November 2025

FONDAZIONE ENI ENRICO MATTEI

Working Paper

23.2025

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Keywords: Climate measures, climate impacts, Multilevel Factor Models, panel local projections

JEL Classification: Q54, O44, C38, C55, Q56

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Abstract

We construct a comprehensive set of climate indices for European countries that account for several variables related to weather, atmospheric conditions, and water availability. Our dataset includes monthly gridded climate observations from ERA5-Land, aggregated at the country level. Employing a Multilevel Dynamic Factor Model, we disentangle a global indicator, capturing overall climate dynamics across Europe, from country-specific local indices. While most empirical studies proxy climate through temperature or precipitation, our approach acknowledges that other atmospheric dimensions, such as humidity, radiation, and evaporation, jointly shape climatic variability and its economic effects. The global index primarily reflects temperature patterns common to most European countries, whereas the local indicators capture other meteorological phenomena and variations in water reserves. Finally, we show, via panel local projections, that different filtering and detrending procedures used to construct climate anomalies influence the estimated effects of climate shocks on economic activity.

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1 Introduction

Climate change is a global phenomenon with severe environmental, social, financial, and economic consequences. As climate patterns shift and extreme weather events become more frequent and intense, the need to quantify and understand the impact on economic systems has become increasingly important. Climate change affects agriculture, health, migration patterns, labour productivity, conflicts, energy consumption, among other aspects of societies.

Not surprisingly, policymakers and economists have devoted substantial effort to estimating the economic damages caused by climate change.

Several studies investigate which economic variables should be incorporated into empirical analyses. For example, Newell et al. (2021) highlight the uncertainty in climate damage estimates depending on model specifications, particularly whether economic activity is measured in levels or growth rates of Gross Domestic Product (GDP). More uncertain is the quantification of the net climate effect: Tol (2018) assesses an average per capita income loss of approximately 1.3 percent for a global temperature increase of 2.5 °C; on the other hand, Bilal and Känzig (2024) estimates a decrease in Real GDP per capita exceeding the 10 percent per 1 °C, using annual and world data.

Another critically important but relatively unexplored issue is the optimal selection of climate variables in such analyses. The choice of which climatic indicators to include can significantly affect the results of climate damage assessments. Most of this literature considers temporal variations in temperature and (or) precipitation as the climatic variable of interest (Ahmadi et al., 2025; Bilal and Känzig, 2024; Burke et al., 2015; Dell et al., 2012; Letta and Tol, 2019). However, this approach tends to oversimplify the climate–economy relationship. In everyday experience, people perceive that the burden of weather depends not only on heat or rainfall but also on factors such as humidity, radiation, or air circulation, yet these dimensions are rarely included in empirical analyses. As noted in Dell et al. (2014), the use of a single indicator (or a limited set) can result in an omitted-variable bias. In fact, climate is a complex phenomenon influenced by a broad set of atmospheric and environmental factors that jointly determine and shape the weather experienced in a particular region at a given time (see the discussion in Hsiang, 2016). However, including as many climate-related variables as possible in empirical analyses exposes to the risk of overparametrisation. Therefore, a trade-off arises between model completeness and parsimony.

At this point, the crucial question is: How can we measure climate? Despite the growing attention climate change receives in social sciences, there are still few contributions that use or attempt to construct valid proxies for climate change. A growing number of studies are based on more complex measures of climate, such as *ad hoc* indices constructed by climatologists. For instance, Cashin et al. (2017) explore the macroeconomic effects of El Niño oscillations, measured through the ENSO cycle. The ENSO pattern is usually measured via some indices as the Oceanic Niño Index (ONI) and the Southern Oscillation Index (SOI), which are technically constructed as moving averages of single variables, such as ocean temperature or sea level pressure.[1] Kim et al. (2025) investigate the impact of extreme climate variables using the Actuaries Climate Index (ACI). This index is available for Canada and the US and is calculated taking into account only a few weather variables[2] Finally, some articles consider the construction of climate indices, usually focusing on a subset of variables, as the indicator of the extent of Arctic sea ice in Diebold et al. (2021).

The use of climate indices has the advantage of capturing multiple dimensions of weather beyond just temperature and (or) precipitation, while remaining parsimonious by summarising a large amount of information into a single variable. However, existing indices are often constructed by computing simple averages of many variables (as in the case of the ACI) or by considering only a limited subset of indicators (*e.g.*, the above-mentioned Artic sea ice index by Diebold et al., 2021, or the ENSO indices).

In this paper, we contribute to the climate econometrics literature by constructing a set of indices for Europe that not only incorporate several climate-related variables but also account for both global and local dimensions, capturing joint European weather dynamics as well as country-specific characteristics. By estimating a Multilevel Dynamic Factor Model (MDFM) (developed by Choi et al., 2018, 2023), we obtain a global European climate index, which captures the common climate variations across all countries, and country-specific indices that synthesise local weather and atmospheric conditions.

Our focus on European countries is motivated by two main reasons. First, we aim to construct indices for a region currently lacking such measures, unlike areas where climate indices such as the ACI are already available.[3] Second, we explore whether our indices can improve the assessment of climate damage in a region where the impacts of climate change are under-investigated. The global-local perspective is justified by the idea that a common pattern among European countries exists, despite individual heterogen-

[1] See `https://origin.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ONI_v5.php` and `https://www.ncei.noaa.gov/access/monitoring/enso/soi`.

[2] The ACI is disposable at `https://actuariesclimateindex.org/home/`.

[3] The ACI is currently available for North America and has been extended to Australian data.

eities. With the MDFM we account for the presence of a such common driver represented by a global factor and preserve the degree of flexibility needed to capture the country-specific effects via local factors. In this sense, the distinction between global and local becomes relevant, as highlighted among others by Bilal and Känzig (2024).

We find evidence that the global index captures various dimensions of temperature effects for most European countries (especially those with a temperate climate), making it a plausible proxy for global warming. In contrast, other meteorological phenomena and changes in water reserves are mostly represented by local indices. This distinction appears to be well motivated: global climatic phenomena are driven by large-scale atmospheric dynamics, with global temperatures as the main determinant, while local events are more closely related to country-specific weather conditions. From a practical perspective, our set of indices provides a valid alternative for measuring climate variation over time in empirical analyses, as our indicators incorporate additional weather dimensions beyond just temperature or precipitation. Importantly, our indices are publicly available and can be accessed from a dedicated dashboard at the following link: `https://climateindex.shinyapps.io/CLIMIND/`. Additional information on the dashboard is reported in Appendix A.

Furthermore, as highlighted in Dong et al. (2025), there is a large heterogeneity in the procedures used to construct different climate variables. Typically, climate indicators are expressed as deviations from a previous reference period. Climatologists refer to this reference period as "climatology", while scientists from other disciplines (e.g. Dong et al. (2025)) call this "return to the prevailing conditions". Climate variables are therefore expressed as anomalies, that is, deviations relative to a selected climatological baseline. Different studies adopt alternative climatologies, which complicates cross-study comparisons. By considering several climatologies in the construction of our climate indices, we show that these choices lead to different index dynamics.[4]

Finally, we quantify the climatic effects, defined as one-unit standard deviation shocks in the global and local indices, on the real GDP of selected European countries. Our analysis is based on panel local projections (Jordà et al., 2020) and incorporates a global/local perspective, following the assumptions in Bilal and Känzig (2024). Our findings show that the detrending procedure used to construct climate anomalies influences the results and leads to differences in the estimated magnitudes of economic damages. In

[4] To support practical applications, we provide users with all available alternatives, allowing practitioners to select the most appropriate climatology for their specific study.

addition, both global and local climate factors significantly affect economic activity, suggesting that relying solely on temperature or precipitation variables may not be sufficient to capture the overall impact of climate on the macro-economy.

The rest of the paper is organized as follows. Section 2 describes the dataset and the variables used for the construction of the indices; Section 3 presents the methodology; Section 4 presents the dynamics of the indices along with a detailed examination of their properties; in Section 5 we use our set of indices to analyse the effects of climate on European macroeconomic output; finally, Section 6 concludes.

2 The climate variables

We consider a total of 37 European countries, following the Eurostat definition of European NUTS-0 administrative units.[5] The complete list of countries includes: Albania (AL), Austria (AT), Belgium (BE), Bulgaria (BG), Croatia (HR), Cyprus (CY), Czechia (CZ), Denmark (DK), Estonia (EE), Finland (FI), France (FR), Germany (DE), Greece (EL), Hungary (HU), Iceland (IS), Ireland (IE), Italy (IT), Latvia (LV), Liechtenstein (LI), Lithuania (LT), Luxembourg (LU), Malta (MT), Montenegro (ME), Netherlands (NL), North Macedonia (MK), Norway (NO), Poland (PL), Portugal (PT), Romania (RO), Serbia (RS), Slovakia (SK), Slovenia (SI), Spain (ES), Sweden (SE), Switzerland (CH), Türkiye (TR), and the United Kingdom (UK).

For each country, we collect 29 variables in different climatological categories: *i)* temperature; *ii)* wind, pressure and precipitation; *iii)* radiation and heat; *iv)* soil water; *v)* snow; *vi)* lakes; *vii)* evaporation and runoff. We list the complete set of variables in Table 1, along with their unit of measure and a brief description.[6]

The variables are sourced from the ECMWF ERA5-Land gridded dataset, provided by Copernicus, which offers a consistent overview of the evolution of climate at a very detailed resolution and over several decades. This dataset is based on a reanalysis that combines actual observations with the so-called "model data", (*i.e.*, derived through combinations of theoretical and statistical models) and comprises among the most accurate and "long" time series

[5]For details, see `https://ec.europa.eu/eurostat/web/gisco/geodata/administrative-units/countries`.

[6]For some variables, we restrict the set of countries according to their climatic characteristics. Specifically, we consider forecast albedo, lake ice depth, snow albedo, snow cover, snow density, snow depth, snowfall and snowmelt only for Austria, Finland, France, Iceland, Italy, Lichtenstein, Montenegro, Norway, Sweden, and Switzerland. Considering other countries for snow-related variables would result in heavily zero-inflated time series.

Table 1: List of climate variables

NAME	UNIT	DESCRIPTION
		Temperature
2m dewpoint temperature	°C	Temperature to which the air, 2 meters above the surface of the Earth, would have to be cooled for saturation to occur. It is a measure of the humidity of the air.
2m temperature	°C	Temperature of air 2m above the surface of land, sea or in-land waters
skin temperature	°C	Temperature of the surface of the Earth. It represents the temperature of the uppermost surface layer, which has no heat capacity and so can respond instantaneously to changes in surface fluxes.
soil temperature lv 1-4	°C	Temperature of the soil layers 0-7 cm (lv1), 7-28cm (lv2), 28-100cm (lv3), 100-289cm (lv4).
		Wind, pressure and precipitation
wind speed	ms^{-1}	Wind speed obtained by combining 10m u-component of wind and 10m v-component of wind
surface pressure	hPa	Pressure (force per unit area) of the atmosphere on the surface of land, sea and in-land water.
total precipitation	m	Accumulated liquid and frozen water, including rain and snow, that falls to the Earth's surface
		Radiation and heat
forecast albedo	NA	Measure of the reflectivity of the Earth's surface.
surface net solar radiation	Wm^{-2}	Amount of solar radiation reaching the surface of the Earth (net of reflection)
surface net thermal radiation	Wm^{-2}	Net thermal radiation at the surface
		Soil water
volumetric soil water lv 1-4	m^3	Volume of water in soil layer 0-7cm (lv1), 7-28cm (lv2), 28-100cm (lv3), 100-289cm (lv4).
		Snow
snow albedo	NA	Fraction of solar radiation reflected by the snow
snow cover	%	Fraction of the cell / grid-box occupied by snow.
snow density	$kg \cdot m^{-3}$	Mass of snow per cubic metre in the snow layer.
snow depth	m	Instantaneous grid-box average of the snow thickness on the ground.
snowfall	m	Accumulated total snow that has fallen to the Earth's surface.
snowmelt	m	Melting of snow averaged over the grid box
		Lakes
lake total temperature	°C	The mean temperature of total water column in inland water bodies
lake ice depth	m	Thickness of ice on inland water bodies
lake shape factor	NA	Temperature changes in the thermocline layer of inland water bodies
		Evaporation and runoff
runoff	m	Water drained away over the surface and under the ground
potential evaporation	m	See `https://cds.climate.copernicus.eu/datasets/reanalysis-era5-land?tab=overview`
total evaporation	m	Accumulated amount of water that has evaporated from the Earth's surface

for climate, spanning from 1950 onward. Each variable comes in the form of cell-observations, *i.e.*, multidimensional arrays containing the measurement of a given phenomenon over a spacial resolution grid of 9 km^2 at a given point in time, with each dimension of the array corresponding to spatial and temporal coordinates,[7]

We match the gridded observations within each country border and aggregate at country level via sample averages. The resulting variables are country-specific monthly time series covering the period from January 1950 to March 2024. These series require further processing to remove deterministic seasonal components and to express observations as deviations from a defined climatology, as is customary in climate econometrics. A climatology refers to an average value or a filtered value for a specific monthly observation, calculated over a predetermined reference period. The anomalies are then computed as the difference between the observed monthly value of a variable and its climatology for that month. In this way, climate anomalies capture deviations from long-term reference conditions, or "normal" climate patterns. This transformation is crucial to separate the signal of climate change from regular seasonal variation.

For each m-th country ($m = 1, \ldots, M$, with $M = 37$) and each i-th climate variable at time t ($i = 1, \ldots, N$; with $N = 29$; $t = 1, \ldots, T$), we compute $x_{mit} = z_{mit} - \mathcal{X}_{mit}$, where z_{mit} is the observed value at time t of the i-th climate variable for the m-th country , $\mathcal{X}_{mit}$ is the climatology, and x_{mit} is the corresponding monthly climate anomaly. We consider three different climatologies, namely:

Fixed-average climatology (FAC): computed as the average of the observed values from the period January 1950 – December 1979 (i.e. $\mathcal{X}_t^{FAC} \equiv \sum_{j=1}^{S} z_{t,j}/S$, where $z_{t,j}$ is the original climatic variable, t is the month, j indicates the year and $S = 30$ is the number of years in the reference period). Similar climatologies are used in the IEA Weather, Climate and Energy Tracker data, with a reference period covering years from 2000 to 2019, or in the computation of the ACI, which considers the average of the values from 1961 to 1990.

Moving-average climatology (MAC): computed as moving averages with a 20-year window ($\mathcal{X}_{tf}^{MAC} \equiv \sum_{j=f-k}^{f} z_{t,j}/S$, where t is the month, f is the year, $k = 20 - 1$ and $S = k + 1$). Similar setups are adopted in Ahmadi et al. (2025); Kahn et al. (2021), who consider returns to the

[7]Gridded data are disposable at `https://cds.climate.copernicus.eu/datasets/reanalysis-era5-land-monthly-means?tab=overview`.

climate of the past 30 years.[8]

Hamilton-filtered climatology (HFC): this filtering technique (Hamilton, 2018) is mostly popular in economics and isolates the dynamics of a variable that is orthogonal to its long-term trend. More formally, we define as anomaly the residuals from the regression of $z_{t,i}$ on a constant and its own lags, from $z_{t-24,i}$ to $z_{t-35,i}$. In our setup, we consider a lag order consistent with the monthly frequency and in line with the literature (Bilal and Känzig, 2024).

3 Methodology

One of the most common ways to summarise information from a large set of variables is via a Dynamic Factor Models (DFM). An approximate DFM can be expressed as a system of an observation and a state equation:

$$x_t = \sum_{j=0}^{p} \Lambda_j f_{t-j} + \varepsilon_t, \quad \varepsilon_t \sim N(0, \Sigma_\varepsilon) \tag{1}$$

$$f_t = \sum_{i=1}^{s} A_i f_{t-i} + u_t, \quad u_t \sim N(0, \Sigma_u) \tag{2}$$

where x_t is a $k \times 1$ vector of observed variables. f_t is a $q \times 1$ vector of unobserved common factors, Λ_j are the loading matrices and A_i are the VAR coefficient matrices of the factors, which describe the evolution of the unobserved components. The matrices Σ_ε and Σ_u contain the variance-covariance elements of the two idiosyncratic components ε_t and u_t, respectively[9] Estimation of a DFM is usually performed parametrically via Maximum Likelihood and Expectation Maximization algorithms (see e.g. Doz et al., 2012), or with nonparametric techniques such as Principal Component Analysis (PCA).

Most of the popularity of this method lies in its simplicity: DFMs are dimensionality reduction tools that compress data information in a limited set of unobservable factors that evolve over time and capture the common movements of observed time series. This technique is widely used in macroeconomics, where the abundance of variables, coupled with the relatively small size of the temporal dimension, requires regularisation (see Stock and Watson, 2016; Doz and Fuleky, 2020). DFMs have also been successfully

[8]We choose a 20-year reference period, rather than the conventional 30 years, in order to limit the loss of observations.

[9]For an extensive review of DFMs, we refer the reader to Barigozzi and Hallin (2024).

used in other settings, such as the study of commodity markets (Delle Chiaie et al., 2022; Casoli and Lucchetti, 2022) or financial econometrics (Ng et al., 1992; Diebold et al., 2008). Crucially, they have been employed for the construction of indices in a variety of contexts (see e.g., Alquist et al., 2020; Baumeister et al., 2022, 2024; Diebold et al., 2021).

What is particularly interesting about DFMs and their potential use in index construction is that they can be naturally extended to embed a *multilevel* structure. In general, a multilevel structure consists in imposing blocks of zero restrictions on the Λ_j matrices of factor loadings, so that some factors are specific only to a subset of variables, while other factors pertain to the whole system of observed time series. This allows them to flexibly incorporate the hierarchical structure often present in the data. For example, Multilevel DFMs (MLDFMs) have been used to construct hierarchical synthetic indicators for global and regional financial markets (Breitung and Eickmeier, 2015), the international and country-specific business cycle (Choi et al., 2018), or the common and group-specific movement of commodity prices (Delle Chiaie et al., 2022).

To construct global and local climate indices, we follow the procedure proposed in Choi et al. (2018), which is computationally efficient and does not require a fully parametric estimation. The observation equation of the MLDFM used in our analysis is defined as follows:

$$x_{mit} = \gamma'_{mi} G_t + \lambda'_{mi} F_{mt} + \varepsilon_{mit}, \tag{3}$$

where x_{mit} is the anomaly *i-th* in country m at time t.[10] Furthermore, G_t identifies the global factor of size $s \times 1$, while F_{mt} is a $r_m \times 1$ country-specific factor;[11] γ_{mi} and λ_{mi} are related loadings and ε_{mit} the idiosyncratic error. The global and local factors in Equation (3), together with the loadings, can be consistently estimated nonparametrically with a four-step procedure, involving PCA and Canonical Correlation Analysis (CCA).[12]

The number of factors s and r_m must be determined and two alternative approaches are used in the literature: either it is assumed that the number of factors is known or fixed *a priori* based on hypotheses relative to the nature of the empirical setting (Choi et al., 2018), or it is selected by some criteria *ad hoc* (see e.g. Bai and Ng, 2002; Choi et al., 2023). In our analysis, we impose the number of factors in order to have only one global index ($s = 1$) and one local factor for each country ($r_m = 1$, $\forall m$).This choice is driven by

[10]Here we do not report again the state equation, governing the evolution of the factors in time, as it is equivalent to Equation (2).

[11]Both the global and the local factors are proved to be weakly stationary.

[12]For more details about the procedure and the asymptotic properties of the estimators, we refer to Appendix B and Choi et al. (2018).

Table 2: Unit root tests for the global factor

Climatology	ADF with const	ADF with const+trend
FAC	-3.31^{**}	-12.28^{***}
MAC	-10.94^{***}	-11.22^{***}
HFC	-5.52^{***}	-6.92^{***}

Notes: The ADF tests are based on the AIC as lag selection criterion. * indicates statistical significance at the 10% level, ** at the 5% level and *** at the 1% level.

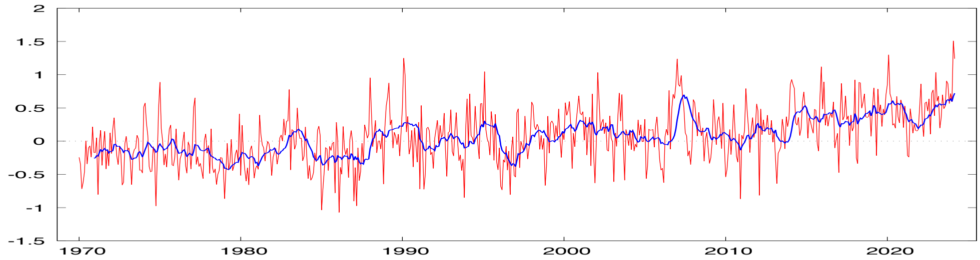
the need for parsimony and interpretability of the model. On the other hand, using a statistical testing procedure for the optimal number of factor may be easily misleading given the potential heterogeneities across countries: these may undermine the detection for a common co-movement.

4 Main results: global vs local indices

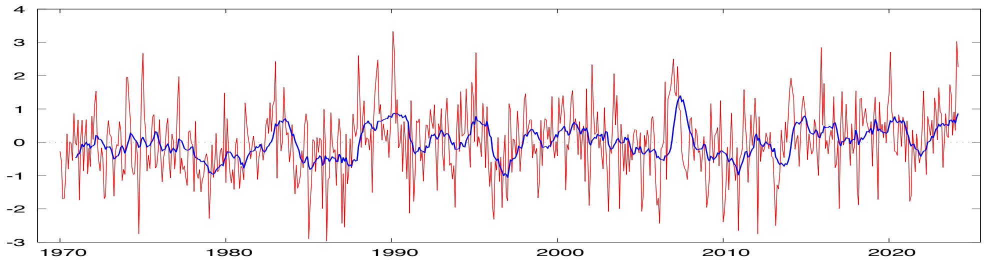
Figure 1 reports the global factor for the three different climatologies, together with its smoothed version, which is included to better isolate the medium-term dynamics from short-term noise.[13] The global index derived using the FAC (panel 1a) shows a clear upward trend over time, indicating a general increase in the climate change index across the European region. This trend is particularly evident when examining the filtered series. By design, the FAC approach produces a trend whenever anomalies show persistent changes over time, and this is reflected in the index that captures permanently changing climate anomalies. Crucially, the indices derived from the other two climatologies (panels 1b and 1c) do not show any trend, because their calculation methods inherently remove long-term changes in the anomalies.

For this reason, the reliability of fixed average methods as filtering techniques is debatable, although they are particularly well suited to capture long-term trends in climate change. This behavior is clearly reflected in the mean reverting properties of the indices, as reported in Table 2, where we report the results of the unit root tests. All indices appear stationary when both a constant and a trend are included. When only a constant is included, FAC may exhibit evidence of a unit root at the 0.01 significance level.

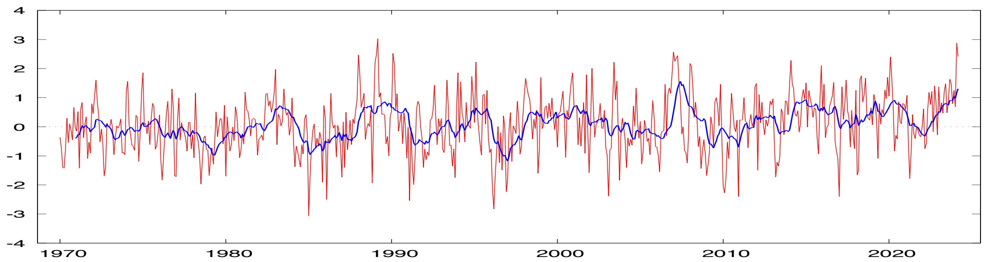
[13] A simple 12-month moving average filter is used as smoother, providing a clearer view of medium-term climatic fluctuations by reducing short-run noise. Note that the selected climatology affects the starting period of the sample. Actually, the Moving-average climatology discards 20 years, while the Hamilton-filtered climatology discards 3 years. Given these discrepancies, we have chosen to normalize the series by fixing a common sample starting in January 1970.



(a) Global factor with FAC



(b) Global factor with MAC



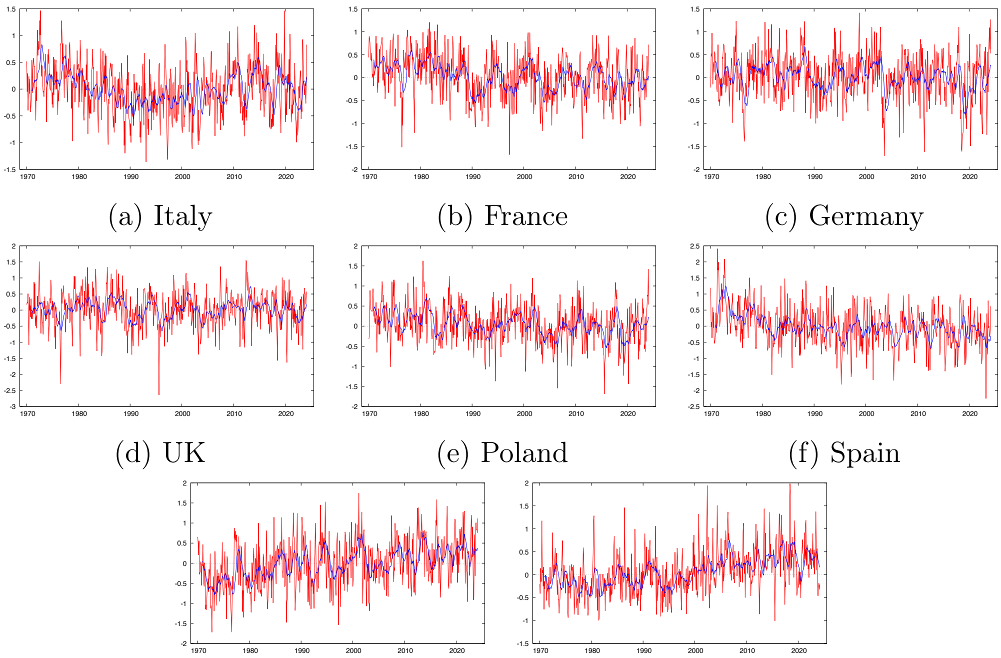
(c) Global factor with HFC

Figure 1: Global factor (red lines) and smoothed global factor (blue lines) with different climatologies.

Apart from the trend, the fluctuations of all the indices are similar, showing recurrent patterns such as peaks (e.g., the positive outlier in July 2007) and periods of persistence (*e.g.*, 1980-1990 and 2014-2021).

We now turn to the inspection of local factors. To provide a concise summary, we focus on eight representative countries, chosen to capture the key patterns observed across the full set of countries. This selection is applied throughout the rest of the section. Specifically, the countries are grouped into eight geographical regions, each designed to represent relatively homogeneous climatic conditions, and one representative country is selected from each region. The countries we consider are Italy, France, Germany, the UK, Poland, Spain, Greece, and Norway (see Appendix C for a detailed description of each geographical group).

In Figure 2 we report the local factors for the selected countries, obtained using the FAC (the other two cases and unit root tests are shown in Appendix D). As illustrated, local factors reveal substantially different characteristics across countries. The dynamics vary from one country to another, reflecting the distinct climatic conditions and regional patterns captured by the local indices. This highlights the importance of examining country-specific factors alongside global dynamics to fully capture the heterogeneity of climate behavior across Europe. The next section will investigate these aspects, providing a variance contribution analysis to understand cross-country heterogeneity and local factor interpretation.



(a) Italy (b) France (c) Germany

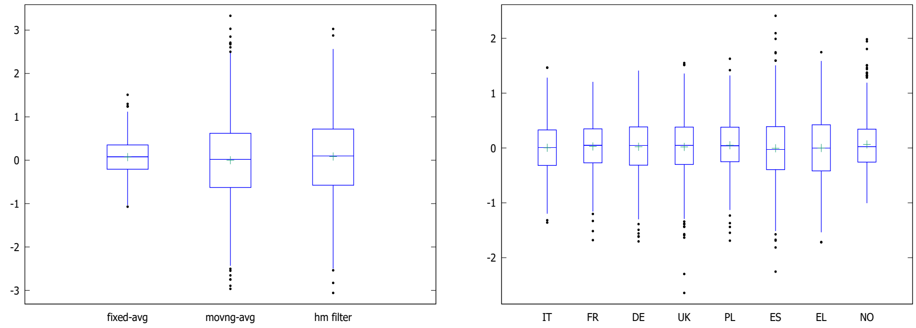
(d) UK (e) Poland (f) Spain

(g) Greece (h) Norway

Figure 2: Local factors for selected countries, FAC. The red (blue) lines correspond to the original (smoothed) series

Finally, Figure 3 presents the summary statistics of both global and local factors. The FAC produces a global index that is more tightly concentrated around the mean, with smaller interquartile ranges and fewer extreme outliers compared to the other climatologies. This property is particularly relevant when the indices are interpreted as “climate shocks” as in the setup of Bilal and Känzig (2024).[14]

[14] Bilal and Känzig (2024) construct temperature shocks using the Hamilton filter. In comparison, fixed-average climatology would produce a shock with reduced variability.



(a) Global factor (b) Local factors

Figure 3: Boxplots of the global factor for the three climatologies (a) and the local factors for the FAC and selected countries (b)

4.1 Variance contribution

The use of factors effectively compresses a large amount of information into a limited set of indices. However, this comes at the cost of reduced interpretability. In this section, we address this issue by relating the indices to the proportion of variance explained for each variable. To save space, we focus only on FAC, while results for the other two variants are reported in Appendix D.

We compute the variance from Equation (3). Since x_{mit} is standardised and each component on the right-hand side is mutually uncorrelated, we have the following:

$$\mathrm{V}(\gamma'_{mi}G_t) + \mathrm{V}(\lambda'_{mi}F_{mt}) + \mathrm{V}(e_{mit}) = 1,$$

with $\mathrm{V}(\gamma'_{mi}G_t)$ being the variance explained by the global factor, $\mathrm{V}(\lambda'_{mi}F_{mt})$ the variance contribution of the local factor, and $\mathrm{V}(e_{mit})$ the idiosyncratic variance.

Table 3 reports the results. Italy, France, Germany, the UK and Poland show broadly similar dynamics, with the global index primarily capturing temperature-related effects, while local factors reflect other variables such as potential evaporation, runoff, soil water, radiation, and precipitation. In contrast, countries with more extreme weather, such as Spain, Greece, and Norway, exhibit different behaviours. In these cases, the global factor becomes almost irrelevant, indicating that the joint dynamics observed across most of Europe diverge from the local patterns in these regions and the local factor takes on a predominant role. Snow-related variables contribute meaningfully only in the case of Norway.

Table 3: Factor contribution in terms of explained variance – FAC

	IT		FR		DE		UK		PL		ES		EL		NO	
	Global	Local	Global	Local	Global	Local	Global	Local	Global	Local	Global	Local	Global	Local	Global	Local
2m dewpoint temp	**0.541**	0.119	**0.649**	0.020	**0.665**	0.076	**0.473**	0.100	**0.519**	0.112	0.192	0.060	0.059	0.144	0.175	0.247
2m temperature	**0.652**	0.013	**0.728**	0.067	**0.859**	0.003	**0.514**	0.268	**0.723**	0.001	**0.287**	0.267	0.077	**0.665**	0.174	0.320
lake shape factor	0.192	0.014	0.129	0.062	0.099	0.070	0.032	0.085	0.090	0.040	0.095	0.054	0.016	0.247	0.000	0.051
lake total temp	**0.579**	0.005	**0.801**	0.021	**0.795**	0.015	**0.593**	0.220	**0.543**	0.034	0.331	0.079	0.051	**0.523**	0.082	**0.440**
pot evaporation	0.092	**0.489**	0.170	**0.429**	**0.408**	0.355	0.172	**0.358**	**0.411**	0.337	0.068	**0.667**	0.007	0.478	0.033	0.260
runoff	0.020	**0.520**	0.000	0.377	0.001	0.300	0.171	0.116	0.004	0.259	0.006	0.351	0.203	0.007	0.060	0.000
tskin temperature	**0.607**	0.008	**0.717**	0.080	**0.861**	0.005	**0.492**	0.307	**0.729**	0.000	0.258	**0.312**	0.055	**0.703**	0.156	0.314
soil temperature 1	**0.510**	0.009	**0.723**	0.103	**0.868**	0.037	**0.526**	0.353	**0.697**	0.033	0.252	**0.330**	0.030	**0.776**	0.150	**0.701**
soil temperature 2	**0.518**	0.008	**0.746**	0.105	**0.878**	0.041	**0.555**	0.352	**0.689**	0.041	0.268	**0.328**	0.031	**0.784**	0.153	**0.693**
soil temperature 3	0.476	0.008	**0.717**	0.108	**0.800**	0.055	**0.565**	0.308	**0.572**	0.071	0.283	**0.299**	0.035	**0.718**	0.153	**0.588**
soil temperature 4	0.267	0.006	0.389	0.079	0.426	0.063	0.333	0.128	0.308	0.082	0.202	0.125	0.042	0.300	0.148	0.292
soil water 1	0.067	**0.714**	0.029	**0.831**	0.075	**0.848**	0.001	**0.784**	0.067	**0.822**	0.016	**0.818**	0.008	0.411	0.066	0.052
soil water 2	0.063	**0.709**	0.027	**0.797**	0.063	**0.826**	0.002	**0.751**	0.053	**0.801**	0.017	**0.758**	0.013	0.349	0.083	0.026
soil water 3	0.052	**0.532**	0.021	**0.562**	0.033	**0.584**	0.007	0.479	0.028	**0.526**	0.031	0.419	0.036	0.168	0.080	0.001
soil water 4	0.064	0.200	0.008	0.228	0.008	0.210	0.058	0.136	0.008	0.200	0.056	0.154	0.082	0.056	0.050	0.024
solar radiation	0.149	**0.589**	0.074	**0.645**	0.226	**0.553**	0.028	0.469	0.311	**0.410**	0.021	**0.681**	0.071	0.291	0.000	0.325
thermal radiation	0.035	**0.732**	0.013	**0.721**	0.112	**0.575**	0.001	0.260	0.182	**0.458**	0.009	**0.729**	0.029	0.215	0.029	0.086
surface pressure	0.124	0.274	0.027	0.249	0.004	0.187	0.049	0.348	0.003	0.180	0.083	0.200	0.167	0.038	0.149	0.053
total evaporation	0.147	0.077	0.293	0.012	0.475	0.000	0.324	0.000	0.393	0.009	0.004	0.388	0.076	0.080	0.044	**0.531**
total precipitation	0.020	**0.651**	0.001	**0.592**	0.001	**0.599**	0.104	0.370	0.013	**0.506**	0.004	0.493	0.091	0.054	0.124	0.000
wind speed	0.012	0.034	0.020	0.053	0.050	0.163	0.098	0.013	0.056	0.055	0.001	0.052	0.010	0.052	0.014	0.034
forecast albedo	0.410	0.083	0.316	0.030											0.025	**0.479**
lake ice depth	0.298	0.002	0.239	0.004											0.155	0.294
snow albedo	0.324	0.044	0.442	0.001											0.003	0.055
snow cover	0.431	0.064	0.328	0.028											0.040	**0.535**
snow density	0.416	0.010	0.468	0.025											0.001	0.229
snow melt	0.135	0.085	0.189	0.118											0.021	0.059
snow fall	0.158	0.209	0.159	0.115											0.049	0.007
snow depth	0.154	0.189	0.234	0.117											0.000	0.138

Notes: Coloured cells identify a joint contribution of the global and local factors ≥ 0.50. In such cases, bold is used to indicate the dominant factor between global and local.

5 The economic effects of climate change

The climate indices presented in the previous sections can be used for a variety of purposes, such as monitoring weather patterns or improving forecasts. In this section, we show that it is possible to use global and local indices to analyse the macroeconomic effects of climate shocks, contributing to the growing literature on the topic.

Specifically, we identify global and local factors as two distinct climate shocks, which allows us to examine how a positive (joint or country-specific) shock affects real GDP in a set of European countries.[15] We build a quarterly dataset that includes real GDP, our target variable, and a set of macroeconomic controls, and estimate impulse response functions from panel local projections on a sample ranging from 1960 (second quarter) to 2022 (second quarter) (Jordà, 2005; Jordà et al., 2020).

The regression setup can be summarized as:

$$y_{m,t+h} - y_{m,t-1} = \alpha_m + \beta_h shock_{m,t} + w'_{m,t}\gamma + w'_t\eta + u_{m,t+h} \tag{4}$$

where $y_{m,t}$ is the quarterly real GDP(in log) of country m, α_m the fixed effect of the country specific, $shock_{m,t}$ is the global index (in which case the dependency of *m-th* country drops, *i.e.*, $shock_t$) or the local factor; w_t collects country-invariant variables while w_{mt} contains controls which vary in both spatial and temporal dimensions; finally, $u_{m,t}$ is the idiosyncratic term. The complete list of variables in $w_{m,t}$ includes the inflation rate, the industrial production index (in log), and the unemployment rate, sourced from the OECD Quarterly Dataset, and a control for pandemic-induced uncertainty: the new confirmed cases of COVID-19 per million people, sourced from Our World in Data and aggregated at a quarterly frequency. The list w_t includes the Brent oil price (in log), the German 3-month interbank rate, a dummy variable for European recession periods, and a time trend.[16] Additionally, the global or local factor that is not used as shock is included among the control variables. For example, when estimating the regression for the global climate shock $shock_t$, we include the local factor in w_{mt}, and vice versa.

To mitigate potential autocorrelation effects, we further expand the set of controls by including lags up to the eighth order of the considered shock, real GDP growth, and the nondummy components of w_{mt} and w_t, in line with Bilal and Känzig (2024). Finally, we also employ robust standard errors from Driscoll-Kraay (Driscoll and Kraay, 1998).

[15]We limit our analysis to 17 countries in order to balance the availability of data and the need for consistent coverage across all economic variables required for the analysis.

[16]The German interbank rate and European recession periods are provided by OECD, while the Brent oil price is sourced from the World Bank's Pink Sheet.

Figure 4 reports the impulse response functions of a global and local climate shock on real GDP.

A positive global climate shock leads to a significant decline in economic activity that persists for up to twelve quarters before being gradually absorbed.

Furthermore, the choice of climatology used to construct climate anomalies materially affects the results. When employing Fixed-average–based anomalies, the estimated economic damages reach approximately -2% after nine quarters. In contrast, using the Hamilton-filtered or the Moving-average climatologies as a detrending procedures yields a smaller maximum impact smaller than -0.8%. This comparison highlights the sensitivity of climate–economy estimates to the underlying data treatment and underscores the importance of methodological consistency when assessing the macroeconomic costs of climate change.

In contrast, a local climate shock has a short-lived positive impact on real GDP, which turns negative after several quarters. This pattern likely reflects the immediate economic response to climate-related disasters, such as floods, when governments and households increase spending on reconstruction and recovery efforts. Such expenditures temporarily boost output, but the longer-term consequences of physical damage and productivity losses ultimately weigh on economic performance. In the medium term, the effect is contained between -0.4% and -0.7%.

Overall, the estimated impact of local climate shocks is comparable in magnitude to the effect of a global shock, with the exception of the results obtained with fixed-average indices. This suggests that both global and local factors exert significant macroeconomic effects.

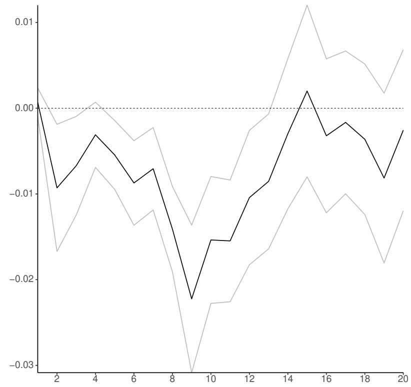
6 Conclusion

This article proposes new climate indices for European countries. Using a novel dataset from ERA5-land, we exploit the granularity present in the gridded data to recover the indices built via an MLDFM strategy. Consequently, we disentangle a global component from country-specific (local) ones. The underlying idea is to trace back global climatic phenomena which affect all the countries under analysis from geographically-specific ones, proposing in this way a clearer overview of the climate dynamics. The MLDFM approach, moreover, allows one to propose a rigorous data reduction framework which encompasses several sources of information. To this end, we tackle the common issue encountered in the literature of conveying climatic effects via the sole temperature variable.

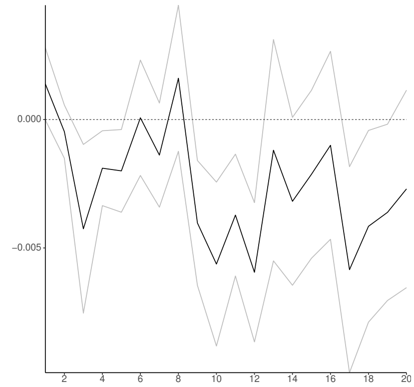
To construct climate anomalies, we consider three widely used procedures: a fixed-average climatology, a moving-average climatology, and a filter based on Hamilton (2018). The resulting indices show different dynamics across these setups, indicating that the choice of method has non-trivial implications. The variance decomposition of the estimated model reveals that the global index primarily reflects temperature patterns, whereas local factors mainly capture variables such as potential evaporation, runoff, soil water, radiation and precipitation.

We conclude with a macroeconomic exercise that analyses the effects of global and local climate shocks on real GDP for 17 European countries, using panel local projections. Our results show that methodological choices in detrending procedures significantly influence the estimated magnitude of climate-related economic damages. In addition, considering a broader set of climate variables – not just temperature or precipitation – helps capture different dimensions of climate variability relevant for economic analysis. Finally, we find that a positive global climate shock has a statistically significant negative effect on economic activity, lasting up to twelve quarters.

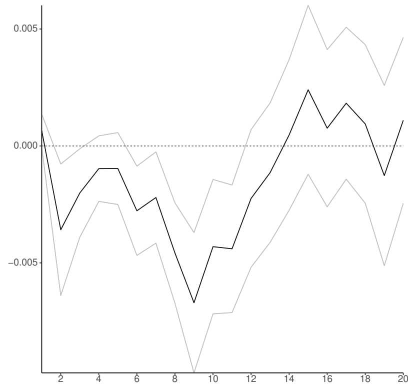
Future extensions of the proposed set of indices will consider: *i*) more granular measures at sub-national administrative units (e.g. NUTS-2, NUTS-3), *ii*) higher frequency, i.e. at daily basis, *iii*) a non-fixed number of local factors (to account for the possibility that different factors could capture the heterogeneity of certain geographical and climatic zones such as mountain areas, dry regions etc.) and *iv*) a focus on extreme events, such as aggregation at quantiles level or monthly aggregation by considering maximum daily registered values rather than averages.



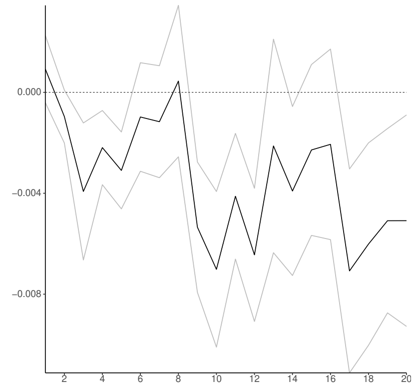
(a) GLB - FAC



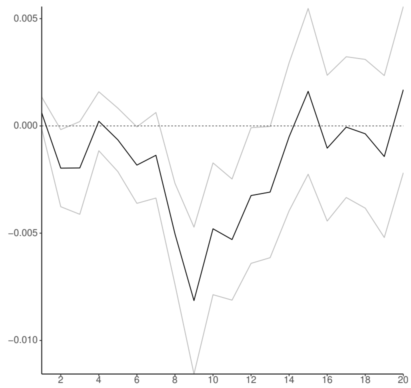
(b) LOC - FAC



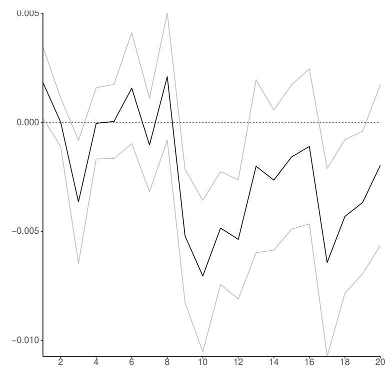
(c) GLB - MAC



(d) LOC - MAC



(e) GLB - HFC



(f) LOC - HFC

Figure 4: Panel local projections of real GDP responses to a 1 standard deviation increase in the global (left column) and local (right column) climate factors.

Notes: sample 1960 (second quarter) – 2022 (second quarter), unbalanced panel. Black lines denote the local projections estimates and gray lines the 68% confidence bands. GLB denotes the global factor, while LOC indicates the local factors.

Acknowledgements: The authors are grateful to Matteo Barigozzi, Andrea Bastianin, Christiane Baumeister, Matt Cole, Jennifer Castle, Raffaella Giacomini, Riccardo (Jack) Lucchetti, Francesco Ravazzolo, Massimiliano Rizzati, Luca Rossini, and Esther Ruiz for their valuable feedback and suggestions. We thank in particular Nicola Crespi and Camillo Salvi for their support in developing the dashboard, and our colleagues at the Fondazione Eni Enrico Mattei (FEEM) for their helpful comments and discussions throughout the project. Finally, we are indebted to all participants of the 2024 International Workshop "Econometrics of the Energy Transition", the Thirteenth IAERE Annual Conference, the 2025 Annual Conference of the International Association for Applied Econometrics, and the 10th Annual Conference of the Society for Economic Measurement for their insightful feedback.

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A Dashboard and Data Access

This section briefly describes the interactive dashboard developed for this project. The dashboard provides public access to the global and local climate indices constructed in this article.

The dashboard is structured in three main sections: "map view", "graphical summary" and "download data". From "map view", users can visualise a map of European countries, interactively select a country of interest, display its local climate index and explore the variance contribution for a selected year. "Graphical summary" is divided in "descriptive summary", when practitioners can look at the density, plot boxplots and detect outliers for a selected climate index, and "time series summary", where each index can be displayed in its raw form or as a smoothed version based on a 12-month rolling window. Finally, the "download data" interface allows users to download the entire set of data or a filtered portion. It is possible to choose the time span, countries of interest, data frequency (monthly, quarterly, or annual), and the climatology used for anomaly computation (fixed-average, moving-average, or Hamilton filter).

The dashboard thus offers an intuitive and flexible tool for exploring climate dynamics across Europe. It is publicly available at: `https://climateindex.shinyapps.io/CLIMIND/`.

B Methodology: additional details

Estimation of a multilevel factor model (Choi et al., 2018) consists of a four-sequential step algorithm:

1. select a pair of countries and obtain a first estimate of G_t, denoted $\hat{G}_t^{(1)}$ from the canonical correlation analysis;

2. replace G_t in Equation (3) with $\hat{G}_t^{(1)}$ and derive the estimators for the country-specific quantities, *i.e.,* $\hat{F}_{mt}^{(1)}$ and $\hat{\lambda}_{mi}^{(1)}$ with PCA;

3. replace F_{mt} and λ_{mi} in Equation (3) with their estimates (assuming G_t unknown), and derive the global quantities $\hat{G}_t^{(2)}$ and $\hat{\gamma}_{mi}^{(1)}$ via PCA. $\hat{G}_t^{(2)}$ is the final global component factor, obtained from the whole panel of countries;

4. repeat again step 2, this time using $\hat{G}_t^{(2)}$ and $\hat{\gamma}_{mi}^{(1)}$. This will lead to the final estimates $\hat{F}_{mt}^{(2)}$ and $\hat{\lambda}_{mi}^{(2)}$, which exploit all the data information, similar to $\hat{G}_t^{(2)}$.

C Geographical regions

In Section 4, we focus on different European regions, using one country from each as a representative case. The regions are expected to reflect the different climatic conditions between different areas. The regions we consider are the following, with the representative country shown in bold.

- Iberian region, comprehending **Spain** and Portugal.
- French region & Benelux, including Belgium, **France**, Luxembourg and Netherlands.
- British region, consisting of Ireland and the **UK**.
- Scandinavian and Baltic Region: Denmark, Estonia, Finland, Iceland, Latvia, Lithuania, **Norway** and Sweden.
- German & Alpine regions, comprehending Austria, **Germany**, Liechtenstein and Switzerland.
- Italian region, consisting in **Italy** and Malta.
- Balkan region: Albania, Bulgaria, Croatia, Cyprus, **Greece**, Montenegro, North Macedonia, Serbia, Slovenia and Türkiye.
- Central-Eastern Europe, consisting in Czechia, Hungary, **Poland**, Romania and Slovakia.

D Additional details

This section shows additional results that are omitted from the paper to save space.

Table D1: Factor contribution in terms of explained variance – Moving-average anomalies

	IT		FR		DE		UK		PL		ES		EL		NO	
	Global	Local	Global	Local	Global	Local	Global	Local	Global	Local	Global	Local	Global	Local	Global	Local
2m dewpoint temp	**0.490**	0.156	**0.665**	0.024	**0.654**	0.093	**0.462**	0.118	**0.465**	0.129	0.171	0.029	0.026	0.202	0.109	0.304
2m temperature	**0.562**	0.007	**0.713**	0.071	**0.875**	0.002	**0.510**	0.299	**0.687**	0.003	0.190	**0.365**	0.022	**0.742**	0.101	0.376
lake shape factor	0.157	0.023	0.120	0.059	0.088	0.076	0.029	0.096	0.081	0.062	0.083	0.082	0.007	0.279	0.006	0.122
lake total temp	0.443	0.019	**0.756**	0.020	**0.772**	0.003	**0.549**	0.239	**0.487**	0.015	0.215	0.132	0.007	**0.569**	0.028	**0.474**
pot evaporation	0.032	**0.551**	0.103	**0.469**	**0.419**	0.330	0.186	**0.315**	**0.392**	0.344	0.012	**0.728**	0.000	0.492	0.028	0.221
runoff	0.018	**0.541**	0.000	0.402	0.007	0.245	0.110	0.180	0.003	0.236	0.003	0.322	0.146	0.024	0.032	0.008
skin temperature	**0.519**	0.003	**0.702**	0.084	**0.876**	0.003	**0.488**	0.340	**0.696**	0.001	0.165	**0.422**	0.012	**0.775**	0.097	0.390
soil temperature 1	0.417	0.004	**0.694**	0.106	**0.864**	0.024	**0.515**	0.386	**0.646**	0.021	0.154	**0.444**	0.001	**0.842**	0.022	**0.852**
soil temperature 2	0.416	0.004	**0.713**	0.109	**0.868**	0.026	**0.536**	0.389	**0.629**	0.027	0.164	**0.448**	0.001	**0.855**	0.018	**0.857**
soil temperature 3	0.346	0.007	**0.656**	0.117	**0.750**	0.037	**0.510**	0.357	**0.472**	0.053	0.160	**0.420**	0.001	**0.793**	0.007	**0.731**
soil temperature 4	0.102	0.014	0.221	0.090	0.248	0.051	0.193	0.160	0.148	0.085	0.059	0.172	0.000	0.310	0.000	0.251
soil water 1	0.069	**0.690**	0.027	**0.813**	0.121	**0.828**	0.001	**0.770**	0.109	**0.799**	0.007	**0.795**	0.006	0.450	0.045	0.050
soil water 2	0.064	**0.689**	0.025	**0.780**	0.096	**0.802**	0.000	**0.753**	0.081	**0.788**	0.006	**0.728**	0.010	0.384	0.056	0.025
soil water 3	0.043	**0.545**	0.014	**0.558**	0.040	**0.549**	0.001	**0.518**	0.030	**0.515**	0.005	0.384	0.017	0.179	0.050	0.003
soil water 4	0.027	0.254	0.006	0.257	0.014	0.168	0.002	0.209	0.004	0.192	0.004	0.140	0.013	0.067	0.030	0.021
solar radiation	0.098	**0.620**	0.062	**0.652**	0.243	**0.521**	0.036	0.427	0.307	**0.412**	0.013	**0.662**	0.046	0.308	0.000	0.327
thermal radiation	0.029	**0.751**	0.021	**0.725**	0.167	**0.566**	0.013	0.223	0.226	**0.457**	0.008	**0.696**	0.029	0.229	0.017	0.102
surface pressure	0.162	0.288	0.039	0.268	0.015	0.207	0.039	0.355	0.013	0.178	0.105	0.239	0.206	0.020	0.173	0.020
total evaporation	0.064	0.103	0.217	0.010	0.408	0.004	0.285	0.002	0.335	0.003	0.005	0.377	0.041	0.087	0.015	**0.524**
total precipitation	0.036	**0.627**	0.000	**0.589**	0.023	**0.606**	0.078	0.380	0.053	**0.518**	0.008	0.462	0.099	0.086	0.115	0.001
wind speed	0.008	0.038	0.029	0.063	0.059	0.172	0.131	0.019	0.090	0.057	0.004	0.048	0.020	0.049	0.021	0.040
forecast albedo	**0.423**	0.109	0.362	0.041											0.010	0.456
lake ice depth	0.226	0.024	0.244	0.005											0.045	0.292
snow albedo	0.328	0.058	0.467	0.002											0.000	0.045
snow cover	**0.441**	0.085	0.373	0.039											0.021	**0.524**
snow density	0.407	0.013	**0.506**	0.031											0.014	0.184
snow melt	0.125	0.119	0.224	0.132											0.016	0.073
snow fall	0.154	0.210	0.188	0.124											0.065	0.001
snow depth	0.154	0.234	0.281	0.142											0.013	0.118

Notes: coloured cells identify a joint contribution of the global and local factors ≥ 0.50. In such cases, bold is used to indicate the dominant factor between global and local.

Table D2: Factor contribution in terms of explained variance – Hamilton-filtered anomalies

	IT		FR		DE		UK		PL		ES		EL		NO	
	Global	Local	Global	Local	Global	Local	Global	Local	Global	Local	Global	Local	Global	Local	Global	Local
2m dewpoint temp	**0.504**	0.080	**0.668**	0.001	**0.681**	0.044	**0.413**	0.175	**0.540**	0.091	0.183	0.019	0.064	0.122	0.092	0.363
2m temperature	**0.533**	0.030	**0.672**	0.109	**0.846**	0.011	**0.454**	0.368	**0.717**	0.000	0.180	**0.359**	0.037	**0.694**	0.083	**0.431**
lake shape factor	0.157	0.009	0.093	0.060	0.080	0.056	0.020	0.107	0.071	0.045	0.081	0.037	0.014	0.204	0.002	0.094
lake total temp	0.444	0.001	**0.753**	0.038	**0.741**	0.021	**0.529**	0.300	**0.476**	0.034	0.205	0.089	0.021	**0.488**	0.038	**0.463**
pot evaporation	0.023	**0.613**	0.118	**0.398**	**0.364**	0.358	0.170	**0.363**	**0.368**	0.341	0.014	**0.709**	0.003	**0.538**	0.029	0.219
runoff	0.013	0.455	0.002	0.323	0.001	0.258	0.194	0.103	0.000	0.203	0.001	0.268	0.188	0.020	0.026	0.001
skin temperature	**0.491**	0.023	**0.659**	0.124	**0.848**	0.014	**0.437**	0.411	**0.725**	0.000	0.156	**0.408**	0.022	**0.731**	0.078	**0.440**
soil temperature 1	0.392	0.022	**0.663**	0.136	**0.840**	0.048	0.459	**0.460**	**0.668**	0.032	0.146	**0.423**	0.006	**0.793**	0.033	**0.842**
soil temperature 2	0.396	0.020	**0.687**	0.134	**0.851**	0.052	**0.486**	0.459	**0.657**	0.038	0.154	**0.421**	0.005	**0.806**	0.030	**0.839**
soil temperature 3	0.350	0.016	**0.655**	0.120	**0.768**	0.064	**0.493**	0.406	**0.528**	0.058	0.147	**0.370**	0.004	**0.754**	0.020	**0.688**
soil temperature 4	0.111	0.006	0.246	0.043	0.317	0.066	0.228	0.152	0.212	0.063	0.040	0.082	0.000	0.278	0.008	0.200
soil water 1	0.044	**0.772**	0.010	**0.792**	0.059	**0.846**	0.000	**0.737**	0.064	**0.812**	0.009	**0.800**	0.001	0.477	0.025	0.043
soil water 2	0.046	**0.755**	0.009	**0.758**	0.045	**0.823**	0.001	**0.720**	0.049	**0.789**	0.009	**0.717**	0.003	0.404	0.030	0.021
soil water 3	0.043	**0.527**	0.005	**0.527**	0.016	**0.568**	0.005	0.484	0.023	**0.509**	0.018	0.332	0.018	0.173	0.022	0.002
soil water 4	0.036	0.138	0.001	0.156	0.000	0.193	0.061	0.126	0.000	0.150	0.021	0.072	0.042	0.058	0.032	0.040
solar radiation	0.075	**0.657**	0.035	**0.626**	0.174	**0.545**	0.024	0.359	0.254	**0.395**	0.008	**0.679**	0.029	0.353	0.000	0.270
thermal radiation	0.016	**0.742**	0.003	**0.704**	0.096	**0.584**	0.005	0.180	0.155	**0.445**	0.004	**0.694**	0.012	0.280	0.026	0.073
surface pressure	0.081	0.278	0.011	0.253	0.000	0.201	0.055	0.320	0.001	0.193	0.072	0.212	0.112	0.020	0.162	0.002
total evaporation	0.086	0.116	0.224	0.014	0.397	0.001	0.270	0.000	0.303	0.002	0.009	0.360	0.064	0.093	0.024	**0.537**
total precipitation	0.012	**0.589**	0.005	**0.552**	0.000	**0.524**	0.097	0.312	0.008	0.475	0.005	0.465	0.066	0.110	0.088	0.031
wind speed	0.004	0.030	0.027	0.029	0.058	0.163	0.104	0.016	0.062	0.050	0.000	0.062	0.007	0.024	0.015	0.029
forecast albedo	0.390	0.084	0.308	0.123											0.011	0.424
lake ice depth	0.271	0.003	0.241	0.001											0.059	0.334
snow albedo	0.296	0.037	0.425	0.021											0.008	0.083
snow cover	0.420	0.063	0.322	0.114											0.021	**0.515**
snow density	0.368	0.005	**0.434**	0.078											0.000	0.180
snow melt	0.127	0.078	0.154	0.226											0.010	0.083
snow fall	0.136	0.204	0.130	0.234											0.048	0.005
snow depth	0.120	0.179	0.178	0.206											0.002	0.123

Notes: coloured cells identify a joint contribution of the global and local factors ≥ 0.50. In such cases, bold is used to indicate the dominant factor between global and local.

Table D3: ADF tests for Fixed-average climatology - selected factors

	ADF with const	**ADF with linear trend**	**ADF with quadratic trend**
GL	-3.31**	-12.28***	-12.84***
IT	-13.03***	-13.03***	-13.02***
FR	-9.30***	-9.31***	-11.65***
DE	-11.04***	-11.04***	-11.29***
UK	-17.74***	-17.76***	-17.76***
PL	-10.78***	-10.80***	-11.36***
ES	-11.79***	-16.84***	-17.14***
EL	-7.37***	-10.17***	-10.98***
NO	-3.40**	-12.64***	-18.05***

Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

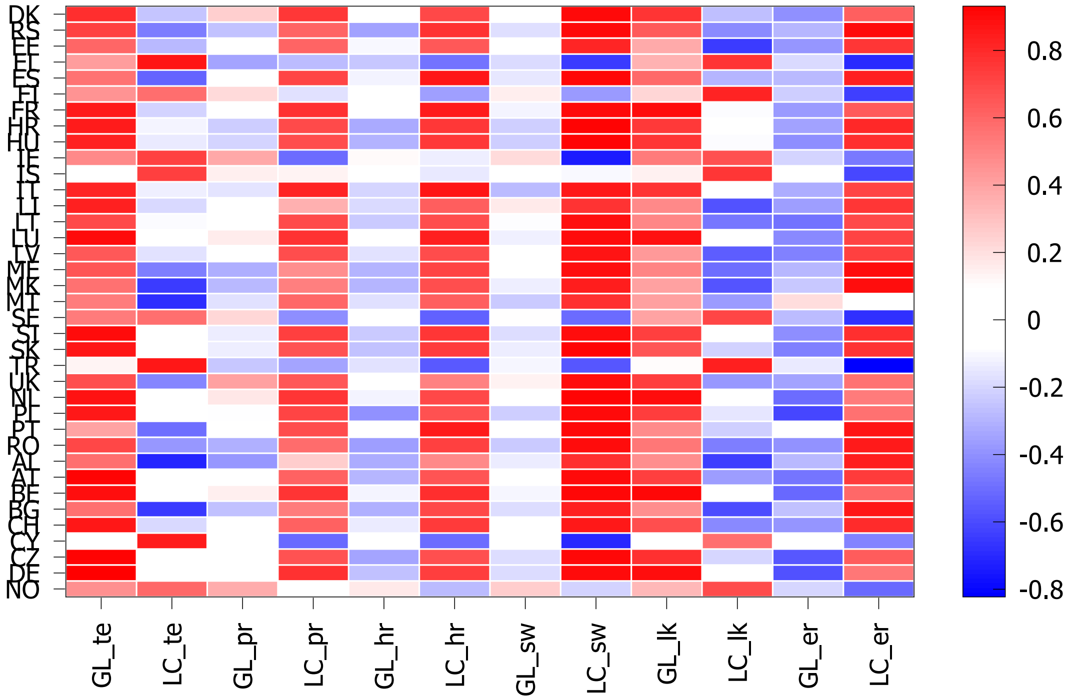

Figure D1: Heatmap of the correlation between global and local factors (Fixed-average climatology) and selected climatic series

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