Long-term climate forecast (in progress[2])

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- Climate is not a 7-14 days issue. Climate is a LONG-TERM matter.
- Therefore, Climate Forecasts must be long-term forecasts (h=1, 10, 25, 50, 100,..., years).
- These forecasts are KEY to design the right global warming MITIGATION economic policies.
- To construct long-term forecast is not an easy task.
- For instance, it is a common practice to select from a set of models (M_1, ...,M_p) via some information criteria, the "best" model and forecast with it. When the process is trending (like the global temperature), very likely the chosen model contains a polynomial trend. For h=1, 10, 25 the performance is ok; but it becomes nonsense for longer horizons (h=50, 100, ...). Table mean
- The main **GOAL** of this paper is to produce long-term temperature forecasts (avoiding the previously mentioned problem).
- We do it by running an OUT OF SAMPLE forecast competition among all the models. The performance is evaluated via a forecasting evaluation test. The models that are not beaten for a given "h" formed the Pareto Superior set of models. Because forecasts are model dependent, we propose to combine them.

WHAT DO WE WANT TO FORECAST?

- In the literature, climate and econometric models produce projections and forecasts of the annual MEAN temperature. This offers an incomplete picture. Notice that the confidence intervals of the Mean may not provide information about the whole temperature distribution.
- This paper produces forecasts of the WHOLE TEMPERATURE DISTRIBUTION and not only of the mean. The forecast of different temperature distributional characteristics offers a much wider angle picture than the one of the simple mean.
- Methodology: The one introduced in Gadea and Gonzalo (*Trends in distributional characteristics: Existence of global warming*, JoE 2019) (GG):
  - Every distributional characteristic (quantiles, moments, etc) are converted into time series objects. ▸ Density ▸ Characteristics
  - There is an increasing trend (warming) in all the quantiles and is stronger in the lower than in the upper quantiles. IQR shrinks through time. ▸ Linear trend test
  - The existing trends suffer a clear acceleration process.

In more detail, the long-term predictions are obtained by the following next steps:

1. Estimate a set of models ($M_1, ..., M_P$) for the different time series objects (C_t=mean, quantiles, min, max, std, etc.). These models capture the main feature of all the distributional characteristics: a trend component (see results in GG).
2. Construct the different distributional characteristics (C_t) forecasts for h (1, 10, 25, 50, 100, ...) years ahead by using the direct forecasting method. This method consists of regressing a given C_t (mean, quantiles,...) at time "t+h" on model information at time "t". The constructed forecast is the estimated latter part. Table q05
3. Run an out of sample forecasting competition among all the Models for a given C_t for each h and select the Pareto superior models via a forecasting evaluation test (Giacomini-White, 2006) for a given h.
4. To eliminate the forecast model dependency, our final proposed forecast is formed (for each h) by a combination of the forecasts produced from the Pareto superior models.

Models considered

Table 1: Model description

Name	Acrimonious	Model
Mean model	mean	$C_t = \beta_0 + u_t$
Linear trend model	linear-trend	$C_t = \beta_0 + \beta_1 t + u_t$
Polynomial trend model	pol-trend	$C_t = \sum_{i=o}^{k} \beta_i t^i + u_t$
Polynomial trend model average slope (1)	pol-trend-av-sl	$C_t = \beta_0 + \tau t + u_t$
Logaritmic polynomial trend model	pol-trend-log	$C_t = \sum_{i=o}^{k} \beta_i (log(t))^i + u_t$
Polynomial trend autoregressive model	pol-trend-arp	$C_t = \sum_{i=o}^{k} \beta_i t^i + \sum_{j=1}^{p} \phi_j C_{t-j} + u_t$
Polynomial trend autoregressive model average slope (1)	pol-trend-arp-av-sl	$C_t = \beta_0 + \tau t + \sum_{j=1}^{p} \phi_j C_{t-j} + u_t$
Autoregressive model	arp	$C_t = \sum_{j=1}^{p} \phi_j C_{t-j} + u_t$
Random walk model	rw	$C_t = C_{t-1} + u_t$
Random walk drift model	rwd	$C_t = \alpha + C_{t-1} + u_t$
Local Level Model, IMA(1,1)	ima	$C_t = \alpha + C_{t-1} + (1 - \theta L) u_t$
Fractional model	arfima	$\Phi(L)(1 - L)^d C_t = \Theta(L)\epsilon_t$
Large autoregressive model	arp20	$C_t = \sum_{j=1}^{20} \phi_j C_{t-j} + u_t$

Notes. (1) The *average* $-$ *slope* models are time varying linear trend models derived from their corresponding polynomial trend models in the following way: $\tau_T = \frac{1}{T} \sum_{t=1}^{T} \frac{\partial}{\partial t} C_t$

Table 2: Long-term temperature density forecast (CRU data, 1880-2018)

Models/horizon	h=1			h=25			h=100		
	q5	q50	q95	q5	q50	q95	q5	q50	q95
mean	0.85	9.48	25.87	0.85	9.48	25.87	0.85	9.48	25.87
linear-trend	1.74	10.30	26.45	2.05	10.58	26.65	3.00	11.47	27.27
pol-trend	2.60	11.06	26.91	5.08	13.11	27.66	24.73	28.51	31.03
pol-trend-av-sl	2.55	11.03	26.91	3.07	11.47	27.11	4.69	12.84	27.73
pol-trend-log	1.55	10.98	26.96	1.71	12.45	27.72	2.12	19.79	30.66
pol-trend-arp	1.80	11.14	26.94	1.92	13.62	27.81	6.86	182.55	14.36
pol-trend-arp-av-sl	1.80	11.11	26.94	1.92	11.55	27.18	6.86	130.74	40.30
arp	1.65	10.80	26.64	1.43	10.48	26.88	1.70	12.03	26.82
rw	2.70	11.36	26.50	2.70	11.36	26.50	2.70	11.36	26.50
rwd	2.72	11.37	26.51	3.23	11.73	26.67	4.83	12.85	27.19
ima	2.30	10.93	26.75	2.82	11.29	26.92	4.42	12.41	27.43
arfima	1.82	10.76	26.52	1.08	9.94	26.19	0.93	9.69	26.03
arp20	1.91	10.75	26.97	0.81	10.78	28.39	6.50	12.22	29.57
combined	1.99	10.88	26.70	2.23	11.45	27.05	5.52	38.56	27.78
combined*	2.03	10.96	26.75	2.07	11.32	27.05	4.06	15.12	27.66

Note. The average values of q05, q50 and q95 for the full sample are, respectively, 0.85, 9.48 and 25.87; in the Paris agreement baseline period (1880-1900) are 0.07, 8.84 and 25.64; in the climatologists reference period (1986-2005) are 1.45, 10.05 and 26.38. Values at the end of the sample are: 2.70, 11.36 and 26.50. "Combination" weights the models using the BICs obtained in-sample; "combination*" removes the four models that produce the four most extreme forecasts (above and below). In these last cases BIC-weights are properly recalculated.

Conclusions

- Global Warming forecasts: $qo5_{t+h}$, $Q50_{t+h}$ and $Q95_{t+h}$ increase with “h”. The FUTURE will be WARMER!!!
- Climate Heterogeneity (asymmetry): Lower quantiles increase more than the upper ones.This is more serious than an increase in the mean.
- Great Compression: IQR_{t+h} gets smaller with “h” (opposite to the inequality found in the income distribution analysis).
- Acceleration Hypothesis: Many models show a clear accelerarion in the Global Warming forecasts, Climate Heterogeneity and Great Compression.
- Our forecasts for the MEAN are similar to Climate Model projections under scenario RCP 8.5 (emissions continue to raise during the 21st century). On top of that, we are able to produce temperature distribution forecasts.
- From our results, the +1.5-2C max increase in the mean with respect the pre-industrial period that is suggested in the Paris Climate Agreement will be overpassed in less than 25 years.
- Recommendation: Due to the existence of Climate Heterogeneity the future Climate Agreements should make proposals in terms of the WHOLE TEMPERATURE DISTRIBUTION and not only the MEAN.

Mean temperature forecast with BIC-selected model

Table 3: Mean forecast with *pol-trend* model ($k = 5$) (CRU data, 1880-2018)

Horizon	LS point forecast	CI	LAD point forecast	CI
1	12.46	(11.97,12.95)	12.53	(12.27,12.63)
10	12.68	(12.19,13.17)	12.85	(13.72,12.65)
25	12.29	(11.80,12.78)	12.84	(18.34,11.50)
50	6.57??	(6.08,7.06)	8.87??	(37.13,2.05)
100	-60.55??	(-61.04,-60.06)	-44.41??	(172.58,-96.60)

Note. The average value of the Mean in the full sample is 11.09; the average value of the Mean in 1880-1900 (the baseline model for the Paris Agreement) is 10.57; the average value of the Mean in the climatologist reference period (1986-2005) is 11.63; the last value of the sample, in 2018, is 12.54.

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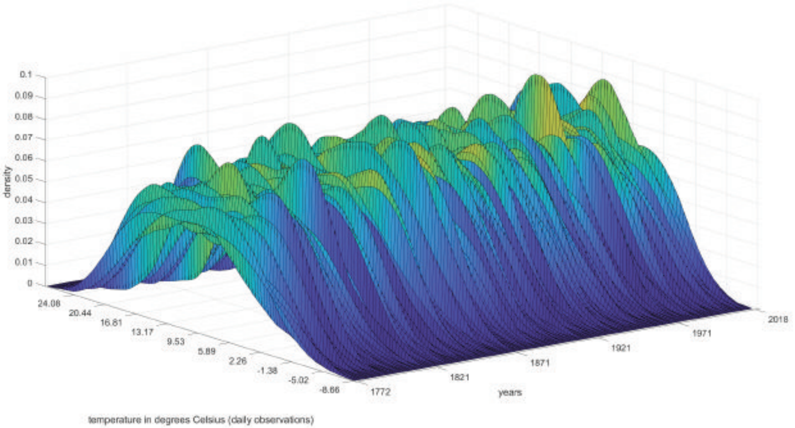
Time-series data (Central-England)



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Time-series data (Central-England)

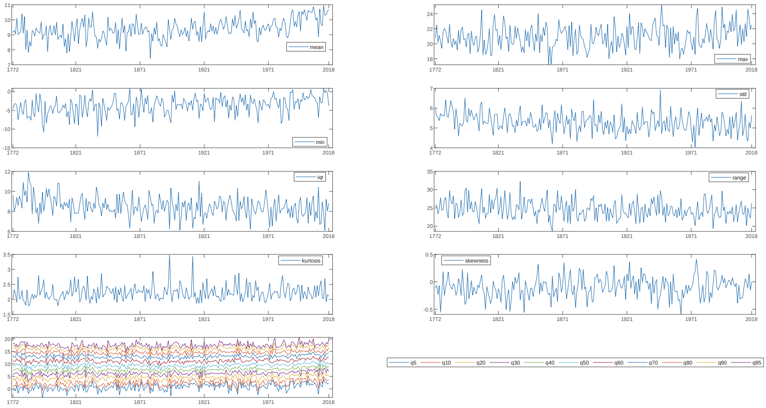

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Table 4: Linear trend with OLS-HAC (CRU data)

Characteristic	Coeff	p-value
mean	0.0107	0.0000
max	0.0069	0.0000
min	0.0188	0.0000
std	-0.0023	0.0000
iqr	-0.0000	0.4817
rank	-0.0119	0.0024
kur	0.0003	0.2839
skw	-0.0001	0.2473
q05	0.0127	0.0000
q10	0.0122	0.0000
q20	0.0112	0.0000
q30	0.0119	0.0000
q40	0.0122	0.0000
q50	0.0118	0.0000
q60	0.0114	0.0000
q70	0.0116	0.0000
q80	0.0097	0.0000
q90	0.0035	0.0247
q95	0.0083	0.0000

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Table 5: q05 temperature forecast with BIC-selected model, *pol-trend-av-sl* model ($k = 3$) (CRU data, 1880-2018)

Horizon	LS point forecast	CI	LAD point forecast	CI
1	2.55	(1.07,4.03)	2.73	(0.87,3.26)
10	2.75	(1.27,4.23)	2.96	(1.04,3.37)
25	3.07	(1.59,4.55)	3.34	(1.33,3.56)
50	3.61	(2.13,5.09)	3.98	(1.82,3.88)
100	4.69	(3.21,6.18)	5.26	(2.79,4.51)

Note. The average value of the q05 in the full sample is 0.850; the average value of q05 in 1880-1900 (the baseline model for the Paris Agreement) is 0.07; the average value of q05 in the climatologist reference period (1986-2005) is 1.45; the last value of the sample, in 2018, is 2.70.

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