



Dynamical adjustment and observational constraints to estimate recent forced European warming

Enora Cariou¹, Julien Cattiaux¹, Saïd Qasmi¹, and Aurélien Ribes¹

¹Centre National de Recherches Météorologiques, Université de Toulouse, CNRS, Météo-France, Toulouse, France

Correspondence: Enora Cariou (enora.cariou@meteo.fr)

Abstract. Europe has experienced rapid warming in recent decades. Previous studies have shown that changes in atmospheric circulation can explain part of this warming, but whether these dynamical changes are driven by internal variability or by external forcings remains unclear. In this study, we provide an estimate of the forced dynamical response over the 1979–2024 period, combining dynamical adjustment and observational constraint methods. While non-dynamical processes account for most of the observed warming, we show that the dynamical component also contains a non-negligible positive forced contribution. Overall, by incorporating dynamical information into observational constraints, we provide a new estimate of the future European warming, but find that this addition does not substantially reduce the uncertainty in climate projections.

1 Introduction

Europe is one of the fastest-warming continents, with temperatures rising at more than twice the global warming rate. Since the mid-1990s, European temperatures have increased by approximately 0.56°C per decade, compared to around 0.27°C per decade globally (C3S/ECMWF and WMO, 2026). The observed warming results from the combined effect of the response of the climate system to anthropogenic forcings modulated by internal variability (Forster et al., 2026). Several mechanisms have been proposed to explain this amplified warming over Europe, including reduction of aerosol concentrations, declining snow cover, and changes in atmospheric circulation (C3S/ECMWF and WMO, 2026).

In the mid-latitudes, weather and climate variability is mainly driven by the North Atlantic atmospheric circulation and particularly by fluctuations in the position and speed of the jet stream. To better understand the contribution of atmospheric circulation to recent temperature trends and to specific events, so-called dynamical adjustment methods have been proposed (Smoliak et al., 2015; Deser et al., 2016). These statistical methods are designed to decompose a climate variable (typically temperature) into a dynamical component, driven by variations in atmospheric circulation, and a residual component, attributable to non-dynamical processes, such as thermodynamic processes. Various methods have been proposed, ranging from linear regression onto circulation indices, multivariate regressions (Dong and Sutton, 2025; Iles and Hegerl, 2017; Sippel et al., 2019; Singh et al., 2023) to analogue-based approaches (Vautard et al., 2023; Cattiaux et al., 2012, 2010; Vautard and Yiou, 2009; Deser et al., 2016; Terray, 2021; Hu et al., 2025; Jézéquel et al., 2018; Noest et al., 2026). More recently, artificial intelligence (AI) methods have also provided relevant results (Cariou et al., 2026). Applied to observations, these methods have consis-



25 tently shown that the large-scale atmospheric circulation has contributed to the increase of recent warming over Europe, both
in annual and seasonal means, accounting for up to 30% of the total trends (Dong and Sutton, 2025; Cariou et al., 2026; Pfei-
derer et al., 2026) and in the number of heatwaves (Vautard et al., 2023; Singh et al., 2023; Terray, 2021; Rousi et al., 2022;
D’Andrea et al., 2024).

These methods can also be applied to climate model simulations (Saffioti et al., 2017) to compare the dynamical contribution
30 between models and observations and to separate the forced response from internal variability in climate projections. Previous
studies concluded that CMIP6 models tend to underestimate the dynamical contribution to the European warming. Dong and
Sutton (2025) show that dynamics has only a small contribution to summer and winter temperature trends in the multimodel
ensemble mean. Schumacher et al. (2024) find weaker dynamical contributions in the CMIP6 models than in observations
but without inconsistency with ERA5. Vautard et al. (2023) and Singh et al. (2023) have similar conclusions with regard to
35 maximum summer temperatures. They show that the simulated thermodynamic trends are close to the observations, suggesting
that it is the representation of the dynamical contribution in models that may explain this underestimation of temperature trends.
This is supported by Oudar et al. (2020); Saffioti et al. (2017); Peings et al. (2018); Breul et al. (2025) who show that climate
models project a strengthening and narrowing of the North-Atlantic jet stream in winter, but they struggle to represent both
the pattern and intensity of the recent temperature trends due to the circulation compared to observations (Blackport and Fyfe,
40 2022; Dorrington et al., 2022; D’Andrea et al., 2024). Explaining this discrepancy between observations and models remains
a challenge, and relies in particular on disentangling the forced component from internal variability in the observed circulation
trends .

Internal variability has been described to generate large interannual and quasi-chaotic variability in the dynamics (Lehner
and Deser, 2025), which complicates both the prediction of future dynamics and the estimation of the dynamical response to
45 external forcings. Large ensembles of simulations can be used to isolate the forced response estimated by the member ensemble
mean, thereby averaging out the contribution of internal variability. Multiple model projections under the same forcing scenario
differ due to model uncertainty, which can be estimated by computing forced responses across large multi-model ensembles
(Shepherd, 2014; Lehner et al., 2020). In order to reduce this model uncertainty in future climate projections, observational
constraint methods have been designed, for both global mean (Brunner et al., 2020; Tokarska et al., 2020; Ribes et al., 2021; Li
50 et al., 2025; Qasmi and Ribes, 2022) and regional temperatures (Ribes et al., 2022). They use observations in addition to multi-
model ensembles to narrow the range of climate projections. So far, these methods have been applied to temperature without
considering its dynamical and residual contributions. Here, we combine an efficient dynamical adjustment technique with an
observational constraint methods to better estimate the forced component of recent and future circulation-induced warming
trends.

55 First, we decompose the temperature into dynamical and residual terms in CMIP6 models using the AI-based method
described in Cariou et al. (2025, 2026), which is based on the UNET architecture. Then, we estimate the forced responses of



these components for all the models and we apply the observational constraints method, Kriging for Climate Change (KCC) (Ribes et al., 2021; Qasmi and Ribes, 2022), to reduce uncertainties on future dynamical and residual projections.

2 Data and Methods

2.1 Data

We use the daily 2-meter temperature (T) and horizontal wind at 850 hPa (UV850) from pre-industrial (piCTL) and transient (historical + SSP5-8.5 scenario) CMIP6 simulations (O'Neill et al., 2016). Table A1 lists all the models used for this study: multi-centennial piCTL simulations from 18 models are used to pre-train the UNET, then historical data (over the 1850–1899 period) from 88 transient simulations from 22 models are used to fine-tune the UNET and finally the inference is done on transient simulations (over 1900–2100) from these models. All model data are regridded on a common horizontal grid of 1.4 ° resolution.

The observed dynamical and residual temperature trends are estimated from the daily 2-meter temperature and UV850 provided by the ERA5 reanalysis (Soci et al., 2024). The decomposition into residual and dynamical components in ERA5 has previously been done in Cariou et al. (2026). We use these estimates over Europe and over the 1970–2024 period to constrain the projections by the models. The observed global surface air temperature (GSAT) is also used to improve the results of the constraints. To be consistent with previous studies (Qasmi and Ribes, 2022; Ribes et al., 2021; Forster et al., 2026) we use GSAT from HadCRUT5 (Morice et al., 2021), over the 1900–2024 period.

2.2 Estimation of dynamical and residual contributions

As in Cariou et al. (2026), we assume that the daily grid-point temperature T from a given CMIP6 realization or the ERA5 reanalysis can be decomposed into:

$$T = \mu + T_{\text{Dyn}} + T_{\text{Res}},$$

where μ is the mean annual cycle at the grid point, T_{Dyn} corresponds to the temperature variations induced by the large scale atmospheric circulation (Figure 1b) and T_{Res} is the residual term (Figure 1c) encompassing all temperature variations due to physical processes which do not involve atmospheric circulation. In order to estimate daily T_{Dyn} and T_{Res} , we adapt the UNET described by Cariou et al. (2025, 2026). This method consists in learning the relationship between daily temperature anomalies $T^* = T - \mu$ over Europe (violet domain in Figure A1) and a variable (or a set of variables) characterising the atmospheric circulation over a large North-Atlantic/European area (green domain in Figure A1). The temperature inferred by the UNET thus provides an estimate of T_{Dyn} , i.e. the dynamical contribution to daily temperature anomalies.



As in Cariou et al. (2026), the UNET is first pre-trained on the multi-model piCTL dataset (Table A1). The UV850 fields are
85 used as the circulation predictors. The choice of this set of variables, rather than, for example, sea-level pressure, is based on
Cariou et al. (2026), who suggest that variables too close to the surface may contain a part of the thermodynamic signal (e.g.,
sea-level pressure affected by thermal lows). The predictand is T' : for each model and grid point, we remove from the raw
temperature T the average annual cycle μ computed by averaging T over all years for every calendar day (365 values) and by
applying on it a periodic smoothing spline (with 12 degrees of freedom, consistent with Rigal et al. (2019)).

90 The pre-trained UNET is then fine-tuned model by model, using all available historical simulations from 1850 to 1899
(Table 1). This period is chosen as we assume the response to anthropogenic forcings to be relatively small. Historical data are
pre-processed in the same way as for the piCTL data, with all historical members concatenated to compute the average annual
cycle of temperature μ . After the pre-training and fine-tuning steps, we have 22 UNETs for CMIP6, pre-trained on the same
initial dataset but fine-tuned individually on each model. The inferences are then performed on the 1900–2100 period for each
95 simulation of each model, and on 1970–2024 for ERA5. Similarly, the estimation of T' in ERA5 is done by fine-tuning the
pre-trained UNET (on piCTL simulations) on the 1940–1969 period.

Figure 1 shows an example of the resulting $T_{\text{Dyn}}/T_{\text{Res}}$ decomposition for a single ensemble member, averaged annually and
over the Western European (WEU) region defined as 10°W-18E, 39°N-61°N, over the 1900–2100 inference period. As shown
in Cariou et al. (2025, 2026), T_{Dyn} captures most of the year-to-year fluctuations in T , meaning that T_{Res} can be interpreted as
100 a dynamically denoised temperature. Averaged across all ensemble members and models, the mean year-to-year variance is
reduced by 82% after removing the circulation-induced component (Table A2). As shown by Cariou et al. (2025), the UNET
performs particularly well to reduce temperature variability compared to other approaches (e.g. circulation analogues).

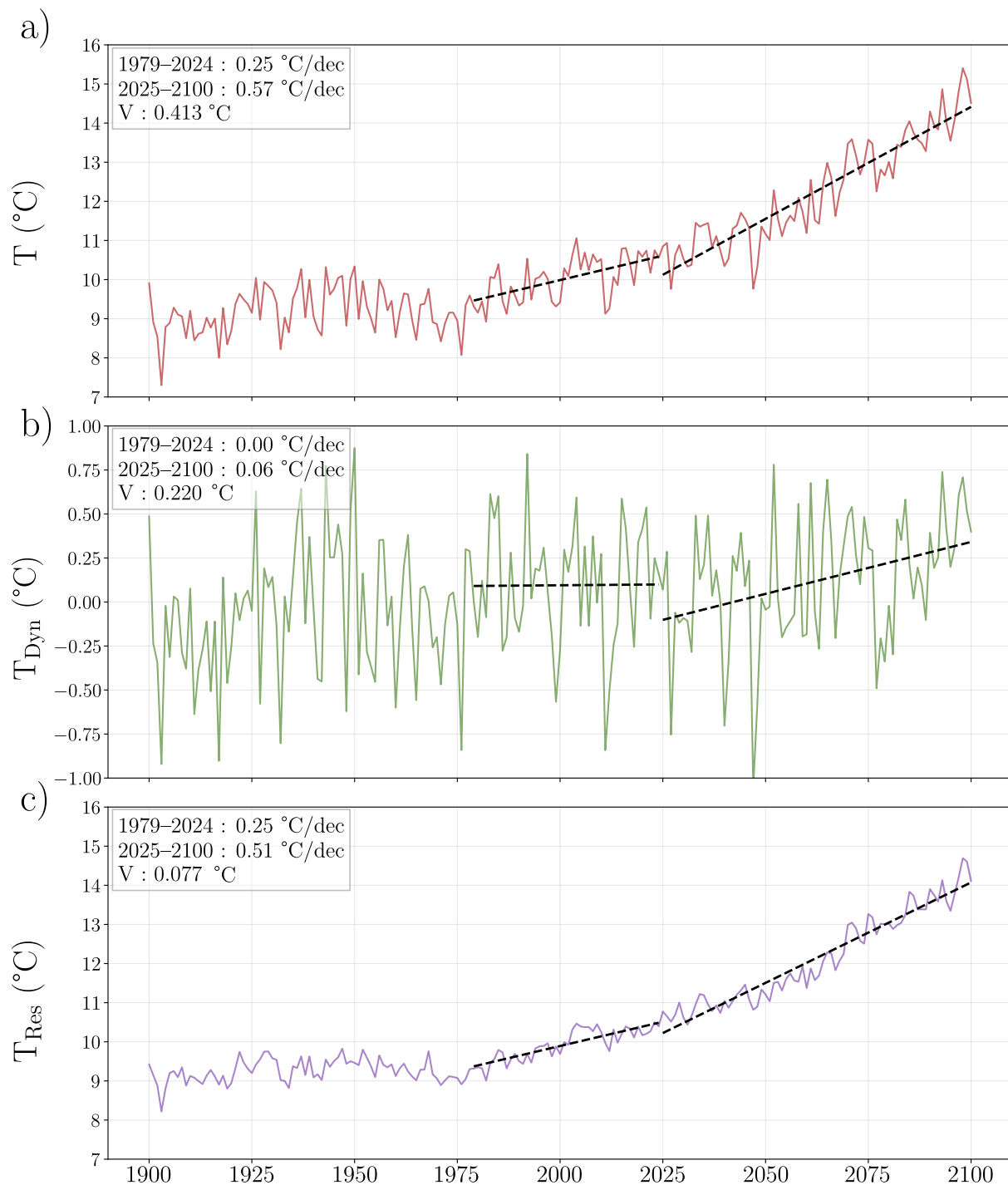


Figure 1. Temperature (a), dynamical (b) and residual (c) components of one MPI-ESM1-2-LR member, averaged over the WEU region (10°W – 18°E , 39°N – 61°N), over the 1900–2100 period. In this study we analyse linear trends over two periods represented in black: 1979–2024 (historical) and 2025–2100 (future, SSP5-8.5) periods; respective values are indicated. The mean year-to-year variation, defined as the average absolute difference between two consecutive years, is indicated.



2.3 Estimation of the forced response with observational constraints (KCC method)

For all the simulations, the temperature T is divided into dynamical (T_{Dyn}) and residual (T_{Res}) terms (Figure 1). All T , T_{Dyn} and T_{Res} contain internal and externally-forced components. The next challenge is therefore to separate the forced response from the internal variability for each of the three time series over the WEU region.

We estimate the forced responses in three successive steps. First, for each climate model, for T , T_{Dyn} and T_{Res} , we average all available ensemble members. Because all members are driven by the same external forcings and differ only by their initial conditions, the signal common to all members provides a first estimate of the model forced response, while internal variability tends to average out. The larger the ensemble, the more accurate the forced response is.

Second, the ensemble-mean estimate of the forced response is further smoothed using a Generalized Additive Model (GAM), following Qasmi and Ribes (2022). Even when averaging over all available members of a given model, the ensemble mean may still contain noise from internal variability, especially for models with only one or a few members. Yet the forced response is expected to evolve smoothly over time, with the exception of volcanic eruptions which produce isolated short peaks of negative radiative forcing. The GAM therefore provides a smooth estimate of the forced response. For T and T_{Res} , the response to natural forcings, including volcanic eruptions, is estimated using a two-layer energy balance model (Geoffroy et al., 2013), while the response to anthropogenic forcings is represented by a smoothing spline. For the dynamical component (T_{Dyn}), we do not include a natural forcing term because the response to volcanic eruptions is hardly distinguishable from internal variability (see Figure 4.1). Therefore, the GAM step is reduced to a smoothing spline that captures the slowly varying anthropogenically forced response in T_{Dyn} .

The third step consists of combining the smooth forced responses from all models to provide a robust multi-model estimate. This is done with the observational constraints method Kriging for Climate Change (KCC), that has been previously applied to global and regional warming (Ribes et al., 2021; Qasmi and Ribes, 2022; Ribes et al., 2022). Applying observational constraints to dynamical and residual contributions is new, and needs small adjustments to the existing KCC method. As described above, smooth responses to all external forcings are computed for each model to estimate samples of plausible forced T_{Dyn} and T_{Res} terms, which are used to derive prior distributions of the real forced responses. Using Bayesian statistics, posterior distributions given observations are derived. These posterior distributions retain estimates of the forced responses that are consistent with observations. In this procedure, three types of observations are used: GSAT ($T_{\text{glo}}^{\text{obs}}$), the regional dynamical term ($T_{\text{Dyn}}^{\text{obs}}$) and the residual ($T_{\text{Res}}^{\text{obs}}$). The procedure can be summarised as

$$y = Hx + \varepsilon, \quad (1)$$

where y is a vector containing observations, $y = (T_{\text{glo}}^{\text{obs}}, T_{\text{Dyn}}^{\text{obs}}, T_{\text{Res}}^{\text{obs}})$ where $T_{\text{glo}}^{\text{obs}}$ stands for the observed GSAT over 1850–2024, $T_{\text{Dyn}}^{\text{obs}}$ ($T_{\text{Res}}^{\text{obs}}$) for ERA5 dynamical (residual) temperatures over the WEU region, over 1970–2024. $x = (T_{\text{glo}}^{\text{f}}, T_{\text{Dyn}}^{\text{f}}, T_{\text{Res}}^{\text{f}})$ where $T_{\text{glo}}^{\text{f}}$ contains the GSAT time series of the 22 CMIP6 models over 1850–2100, and $T_{\text{Dyn}}^{\text{f}}$ ($T_{\text{Res}}^{\text{f}}$) is the dynamical (residual) forced



135 responses over 1900–2100 of the 22 models. We follow Qasmi and Ribes (2022) in considering GSAT T_{glo} in this constraint, as they show that having this variable increases skill scores of regional observational constraints due to the correlation between global and local warmings. Furthermore, since T_{Dyn} and T_{Res} warming are themselves correlated (Figure A2), they are jointly constrained with GSAT rather than independently.

The prior distribution of x is assumed to be Gaussian: $\pi(x) = \mathcal{N}(\mu_x, \Sigma_{\text{mod}})$. μ_x and Σ_{mod} are estimated as the sample mean and sample covariance across the 22 models. The posterior given observations y : $p(x | y) = \mathcal{N}(\mu_p, \Sigma')$ can be derived
140 analytically. H is the observation matrix operator, indicating which year in x (inputs) has been observed in y . $\varepsilon \sim \mathcal{N}(0, \Sigma_{\text{obs}})$ is a random noise representing the uncertainty in the observations y . Two sources of uncertainty exist in y : internal variability and measurement errors. $\Sigma_{\text{obs}} = \Sigma_{\text{meas}} + \Sigma_{\text{iv}}$ is the observation error covariance matrix describing GSAT measurement error (Σ_{meas}) and internal variability (Σ_{iv}). Σ_{meas} is estimated over the 200-member ensemble of HadCRUT5. Note that we do not consider the measurement uncertainty in ERA5 for computational reasons as many fine-tunings are needed to derive a
145 robust estimate of the error from the 10-members of the ERA5 reanalysis. Σ_{iv} is assumed to be the sum of two AR1 processes, following Qasmi and Ribes (2022).

This method is also applied to the temperature T (without its decomposition), with $y=(T_{\text{glo}}^{\text{obs}}, T^{\text{obs}})$ and $x=(T_{\text{glo}}^{\text{f}}, T^{\text{f}})$, thus following very closely the method of Qasmi and Ribes (2022). This standard application of KCC is here used as a benchmark to assess the potential added value of the dynamical and residual decomposition.

150 3 Results

3.1 T_{Dyn} and T_{Res} trends in CMIP6 models

3.1.1 CMIP6 recent trends over 1979–2024

CMIP6 models show positive annual temperature trends over the recent period, with large inter-model and intra-model uncertainties (Figure 2a). Trends of T range from 0.02°C per decade for a CMCC-ESM2 member to 0.80°C per decade for a
155 EC-Earth3-Veg member. The total standard deviation in the best-estimate trends across all models and ensemble members is 0.14°C/decade. Within a single model, the spread in temperature trends is also large. With an ANOVA method (?), applied only on models containing at least 2 members, we estimate that 60% of the total variance in temperature trends is explained by model uncertainty (inter-model variance) and thus, 40% by internal variability (intra-model variance).

The dynamical adjustment method provides an estimate of the dynamical contribution to these temperature trends. Most of
160 the dynamical trends are positive across models and members (Figure 2b). The ANOVA analysis on T_{Dyn} shows that 75% of the variance in trends is explained by internal variability which dominates inter-model uncertainty. For example, the 17 members of the MPI-ESM1-2-LR model show dynamical trends ranging from -0.04°C per decade to 0.07°C per decade, over WEU, with 7 members giving negative trends and 10 positive. For this model, Figure A4 shows that spatial patterns and signs of the

dynamical trends are different from one member to another and over the 1979–2024 period are small or even non-significant according to a Student’s t-test at a 90% confidence level. The fact that dynamical trends are dominated by internal variability is in line with previous studies (Deser et al., 2016; Lehner and Deser, 2025).

The dynamical adjustment method secondly can reduce the year-to-year variations (see Data and Methods), resulting in smaller uncertainties in trends for T_{Res} compared to T (Figure 2c). Intra-model variance is also reduced. Table 1 shows for models having at least 2 members, the reduction of the intra-model spread. The variance is reduced on average by 48%, ranging from 9% for CNRM-ESM2-1 to 92% for EC-Earth3-Veg-LR. Nevertheless, this reduction is smaller than the inter-annual variance reduction (Table 1). The ANOVA analysis applied to T_{Res} trends shows that the inter-model variability is smaller than the intra-model variability: only 17% of the variance is explained by internal variability.

Models	Members	var(T)	var(T_{Dyn})	var(T_{Res})	Reduction (%)
CESM2	2	9.46×10^{-4}	1.25×10^{-4}	3.84×10^{-4}	59
CESM2-WACCM	3	4.73×10^{-3}	1.41×10^{-3}	9.79×10^{-4}	79
CNRM-CM6-1	6	2.87×10^{-3}	1.50×10^{-4}	2.47×10^{-3}	14
CNRM-ESM2-1	5	6.08×10^{-3}	1.16×10^{-3}	5.55×10^{-3}	9
CanESM5	10	5.32×10^{-3}	1.49×10^{-3}	3.62×10^{-3}	32
EC-Earth3-Veg	5	4.84×10^{-2}	5.49×10^{-3}	2.15×10^{-2}	56
EC-Earth3-Veg-LR	3	2.95×10^{-2}	1.50×10^{-2}	2.41×10^{-3}	92
IPSL-CM6A-LR	7	4.07×10^{-3}	1.07×10^{-3}	2.89×10^{-3}	29
KACE-1-0-G	3	1.03×10^{-2}	3.72×10^{-4}	7.16×10^{-3}	31
MIROC-ES2L	10	2.86×10^{-3}	3.65×10^{-4}	1.57×10^{-3}	45
MIROC6	3	9.10×10^{-3}	1.31×10^{-3}	3.52×10^{-3}	61
MPI-ESM1-2-LR	17	2.34×10^{-3}	1.05×10^{-3}	6.94×10^{-4}	70
UKESM1-0-LL	5	5.39×10^{-3}	7.69×10^{-4}	3.12×10^{-3}	42
Mean		1.01×10^{-2}	2.29×10^{-3}	4.30×10^{-3}	48

Table 1. Intra-model variance for each model having at least 2 members, and the associated reduction of this variance after the dynamical adjustment process (between T and T_{Res}). The last row shows the average variances and reduction.

3.1.2 Comparison with ERA5 trends

Over the 1979–2024 period, whether for the temperature T , or its dynamical and residual contributions, the observed trends assessed from ERA5 are included in the CMIP6 90% intervals [Q05;Q95] (Figure 2). Trends in models are therefore consistent with observations. However, the majority of simulated trends of the term T are lower than the observed trend: 72% of the members show trends below the observed value. After denoising the temperature from the dynamical term T_{Dyn} , this value



decreases to 64%. The difference between observed and simulated trends is more pronounced: 78% of simulations show lower trends than observed, and only 3 of the 13 multi-member ensembles give average trends that exceed it. The CMIP6 ensemble mean of the circulation-induced warming is therefore smaller than the estimate from the observations. This is consistent with Dong and Sutton (2025) and Vautard and Yiou (2009), though these studies focused on specific seasons (summer and winter) rather than annual means as considered here. Most simulations give positive dynamical trends: of the 88 members analysed, 67 (76%) show positive dynamical trends, even if according to a Student's t-test, only 15 of these (17%) are significant at a 90% confidence level (because of the noise generated by internal variability). All models with at least two members give positive ensemble mean trends.

The seasonal analysis reveals contrasting patterns between winter (December, January, February – DJF) and summer (June, July, August – JJA) (Figure A3). The variability of the T trends is larger in winter than in summer, consistent with a larger internal variability during winter. This difference is explained by the dynamical contribution T_{Dyn} , with a larger spread in trends compared to the T_{Res} trends: the standard deviation of the dynamical trends is $0.10^{\circ}\text{C}/\text{decade}$ in winter compared to $0.06^{\circ}\text{C}/\text{decade}$ in summer, whereas for T_{Res} , standard deviations are of $0.13^{\circ}\text{C}/\text{decade}$ in winter and $0.12^{\circ}\text{C}/\text{decade}$ in summer. Trends of T are also more strongly underestimated in winter than in summer: 75% of ensemble members simulate a trend lower than the observed one in winter, compared to 58% in summer. Furthermore, in winter, the observed dynamical trend is closer to the median of the simulated dynamical trend distribution than to that of T_{Res} , whereas it is the opposite in summer: the observed T_{Res} trend is closer to the median of the simulated distribution compared to the dynamical trend.

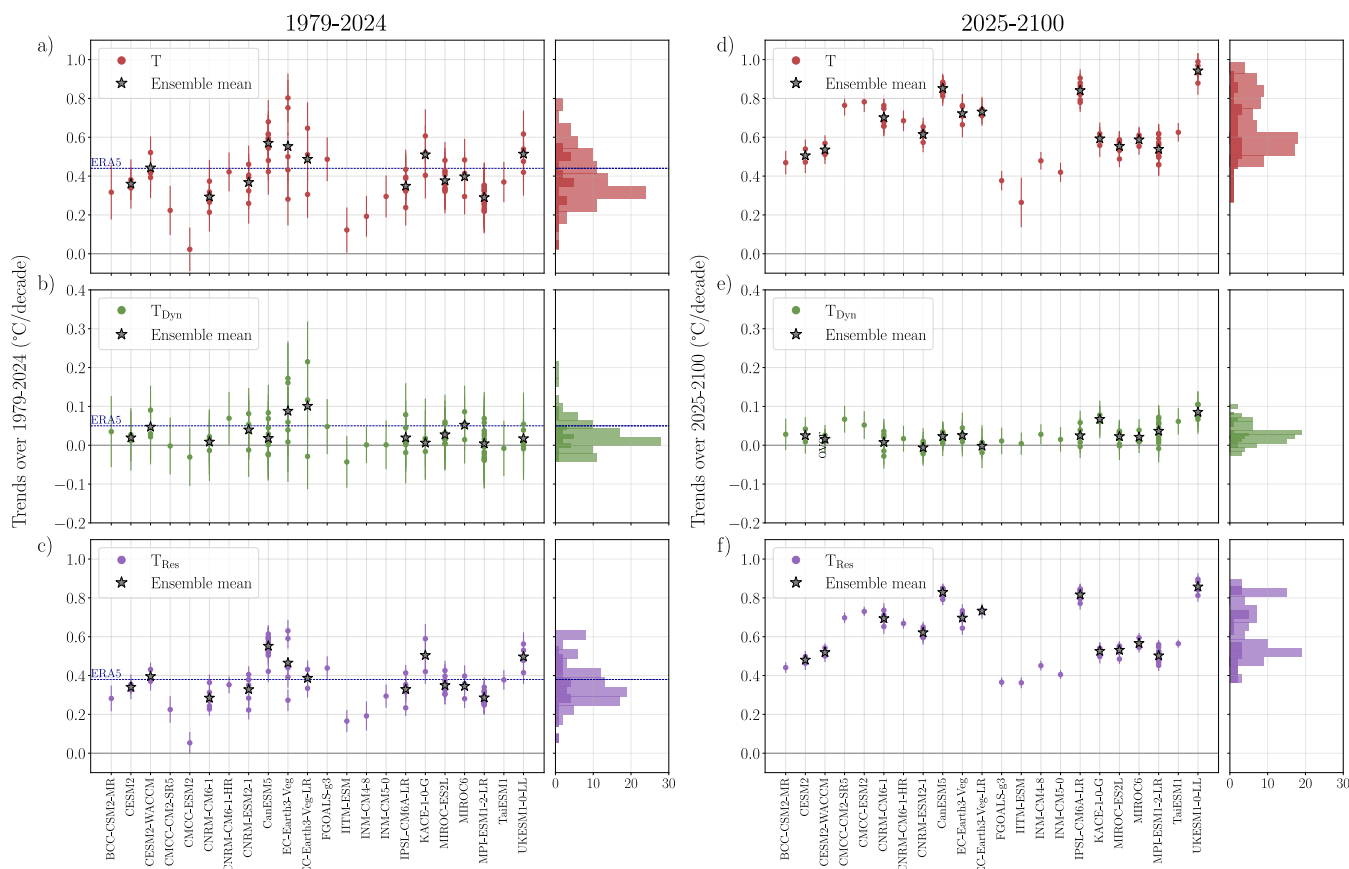


Figure 2. Linear trends of temperature T (red), T_{Dyn} (green) and T_{Res} (purple), averaged over WEU, for (a,b,c) the 1979–2024 period and (d,e,f) the 2025–2100 period. Error bars show the 95% confidence interval of the trend estimated with a Student’s t-test. For each model, light-colored bars show the trend of individual members, and dark-colored bars show the ensemble mean trend; stars indicate the ensemble mean for models with at least two members. In panels (a,b,c), observed trends over 1979–2024 (from ERA5 data) are shown in blue for comparison with the models. Note that the y-axis scale for T_{Dyn} differs from that for T and T_{Res} .

195 3.1.3 CMIP6 future trends over 2025-2100

Temperature trends over the 2025–2100 period are higher than over the recent period (the median trend increases from 0.36°C per decade in the recent period to 0.62°C per decade in the future period, Figure 2d). Model simulations generally project a positive dynamical trend (Figure 2e), but most of the future warming is explained by the residual contribution (Figure 2e). The ANOVA test shows that for the T , T_{Dyn} and T_{Res} future trends, model uncertainty dominates internal variability. This is especially true for T and T_{Res} , where inter-model variance accounts for 94% and 97% of the trend variance, respectively. For the dynamical component, model uncertainty explains a smaller but still substantial part of the variance (59%). As future trends are computed over a longer period compared to recent trends, variance is smaller, reducing the impact of internal variability while it



does not affect the inter-model spread: the standard deviation of T (T_{Res}) trends increases from $0.14^{\circ}\text{C}/\text{decade}$ ($0.11^{\circ}\text{C}/\text{decade}$) over the recent period to $0.15^{\circ}\text{C}/\text{decade}$ ($0.14^{\circ}\text{C}/\text{decade}$) over the future period. For T_{Dyn} , the inter-model uncertainty over the
205 future period is smaller compared to the recent period. Within a single model having several members, patterns and signs of the dynamical trends are more consistent: for example for the MPI-ESM1-2-LR model, only one member shows a negative dynamical trend over WEU and among the 17 members, the spatial patterns are similar with a majority of grid points showing significant positive trends (Figure A4).

Among the 13 model ensembles providing at least two members, 11 models give positive ensemble-mean trends over WEU
210 (Figure A3e). This suggests that the dynamics robustly tend to increase the future warming. However, these ensemble means may still be affected by internal variability: Figures A4 and A5 show that ensemble means are still noisy even for relatively large ensembles. Isolating the forced response from internal variability in all models is the aim of section 3.2.2.

3.1.4 Spatial patterns of T_{Dyn} and T_{Res} trends in CMIP6 models (2025-2100)

Figure 3 shows the multi-model ensemble mean of T , T_{Dyn} and T_{Res} trends at the grid-point scale, for all seasons. The multi-
215 model mean can be interpreted as a first estimate of the CMIP6 forced response, as it smooths out the noise attributable to internal variability and brings out the common signal to all simulations, i.e. the response to external forcings.

Future warming is dominated by the non-dynamical component (Figure 3, k,l,m,n,o) mostly associated with anthropogenic forcings. Averaged annually, the forced dynamical component accounts for a maximum of 12% (one grid point reaches 12%; the others are below) of the future total warming. The dynamical trends computed in annual, DJF, JJA and SON averages are
220 significantly positive, suggesting that the future warming associated with the dynamical component may be forced. This is also true for the 1979–2024 period (Figure A5). Spatial contrasts emerge depending on the season: in winter, the strongest trends are located in north-eastern Europe, accounting for up to 17% of the total trend. In summer, however, the most intense warming is found in southern Europe, particularly over the Mediterranean region, accounting for up to 11% of the total trend. In contrast, significantly negative trends are observed in spring (MAM), reducing the total warming over central Europe.

225 Atmospheric circulation over the North Atlantic region is dominated by the zonal component of the wind (u_a). In line with Oudar et al. (2020); Saffioti et al. (2017); Peings et al. (2018); Breul et al. (2025), Figure 4 shows that in winter, zonal wind is strengthening and narrowing over Europe in the future, particularly over north-western Europe, leading to warm and wet conditions, due to advection of oceanic air masses (Hurrell et al., 2003). The meridional component is also strengthening over north-western Europe, bringing warm air from the South. Consequently, over north-western Europe, south-westerly fluxes are
230 strengthening (Figure 4l). In summer, a weakening of westerly winds is simulated over Europe, leading to fewer cyclonic storms traveling over the Mediterranean and less oceanic advection bringing warm continental air favoring drier continental air masses and drier summers in Southern Europe (Dong and Sutton, 2021).

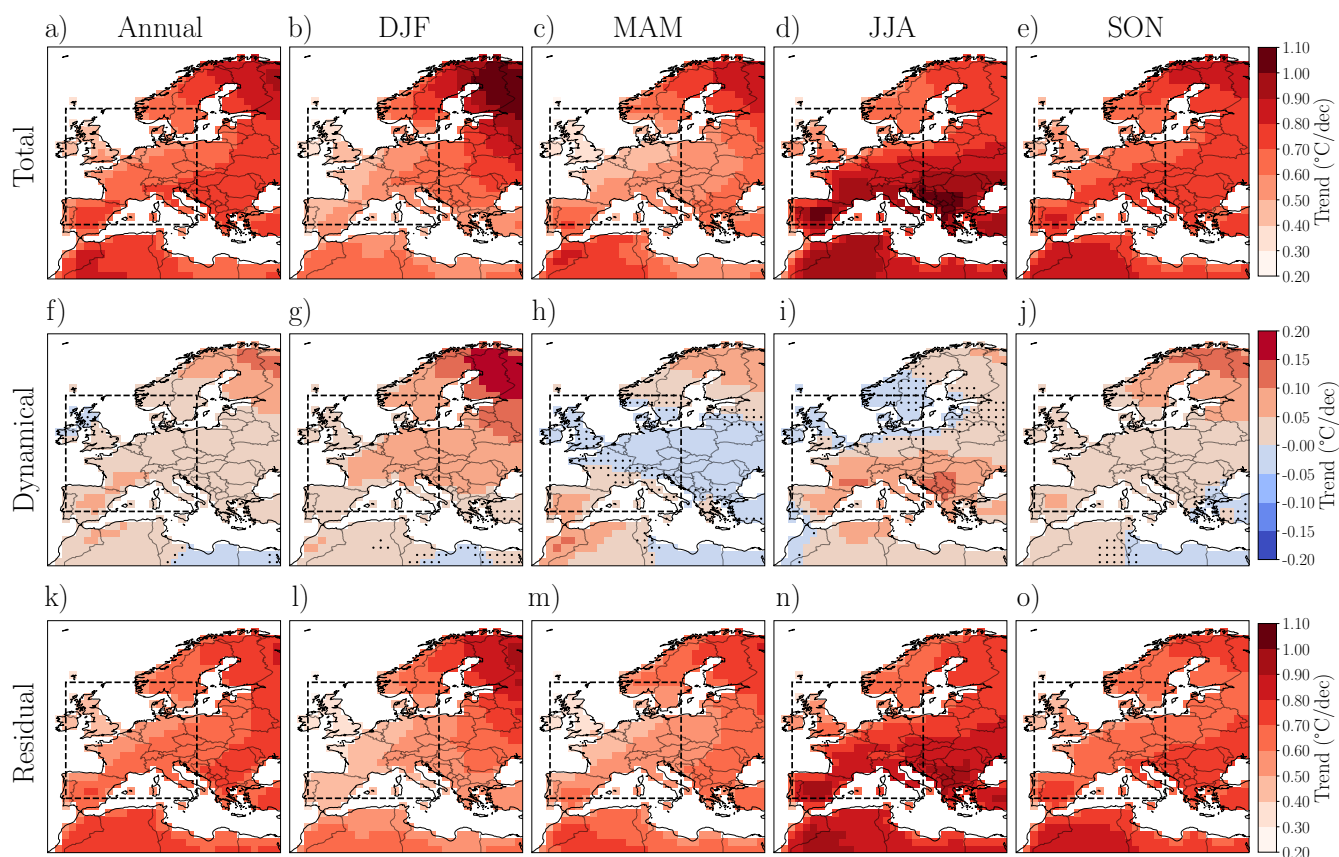


Figure 3. Annual and seasonal trends (°C/decade) computed on CMIP6 ensemble mean of raw temperature (ERA5 data) for each grid point on the 2025-2100 period, (middle) CMIP6 T_{Dyn} and (bottom) on CMIP6 T_{Res} . Black dots corresponds to trends that are not significant according to a Student's t-test at 90%.

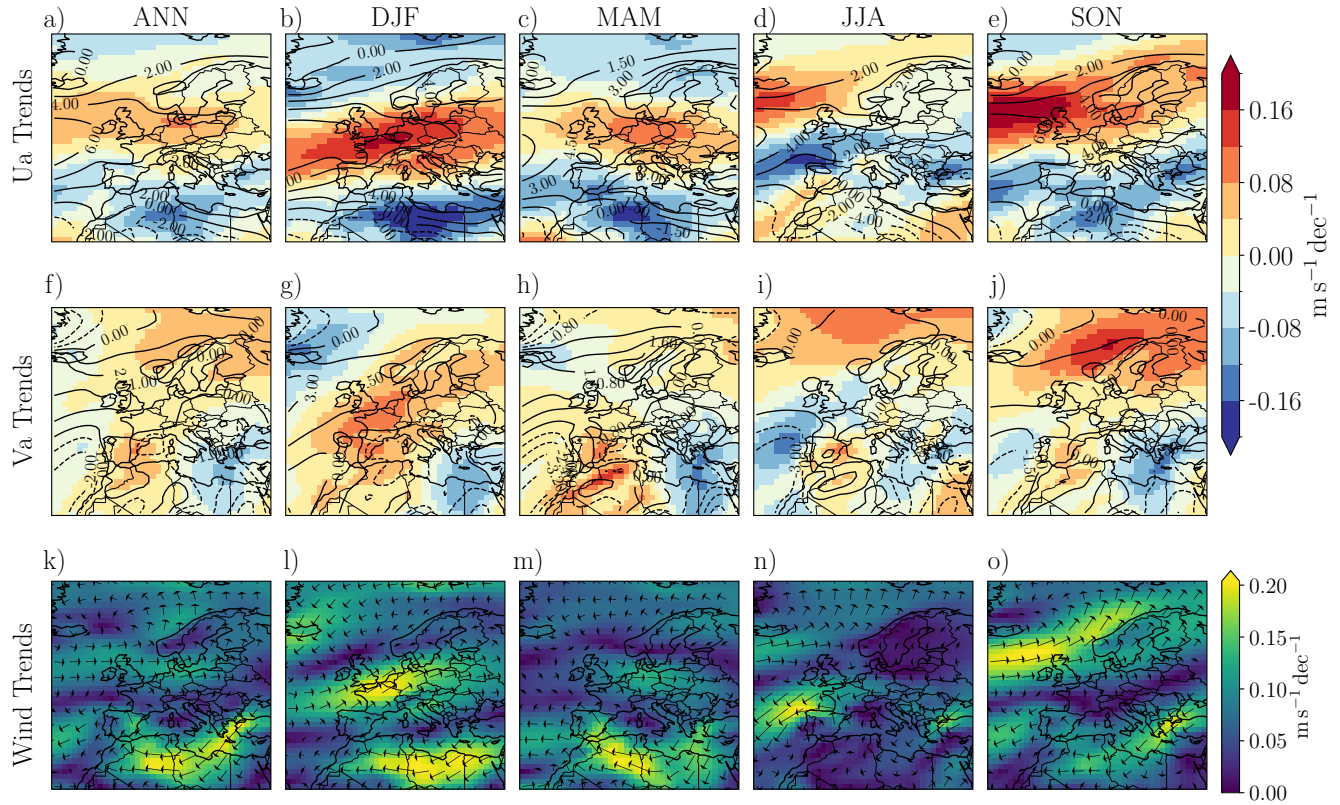


Figure 4. Annual and seasonal trends (m/s/dec) computed on CMIP6 ensemble mean of zonal wind ua (a,b,c,d,e; positive values indicate increasing Westerlies) and meridional wind va (f,g,h,i,j; positive values indicate increasing Southerlies) over 2025-2100. Contours correspond to the average winds over 2000-2025. Black dots corresponds to trends that are not significant according to a Student's t-test at 90%. (k,l,m,n,o) show total wind direction and speed changes.

3.2 Constraining future projections with KCC

3.2.1 Prior distribution of forced responses

235 The model ensemble means computed in the previous section provide a first estimate of the forced response for each component T , T_{Dyn} and T_{Res} . However, these estimates are still affected by internal variability because each model ensemble contains a limited number of realisations. To obtain a more accurate multi-model forced response, we first fit a Generalized Additive Model to each model-specific ensemble mean (Figure 5, left) and then fit a normal distribution to the resulting multi-model sample of the smoothed forced responses (Figure 5, right, see also Data and Methods). This normal distribution is the prior

240 distribution in the Bayesian framework of the KCC method. We now consider the regional averages over the WEU region only. Future temperature changes are anomalies in 2100 relative to the 1970–2024 baseline, and we quantify model uncertainty by the spread within the prior distribution, represented by the 5 to 95% confidence interval.



Future T changes range from 3.40°C to 7.75°C in 2100 compared to 1970–2024 with a spread (90% confidence interval) of 4.35°C. For T_{Dyn} , changes range from -0.05°C to 0.63°C with a spread of 0.67°C. Until the mid-20th century, most models simulate dynamical responses close to 0 (Figure 5e and Figure A6). However, all models point to a positive forced response by the end of the century, with a warming of $0.30^{\circ}\text{C} \pm 0.20^{\circ}\text{C}$ relative to the 1970–2024 period. T_{Res} reaches 4.04°C, which is slightly lower than T, as we denoised it from its dynamical component.

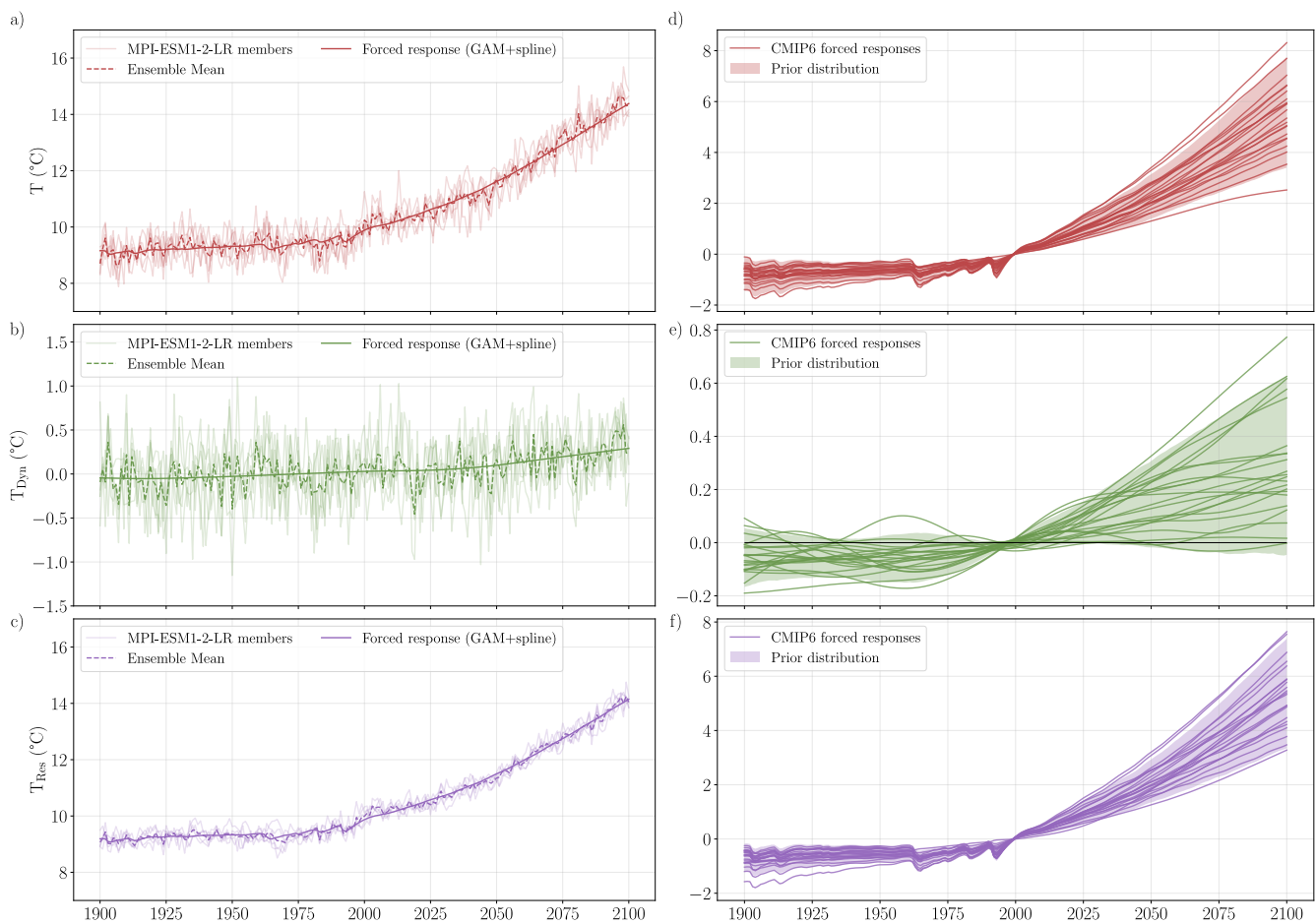


Figure 5. (left) Example of the GAM fit for one CMIP6 model. Light times series represent T (a), T_{Dyn} (b) and T_{Res} (c) for all the MPI-ESM1-2-LR simulations. Dotted time series are the ensemble means for the three components and the dark time series the estimation of the forced responses with the GAM model. (right) Normal fit of the prior distribution. Dark time series correspond to the forced responses for all CMIP6 models and the light colours to the 5 to 95% spread (prior distribution) computed using the 22 forced responses. Series are centered on the 1970–2024 period.



3.2.2 Observational constraints and posterior distribution with KCC

In Figure 5, the model-by-model estimates of the forced response have been used to provide a prior distribution of the real
250 forced response, assuming that the observed forced response is included in the range of the models. Whether for the T , $T_{D_{\text{dyn}}}$
or T_{Res} , these prior distributions assign equal weights to all models, regardless of their consistency with observations. The
objective of this section is to reduce future uncertainties by deriving a posterior distribution that is consistent with observations.
This is done with the observational constraint method KCC (Qasmi and Ribes, 2022) (see Data and Methods).

First, we apply KCC on T averaged over WEU, similarly as in Qasmi and Ribes (2022). The prior distribution is constrained
255 by the observations of GSAT (HadCRUT5) and the yearly WEU temperatures (ERA5). The KCC method narrows the uncer-
tainties on temperatures by 31% at the end of the 21st century (Figure 6a and Table 2). According to the SSP5-8.5 scenario, T
reaches 5.54°C [3.41 to 7.75] before constraints and 5.55°C [4.04 to 7.04] after constraints relative to the 1970–2024 period.
The posterior best estimate is similar to raw multi-model ensemble mean: the GSAT constraint tends to revise downwards
CMIP6 projections, while the WEU constraint tends to increase them (this is because T time series from ERA5 data increases
260 faster than the CMIP6 ensemble mean, see Figure 2a). Overall, our results are consistent with Qasmi and Ribes (2022), even if
uncertainties are less reduced here. This discrepancy can be due to the geographical area studied, the models or the observations
used.

Second, we apply KCC to T_{Res} and $T_{D_{\text{dyn}}}$ simultaneously, using, in addition to GSAT, our estimates of the observed $T_{D_{\text{dyn}}}^{\text{obs}}$
and $T_{\text{Res}}^{\text{obs}}$. For $T_{D_{\text{dyn}}}$ (Figure 6b), the uncertainty is reduced by 25% and the best estimate is revised slightly downward, reaching
265 0.25°C [0.00; 0.51] in 2100 compared to the 1970–2024 period. Recent years show strong $T_{D_{\text{dyn}}}$ values, and the observed
trend (0.06°C/dec [-0.00; 0.12] over 1970–2024) appears noticeably stronger than the prior (0.03°C/dec [0.03; 0.03]). However,
because internal variability is very large in this component, the observational constraint does not lead to an upward revision of
the forced contribution. If this succession of strong $T_{D_{\text{dyn}}}$ years were to continue, this part of the assessment would likely need to
be revisited. The downward revision and the reduction of uncertainty in $T_{D_{\text{dyn}}}$ projections are explained by the GSAT constraint:
270 Figure A9 shows that when constraining with observed $T_{D_{\text{dyn}}}$ only, the posterior is very close to the prior distribution.

For T_{Res} , the reduction of uncertainty in projections is similar to T (33%) (Figure 6c). Compared with the 1970–2024 period,
the warming in T_{Res} is estimated at +5.30°C [3.35 ; 7.39] before constraints and at +5.21°C [3.96; 6.53] after constraints. Despite
the lower inter-annual variance observed in T_{Res} compared with the observations of T (1.7 times lower in T_{Res} compared to
 T , see Data and Methods), we expected the constraint method to be more effective on T_{Res} than on T , thanks to the denoising
275 provided by the dynamical adjustment. Several reasons could explain why this is not the case: observed T_{Res} values are highly
autocorrelated, which reduces the amount of independent information available for constraining the forced response (this
information is contained in Σ_{obs} used to derive the posterior distribution). Furthermore, the statistical relationship between
past and future T_{Res} warming in the models (contained in Σ_{mod}) is weaker than for T (Figure A8,a,c). Σ_{mod} captures the



statistical relationship between what the models simulate in the past and what they project for the future. The constraint is
280 more effective when models exhibit a strong correlation between past and future trends.

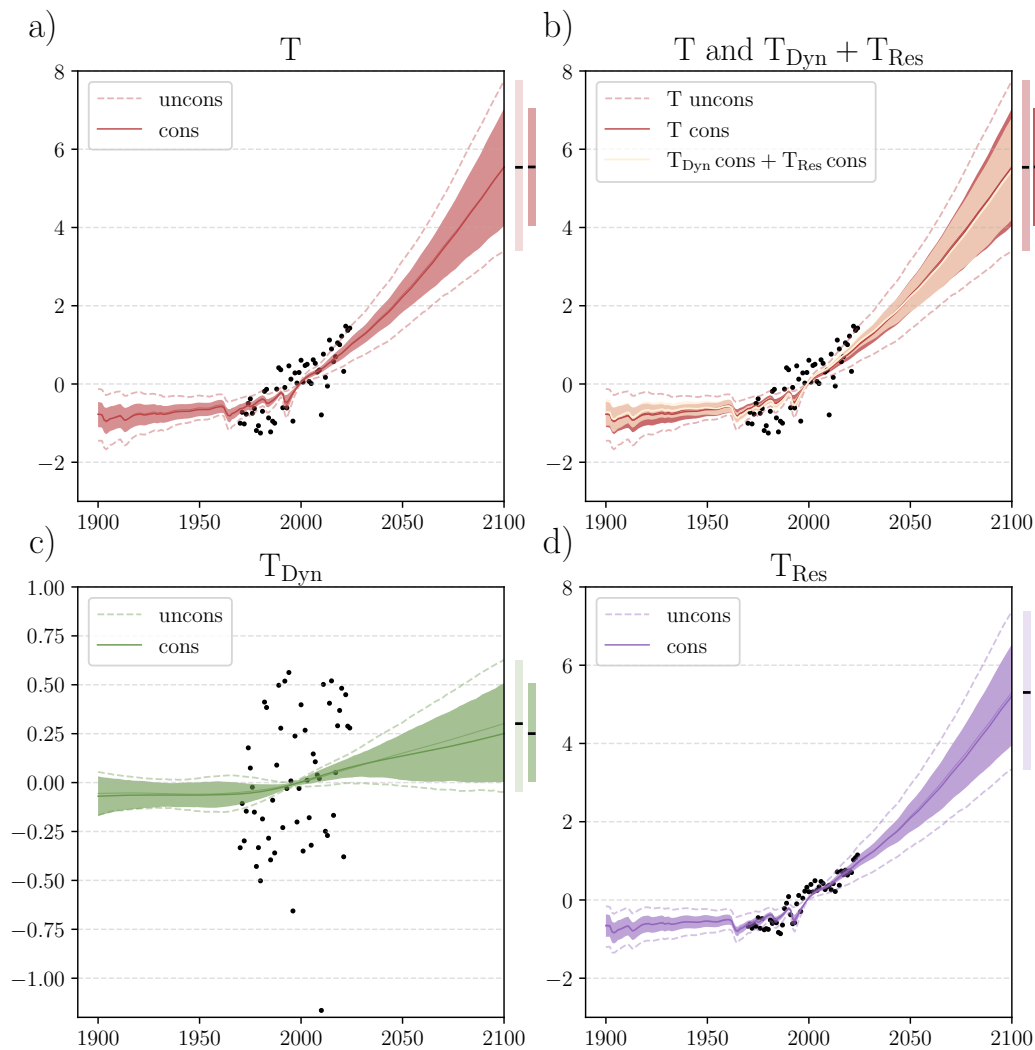


Figure 6. Observational constraints on historical and SSP5-8.5 over the WEU region for temperature (a), dynamical contribution (d) and residual contribution (c) changes. Black dots correspond to observed data (ERA5). (b) Compares prior and posterior of the temperature (without decomposition) with the sum of distributions of T_{Res} and T_{Dyn}.

The above results are also relevant in terms of estimation of internal variability within T and its components, as it can be derived by removing the estimate of the forced response from the constrained temperature time series. The recent trends in



	Prior (BE [Q05;Q95])	Posterior (BE [Q05;Q95])	Spread reduction (%)
T	5.54 [3.41 ; 7.75]	5.55 [4.04 ; 7.04]	31
T _{Dyn}	0.30 [-0.05 ; 0.63]	0.25 [0.00 ; 0.51]	25
T _{Res}	5.30 [3.35 ; 7.39]	5.21 [3.96 ; 6.53]	36
T _{Dyn} +T _{Res}	5.64 [3.49 ; 7.74]	5.46 [4.20 ; 6.81]	39

Table 2. Estimate of warming in 2100 relative to the 1970—2024 period (best estimate, BE), before and after constraints, and the percentage reduction in the spread ([Q05;Q95]) between the prior and the posterior.

annual mean temperature is then broken down into four components: forced dynamics, internal dynamics, forced residual and internal residual (Table 3).

	Observations trends (°C/dec)	Forced (KCC) trends (°C/dec)	Internal variability trends (°C/dec)
T	0.44 [0.33 ; 0.54] ⁽¹⁾	0.34 [0.32 ; 0.36] ⁽²⁾	0.10 [-0.00 ; 0.20]
T _{Dyn}	0.06 [-0.03 ; 0.14]	0.03 [0.03 ; 0.03]	0.03 [-0.06 ; 0.11] ⁽⁵⁾
T _{Res}	0.38 [0.33 ; 0.42]	0.34 [0.32 ; 0.37]	0.04 [-0.00 ; 0.08] ⁽⁵⁾
T _{Dyn} + T _{Res}	0.44 [0.30 ; 0.56]	0.37 [0.35 ; 0.40] ⁽³⁾	0.06 [-0.04 ; 0.17] ⁽⁴⁾

Table 3. Linear trends over 1979–2024 (with interval confidence at 95% estimated with a Student's t-test), for observed temperature over WEU (first column) and its dynamical and residual components (second column), forced estimates of T, T_{Dyn}, T_{Res} and T_{Dyn}+T_{Res} (third column); and finally, the difference between columns 2 and 3 gives the trends in the contributions from internal variability of T, T_{Dyn}, T_{Res} and T_{Dyn} + T_{Res} (fourth column). Values marked with a footnote number (*) are further discussed in the main text.

285 According to our estimates, 77% of the recent trend in T is explained by the external forcings, and the remaining 23% by internal variability (first row). This percentage rises to 89% for T_{Res}, as a significant proportion of the internal variability linked to the dynamics has been removed through the dynamical adjustment. The trend in T_{Dyn}, which is smaller (about 15% of the trend of T), is equally split between the forced and internal contributions.

As found by Ribes et al. (2022) for France, the forced response estimated on temperatures with KCC is substantially
290 lower than observations during the last decade over WEU (Figure 6a). For the 1979—2024 period, we estimate a trend of 0.44°C/decade⁽¹⁾ for the observed temperature T (including both internal and forced contributions), while the forced trend estimated using KCC⁽²⁾ is 0.1°C/decade lower. The sum of the forced contributions from the T_{Dyn} and T_{Res} estimates is 0.37°C/decade⁽³⁾ which is close to the T trend, but with a difference of 0.06°C/decade⁽⁴⁾. This missing portion is equally explained by the contribution of the internal variability of these two components⁽⁵⁾, but with uncertainties on the trends, espe-
295 cially for T_{Dyn}, on which internal variability is strong. Our results seem to indicate that the discrepancy between observations



and models originates from both dynamical and non-dynamical terms, with internal variability being a potential explanation to this missing warming.

As T is, by construction, the sum of the T_{Dyn} and T_{Res} components, applying this decomposition is attractive to further reduce uncertainty on T . Figure 6 suggests that the sum of the posterior distributions of T_{Dyn} and T_{Res} is consistent with the posterior distribution of T (Figure 6d). However, applying the method separately to the dynamical and non-dynamical components does not further reduce uncertainty in future projections compared to T , meaning that considering the dynamical and residual components does not necessarily provide additional observational constraints on the future warming over Europe.

4 Conclusion and Discussion

The objective of this study is to estimate the internal and forced parts of the dynamical and residual contributions to observed temperatures in Europe. To this end, we first decompose the observed (ERA5) and model (CMIP6) daily temperatures into dynamical and residual components, using the UNET as a new dynamical adjustment method. This daily decomposition allows us to estimate the dynamical and residual trends not only for the four seasons but also on an annual-mean basis, thereby complementing the existing literature, which has largely focused on specific seasons — mostly summer (Vautard et al., 2023; Dong and Sutton, 2025; Schumacher et al., 2024).

Then we use an observational constraint method (KCC) combining models and observations to estimate the forced and internal components of these two terms, as well as their projections. Our results show that the forced dynamic contribution in the current and future warming is not negligible. This suggests that most studies that remove the dynamical component tend to underestimate the forced response Deser et al. (2016); Deser and Phillips (2023); Sippel et al. (2019). Here, we find in observations, that the T_{Res} term is not strictly equal to the forced response within T , suggesting a role for the forced dynamical component.

The observational constraint method is based on the assumption that “models are statistically indistinguishable from the truth”. While this assumption is commonly made for T (Ribes et al., 2021), we show that T_{Dyn} trends are lower than observed in the majority of models, in line with previous studies (Vautard et al., 2023; Singh et al., 2023; Schumacher et al., 2024). If models misrepresent T_{Dyn} trends then results obtained with KCC should be interpreted with caution. Note that the observed trends of T_{Dyn} do not fall entirely outside the model range, which is why we do not reject the method. This underestimation of T_{Dyn} may be explained by biases in the changes in atmospheric circulation, particularly in summer (Boé et al., 2020; Faranda et al., 2023; D’Andrea et al., 2024). If all models actually underestimate the forced dynamical trend, then our observationally constrained estimate would be affected, and similarly underestimated. Additional analyses of the dynamically-induced warming are therefore needed. The cause of the observed T_{Dyn} trend remains an open question: Roldán-Gómez et al. (2026) suggest that it is largely explained by external forcings linked to anthropogenic aerosols, and more specifically to the reduction in sulphate aerosol emissions over Europe since the 1980s. Dong and Sutton (2021) also suggest the role of aerosols in circulation changes.



Alternatively, Al-Yaari et al. (2026) explain the changes in the dynamics by a low-frequency internal variability mode related to the Atlantic Meridional Overturning Circulation. Assuming that these changes are attributable to internal variability, we can expect the excess warming to reverse at some point in the coming years or decades. If the observed circulation changes are driven by the aerosol forcing, we can expect its contribution to revise downward the T_{Dyn} trend, as aerosol emissions tend to be stabilized over Europe — although the extent and timescale remain uncertain. Note that this study is limited to the distinction between internal variability and the forced response, without attributing the role of GHGs and aerosols. This distinction would be useful for determining whether the observed dynamically-induced warming would be temporary or long-lasting.

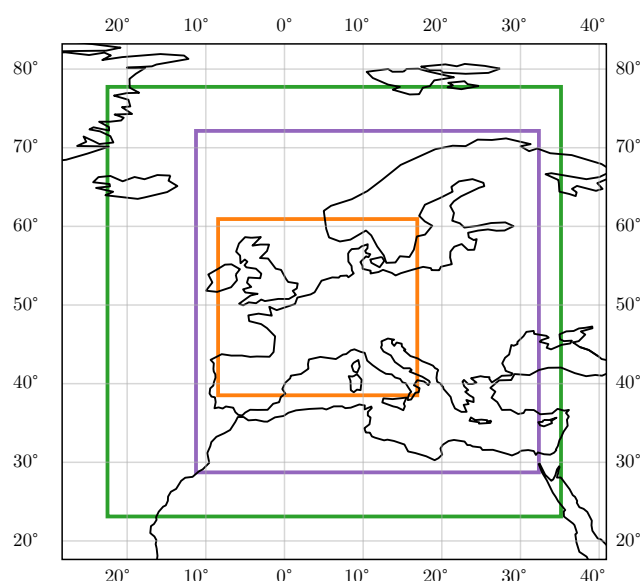


Figure A1. (Green) input (UV850) domain (23N-78N, 23W-35E) , (purple) output (temperature) domain (29N-72N, 11W-32E) and (orange) WEU domain (39N-61N, 10W-18E).

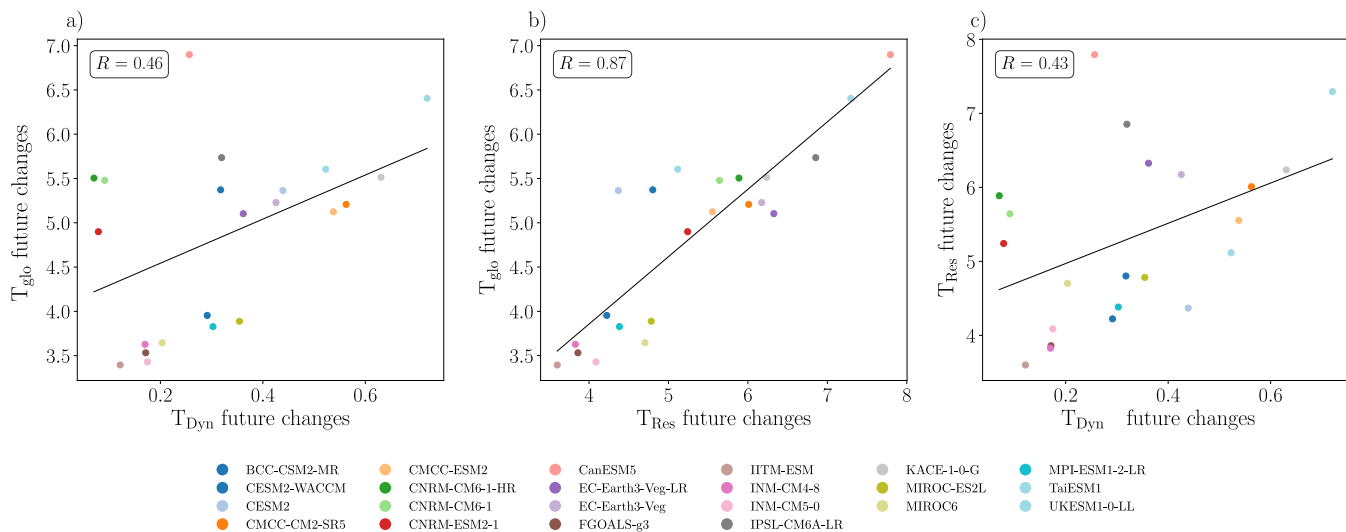


Figure A2. (a) Correlations between CMIP6 forced future T_{glo} anomalies and future T_{Dyn} anomalies. (b) Correlations between CMIP6 forced future T_{glo} anomalies and future T_{Res} anomalies. (c) Correlations between CMIP6 forced future T_{Res} anomalies and future T_{Dyn} anomalies. For each model, future anomaly corresponds to the difference between the mean over the 2080–2100 period and the 1900–1930.

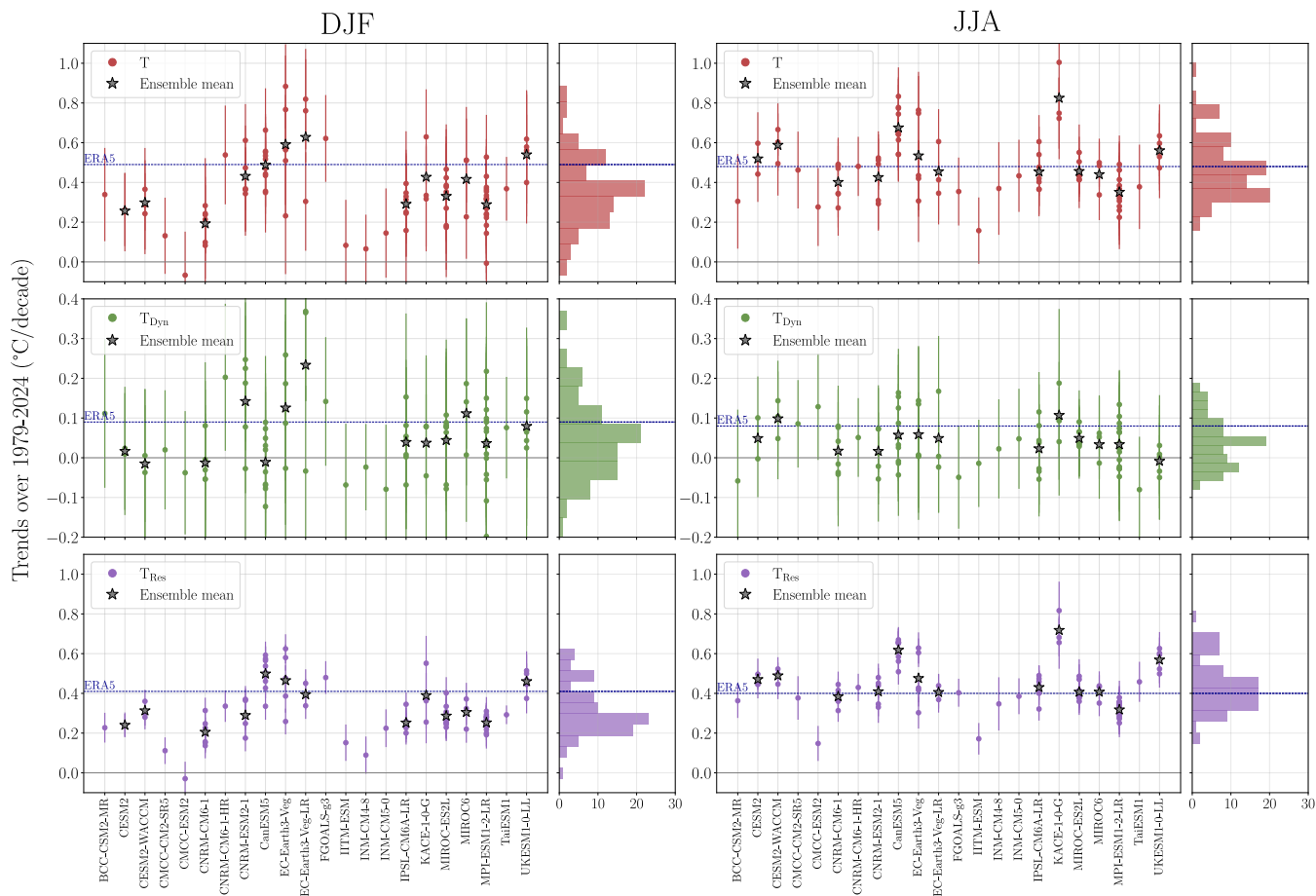


Figure A3. T (red), T_{dyn} (green) and T_{res} (purple) linear trends computed over WEU over the 1979–2024 period in DJF (a,b,c) and in JJA (d,e,f). Stars represent the ensemble mean for models containing at least 2 members. Observed recent trends (blue) are compared with model trends.

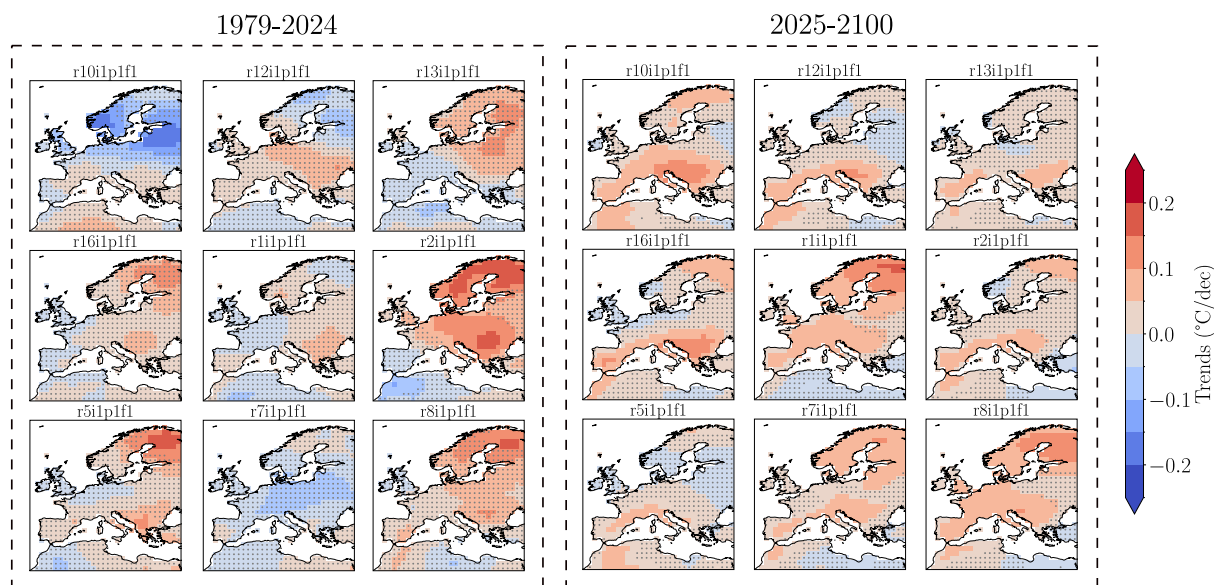


Figure A4. Linear trends computed on the dynamical component (T_{Dyn}) for 9 random members of the MPI-ESM1-2-LR model, over the 1979–2024 period (left) and over the 2025–2100 period (right). Stippling shows no significant trends according to a Student's t-test at a 90% confidence level.

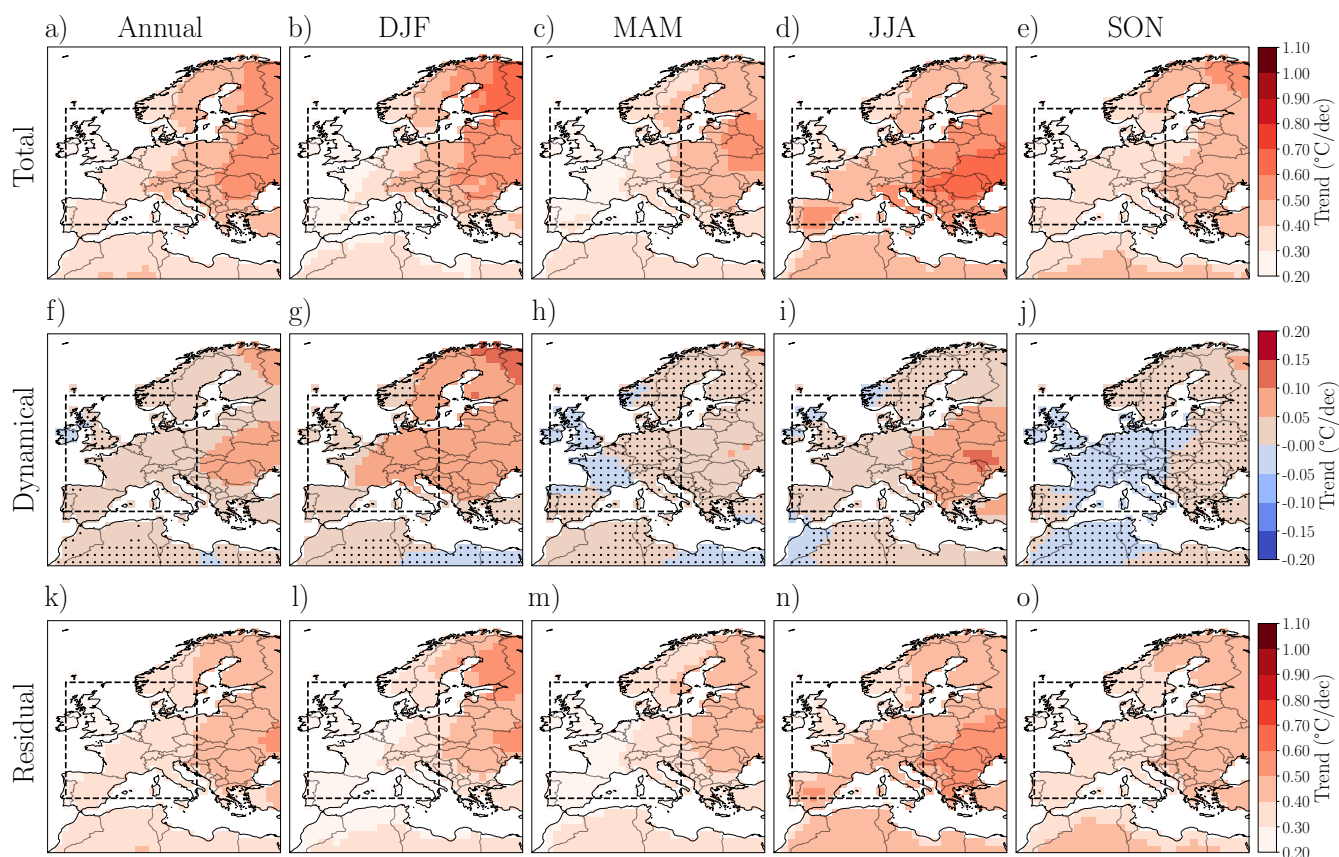


Figure A5. Annual and seasonal trends (°C/decade) computed on CMIP6 ensemble mean of raw temperature (ERA5 data) for each grid point on the 1979–2024 period, (middle) CMIP6 T_{Dyn} and (bottom) on CMIP6 T_{Res} . Black dots corresponds to trends that are not significant according to a Student's t-test at 90%.

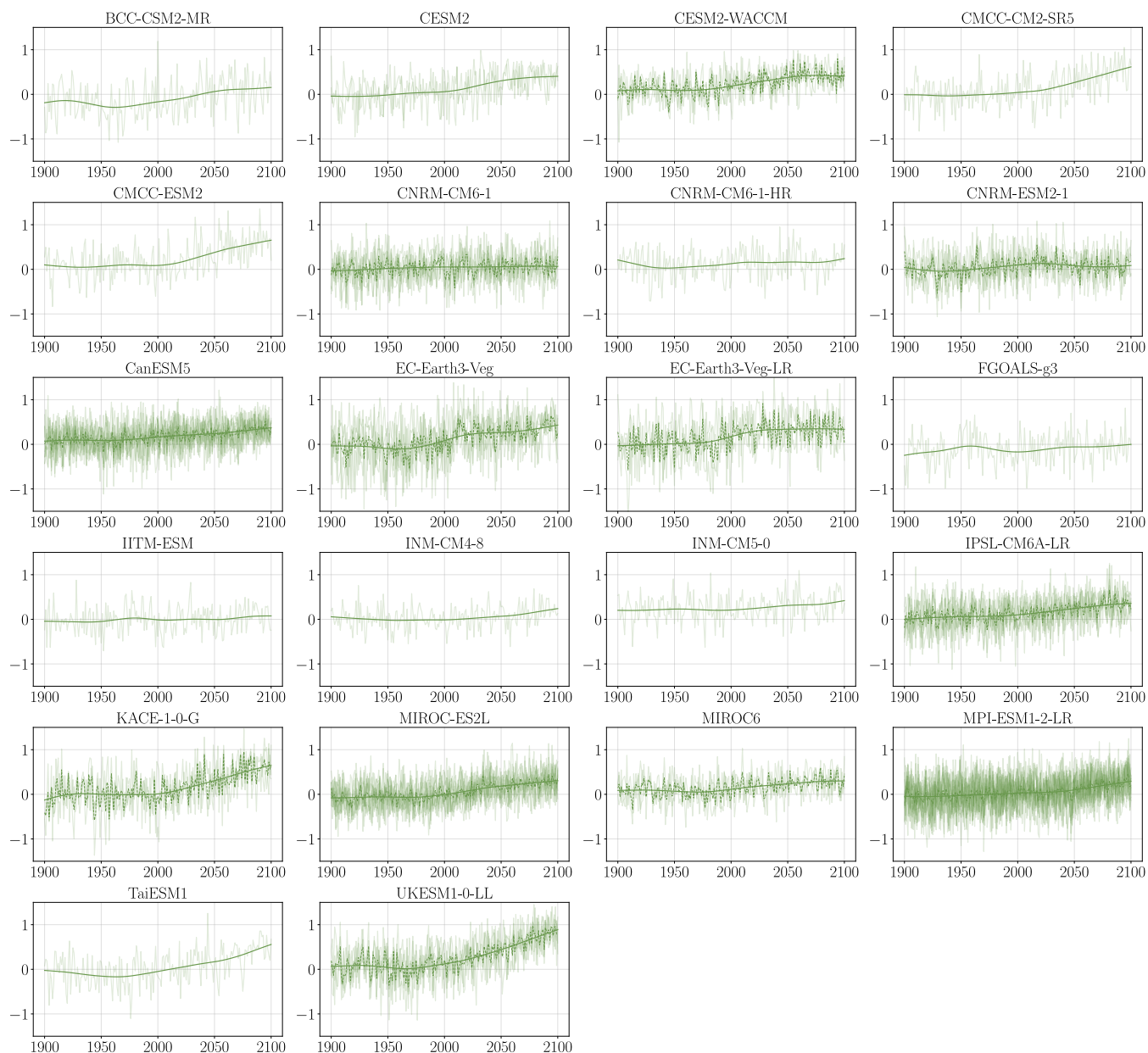


Figure A6. Light time series represent T_{Dyn} for all members of all CMIP6 models. Dotted time series are the ensemble means for models with at least 2 members and the dark time series the estimation of the forced responses with the GAM model.

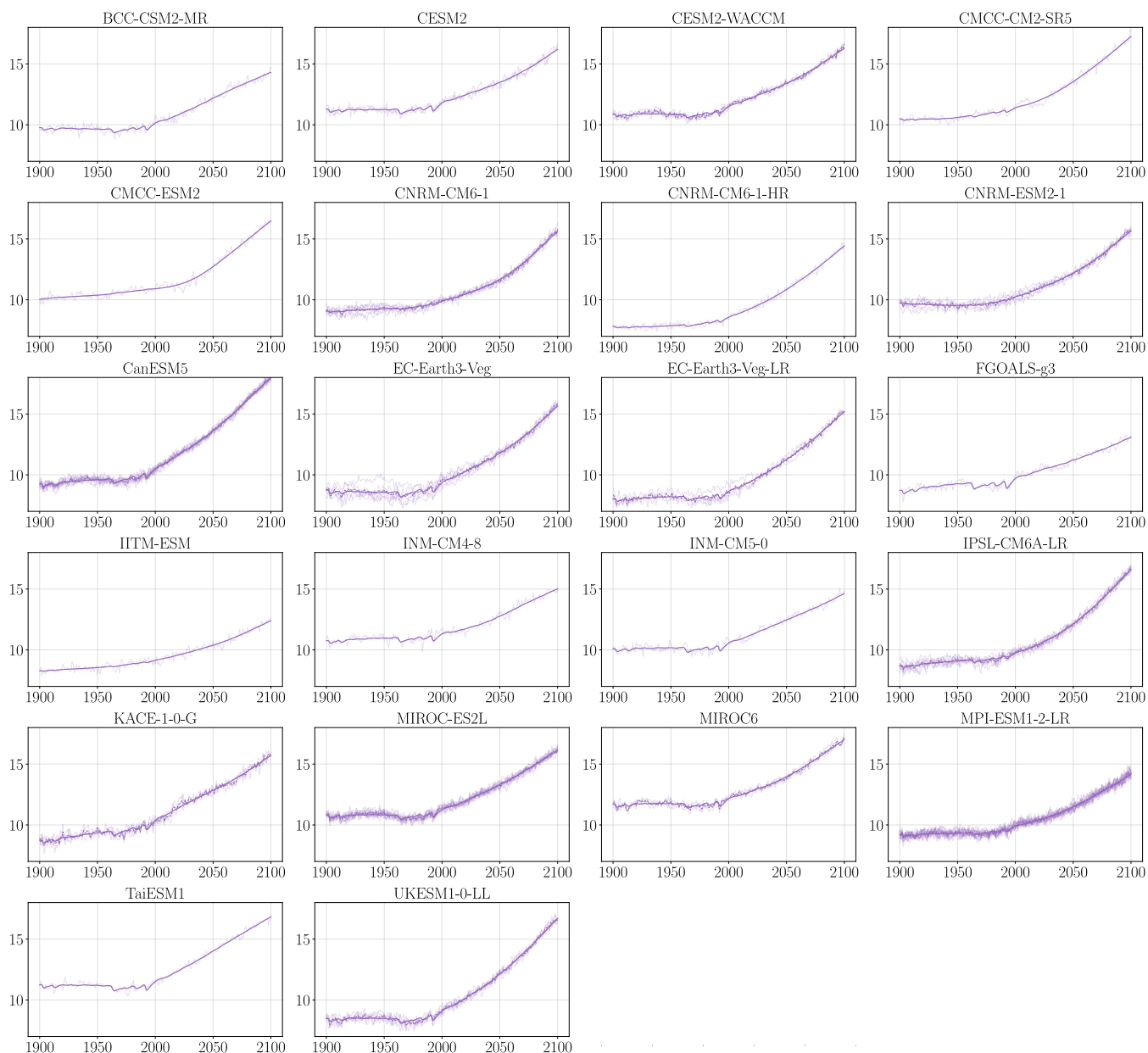


Figure A7. Light times series represent T_{Res} for all members of all CMIP6 models. Dotted times series are the ensemble means for models with at least 2 members and the dark time series the estimation of the forced responses with the GAM model.

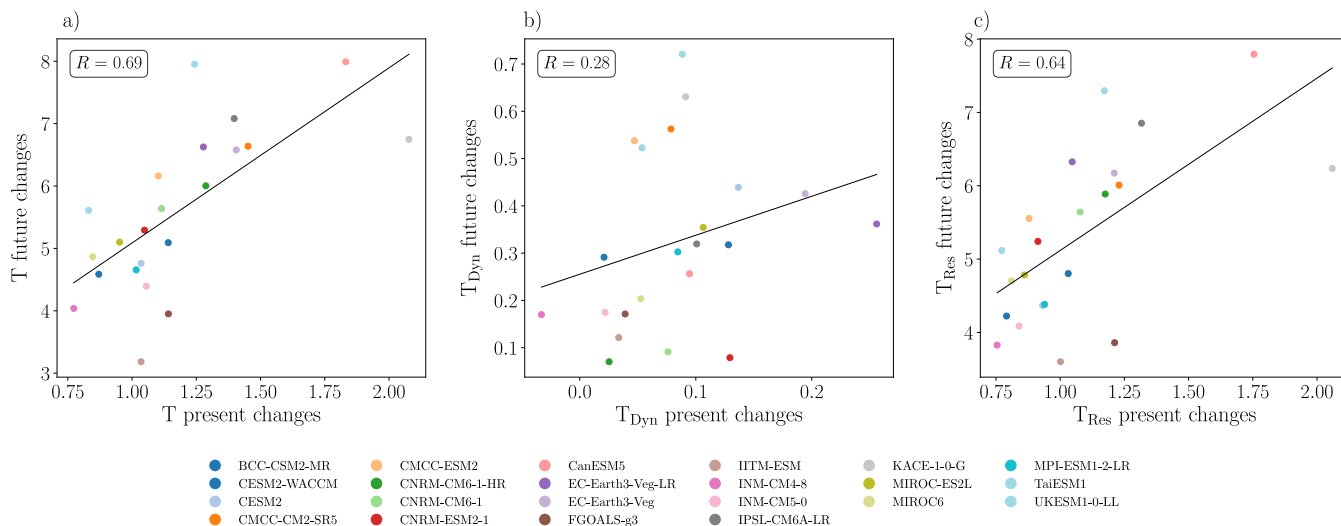


Figure A8. correlations between CMIP6 forced future T anomalies and CMIP6 forced present T anomalies (a). b) same as in a) but with T_{Dyn} and c) same as in a) but with T_{Res} . For each model, present anomaly corresponds to the difference between the mean over the 2000–2020 period and the mean over the 1900–1930 period. Future anomaly is the difference between the mean over the 2080–2100 period and the 1900–1930 period.

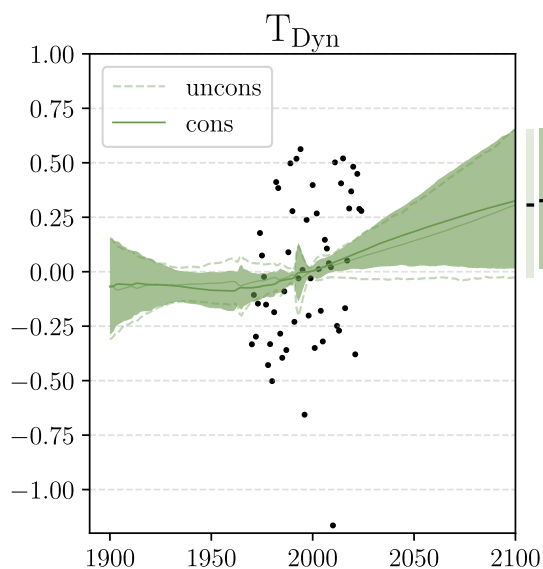


Figure A9. Observational constraints on historical and SSP5-8.5 WEU T_{Dyn} with observed dynamical temperatures only (without GSAT).



Models	Years of piCTL	Number of transient simulations
BCC-CSM2-MR	0	1
CanESM5	1051	10
CESM2	1200	2
CESM2-WACCM	509	3
CMCC-CM2-SR5	500	1
CMCC-ESM2	0	1
CNRM-CM6-1	500	6
CNRM-CM6-1-HR	300	1
CNRM-ESM2-1	500	5
EC-Earth3-Veg	190	5
EC-Earth3-Veg-LR	501	3
FGOALS-g3	0	1
IITM-ESM	200	1
INM-CM4-8	531	1
INM-CM5-0	1201	1
IPSL-CM6A-LR	2000	7
KACE-1-0-G	0	3
MIROC-ES2L	500	10
MIROC6	500	3
MPI-ESM1-2-LR	1000	17
TaiESM1	450	1
UKESM1-0-LL	1100	5

Table A1. List of available CMIP6 models and the associated number of years in their pre-industrial (piCTL) simulations and number of members in the historical and SSP5-8.5 simulations used for this study.



Models	V(T)	V(T _{dyn})	V(T _{res})	Reduction (%)
BCC-CSM2-MR	0.29	0.14	0.05	81
CESM2	0.19	0.09	0.04	80
CESM2-WACCM	0.18	0.09	0.03	83
CMCC-CM2-SR5	0.23	0.11	0.04	83
CMCC-ESM2	0.20	0.11	0.03	83
CNRM-CM6-1	0.18	0.10	0.03	85
CNRM-CM6-1-HR	0.23	0.10	0.04	81
CNRM-ESM2-1	0.18	0.10	0.03	83
CanESM5	0.18	0.09	0.03	85
EC-Earth3-Veg	0.31	0.17	0.04	87
EC-Earth3-Veg-LR	0.31	0.17	0.04	86
FGOALS-g3	0.23	0.11	0.04	82
IITM-ESM	0.46	0.08	0.05	89
INM-CM4-8	0.17	0.06	0.05	73
INM-CM5-0	0.21	0.09	0.04	79
IPSL-CM6A-LR	0.21	0.10	0.03	84
KACE-1-0-G	0.27	0.15	0.08	72
MIROC-ES2L	0.17	0.08	0.04	79
MIROC6	0.16	0.07	0.03	80
MPI-ESM1-2-LR	0.21	0.11	0.04	83
TaiESM1	0.19	0.10	0.03	84
UKESM1-0-LL	0.25	0.12	0.04	82
Mean	0.23	0.11	0.04	82

Table A2. Mean year-to-year variation (V), defined as the average absolute difference between two consecutive years, computed over the 1900–2100 period for each model and for T, T_{Dyn} and T_{Res}, together with the percentage reduction in V resulting from the dynamical adjustment process (computed as $100 \times \frac{V(T) - V(T_{Res})}{V(T)}$). The mean year-to-year variation is used here as a proxy for the variability of the detrended time series. It has the advantage of being directly computed from the raw time series without requiring detrending, assuming that the contribution of the long-term trend to year-to-year changes is negligible (see e.g. Cattiaux et al. (2015)).

Code availability. The codes used to train the UNET on models and to process the constraints with KCC are available on a Github repository

335 <https://doi.org/10.5281/zenodo.22644438>. Results of the constraints can also be found on this repository.



Data availability. Ensemble mean of dynamical and residual estimates on annual average can be found on this Zenodo link <https://doi.org/10.5281/zenodo.22644083>. However we do not provide the daily data used to train the UNET, as well as the daily estimates of T_{Dyn} and T_{Res} , but they can be supplied on request.

Author contributions. EC drew the figures, and all the authors analyzed the results and wrote the article.

340 *Competing interests.* The contact author has declared that none of the authors has any competing interests.



References

- Al-Yaari, A., Swingedouw, D., Braconnot, P., Boyall, L., Lincoln, P., Marti, O., Caley, T., Extier, T., and Martin-Puertas, C.: Multi-centennial internal variability in the North Atlantic could drive additional warming over Europe, *Nat Commun*, 17, 2614, <https://doi.org/10.1038/s41467-026-69209-2>, 2026.
- 345 Blackport, R. and Fyfe, J. C.: Climate models fail to capture strengthening wintertime North Atlantic jet and impacts on Europe, *Science Advances*, 8, eabn3112, <https://doi.org/10.1126/sciadv.abn3112>, 2022.
- Boé, J., Terray, L., Moine, M.-P., Valcke, S., Bellucci, A., Drijfhout, S., Haarsma, R., Lohmann, K., Putrasahan, D. A., Roberts, C., Roberts, M., Scoccimarro, E., Seddon, J., Senan, R., and Wyser, K.: Past long-term summer warming over western Europe in new generation climate models: role of large-scale atmospheric circulation, *Environ. Res. Lett.*, 15, 084 038, <https://doi.org/10.1088/1748-9326/ab8a89>,
350 2020.
- Breul, P., Ceppi, P., Simpson, I. R., and Woollings, T.: Seasonal and regional jet stream changes and drivers, *Nat Rev Earth Environ*, 6, 824–842, <https://doi.org/10.1038/s43017-025-00749-9>, 2025.
- Brunner, L., McSweeney, C., Ballinger, A. P., Befort, D. J., Benassi, M., Booth, B., Coppola, E., Vries, H. d., Harris, G., Hegerl, G. C., Knutti, R., Lenderink, G., Lowe, J., Nogherotto, R., O'Reilly, C., Qasmi, S., Ribes, A., Stocchi, P., and Undorf, S.: Compar-
355 ing Methods to Constrain Future European Climate Projections Using a Consistent Framework, *Journal of Climate*, 33, 8671–8692, <https://doi.org/10.1175/JCLI-D-19-0953.1>, 2020.
- C3S/ECMWF and WMO: European State of the Climate 2025, Tech. rep., Copernicus Climate Change Service (C3S) and World Meteorological Organization (WMO), <https://doi.org/doi.org/10.24381/zy93-sb27>, 2026.
- Cariou, E., Cattiaux, J., Qasmi, S., Ribes, A., Cassou, C., and Doury, A.: Linking European Temperature Variations to Atmospheric
360 Circulation With a Neural Network: A Pilot Study in a Climate Model, *Geophysical Research Letters*, 52, e2024GL113 540, <https://doi.org/10.1029/2024GL113540>, _eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1029/2024GL113540>, 2025.
- Cariou, E., Cattiaux, J., Qasmi, S., and Ribes, A.: Role of the Atmospheric Circulation in the Observed Warming Over Europe Using a Neural Network, *Geophysical Research Letters*, 53, e2026GL121 861, <https://doi.org/10.1029/2026GL121861>, 2026.
- Cattiaux, J., Vautard, R., Cassou, C., Yiou, P., Masson-Delmotte, V., and Codron, F.: Winter 2010 in Europe: A cold
365 extreme in a warming climate, *Geophysical Research Letters*, 37, <https://doi.org/10.1029/2010GL044613>, _eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1029/2010GL044613>, 2010.
- Cattiaux, J., Yiou, P., and Vautard, R.: Dynamics of future seasonal temperature trends and extremes in Europe: a multi-model analysis from CMIP3, *Clim Dyn*, 38, 1949–1964, <https://doi.org/10.1007/s00382-011-1211-1>, 2012.
- Cattiaux, J., Douville, H., Schoetter, R., Parey, S., and Yiou, P.: Projected increase in diurnal and interdiurnal variations
370 of European summer temperatures, *Geophysical Research Letters*, 42, 899–907, <https://doi.org/10.1002/2014GL062531>, _eprint: <https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1002/2014GL062531>, 2015.
- D'Andrea, F., Duvel, J.-P., Rivière, G., Vautard, R., Cassou, C., Cattiaux, J., Coumou, D., Faranda, D., Happé, T., Jézéquel, A., Ribes, A., and Yiou, P.: Summer Deep Depressions Increase Over the Eastern North Atlantic, *Geophysical Research Letters*, 51, e2023GL104 435, <https://doi.org/10.1029/2023GL104435>, _eprint: <https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1029/2023GL104435>, 2024.
- 375 Deser, C. and Phillips, A. S.: A range of outcomes: the combined effects of internal variability and anthropogenic forcing on regional climate trends over Europe, *Nonlinear Processes in Geophysics*, 30, 63–84, <https://doi.org/10.5194/npg-30-63-2023>, 2023.



- Deser, C., Terray, L., and Phillips, A. S.: Forced and Internal Components of Winter Air Temperature Trends over North America during the past 50 Years: Mechanisms and Implications, *Journal of Climate*, 29, 2237–2258, <https://doi.org/10.1175/JCLI-D-15-0304.1>, 2016.
- Dong, B. and Sutton, R. T.: Recent Trends in Summer Atmospheric Circulation in the North Atlantic/European Region: Is There a Role for Anthropogenic Aerosols?, *Journal of Climate*, 34, 6777–6795, <https://doi.org/10.1175/JCLI-D-20-0665.1>, 2021.
- Dong, B. and Sutton, R. T.: Drivers and mechanisms contributing to excess warming in Europe during recent decades, *npj Clim Atmos Sci*, 8, 1–13, <https://doi.org/10.1038/s41612-025-00930-3>, 2025.
- Dorrington, J., Strommen, K., and Fabiano, F.: Quantifying climate model representation of the wintertime Euro-Atlantic circulation using geopotential-jet regimes, *Weather and Climate Dynamics*, 3, 505–533, <https://doi.org/10.5194/wcd-3-505-2022>, 2022.
- Faranda, D., Messori, G., Jezequel, A., Vrac, M., and Yiou, P.: Atmospheric circulation compounds anthropogenic warming and impacts of climate extremes in Europe, *Proceedings of the National Academy of Sciences*, 120, e2214525120, <https://doi.org/10.1073/pnas.2214525120>, 2023.
- Forster, P. M., Walsh, T., Smith, C., Lamb, W. F., Lamboll, R., Cassou, C., Hauser, M., Hausfather, Z., Lee, J.-Y., Palmer, M. D., von Schuckmann, K., Slangen, A. B. A., Szopa, S., Trewin, B., Yun, J., Gillett, N. P., Jenkins, S., Matthews, H. D., Raghavan, K., Ribes, A., Rogelj, J., Rosen, D., Zhang, X., Allen, M., Andrew, R. M., Atkinson, C., Betts, R. A., Bombelli, A., Burgess, S. N., Cheng, L., Claxton, H. E., Friedlingstein, P., Frölicher, T. L., Domingues, C. M., Gasser, T., Gregory, C. H., Hoesly, R. M., Huppmann, D., Ishii, M., Kadow, C., Karwat, A., Kennedy, J., Killick, R. E., Kovilakam, M. V. M., Krummel, P. B., Lan, X., Lamarque, J.-F., Liné, A., Martín-Míguez, B., Monselesan, D. P., Morice, C., Mühle, J., Mussak, P., Peters, G. P., Pirani, A., Pongratz, J., Rigby, M., Rohde, R., Savita, A., Seneviratne, S. I., Smith, S. J., Taha, G., Tassone, C., Thorne, P., Wells, C., Western, L. M., van der Werf, G. R., Wijffels, S. E., Zecchetto, M., Zhong, J., Zhang, X.-Y., Masson-Delmotte, V., and Zhai, P.: Indicators of Global Climate Change 2025: annual update of key indicators of the state of the climate system and human influence, *Earth System Science Data*, 18, 3889–3933, <https://doi.org/10.5194/essd-18-3889-2026>, 2026.
- Geoffroy, O., Saint-Martin, D., Olivié, D. J. L., Voldoire, A., Bellon, G., and Tytéca, S.: Transient Climate Response in a Two-Layer Energy-Balance Model. Part I: Analytical Solution and Parameter Calibration Using CMIP5 AOGCM Experiments, *Journal of Climate*, 26, 1841–1857, <https://doi.org/10.1175/JCLI-D-12-00195.1>, 2013.
- Hu, Y., Zuo, Z., Chen, H., and Hua, W.: Attribution of multidecadal summer temperature variations over Eurasia, *Environ. Res. Lett.*, 20, 054005, <https://doi.org/10.1088/1748-9326/adc293>, 2025.
- Hurrell, J. W., Kushnir, Y., Ottersen, G., and Visbeck, M.: An overview of the North Atlantic Oscillation, in: *Geophysical Monograph Series*, edited by Hurrell, J. W., Kushnir, Y., Ottersen, G., and Visbeck, M., vol. 134, pp. 1–35, American Geophysical Union, Washington, D. C., ISBN 978-0-87590-994-3, <https://doi.org/10.1029/134GM01>, 2003.
- Iles, C. and Hegerl, G.: Role of the North Atlantic Oscillation in decadal temperature trends, *Environ. Res. Lett.*, 12, 114010, <https://doi.org/10.1088/1748-9326/aa9152>, 2017.
- Jézéquel, A., Yiou, P., and Radanovics, S.: Role of circulation in European heatwaves using flow analogues, *Clim Dyn*, 50, 1145–1159, <https://doi.org/10.1007/s00382-017-3667-0>, 2018.
- Lehner, F. and Deser, C.: The Importance of Internal Variability for the Uncertainty in Climate Change Projections and Decision-Making, in: *Uncertainty in Climate Change Research: An Integrated Approach*, edited by Mearns, L. O., Forest, C. E., Fowler, H. J., Lempert, R., and Wilby, R. L., pp. 177–183, Springer Nature Switzerland, Cham, ISBN 978-3-031-85542-9, https://doi.org/10.1007/978-3-031-85542-9_17, 2025.



- Lehner, F., Deser, C., Maher, N., Marotzke, J., Fischer, E. M., Brunner, L., Knutti, R., and Hawkins, E.: Partitioning climate projection
415 uncertainty with multiple large ensembles and CMIP5/6, *Earth System Dynamics*, 11, 491–508, <https://doi.org/10.5194/esd-11-491-2020>,
2020.
- Li, T., Zwiers, F. W., and Zhang, X.: Should we think of observationally constrained multidecade climate projections as predictions?, *Science
Advances*, 11, eadt6485, <https://doi.org/10.1126/sciadv.adt6485>, 2025.
- Morice, C. P., Kennedy, J. J., Rayner, N. A., Winn, J. P., Hogan, E., Killick, R. E., Dunn, R. J. H., Osborn, T. J., Jones, P. D., and Simpson,
420 I. R.: An Updated Assessment of Near-Surface Temperature Change From 1850: The HadCRUT5 Data Set, *Journal of Geophysical
Research: Atmospheres*, 126, e2019JD032361, <https://doi.org/10.1029/2019JD032361>, 2021.
- Noest, D. S., Pinto, I., Thompson, V., and Coumou, D.: The role of atmospheric circulation changes in Western European warm season heat
extremes, *Weather and Climate Dynamics*, 7, 439–452, <https://doi.org/10.5194/wcd-7-439-2026>, 2026.
- O'Neill, B. C., Tebaldi, C., Van Vuuren, D. P., Eyring, V., Friedlingstein, P., Hurtt, G., Knutti, R., Kriegler, E., Lamarque, J.-F., Lowe, J.,
425 Meehl, G. A., Moss, R., Riahi, K., and Sanderson, B. M.: The Scenario Model Intercomparison Project (ScenarioMIP) for CMIP6, *Geosci.
Model Dev.*, 9, 3461–3482, <https://doi.org/10.5194/gmd-9-3461-2016>, 2016.
- Oudar, T., Cattiaux, J., and Douville, H.: Drivers of the Northern Extratropical Eddy-Driven Jet Change in CMIP5 and CMIP6 Models,
Geophysical Research Letters, 47, e2019GL086695, <https://doi.org/10.1029/2019GL086695>, 2020.
- Peings, Y., Cattiaux, J., Vavrus, S. J., and Magnusdottir, G.: Projected squeezing of the wintertime North-Atlantic jet, *Environ. Res. Lett.*, 13,
430 074016, <https://doi.org/10.1088/1748-9326/aacc79>, 2018.
- Pfleiderer, P., Merrifield, A., Dunkl, I., Durand, H., Cariou, E., Cattiaux, J., Camps-Valls, G., and Sippel, S.: Considerable yet contrasting
regional imprint of circulation change on summer temperature trends across the Northern hemisphere mid-latitudes, *Weather and Climate
Dynamics*, 7, 89–108, <https://doi.org/10.5194/wcd-7-89-2026>, 2026.
- Qasmi, S. and Ribes, A.: Reducing uncertainty in local temperature projections, *Science Advances*, 8, eabo6872,
435 <https://doi.org/10.1126/sciadv.abo6872>, 2022.
- Ribes, A., Qasmi, S., and Gillett, N. P.: Making climate projections conditional on historical observations, *Science Advances*, 7, eabc0671,
<https://doi.org/10.1126/sciadv.abc0671>, 2021.
- Ribes, A., Boé, J., Qasmi, S., Dubuisson, B., Douville, H., and Terray, L.: An updated assessment of past and future warming over France
based on a regional observational constraint, *Earth System Dynamics*, 13, 1397–1415, <https://doi.org/10.5194/esd-13-1397-2022>, 2022.
- 440 Rigal, A., Azaïs, J.-M., and Ribes, A.: Estimating daily climatological normals in a changing climate, *Clim Dyn*, 53, 275–286,
<https://doi.org/10.1007/s00382-018-4584-6>, 2019.
- Roldán-Gómez, P. J., Donat, M. G., Marcet-Carbonell, G., and Smith, D. M.: Accelerated European Summer Warming Driven
by Atmospheric Circulation Changes in Response to Aerosol Forcing, *Geophysical Research Letters*, 53, e2026GL122424,
<https://doi.org/10.1029/2026GL122424>, 2026.
- 445 Rousi, E., Kornhuber, K., Beobide-Arsuaga, G., Luo, F., and Coumou, D.: Accelerated western European heatwave trends linked to more-
persistent double jets over Eurasia, *Nat Commun*, 13, 3851, <https://doi.org/10.1038/s41467-022-31432-y>, 2022.
- Saffioti, C., Fischer, E. M., and Knutti, R.: Improved Consistency of Climate Projections over Europe after Accounting for Atmospheric
Circulation Variability, *Journal of Climate*, 30, 7271–7291, <https://doi.org/10.1175/JCLI-D-16-0695.1>, 2017.
- Schumacher, D. L., Singh, J., Hauser, M., Fischer, E. M., Wild, M., and Seneviratne, S. I.: Exacerbated summer European warming not
450 captured by climate models neglecting long-term aerosol changes, *Commun Earth Environ*, 5, 1–14, <https://doi.org/10.1038/s43247-024-01332-8>, 2024.



- Shepherd, T. G.: Atmospheric circulation as a source of uncertainty in climate change projections, *Nature Geosci*, 7, 703–708, <https://doi.org/10.1038/ngeo2253>, 2014.
- 455 Singh, J., Sippel, S., and Fischer, E. M.: Circulation dampened heat extremes intensification over the Midwest USA and amplified over Western Europe, *Commun Earth Environ*, 4, 1–9, <https://doi.org/10.1038/s43247-023-01096-7>, 2023.
- Sippel, S., Meinshausen, N., Merrifield, A., Lehner, F., Pendergrass, A. G., Fischer, E., and Knutti, R.: Uncovering the Forced Climate Response from a Single Ensemble Member Using Statistical Learning, *Journal of Climate*, 32, 5677–5699, <https://doi.org/10.1175/JCLI-D-18-0882.1>, 2019.
- 460 Smoliak, B. V., Wallace, J. M., Lin, P., and Fu, Q.: Dynamical Adjustment of the Northern Hemisphere Surface Air Temperature Field: Methodology and Application to Observations, *Journal of Climate*, 28, 1613–1629, <https://doi.org/10.1175/JCLI-D-14-00111.1>, 2015.
- Soci, C., Hersbach, H., Simmons, A., Poli, P., Bell, B., Berrisford, P., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Radu, R., Schepers, D., Villaume, S., Haimberger, L., Woollen, J., Buontempo, C., and Thépaut, J.-N.: The ERA5 global reanalysis from 1940 to 2022, *Quarterly Journal of the Royal Meteorological Society*, 150, 4014–4048, <https://doi.org/10.1002/qj.4803>, <https://rmets.onlinelibrary.wiley.com/doi/pdf/10.1002/qj.4803>, [_eprint: https://doi.org/10.1002/qj.4803](https://doi.org/10.1002/qj.4803), 2024.
- 465 Terray, L.: A dynamical adjustment perspective on extreme event attribution, *Weather and Climate Dynamics*, 2, 971–989, <https://doi.org/10.5194/wcd-2-971-2021>, 2021.
- Tokarska, K. B., Stolpe, M. B., Sippel, S., Fischer, E. M., Smith, C. J., Lehner, F., and Knutti, R.: Past warming trend constrains future warming in CMIP6 models, *Science Advances*, 6, eaaz9549, <https://doi.org/10.1126/sciadv.aaz9549>, 2020.
- Vautard, R. and Yiou, P.: Control of recent European surface climate change by atmospheric flow, *Geophysical Research Letters*, 36, <https://doi.org/10.1029/2009GL040480>, [_eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1029/2009GL040480](https://onlinelibrary.wiley.com/doi/pdf/10.1029/2009GL040480), 2009.
- 470 Vautard, R., Cattiaux, J., Happé, T., Singh, J., Bonnet, R., Cassou, C., Coumou, D., D’andrea, F., Faranda, D., Fischer, E., Ribes, A., Sippel, S., and Yiou, P.: Heat extremes in Western Europe increasing faster than simulated due to atmospheric circulation trends, *Nature Communications*, 14, 6803, <https://doi.org/10.1038/s41467-023-42143-3>, 2023.