Investigating the differences in calculating global mean surface CO₂ abundance: the impact of analysis methodologies and site selection

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Abstract. The World Meteorological Organization (WMO) Global Atmosphere Watch (GAW) coordinates high-quality atmospheric greenhouse gas observations globally and provides these observations through the WMO World Data Centre for Greenhouse Gases (WDCGG) supported by Japan Meteorological Agency. The WDCGG and the National Oceanic and Atmospheric Administration (NOAA) analyse these measurements using different methodologies and site selection to calculate global annual mean surface CO₂ and its growth rate as a headline climate indicator. This study introduces a third hybrid method named semi-NOAA GFIT, which serves as an independent validation and open-source alternative to the methods described by NOAA and WDCGG. We apply the semi-NOAA GFIT to incorporate observations from most WMO GAW stations and 3D modelled CO₂ fields from CarbonTracker Europe (CTE). We find that different observational networks (i.e., the NOAA, GAW, and CTE networks) and analysis methods result in differences in the calculated global surface CO₂ mole fractions equivalent to the current atmospheric growth rate over a three-month period. However, the CO₂ growth rate derived from these networks and CTE model output shows good agreement. Over the long-term period (40 years), both networks with and without continental sites exhibit the same trend in the growth rate (0.030 ± 0.002 ppm per year each year). However, a clear difference emerges in the short-term (one-month) change in the growth rate. The network that includes continental sites improves the early detection of changes in biogenic emissions.

1 Introduction

Global mean surface temperature averaged over 2011-2020 has increased by about 1.09°C relative to the average temperature of 1850–1900 (Gulev et al., 2021). The increasing amount of atmospheric carbon dioxide (CO₂), together with increases in other greenhouse gases, is the main driver of the warming (Eyring et al., 2021). After being relatively stable between 180 ppm
(ice age) and 280 ppm (interglacial) for the last 800,000 years (Lüthi et al., 2008), the annual average CO₂ level of the atmosphere has increased since the industrial revolution from roughly 277 ppm in 1750 to 415.7±0.2 ppm in 2021 (WMO, 2022), due to emissions of CO₂ related to human activities like burning of fossil fuels and land use changes (Friedlingstein et al., 2022). Mean global atmospheric CO₂ annual growth rate ($G_{\text{ATM}}$) is an important constraint on the global carbon cycle. Based on the most recent Global Carbon Budget (GCB) analysis (Friedlingstein et al., 2022), the total emission of CO₂ due to human activities was 10.2 ± 0.8 GtC yr⁻¹ in 2020, of which 3.0 ± 0.4 GtC yr⁻¹ was captured by the ocean sink and 2.9 ± 1 GtC yr⁻¹ by the terrestrial sink, leaving a net increase of 5.0 ± 0.2 GtC yr⁻¹ of CO₂ in the atmosphere, corresponding to an atmospheric CO₂ mole fraction increase of 2.4 ± 0.1 ppm yr⁻¹ (the conversion factor comes from Ballantyne et al. (2012)).

As the atmosphere mixes the contributions of all sources and sinks, an observational global average CO₂ mole fraction can be constructed if there are enough observations to represent the spatial and temporal variation across the globe. Since most land masses are concentrated in the Northern Hemisphere, and the highest anthropogenic emissions (e.g. during winter) occur in the relatively narrow latitudinal band between 30°N and 60°N, relatively large spatial and temporal gradients in CO₂ mole fraction exist in and around that region. Due to convective and advective mixing, the average mixing time of air within the same latitudinal bands varies from several weeks to a month. However, mixing between latitudinal bands is slower, especially the exchange between the northern and southern hemispheres, which has an approximate interhemispheric transport time of 1.4 ± 0.2 years (Patra et al., 2011). The interplay of the latitudinal and interhemispheric differences in fossil fuel emissions and seasonal exchange with land biota (Demming et al., 1995) creates a latitudinal and interhemispheric gradient that requires a sufficiently dense network to capture a representative global annual mean.

However, measurement stations that are close to sources or sinks may not be representative of a large atmospheric volume and the average signal at their latitude. Therefore, inclusion of these observations might introduce systematic biases on the global mean CO₂ and its growth rate. These biases can be avoided by filtering of data and a careful selection of spatially representative stations, as done by NOAA in their use of 43 stations (Fig. 1) that are considered to be representative for the Marine Boundary Layer (MBL reference network, https://www.esrl.noaa.gov/gmd/ccgg/mbl/mbl.html). An additional data processing step developed by NOAA to further avoid biases due to unrepresentative local signals is filtering and smoothing, by using a combination of a low pass filter and decomposition into a fitted long-term trend and seasonal cycle (Thorning et al., 1989), hereafter referred to as the NOAA analysis. These fits can also be used to fill gaps for missing data, though care must be taken to avoid extrapolation errors before and beyond the time covered by the data record of the station. The WMO Global Atmosphere Watch (GAW) World Data Centre for Greenhouse Gases (WDCGG) publishes global averages mole fraction for CO₂ and the other major greenhouse gases in the annual WMO GAW Greenhouse Gas Bulletin (latest version: WMO, 2022). They use curve fitting and filter methods that are very similar to those developed by NOAA, but WDCGG includes continental locations that are potentially more influenced by local sources and sinks (Tsutsumi et al., 2009).

The NOAA MBL observations are all part of the NOAA cooperative global air sampling network and analysed in the same laboratory. All NOAA flask-air observations are traceable to the current WMO X2019 CO₂ scale that is maintained by NOAA Global Monitoring Laboratory (GML). In contrast, the WDCGG data originate from multiple independent laboratories (including NOAA GML), that together form a network of hundreds of stations coordinated by WMO GAW (http://gaw.is.u-tokyo.ac.jp). Having a multitude of independent laboratories carries an additional risk of biases due to differences in sampling, measurement, and analysis methods, for example calibration scales, although much care is taken to avoid these by coordination in the network and use of a common calibration scale from the WMO Central Calibration Laboratory (CCL) guided by a set of strict measurement compatibility goals (WMO, 2022). The different selection of stations results in a larger seasonal cycle amplitude in WDCGG results compared to those of NOAA and a small but quite consistent bias in global surface annual mean CO₂ mole fraction (Tsutsumi et al., 2009). The NOAA estimate of global surface annual mean CO₂ mole fraction is expected to be negatively biased lower (e.g. ~0.35 ppm lower than the WDCGG estimate,
Tsutsumi et al., 2009) compared to a full global surface average because areas with large sources are not represented. However, none of the two afore-mentioned approaches neither represents these parts of the atmosphere with low CO$_2$ mole fraction levels (i.e., the full troposphere, up to ~8-15 km altitude, and the stratosphere) nor do they cover the regions of the world with substantial observational gaps.

In this paper, we propose a data integration method to estimate the global mean surface CO$_2$ and its growth rate, named semi-NOAA-GFIT. This method serves as an independent validation of the methods as described by NOAA and WDCGG through a completely independent and open-source implementation. The global mean surface CO$_2$ refers to the mean CO$_2$ mole fraction within the planetary boundary layer, which extends from the Earth’s surface up to a few hundred or thousand meters in height. We apply the semi-NOAA-GFIT methodology to incorporate CO$_2$ data from the GAW network (139 stations, Fig. 1) and the modelled CO$_2$ distribution from a well-established 3D global transport model (TM5: Transport Model 5, Peters et al., 2004, Krol et al., 2005). We investigate the influence of small differences between the three methodologies and whether these are significant or not for calculating the global mean surface CO$_2$ and its growth rate, how consistent the semi-NOAA-GFIT and WDCGG approaches are with each other, and how they compare with NOAA analysis and estimates derived from a CO$_2$ simulation with the 3D transport model TM5. These 3D CO$_2$ results for 2001-2020 using TM5 are performed in the CarbonTracker Europe framework (CTE, Peters et al., 2004, van der Laan-Luijkx et al., 2017), where the CO$_2$ uptake and emission fluxes are optimized by the inversion system to minimize the mismatch between the in situ observations and the modelled CO$_2$ mole fraction. CTE generally has a good representation of the CO$_2$ field, with mean biases with respect to independent aircraft measurements of generally less than 0.5 ppm (Friedlingstein et al., 2022). Furthermore, the inferred CO$_2$ fluxes from CTE fit well within the ensemble of those of other inversions used for the evaluation of Global Carbon Budget (e.g. Friedlingstein et al., 2022).

2 Methods and data

Figure 1. Three observation networks are employed to assess the impact of continental site inclusion when calculating global CO$_2$ mole fraction and its growth rates. The NOAA network (43 sites, yellow stars) comprises MBL sites only. The selected GAW global network, for CO$_2$ measurement (139 sites, red dots) includes both MBL sites and continental sites, for example from the Advanced Global Atmospheric Gases Experiment (AGAGE) and European ICOS contribution network. The CTE network serves as the global network for the CTE model evaluations (230 sites, blue dots), comprises MBL sites and a more extensive inclusion of continental sites and the NOAA network (43 sites, yellow stars).
2.1 The WMO GAW observations and WDCGG analysis method

The WMO GAW network measurements are archived and distributed by WDCGG (World Data Center for Greenhouse Gases), hosted by the Japan Meteorological Agency. The GAW observations used in this study originate from 139 selected stations of the GAW network, and all observations are on the WMO standard scale, WMO-CO₂-X2019 (Hall et al., 2021). The details on the station selection are described in Tsutsumi et al., (2009), which mainly excludes stations located in the northern hemisphere that show large standard deviations from the latitudinal fitted curve. The remaining 139 stations show a more reasonable latitudinal scatter range (Fig. 1).

The WDCGG global analysis method (hereafter WDCGG method), as described in Tsutsumi et al., (2009), includes the mentioned station selection, a data fitting and filter (involves data interpolation and extrapolation), and calculation of the zonal and global mean mole fractions, trends, and growth rates. The procedure is also summarized in Text S1.

The output from the global analysis by the WDCGG method was used to compare against an alternative method (section 2.3) and attempts to estimate global mean CO₂ mole fraction at 1x1 degree horizontal resolution and 25 levels in the vertical, the data period ranges from 2001 to 2020 which has no influence of model spin-up (Krol et al., 2018). From the CTE output a set of simulated synthetic atmospheric CO₂ mole fractions with monthly resolution can be extracted within grid cells where stations are situated. This study analyzes monthly observation data (1980-2020) by using the WDCGG analysis method and global mean mole fractions with monthly resolution can be compared to the WDCGG method without extrapolation. The station selection and CO₂ mole fraction at 1x1 degree horizontal resolution and 25 levels in the vertical, the data period ranges from 2001 to 2020 which has no influence of model spin-up (Krol et al., 2018). From the CTE output a set of simulated synthetic atmospheric CO₂ mole fractions with monthly resolution can be extracted within grid cells where stations are situated. This study analyzes monthly observation data (1980-2020) by using the GFIT method (section 2.3) and attempts to estimate global mean CO₂ mole fraction and its growth rate. The observed CO₂ mole fractions are taken from 230 out of 290 global-wide distributed stations (Fig. 1, the station selection is summarized in Text S2), the data come from the GLOBALVIEW-Plus V8 ObsPack data product (Schuldī et al., 2022) and include surface-based, shipboard-based and tower-based measurements.

2.2 CTE model output and station observations

CarbonTracker Europe (CTE) is a global model of atmospheric CO₂ and designed to keep track of CO₂ uptake and release at the Earth's surface over time (van der Laan-Luijkx et al., 2017). CTE incorporates an off-line atmospheric transport module (TM5, Peters et al., 2004, Krol et al., 2005) driven by ECMWF ERA5 data, and there are four prescribed fluxes (i.e. from ocean, biosphere, fire and fossil fuel), which are transported in the model, together with the transported initial CO₂ field. CTE also includes a data assimilation system that applies an ensemble Kalman filter to optimize the biogenic and ocean fluxes for a combination of plant-functional types and climate zones to improve the fit of the simulated concentrations with observations.

The optimized fluxes from the data assimilation have been used in Global Carbon Project (GCP) 2021 (Friedlingstein et al., 2022), and the comparison of CTE CO₂ product to the other data assimilation systems used in GCP shows good agreement (within 0.8 ppm at all latitude bands) and CTE compares well to the other data assimilation systems used in GCP (Friedlingstein et al., 2022).

The CTE model data used here consisted of simulated monthly CO₂ mole fraction at 1x1 degree horizontal resolution and 25 levels in the vertical, the data period ranges from 2001 to 2020 which has no influence of model spin-up (Krol et al., 2018). From the CTE output a set of simulated synthetic atmospheric CO₂ mole fractions with monthly resolution can be extracted within grid cells where stations are situated. This study analyzes monthly observation data (1980-2020) and synthetic time series (2001-2020) by using the GFIT method (section 2.3) and attempts to estimate global mean CO₂ mole fraction and its growth rate. The observed CO₂ mole fractions are taken from 230 out of 290 global-wide distributed stations (Fig. 1, the station selection is summarized in Text S2), the data come from the GLOBALVIEW-Plus V8 ObsPack data product (Schuldī et al., 2022) and include surface-based, shipboard-based and tower-based measurements.

2.3 The semi-GFITE method

The temporal pattern of CO₂ measurement records at locations around the globe can be explained as the combination of roughly three components: a long-term trend, a non-sinusoidal yearly cycle (or seasonality), and short-term variations. This study synchronizes monthly CO₂ records with the fitting and filter method of the NOAA Global Monitoring Laboratory (Thoning et al., 1989, Conway et al., 1994), without extrapolation. The station selection and CO₂ averaging method are kept the same as in the WDCGG method (Text S1). This method will be referred to as the semi-GFITE method and will be compared to the WDCGG method without extrapolation. The only difference from WDCGG method without extrapolation is the fitting and filter method. All code for the method described here was developed in Python and is available.
2.3.1. Fitting and filter

CO$_2$ records from each station can be abstracted as a combination of long-term trend and seasonality, which can be fitted by a function consisting of polynomial and harmonics. We applied a linear regression analysis based on 3 polynomial coefficients and 4 harmonics (Eq. 1) to fit CO$_2$ data using general linear least-squares fit (LFIT, Press et al., 1988).

$$f(x) = a_0 + a_1 t + a_2 t^2 + \cdots + a_k t^k + \sum_{n=1}^{n_h} (A_n \cos 2\pi n t + B_n \sin 2\pi n t)$$

where $a_k$, $A_n$ and $B_n$ are fitted parameters, $t$ is the time from the beginning of the observation and it is in months and expressed as a decimal of its year. $k$ denotes polynomial number, $k = 2$, $n_h$ denotes harmonic number, $n_h = 4$. Fig. 2 illustrates the function fit to CO$_2$ data to obtain the annual oscillation (red line in Fig. 2a), is a combination of a polynomial fit to the trend (blue line in Fig. 2a) and harmonic fit to the seasonality (green line in Fig. 2b).

The residuals are the difference between raw data and the function fit (black dots in Fig. 2c). The filtering method is based on Thoning et al. (1989) which transforms CO$_2$ data from time domain to frequency domain using a Fast Fourier Transform (FFT), then applies a low pass filter to the frequency data to remove high-frequency variations, and then transforms the filtered data back to the time domain using an inverse FFT. The short term (a cut-off value of 80 days, red line in Fig. 2c) and long term (a cut-off value of 667 days, blue line in Fig. 2c) filters used here are the same as in NOAA method, and applied to obtain the short term and interannual variations that are not determined by the fit function. The original Python code is also available as Python code from the NOAA website [https://gml.noaa.gov/aftp/user/thoning/ccgcrv/].

2.3.2. Calculate smoothed CO, and long-term trend

The results of the filtering residuals are added to the fitted curve to obtain smoothed CO$_2$ and its long-term trend. The smoothed CO$_2$ comprises the fitted trend, the fitted seasonality and the smoothed residuals (red line in Fig. 2d), which only removes short-term variations or noise. The long-term trend comprises fitted trend and residual trend, which removes seasonal cycle and noise (blue line in Fig. 2d).

2.3.3. Calculate CO$_2$ growth rate, $G_{ATM}$

The CO$_2$ growth rate ($G_{ATM}$) is determined by taking the first derivative of the long-term trend. However, the growth is made up of discrete points, e.g. the black dots in Fig. 3a shows the trend points. In this case, a cubic spline interpolation is applied to the trend points, in which the spline curve passes through each trend points, as the blue line in Fig. 3a. $G_{ATM}$ is obtained by taking the derivative of the spline at each trend point (Fig. 3b).
Figure 2. Example of analysed CO₂ data from PALL station (Pallas, PAL, Finland), illustrating semi-NOAA GFIT curve fitting and filter method. Panel (a) shows monthly averaged CO₂ (dots), curve fitting with 2-degree polynomial and 4-degree harmonics (red line), and long-term trend estimated by a 2-degree polynomial (blue line). Panel (b) shows seasonality estimated by 4-degree harmonics. Panel (c) shows the residuals of raw data from the function fit (black dots), the red line is obtained by the short-term filter and the blue line is obtained by the long-term filter. The cyan dots show the residuals of raw data from the sum of fitted curve and smoothed residuals. Panel (d) shows final processed CO₂, which comprises fitted trend, fitted seasonality and smoothed residuals (red line). The blue line shows the final trend which comprises fitted trend and residuals trend.
3 Results

Global averaged surface CO$_2$ and its $G_{ATM}$ are calculated from the GAW observations from 139 sites (Fig. 1) using the WDCGG method with and without extrapolation and our semi-NOAA GFIT method based on the data from the GAW and CTE networks (Fig. 1), namely GAW (WDCGG+), GAW (WDCGG), and GAW (semi-NOAA). The different observation networks and their analysis methods are listed in Table 1. The semi-NOAA method is also applied to three CTE datasets: 1) observations from 230 sites selected in the CTE dataset (hereafter these sites are named as CTE network, Fig. 1) which comes from the ObsPack data product (Kenneth N., 2022), namely CTE_obs (semi-NOAA); 2) CTE model output at the sites sampled at the same location, altitude and time, namely CTE_output (semi-NOAA); and 3) model output for full global grids (averaged over the first three levels, 0 to 0.35 km Alt.), namely CTE_global (semi-NOAA). We calculated the global means and its $G_{ATM}$ by area-weighted averaging the zonal means over each latitudinal band (30°), as same as following the same CO$_2$ averaging method method as described in Tsutsumi et al. (2009). A bootstrap method is used to estimate the uncertainties of global CO$_2$ mean and its $G_{ATM}$, which is an almost identical uncertainty analysis as presented by Conway et al. (1994) who constructed 100 bootstrap networks for the NOAA analysis. We construct 200 bootstrap networks, which is consistent with the WDCGG analysis in Tsutsumi et al., (2009). For each bootstrap network, we randomly draw the same number of sites (as the actual network, e.g. 139 sites for GAW network) with replacement (or restitution) from the actual network, which means some sites are missing whereas others will be represented twice or more often. We calculate global mean CO$_2$ mole fraction and its $G_{ATM}$ for each network, and then calculate the statistics (i.e. mean and 68% confidence interval, CI) on the 200 networks.

Table 1. Description of the three observation networks and their analysis methods.

<table>
<thead>
<tr>
<th>Network</th>
<th>Description</th>
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<tbody>
<tr>
<td>GAW (WDCGG+)</td>
<td>Observations from 239 sites selected in the CTE dataset.</td>
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<tr>
<td>CTE_obs (semi-NOAA)</td>
<td>Observations from 230 sites selected in the CTE dataset.</td>
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<tr>
<td>CTE_output (semi-NOAA)</td>
<td>CTE model output at the sites sampled at the same location, altitude and time.</td>
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<tr>
<td>CTE_global (semi-NOAA)</td>
<td>Model output for full global grids (averaged over the first three levels, 0 to 0.35 km Alt.).</td>
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<td>Terminology</td>
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<td>GAW network observations analysed using the GFIT method.</td>
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<tr>
<td>GAW (WDCCG)</td>
<td>GAW network observations analysed using the WDCGG method without extrapolation.</td>
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<tr>
<td>CTE_obs (GFIT)</td>
<td>CTE network observations analysed using the GFIT method. The observations come from the ObsPack data product (Schuldt et al., 2022)</td>
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<td>CTE_output (GFIT)</td>
<td>CTE model output at the 230 sites (sampled at the same location, altitude and time) analysed using the GFIT method.</td>
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<td>CTE_global (GFIT)</td>
<td>CTE model output for full global grids (averaged over the first three levels, 0 to 0.35 km Alt.) analysed using the GFIT method.</td>
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<td>MLO (GFIT)</td>
<td>Mauna Loa (MLO) observations analysed using the GFIT method.</td>
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<tr>
<td>SPO (GFIT)</td>
<td>South Pole (SPO) observations analysed using the GFIT method.</td>
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</table>
3.1 Globally averaged surface CO$_2$ mole fraction and its G$_{ATM}$
Figure 4. Comparison of globally and locally averaged CO\textsubscript{2} mole fraction (a) and its \textit{GATM} (b) from 1980 to 2020. Panel (a) shows the global monthly CO\textsubscript{2} mole fraction from 139 GAW sites (estimated from observations only), 43 NOAA MBL sites and those from 230 sites used in CTE (either from observations or model output). The two local CO\textsubscript{2} mole fractions are from Mauna Loa (MLO, cyan line) and South Pole (SPO, magenta line) stations, analysed using the GFIT method. The red and blue lines show the CO\textsubscript{2} derived from GAW (GFIT) and GAW (WDCGG), respectively. The green and orange lines show the CO\textsubscript{2} derived from CTE\textsubscript{obs} (GFIT) and CTE\textsubscript{output} (GFIT), respectively. The right y-axis shows their difference from NOAA CO\textsubscript{2} mole fraction, and the dashed lines show the mean of the difference over the available period. Panel (b) compares the corresponding global and local CO\textsubscript{2} growth rate, the legend refers to panel (a). The shadow area shows the uncertainty as 68% confidence interval obtained by the bootstrap analysis. Comparison of globally averaged CO\textsubscript{2} mole fraction (a) and its \textit{GATM} (b) from 1980 to 2020. Panel (a) shows the global monthly CO\textsubscript{2} mole fraction from 139 GAW site (estimated from observations only) and those from 230 sites used in CTE (either from observations or model outputs) differs from NOAA estimates based on 43 MBL sites. Red and blue lines show the CO\textsubscript{2} derived from the GAW observations using semi-NOAA and GAW (WDCGG) method without extrapolation, respectively. Green and orange lines show the CO\textsubscript{2} derived from observations and model output at the 230 sites assimilated by CTE using semi-NOAA method, respectively. The dash lines show the mean over the available period. Panel (b) compares the global CO\textsubscript{2} growth rate derived from GAW observations using semi-NOAA (red line) and WDCGG method without extrapolation (blue line), CTE observations (green line) and model output (orange line) using semi-NOAA method, and the NOAA analysis (black line). The shadow area shows the uncertainty as 68% confidence interval obtained by the bootstrap analysis.

Fig. 4 presents a monthly comparison of globally and locally averaged CO\textsubscript{2} mole fractions and their \textit{GATM} from 1980 to 2020.

The statistical metrics assessing the agreement of these monthly comparisons are available in Fig. 5 (for 2001-2020) and Fig. S1 (for 1980-2020). The statistical metrics for the annual comparisons can be found in Fig. S2 (for 2001-2020) and Fig. S3 (for 1980-2020). They exhibit a similar pattern to the monthly comparisons (i.e. Fig. 5 and Fig. S1).

Globally-averaged monthly surface CO\textsubscript{2} mole fraction\textsubscript{GAW} derived from the GAW network (GAW (semi-NOAA/GFIT) or GAW (WDCGG)), are significantly ($p<0.05$) higher by 0.329, 0.292, 0.312 ppm during 1980-2020 (Fig. S1a) and 0.370, 0.390 ppm during 2001-2020 (Fig. 5a), significantly ($p<0.05$) higher than when compared to the NOAA analysis during 1980.
Both global CO$_2$ and its G$_{GFI}$ derived from the GAW (semi-NOAA/GFIT) and GAW (WDCGG) are nearly overlapping (the red and blue lines) in Fig. 4a and d. This can also be seen by comparing Figs. S1 and S2. The statistical metrics (Tables S1-S2) indicate a high agreement (ME=0.005 ppm, RMSE=0.108 ppm, r=0.999) for the CO$_2$ mole fraction; ME=0.005 ppm, RMSE=0.108 ppm yr$^{-1}$, ME=0.096 ppm yr$^{-1}$, for the G$_{GFI}$ between these two methods, which confirms that the semi-NOAA/GFIT method agrees well with WDCGG method without extrapolation. The WDCGG method with extrapolation (i.e. GAW (WDCGG+)), which involves extrapolating the long-term trend of each station to match the period of the most long-running station and adding it to the average seasonal variation to synchronize data period of all stations (Tsuchumi et al., 2009), produces a 0.096 ppm significantly (p<0.05) higher than the global monthly CO$_2$ mole fraction derived from the GAW (WDCGG) during the common period 1984-2020 (see Table S2 and S1). However, while the extrapolation has a minimizing effect (RMSE=0.062 ppm yr$^{-1}$, ME=0.011 ppm yr$^{-1}$, Table S2 and S1) on the CO$_2$ growth rate.

Global, globally averaged monthly surface CO$_2$ derived from CTE$_{obs}$ (semi-NOAA/GFIT) and CTE$_{output}$ (semi-NOAA/GFIT) are 422-472 ppm (1980-2020, Fig. S1) and 0.453-0.568 ppm (2001-2020, Fig. S1) significantly (p<0.05) higher compared to the NOAA analysis, respectively (green and orange lines in Fig. 4a). Comparing the global mean of CTE$_{obs}$ (semi-NOAA/GFIT) with CTE$_{output}$ (semi-NOAA/GFIT) during the common period of 2001-2020, we find a low bias (0.069 ppm in CTE$_{output}$, Table S1 and S2, Fig. 5a), which suggests that the CTE model results can reasonably reproduce the global mean CO$_2$ levels reasonably well. The global annual CO$_2$ mole fraction from CTE$_{obs}$ (semi-NOAA/GFIT), CTE$_{output}$ (semi-NOAA/GFIT) and CTE$_{global}$ (semi-NOAA/GFIT) is 0.468-0.567 (2001-2020), 0.299 (2001-2020) and 0.186 (2001-2020) ppm significantly (p<0.05) higher than the result of the GAW (semi-NOAA/GFIT), respectively (Fig. 5a and Table S1-4). The higher global mean from CTE$_{obs}$ (semi-NOAA/GFIT) and CTE$_{output}$ (semi-NOAA/GFIT) is mainly due to the presence of more sites in the Northern Hemisphere within the CTE network compared to the GAW network. The lower bias observed between GAW (semi-NOAA/GFIT) and CTE$_{global}$ (semi-NOAA/GFIT) indicates that the GAW network provides a good representation of the low-level atmosphere (i.e. 0 to 0.35 km altitude) at global scale (Table S2), or the CTE model can perform well in the low-level atmosphere.

A common approach to estimate global surface CO$_2$ mole fraction is by using one or two representative sites, such as Mauna Loa (MLO) and South Pole (SPO). The globally averaged monthly surface CO$_2$ mole fractions, derived from the GAW, CTE, and NOAA networks, are significantly (p<0.05) lower by 0.46-0.88 ppm during 1980-2020 (Fig. S1a) and 0.45-1.19 during 2001-2020 (Fig. 5a) than the local CO$_2$ estimates solely based on MLO measurements. Conversely, these global monthly CO$_2$ mole fractions are significantly (p<0.05) higher by 1.91-2.24 ppm during 1980-2020 (Fig. S1a) and 2.21-2.94 during 2001-2020 (Fig. 5a) when compared to local measurements at SPO site. Furthermore, the global seasonal cycle leads the local cycle at MLO by approximately one month (estimated by averaging the time difference between the peaks of their seasonal cycles). In contrast, the local cycle at SPO is not evident and is opposite to the global seasonal cycle (Fig. 4a).
Figure 5. Pair-wise statistical metrics assess the agreement of monthly global and local CO\textsubscript{2} mole fraction (ppm) and its \textit{GATM} (ppm yr\textsuperscript{-1}) across various networks and methodologies (see Table 1 and Fig. 4) for the period 2001-2020. Panel (a) presents the Mean Error (ME) quantifying the difference for each pair, focusing on CO\textsubscript{2} mole fraction, while panel (b) does the same for \textit{GATM}. The significance levels of paired t-test for ME are indicated as follows: * p<0.1, ** p<0.05, *** p<0.01. Panel (c) and (d) present the Root Mean Squared Error (RMSE) for CO\textsubscript{2} mole fraction and \textit{GATM}, respectively. Panel (e) and (f) present the Pearson Correlation Coefficient (r) for CO\textsubscript{2} mole fraction and \textit{GATM}, respectively.
Figure 5: Trend analysis of the global CO₂ growth rate from 1980 to 2020. Panel (a) shows the trends of CO₂ growth rate for the GAW network (red line), the CTE network (green line) and the NOAA network (black line) during the whole period 1980-2020, the CO₂ growth rate is derived from GAW (semi-NOAA GFIT), CTE_obs (semi-NOAA GFIT) and NOAA analysis (Fig. 4b). Panel (b) shows the trend of CO₂ growth rate for each month during 1980-2020, calculated as the derivative of the growth rate. The grey bands mark the period of three strong El Niño events, i.e. 1987-1988, 1997-1998 and 2014-2016.

Despite differences in the global averaged surface CO₂ mole fractions derived from different networks and analysis methods, the G_ATM derived from GAW network, CTE network and its model output, and NOAA network agree well during 1980-2020 (ME<0.031 ppm yr⁻¹, RMSE<0.217 ppm yr⁻¹, r>0.948, Fig. 4b and S1). The differences in the G_ATM remain below 0.023 ppm yr⁻¹ during 2001-2020, with low or no significance level (Fig. 5b), especially when comparing the annual G_ATM (Fig. S2b) (ME<0.035 ppm yr⁻¹, MAE<0.158 ppm yr⁻¹, ME<0.0 ppm yr⁻¹, Table S1) during the common period (Fig. 4b). Furthermore, over the long-term period of 40 years, the estimated local growth rate at MLO (ME<0.046 ppm yr⁻¹ higher, RMSE<0.272 ppm yr⁻¹, r>0.915) and SPO (ME<0.049 ppm yr⁻¹ lower, RMSE<0.305 ppm yr⁻¹, r>0.888) behaves similarly to the G_ATM derived from GAW, CTE and NOAA network (Fig. 4b and S1). However, noticeable monthly differences between the local and global growth rates, deviating up to approximately 0.8 ppm yr⁻¹, and time shifts are observed (Fig. 4b).

The trend analysis reveals that with development of continental sites, the slope of the trend of annual global CO₂ mole fraction changes from NOAA network (1.832 ± 0.029 ppm yr⁻¹) to CTE network (1.859 ± 0.029 ppm yr⁻¹) during 1980-2020 (Fig. S4). However, the trend analysis shows that the G_ATM increased steadily at a rate of 0.030 ± 0.002 ppm per year each year from 1980 to 2020 (Fig. 5a), based on the observations from the three networks (i.e. GAW, CTE and NOAA). This implies that the role of CO₂ advective
transport and mixing play a negligible role in estimating the long-term change of the $G_{ATM}$ appears negligible. However, there is a clear notable difference emerges in the short-term (here one month) change of the $G_{ATM}$ between the networks with and without continental sites (Fig. S4b). The El Niño events are known to diminish net global C uptake (due to factors such as droughts, floods and fires) and while increasing the global CO₂ growth rate (Sarmiento et al., 2010). During three strong El Niño events, which are marked as grey bands in Fig. 6b, the $G_{ATM}$ derived from the GAW and CTE network (red and blue-green lines) begins to increase approximately 1-2 months (Table S2) earlier than the El Niño events (Table S2) earlier than the El Niño events (marked as orange circles in Fig. 5b), compared to the $G_{ATM}$ derived from the NOAA network (black line). This indicates suggests that continental sites can help aid in the early detection of the change of $G_{ATM}$ changes resulting from changes in which is caused by biogenic emission or uptake changes. The CTE network (green line) even detects the change approximately one month earlier than the GAW network (red line) e.g. the El Niño event 1997-1998 events (Fig. 5b, Table S2). This earlier detection which is attributed due to the inclusion of even more continental sites included in the CTE network (Fig. 1), although the more continental sites also induce the larger greater variability.

Table 1a shows presents the global annual CO₂ mole fraction and its $G_{ATM}$ derived from GAW (semi-GOAAGFIT), together with the uncertainty estimates during the bootstrap method. The global average surface CO₂ mole fraction has increased from 339.17±0.38 ppm in 1980 to 413.06±0.16 ppm in 2019 (Table 1a, Table S4). Notably, the uncertainty is greater before 1990 is larger than after 1980, primarily due to the limited number of fewer measurement stations worldwide during that period over the globe before 1990. The average $G_{ATM}$ for the two decades before 2000 is about 1.54±0.08 ppm yr⁻¹. However, in the following two decades, it has experienced an increase reaching 1.91±0.05 ppm yr⁻¹ during 2000-2009 and further rising to 2.4±0.06 ppm yr⁻¹ during 2010-2019 (Table 1a, Table S4).

Table 2. Annual global averaged CO₂ mole fraction (Mean, ppm) and its $G_{ATM}$ (ppm yr⁻¹) derived from GAW observations using semi-GOAAGFIT method. U(Mean) and U($G_{ATM}$) respectively indicate the uncertainty of Mean and its $G_{ATM}$ as 68% confidence interval. The annual value is averaged over the monthly values of the year.

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### Yearly Mean Global CO₂ Mole Fraction

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#### 3.2 Vertical profile of global CO₂ mole fraction

![Global vertical profile of CO₂ mole fraction derived from CTE model output. Panel (a) presents the vertical profile in 2020. Panel (b) presents the difference of the vertical profile between 2001 and 2020. Panel (c) presents the annual mean vertical profile from 2001 to 2020, the dots mark CTE vertical level heights and lines are the linear interpolation between the heights.](image_url)

The CTE model simulates CO₂ mole fraction over a global 3D grid, which allows us to visualize the modelled vertical CO₂ profile. In the lower atmosphere, highest CO₂ mole fraction was found in the Northern mid-latitude region (dark red between 30°N and 40°N, Fig. 6). This area experiences more anthropogenic emissions, which are...
subsequently transported towards both northern and southern latitudes. The latitudinal and interhemispheric gradient of atmospheric CO₂, as shown in Fig. 6a-7a, is influenced not only by differences in the latitudinal and interhemispheric differences in fossil fuel emissions and seasonal exchange with terrestrial biota (Denning et al., 1995), but is also by due to atmospheric transport (Patra et al., 2011). With increasing altitude increases, the gradient between the Northern and Southern hemisphere becomes small and levels out at higher altitudes (e.g. >50 km). When comparing the vertical profile change between 2001 and 2020 (Fig. 6b-7b and 6c-7c), we observe that the CO₂ mole fraction increases slowly in the higher atmosphere (>25 km altitude) than compared to the increase at the lower atmosphere (<25 km altitude). Fig. 6c-7c shows that the vertical gradient (difference between 50 km and 0.05 km) changes from approximately 5 ppm in 2001 to around ≈13 ppm in 2020. The high vertical gradient in 2020 reflects the accumulation of CO₂ in the lower atmosphere, which is caused by resulting from continuous CO₂ emissions from the surface during 2001-2020 and slow vertical transport.

The low vertical gradient in 2001 is partly due to low surface emission. Pressure-weighted average CO₂ mole fraction in the lower atmosphere (0 to 0.35 km altitude) and the entire atmosphere are calculated from CTE output. The annual absolute change in CO₂ mole fraction, computed as the difference between annual means, is more pronounced in the lower atmosphere (orange bars in Fig. S6a) than in the entire atmosphere (blue bars in Fig. S6a). The reason is that the entire atmosphere has a larger air volume than the lower atmosphere, and changes in the surface CO₂ sinks and sources are diluted due to atmospheric horizontal and vertical transport. The CO₂ annual absolute change derived from GAW (GFIT), GAW (WDCGG) and NOAA (represented by red, purple and brown bars in Fig S6a) shows small positive or negative differences from the CTE output (GFIT) and CTE_global (GFIT) across different years. However, over the long term (e.g. on a decadal scale, 2001-2010 and 2011-2020), the CTE model-derived changes in lower and entire atmospheric CO₂ shows good agreement (<±0.09 ppm yr⁻¹) with the surface observation-based estimate, especially for lower atmospheric CO₂(<±0.07 ppm yr⁻¹). In Fig. S6b, the interannual variability (IAV) of CO₂ mole fraction derived from CTE model follows a similar temporal pattern as the observation-based IAV derived from the GAW and NOAA network, especially the IAV of the low-level atmosphere (orange bars) exhibits strong agreement with the observation-based IAV (r>0.971, RMSE<0.178 ppm).
3.3 Relationship between the surface CO$_2$ mole fraction and atmospheric CO$_2$ mass

The atmospheric CO$_2$ mass, calculated from the CTE output as a function of air mass and CO$_2$ concentration (Text S3), has increased from 789.46 PgC in 2001 to 877.88 PgC in 2020 (Fig. S3a). The spatial distribution of the atmospheric CO$_2$ mass can be seen in Fig. S3b and Fig. S3c. Monthly global surface CO$_2$ mole fraction derived from the CTE output and NOAA analysis, presented as blue, red and green dots, respectively, at 230 sites used in CTE with the semi-NOAA method (CTE output (semi-NOAA)). The IAV is calculated as the anomaly departure from a quadratic trend. The atmospheric CO$_2$ mass, calculated from the CTE output as a function of air mass and CO$_2$ concentration (Text S3), has increased from 789.46 PgC in 2001 to 877.88 PgC in 2020 (Fig. S3a). The spatial distribution of the atmospheric CO$_2$ mass can be seen in Fig. S3b and Fig. S3c. Monthly global surface CO$_2$ mole fraction derived from the CTE output and NOAA analysis, presented as blue, red and green dots, respectively, at 230 sites used in CTE with the semi-NOAA method (CTE output (semi-NOAA)). The IAV is calculated as the anomaly departure from a quadratic trend.
We further compare the interannual variability (IAV) calculated as the anomaly departure from a quadratic trend of the atmospheric CO$_2$ mass and the surface CO$_2$ (Fig. 2b). The coefficient of the linear relationship is very close to 1.0, which indicates the temporal change in atmospheric CO$_2$ mass aligns with the temporal change in surface CO$_2$ mole fraction. The CO$_2$ IAV based on the NOAA network exhibits a slightly closer relationship (r=0.938) with the CTE atmospheric CO$_2$ mass estimates. The NOAA network tracks atmospheric CO$_2$ change slightly better (r=0.938) than the GAW (r=0.861) and CTE (r=0.812) networks. This finding is consistent with the long atmospheric residence time and well-mixed nature of atmospheric CO$_2$ in the NOAA network. Overall, the relationship found in Fig. 2b implies that the current surface CO$_2$ network can effectively serve as an indicator of the CO$_2$ mass change throughout the entire atmosphere through a linear relationship.

### 3.4 Annual absolute change and interannual variability of global CO$_2$ mole fraction

![Annual absolute change and interannual variability of global CO$_2$ mole fraction](image)

Panel (a) shows the annual absolute change which is the difference between annual mean. Averages over 2001-2010 and 2011-2020 are also shown. Panel (b) shows the IAV which is calculated as the anomaly departure from a quadratic trend.

Pressure-weighted average CO$_2$ in the lower atmosphere and whole atmosphere is derived from CTE output. The annual absolute change (calculated as the difference between annual mean) of CO$_2$ in the lower atmosphere (0 to 0.35 km altitude, orange bars in Fig. 8a) is more sensitive to surface sink and source than the change in the whole atmosphere (blue bars). The reason is that the whole atmosphere has a larger air volume than the lower atmosphere, and the change of the surface CO$_2$ is...
diluted due to horizontal and vertical transport. The CO₂ change derived from the observations of the GAW network (red bars for semi-NOAA method, purple bars for WDCGG method) and the NOAA network (brown bars) shows a small positive or negative difference from the CTE results over the different years. However, over the long term (e.g., decadal scale, 2001–2010 and 2011–2020), the CTE model derived change of lower and whole atmospheric CO₂ show good agreement (c. 0.09 ppm yr⁻¹) with the surface observation-based estimate, especially for the lower atmospheric CO₂ (c. 0.07 ppm yr⁻¹). Fig. 8b shows the IVA derived from CTE (blue, orange and green bars) follows a similar temporal pattern to the observation-based IVA derived from the GAW and NOAA network (red, purple and brown bars) and shows good agreement with the observation-based IVA (c. 0.071, RMSE = 0.178 ppm).

4 Discussion

During the past few decades, observational networks have been extended beyond the NOAA MBL network to include more continental sites such as in the GAW network and CTE network (Fig. 1). These expansions aim to monitor global CO₂ concentrations and quantify CO₂ sources and sinks. Although the continental observations encompass contributions from both substantial sources of anthropogenic emissions and big sources/sinks from terrestrial vegetation off during the growing season and soil, these continental observations show consistently higher global surface CO₂ mole fraction in the overall global CO₂ analysis, which indicates that they are influenced by a bigger net source. We find that the global mean derived from the GAW network is consistently higher global mean (0.42 ppm during 1980) and a greater amplitude in Fig. 1) with the surface observation-based estimate, especially for the lower atmospheric CO₂ (<0.07 ppm yr⁻¹). Therefore, the CTE network leads to an overall higher global mean (0.422 ppm during 1980–2020), which is likely due to more observational sites located in the Northern Hemisphere, where the highest anthropogenic emissions take place. This also explains the large fluctuation of CO₂ concentrations observed during the winters and summers during 2001–2020 (green and orange lines, Fig. 4a). In the future, we expect that the addition of new observation sites, particularly in the Northern Hemisphere, will lead to higher global surface CO₂ levels and a greater amplitude in the global CO₂ seasonal cycle in the global CO₂ analysis.

Although Friedlingstein et al. (2022) reported a 5.4% drop (~0.52 PgC) in fossil fuel CO₂ emissions in 2020 due to restrictions on e.g., transport, industry, power etc during the COVID-19 pandemic, the increase in annual CO₂ from 2019 to 2020 (2.60±0.16 ppm yr⁻¹) remains at a similar level as from 2018 to 2019 (2.61±0.05 ppm yr⁻¹). In principle, an equivalent drop of roughly 0.25 ppm yr⁻¹ (according to the conversion factor 2.08 PgC ppm⁻¹ in Fig. 2a) or roughly 0.13 ppm yr⁻¹ (according to the annual absolute change, red bars in Fig. 2a) in the growth rate should be visible for period 2019–2020 due to the declined CO₂ emissions. However, such a short-term human activity induced change in the CO₂ growth rate may be hidden by the natural variability. The bootstrap analysis is used in this study (also in Conway et al., 1994 and Tsutsumi et al., 2009) to estimate the uncertainty of the CO₂ temporal mean and its growth rate and to assess how sensitive the global value is to the distribution of sampling sites. The relatively large uncertainty (±0.16 ppm yr⁻¹) at the end of 2020 compared to previous years (Table 4) is likely due to an end-effect associated with the curve fitting and filter procedure. The end-effect is a tendency for the growth rate to converge toward the mean value at the end of the record (Conway et al., 1994). Therefore, Conway et al. (1994) suggested that the last 6 months of the growth rate curves should be viewed with caution.

Reducing the end-effect requires further study, such as using machine learning or bias-correction methods to extrapolate the smoothed trend for a short period (e.g., one year) before and after. This extrapolated portion is used exclusively for calculating local mole fraction and growth rate, while it is not included in the global or zonal average, as it could introduce additional uncertainty.
Extrapolation beyond the measurement period extends knowledge gained from a limited period of measurements. During a limited measurement period, we can only make an average seasonal, long-term trend, and short-term variation at a measurement site. The long-term trend of an individual site can be extrapolated by various methods, such as referring to the latitude reference time series (Masarie and Tans, 1995) or calculating the mean long-term trend over sites within a certain latitudinal zone (e.g. 30°’s (Tsutsumi et al., 2009)). This extrapolated trend is then combined with the average seasonality to produce estimates beyond the measurement period. However, the extrapolation process relies on the assumption that the relationship of an individual site to the latitude reference remains invariant in time, which may not be always true. The relationship between nearby sites is continuously changing (Masarie and Tans, 1995). In addition, the short-term variation is often ignored or estimated from nearby sites, introducing extra uncertainty into the extrapolation process. In this study, we find that the WDCGG method with extrapolation (GAW (WDCGG)) results in a global surface CO₂ mole fraction approximately 0.096 ppm higher than the WDCGG method without extrapolation (GAW (WDCGG)) using the same GAW observations, although the extrapolation has a minor effect on the growth rate (Table S1). Therefore, we chose not to use extrapolation beyond the measurement period in our analysis. As the number of long-term measurements increases, the need for such extrapolation becomes less necessary.

Our analysis shows that basing the CO₂ growth rate on GAW surface observations does not introduce a large bias (with an average agreement within 0.045 ppm yr⁻¹) compared to a full atmospheric analysis (Fig. 4b and S1). This full atmospheric CO₂ was provided by the CTE model, in which the global annual mean CO₂ is significantly overestimated compared to GAW observations (e.g. 0.298 ppm higher in CTE output (CTE_output), or 0.186 ppm higher in the CTE_global (semi-NOAA/GFIT) during 2001-2020). The overestimate derived from the CTE_output (semi-NOAA/GFIT), i.e. CTE output at the CTE 220 sites, is mainly due to more sites in the Northern Hemisphere in the CTE network than in the GAW network. The lower overestimate derived from the CTE_global (semi-NOAA/GFIT), i.e. CTE output at full global grids at the low-level atmosphere, implies that the biases in CTE outputs are not uniform spatially and attempt to balance out. We estimate the CTE bias by comparing the observations and CTE outputs at the same sites, which results in a 0.069 ppm low bias derived from the CTE outputs in calculating the global surface CO₂ mole fraction.

The local growth rate at MLO and SPO generally behaves similarly to the global growth rate derived from the GAW, CTE, and NOAA networks (Fig. 4b and S1). However, the local CO₂ mole fraction and its seasonal cycle noticeably differ from global estimates derived from different observational networks. In this regard, the utilization of individual sites for the evaluation of the global average mole fraction and its growth rate is not precise and can only be used for illustration rather than as a substitute for the proper global average calculation. The local observation sites, often situated away from significant local sources and sinks, such as MLO, provide long-term and high-quality data, serving as reference data for global CO₂ mole fraction. However, a single observation site cannot capture the CO₂ spatial variability, transport, and mixing. To overcome these limitations, global CO₂ trends and variations are best assessed by integrating data from multiple sources and locations.

Different observational networks (i.e. NOAA network, GAW network and CTE network) are analysed in this study, which reveals some differences in calculated global surface CO₂ mole fractions equivalent to the current atmospheric growth rate over a three-month period. This implies that the station selection, especially if and how many continental observations are used, has some influence on but not a particularly strong influence on the derived global surface CO₂ levels, but it is not particularly strong. Nowadays, more and more increasing number of continental observations are established in order to monitor biogenic sources and sinks, and provide further insight into the climate change and the associated ecosystem processes (Ciais et al., 2005, Ramonet et al., 2020). Such continental observations carry more variability in measurements than the marine observations, which need some caution when including them in the mix of stations used to determine the global surface CO₂ mole fraction. Otherwise, our study demonstrates that continental sites can help early detect changes in CO₂ growth rate caused by biogenic emission changes, such as those resulting from e.g. caused by El Niño events. Furthermore, the current observational networks (with and without continental sites) and CTE model show a good agreement within 0.025 ppm yr⁻¹ on the global CO₂ growth rate, with low or no significant differences within this range.
The current CO₂ growth rate approaches 0.07 ppm yr⁻¹, as derived from GAW (equivalent to 1% of the global CO₂ growth rate) and averaged over 1980-2020 (Table 42). In order to reduce the uncertainty to 0.02 ppm yr⁻¹ (equivalent to 1% of the global CO₂ growth rate), we recommend extrapolation beyond the measurement period extends knowledge gained from a limited period of measurements. During a limited period of measurements, we can define the average seasonality, long-term trend, and short-term variation at a measurement site. The long-term trend of individual site is extrapolated, for example by referring to the latitude reference time series (Masarie and Tans, 1995) or the mean long-term trend over sites within a certain (e.g. 30°) latitudinal zone (Tsutsumi et al., 2009), and then combining the extrapolated trend with average seasonality to produce the estimate beyond measurement period. The extrapolation requires the assumption that the relationship of an individual site to the latitude reference is invariant in time; however, the relationship between nearby sites is continuously changing (Masarie and Tans, 1995). Besides, the short-term variation is ignored or estimated from nearby sites, which introduces extra uncertainty from extrapolation. In this study, we find that the WDCGG method with extrapolation (GAW (WDCGG+)) results in ~0.096 ppm higher in the global surface CO₂ mole fraction than the WDCGG method without extrapolation (GAW (WDCGG)) using the same GAW observations, although the extrapolation has a tiny effect on the growth rate (Table S2). Therefore, extrapolation beyond the measurement period is not used in our analysis. With the increasing number of long-term measurements, this extrapolation becomes less and less necessary.

5 Conclusions

The WMO GAW Global Atmosphere Watch CO₂ network documents the gradual global accumulation of CO₂ in the atmosphere due to human activities. It has been used to assess the large-scale and long-term environmental consequence of fossil CO₂ emission and land use changes. The high-quality observations conducted by the WMO GAW network include not only background stations (most of NOAA MBL stations) but also continental stations. This comprehensive network enables proper global average calculation. Furthermore, the WMO has initiated a new program, Global Greenhouse Gas Watch (GGGW), with the aim of establishing a reference network. This network will be built on the high-quality observations already performed under the WMO GAW program that follows consistent good practices and standards. Although the current monitoring networks have limitations in terms of geographical coverage, data consistency, and long-term measurements, they are well-equipped and have the capacity to effectively represent global surface CO₂ mole fraction and its growth rate and trends in atmospheric CO₂ mass changes. The three different analysis methods yield very similar global CO₂ increases from 2001 to 2020, which gives confidence in using any one of them in climate change studies.

Although the current CO₂ network is sparse due to operational costs and logistical constraints, it has a good capacity to represent global surface CO₂ mole fraction.
and its growth rate and trends in atmospheric CO₂ mass changes. The three different analysis methods yield very similar global CO₂ increase from 2001 to 2020, which gives confidence to use either one of them in climate change study. The continuous monitoring of atmospheric CO₂, basis-based on the current GAW network together with reliable global data integration methods, provides essential information. This includes understanding trends in atmospheric CO₂ concentration, assessing the impacts of past policies, identifying high-emission areas, informing climate models, forecasting future scenarios, and raising public awareness. Policymakers can rely on this information to support their efforts in mitigating the global warming. Although the current CO₂ network is sparse due to operational cost and logistical constraints, it has a good capacity to represent global surface CO₂ mole fraction and its growth rate and trends in atmospheric CO₂ mass changes.

6 Data and Code Availability

All data and code necessary to calculate the global mean surface CO₂ mole fraction and Atmospheric CO₂ mass is freely available from ICOS Carbon Portal [https://doi.org/10.18160/Q788-9081]. The file list of results and code can be found in Text S4.

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Author Contributions

A.V. and Z.W. designed this study in discussion with Y.S., O.T and U.K.
Z.W. performed analysis and led the writing.
Y.S., Y.N. and A.O. provided the GAW data, and commented on the manuscript.
W.P. and R.K. provided CTE model results and relevant ObsPack data, and commented on the manuscript.
X.L. provided NOAA data and commented on the manuscript.
All authors contributed to the writing of the paper and interpretation of the results.

Competing Interests

The authors declare no competing interests.

Financial support

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References


Supporting Information

Text S1. The WDCGG global analysis method

The WDCGG method consists of seven separate steps. The full documentation can be found in Tsutsumi et al. (2009).
Step 1: Station selection based on traceability to the WMO standard scale

In order to avoid the potential biases that can be introduced by using different concentration scales, WDCGG only uses data from stations that report results traceable to the most recent CO$_2$ scale from the GAW Central Calibration Laboratories (CCL) assigned for that parameter. The current scale is the WMO standard scale WMO-CO2-X2019.

Step 2: Integration of parallel data from the same station

The WDCGG method uses continuous (hourly averaged) observations as these better represent the average concentrations compared to the flask-air samples taking during daytime once per two weeks. For remote stations where both flask and continuous data exist, NOAA found offsets between continuous and flask based monthly averages of 0.16–0.35 ppm (Tans et al., 1990), in less remote areas this difference can be expected to be larger. For selected stations flask data are used for gap filling when continuous data is lacking.

Step 3: Selection of stations suitable for global analysis

All of station data are normalized against the South Pole and averaged for the whole observation period. The normalized and averaged data points are plotted against latitude, and a curve is fitted by using a nearest-neighbour local-quadratic regression. The stations with normalized data locate outside the 3 standard deviations of the latitudinal fitted curve are excluded from the selection. This selection procedure is repeated until all stations in the selection locating within the 3 standard deviations of the latitudinal fitted curve. This procedure results in 139 stations remaining, which have a reasonable latitudinal scatter range (Figure 1).

Step 4: Abstraction of a station’s average seasonal variation expressed by the Fourier harmonics

The average seasonal variation is obtained from the longest continuous segment of data by using three Fourier harmonics. Here is loop procedure where the following processes a-d are repeated until neither the long-term trend nor the average seasonal variation changes: a) de-trend original data, b) apply the harmonics to obtain seasonality, c) de-seasonality from original data to obtain long-term trend, d) smooth the long-term trend by using low-pass filter (a cut-off frequency of 0.48 cycle / year). After reaching this condition the average seasonal variation is determined and subtracted from the full data which leaves us with deseasonalized data that still can contain gaps.

Step 5: Interpolation of data gaps

The gaps of the deseasonalized data are filled by linear interpolation. Subsequently, the CO$_2$ time series without gaps is the sum of the interpolated trend and the average seasonality.

Step 6: Extrapolation for synchronization of data period

Extrapolate the long-term trend to the synchronization period and then add the average seasonal variation to obtain the synchronized data. This is an optional step that is excluded in this analysis.

Step 7: Calculation of the zonal and global mean mole fractions, trends, and growth rates.

Global and hemispheric means, trends and growth rates are calculated by area-weighted averaging the zonal means over each latitudinal band (30°). The growth rate is determined by taking the first derivative of the long-term trend.
Text S2. The CTE station network

290 stations are evaluated in the CTE inversion, the observations come from the ObsPack data product (Schuldt et al., 2022). The measurement methods at the stations include surface-based, shipboard-based, tower-based and aircraft-based. In this study, we only focus on data derived from the first three measurement types (i.e. aircraft-based measurements are excluded), and in total 230 out of 290 stations are selected (Fig. 1). For the stations that have both surface-based and tower-based measurements, we used the tower-based measurements for analysis. For the stations that have tower-based measurements, we selected the highest measurement.

Text S3. Calculation of atmospheric CO$_2$ mass

CTE simulates 3D CO$_2$ mole fraction with 25 levels in the vertical direction. The CO$_2$ mass at each level of the atmosphere can be calculated as a function of air mass and CO$_2$ concentration by weight.

\[ m_{CO_2} = Cw_{CO_2} \times m_{air} \]  

(1)

where \( m_{CO_2} \) is the mass of the CO$_2$, kg. \( Cw_{CO_2} \) is the CO$_2$ concentration by weight, w %. \( m_{air} \) is the mass of the air, kg.

\[ Cw_{CO_2} = \frac{Cv_{CO_2} \times M_{CO_2}}{M_{air}} \]  

(2)

where \( Cv_{CO_2} \) is the mole fraction of CO$_2$ in air, mol / mol. According to the ideal gas assumption, equal volume of gases at same temperature and pressure contains equal number of moles regardless of chemical nature of gases, i.e. the CO$_2$ concentration by mole equals the CO$_2$ concentration by volume. \( M_{CO_2} \) is the CO$_2$ molar mass (44.009 g/mol). \( M_{air} \) is the average molar mass of dry air (28.9647 g / mol).

Pressure is the force applied perpendicular to the surface of an object, therefore, air pressure can be expressed by:

\[ p_{air} = \frac{F_{air}}{S} \]  

(3)

where \( p_{air} \) is the pressure of air, Pa or N / m$^2$. In this case, \( p_{air} \) is the difference of air pressure between adjacent level boundaries, e.g. air pressure at level 1 is \( p_1 - p_2 \). \( F_{air} \) is the magnitude of the normal force of air or gravity of air, N or kg m / s$^2$. The gravity of air at each level can be estimated by:

\[ F_{air} = m_{air} \times g \]  

(4)

where \( g \) is the gravitational field strength, about 9.81 m / s$^2$ or N / kg.

\( S \) is the area of the surface, m$^2$. Here \( S \) is the area of grid cell at each level, increasing with geopotential height (gph). It is calculated as a function of latitude and longitude on earth’s surface, radius of the earth \( R \), and gph.

\[ S = 2 \times \pi \times (R + gph)^2 \times \left( \sin(lat1) - \sin(lat2) \right) \times \left( \frac{lon1 - lon2}{360} \right) \]  

(5)

Where, \( lat1, lat2, lon1 \) and \( lon2 \) are the boundary of grid cell. \( R = 6378.1370 \) km, here we use the equatorial radius which is the distance from earth’s center to the equator.

Hence the mass of the air in Eq. 1 can be estimated by:

\[ m_{air} = \frac{p_{air} \times S}{g} \]  

(6)

Text S4. File list

All code necessary to calculate the global mean surface CO$_2$ mole fraction and Atmospheric CO$_2$ mass is freely available on ICOS Carbon Portal as a zipped archive (GAW_code.zip) [https://doi.org/10.18160/Q788-9081]. When unzipped, the code include:
Apply the semi-NOAA GFIT method to GAW observations (139 stations), CTE observations (230 stations), CTE model output at stations (230 stations) and CTE model output (full global).

Calculate global co2 mole fraction average and its growth rate, and estimate their uncertainty, using output from GAW(semi-NOAA GFIT).

Calculate global co2 mole fraction average and its growth rate, and estimate their uncertainty, using output from GAW(WDCGG).

Calculate global co2 mole fraction average and its growth rate, and estimate their uncertainty, using output from CTE_obs(semi-NOAA GFIT).

Calculate global co2 mole fraction average and its growth rate, and estimate their uncertainty, using output from CTE_output(semi-NOAA GFIT).

Calculate global co2 mole fraction average and its growth rate, and estimate their uncertainty, using output from CTE_global(semi-NOAA GFIT).

Calculate global co2 mole fraction and global atmospheric co2 mass, using the 3D co2 output from CTE model.

Statistically compare the co2 mole fraction and its growth rate among different data sources and analysis methods.

The script is used to analyze and plot the results in the paper.

In order to run the jupyter notebooks, it needs to download the data (GAW_data.zip) [https://doi.org/10.18160/Q788-9081] and change the data path in jupyter notebooks to where the data is unzipped.

The key results with CSV format are accessible on ICOS Carbon Portal as a zipped archive (GAW_results.zip) [https://doi.org/10.18160/Q788-9081], when unzipped, the data include:

- Global monthly and annual surface CO$_2$ mole fraction and its growth rate for 1980-2020 derived from the GAW observations by using the semi-NOAA GFIT method, i.e. GAW (semi-NOAA GFIT).

Global mean:

```
df_co2_annual_global_NH_SH_gaw_GFITseminoaa.csv
df_co2_monthly_global_NH_SH_gaw_GFITseminoaa.csv
df_co2rate_annual_global_NH_SH_gaw_GFITseminoaa.csv
df_co2rate_monthly_global_NH_SH_gaw_GFITseminoaa.csv
```

Their uncertainty basing on bootstrap method:

```
bootstats_co2_annual_global_gaw_GFITseminoaa.csv
bootstats_co2_monthly_global_gaw_GFITseminoaa.csv
bootstats_co2rate_annual_global_gaw_GFITseminoaa.csv
bootstats_co2rate_monthly_global_gaw_GFITseminoaa.csv
```

- Global monthly and annual surface CO$_2$ mole fraction and its growth rate for 1980-2020 derived from the GAW observations by using the WDCGG method without extrapolation, i.e. GAW (WDCGG).

Global mean:

```
```
Global monthly and annual surface CO₂ mole fraction and its growth rate for 1980-2020 derived from the observations at the CTE 230 stations by using semi-NOAA/GFIT method, i.e. CTE_obs (semi-NOAA/GFIT).

Global mean:
co2obs_co2_annual_global_NH_SH_ct2021_obs.csv
c02obs_co2_monthly_global_NH_SH_ct2021_obs.csv
c02obs_co2rate_annual_global_NH_SH_ct2021_obs.csv
c02obs_co2rate_monthly_global_NH_SH_ct2021_obs.csv

Their uncertainty basing on bootstrap method:
bootstats_co2_annual_global_gaw_wdcg.csv
bootstats_co2_monthly_global_gaw_wdcg.csv
bootstats_co2rate_annual_global_gaw_wdcg.csv
bootstats_co2rate_monthly_global_gaw_wdcg.csv

Global monthly and annual surface CO₂ mole fraction for 2001-2020 derived from the CTE model output covers full global with different heights (i.e. level1-3 and level1-25).

c2000_2020_annual.csv

c02_annual_global_cte2021(level1-3).GFFT_seminoaa.csv
c02_monthly_global_cte2021(level1-3).GFFT_seminoaa.csv
c02rate_annual_global_cte2021(level1-3).GFFT_seminoaa.csv
c02rate_monthly_global_cte2021(level1-3).GFFT_seminoaa.csv

Global monthly and annual surface CO₂ mole fraction for 2001-2020 derived from the CTE model output covers full global (averaged over the first three levels, 0 to 0.35 km Alt.) by using semi-NOAA/GFIT method, i.e. CTE_output (semi-NOAA/GFIT).

Global mean:
c02model_co2_annual_global_NH_SH_ct2021_modelsample.csv
c02model_co2_monthly_global_NH_SH_ct2021_modelsample.csv
c02model_co2rate_annual_global_NH_SH_ct2021_modelsample.csv
c02model_co2rate_monthly_global_NH_SH_ct2021_modelsample.csv

Their uncertainty basing on bootstrap method:
bootstats_co2_annual_global_cal_ct2021_modelsample.csv
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bootstats_co2rate_annual_global_cal_ct2021_modelsample.csv
bootstats_co2rate_monthly_global_cal_ct2021_modelsample.csv
Global monthly and annual atmospheric CO$_2$ mass (up to ~200 km) for 2000-2020 derived from the CTE model output by using the method described in Text S3.
Figure S1. Pair-wise statistical metrics assess the agreement of monthly global and local CO\textsubscript{2} mole fraction (ppm) and its GATM (ppm yr\textsuperscript{-1}) across various networks and methodologies (see Table 1 and Fig. 4) for the period 1980-2020. Panel (a) presents the Mean Error (ME) quantifying the difference for each pair, focusing on CO\textsubscript{2} mole fraction, while panel (b) does the same for GATM. The significance levels of paired t-test for ME are indicated as follows: * p<0.1, ** p<0.05, *** p<0.01. Panel (c) and (d) present the Root Mean Squared Error (RMSE) for CO\textsubscript{2} mole fraction and GATM, respectively. Panel (e) and (f) present the Pearson Correlation Coefficient (r) for CO\textsubscript{2} mole fraction and GATM, respectively.

Figure S1. Globally averaged CO\textsubscript{2} mole fraction (a) and its GATM (b) from 1980 to 2021. In panel (a), the red line shows the mean CO\textsubscript{2} mole fraction, black lines show the mean CO\textsubscript{2} mole fraction over 10 years, the grey area shows the uncertainty derived from the 200 bootstrap networks. Similarly, panel (b) shows the GATM instead of the mole fraction. The CO\textsubscript{2} and its GATM results are derived from the GAW observations from 139 stations by using semi-NOAA method.
Figure S2. Pair-wise statistical metrics assess the agreement of annual global and local CO$_2$ mole fraction (ppm) and its G$_{ATM}$ (ppm yr$^{-1}$) across various networks and methodologies (see Table 1 and Fig. 4) for the period 2001-2020. Panel (a) presents the Mean Error (ME) quantifying the difference for each pair, focusing on CO$_2$ mole fraction, while panel (b) does the same for G$_{ATM}$. The significance levels of paired t-test for ME are indicated as follows: * p<0.1, ** p<0.05, *** p<0.01. Panel (c) and (d) present the Root Mean Squared Error (RMSE) for CO$_2$ mole fraction and G$_{ATM}$, respectively. Panel (e) and (f) present the Pearson Correlation Coefficient (r) for CO$_2$ mole fraction and G$_{ATM}$, respectively.
Figure S3. Pair-wise statistical metrics assess the agreement of annual global and local CO₂ mole fraction (ppm) and its G_ATM (ppm yr⁻¹) across various networks and methodologies (see Table 1 and Fig. 4) for the period 1980-2020. Panel (a) presents the Mean Error (ME) quantifying the difference for each pair, focusing on CO₂ mole fraction, while panel (b) does the same for G_ATM. The significance levels of paired t-test for ME are indicated as follows: * p<0.1, ** p<0.05, *** p<0.01. Panel (c) and (d) present the Root Mean Squared Error (RMSE) for CO₂ mole fraction and G_ATM respectively. Panel (e) and (f) present the Pearson Correlation Coefficient (r) for CO₂ mole fraction and G_ATM respectively.
Figure S4. shows the trends of global CO$_2$ mole fraction for the GAW network (red line), the CTE network (green line) and the NOAA network (black line) during the whole period 1980-2020. The cycles show the annual CO$_2$ mole fraction, respectively.

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Figure S15. Globally averaged CO$_2$ mole fraction (a) and its $G\text{ATM}$ (b) from 1980 to 2021. In panel (a), the red line shows the mean CO$_2$ mole fraction, black lines show the mean CO$_2$ mole fraction over 10 years, the grey area shows the uncertainty derived from the 200 bootstrap networks. Similarly, panel (b) shows the $G\text{ATM}$ instead of the mole fraction. The CO$_2$ and its $G\text{ATM}$ results are derived from the GAW observations from 139 stations by using NOAA/GFIT method.

Figure S86. Annual absolute change and interannual variability of global CO$_2$ mole fraction derived from different data (CTE model, GAW observation and NOAA observation) and analysis methods (GFIT method, WDCGG method and NOAA method) for 2000-2020. Panel (a) shows the annual absolute change which is the difference between annual mean. Averages over 2001-2010 and 2011-2020 are also shown. Panel (b) shows the IAV which is calculated as the anomaly departure from a quadratic trend.

Figure S2. Globally averaged CO$_2$ mole fraction (a) and its $G\text{ATM}$ (b) from 1980 to 2021. In panel (a), black lines show the mean CO$_2$ mole fraction over 10 years, the grey lines show the 200 bootstrap networks, the red line shows the mean of the 200 bootstrap networks. Similarly, panel (b) shows the $G\text{ATM}$ results instead of CO$_2$ mole fraction. This result is derived from the GAW observations from 139 stations by using WDCGG method.
Figure S3S7. Atmospheric CO$_2$ mass derived from CTE output. Panel (a) shows the global monthly CO$_2$ mass in atmosphere (from surface up to 200 km altitude). Panel (b) shows the zonal (5°) average of monthly CO$_2$ mass. Panel (c) shows accumulated CO$_2$ mass with altitudes from 2001 to 2020, the dots mark CTE vertical level altitudes and lines are the linear interpolation between the altitudes.
Figure 8. Annual absolute change and interannual variability of global CO\textsubscript{2} mole fraction derived from different data (CTE model, GAW observation, and NOAA observation) and analysis methods (semi-NOAA method, WDCGG method, and NOAA method) for 2000-2020. Panel (a) shows the annual absolute change which is the difference between annual mean. Averages over 2001-2010 and 2011-2020 are also shown. Panel (b) shows the IAV which is calculated as the anomaly departure from a quadratic trend.

Figure S4. The relationship between the uncertainty of the global CO\textsubscript{2} growth rate and the number of observation sites. The relationship is estimated using CTE\textsubscript{global} (all global grids excluding ocean grids) with different resolutions (1x1, 2x2, 3x3, 4x4, 5x5, and 10x10 degrees) to estimate the uncertainty of the global CO\textsubscript{2} growth rate. The bootstrap method mentioned in the main text is used to estimate the uncertainty, and the results are represented as blue dots. The
red dashed line shows the linear interpolation between the experimental results, while the black line shows an exponential curve fitting.

Figure S9 presents the smoothed trend of CO$_2$ growth rate for each month during 1980-2020. The trends (depicted in Figure 6b) are smoothed by using a Gaussian filter (with sigma=1.96). The dots represent the local extrema, which aid in identifying the start of CO$_2$ growth rate increase/decrease.

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</tr>
<tr>
<td>ME</td>
<td>0.008</td>
<td>0.008</td>
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</tr>
</tbody>
</table>
Table S1. Statistic metrics assessing the agreement of the global CO₂ mole fraction (ppm) and its b焙 (ppm yr⁻¹) from GAW observations (139 sites) using the semi-NOAA method (GAW (semi-NOAA)) with a. GAW (WDCGG) method. The statistical metrics include: Pearson Correlation Coefficient (r), which ranges from -1 to 1, Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Error (ME). The negative value in ME means that the GAW (semi-NOAA) has higher values, vice versa.

<table>
<thead>
<tr>
<th>Statistic</th>
<th>CO₂</th>
<th>G_AW</th>
<th>CO₂</th>
<th>G_AW</th>
</tr>
</thead>
<tbody>
<tr>
<td>r</td>
<td>0.999</td>
<td>0.994</td>
<td>0.999</td>
<td>0.992</td>
</tr>
<tr>
<td>RMSE</td>
<td>0.130</td>
<td>0.062</td>
<td>0.180</td>
<td>0.076</td>
</tr>
<tr>
<td>MAE</td>
<td>0.115</td>
<td>0.037</td>
<td>0.151</td>
<td>0.042</td>
</tr>
<tr>
<td>ME</td>
<td>0.096***</td>
<td>-0.011</td>
<td>0.096***</td>
<td>-0.011***</td>
</tr>
</tbody>
</table>

Note paired t-test significance level for ME: * p<0.1, ** p<0.05, *** p<0.01.

Table S2S1. Statistic metrics assessing the agreement of the global CO₂ mole fraction (CO₂, ppm) and its GAW (ppm yr⁻¹) from GAW (WDCGG) and GAW (WDCGG+) during common period 1984-2020. GAW (WDCGG) is CTE observations (230 sites) using the WDCGG method without extrapolation. GAW (WDCGG+) is CTE observations (139 sites) using the WDCGG method with extrapolation. The statistical metrics include: Pearson Correlation Coefficient (r), which ranges from -1 to 1, Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Error (ME). The negative values in ME means the GAW (semi-NOAA) has higher values, vice versa.

<table>
<thead>
<tr>
<th>Statistic</th>
<th>CO₂</th>
<th>G_AW</th>
<th>CO₂</th>
<th>G_AW</th>
</tr>
</thead>
<tbody>
<tr>
<td>r</td>
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<td>0.890</td>
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<tr>
<td>RMSE</td>
<td>0.195</td>
<td>0.101</td>
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<td>MAE</td>
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<td>0.165</td>
<td>0.232</td>
<td>0.146</td>
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<td>ME</td>
<td>0.040</td>
<td>-0.008</td>
<td>0.069***</td>
<td>-0.008***</td>
</tr>
</tbody>
</table>

Note paired t-test significance level for ME: * p<0.1, ** p<0.05, *** p<0.01.

Table S3. Statistic metrics assessing the agreement of the global CO₂ mole fraction (CO₂, ppm) and its GAW (ppm yr⁻¹) from CTE output (semi-NOAA) and CTE_obs (semi-NOAA) during common period 2001-2020. CTE_obs (semi-NOAA) is CTE observations (230 sites) analysed by using the semi-NOAA method. CTE output (semi-NOAA) is CTE output at the 230 sites analysed by using the semi-NOAA method. The statistical metrics include: Pearson Correlation Coefficient (r), which ranges from -1 to 1, Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Error (ME). The negative values in ME means the CTE_obs (semi-NOAA) has higher values, vice versa.

<table>
<thead>
<tr>
<th>Statistic</th>
<th>CO₂</th>
<th>G_AW</th>
<th>CO₂</th>
<th>G_AW</th>
</tr>
</thead>
<tbody>
<tr>
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<td>0.999</td>
<td>0.999</td>
</tr>
<tr>
<td>RMSE</td>
<td>0.130</td>
<td>0.062</td>
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<td>0.076</td>
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<tr>
<td>MAE</td>
<td>0.115</td>
<td>0.037</td>
<td>0.151</td>
<td>0.042</td>
</tr>
<tr>
<td>ME</td>
<td>0.096***</td>
<td>-0.011</td>
<td>0.096***</td>
<td>-0.011***</td>
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</tbody>
</table>

Note paired t-test significance level for ME: * p<0.1, ** p<0.05, *** p<0.01.


<table>
<thead>
<tr>
<th>Date</th>
<th>Decadal year</th>
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<th>Days of year</th>
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42
<table>
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<tbody>
<tr>
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<tr>
<td>NOAA</td>
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<td>46</td>
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**El Niño 1997-1998**

<table>
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<tr>
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</tr>
</thead>
<tbody>
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<td>GAW</td>
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</tr>
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<td>NOAA</td>
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<td>1997.624975</td>
<td>228</td>
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</table>

**El Niño 2014-2016**

<table>
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<tr>
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<th>137</th>
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<tbody>
<tr>
<td>CTE</td>
<td>2013.374985</td>
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<td>137</td>
<td>2015.374985</td>
<td>137</td>
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</tbody>
</table>

Table S2 displays the estimates of CO₂ growth rate increase/decrease for the three strong El Niño events (i.e., 1987-1988, 1997-1998, and 2014-2016). These estimates are calculated from the smoothed trend of CO₂ growth rate based on CTE, GAW, and NOAA networks (Fig. S9).