

## Supplementary Information for

# **A traceable global warming record and clarity for the 1.5°C and well-below-2°C goals**

Gottfried Kirchengast<sup>1,2,\*</sup> and Moritz Pichler<sup>1</sup>

<sup>1</sup>Wegener Center for Climate and Global Change, University of Graz, Graz, Austria

<sup>2</sup>Institute of Physics, University of Graz, Graz, Austria

\* Corresponding author. E-mail: [gottfried.kirchengast@uni-graz.at](mailto:gottfried.kirchengast@uni-graz.at)

### **This PDF file includes:**

Supplementary Methods (Pages S2–S8)

Supplementary References (Page S9)

## Supplementary Methods

### MW-EOT smoothing algorithm for computing decadal mean records and trend rates

The moving-window ensemble-of-trendlines (MW-EOT) algorithm was developed as part of the Graz Climate Change Indicators|ClimateTracer.Earth project<sup>1</sup> for serving the climate-warming-monitoring class (GCCCI-CWM) of global warming indicators (<https://gccci.uni-graz.at/cwm>). These GCCCI-CWM indicators range from greenhouse gas concentration and radiative forcing variables via Earth energy uptake and imbalance variables to the global surface temperature (GST) change variables which are in the focus of this study. Without loss of generality, we hence describe the algorithm here as applied to GST; that is, to either the global surface air temperature (GSAT) or global mean surface temperature (GMST) data.

The MW-EOT algorithm is used in this context to compute decadal-mean timeseries from annual anomaly data of the GST variables. It consistently co-computes also the related GST trend rates and the corresponding uncertainty estimates for both the mean and trend rates. In addition, it includes a capacity for trend-rate extrapolation that can also be used to obtain decadal-mean projections beyond the last observational year (used up to 2034 in this study). Based on the EOT filter (see next subsection), we designed the algorithm to furnish a separation of “long-term change signal” (20-year-mean in this study) and “delta signal” (the residual signal between annual data and 20-year-mean) that is as clean as possible for a given (limited) window width and incurs minimal boundary effects in the margin years near start and end of the timeseries. Sensitivity tests of the EOT filter against standard filters, from moving boxcar averaging to more elaborated smoothers such as weighted-averaging, Savitzky-Golay and LO(W)ESS filters<sup>2–6</sup>, verified its strong performance for isolating “climate change” from “interannual variability” for a given averaging period (e.g., 20 years).

The algorithm uses annual-mean anomaly timeseries and the associated standard uncertainty estimates as input data and works in an identical manner for GMST and GSAT (and any other similar anomaly variable); we generically refer to GST here, denoting any of these variables. Also, for brevity and simplicity of the terminology used below, the moving-window center (or core) years are termed ‘CY’, the window widths ‘WW’, the input data ‘GST observations’, the resulting 20-year-mean GST change ‘GST mean’, the corresponding GST trend rate ‘GST derivative’, the GST trend rate change ‘GST curvature’; the related standard uncertainty (SU) estimates are often just termed ‘uncertainty’ (with 90% CI equal to 1.645·SU), and the in-quadrature (r.m.s.) combination of SUs is phrased through ‘r.m.s.-combine’.

### **Ensemble-of-trendlines (EOT) filtering**

The EOT filter, serving as key tool of the MW-EOT algorithm, was deployed in this study as a moving-window smoother with a core WW of 20 years and a  $\pm 15\%$  WW range of 17-23 years about the core WW, for obtaining at every CY an ensemble of trendline fits through ordinary-least-squares (OLS) fitting (see the Methods section of the main paper, subsection “Computing the 20-year-mean GST records and trend rates”, for detailed settings). As basic part of the filtering, each individual OLS trendline fit (ensemble member) yields a slope and intercept value together with the related uncertainty estimates, all attributed to the CY. The intercept value expresses a GST mean, the slope a GST derivative, and the uncertainties derive from the interannual variability (main contribution) and observational uncertainties in the GST observations within the adopted smoother-WWs (at and near 20 years in this study). The ensemble-mean based on the individual trendline fits is computed as arithmetic mean for the GST mean and derivative values and as r.m.s. of the variances for the uncertainty estimates, respectively. In this way, the filter delivers, at every CY, reliable estimates of the GST mean and derivative as well as of their uncertainty.

The EOT settings finally adopted for this study were found most suitable for the purpose based on careful and comprehensive sensitivity tests. We tested, among other detailed aspects, the WW range options within a reasonable maximum of  $\pm 20\%$  WW | nine members and just W20 | one member (the latter essentially mimicking a boxcar filter); the reliability of the mean OLS uncertainty estimates under a wide diversity of annual anomaly input data; and the dominance of these estimated uncertainties over the r.m.s. spread of individual-fit GST mean or derivative values about the ensemble-mean GST mean or derivative.

The EOT filter also robustly deals with boundary effects in the margin years near start and end of a timeseries. CYs where the core-WW years  $CY \pm WW/2$  fully fit within the timeseries length form the CYs core domain (e.g., 1860 to 2013 within 1850 to 2023). This domain is complemented by the near-margin years, where the widths  $CY \pm WW/2$  of the trendlines ensemble (partially) exceed the start or end year of the GST observations (e.g., in 2014-2023 for observations to a marginal year 2023). For these years, the EOT filter takes the marginal year as a “hard boundary” for the windowing, i.e., it applies the smoother-WWs from the marginal year inwards so that any such near-margin CY actually is a non-central “core year” rather than a “center year”. Nevertheless, because the ensemble-mean of any ensemble of trendlines is again a trendline, with average intercept and slope, the filter result along the CYs

towards a marginal year is always a meaningful smooth transition to a linear mean and constant trend rate behavior.

In the case of the GST observations of this study, we hence adopt 1860-2013 as the CYs core domain, while 1850-1859 and 2014-2023 are the near-margin years. As a technical detail we note that by this definition we as well count the year 1860|2013 itself as core domain CY, though not all smoother-WWs of the 17-23 years range entirely match the timeseries length. This is reasonable, since we found the EOT results negligibly affected by only the W22 and W23 fits being forced for CY 1860|2013 to use the margin range 1850-1872|2001-2023 instead of the nominal range 1849-1871|2002-2024. We therefore adopt the CY mean and trend rate results up to 2013 as they are, while we include a separate extension approach over 2014 to 2034. The latter is based on linear trend-rate extrapolation to 2019 followed by a gradual transition to a constant trend rate from 2024; the details to this end are described as part of the following subsection on algorithmic steps.

### **MW-EOT algorithmic steps**

Building on the EOT filtering method and based on the GST observations ( $X_n$ ) and associated standard uncertainties ( $SU_{Xn}$ ), spanning over 1850 to 2023 (years  $n$ ) in this study, the MW-EOT smoothing algorithm comprises the following steps (the equations quoted are always listed below the step's description):

**1)** Apply the EOT filter  $F_{EOT}^{CY}[\cdot]$  to the GST observations  $X_n$  across CY1850 to CY2023 (years  $CYn$ ) to obtain the GST mean and mean uncertainty output,  $\bar{X}_n^{EOT}$  and  $SU_{\bar{X}_n}^{EOT}$ , over this time period (Eq. 1);

then r.m.s.-combine the mean uncertainty  $SU_{\bar{X}_n}^{EOT}$  (mainly from interannual variability) with the observational uncertainty of the input data  $SU_{Xn}$  (conservatively assumed to be of bias-type character across a window-width and uncorrelated with  $SU_{\bar{X}_n}^{EOT}$ , hence fully adding its variance to the EOT mean variance) to obtain the total mean uncertainty  $SU_{\bar{X}_n}^{CYt}$  (Eq. 2);

then smooth both the GST mean and total mean uncertainty on top by a standard  $CY \pm 2$  years moving boxcar filter  $F_{MBC}^{CY}[\cdot]$  (over CY1852-CY2021; also the further margin-year values are smooth, by construction, and assigned as are), for safely “polishing off” any possible remaining jitter noise (Eq. 3), and keep the resulting GST mean and mean uncertainty,  $\bar{X}_n^{CY}$  and  $SU_{\bar{X}_n}^{CY}$ , for further use in steps 2 and 7;

moreover, keep the EOT filter's GST derivative output  $\overline{DX}_n^{\text{EOT}}$  (Eq. 1) for optional use (e.g., in testing) and the derivative uncertainty output  $SU_{\overline{DX}_n}^{\text{EOT}}$  (Eq. 1) for further use in step 4.

$$F_{\text{EOT}}^{\text{CY}}[X_n] \text{ for } \forall \text{ CY}_n \xrightarrow{\text{yields}} \{ \overline{X}_n^{\text{EOT}}, SU_{\overline{X}_n}^{\text{EOT}} \mid \overline{DX}_n^{\text{EOT}}, SU_{\overline{DX}_n}^{\text{EOT}} \} \quad (1)$$

$$SU_{\overline{X}_n}^{\text{CYt}} = \text{SqRt} \left[ (SU_{\overline{X}_n}^{\text{EOT}})^2 + (SU_{X_n})^2 \right] \quad (2)$$

$$F_{\text{MBC}}^{\text{CY}}[\overline{X}_n^{\text{EOT}}] \text{ and } F_{\text{MBC}}^{\text{CY}}[SU_{\overline{X}_n}^{\text{CYt}}] \text{ for } \forall \text{ CY}_n \xrightarrow{\text{yields}} \{ \overline{X}_n^{\text{CY}}, SU_{\overline{X}_n}^{\text{CY}} \} \quad (3)$$

**2)** Building on the GST mean time series of step 1,  $\overline{X}_n^{\text{CY}}$ , compute a smooth 20-year-mean GST derivative across the core domain portion CY1960 to CY2013 (years  $nCD$ ) via a moving 21-year-window trendline fit  $F_{\text{MWT}}^{\text{CY}}[\cdot]$  (W20 window; outermost  $\text{CY} \pm 10$  years half-weighted) and adopt the slope values as the resulting GST derivative time series  $\overline{DX}_{nCD}^{\text{MWT}}$  over the core domain (Eq. 4), for further use in steps 3 and 6.

$$F_{\text{MWT}}^{\text{CY}}[\overline{X}_n^{\text{CY}}] \text{ for } \forall nCD \xrightarrow{\text{yields}} \{ \overline{DX}_{nCD}^{\text{MWT}} \} \quad (4)$$

**3)** Using the GST derivative time series  $\overline{DX}_{nCD}^{\text{MWT}}$  of step 2 back from the core domain end-year CY2013 ( $nEndCD$ ) to 1993 across 20 years (i.e., one W20 window width back), compute the 20-year-mean annual GST curvature  $\overline{CX}_{\text{EndCD.W20}}^{\text{ymean}}$  over 1994 to 2013 by averaging the GST derivative changes vs. previous year of the twenty individual CYs (Eq. 5); then use this mean annual curvature  $\overline{CX}_{\text{EndCD.W20}}^{\text{ymean}}$  in cumulative addition along 2014 to 2019, to linearly extrapolate the derivative time series  $\overline{DX}_{nCD}^{\text{MWT}}$  from CY2013 ( $nEndCD$ ) to CY2019 ( $nStartFT$ , from where on flatter trends are then modeled), yielding  $\overline{DX}_{nCDExt}^{\text{MWT}}$  (Eq. 6); afterwards also apply here a  $\text{CY} \pm 2$  years jitter-noise filter over CY1962-CY2017 ( $F_{\text{MBC}}^{\text{CY}}[\cdot]$ ; applied as done so in step 1 for the mean and its uncertainty, for a safely smooth result), yielding the final linearly extended GST derivative time series  $\overline{DX}_{nCDExt}^{\text{CY}}$  up to CY2019 (Eq. 7), for further use in step 5.

This extrapolation from 2013 to 2019 is by construction consistent with the mean trend rate change during the two decades before and also physically plausible in light of the recent GHG emissions that generally maintained a similar increase up to 2019 as they did since the early 1990s (see Fig. 1c,d in the main paper).

$$\overline{CX}_{\text{EndCD.W20}}^{\text{ymean}} = \frac{1}{20} \sum_{nEndCD-20+1}^{nEndCD} (\overline{DX}_n^{\text{MWT}} - \overline{DX}_{n-1}^{\text{MWT}}) \quad (5)$$

$$\overline{DX}_{nCDExt}^{MWT} = \left\{ \overline{DX}_{nCD}^{MWT} \text{ for } \forall nCD, [\overline{DX}_{n-1}^{MWT} + \overline{CX}_{EndCD.W20}^{ymean}]_{nEndCD+1}^{nStartFT} \right\} \quad (6)$$

$$F_{MBC}^{CY}[\overline{DX}_{nCDExt}^{MWT}] \text{ for } \forall nCDExt \xrightarrow{\text{yields}} \{ \overline{DX}_{nCDExt}^{CY} \} \quad (7)$$

**4)** Compute the uncertainty estimate  $SU_{\overline{DX}nCD}^{CYt}$  (Eq. 8) for the GST derivative timeseries  $\overline{DX}_{nCDExt}^{CY}$  of step 3 over CY1960 to CY2013 (years  $nCD$ ) by r.m.s.-combining the step-1 GST derivative uncertainty output  $SU_{\overline{DX}n}^{EOT}$  (Eq. 1; mainly induced by interannual variability, the main driver of the trend rate uncertainty) with the observational GST derivative uncertainty  $SU_{DXn}$ ; the latter is conservatively assumed proportional to the bias-type observational uncertainty of the GST input data  $SU_{Xn}$  via the ratio of the GST derivative to the mean (i.e.,  $SU_{DXn} = |\overline{DX}_n / \bar{X}_n| \cdot SU_{Xn}$ , safeguarded for small  $\bar{X}_n$  in early CYs to  $SU_{DXn} \leq 0.25 \cdot |\overline{DX}_n|$ ); then extend this uncertainty estimate by using the core domain end-year estimate  $SU_{\overline{DX}nEndCD}^{CYt}$  also for the years until  $nStartFT$  to obtain  $SU_{\overline{DX}nCDExt}^{CYt}$  fully up to CY2019 (Eq. 9); afterwards apply also on this output a routine  $CY \pm 2$  years jitter-noise filter over CY1962-CY2017 ( $F_{MBC}^{CY}[\cdot]$ ; as in steps 1 and 3), and keep the resulting GST derivative uncertainty  $SU_{\overline{DX}nCDExt}^{CY}$  (Eq. 10) for further use in step 6.

$$SU_{\overline{DX}nCD}^{CYt} = \text{SqRt} \left[ (SU_{\overline{DX}n}^{EOT})^2 + (SU_{DXn})^2 \right] \quad (8)$$

$$SU_{\overline{DX}nCDExt}^{CYt} = \left\{ SU_{\overline{DX}nCD}^{CYt} \text{ for } \forall nCD, [SU_{\overline{DX}nEndCD}^{CYt}]_{nEndCD+1}^{nStartFT} \right\} \quad (9)$$

$$F_{MBC}^{CY}[SU_{\overline{DX}nCDExt}^{CYt}] \text{ for } \forall nCDExt \xrightarrow{\text{yields}} \{ SU_{\overline{DX}nCDExt}^{CY} \} \quad (10)$$

**5)** Further extrapolate and in this way complete the GST derivative timeseries  $\overline{DX}_{nCDExt}^{CY}$  of step 3 from CY2019 ( $nStartFT$ ) to CY2034 ( $nEnd$ , end year of the projection) via gradually transitioning, within five years, from the annual mean curvature used over 2013 to 2019 ( $\overline{CX}_{EndCD.W20}^{ymean}$ ) to zero-curvature as of 2024 (using half-cosine-downweighting of the curvature adds along 2020 to 2024, i.e., weights  $w_n^{CX}$  of 0.933, 0.75, 0.5., 0.25, 0.067 to  $\overline{CX}_{EndCD.W20}^{ymean}$ ), and afterwards maintain the derivative as a constant (i.e.,  $w_n^{CX} = 0$  for 2025-2034), yielding the final GST derivative timeseries  $\overline{DX}_n^{CY}$  over CY1960 to CY2034 (Eq. 11).

This is consistent with assuming a constant GST trend rate achieved towards the mid-2020s.

It is in this way a physically plausible estimate, which reflects a GHG emissions pathway

from 2025 to 2034 that exhibits a similar emission level as in the decade before from 2015 to 2024 (see Fig. 1c,d in the main paper).

$$\overline{DX}_n^{CY} = \left\{ \overline{DX}_{nCDExt}^{CY} \text{ for } \forall nCDExt, \left[ \overline{DX}_{n-1}^{CY} + w_n^{CX} \cdot \overline{CX}_{EndCD.W20}^{ymean} \right]_{nStartFT+1}^{nEnd} \right\} \quad (11)$$

**6)** Using the GST derivative timeseries  $\overline{DX}_{nCD}^{MWT}$  of step 2 back from 2013 ( $nEndCD$ ) to 1971 ( $nStartCX$ , the year from which on  $\overline{DX}_{nCD}^{MWT}$  is considered reliable for the purpose) across more than four decades of GST change, compute the standard deviation of the annual GST curvature values over 1972 to 2013,  $\overline{CX}_{CD1971+}^{ysdev}$  (relative to  $\overline{CX}_{CD1971+}^{ymean}$  that is computed in the same way as  $\overline{CX}_{EndCD.W20}^{ymean}$  in step 3) (Eq. 12);

then use the curvature standard deviation  $\overline{CX}_{CD1971+}^{ysdev}$  in cumulative addition along 2014 ( $nEndCD+1$ ) to 2034 ( $nEnd$ ) to conservatively estimate a (systematically increasing) GST derivative extrapolation uncertainty  $SU_{DXnExt}^{CY}$  along this extrapolation range (Eq. 13); subsequently r.m.s.-combine the extrapolation uncertainty  $SU_{DXnExt}^{CY}$  from 2014 to 2034 with the GST derivative uncertainty  $SU_{DXnEndCD}^{CY}$  of the last core domain year CY2013, in order to complete in this way the derivative uncertainty timeseries  $SU_{DXnCD}^{CY}$  over CY1960-CY2013 (available as part of  $SU_{DXnCDExt}^{CY}$  from step 4, Eq. 10) by this extension to CY2034, yielding the final GST derivative uncertainty timeseries  $SU_{DXn}^{CY}$  over CY1960 to CY2034 (Eq. 14).

$$\overline{CX}_{CD1971+}^{ysdev} = \text{SqRt} \left[ \frac{1}{nEndCD - nStartCX - 1} \sum_{nStartCX+1}^{nEndCD} \left( (\overline{DX}_n^{MWT} - \overline{DX}_{n-1}^{MWT}) - \overline{CX}_{CD1971+}^{ymean} \right)^2 \right] \quad (12)$$

$$SU_{DXnExt}^{CY} = \left[ SU_{DXnExt-1}^{CY} + \overline{CX}_{CD1971+}^{ysdev} \right]_{nEndCD+1}^{nEnd} \quad (\text{initial } SU_{DXnExt-1}^{CY} = 0) \quad (13)$$

$$SU_{DXn}^{CY} = \left\{ SU_{DXnCD}^{CY} \text{ for } \forall nCD, \left[ \text{SqRt} \left[ (SU_{DXnEndCD}^{CY})^2 + (SU_{DXnExt}^{CY})^2 \right] \right]_{nEndCD+1}^{nEnd} \right\} \quad (14)$$

**7)** For finally completing the GST mean timeseries available from step 1,  $\overline{X}_n^{CY}$ , adopt it as is from CY1850 to the last core domain year CY2013 and extend it along the derivatives extrapolation range from CY2014 ( $nEndCD+1$ ) to CY2034 ( $nEnd$ ) by cumulative addition of the (mid-point) GST derivatives from step 5 ( $\overline{DX}_n^{CY}$ ) to the CY2013 GST mean  $\overline{X}_{nEndCD}^{CY}$ , ensuring in this way strict consistency of the final GST mean timeseries  $\overline{X}_n^{CY}$  with the GST derivatives timeseries in the extrapolation domain up to 2034 (Eq. 15); in addition, towards completing the GST mean uncertainty time series of step 1,  $SU_{Xn}^{CY}$ , perform

a similar cumulative addition over the GST derivative extrapolation uncertainties  $SU_{\overline{DX}nExt}^{CY}$  of step 6 from CY2014 to CY2034 as done in that step over the annual GST curvature standard deviation (Eq. 13), for obtaining a consistent GST mean extrapolation uncertainty  $SU_{\overline{X}nExt}^{CY}$  along this extrapolation range (Eq. 16);

finally, r.m.s.-combine this extrapolation uncertainty  $SU_{\overline{X}nExt}^{CY}$  from 2014 to 2034 with the GST mean uncertainty  $SU_{\overline{X}nEndCD}^{CY}$  of the last core domain year CY2013, in order to complete in this way the GST mean uncertainty time series  $SU_{\overline{X}n}^{CY}$  over CY1850-CY2013 available from step 1 by this extension to CY2034, yielding the final GST mean uncertainty timeseries  $SU_{\overline{X}n}^{CY}$  over CY1850 to CY2034 (Eq. 17).

$$\overline{X}_n^{CY} = \left\{ \overline{X}_n^{CY} \text{ for } n \leq nEndCD, \left[ \overline{X}_{n-1}^{CY} + \frac{1}{2} (\overline{DX}_{n-1}^{CY} + \overline{DX}_n^{CY}) \right]_{nEndCD+1}^{nEnd} \right\} \quad (15)$$

$$SU_{\overline{X}nExt}^{CY} = [SU_{\overline{X}nExt-1}^{CY} + SU_{\overline{DX}nExt}^{CY}]_{nEndCD+1}^{nEnd} \quad (\text{initial } SU_{\overline{X}nExt-1}^{CY} = 0) \quad (16)$$

$$SU_{\overline{X}n}^{CY} = \left\{ SU_{\overline{X}n}^{CY} \text{ for } n \leq nEndCD, \left[ \text{SqRt} \left[ (SU_{\overline{X}nEndCD}^{CY})^2 + (SU_{\overline{X}nExt}^{CY})^2 \right] \right]_{nEndCD+1}^{nEnd} \right\} \quad (17)$$

### Detailed specification and Python code

A detailed specification of the whole MW-EOT smoothing algorithm is contained in the documentation file of the Python 3 code that implements the algorithm (for access information see the Code availability section in the main paper).

This current code implementation, used for the GST variables and for all other GCCI-CWM indicator variables of the GCCI|ClimateTracer.Earth data portal<sup>1</sup> (current version GCCIV2.3), was tailored to compute decadal means and trend rates, including projections, based on annual anomaly input data defined relative to preindustrial or other reference levels before 1990.

These input timeseries were well quality-controlled before algorithm insertion (no outliers, no missing values, reasonable long-term homogeneity, plausible uncertainty estimates), i.e., the current implementation assumes such a reliable input data quality.

While the MW-EOT algorithm nevertheless is applicable to any reasonable time series, like any other existing smoothing algorithm (e.g., refs 2–6), we hence caution that application of the current code to other types of time series needs due care in the preparation of the input datasets and possibly some adjustments and fine-tunings.

## Supplementary References

1. Kirchengast, G. & Pichler, M. Graz Climate Change Indicators: A data portal backing climate narratives towards reaching the Paris climate goals. EGU General Assembly 2024, Vienna, Austria. Abstract at EGU sphere <https://doi.org/10.5194/egusphere-egu24-12998> (2024).
2. Smith, S. W. Digital Filters. in *The Scientist and Engineer's Guide to Digital Signal Processing – Second Edition* (Smith, S. W.) 261–350 (California Technical Publishing, 1999).
3. Schwarz, J., Kirchengast, G. & Schwaerz, M. Integrating uncertainty propagation in GNSS radio occultation retrieval: from excess phase to atmospheric bending angle profiles. *Atmos. Meas. Tech.* **11**, 2601–2631 (2018).
4. Martinson, D. G. Filtering and Deconvolution. in *Quantitative Methods of Data Analysis for the Physical Sciences and Engineering* (Martinson, D. G.) 425–455 (Cambridge Univ. Press, 2018).
5. Haslwanter, T. Data Filtering. in *Hands-on Signal Analysis with Python* (Haslwanter, T.) 71–104 (Springer Cham, 2021).
6. MATLAB Help Center – Curve Fitting Toolbox – Filtering and Smoothing Data. Online at <https://www.mathworks.com/help/curvefit/smoothing-data.html> (2024).

– end of document –