

“It’s not the heat, it’s the humidity!” New Climate Indices for Europe with a Multilevel Factor Model

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Climate damages



Figure: Source: CLIMap (<https://gisaction.com/>)

How do we measure the climate?

Economists usually proxy climate with one or two variables:
temperature and/or precipitation...



Climate is a complex phenomenon in which a large number of variables are determined *jointly* (Dell et al., 2014), therefore practitioners face a trade-off:

- including many variables → *overparametrization*
- including few variables → *omitted variable bias*

A potential solution is using **indices**:

- temperature, precipitation, humidity indices;
- Niño/Niña events (e.g., ONI, SOI);
- Artic Sea Ice extent ([Diebold et al., 2021](#));
- extreme weather conditions (e.g., ACI, used in [Kim et al. \(2022\)](#))

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However...

Climate indices are often naively defined: simple averages or with *ad-hoc* weights; included variables are often arbitrary; lack of capillarity.

Our contribution

We propose **global** and **local** climate indices for Europe with these features:

- “all-encompassing” → several variables;
- statistically and methodologically rigorous → Dynamic Factor Models;
- global (Europe as a whole) and local (country-specific) perspective;
- granularity → data at grid level.

Methodology & Data

Dynamic factor models in a nutshell

A very popular tool to summarize variable information into one or more series is using Dynamic Factor Models (DFM) as in [Alquist et al. \(2020\)](#); [Delle Chiaie et al. \(2022\)](#); [Baumeister et al. \(2022, 2024\)](#).

$$\begin{aligned}x_t &= \sum_{j=0}^p \Lambda_j f_{t-j} + \varepsilon_t, \quad \varepsilon_t \sim N(0, \Sigma_\varepsilon) \\f_t &= \sum_{i=1}^s A_i f_{t-i} + u_t, \quad u_t \sim N(0, \Sigma_u)\end{aligned}$$

Estimation: PC, TS ([Doz et al., 2011](#)), ML-EM ([Doz et al., 2012](#)).

Multilevel factor models: global and local factors

Suppose that **some factors are common to all variables**, while others **only to some groups**:

- *hierarchical* approach (Breitung and Eickmeier, 2015; Delle Chiaie et al., 2022);
- *multilevel* approach (Choi et al., 2018);

Multilevel approach

We exploit the second methodology since it is:

- non-parametric,
- more flexible and robust,
- computationally efficient.

$$x_{mit} = \underbrace{\gamma'_{mi} G_t}_{Global} + \underbrace{\lambda'_{mi} F_{mt}}_{Local} + e_{mit},$$

where

- $m = 1, \dots, M \rightarrow$ country index;
- $i = 1, \dots, k_m \rightarrow$ variable (per country) index;
- $t = 1, \dots, T \rightarrow$ time index.

The number of global factors can be **assumed** (Choi et al., 2018) or **estimated** (Choi et al., 2023); the number of local factors is then derived via common procedures (Bai and Ng, 2002).

Estimation: 4-step procedure (Choi et al., 2018) [► Details](#)

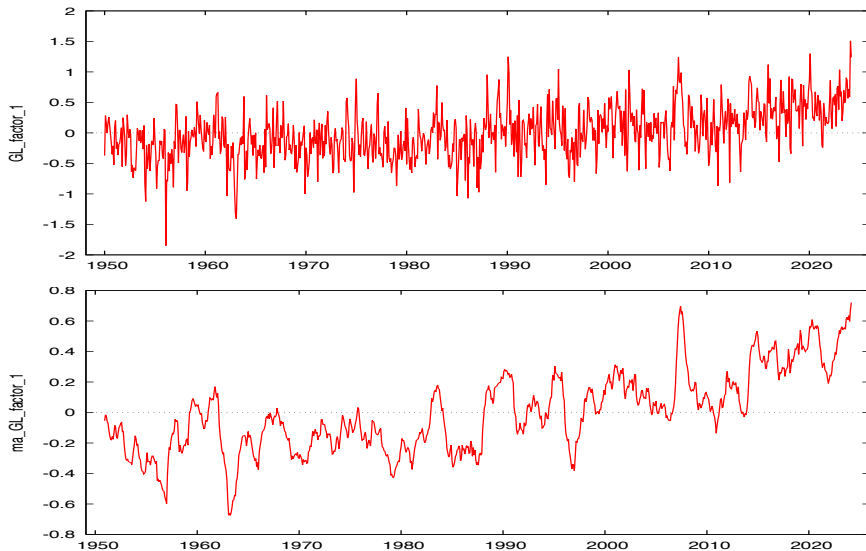
Data comes from **Copernicus ERA5-land** database (*grib*).

- Different level of spatial-temporal detail
⇒ EU countries, monthly (1950:01-2024:04)
- Different classes of climate variables:
 - **temperature**: 2m temperature, 2m dewpoint temperature,...
 - **lakes**: lake temperatures, lake ice measures,...
 - **snow**: snow cover, snow density, snow albedo,...
 - **soil water**: volumetric soil water at different layers;
 - **radiation/heat**: solar and thermal radiation;
 - **evaporation**: potential and total evaporation, runoff;
 - **wind, precipitation**: wind speed, total precipitation,...

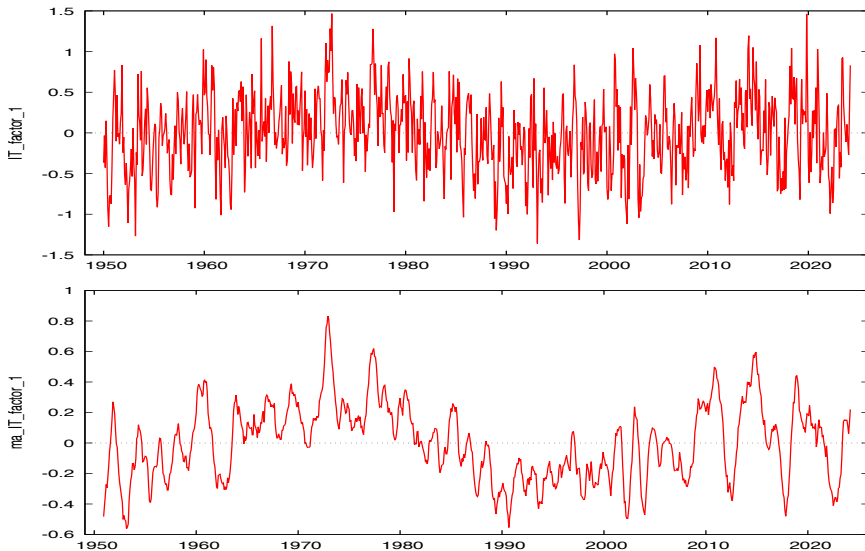
► Details

Results

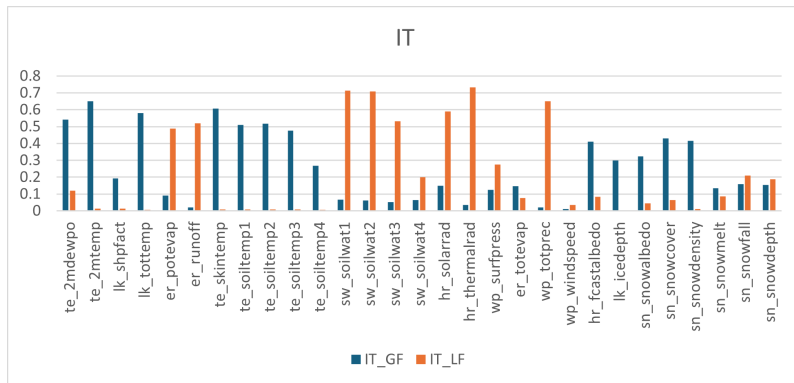
The global factor



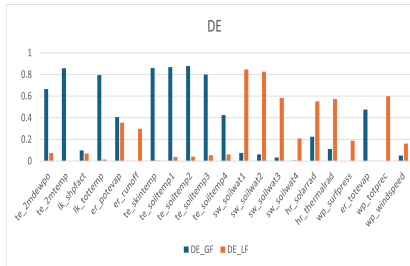
A country-specific example: Italy



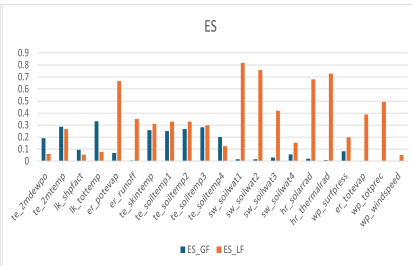
Variance contribution



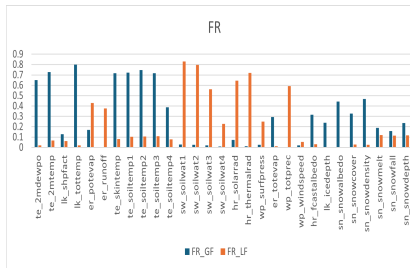
Variance contribution ratio for Italy: blue indicates the global factor, orange the local one.



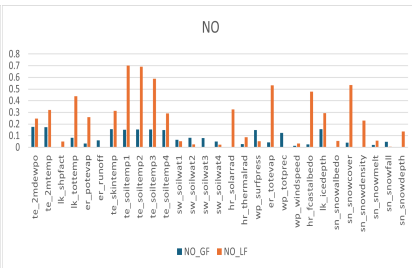
(a) Variance contribution for DE



(b) Variance contribution for ES



(c) Variance contribution for FR



(d) Variance contribution for NO

- For temperate climate countries the global factor accounts for temperature effects; the local one for precipitation, radiation and water → valid proxies for climate change?
- For hotter/colder countries this distinction becomes less clear.
- What if...
 - more local factors?
 - different climatologies?

Application

Application

We use our indices to estimate the effect of a climate shock on European economic activity in the spirit of [Bilal and Känzig \(2024\)](#)'s application.

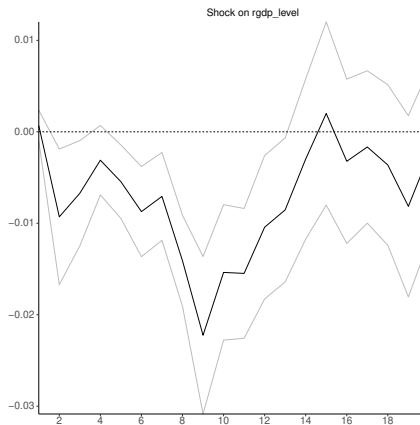
We rely on quarterly data, sourced from OECD and FRED, and *local projections* ([Jordà, 2005](#)).

$$y_{i,t+h} - y_{i,t-1} = \alpha_i + \beta_h \text{shock}_{(i),t} + w'_{i,t} \gamma + w'_t \eta + u_{i,t+h}$$

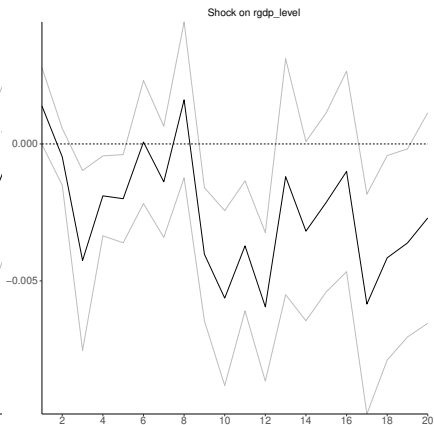
- y : log GDP;
- shock : global/local climate index;
- w : controls;
- u : error term.

Setup

- Countries: AUT, BEL, CHE, DEU, DNK, ESP, FIN, FRA, GBR, GRC, ISL, ITA, LUX, NLD, NOR, PRT, SWE
- Time span: $\approx 1982q2:2023q2$
- $h = 1, \dots, 20$;
- controls: local/global index, inflation, unemployment, industrial production, COVID-19 cases, EU recessions, Brent, DE interest rate, (time trend)
- lagged controls: shock, GDP growth and controls up to 8 lags;
- Driscoll-Kraay standard errors;



(a) Global index shock



(b) Local index shock

Conclusion

- we device global-local indices for EU using multilevel factor models;
- the global component catches temperature effects; the local one precipitation, radiation, water effects in most countries
- local projection: global vs local

Future developments:

- more granular data!
- what about extreme events?

References I

- Ahmadi, M., Casoli, C., Manera, M., and Valenti, D. (2022). Modelling the effects of climate change on economic growth: a bayesian structural global vector autoregressive approach. *FEEM Working Paper*.
- Alquist, R., Bhattarai, S., and Coibion, O. (2020). Commodity-price comovement and global economic activity. *Journal of Monetary Economics*, 112:41–56.
- Bai, J. and Ng, S. (2002). Determining the number of factors in approximate factor models. *Econometrica*, 70(1):191–221.
- Baumeister, C., Korobilis, D., and Lee, T. K. (2022). Energy markets and global economic conditions. *Review of Economics and Statistics*, 104(4):828–844.
- Baumeister, C., Leiva-León, D., and Sims, E. (2024). Tracking weekly state-level economic conditions. *Review of Economics and Statistics*, pages 1–22.
- Bilal, A. and Känzig, D. R. (2024). The macroeconomic impact of climate change: Global vs. local temperature. Technical report, National Bureau of Economic Research.
- Breitung, J. and Eickmeier, S. (2015). Analyzing business cycle asymmetries in a multi-level factor model. *Economics Letters*, 127:31–34.

References II

- Choi, I., Kim, D., Kim, Y. J., and Kwark, N.-S. (2018). A multilevel factor model: Identification, asymptotic theory and applications. *Journal of Applied Econometrics*, 33(3):355–377.
- Choi, I., Lin, R., and Shin, Y. (2023). Canonical correlation-based model selection for the multilevel factors. *Journal of Econometrics*, 233(1):22–44.
- Dell, M., Jones, B. F., and Olken, B. A. (2014). What do we learn from the weather? the new climate-economy literature. *Journal of Economic literature*, 52(3):740–798.
- Delle Chiaie, S., Ferrara, L., and Giannone, D. (2022). Common factors of commodity prices. *Journal of Applied Econometrics*, 37(3):461–476.
- Diebold, F. X., Göbel, M., Coulombe, P. G., Rudebusch, G. D., and Zhang, B. (2021). Optimal combination of arctic sea ice extent measures: A dynamic factor modeling approach. *International Journal of Forecasting*, 37(4):1509–1519.

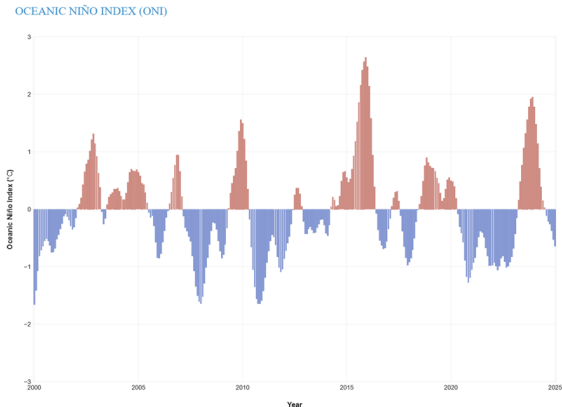
References III

- Doz, C., Giannone, D., and Reichlin, L. (2011). A two-step estimator for large approximate dynamic factor models based on kalman filtering. *Journal of Econometrics*, 164(1):188–205.
- Doz, C., Giannone, D., and Reichlin, L. (2012). A quasi–maximum likelihood approach for large, approximate dynamic factor models. *Review of economics and statistics*, 94(4):1014–1024.
- Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American economic review*, 95(1):161–182.
- Kim, H. S., Matthes, C., and Phan, T. (2022). Severe weather and the macroeconomy. *Federal Reserve Bank of Richmond Working Papers*, 21-14R.

Example 1: ONI index

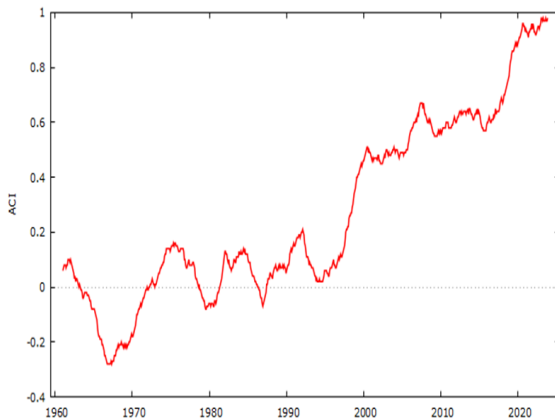
Used variable: average sea surface temperature

- The ONI is NOAA's primary index for tracking the ocean part of ENSO, the [El Niño-Southern Oscillation](#) climate pattern.
- Rolling 3-month average temperature *anomaly* (difference from average) in the surface waters of the east-central tropical Pacific.
- Index values of +0.5 or higher indicate El Niño. Values of -0.5 or lower indicate La Niña.



Example 2: ACI index

Actuaries Climate Index, USA and Canada



Reference period: 1961 – 1990
5-year moving average

Simple average of 6 components:

- High temperatures
- Low temperatures
- Heavy rain
- Drought
- High wind
- Sea level

Multilevel factor model estimation

- Step 1. Select two countries and get $\hat{G}_t$ via canonical correlation analysis;
- Step 2. Replace G_t with $\hat{G}_t$ and estimate λ_{mi} and F_{mt} via PC;
- Step 3. Replace λ_{mi} and F_{mt} with their previously obtained estimates and compute/revise $\hat{G}_t$ and $\hat{\gamma}_{mi}$ via PC;
- Step 4. Substitute the newly obtained quantities and revise $\hat{\lambda}_{mi}$ and $\hat{F}_{mt}$ again via PC

Global and local factor spaces are estimated *consistently* and are *asymptotically normal*.

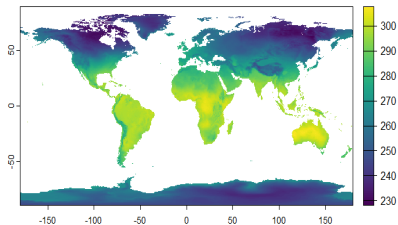
Data in details

Category	Variables
<i>Temperature</i>	2m dewpoint temperature 2m temperature skin temperature soil temperature (lvls 1-4)
<i>Lakes</i>	lake total temperature lake shape factor lake ice depth*
<i>Snow</i>	snow cover* snow density* snow albedo*
<i>Soil Water</i>	volumetric soil water (lvls. 1-4)
<i>Heat/Radiation</i>	forecast albedo* surface net solar radiation surface net thermal radiation
<i>Evaporation</i>	runoff potential evaporation total evaporation
<i>Wind, precipitation</i>	surface pressure total precipitation wind speed

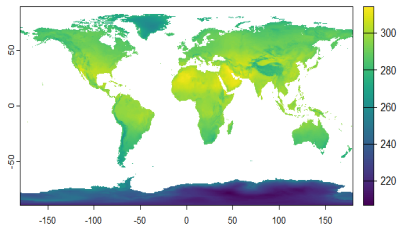
Notes: * only for IS, LI, SE, AT, CH, NO, FI, IT, FR, ME.

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Data processing



(a) Temperature, January 1950



(b) Temperature, July 2000



Filtering: climatologies and anomalies

- **Monthly climatology:** averaged or filtered values for a specific month over a reference period.
- **Monthly anomaly:** difference between a monthly value and the climatology of that variable for that specific month.

Examples

IEA (Weather, Climate and Energy Tracker) uses a reference period 2000-2019 for climatologies, ACI uses 1961-1990. Ahmadi et al. (2022) use a 30-year rolling average. Bilal and Känzig (2024) use Hamilton filtering.

We use:

- 1 fixed averages: 1950-1979;
- 2 moving average: 20 years;
- 3 Hamilton filter: 2 years.

A closer look at anomalies

What is a climate anomaly?

Climate anomaly is defined as the departure from the **normal conditions** (or **climatology**). It is a critical concept to separate the signal of **climate change** from the **seasonal cycle**.

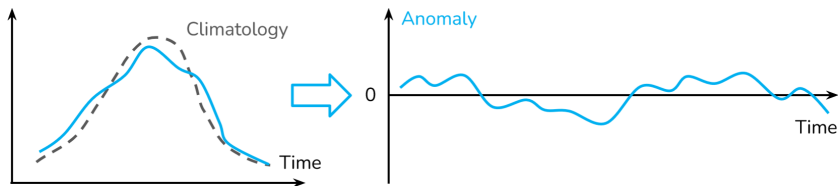


Figure: Source: https://comptools.climatematch.io/tutorials/W1D3_RemoteSensing/student/W1D3_Tutorial5.html

Example: constructing anomalies for precipitation

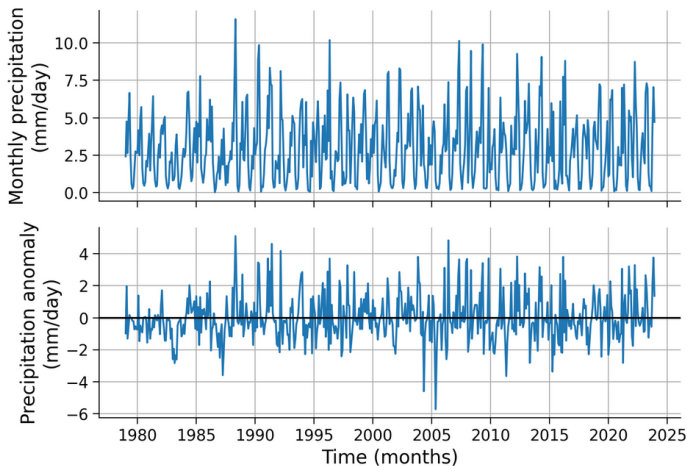


Figure: Source: https://comptools.climatematch.io/tutorials/W1D3_RemoteSensing/student/W1D3_Tutorial5.html

Factor contributions - country-specific DFM

	DE	ES	FR	IT	NO
2m dewpoint	0.660	0.318	0.701	0.718	0.489
2m temp	0.876	0.966	0.969	0.983	0.558
lake shape	0.128	0.228	0.202	0.240	0.021
lake temp	0.843	0.640	0.795	0.768	0.498
pot evap	0.467	0.504	0.423	0.294	0.195
runoff	0.031	0.016	0.027	0.033	0.045
skin temp	0.884	0.989	0.979	0.992	0.536
soil temp1	0.992	0.998	0.996	0.947	0.997
soil temp2	0.993	0.994	0.993	0.943	0.999
soil temp3	0.947	0.951	0.947	0.914	0.976
soil temp4	0.977	0.828	0.979	0.966	0.809
soil water1	0.154	0.213	0.186	0.206	0.020
soil water2	0.152	0.183	0.187	0.181	0.013
soil water3	0.170	0.143	0.201	0.175	0.029
soil water4	0.079	0.173	0.108	0.191	0.078
solar rad	0.279	0.203	0.245	0.179	0.197
surf press	0.011	0.052	0.018	0.048	0.006
therm rad	0.132	0.123	0.096	0.031	0.007
tot evap	0.460	0.110	0.271	0.043	0.423
tot prec	0.010	0.051	0.012	0.025	0.051
wind speed	0.020	0.040	0.003	0.086	0.063
fcast albedo	-	-	0.241	0.249	0.325
lake ice	-	-	0.160	0.266	0.557
snow albedo	-	-	0.361	0.356	0.077
snow cover	-	-	0.254	0.263	0.382
snow dens	-	-	0.373	0.351	0.110

Notes: variance contribution (ratio) of the common component.

Factor contribution: IT

	Global	Local	Tot Factor
2m dewpoint	0.539	0.111	0.650
2m temp	0.655	0.022	0.677
lake shape	0.192	0.014	0.206
lake temp	0.581	0.001	0.583
pot evap	0.096	0.572	0.668
runoff	0.021	0.471	0.492
skin temp	0.610	0.017	0.627
soil temp1	0.515	0.025	0.540
soil temp2	0.523	0.024	0.546
soil temp3	0.481	0.024	0.505
soil temp4	0.271	0.017	0.288
soil water1	0.069	0.784	0.853
soil water2	0.065	0.776	0.841
soil water3	0.054	0.573	0.626
soil water4	0.065	0.208	0.273
solar rad	0.152	0.604	0.756
surf press	0.122	0.221	0.343
therm rad	0.036	0.728	0.764
tot evap	0.147	0.094	0.241
tot prec	0.021	0.606	0.627
wind speed	0.011	0.027	0.038
fcast albedo	0.407	0.040	0.447
lake ice	0.296	0.005	0.300
snow albedo	0.323	0.035	0.358
snow cover	0.428	0.028	0.456
snow dens	0.414	0.003	0.417

Factor contribution: other countries

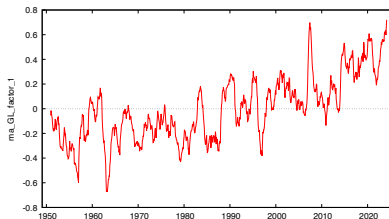
	DE		ES		FR		NO	
	Global	Local	Global	Local	Global	Local	Global	Local
2m dewpoint	0.662	0.076	0.192	0.061	0.638	0.026	0.168	0.282
2m temp	0.856	0.003	0.289	0.264	0.732	0.067	0.166	0.359
lake shape	0.101	0.069	0.094	0.054	0.133	0.072	0.000	0.050
lake temp	0.795	0.014	0.330	0.078	0.800	0.018	0.081	0.442
pot evap	0.409	0.353	0.069	0.663	0.184	0.495	0.032	0.262
runoff	0.001	0.299	0.006	0.353	0.000	0.365	0.057	0.005
skin temp	0.859	0.005	0.260	0.308	0.722	0.081	0.150	0.350
soil temp1	0.869	0.036	0.253	0.326	0.732	0.114	0.147	0.716
soil temp2	0.879	0.040	0.270	0.324	0.756	0.115	0.150	0.707
soil temp3	0.802	0.053	0.285	0.295	0.728	0.120	0.151	0.599
soil temp4	0.429	0.062	0.204	0.122	0.398	0.092	0.147	0.300
soil water1	0.076	0.847	0.016	0.818	0.034	0.872	0.064	0.037
soil water2	0.063	0.824	0.016	0.759	0.032	0.839	0.080	0.014
soil water3	0.033	0.582	0.031	0.419	0.024	0.588	0.077	0.000
soil water4	0.008	0.209	0.056	0.153	0.009	0.231	0.048	0.036
solar rad	0.225	0.551	0.020	0.682	0.081	0.679	0.000	0.305
surf press	0.004	0.189	0.080	0.201	0.025	0.196	0.145	0.042
therm rad	0.111	0.575	0.008	0.730	0.016	0.723	0.028	0.078
tot evap	0.474	0.000	0.004	0.387	0.292	0.010	0.043	0.505
tot prec	0.001	0.600	0.003	0.496	0.000	0.554	0.119	0.004
wind speed	0.049	0.163	0.001	0.052	0.018	0.061	0.013	0.038
fcast albedo	-	-	-	-	0.299	0.003	0.024	0.459
lake ice	-	-	-	-	0.230	0.012	0.151	0.324
snow albedo	-	-	-	-	0.431	0.000	0.002	0.048
snow cover	-	-	-	-	0.310	0.002	0.039	0.518
snow dens	-	-	-	-	0.452	0.005	0.000	0.176

More local factors

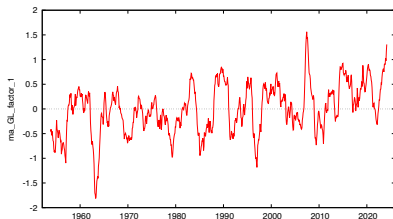
Suppose 1 Global factor - 2 local factors

- For temperate climate countries the explanatory power of the global factor shifts to the 1st local factor, and the former local factor to the 2nd one;
- on the other hand, the global factor starts to capture the dynamics of more continental countries (East Europe).

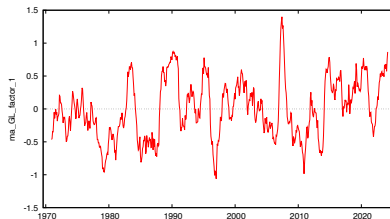
Different climatologies: global factor



(a) Fixed period: 1950-1979

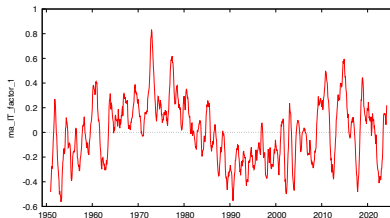


(b) Hamilton filter

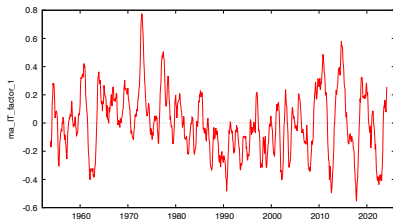


(c) 20-years rolling mean

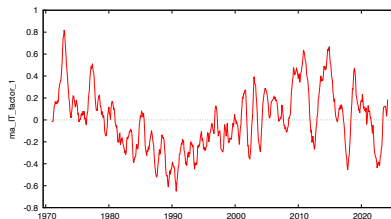
Different climatologies: IT factor



(a) Fixed period: 1950-1979



(b) Hamilton filter



(c) 20-years rolling mean