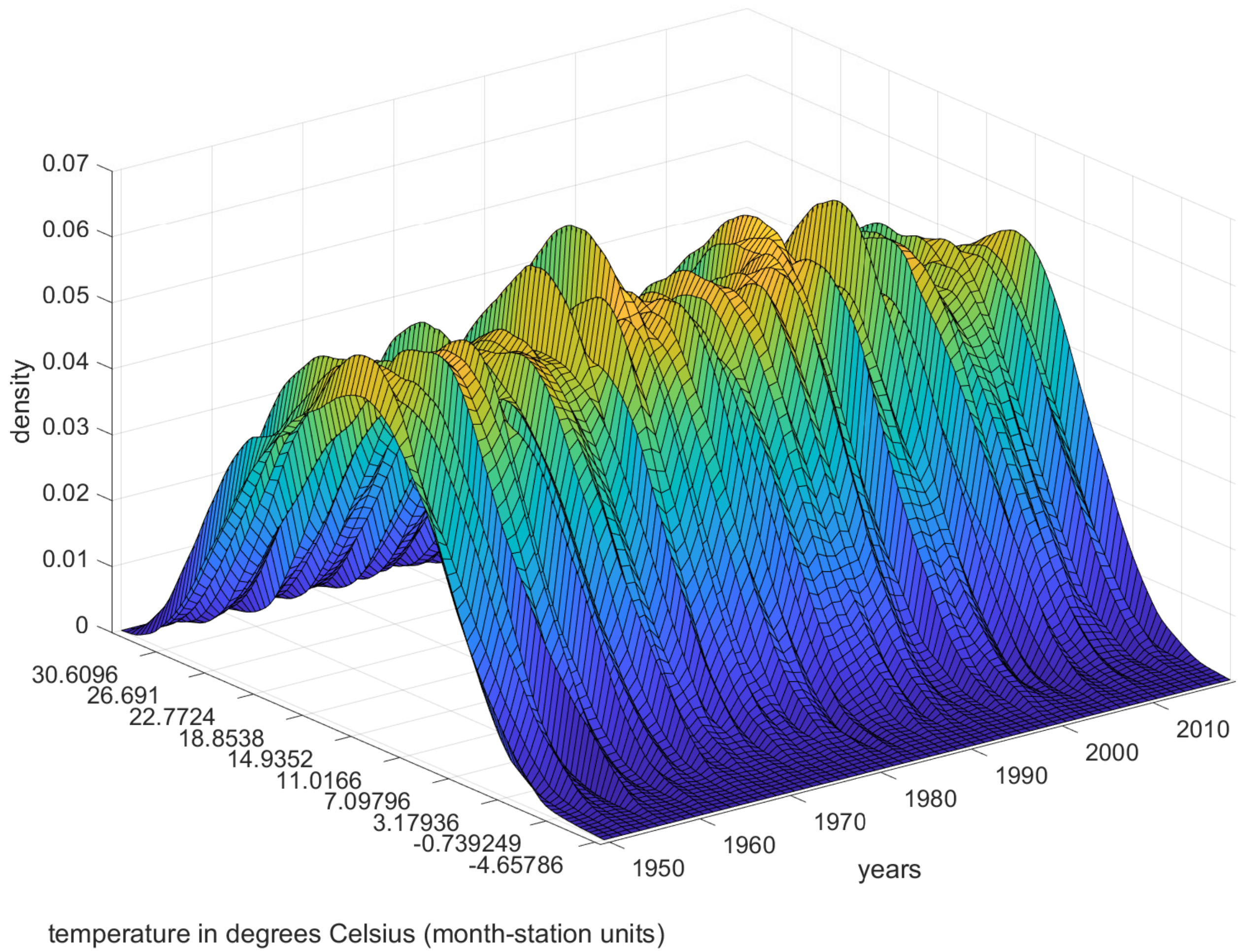
Empirical strategy

Our empirical strategy comprises the following steps:

1. Test for **trends** in all the distributional characteristics
2. Test for **warming acceleration**
3. Test different **co-trending hypotheses**
4. Test for **warming amplification**: “inner” and “outer”
5. Put together the pieces and assign the corresponding **Warming typology**
6. Determine which regions **Warming Dominate**.
7. NEXT?...

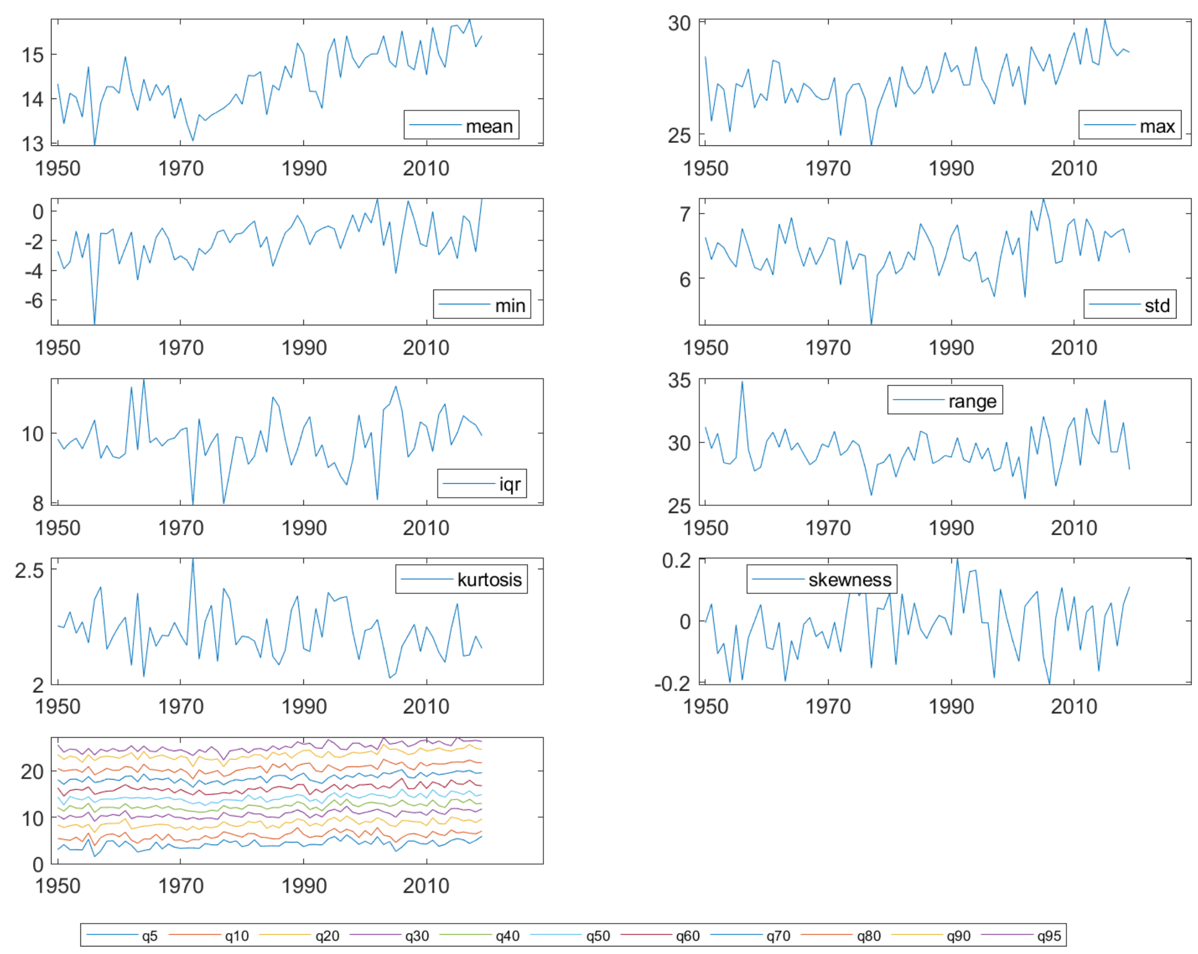
Local Warming: Spain

Spain annual temperature density calculated with monthly data across stations



Local Warming: Spain

Characteristics of temperature data in Spain with station selected since 1950 (monthly data across stations, AEMET, 1950-2019)



Local Warming: Spain

Table 1: Trend acceleration hypothesis (Spain monthly data across stations, AEMET, 1950-2019)

	Trend test by periods		Acceleration test
names/periods	1950-2019	1970-2019	1950-2019, 1970-2019
mean	**0.0242**	**0.0389**	**3.0294**
	(0.0000)	(0.0000)	(0.0015)
max	0.0312	0.0526	2.7871
	(0.0000)	(0.0000)	(0.0030)
min	0.0289	0.0251	-0.2557
	(0.0000)	(0.0654)	(0.6007)
std	0.0036	0.0098	1.7952
	(0.0518)	(0.0021)	(0.0374)
iqr	**0.0051**	**0.0158**	**1.8197**
	(0.1793)	(0.0028)	(0.0355)
rank	0.0023	0.0276	1.2705
	(0.8249)	(0.1127)	(0.1030)
kur	-0.0010	-0.0018	-0.9191
	(0.0203)	(0.0198)	(0.8202)
skw	0.0011	-0.0002	-1.5989
	(0.0271)	(0.7423)	(0.9439)
q05	**0.0227**	**0.0206**	**-0.2559**
	(0.0000)	(0.0059)	(0.6008)
q10	0.0200	0.0203	0.0406
	(0.0000)	(0.0077)	(0.4838)
q20	0.0209	0.0300	1.4158
	(0.0000)	(0.0000)	(0.0796)
q30	0.0221	0.0333	2.0100
	(0.0000)	(0.0000)	(0.0232)
q40	0.0213	0.0366	2.4867
	(0.0000)	(0.0000)	(0.0071)
q50	0.0211	0.0404	3.2496
	(0.0000)	(0.0000)	(0.0007)
q60	0.0246	0.0446	3.1147
	(0.0000)	(0.0000)	(0.0011)
q70	0.0273	0.0478	3.3143
	(0.0000)	(0.0000)	(0.0006)
q80	0.0275	0.0471	2.6949
	(0.0000)	(0.0000)	(0.0040)
q90	0.0321	0.0548	3.2441
	(0.0000)	(0.0000)	(0.0007)
q95	**0.0335**	**0.0526**	**3.3568**
	(0.0000)	(0.0000)	(0.0005)

Local Warming: Spain

Table 2: Trend acceleration hypothesis (Spain monthly data across stations, AEMET, 1950-2019)

	Trend test by periods		Acceleration test
names/periods	1950-2019	1970-2019	1950-2019, 1970-2019
mean	**0.0242**	**0.0389**	**3.0294**
	(0.0000)	(0.0000)	(0.0015)
max	0.0312	0.0526	2.7871
	(0.0000)	(0.0000)	(0.0030)
min	0.0289	0.0251	-0.2557
	(0.0000)	(0.0654)	(0.6007)
std	0.0036	0.0098	1.7952
	(0.0518)	(0.0021)	(0.0374)
iqr	**0.0051**	**0.0158**	**1.8197**
	(0.1793)	(0.0028)	(0.0355)
rank	0.0023	0.0276	1.2705
	(0.8249)	(0.1127)	(0.1030)
kur	-0.0010	-0.0018	-0.9191
	(0.0203)	(0.0198)	(0.8202)
skw	0.0011	-0.0002	-1.5989
	(0.0271)	(0.7423)	(0.9439)
q05	**0.0227**	**0.0206**	**-0.2559**
	(0.0000)	(0.0059)	(0.6008)
q10	0.0200	0.0203	0.0406
	(0.0000)	(0.0077)	(0.4838)
q20	0.0209	0.0300	**1.4158**
	(0.0000)	(0.0000)	(0.0796)
q30	0.0221	0.0333	**2.0100**
	(0.0000)	(0.0000)	(0.0232)
q40	0.0213	0.0366	**2.4867**
	(0.0000)	(0.0000)	(0.0071)
q50	0.0211	0.0404	**3.2496**
	(0.0000)	(0.0000)	(0.0007)
q60	0.0246	0.0446	**3.1147**
	(0.0000)	(0.0000)	(0.0011)
q70	0.0273	0.0478	**3.3143**
	(0.0000)	(0.0000)	(0.0006)
q80	0.0275	0.0471	**2.6949**
	(0.0000)	(0.0000)	(0.0040)
q90	0.0321	0.0548	**3.2441**
	(0.0000)	(0.0000)	(0.0007)
q95	**0.0335**	**0.0526**	**3.3568**
	(0.0000)	(0.0000)	(0.0005)

Table 3: Co-trending analysis (Spain monthly data across stations, AEMET, 1950-2019)

Joint hypothesis tests	Wald test	p-value
All quantiles (q05, q10,...,q90, q95)	**13.235**	**0.211**
Lower quantiles (q05, q10, q20, q30)	0.310	0.958
Medium quantiles (q40, q50, q60)	0.438	0.803
Upper quantiles (q70, q80, q90, q95)	1.515	0.679
Lower-Medium quantiles (q05, q10, q20, q30, q40, q50, q60)	0.771	0.993
Medium-Upper quantiles (q40, q50, q60, q70, q80, q90, q95)	8.331	0.215
Lower-Upper quantiles (q05, q10, q20,q30, q70, q80, q90, q95)	11.705	0.111
Spacing hypothesis	Trend-coeff.	p-value
q50-q05	-0.002	0.786
q95-q50	0.012	0.000
q95-q05	0.011	0.096
q75-q25 (iqr)	**0.005**	**0.179**

W1

Table 4: Co-trending analysis (Spain monthly data across stations, AEMET, 1970-2019)

Joint hypothesis tests	Wald test	p-value
All quantiles (q05, q10,...,q90, q95)	**38.879**	**0.000**
Lower quantiles (q05, q10, q20, q30)	3.121	0.373
Medium quantiles (q40, q50, q60)	1.314	0.518
Upper quantiles (q70, q80, q90, q95)	1.719	0.633
Lower-Medium quantiles (q05, q10, q20, q30, q40, q50, q60)	12.771	0.047
Medium-Upper quantiles (q40, q50, q60, q70, q80, q90, q95)	10.675	0.099
Lower-Upper quantiles (q05, q10, q20,q30, q70, q80, q90, q95)	37.892	0.000
Spacing hypothesis	Trend-coeff.	p-value
q50-q05	0.020	0.029
q95-q50	0.012	0.050
q95-q05	0.032	0.002
q75-q25 (iqr)	**0.016**	**0.003**

W3

Table 5: Amplification hypothesis (Spain monthly data, AEMET 1950-2019)

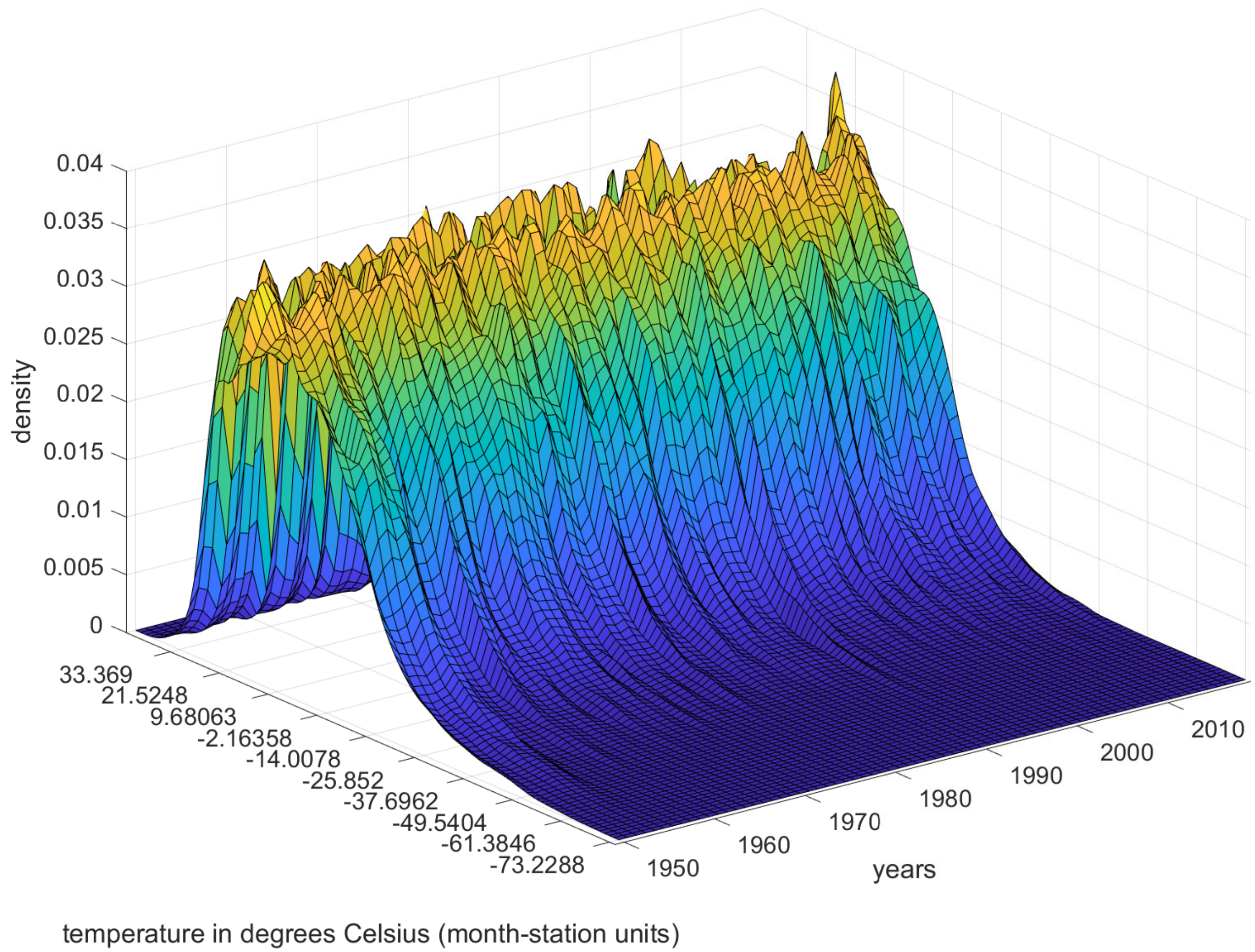
periods/variables	1950-2019	1970-2019
q05	0.55	0.39
	(0.990)	(0.996)
q10	0.62	0.52
	(0.992)	(0.986)
q20	0.76	0.81
	(0.993)	(0.899)
q30	0.77	0.87
	(0.997)	(0.834)
q40	0.80	0.97
	(0.978)	(0.566)
q50	0.83	1.12
	(0.944)	(0.212)
q60	0.96	1.23
	(0.619)	(0.056)
q70	1.05	1.30
	(0.350)	(0.028)
q80	1.06	**1.29**
	(0.325)	**(0.060)**
q90	**1.19**	**1.45**
	(0.078)	**(0.007)**
q95	**1.18**	**1.36**
	(0.051)	**(0.008)**

Local Warming: Spain

- The co-trending tests for the full sample 1950-2019 show a similar trend evolution for all the quantiles with a constant ***iqr***: Spain is of type ***W1***.
- More recently, 1970-2019, the co-trending tests indicate the upper quantiles growth faster than the lower ones. This together with a positive trend in the dispersion measured by the ***iqr*** shows that Spain has evolved from a ***W1*** to a ***W3*** warming type process.
- Spain suffers **warming acceleration** in all the quantiles above **q10**. There is **warming amplification** in the upper quantiles (above **q80**).

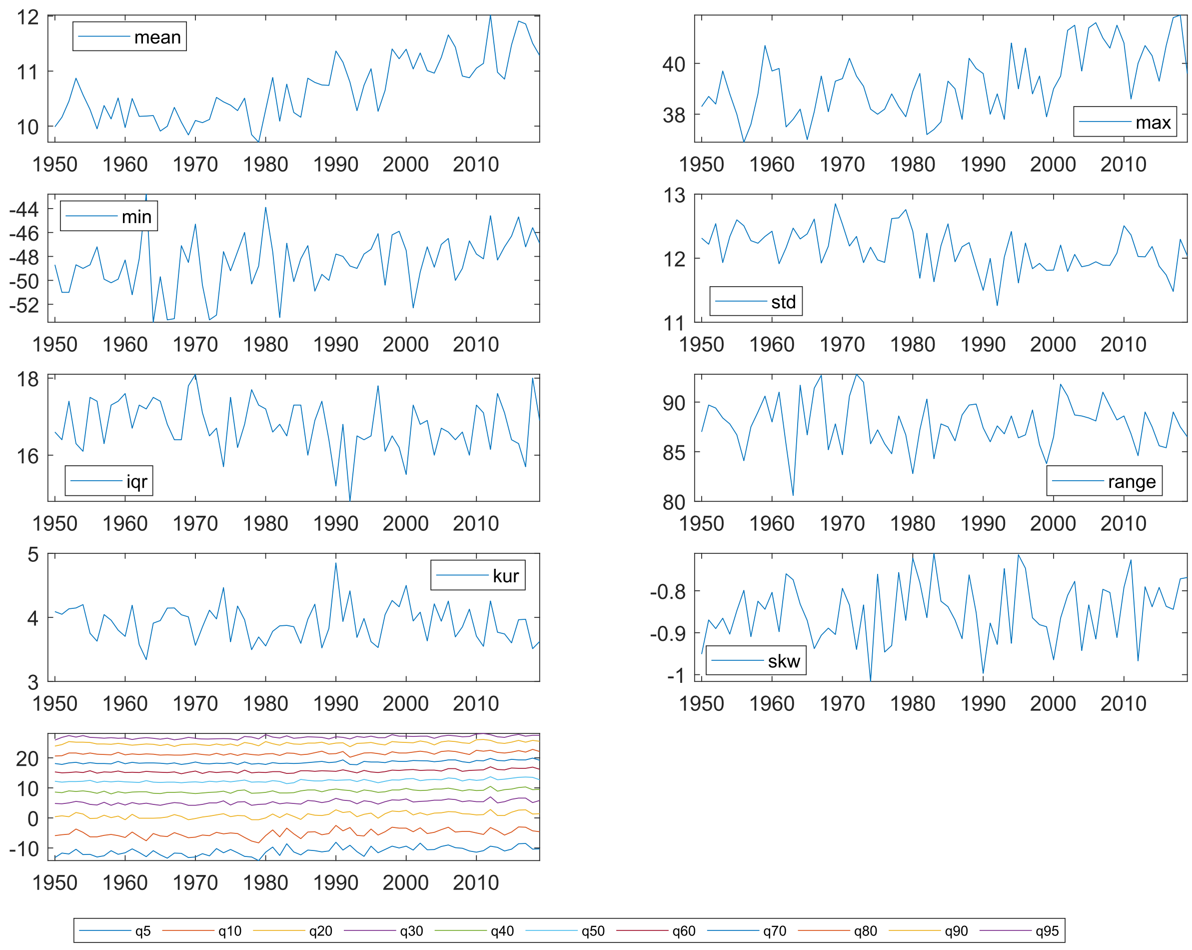
Global Warming: The Globe

Global annual temperature density calculated with monthly data across stations



Global Warming: The Globe

Characteristics of temperature data in the Globe (monthly data across stations, CRU, 1950-2019)



Global Warming: The Globe

Table 6: Trend acceleration hypothesis (CRU monthly data across stations, 1950-2019)

	Trend test by periods		Acceleration test
names/periods	1950-2019	1970-2019	1950-2019, 1970-2019
mean	**0.0213**	**0.0300**	**2.2023**
	(0.0000)	(0.0000)	(0.0147)
max	0.0361	0.0523	1.1217
	(0.0000)	(0.0001)	(0.1320)
min	0.0423	-0.0109	0.5016
	(0.0000)	(0.5867)	(0.3084)
std	**-0.0070**	**-0.0057**	**0.1776**
	(0.0000)	(0.0570)	(0.4296)
iqr	-0.0067	-0.0043	0.2454
	(0.0435)	(0.4183)	(0.4033)
rank	-0.0062	0.0632	0.2181
	(0.5876)	(0.0005)	(0.4138)
kur	-0.0010	0.0001	0.0445
	(0.5205)	(0.9566)	(0.4823)
skw	0.0006	0.0003	0.0301
	(0.0577)	(0.5726)	(0.4880)
q05	**0.0404**	**0.0468**	**0.7035**
	(0.0000)	(0.0000)	(0.2415)
q10	0.0305	0.0406	0.9273
	(0.0000)	(0.0001)	(0.1777)
q20	0.0253	0.0342	1.0156
	(0.0000)	(0.0000)	(0.1558)
q30	0.0215	0.0280	1.2056
	(0.0000)	(0.0000)	(0.1150)
q40	0.0192	0.0293	1.9873
	(0.0000)	(0.0000)	(0.0245)
q50	0.0179	0.0268	1.8614
	(0.0000)	(0.0000)	(0.0324)
q60	0.0185	0.0291	2.1971
	(0.0000)	(0.0000)	(0.0149)
q70	0.0185	0.0288	2.5770
	(0.0000)	(0.0000)	(0.0055)
q80	0.0160	0.0257	2.2460
	(0.0000)	(0.0000)	(0.0132)
q90	0.0146	0.0243	2.0848
	(0.0005)	(0.0000)	(0.0195)
q95	**0.0143**	**0.0239**	**1.7520**
	(0.0001)	(0.0000)	(0.0410)

Global Warming: The Globe

Table 7: Trend acceleration hypothesis (CRU monthly data across stations, 1950-2019)

	Trend test by periods		Acceleration test
names/periods	1950-2019	1970-2019	1950-2019, 1970-2019
mean	**0.0213**	**0.0300**	**2.2023**
	(0.0000)	(0.0000)	(0.0147)
max	0.0361	0.0523	1.1217
	(0.0000)	(0.0001)	(0.1320)
min	0.0423	-0.0109	0.5016
	(0.0000)	(0.5867)	(0.3084)
std	**-0.0070**	**-0.0057**	**0.1776**
	(0.0000)	(0.0570)	(0.4296)
iqr	-0.0067	-0.0043	0.2454
	(0.0435)	(0.4183)	(0.4033)
rank	-0.0062	0.0632	0.2181
	(0.5876)	(0.0005)	(0.4138)
kur	-0.0010	0.0001	0.0445
	(0.5205)	(0.9566)	(0.4823)
skw	0.0006	0.0003	0.0301
	(0.0577)	(0.5726)	(0.4880)
q05	**0.0404**	**0.0468**	**0.7035**
	(0.0000)	(0.0000)	(0.2415)
q10	0.0305	0.0406	0.9273
	(0.0000)	(0.0001)	(0.1777)
q20	0.0253	0.0342	1.0156
	(0.0000)	(0.0000)	(0.1558)
q30	0.0215	0.0280	1.2056
	(0.0000)	(0.0000)	(0.1150)
q40	0.0192	0.0293	**1.9873**
	(0.0000)	(0.0000)	(0.0245)
q50	0.0179	0.0268	**1.8614**
	(0.0000)	(0.0000)	(0.0324)
q60	0.0185	0.0291	**2.1971**
	(0.0000)	(0.0000)	(0.0149)
q70	0.0185	0.0288	**2.5770**
	(0.0000)	(0.0000)	(0.0055)
q80	0.0160	0.0257	**2.2460**
	(0.0000)	(0.0000)	(0.0132)
q90	0.0146	0.0243	**2.0848**
	(0.0005)	(0.0000)	(0.0195)
q95	**0.0143**	**0.0239**	**1.7520**
	(0.0001)	(0.0000)	(0.0410)

Global Warming: The Globe

Table 8: Co-trending analysis (CRU montly data, 1950-2019)

Joint hypothesis tests	Wald test	p-value
All quantiles (q05, q10,...,q90, q95)	**25.143**	**0.005**
Lower quantiles (q05, q10, q20, q30)	9.545	0.023
Medium quantiles (q40, q50, q60)	0.078	0.962
Upper quantiles (q70, q80, q90, q95)	1.099	0.777
Lower-Medium quantiles (q05, q10, q20, q30, q40, q50, q60)	17.691	0.007
Medium-Upper quantiles (q40, q50, q60, q70, q80, q90, q95)	2.041	0.916
Lower-Upper quantiles (q05, q10, q20,q30, q70, q80, q90, q95)	24.683	0.001
Spacing hypothesis	Trend-coeff.	p-value
q50-q05	-0.022	0.000
q95-q50	-0.004	0.193
q95-q05	-0.026	0.000
q75-q25 (iqr)	**-0.007**	**0.043**

W2

Global Warming: The Globe

Table 9: Co-trending analysis (CRU montly data, 1970-2019)

Joint hypothesis tests	Wald test	p-value
All quantiles (q05, q10,...,q90, q95)	*18.478*	**0.047**
Lower quantiles (q05, q10, q20, q30)	5.523	0.137
Medium quantiles (q40, q50, q60)	0.569	0.752
Upper quantiles (q70, q80, q90, q95)	2.667	0.446
Lower-Medium quantiles (q05, q10, q20, q30, q40, q50, q60)	7.606	0.268
Medium-Upper quantiles (q40, q50, q60, q70, q80, q90, q95)	6.714	0.348
Lower-Upper quantiles (q05, q10, q20,q30, q70, q80, q90, q95)	14.520	0.043
Spacing hypothesis	Trend-coeff.	p-value
q50-q05	-0.020	0.047
q95-q50	-0.003	0.462
q95-q05	**-0.023**	**0.048**
q75-q25 (iqr)	-0.004	0.418

W2

Global Warming: The Globe

Table 10: Amplification hypotheses (CRU monthly data across stations, 1950-2019)

periods/variables	1950-2019	1970-2019
q05	**2.00**	**1.83**
	(0.000)	(0.000)
q10	**1.79**	**1.73**
	(0.000)	(0.001)
q20	**1.41**	**1.37**
	(0.000)	(0.000)
q30	**1.07**	1.00
	(0.089)	(0.502)
q40	0.88	0.91
	(0.999)	(0.973)
q50	0.74	0.81
	(1.000)	(0.997)
q60	0.74	0.85
	(0.999)	(0.973)
q70	0.77	0.85
	(1.000)	(0.988)
q80	0.72	0.78
	(1.000)	(1.000)
q90	0.69	0.70
	(1.000)	(1.000)
q95	0.60	0.64
	(1.000)	(1.000)

Global Warming: The Globe

- In both periods 1950-2019 and 1970-2019 the Globe experiments a ***W2*** warming type. The lower quantiles grow faster than the middle and upper ones implying that ***iqr*** has a negative trend (similar results for Central England in Gadea and Gonzalo *JoE* 2022 and for the US in Diebold and Rudebusch *AE* 2022).
- The Globe suffers **warming acceleration** in all the quantiles above **q30**.
- There is **warming amplification** in the lower quantiles (below **q40**). Notice that this **amplification** goes **beyond the Arctic** ($q05$): $q10$, $q20$ and $q30$.

Micro-local Warming: Madrid and Barcelona

- The existence of warming heterogeneity implies that in order to design efficient mitigation-adaptation policies they have to be elaborated at different levels: global, country, region, etc. How much further down we need to go will depend on the existing micro-warming heterogeneity degree.
- Now, we go to the smallest level, climate station level.
- We analyze, inside **Spain**, the warming process in two weather stations corresponding to two cities: **Madrid** (Retiro station) and **Barcelona** (Fabra station).
- Obviously, the data provided by these stations is not cross-sectional data but directly pure daily time series data.
- Our methodology can be easily applied to higher frequency time series, in this case, daily data (see the application to Central England in GG2020).

▸ Madrid ▸ Barcelona

Micro-local Warming: Madrid and Barcelona

- Even within **Spain** we find evidence of a CLEAR warming heterogeneity. While **Madrid** (Continental Mediterranean climate) has a similar pattern as peninsular Spain (1970-2019) ***W3***, **Barcelona** (Mediterranean coastline climate) maintains a ***W1*** typology.
- The **acceleration** warming process is more global in Barcelona than in Madrid. To mitigate the effects of these two different warming processes will require mitigation-adaptation policies at the country as well as at the local level.
- MORE RESULTS NEXT!!!

Warming Dominance

Table 11: Warming dominance

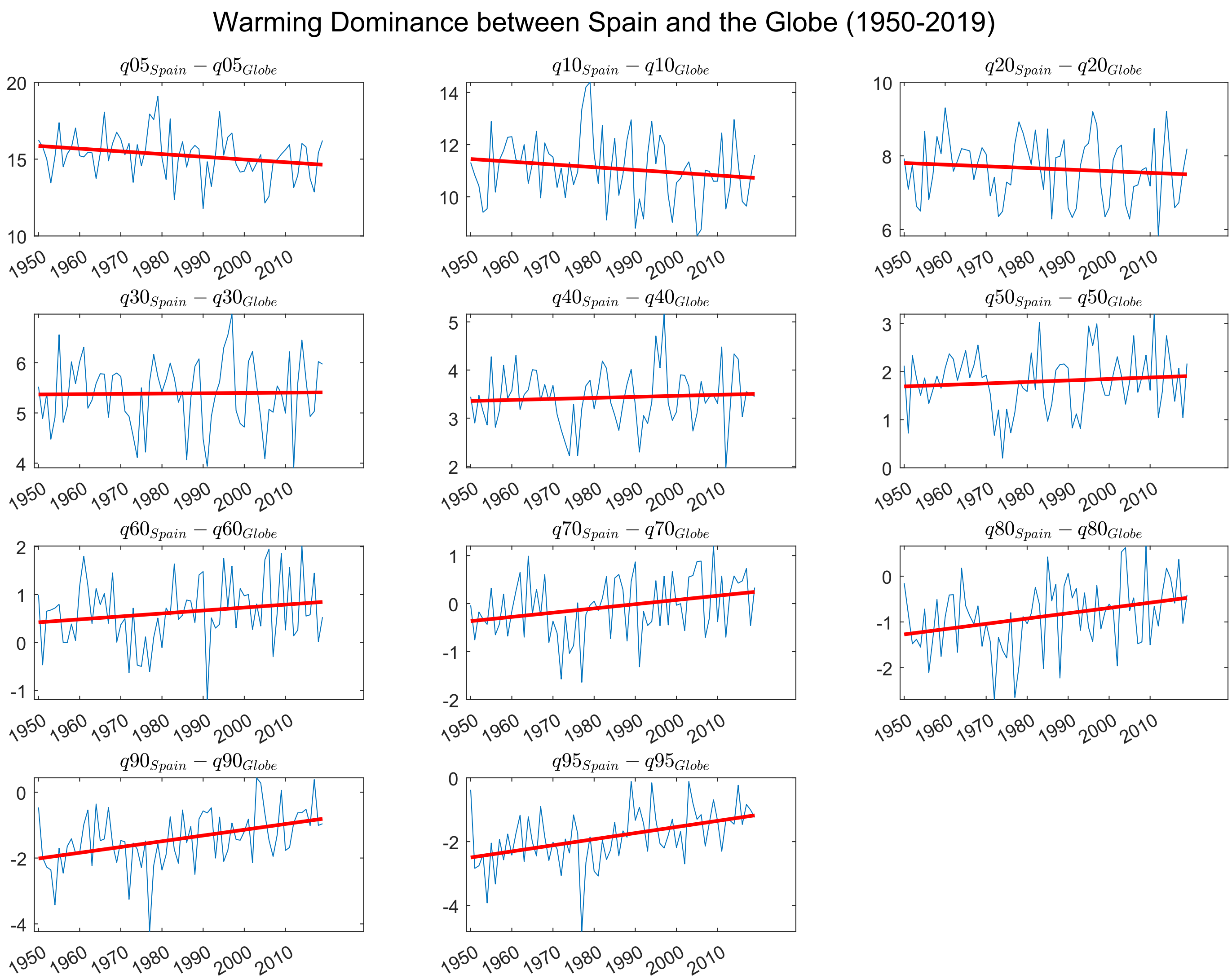
	Spain-Globe		Madrid-Barcelona	
Quantile	β	pvalue	β	pvalue
q05	-0.018	(0.007)	-0.013	(0.000)
q10	-0.010	(0.137)	-0.013	(0.000)
q20	-0.004	(0.345)	-0.012	(0.004)
q30	0.001	(0.857)	-0.013	(0.000)
q40	0.002	(0.434)	-0.009	(0.005)
q50	0.003	(0.309)	-0.003	(0.486)
q60	0.006	(0.057)	-0.001	(0.828)
q70	0.009	(0.002)	0.006	(0.215)
q80	0.012	(0.002)	0.016	(0.001)
q90	0.017	(0.000)	0.010	(0.066)
q95	0.019	(0.000)	0.014	(0.050)

Warming Dominance

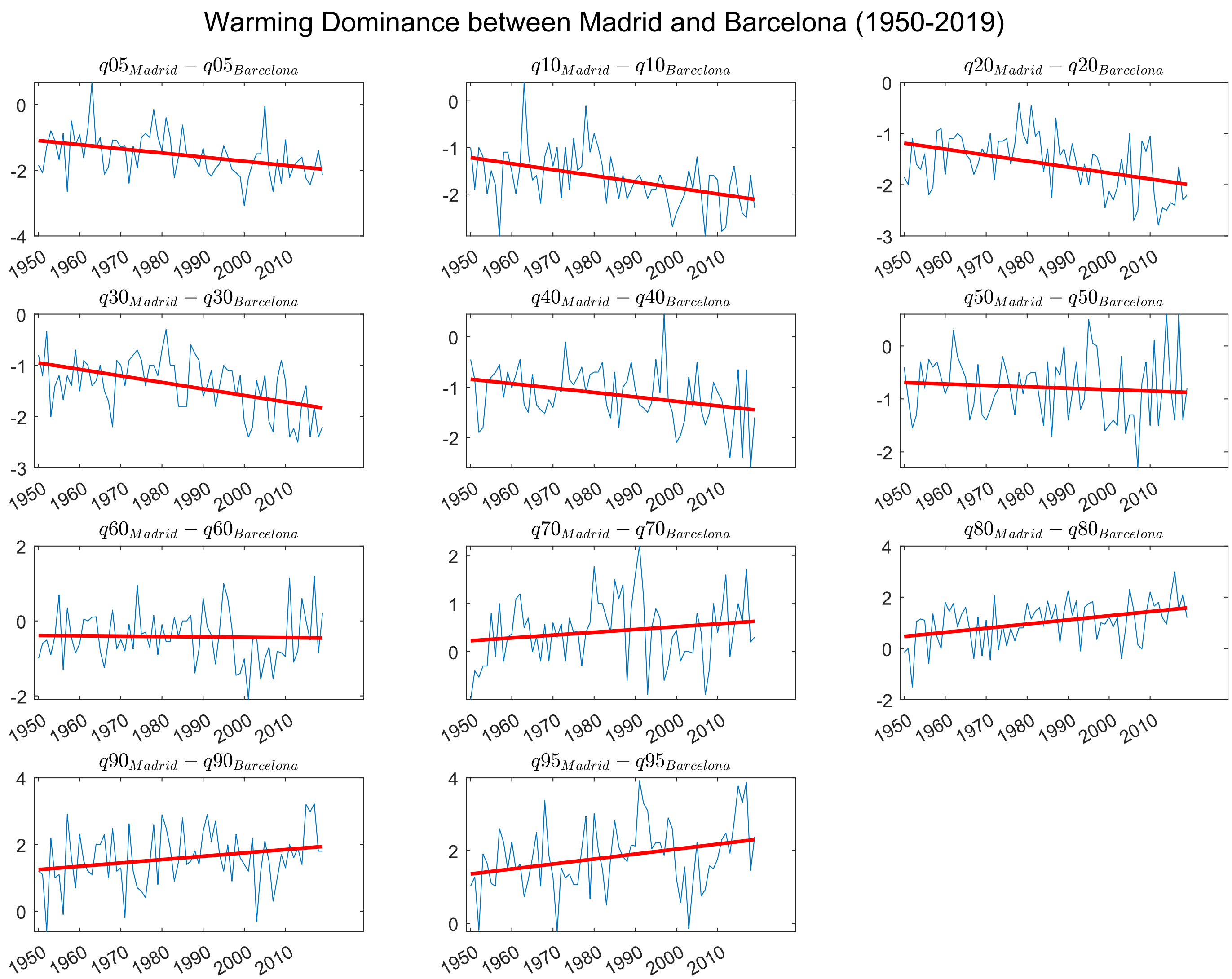
Table 12: Warming dominance

	Spain-Globe		Madrid-Barcelona	
Quantile	β	pvalue	β	pvalue
q05	-0.018	(0.007)	-0.013	(0.000)
q10	-0.010	(0.137)	-0.013	(0.000)
q20	-0.004	(0.345)	-0.012	(0.004)
q30	0.001	(0.857)	-0.013	(0.000)
q40	0.002	(0.434)	-0.009	(0.005)
q50	0.003	(0.309)	-0.003	(0.486)
q60	0.006	(0.057)	-0.001	(0.828)
q70	0.009	(0.002)	0.006	(0.215)
q80	0.012	(0.002)	0.016	(0.001)
q90	0.017	(0.000)	0.010	(0.066)
q95	0.019	(0.000)	0.014	(0.050)

Waming Dominance



Waming Dominance



Comparing results

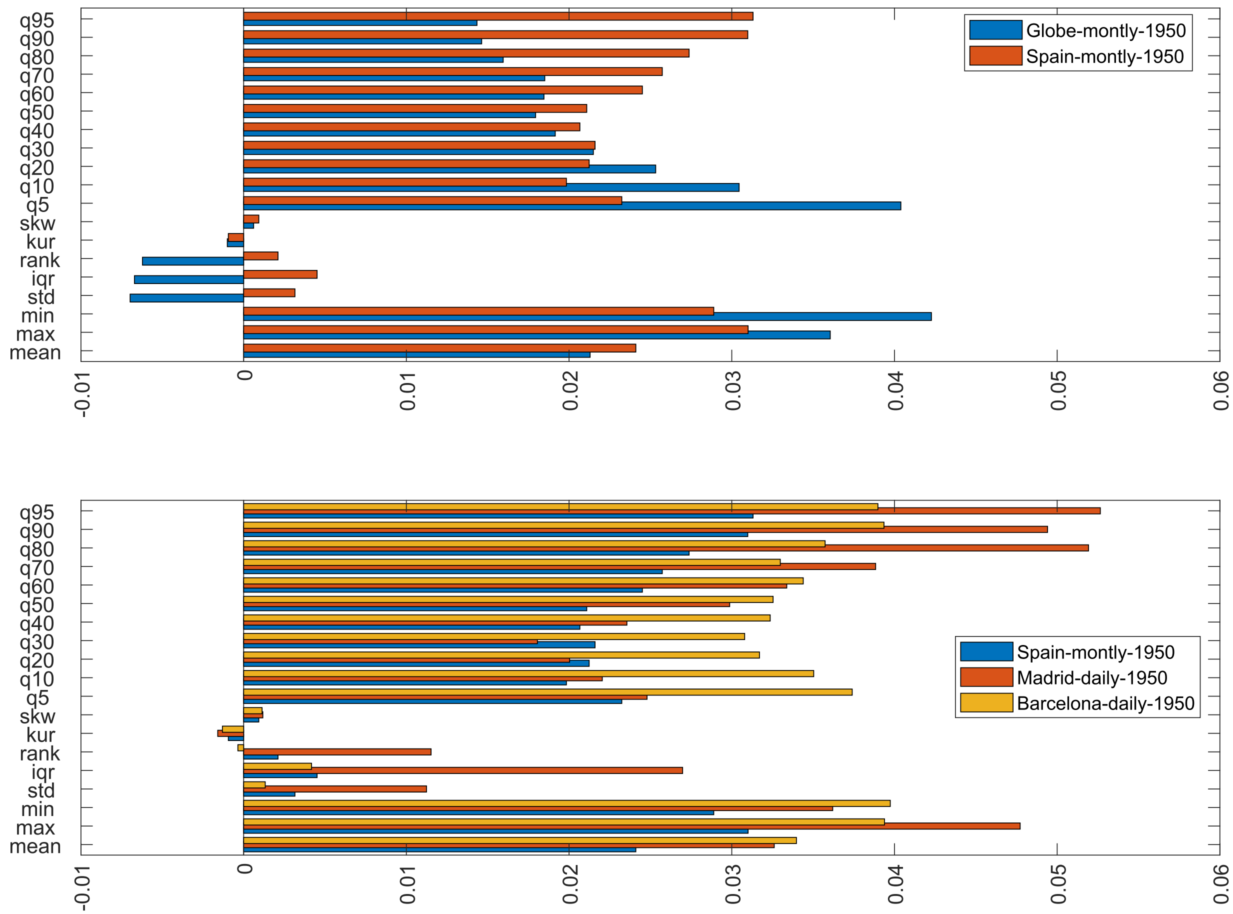
Table 13: Summary of results

Sample	Period	Type	Acceleration	Amplification: Inner	Amplification: Outer	Dominance
Cross analysis						
Spain	1950-2019	W1	[mean, std, iqr, rank, q20,..., q95]	[q70, q80, q95]	[q90, q95]	[q60,..., q95]
	1970-2019	W3		[q50,..., q80]	[q60,..., q95]	
The Globe	1950-2019	W2	[mean q40,..., q95]	[q05,..., q30]		[q05]
	1970-2019	W2		[q05,..., q20]		
Time analysis						
Madrid, Retiro Station	1950-2019	W3	[mean, std, rank, q40, ..., q95]	[q50,..., q95]	[q40,..., q95]	[q80,..., q95]
	1970-2019	W3		[q50,..., q95]	[q40,..., q95]	
Barcelona, Fabra Station	1950-2019	W1	[mean, q20,..., q95]	-	[q30,..., q90]	[q05,..., q40]
	1970-2019	W1		[q60, q70]	[q30,..., q70]	

Note: For Spain and the Globe we build characteristics from station-months units. For Madrid and Barcelona we use daily frequency time series. A significance level of 10% is considered for all tests and characteristics.

Comparing results

Trend evolution of different temperature distributional characteristics



Note: The bars represent the intensity of the trends found in each characteristic measured through the value of the β-coefficient estimated in the regression $C_t = \alpha + \beta t + u_t$.

Pre-Conclusions

Permanent questions: How was the Climate in the PAST? How will it be in the FUTURE ?

- The past ▸ Past
- The future ▸ Future

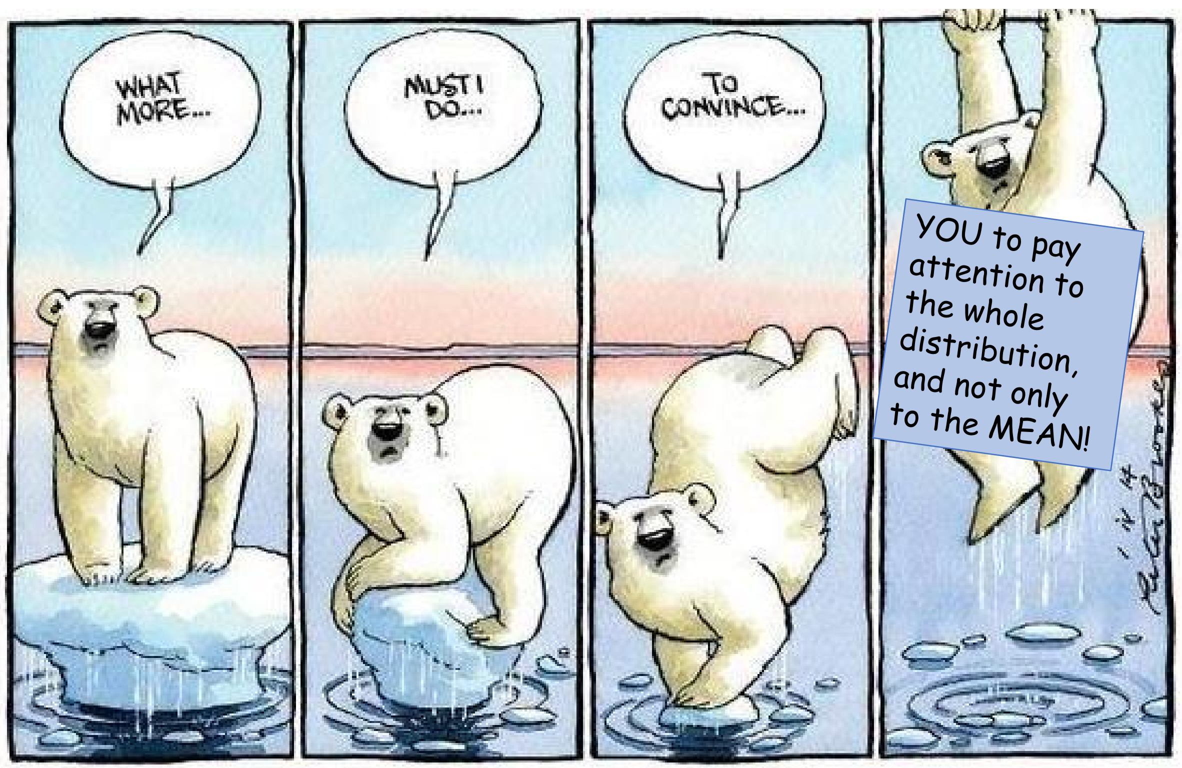
Conclusions

This research introduces a **Low-Cost quantitative methodology** (all the proposals can be easily tested) to study climate change.

1. There is a clear **Local** and **Global Warming** in all the important distributional characteristics and not only in the average.
2. The warming process differs by regions: climate change heterogeneity(**CCH**). Notice that to capture warming heterogeneity we need to go beyond the standard mean temperature analysis.
3. This **CCH** is described via a new **Warming Typology** and measured by **Warming Dominance**.
4. The existence of **CCH** opens the following doors:
    - The need to develop a NEW NON-UNIFORM causal-effect analysis that incorporates **CCH** (see Tol *ANYAS* 2021).
    - The mitigation-adaptation policies should be designed following a factor structure: common-global and idiosyncratic-local policies (see D ' Autume et al. *JPET* 2016, Brock and Xepapadeas *EER* 2020, and Peng et al. *NCC* 2021).

Conclusions

Every place in the Globe has a Polar Bear like this one



CLIMATE IS NOT WHAT IT USED TO BE
STAY TUNED
MORE RESULTS TO COME
THANKS!!!!

GG 2020 Methodology

Throughout this paper, similarly to the assumptions made in Park and Qian (2012) and Chang et al. (2016), we assume that in each period, t, there are sufficient temporal or cross-sectional observations ($N \to \infty$) for these characteristics to be estimated consistently.

Assumption: In each period, t, the stochastic functional process $X = (X_t(\omega), t \in T)$ satisfies certain regularity conditions, such that the state densities, distribution and, therefore, quantiles are estimated consistently.

In the temporal framework, local stationarity (Dahlhaus, 2009) plus some strong mixing conditions (Hansen, 2008) are sufficient to obtain uniform ""strong"" consistency for suitable regular kernel estimators of the state densities. Local stationarity plus some φ-mixing conditions (see Degenhardt et al. 1996) are sufficient for the central limit theorem to hold for smoothed empirical distribution functions and for smoothed sample quantiles for each period or segment, t. For the cross-sectional situation, similar results hold (e.g., Silverman, 1978) if the state distributions are defined as cross-sectional distributions, and if independent and identically distributed observations are available to estimate them for each period (for dependency among N observations, see Bosq (1998, Thm 2.2)). Back

GG 2020 Methodology: Proposition 1

Proposition 1

Let $C_t = I(0)$. In the LS regression

$$C_t = \alpha + \beta t + u_t, \tag{8}$$

the OLS estimator satisfies

$$T^{3/2}\widehat{\beta} = O_p(1) \tag{9}$$

and asymptotically ($T \to \infty$)

$$t_{\beta=0} \text{ is } N(0, 1).$$

Back

GG 2020 Methodology: Proposition 2

Proposition 2

Let $C_t = h(t) + I(0)$, such that $h(t)$ is an increasing $S(\delta)$ function with $\delta \geq 0$, and the function $g(t) = h(t)t$ is $S(\delta + 1)$. In the LS regression

$$C_t = \alpha + \beta t + u_t, \tag{10}$$

the OLS $\widehat{\beta}$ estimator satisfies

$$T^{(1-\delta)}\widehat{\beta} = O_p(1). \tag{11}$$

In order to analyze the behavior of the t-statistic $t_\beta = 0$, we assume that the function $h(t)^2$ is $S(1 + 2\delta - \gamma)$, with $0 \leq \gamma \leq 1 + \delta$. Then, the t-statistic diverges at the following rates

$$t_{\beta=0} = \begin{cases} O_p(T^{\gamma/2}) \text{ for } 0 \leq \gamma \leq 1 \\ O_p(T^{1/2}) \text{ for } 1 \leq \gamma \leq 1 + \delta. \end{cases} \tag{12}$$

Back

GG 2020 Methodology: Proposition 3

Proposition 3

Let $C_t = \mu + z_t, t = 1, ..., T$, with z_t any of the following three processes: (i) a fractional or long-memory model, with $1/2 < d < 3/2$; (ii) a near-unit-root AR model; or (iii) a local-level model. Furthermore, $T^{-1/2+\delta} \sum_{t=1}^{T} z_t \longrightarrow \sigma\ H(.)$, where "$\delta$" is a model-specific constant and H is a model-specific zero-mean Gaussian process with a given covariance kernel $k(r, s)$. Then, in the LS regression

$$C_t = \alpha + \beta t + u_t,$$

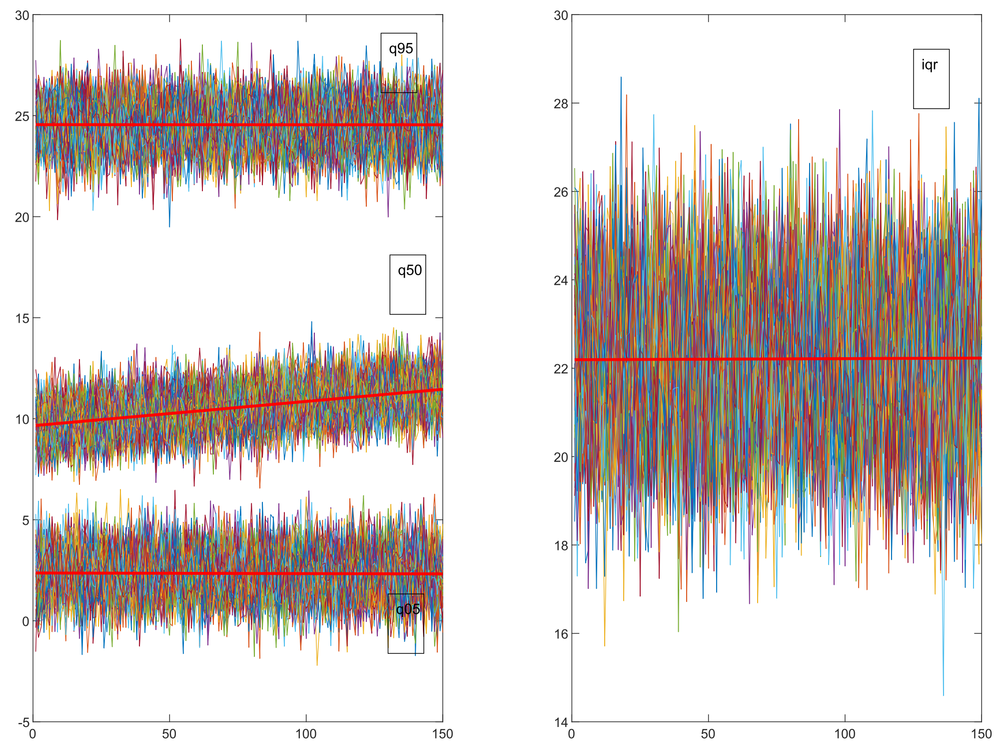
the t-statistic diverges,

$$t_{\beta=0} = O_p(T^{1/2}).$$

Back

Simulations of types of Climate Change

Figure 2: W0 type of Warming process

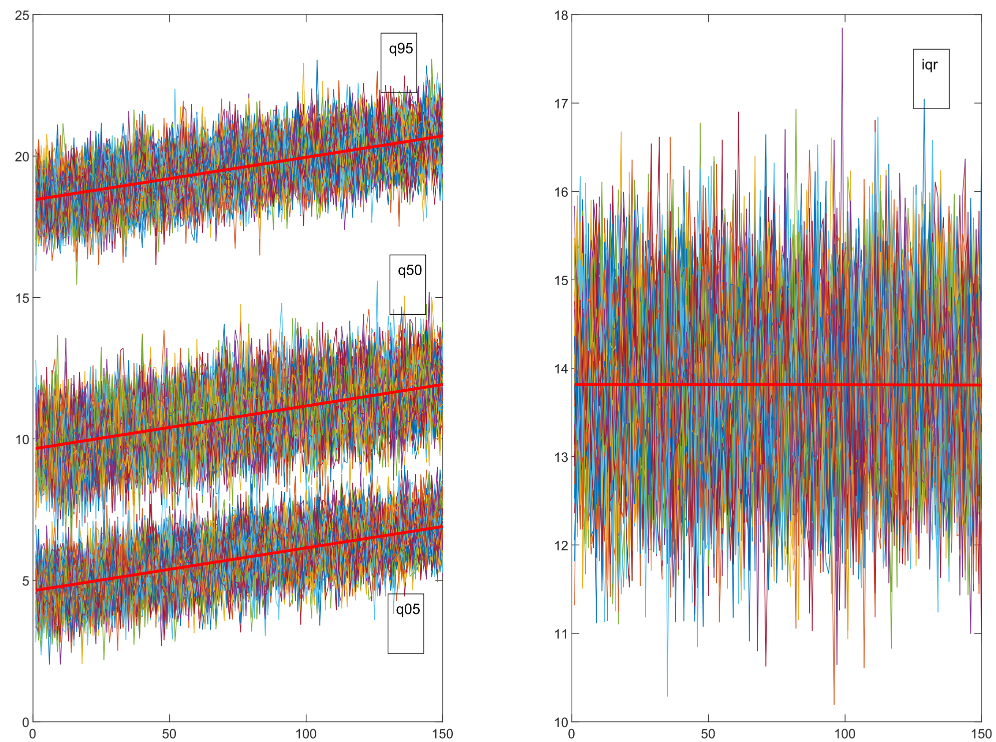


Notes: The estimated trends are -0.0002, 0.0118, 0.0002, 0.0004 for the average across replications of *q05*, *q50*, *q95* and *iqr=q95-q05*, respectively. The only significant one is the corresponding to *q50*.

Back

Simulations of types of Climate Change

Figure 3: W1 type of Warming process

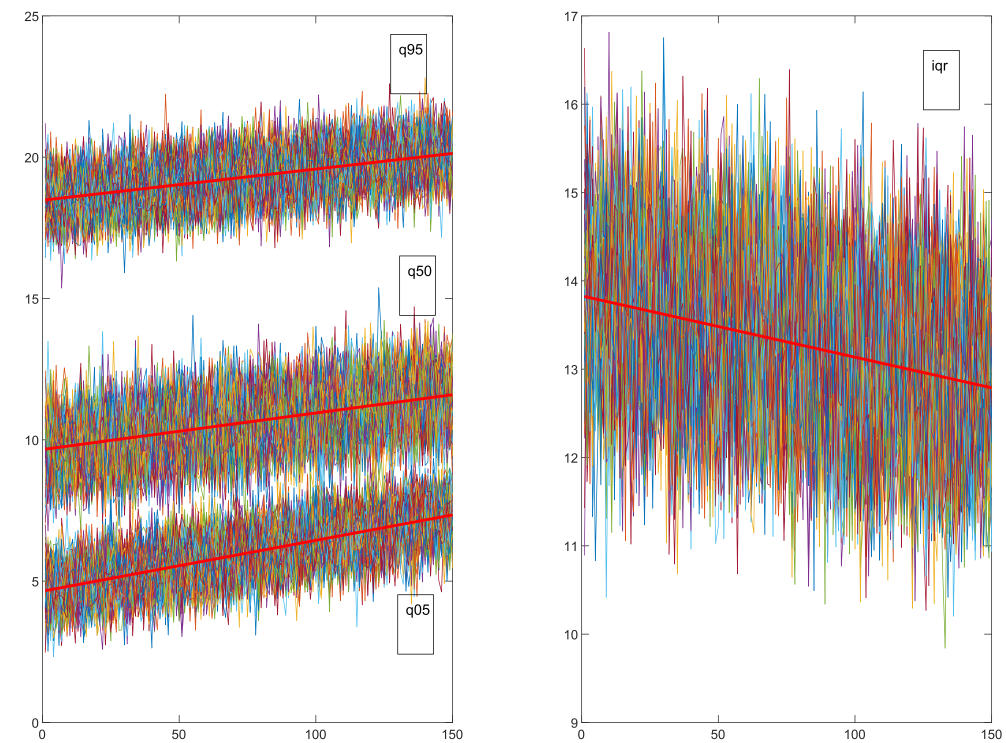


Notes: The estimated trends are 0.0148, 0.0148, 0.0149, 0.0001 for the average across replications of *q05*, *q50*, *q95* and *iqr=q95-q05*, respectively. All the trends are significant but the one corresponding to *iqr*.

Back

Simulations of types of Climate Change

Figure 4: W2 type of Warming process

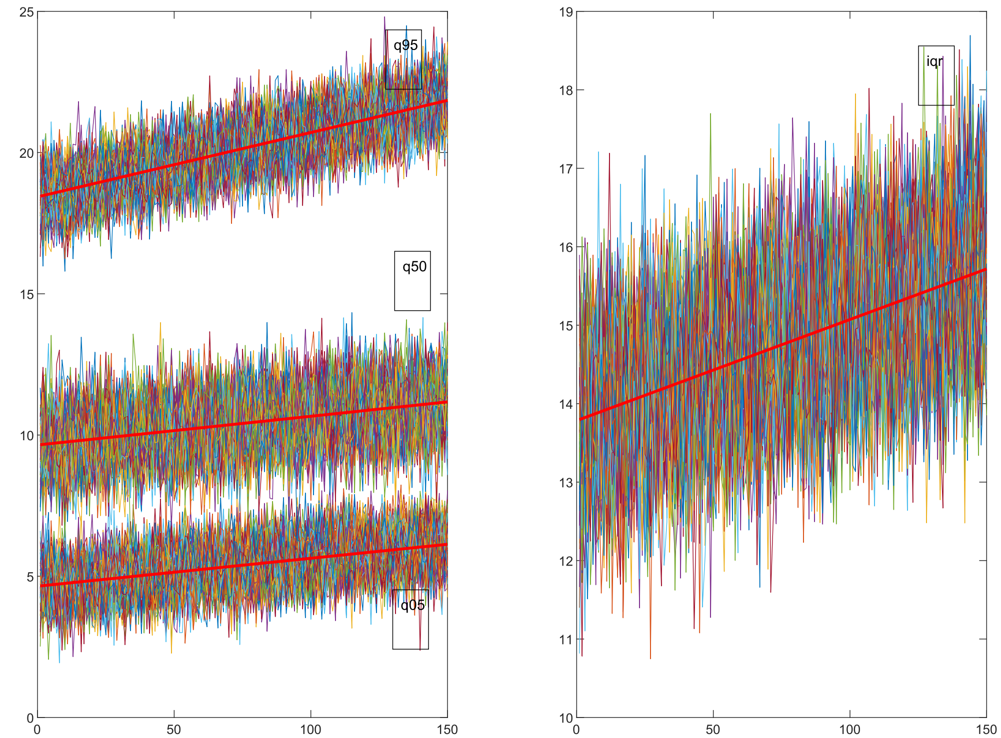


Notes: The estimated trends are 0.0179, 0.0127, 0.0112, -0.0067 for the average across replications of *q05*, *q50*, *q95* and *iqr=q95-q05*, respectively. All of them are significant.

Back

Simulations of types of Climate Change

Figure 5: W3 type of Warming process

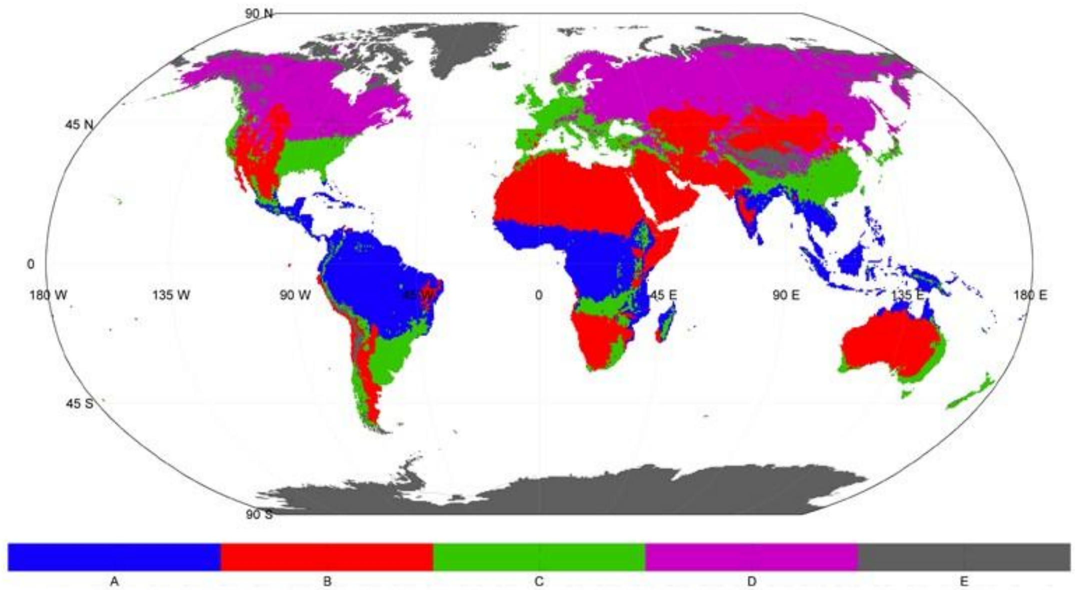


Notes: The estimated trends are 0.0098, 0.0098, 0.0224, 0.0126 for the average across replications of *q05*, *q50*, *q95* and *iqr=q95-q05*, respectively. All of them are significant.

Back

Typology of Climate

Wladimir KOPPEN: Five climate types, 4 based on temperature and one on humidity (precipitations)



- Zone A: tropical or equatorial zone (represented by blue colors on most maps)
- Zone B: arid or dry zone (represented by red, pink, and orange colors on most maps)
- Zone C: warm/mild temperate zone (represented by green colors on most maps)
- Zone D: continental zone (represented by purple, violet, and light blue colors on most maps)
- Zone E: polar zone (represented by gray colors on most maps)

Back

Warming dominance

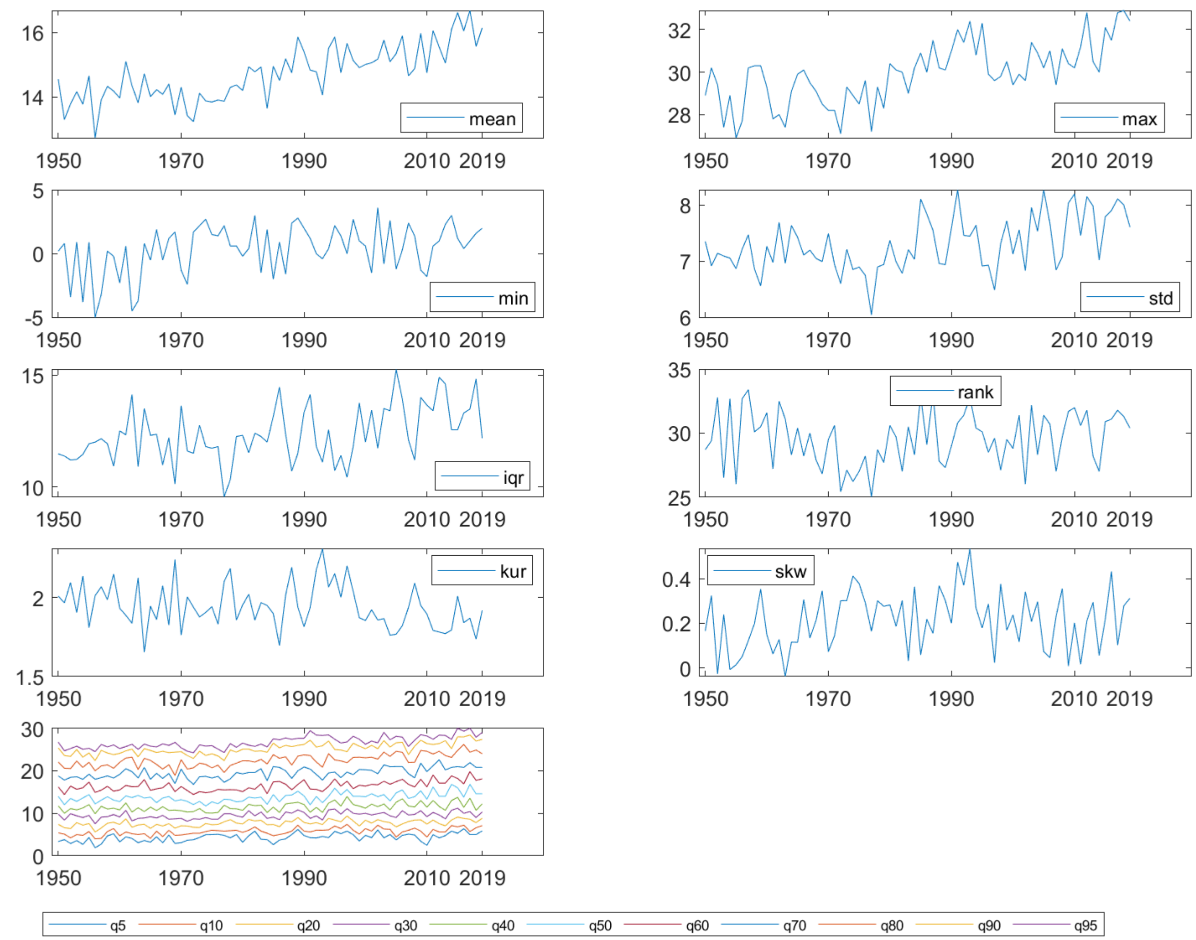
Table 14: Results of Warming dominance

	Arctic Region-Globe	
Quantile	β	p-value
q05	0.005	(0.629)
q10	0.014	(0.102)
q20	0.030	(0.002)
q30	0.030	(0.013)
q40	0.031	(0.016)
q50	0.020	(0.012)
q60	0.009	(0.091)
q70	0.004	(0.218)
q80	0.005	(0.177)
q90	-0.003	(0.246)
q95	-0.003	(0.468)

Back

Micro-local warming: Madrid

Characteristics of temperature data in Madrid-Retiro (AEMET daily data, 1950-2019)



Back

Micro-local warming: Madrid

Table 15: Trend acceleration hypothesis (Madrid, daily data, AEMET, 1950-2019)

names/periods	Trend test by periods 1950-2019	Trend test by periods 1970-2019	Acceleration test 1950-2019, 1970-2019
mean	**0.0326**	**0.0447**	**2.0972**
	(0.0000)	(0.0000)	(0.0189)
max	0.0477	0.0636	1.2043
	(0.0000)	(0.0000)	(0.1153)
min	0.0362	0.0087	-1.5077
	(0.0011)	(0.5859)	(0.9330)
std	0.0112	0.0197	2.1160
	(0.0000)	(0.0000)	(0.0181)
iqr	**0.0270**	**0.0399**	**1.1110**
	(0.0000)	(0.0004)	(0.1343)
rank	0.0115	0.0549	2.0160
	(0.3666)	(0.0045)	(0.0229)
kur	-0.0016	-0.0022	-0.4449
	(0.0278)	(0.0660)	(0.6714)
skw	0.0012	-0.0013	-1.7769
	(0.1538)	(0.2695)	(0.9611)
q05	**0.0248**	**0.0183**	**-0.5712**
	(0.0000)	(0.0774)	(0.7156)
q10	0.0220	0.0174	-0.5815
	(0.0000)	(0.0162)	(0.7191)
q20	0.0200	0.0187	-0.1777
	(0.0000)	(0.0099)	(0.5704)
q30	0.0181	0.0235	0.6959
	(0.0000)	(0.0019)	(0.2438)
q40	0.0236	0.0362	1.6625
	(0.0000)	(0.0000)	(0.0494)
q50	0.0299	0.0545	2.8801
	(0.0000)	(0.0000)	(0.0023)
q60	0.0334	0.0604	3.1655
	(0.0000)	(0.0000)	(0.0010)
q70	0.0388	0.0550	1.7385
	(0.0000)	(0.0000)	(0.0422)
q80	0.0519	0.0712	1.9750
	(0.0000)	(0.0000)	(0.0251)
q90	0.0494	0.0687	1.7956
	(0.0000)	(0.0000)	(0.0374)
q95	**0.0527**	**0.0710**	**1.7839**
	(0.0000)	(0.0000)	(0.0383)

Micro-local warming: Madrid

Table 16: Trend acceleration hypothesis (Madrid, daily data, AEMET, 1950-2019)

	Trend test by periods		Acceleration test
names/periods	1950-2019	1970-2019	1950-2019, 1970-2019
mean	**0.0326**	**0.0447**	**2.0972**
	(0.0000)	(0.0000)	(0.0189)
max	0.0477	0.0636	1.2043
	(0.0000)	(0.0000)	(0.1153)
min	0.0362	0.0087	-1.5077
	(0.0011)	(0.5859)	(0.9330)
std	0.0112	0.0197	2.1160
	(0.0000)	(0.0000)	(0.0181)
iqr	**0.0270**	**0.0399**	**1.1110**
	(0.0000)	(0.0004)	(0.1343)
rank	0.0115	0.0549	2.0160
	(0.3666)	(0.0045)	(0.0229)
kur	-0.0016	-0.0022	-0.4449
	(0.0278)	(0.0660)	(0.6714)
skw	0.0012	-0.0013	-1.7769
	(0.1538)	(0.2695)	(0.9611)
q05	**0.0248**	**0.0183**	**-0.5712**
	(0.0000)	(0.0774)	(0.7156)
q10	0.0220	0.0174	-0.5815
	(0.0000)	(0.0162)	(0.7191)
q20	0.0200	0.0187	-0.1777
	(0.0000)	(0.0099)	(0.5704)
q30	0.0181	0.0235	0.6959
	(0.0000)	(0.0019)	(0.2438)
q40	0.0236	0.0362	**1.6625**
	(0.0000)	(0.0000)	(0.0494)
q50	0.0299	0.0545	**2.8801**
	(0.0000)	(0.0000)	(0.0023)
q60	0.0334	0.0604	**3.1655**
	(0.0000)	(0.0000)	(0.0010)
q70	0.0388	0.0550	**1.7385**
	(0.0000)	(0.0000)	(0.0422)
q80	0.0519	0.0712	**1.9750**
	(0.0000)	(0.0000)	(0.0251)
q90	0.0494	0.0687	**1.7956**
	(0.0000)	(0.0000)	(0.0374)
q95	**0.0527**	**0.0710**	**1.7839**
	(0.0000)	(0.0000)	(0.0383)

Micro-local warming: Madrid

Table 17: Co-trending analysis (Madrid-Retiro daily data, AEMET 1950-2019)

Joint hypothesis tests	Wald test	p-value
All quantiles (q05, q10,...,q90, q95)	**77.046**	**0.000**
Lower quantiles (q05, q10, q20, q30)	1.360	0.715
Medium quantiles (q40, q50, q60)	2.036	0.361
Upper quantiles (q70, q80, q90, q95)	3.944	0.268
Lower-Medium quantiles (q05, q10, q20, q30, q40, q50, q60)	6.707	0.349
Medium-Upper quantiles (q40, q50, q60, q70, q80, q90, q95)	31.822	0.000
Lower-Upper quantiles (q05, q10, q20,q30, q70, q80, q90, q95)	74.967	0.000
Spacing hypothesis	Trend-coeff.	p-value
q50-q05	0.005	0.505
q95-q50	0.023	0.000
q05-q95	-0.028	0.000
q75-q25 (iqr)	0.027	0.000

W3

Micro-local warming: Madrid

Table 18: Co-trending analysis (Madrid-Retiro daily data, AEMET, 1970-2019)

Joint hypothesis tests	Wald test	p-value
All quantiles (q05, q10,...,q90, q95)	**81.371**	**0.000**
Lower quantiles (q05, q10, q20, q30)	0.424	0.935
Medium quantiles (q40, q50, q60)	8.111	0.017
Upper quantiles (q70, q80, q90, q95)	3.214	0.360
Lower-Medium quantiles (q05, q10, q20, q30, q40, q50, q60)	45.687	0.000
Medium-Upper quantiles (q40, q50, q60, q70, q80, q90, q95)	18.851	0.004
Lower-Upper quantiles (q05, q10, q20,q30, q70, q80, q90, q95)	71.094	0.000
Spacing hypothesis	Trend-coeff.	p-value
q50-q05	0.036	0.004
q95-q50	0.017	0.051
q05-q95	-0.053	0.000
q75-q25 (iqr)	**0.040**	**0.000**

W3

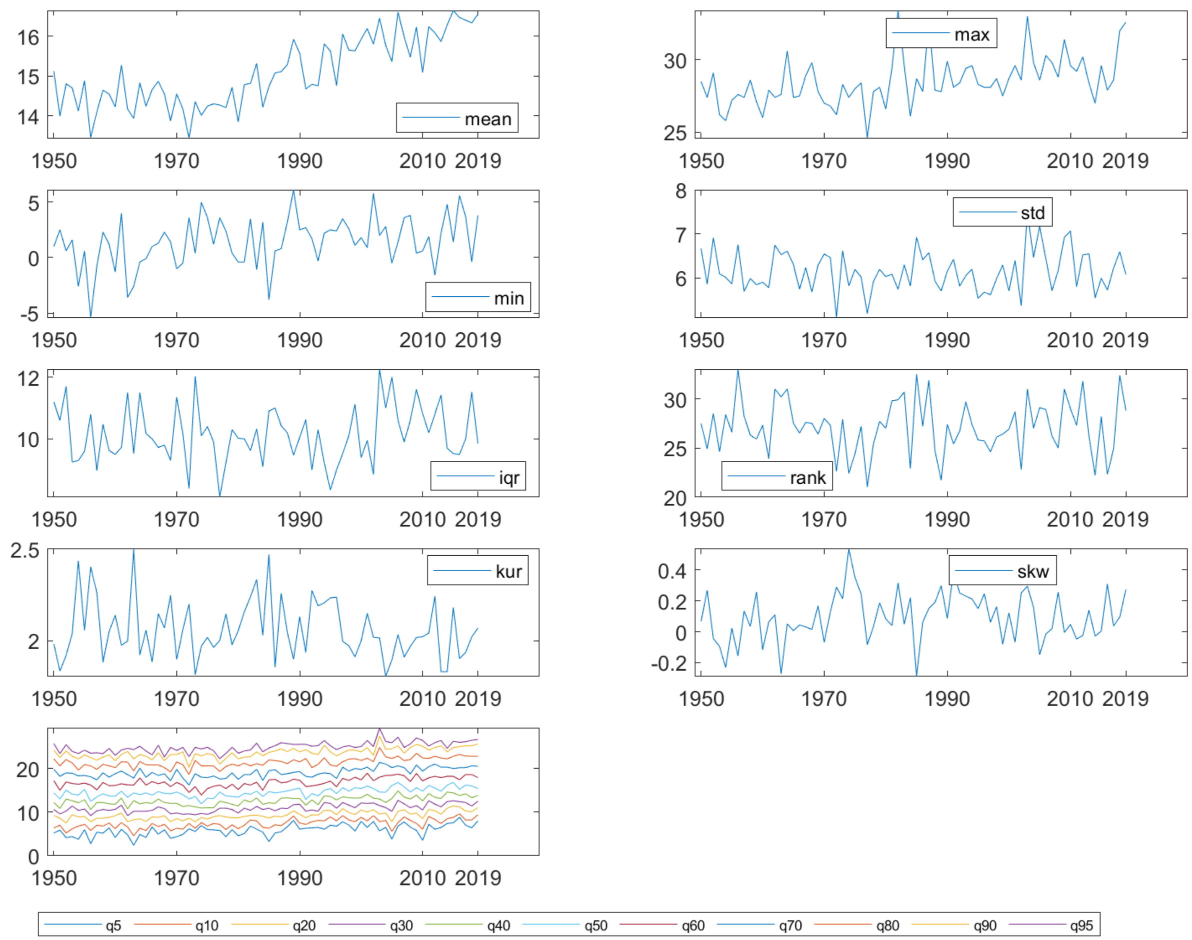
Micro-local warming: Madrid

Table 19: Amplification hypothesis (Madrid daily data, AEMET 1950-2019)

periods/variables	1950-2019	1970-2019	1950-2019	1970-2019
	Inner		Outer	
q05	0.66	0.43	0.83	0.56
	(0.993)	(1.000)	(0.802)	(0.990)
q10	0.58	0.42	0.73	0.54
	(1.000)	(1.000)	(0.974)	(1.000)
q20	0.66	0.53	0.81	0.65
	(1.000)	(1.000)	(0.961)	(0.999)
q30	0.72	0.74	0.94	0.90
	(1.000)	(0.996)	(0.758)	(0.836)
q40	0.90	1.02	1.15	1.21
	(0.887)	(0.436)	(0.072)	(0.041)
q50	1.08	1.29	1.38	1.53
	(0.188)	(0.001)	(0.001)	(0.000)
q60	1.14	1.31	1.44	1.54
	(0.040)	(0.000)	(0.000)	(0.000)
q70	1.22	1.23	1.46	1.38
	(0.012)	(0.019)	(0.000)	(0.002)
q80	1.45	1.36	1.70	1.52
	(0.000)	(0.003)	(0.000)	(0.002)
q90	1.31	1.29	1.48	1.38
	(0.004)	(0.041)	(0.005)	(0.064)
q95	1.31	1.33	1.46	1.39
	(0.001)	(0.021)	(0.007)	(0.073)

Micro-local warming: Barcelona

Characteristics of temperature data in Barcelona-Fabra (AEMET daily data, 1950-2019)



Back

Micro-local warming: Barcelona

Table 20: Trend acceleration hypothesis (Barcelona, daily data, AEMET, 1950-2019)

	Trend test by periods		Acceleration test
names/periods	1950-2019	1970-2019	1950-2019, 1970-2019
mean	**0.0340**	**0.0512**	**3.2979**
	(0.0000)	(0.0000)	(0.0006)
max	0.0394	0.0531	0.7280
	(0.0000)	(0.0038)	(0.2339)
min	0.0397	0.0231	-0.7411
	(0.0011)	(0.2654)	(0.7700)
std	0.0013	0.0057	0.9146
	(0.6185)	(0.1787)	(0.1810)
iqr	**0.0042**	**0.0113**	**0.7351**
	(0.4418)	(0.1892)	(0.2318)
rank	-0.0004	0.0300	0.9299
	(0.9806)	(0.3322)	(0.1770)
kur	-0.0013	-0.0018	-0.2693
	(0.1555)	(0.2075)	(0.6060)
skw	0.0011	-0.0022	-1.7869
	(0.2678)	(0.1942)	(0.9619)
q05	0.0374	0.0358	-0.1381
	(0.0000)	(0.0015)	(0.5548)
q10	0.0350	0.0385	0.4361
	(0.0000)	(0.0000)	(0.3317)
q20	0.0317	0.0439	1.7009
	(0.0000)	(0.0000)	(0.0456)
q30	0.0308	0.0488	2.4813
	(0.0000)	(0.0000)	(0.0072)
q40	0.0324	0.0537	2.9244
	(0.0000)	(0.0000)	(0.0020)
q50	0.0325	0.0548	2.7535
	(0.0000)	(0.0000)	(0.0034)
q60	0.0344	0.0636	3.0915
	(0.0000)	(0.0000)	(0.0012)
q70	0.0330	0.0583	2.9241
	(0.0000)	(0.0000)	(0.0020)
q80	0.0357	0.0551	2.4081
	(0.0000)	(0.0000)	(0.0087)
q90	0.0394	0.0567	2.0957
	(0.0000)	(0.0000)	(0.0190)
q95	**0.0390**	**0.0525**	**1.3435**
	(0.0000)	(0.0000)	(0.0907)

Micro-local warming: Barcelona

Table 21: Trend acceleration hypothesis (Barcelona, daily data, AEMET, 1950-2019)

	Trend test by periods		Acceleration test
names/periods	1950-2019	1970-2019	1950-2019, 1970-2019
mean	**0.0340**	**0.0512**	**3.2979**
	(0.0000)	(0.0000)	(0.0006)
max	0.0394	0.0531	0.7280
	(0.0000)	(0.0038)	(0.2339)
min	0.0397	0.0231	-0.7411
	(0.0011)	(0.2654)	(0.7700)
std	0.0013	0.0057	0.9146
	(0.6185)	(0.1787)	(0.1810)
iqr	**0.0042**	**0.0113**	**0.7351**
	(0.4418)	(0.1892)	(0.2318)
rank	-0.0004	0.0300	0.9299
	(0.9806)	(0.3322)	(0.1770)
kur	-0.0013	-0.0018	-0.2693
	(0.1555)	(0.2075)	(0.6060)
skw	0.0011	-0.0022	-1.7869
	(0.2678)	(0.1942)	(0.9619)
q05	0.0374	0.0358	-0.1381
	(0.0000)	(0.0015)	(0.5548)
q10	0.0350	0.0385	0.4361
	(0.0000)	(0.0000)	(0.3317)
q20	0.0317	0.0439	**1.7009**
	(0.0000)	(0.0000)	(0.0456)
q30	0.0308	0.0488	**2.4813**
	(0.0000)	(0.0000)	(0.0072)
q40	0.0324	0.0537	**2.9244**
	(0.0000)	(0.0000)	(0.0020)
q50	0.0325	0.0548	**2.7535**
	(0.0000)	(0.0000)	(0.0034)
q60	0.0344	0.0636	**3.0915**
	(0.0000)	(0.0000)	(0.0012)
q70	0.0330	0.0583	**2.9241**
	(0.0000)	(0.0000)	(0.0020)
q80	0.0357	0.0551	**2.4081**
	(0.0000)	(0.0000)	(0.0087)
q90	0.0394	0.0567	**2.0957**
	(0.0000)	(0.0000)	(0.0190)
q95	**0.0390**	**0.0525**	**1.3435**
	(0.0000)	(0.0000)	(0.0907)

Micro-local warming: Barcelona

Table 22: Co-trending analysis (Barcelona-Fabra daily data, AEMET, 1950-2019)

Joint hypothesis tests	Wald test	p-value
All quantiles (q05, q10,...,q90, q95)	**3.368**	**0.971**
Lower quantiles (q05, q10, q20, q30)	1.036	0.792
Medium quantiles (q40, q50, q60)	0.073	0.964
Upper quantiles (q70, q80, q90, q95)	0.784	0.853
Lower-Medium quantiles (q05, q10, q20, q30, q40, q50, q60)	1.171	0.978
Medium-Upper quantiles (q40, q50, q60, q70, q80, q90, q95)	1.901	0.929
Lower-Upper quantiles (q05, q10, q20,q30, q70, q80, q90, q95)	2.969	0.888
Spacing hypothesis	Trend-coeff.	p-value
q50-q05	-0.005	0.528
q95-q50	0.006	0.233
q05-q95	-0.002	0.856
q75-q25 (iqr)	**0.004**	**0.442**

W1

Micro-local warming: Barcelona

Table 23: Co-trending analysis (Barcelona-Fabra daily data, AEMET, 1970-2019)

Joint hypothesis tests	Wald test	p-value
All quantiles (q05, q10,...,q90, q95)	**13.165**	**0.215**
Lower quantiles (q05, q10, q20, q30)	1.904	0.593
Medium quantiles (q40, q50, q60)	1.267	0.531
Upper quantiles (q70, q80, q90, q95)	0.384	0.943
Lower-Medium quantiles (q05, q10, q20, q30, q40, q50, q60)	10.103	0.120
Medium-Upper quantiles (q40, q50, q60, q70, q80, q90, q95)	1.642	0.949
Lower-Upper quantiles (q05, q10, q20,q30, q70, q80, q90, q95)	9.693	0.207
Spacing hypothesis	Trend-coeff.	p-value
q50-q05	0.019	0.192
q95-q50	-0.002	0.821
q05-q95	-0.017	0.241
q75-q25 (iqr)	**0.011**	**0.189**

W1

Micro-local warming: Barcelona

Table 24: Amplification hypothesis (Barcelona daily data, AEMET 1950-2019)

periods/variables	1950-2019	1970-2019	1950-2019	1970-2019
	Inner		Outer	
q05	0.99	0.76	1.19	0.87
	(0.523)	(0.918)	(0.225)	(0.720)
q10	0.90	0.79	1.10	0.94
	(0.824)	(0.980)	(0.263)	(0.668)
q20	0.89	0.85	1.09	1.04
	(0.931)	(0.964)	(0.192)	(0.318)
q30	0.96	0.98	1.22	1.25
	(0.813)	(0.585)	(0.000)	(0.000)
q40	0.99	1.04	1.27	1.33
	(0.570)	(0.300)	(0.000)	(0.000)
q50	1.01	1.07	1.27	1.32
	(0.466)	(0.224)	(0.002)	(0.003)
q60	1.09	1.23	1.29	1.42
	(0.175)	(0.005)	(0.014)	(0.001)
q70	1.09	1.17	1.26	1.31
	(0.128)	(0.012)	(0.022)	(0.008)
q80	1.06	1.04	1.22	1.17
	(0.191)	(0.338)	(0.052)	(0.117)
q90	1.09	1.08	1.22	1.20
	(0.125)	(0.241)	(0.047)	(0.121)
q95	1.06	1.03	1.16	1.12
	(0.304)	(0.432)	(0.192)	(0.298)

The past

THE PAST:
Paleocooling, Paleowarming,
Paleo-Heterogeneity (in progress^2)

Andrey Ramos (UC3M) and
Jesus Gonzalo (UC3M) Back

Paleo-global Cooling: Last 400.000 years (Ice Cores)

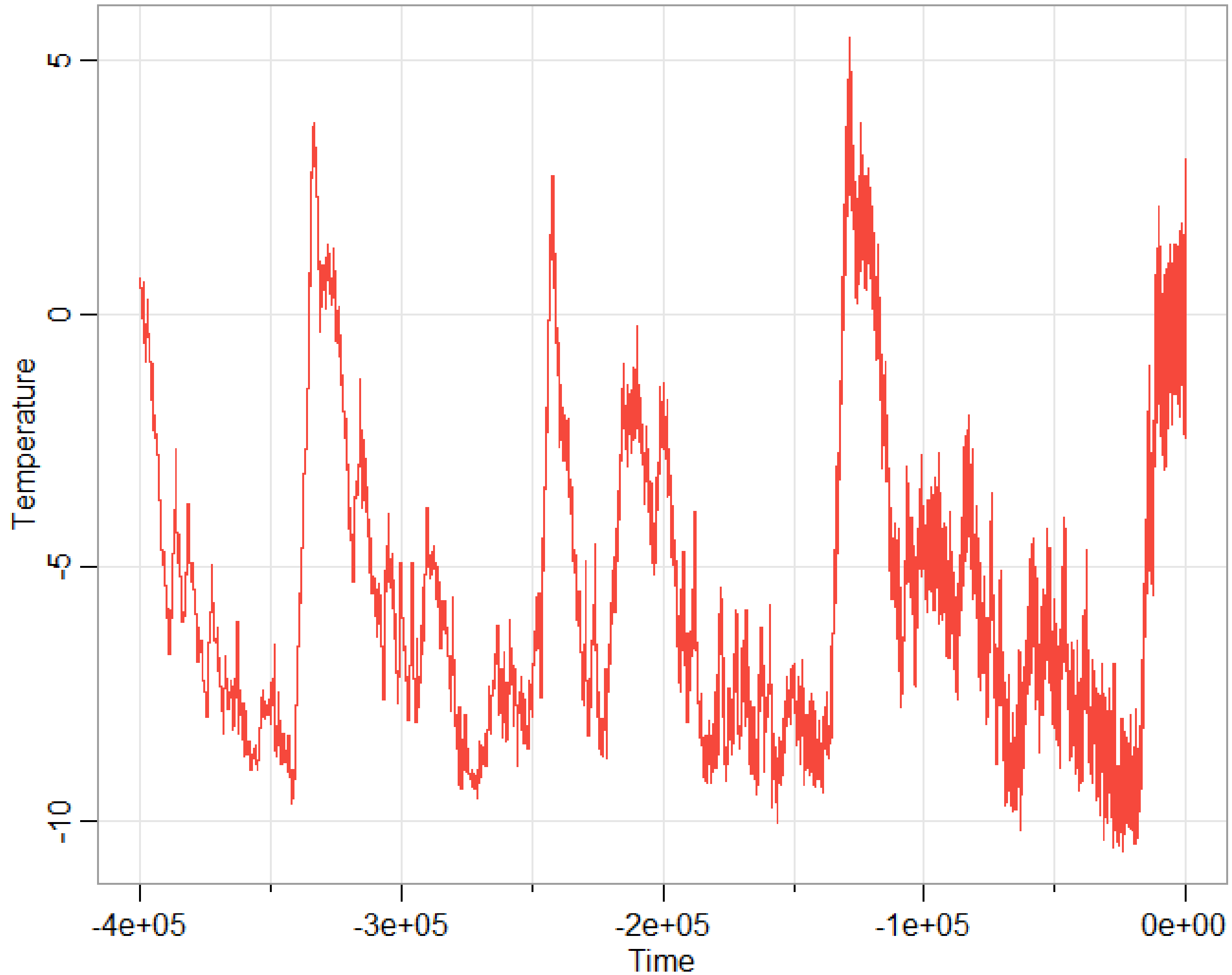


Figure 6: Temperature time series over the last 400.000 years.

Paleo-global Cooling: Last 400.000 years

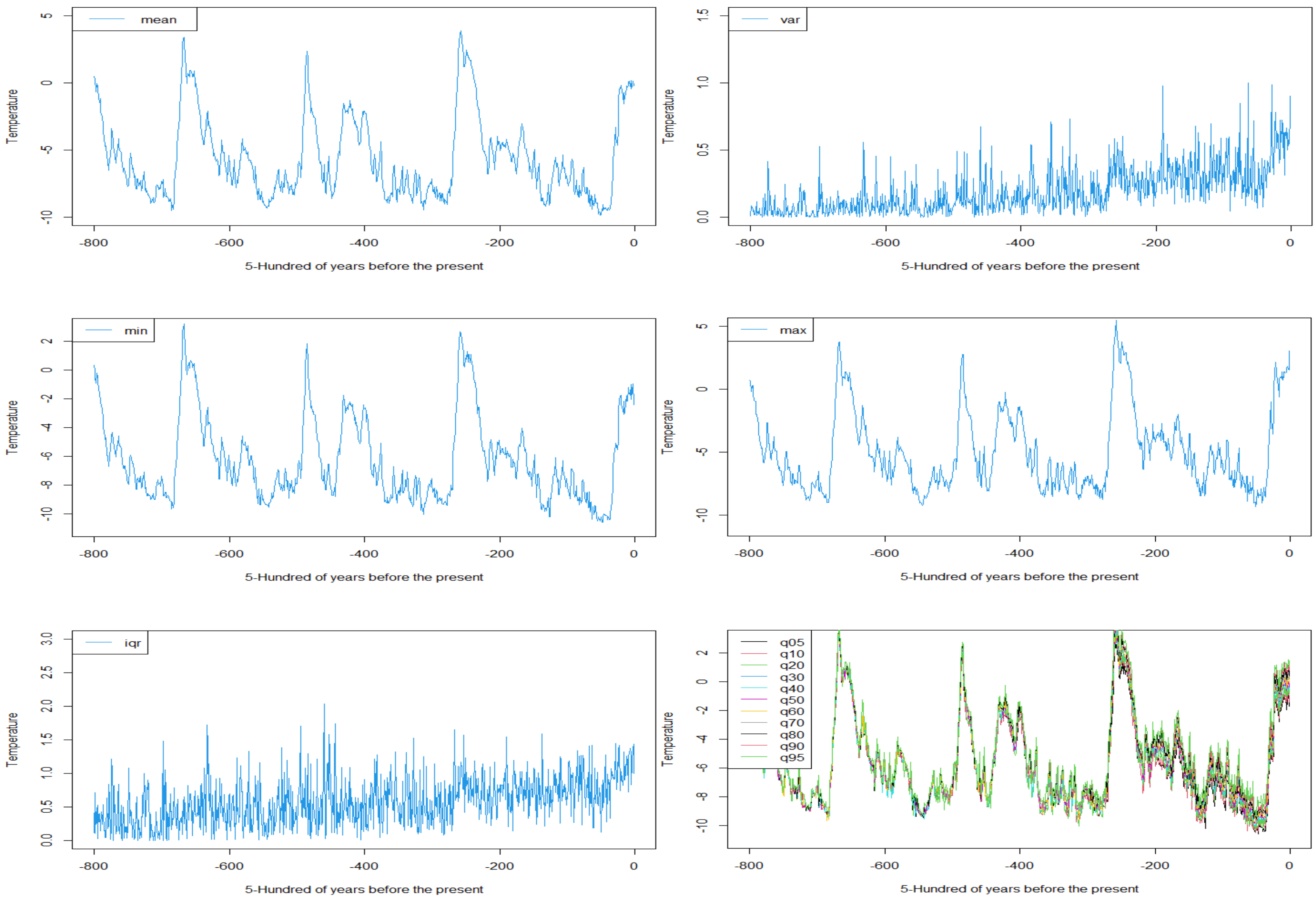


Figure 7: Estimated distributional characteristics.

Paleo-global Cooling: Last 400.000 years

Table 25: Trend test (last 400.000 years)

Characteristic	Test-statistic	p-value
mean	-1.35×10^{-6}	0.0000
var	9.77×10^{-7}	0.0000
min	-3.76×10^{-6}	0.0000
max	1.22×10^{-6}	0.0000
iqr	1.41×10^{-6}	0.0000
q05	-3.54×10^{-6}	0.0000
q10	-3.04×10^{-6}	0.0000
q20	-2.37×10^{-6}	0.0000
q30	-1.92×10^{-6}	0.0000
q40	-1.61×10^{-6}	0.0000
q50	-1.40×10^{-6}	0.0000
q60	-1.15×10^{-6}	0.0000
q70	-9.06×10^{-7}	0.0000
q80	-3.63×10^{-7}	0.1030
q90	3.66×10^{-7}	0.1029
q95	1.02×10^{-6}	0.0000

Note: Annual observations constructed based on 4.934 original observations using step interpolation. Distributional characteristics estimated using a fixed window approach, assuming an interval length of 500 observations. OLS estimates and HAC p-values of the $t_{\beta=0}$ test from regression $C_t = \alpha + \beta t + u_t$, are reported.

Paleo-global Cooling: Last 400.000 years

Table 26: Co-trending analysis (last 400.000 years)

Joint hypothesis tests	Wald test	p-value
All quantiles (q05, q10,...,q90, q95)	155.546	0.000
Lower quantiles (q05, q10, q20, q30)	4.038	0.257
Medium quantiles (q40, q50, q60)	10.614	0.005
Upper quantiles (q70, q80, q90, q95)	3.805	0.283
Spacing hypothesis	**Trend-coeff.**	**p-value**
q50-q05	2.14×10^{-6}	0.000
q95-q50	2.42×10^{-6}	0.000
q95-q05	4.56×10^{-6}	0.000

Note: Annual observations constructed based on 4.934 original observations using step interpolation. Distributional characteristics estimated using a fixed window approach, assuming an interval length of 500 observations. In the top panel, Wald test of the null hypothesis of equality of trend coefficients for a given set of characteristics. In the bottom panel, the trend-test is applied to the difference between two representative quantiles.

Paleo-global Warming: Last 12.000 years (Ice Cores)

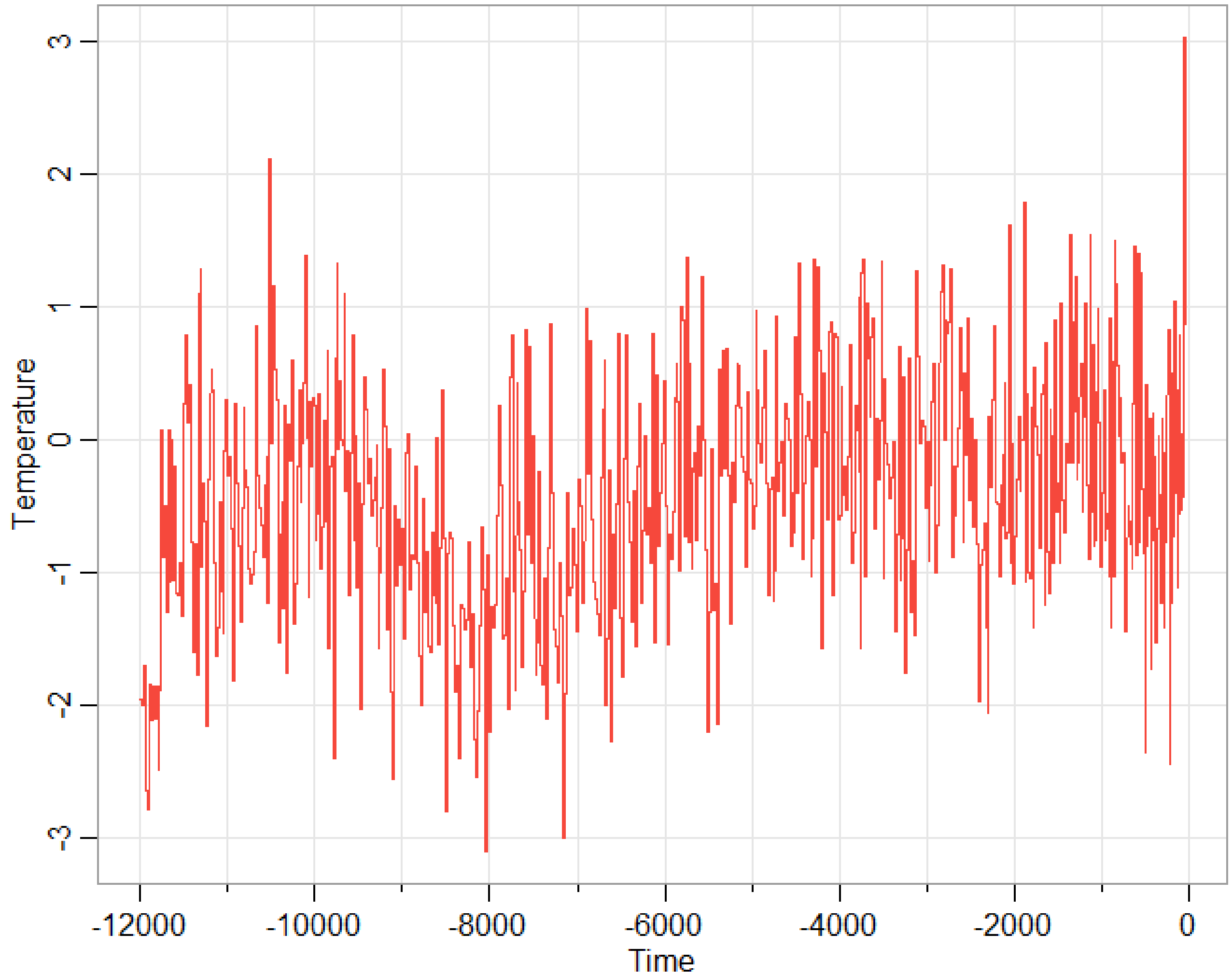


Figure 8: Temperature time series over the last 12.000 years.

Paleo-global Warming: Last 12.000 years

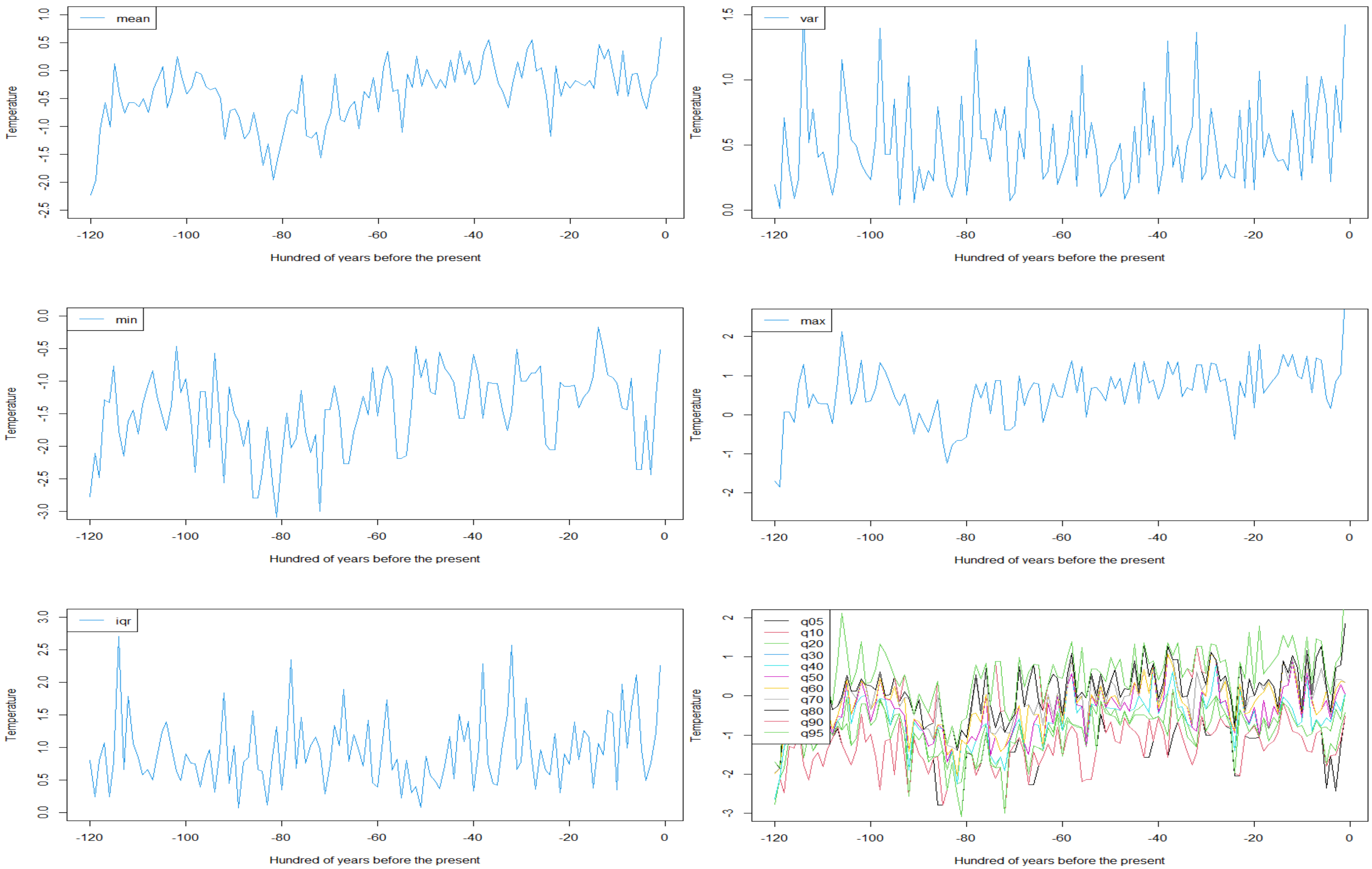


Figure 9: Estimated distributional characteristics.

Paleo-global Warming: Last 12.000 years

Table 27: Trend test (last 12.000 years)

Characteristic	Test-statistic	p-value
mean	7.42×10^{-5}	0.0000
var	9.16×10^{-6}	0.0052
min	5.15×10^{-5}	0.0000
max	8.97×10^{-5}	0.0000
iqr	2.03×10^{-5}	0.0001
q05	6.00×10^{-5}	0.0000
q10	6.88×10^{-5}	0.0000
q20	5.65×10^{-5}	0.0000
q30	7.43×10^{-5}	0.0000
q40	6.18×10^{-5}	0.0000
q50	7.72×10^{-5}	0.0000
q60	7.81×10^{-5}	0.0000
q70	6.88×10^{-5}	0.0000
q80	8.28×10^{-5}	0.0000
q90	9.27×10^{-5}	0.0000
q95	8.71×10^{-5}	0.0000

Note: Annual observations constructed based on 676 original observations using step interpolation. Distributional characteristics estimated using a fixed window approach, assuming an interval length of 100 observations. OLS estimates and HAC p-values of the $t_{\beta=0}$ test from regression $C_t = \alpha + \beta t + u_t$ are reported.

Paleo-global Warming: Last 12.000 years

Table 28: Co-trending analysis (last 12.000 years)

Joint hypothesis tests	Wald test	p-value
All quantiles (q05, q10,...,q90, q95)	22.872	0.011
Lower quantiles (q05, q10, q20, q30)	5.914	0.116
Medium quantiles (q40, q50, q60)	4.686	0.096
Upper quantiles (q70, q80, q90, q95)	6.130	0.105
Spacing hypothesis	**Trend-coeff.**	**p-value**
q50-q05	1.73×10^{-5}	0.003
q95-q50	9.88×10^{-6}	0.075
q95-q05	2.71×10^{-5}	0.000

Note: Annual observations constructed based on 676 original observations using step interpolation. Distributional characteristics estimated using a fixed window approach, assuming an interval length of 100 observations.

Back

The future

Long-term Climate Forecast:
A Future Heterogeneous Warming (in progress[2])

María Dolores Gadea (U. Zaragoza) and
Jesus Gonzalo (UC3M) Back

Some preliminaries

How to Interpret $\underline{+x^oC}$ warmer than pre-industrial (1850-1900) levels?

The book "Six Degrees: Our future on a hotter planet" by Mark Lynas (2008) can help:

- Last Ice Age (100000-10000 years ago) -4^oC with respect pre-industrial levels.
- $\underline{+1^oC}$ is NOW.
- $\underline{+2^oC}$ like 125000 years ago (Eemian interglacial period): North China thirsty, Peru glacier disappears, Ice loss would accelerate, Arctic species threaten, sea level would increase, Oceans warmer and more acidic, etc.
- **TIPPING POINT** $\underline{+3^oC}$, three million years before (the Pliocene epoch): At that time CO2 360-400ppm (now higher than that), food problems, drought in Central America, Pakistan, western US or Australia, etc.
- $\underline{+4^oC}$, 40 million years ago, the Alps will resemble the Atlas of North Africa, Arctic free of sea ice, an acceleration of the sea level rise (world's coasts under sentence of inundation).
- $\underline{+5^oC}$ like 55 million years deep into the past (Paleocene.Eocene Thermal Maximum), Alligators in the Arctic, to be caught without shelter would be to die.
- $\underline{+6^oC}$ 144 to 65 millions years ago (the Cretaceous period): Sea levels 200 meters higher, ocean anoxia, 95% of all life was wiped out, ...

To warm up

The most popular graph showing the existence of GW is the *hockey stick* based on the annual MEAN temperature (across weather stations)

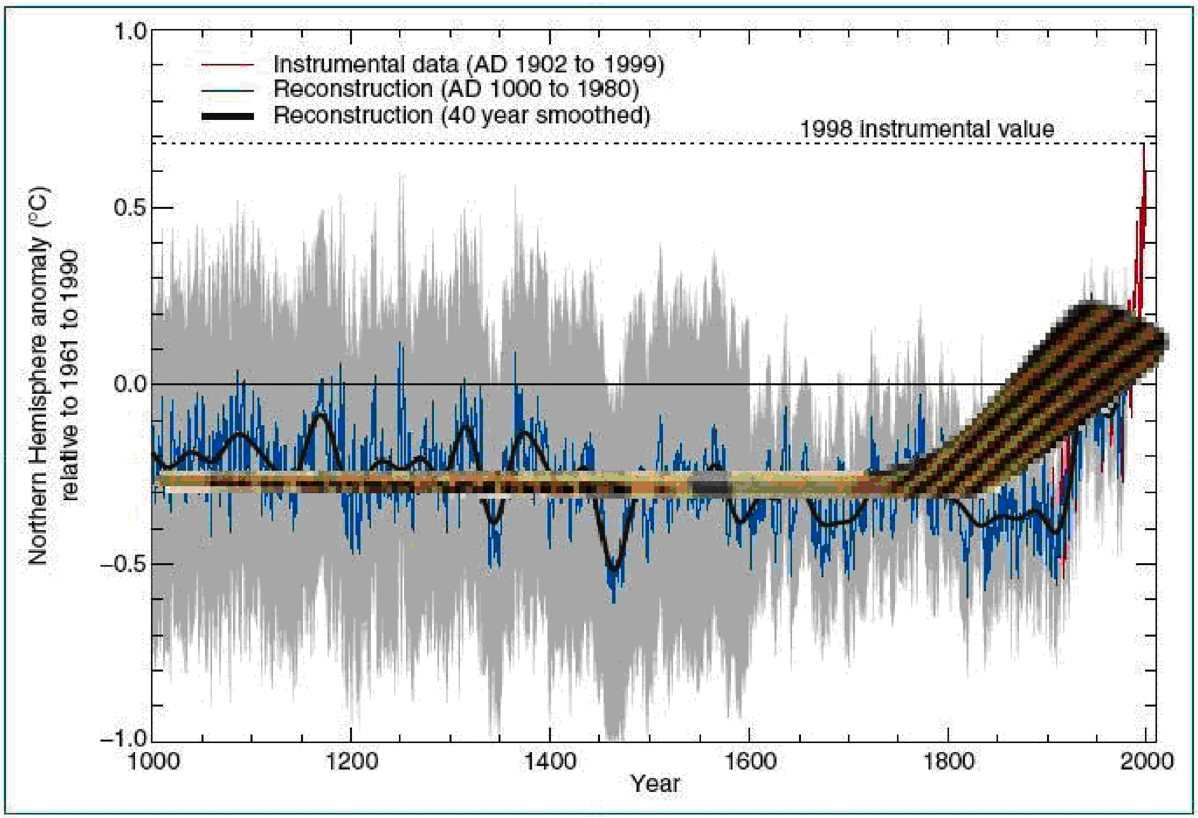


Figure 5: Millennial Northern Hemisphere (NH) temperature reconstruction (blue – tree rings, corals, ice cores, and historical records) and instrumental data (red) from AD 1000 to 1999. Smoother version of NH series (black), and two standard error limits (gray shaded) are shown. [Based on Figure 2.20]

Long-run forecast methodology

There is a TREND in all the distributional characteristics(see Gadea and Gonzalo JoE 2020, GG). Unit roots Trend test BUT what type of trend???

1. Unconditional mean model (mean)
2. Linear-trend model (linear-trend)
3. Polynomial trend model of degree k (pol-trend)
4. Slope-average polynomial trend model (pol-trend-av-sl) av-sl model
5. Logarithmic polynomial trend model of degree k, proxy for a slowly varying trend model (log-trend)
6. Polynomial trend autoregressive model of degree k and order p (pol-trend-arp)
7. Slope-average polynomial trend autoregressive model of degree k and order p (pol-trend-arp-av-sl)
8. Autoregressive model of order p (arp)
9. Random walk model (rw)
10. Random walk + drift model (rwd)
11. IMA model (ima)
12. ARFIMA model (0,d,0) (arfima)
13. AR model with p=20, proxy for an arfima model (arp20)

Long-run forecast methodology

For a given distributional characteristic (time series objects) and a horizon "h", the long-term predictions are constructed following the next steps:

1. We start by proposing a set of families of **trend models**: $M_1, ..., M_m$.
2. For each model family, i.e. $M_2 =$(polynomial trend), we select the best model M_2^* via an information criteria (BIC, AIC, etc).
3. Mean (q05, q50, q95,...) forecasts for $h = 1, 10, 25, 50, 100, \ldots$ years ahead are constructed by using the **direct predicting method** (predictive regression). This method consists on regressing the mean (q05, q50, q95,...) time series at time "$t + h$" on the model information at time "t". The forecast is the estimated latter part. Forecast for the mean are constructed by using the bic-selected model $M_j{}^*$ jointly with the direct method.
4. Forecasts are model dependent. We propose **FORECAST COMBINATIONS** (BIC weights) with some "ad-hoc" trimming.
5. As an alternative to this "ad-hoc" trimming: we propose for a given distributional characteristic and a given "h" to combine only the **Pareto superior** models (models that are not beaten in an out-of-sample forecast competition).

LETS GO TO THE FORECAST RESULTS (first the MEAN and then the whole temperature distribution)

Results for the Mean temperature

Table 29: Mean temperature forecasts (CRU data, 1880-2020)

Horizon	Benchmark model: linear trend	Selected model: pol-trend	Selected model: pol-trend-av-sl
1	11.98	12.71	12.72
	(10.71,13.26)	(11.28,14.13)	(11.29,14.14)
10	**12.08**	13.02	**12.84**
	(10.81,13.36)	(11.60,14.44)	(11.42,14.27)
25	12.25	12.94	13.05
	(10.97,13.52)	(11.51,14.36)	(11.62,14.47)
50	12.53	8.51	13.38
	(11.25,13.80)	(7.09,9.94)	(11.96,14.81)
100	**13.08**	-48.53	**14.06**
	(11.81,14.36)	(-49.95,-47.10)	(12.64,15.49)

Note: The average value of the Mean temperature in the full sample is 11.19; the average value of the Mean in 1880-1900 (the baseline period for the Paris Agreement) is 10.57.

Results for the Mean temperature

Table 30: Long-term forecast COMBINATIONS for the Mean (CRU data, 1880-2020)

Models/horizon	h=1	h=25	h=50	h=100
mean	11.19	11.19	11.19	11.19
	(10.23,12.16)	(10.23,12.16)	(10.23,12.16)	(10.23,12.16)
linear-trend	11.98	12.25	12.53	13.08
	(11.37,12.59)	(11.64,12.86)	(11.92,13.13)	(12.47,13.69)
pol-trend	12.71	12.94	8.51	-48.53
	(12.22,13.20)	(12.45,13.43)	(8.02,9.00)	(-49.02,-48.04)
pol-trend-av-sl	12.72	13.05	13.38	14.06
	(12.23,13.21)	(12.56,13.53)	(12.90,13.87)	(13.57,14.55)
pol-trend-log	12.89	15.41	19.63	33.79
	(11.47,14.32)	(13.98,16.83)	(18.20,21.05)	(32.36,35.22)
pol-trend-arp	12.78	15.18	17.53	129.97
	(12.28,13.28)	(14.67,15.69)	(17.03,18.04)	(129.51,130.42)
pol-trend-arp-av-sl	12.76	13.23	12.89	93.20
	(12.26,13.26)	(12.73,13.74)	(12.38,13.39)	(92.74,93.66)
arp	12.62	12.72	12.71	13.62
	(12.02,13.23)	(11.88,13.56)	(11.85,13.58)	(12.82,14.43)
rw	12.88	12.88	12.88	12.88
	(12.24,13.52)	(11.98,13.78)	(11.82,13.94)	(11.76,14.01)
rwd	12.90	13.25	13.62	14.35
	(12.26,13.54)	(12.47,14.03)	(12.79,14.45)	(13.80,14.91)
ima	12.66	13.01	13.38	14.12
	(11.91,13.41)	(12.19,13.83)	(12.59,14.17)	(13.64,14.59)
arfima	12.52	11.79	11.64	11.52
	(5.92,19.12)	(5.19,18.39)	(5.04,18.24)	(4.92,18.12)
arp20	12.73	12.97	13.63	16.02
	(12.20,13.27)	(12.10,13.84)	(13.07,14.20)	(–,-)
combined	12.61	13.15	13.42	26.65
	(11.87,13.35)	(12.29,14.01)	(12.54,14.30)	(25.86,27.45)
combined2	12.71	12.93	12.95	16.04
	(12.00,13.41)	(12.03,13.82)	(12.01,13.88)	(15.20,16.87)
combined3	12.71	**12.98**	13.06	**13.98**
	(12.03,13.40)	(12.11,13.85)	(12.05,14.06)	(13.09,14.88)

Note: The average value of the Mean in the full sample is 11.19; the average value of the Mean in 1880-1900 (the baseline period for the Paris Agreement) is 10.57. “Combination” weights ALL the models using the BICs values; “combination 2” removes four extreme values and “combination 3” six extreme values. In these last cases BIC-weights are properly recalculated.

Results for temperature QUANTILES forecasts

Table 31: Long-term Quantiles forecasts (CRU data), 1880-2020

Models/horizon	h=1			h=25			h=50			h=100		
	q05	q50	q95	q05	q50	q95	q05	q50	q95	q05	q50	q95
mean	0.79	9.66	26.08	0.79	9.66	26.08	0.79	9.66	26.08	0.79	9.66	26.08
linear-trend	1.72	10.57	26.76	2.04	10.88	26.99	2.37	11.21	27.23	3.02	11.85	27.71
pol-trend	2.65	11.39	27.25	5.24	13.47	28.05	9.65	16.88	29.07	25.44	28.65	31.65
pol-trend-av-sl	2.60	11.36	27.25	3.14	11.82	27.48	3.70	12.30	27.72	4.82	13.26	28.20
pol-trend-log	2.62	11.31	27.32	4.77	12.85	28.17	7.87	14.94	29.17	16.53	20.44	31.44
pol-trend-arp	2.65	11.46	27.31	6.67	14.02	28.28	8.90	16.65	29.57	143.07	183.13	13.34
pol-trend-arp-av-sl	2.60	11.43	27.31	3.68	11.90	27.55	1.91	11.66	27.77	100.85	128.76	41.47
arp	1.67	11.15	26.66	1.42	10.96	27.01	1.32	10.89	26.90	1.52	12.46	27.20
rw	3.26	11.68	26.74	3.26	11.68	26.74	3.26	11.68	26.74	3.26	11.68	26.74
rwd	3.29	11.70	26.75	3.90	12.10	26.95	4.53	12.51	27.16	5.80	13.33	27.58
ima	2.37	11.29	27.03	2.98	11.69	27.24	3.61	12.10	27.45	4.88	12.93	27.86
arfima	1.91	11.14	26.74	1.04	10.24	26.42	0.94	10.08	26.32	0.87	9.95	26.24
arp20	2.56	11.52	27.03	0.72	12.02	29.55	1.89	12.18	28.62	1.71	13.39	25.52
combination	2.34	11.23	26.97	3.10	11.86	27.43	3.98	12.65	27.73	25.42	38.72	27.90
combination 2	2.41	11.34	27.00	2.89	11.76	27.38	3.41	12.18	27.64	7.80	15.58	27.76
combination 3	**2.47**	**11.35**	**26.98**	**2.88**	**11.73**	**27.35**	**3.02**	**11.94**	**27.53**	**5.91**	**14.01**	**27.38**

Note: The average values of q05, q50 and q95 for the full sample are 0.76, 9.64 and 26.07, AND for the Paris agreement baseline period (1880-1900) -0.03, 8.98 and 25.74. "Combination" weights ALL the models using the BICs values; "combination 2" removes four extreme forecasts and "combination 3" six extreme forecasts. In these last cases BIC-weights are properly recalculated.

Conclusions about the Future

This paper offers a wide angle picture of the global WARMING process. This process shows certain HETEROGENEITY.

- Our results for the MEAN coincides with the climate model projections corresponding to scenario RCP8.5 (business as usual)
  - The **1.5** – **2.0C** increase will be reached in **10** – **25** years
  - In **100** years there will be an increase $\geq$ **4C** (tipping point???)
  - A clear ACCELERATION in Mean warming process
- For the whole temperature distribution
  - A serious temperature increase ($>$ **2C**) in the lower part of the distribution in **25** – **50** years
  - In **100** years **q05** will increase $\geq$ **4C** (super tipping point!!!!)
  - A long-run shrinking process in the distribution
  - A clear ACCELERATION process.

Back

RECOMMENDATION: Future Climate Agreements should focus on the whole distribution and not only on the mean.

Conclusions about the Future

THE FUTURE is not what it used to be

THE FUTURE will be warmer

THE FUTURE looks HETEROGONOUSLY scary

THANKS for paying attention to these not very optimistic FUTURE forecasts!!!!

Back

Average slope trend models

The *average* − *slope* models are time varying linear trend models derived from their corresponding polynomial trend models:

$$C_t = f(t) + \epsilon_t \tag{13}$$

in the following way

$$C_t = \beta_0 + \tau_T t + u_t \tag{14}$$

where

$$\tau_T = \frac{1}{T} \sum_{t=1}^{T} \frac{\partial}{\partial t} ft \tag{15}$$

▸ Back

Preliminary results

Table 32: Unit root tests (CRU data, 1880-2020)

Characteristic	ADF-BIC	p-value	lags
mean	-4.50	0.003	1
max	-8.30	0.000	0
min	-10.87	0.000	0
std	-11.25	0.000	0
iqr	-7.78	0.000	1
rank	-10.79	0.000	0
kur	-4.23	0.005	3
skw	-11.44	0.000	0
q05	-10.44	0.000	0
q10	-8.25	0.000	0
q20	-5.67	0.000	1
q30	-8.92	0.000	0
q40	-5.32	0.000	1
q50	-8.57	0.000	0
q60	-5.13	0.000	1
q70	-4.38	0.004	1
q80	-4.88	0.000	1
q90	-7.73	0.000	0
q95	-7.89	0.000	0

Back

Preliminary results

Table 33: Linear trend with OLS-HAC (CRU data, 1880-2020)

Characteristic	Coeff	p-value
mean	0.0111	0.0000
max	0.0070	0.0000
min	0.0204	0.0000
std	-0.0022	0.0000
iqr	-0.0001	0.8607
rank	-0.0134	0.0023
kur	-0.0000	0.9522
skw	-0.0001	0.4055
q05	0.0132	0.0000
q10	0.0119	0.0000
q20	0.0111	0.0000
q30	0.0123	0.0000
q40	0.0127	0.0000
q50	0.0129	0.0000
q60	0.0117	0.0000
q70	0.0119	0.0000
q80	0.0102	0.0000
q90	0.0062	0.0026
q95	0.0096	0.0000

Back