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Detection of fossil fuel emission trends in the presence of natural carbon cycle variability

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Abstract

Atmospheric CO₂ observations have the potential to monitor regional fossil fuel emission (FFCO₂) changes to support carbon mitigation efforts such as the Paris Accord, but they must contend with the confounding impacts of the natural carbon cycle. Here, we quantify trend detection time and magnitude in gridded total CO₂ fluxes—the sum of FFCO₂ and natural carbon fluxes—under an idealized assumption that monthly total CO₂ fluxes can be perfectly resolved at a 2° × 2° resolution. Using Coupled Model Intercomparison Project 5 (CMIP5) ‘business-as-usual’ emission scenarios to represent FFCO₂ and simulated net biome exchange (NBE) to represent natural carbon fluxes, we find that trend detection time for the total CO₂ fluxes at such a resolution has a median of 10 years across the globe, with significant spatial variability depending on FFCO₂ magnitude and NBE variability. Differences between trends in the total CO₂ fluxes and the underlying FFCO₂ component highlight the role of natural carbon cycle variability in modulating regional detection of FFCO₂ emission trends using CO₂ observations alone, particularly in the tropics and subtropics where mega-cities with large populations are developing rapidly. Using CO₂ estimates alone at such a spatiotemporal resolution can only quantify fossil fuel trends in a few places—mostly limited to arid regions. For instance, in the Middle East, FFCO₂ can explain more than 75% of the total CO₂ trends in ~70% of the grids, but only ~20% of grids in China can meet such criteria. Only a third of the 25 megacities we analyze here show total CO₂ trends that are primarily explained (>75%) by FFCO₂. Our analysis provides a theoretical baseline at a global scale for the design of regional FFCO₂ monitoring networks and underscores the importance of estimating biospheric interannual variability to improve the accuracy of FFCO₂ trend monitoring. We envision that this can be achieved with a fully integrated carbon cycle assimilation system with explicit constraints on FFCO₂ and NBE, respectively.

1. Introduction

Current estimates of fossil fuel CO₂ emissions (FFCO₂) rely primarily on self-reported energy data from individual countries (IPCC 2013). Despite efforts to improve emission inventories, there is an increase in both relative and absolute errors in global FFCO₂ emissions because emissions are rising faster in nations with less accurate estimates (Andres et al 2014). To support individual countries’ objectives for the Paris Agreement, atmospheric observations of CO₂ have the potential to provide an independent assessment of reported FFCO₂ emissions and associated trends (Peters et al 2017b, Battersby 2018). However, these observations provide constraints on the net contribution of both anthropogenic and natural sources and sinks. The annual atmospheric CO₂ growth rate owing to FFCO₂ is reduced by roughly a half due to ocean and land sinks, with the latter exhibits significant interannual variability (IAV) (Le Quéré et al 2018, Sellers et al 2018). This IAV is one of the primary confounding factors in the attribution of changes in FFCO₂ based on CO₂ concentrations.
Historically, global surface networks were designed to study ecosystem CO$_2$ fluxes (i.e., net biome exchange (NBE)) measuring CO$_2$ far away from urban locations. Atmospheric simulations of these observations relied upon ‘bottom-up’ inventories for FFCO$_2$ (Gurney et al. 2002, Rödenbeck et al. 2003, Peters et al. 2007, Chevallier et al. 2010, Francy et al. 2013, Peylin et al. 2013, Liu et al. 2014, Gaubert et al. 2019) to account for increases in background CO$_2$. With increasing surface observations in urban regions (McKain et al. 2012, Stauffer et al. 2016, Turner et al. 2016, Wu et al. 2016, Wu et al. 2018, Verhulst et al. 2017, Mitchell et al. 2018) and the advent of satellite constellation dedicated to carbon gas measurements (O’Brien et al. 2016, Pillai et al. 2016, Broquet et al. 2018, Crisp 2018), atmospheric CO$_2$ concentrations will be measured with much higher precision and resolution than before (Battersby 2018), with greater potential to distinguish natural and anthropogenic contributions. Nevertheless, the attribution of temporal-spatial variations in the atmospheric CO$_2$ concentration to anthropogenic emission trends is fundamentally limited by the balance of natural and anthropogenic variability and magnitude (National Research Council et al. 2010, Shiga et al. 2014).

One approach is to focus on limited domains where anthropogenic CO$_2$ emissions dominate CO$_2$ variability. For example, urban regions contribute to more than 70% of the global FFCO$_2$ emissions and are likely to increase as metropolitan areas are projected to grow (Duren and Miller 2012, Hutyra et al. 2014), making them an especially attractive target for FFCO$_2$ monitoring. Urban CO$_2$ monitoring networks estimate city-scale FFCO$_2$ emissions using high-frequency measurements of CO$_2$ gradients between emitting sources and surrounding suburbs (McKain et al. 2012, Lauvaux et al. 2016, Stauffer et al. 2016, Wu et al. 2016, Verhulst et al. 2017, Mitchell et al. 2018). On the other hand, space-borne column-integrated CO$_2$ (X$_{CO2}$) mixing ratio observations are also shown to be sensitive to CO$_2$ enhancements over megacity ‘urban domes’, e.g., Los Angeles (Kort et al. 2012, Schwander et al. 2017) or power plants (Nassar et al. 2017). However, the isolation of local FFCO$_2$ emission sources using such methods depend on CO$_2$ observations with relatively low and stable biosphere influences such as in arid regions.

Globally, extended urban landscapes exhibit considerable heterogeneity with a mosaic of residential, transportation, industrial, vegetation and agriculture areas, which may be situated in complex terrain. Wu et al. (2018) showed that for Indianapolis, which has flat terrain but with similar magnitudes of biogenic and anthropogenic CO$_2$ fluxes, a CO$_2$ observation network of up to 12 sites at the city scale is not able to constrain FFCO$_2$ emissions effectively. The Indianapolis case indicates that the relative contribution from FFCO$_2$ and NBE to the total CO$_2$ has a direct impact on the accuracy of estimating FFCO$_2$. Consequently, any attempt to scale these city-scale case studies globally will need to account for this contribution and how it changes in space and time. Moreover, it is unclear if or when surface and aircraft measurement system would be deployed globally (e.g., Lagos, Moscow, Ho Chi Minh City).

Satellite remote sensing measurements with global coverage have been available for nearly a decade (Buchwitz et al. 2018) with an increasing constellation that will include geostationary sounders (Polonsky et al. 2014, Rayner et al. 2014), which could provide critical constraints on the global time series of total CO$_2$ fluxes. It is unclear, however, how that time series will relate to the underlying FFCO$_2$ emissions at those scales. To that end, we focus on two factors here: (1) how long it takes for a significant trend to emerge in the total CO$_2$ fluxes, noted as detection time, given the confounding impact of NBE variability across the globe, and (2) the relationship between trends in the total CO$_2$ fluxes and trends in the FFCO$_2$ at each grid. In order to isolate the impact of the intrinsic variability of NBE from the accuracy and precision of a particular observing system, we make an important assumption that monthly total CO$_2$ flux time series could be perfectly known at a 2° × 2° resolution. This corresponds to an idealized atmospheric CO$_2$ observing and attribution system that can fully solve monthly gridded carbon fluxes at such a resolution with a perfect transport model and sufficient CO$_2$ measurements. Consequently, these results are an upper bound in the detection time and accuracy of the trends at such a temporal and spatial resolution.

2. Data and method

2.1. CMIP5 emsRCP8.5 simulations

We use synthetic total CO$_2$ fluxes by combining FFCO$_2$ emissions under a ‘business-as-usual’ scenario, commonly noted as emsRCP8.5 (Taylor et al. 2012), and corresponding emission-driven simulations of biospheric carbon fluxes—denoted as NBE—from the Coupled Model Intercomparison Project 5 (CMIP5, https://esgf-node.llnl.gov/search/cmip5/). The mean annual global FFCO$_2$ during 2005–2015 in emsRCP8.5 is 9.24 ± 0.74 PgC·yr$^{-1}$, which agrees well with the emission inventories suggesting 9.22 ± 0.56 PgC·yr$^{-1}$ (Le Quéré et al. 2016) (figure 1(a)). To mitigate some known model biases in the CMIP5 carbon-climate feedback mechanisms that manifest as unrealistic trends in the land carbon sink (Friedlingstein et al. 2014, Hoffman et al. 2014), we applied a model selection based on the agreement between simulated CO$_2$ growth rate and the observed changes during 2005–2015 (see supplementary text 1 online at stacks.iop.org/ERL/14/084050/mmedia).

Four models are included for further analysis, namely BNU-ESM, HadGEM2-ES, IPSL-CM5A-LR, and MPI-ESM-LR. The resulting model ensemble provides an uncertainty estimate of NBE fluxes. All
models are resampled to $2^\circ \times 2^\circ$. This spatial resolution is limited by current global ESM simulations, but at the same time, equivalent to our current global inversions (Gurney et al 2002, Rödenbeck et al 2003, Peters et al 2007, Chevallier et al 2010, Francey et al 2013, Peylin et al 2013, Liu et al 2014, Gaubert et al 2019). Monthly time series for trend detection were selected to represent seasonal flux variabilities. The time series of the global FFCO$_2$ and NBE are shown in figure 1(b). FFCO$_2$ and NBE for the grid cell containing Beijing are shown in figure 1(c) as an example. The variation coefficient (vc, defined as the ratio of the standard deviation to the mean) for the global FFCO$_2$ is 0.3, while $-6.4$ for the global NBE. For Beijing, the vc is 0.11 for FFCO$_2$ and $-14.2$ for NBE. In both cases, NBE variation dominates the variability from FFCO$_2$. 

Figure 1. Time series of global fossil fuel CO$_2$ emission (FFCO$_2$) and net biome emission (NBE). (a) Global annual FFCO$_2$ and NBE simulated by the four models we use from CMIP5 esmRCP8.5 ensembles from 2005 to 2100. Dotted black lines represent FF emissions along with GCP estimates shown in red; color-coded lines represent individual ESM while black solid line represents the median of the selected ESMs. (b) Global monthly FFCO$_2$ and NBE for the period 2005–2015. The monthly FFCO$_2$ emissions are represented by the dotted-black line, which has a small seasonal cycle relative to NBE shown in color-coded lines. The added annual total emissions are shown in (a). (c) Monthly FFCO$_2$ and total CO$_2$ fluxes in the model grid Beijing locates. The blue line shows the monthly time series of the total CO$_2$ fluxes, the vertical dotted blue line indicates the trend detection time, the corresponding trend is shown in dashed-blue line. The cyan line shows the modeled seasonal cycle as represented by equation (2), and the shaded areas show the 95% confidence interval. Corresponding results for the FFCO$_2$ are shown in red.
2.2. Trend detection method

For simplicity, we define a linear trend to estimate the first-order change in the time series, as changes in FFCO$_2$ are expected to be gradual in the near future; this approach also allows for a simple comparison across different regions. The time series of observed fluxes can be defined by a simple additive noise model:

$$y(t) = F(t) + \epsilon,$$

where $y(t)$ are the derived fluxes at a gridded location, $F(t)$ is a function to describe how fluxes change in time, and $\epsilon$ represents the ‘unexplained variability’ in the system. We represent the times series as a simple model that includes a linear trend and seasonal cycle:

$$F_{SC}(t; a_0, a_1, C, D) = a_0 + a_1 t + \sum_{n=1}^{4}[C_n \sin(2\pi nt) + D_n \cos(2\pi nt)],$$

where $t$ is the decimal year, $a_0$ and $a_1$ are offset and slope, $C_n$ and $D_n$ are coefficients for the amplitude of seasonal variations, and $n$ represents the normalized frequency index of the harmonics-4 are chosen here. IAVs not captured by the harmonics is attributed to the unexplained variability term ($\epsilon$). The least square method of the optimization function in the Python package scpy is used.

We use a search method that starts with a 3 year temporal window and extends 1 more year at each iteration until a significant trend emerges (defined by the $p$-value of $a_1$ being less than 0.05 for two consecutive end years). The length of this temporal window thus represents the trend detection time. We first estimate the detection time and associated trend ($a_1$) of the total CO$_2$ fluxes at each model grid cell from 2015 onward, and then, we compare the estimated total CO$_2$ trends with corresponding trends imbedded in FFCO$_2$ emissions to evaluate whether trends in the total fluxes are directly relevant for FFCO$_2$ in different places across the world.

3. Results

3.1. Spatial distribution of the detection time and corresponding trend

The detection time has a global median of 10 years, which means that a significant trend in the total CO$_2$ fluxes could be identified within a decade for over a half of the land grids (figure 2). In 4% of the grids, no significant trend emerges over the 85 simulation years. The median of detected trends in the total CO$_2$ fluxes are 0.9 gC m$^{-2}$ yr$^{-2}$, but the spatial variations are very large (the 10th and 90th percentiles being $-87.5$ and 78.5 gC m$^{-2}$ yr$^{-2}$). To relate these changes to anthropogenic emission variability, we also compute FFCO$_2$ trends in the absence of the biosphere. Trends in the FFCO$_2$ component have a median of 0.4 gC m$^{-2}$ yr$^{-2}$, with their 10th and 90th percentiles being 0.01 and 4.3 gC m$^{-2}$ yr$^{-2}$ at corresponding detection time of the total CO$_2$ fluxes. The magnitude of trends in the FFCO$_2$ are over a factor of 2 smaller than trends in the total CO$_2$ fluxes and an order of magnitude less variable. This difference is driven primarily by the IAV in NBE, in particular extreme events in the natural carbon cycle. For example, a period of successive droughts can impose a large sub-decadal trend in the total CO$_2$ flux that is not representative of longer-term biospheric or FFCO$_2$ fluxes. Consequently, caution must be exercised in the interpretation of short-term total CO$_2$ trends in regions with an active biosphere.

A regional summary of the detection time and corresponding trend is shown in figure 3. The Middle East has the shortest detection time across the globe—5 years, with the least divergence between the FFCO$_2$ (2.5$^{\pm}$0.3 gC m$^{-2}$ yr$^{-2}$) and the total CO$_2$ (4.2$^{\pm}$2.0 gC m$^{-2}$ yr$^{-2}$) trends (the median is reported here, with the subscript and superscript showing the 10th and 90th percentiles, respectively, hereafter). In contrast, Canada has the longest detection time (29$^{\pm}$5 years), followed by Russia (23$^{\pm}$5 years). Detection time in the tropics is not particularly long, but large divergences between the total CO$_2$ and FFCO$_2$ trends are found indicating that trends in the total CO$_2$ fluxes are induced by NBE instead of FFCO$_2$. Although the median of the total CO$_2$ trends in the Central and South America agree roughly with the FFCO$_2$ trends, their variability are larger by more than an order of magnitude than FFCO$_2$ (2.4$^{\pm}$0.4 and $-1.1$ to $-76.1$ gC m$^{-2}$ yr$^{-2}$ for the total CO$_2$, whereas 0.6$^{\pm}$0.2 and 0.2$^{\pm}$0.2 gC m$^{-2}$ yr$^{-2}$ for the FFCO$_2$, respectively). Also, NBE from deforestation and land use changes are also important anthropogenic signals in those regions, but not addressed here. As for Southeast Asia and Oceania, the median of the total CO$_2$ trends also differ significantly from the FFCO$_2$ trends, as the model ensemble mean suggest enhanced land carbon sink over the corresponding total CO$_2$ trend detection time ($-28.7^{\pm}$6.2 and $-19.1^{\pm}$7.3 gC m$^{-2}$ yr$^{-2}$ for the total CO$_2$, whereas $-1.1^{\pm}0.4$ and 0.03$^{\pm}$0.1 gC m$^{-2}$ yr$^{-2}$ for the FFCO$_2$).

Each region, however, is a combination of grids with strong and weak FFCO$_2$ trends. Focusing on grids where FFCO$_2$ trends are greater than 5 gC m$^{-2}$ yr$^{-2}$ (~300 locations globally), approximately a third of grids show total CO$_2$ trends within 25% of concomitant FFCO$_2$ trends. These trends are primarily in Eastern China, Europe, Middle East, and North America. For example, China contributes to ~25% of these large FFCO$_2$ trends. Of those, about 20% show total CO$_2$ trends within 25% of the FFCO$_2$ trends, while ~40% differ by more than 100%. The differences are less pronounced in the Middle East, where over 70% of total CO$_2$ trends is within 25%. It is in this region where top-down systems may be the most effective in the near-term at a sub-decadal scale, even at a coarse resolution. We note that although the specific numbers are dependent on the current model simulations and the starting year, the spatial distribution of the relative contribution of biosphere to the detection of FFCO$_2$ trends should be robust given our current understanding of the natural carbon cycle.
However, we also expect that as more extensive regional monitoring networks become available, the relative weight of FFCO$_2$ and natural carbon fluxes will change when moving towards a higher spatiotemporal resolution, and hence, the signal-detection may improve upon the baselines we documented here.

### 3.2. Tradeoff between the detection time and the representativeness of estimated trend

The magnitude of estimated trends decreases exponentially with the increase of detection time because the trend in NBP is closer to neutral over longer time scales (figure S3). This is not surprising as short-term variations that qualify as a statistically significant trend at sub-decadal scales may not be representative of the long-term change. We further test that trends obtained using longer initial window lengths for the search method are generally of smaller magnitudes than those estimated using a shorter initial window (figure S4).

Using longer initial window of 5 and 10 years result in longer median detection time of 12 and 19 years with the differences between the total CO$_2$ and FFCO$_2$ trends reduced to 0.13$^{+0.9}_{-0.6}$ and 0.21$^{+0.8}_{-0.5}$ gC m$^{-2}$ yr$^{-2}$ using 5 and 10 year windows, respectively, with 43% and 79% reductions in the 10th and 90th quantile range compared to the results using 3 year initial window (0.22$^{+3.6}_{-4.4}$ gC m$^{-2}$ yr$^{-2}$). Although it is preferable to monitor short-term variations of regional FFCO$_2$ emissions, this analysis indicates that the use of CO$_2$ observations to infer FFCO$_2$ flux changes at a relatively short time scale should be treated with caution as the variations in the NBE over a few years could confound the attribution of observed CO$_2$ trends even though those short-term NBE trends are not indicative of the long-term biosphere trends. A higher accuracy with longer detection time only occurs where the natural biosphere is balanced over several decades; in regions where land-use change and carbon feedbacks are important, natural trends could still dominate the total CO$_2$ trend (figure 2).

To isolate the role of NBE variability in shaping the distribution of trend detection time, we created a test scenario $S_{FF_{-Uniform}}$ in which both the emission intensity and trend in the FF fluxes are uniformly distributed in space with the global total FFCO$_2$ equal to that of RCP8.5 (figure S5). The spatial variations are...
now determined by the variability and trends embedded in the NBE fluxes alone. Compared to the reference (shown in figure 2 and noted as $S_{FF\_RCP8.5}$), the detection time in $S_{FF\_Uniform}$ for trend in the total CO$_2$ fluxes becomes longer in regions where the original FFCO$_2$ are high, e.g. such as East Asia, India, Europe and Northeast US, while detection time shortens significantly in regions where the uniformly distributed FFCO$_2$ induce more detectable trends (figure S5). The comparison between $S_{FF\_RCP8.5}$ and $S_{FF\_Uniform}$ illuminates the interplay between FF and NBE to the detection of trends in the total CO$_2$ fluxes. Variability in the NBE remains to be the largest drawback of detection time. For example, the short detection time for the Middle East (less than 5 years) for both $S_{FF\_RCP8.5}$ and $S_{FF\_Uniform}$ show that low NBE in the arid regions allow FF trends to emerge more easily regardless of the choice of detection method. As for Eastern China, which has a large absolute FF emission flux in the original emission scenario, it requires a much longer detection time for the case of $S_{FF\_Uniform}$. However, future CO$_2$ emissions may deviate from the RCP8.5 scenario and plateau or even decrease in the future if emissions follow the Intended Nationally Determined Contributions submitted to UN Framework Convention on Climate Change. In such cases, independent constraints on the natural carbon cycle fluxes are even more critical to quantify actual changes in FFCO$_2$ fluxes.

3.3. Detection time and trends in megacities

Megacities are of particular interest because of their disproportionate impact on the anthropogenic carbon budget and we expect that future observing systems will focus on quantifying megacity emissions and trends. We use population as a criterion to focus on the grids where the top 25 mega-cities are located. Significant trends can be detected in approximately one third to a half of the cities within a decade with a monthly $2^\circ \times 2^\circ$ resolution (14 out of 25; figure 4). Intuitively, cities with a relatively short detection time are associated with either a relatively large trend in FF flux (>10 gC m$^{-2}$ yr$^{-1}$) or a significant trend in NBE over the detection window. For the former, trends in the total CO$_2$ fluxes are in good agreement with trends in the FFCO$_2$ fluxes (e.g. New York, Seoul, Los Angeles, Tokyo); whereas for the latter case, the divergences between the total CO$_2$ and FFCO$_2$ trends are large, in some cases differ in an order of magnitude (e.g. London, Dhaka, Sydney). There is also a large uncertainty range in the trends of the total CO$_2$ flux using individual ESMs, due to differences in trends embedded in each NBE simulations and in the detection time.

Figure 3. Regional summary of (a) trend detection time and (b) corresponding magnitude of trends in the total CO$_2$ fluxes and in the FFCO$_2$ component, respectively. For each region, the central rectangle spans the first quartile to the third quartile with a segment inside the rectangle showing the median; whiskers above and below the box show the minimum and maximum; outliers are noted as small dots (defined as $1.5 \times$ interquartile range more above the third-quartile or below the first-quartile). Regional mask is shown in figure S2.
Overall, there are eight cities whose total CO\textsubscript{2} trends matches trends in the FFCO\textsubscript{2} to within 25\%. Based upon these results and the detection time for both methods, we would expect that only in arid regions like Middle East, it would be possible to observe FFCO\textsubscript{2} change effectively in the near term with a CO\textsubscript{2}—only monitoring system. Tropical regions remain a significant challenge. At 2° × 2° degree resolution the detection time for Sao Paulo, Bangkok, and Lagos are close to a decade, the weak FF trend is masked by strong NBE trends leading to total CO\textsubscript{2} trends of −13, −9, and 25 gC m\textsuperscript{-2} yr\textsuperscript{-2}, respectively (comparing to FFCO\textsubscript{2} trend of 2.6, 3.5, and 1 gC m\textsuperscript{-2} yr\textsuperscript{-2}).

4. Uncertainty and perspectives

In this study, we show the spatial distribution of trend detection time of total CO\textsubscript{2} fluxes and how these derived total CO\textsubscript{2} trends are representative of the FFCO\textsubscript{2} trends at a 2° × 2° degree with monthly data. This analysis provides us helpful information at a global scale regarding how feasible it is at a certain location to define an ‘urban dome’, where the background air that has a small influence from natural carbon fluxes and their associated IAVs. We note that the analysis is performed at a relatively coarse spatial resolution, which is limited by current available global NBE simulations and at the same time equivalent to global atmospheric inversions that ingest the currently available global observations. Higher resolution in both space and time would likely be achieved for city scale FFCO\textsubscript{2} studies where local CO\textsubscript{2} gradient between the urban center and the rural area would be the key information to quantify FFCO\textsubscript{2}. Nevertheless, our analysis is relevant as urban landscapes often exhibit considerable heterogeneity in the land cover and land use, thus the mixed contribution from anthropogenic and biospheric sources will not be automatically solved with increasing spatial and temporal resolution alone. At a higher resolution, the relative contribution of FFCO\textsubscript{2} and NBE would change, e.g. it will become easier to detect FFCO\textsubscript{2} signal from the total CO\textsubscript{2} fluxes if the magnitude of FFCO\textsubscript{2} fluxes outweigh the NBE over the estimated domain, as we illustrate here using different FFCO\textsubscript{2} scenarios. Still, for cases where a clear ‘urban dome’ could be identified, inter-annual variations in the NBE of the background region could be aliased into the FFCO\textsubscript{2} trend estimates if they are not adequately considered. For instance, an increase in the CO\textsubscript{2} enhancement over the urban dome could result from an increase in the city FFCO\textsubscript{2} or an increase in the net carbon uptake by the suburban vegetation.

As we expect to monitor progressive changes in FFCO\textsubscript{2}, trend detection is an efficient way to define the relative change and whether a certain region is on track of the promised emission reduction trajectory. However, a linear trend determined with a statistical model has limited skill in representing non-monotonic or nonlinear changes and is sensitive to the starting and ending points. In addition, a regular seasonal cycle we considered here may not model well ecosystems without regular seasonality (e.g. ecosystem with larger variations in the onset of dry and wet seasons). Nevertheless, our simple approach derives a global reference for regionally specific studies prior to the establishment of global, but fine-scale detailed observations. Our sensitively test starting from

![Figure 4. Results of the top 25 megacities (a) the trend detection time and (b) trends in the total CO\textsubscript{2} fluxes versus trends imbedded in the FFCO\textsubscript{2} at the trend detection time of the total CO\textsubscript{2} fluxes. Individual scatter shown in small crosses represent results using NBE simulated by different ESMs, the solid markers represent the ensemble mean and the error bars along the y-axis indicate standard deviations using different NBE simulations.](image)
random years instead of 2015 to test the sensitivity of the starting point suggest the resultant global pattern being quite robust. Our test using different length of the initial searching window also confirm this point.

This analysis highlighted, on the one hand, a few regions that are feasible for using top-down FFCO$_2$ constraints, and on the other hand, the difficulty of disentangling FFCO$_2$ changes from the natural carbon cycle with CO$_2$ observations alone. Therefore, multiple pieces of information will be needed to observe regional FFCO$_2$ trend accurately. For instance, periodic $^{14}$C measurements (Basu et al. 2016, Wang et al. 2017) and the combination of other fossil fuel tracers (e.g. NO$_2$, CO) could bring in additional information even though there are complications due to the variation and uncertainty in their emission factor ratio to CO$_2$ and by atmospheric chemistry (Gammitzer et al. 2006, Rayner et al. 2014). In addition, proxies to constrain the terrestrial ecosystem production (e.g. solar induced fluorescence and carbonyl sulfide, OCS) could also contribute essential information by adding more constraints to different components of the carbon cycle to estimate the progress of climate mitigation (Schimel et al. 2015, Bloom et al. 2016, Bowman et al. 2017, Liu et al. 2017, Sellers et al. 2018). Also, many countries also invoke land use management for their National Determined Contributions (Grassi et al. 2017), thus monitoring corresponding biospheric fluxes remains highly relevant. Furthermore, from the inventory viewpoint, indicators to track emission activity and technology development are also important (Peters et al. 2017a). With increasing spatial-temporal resolution and coverage of the above-mentioned features (Broquet et al. 2018), a data assimilation scheme that includes consideration for both FFCO$_2$ and NBE uncertainties and integrates multiple observational streams will help to account for variations in these two fluxes consistently.

5. Conclusion

Our results provide an initial assessment of the trend detection time and associated trends in the gridded total CO$_2$ fluxes over the globe with synthetic fluxes from CMIP5 under the assumption of an idealized CO$_2$ observing and attribution system that can derive such fluxes. The trend detection time for gridded total CO$_2$ has a median of 10 years at a resolution of $2^\circ \times 2^\circ$ degree using monthly flux data, with large spreads depending on fossil fuel emission magnitude versus NBE variability. The differences between trends in the total CO$_2$ fluxes and in the underlying FFCO$_2$ component highlight the role of natural carbon cycle variability in modulating regional detection of FFCO$_2$ emission trends using CO$_2$ observations alone, particularly in the tropics and subtropics where mega-cities with large populations are emerging and developing rapidly. As we have shown, using CO$_2$ flux estimates alone at such a resolution can only quantify fossil fuel trends in a few places—mostly limited to the arid region. Monitoring FFCO$_2$ at a city scale with a finer spatial resolution may become easier when the magnitude of FFCO$_2$ fluxes outweigh the NBE variations. However, these local estimates will still need to be integrated with regional, national, and ultimately global estimates of natural and anthropogenic carbon. Consequently, it will be important to constrain the background biosphere fluxes so that their uncertainties are not aliased into the FFCO$_2$ estimates. Therefore, the challenge of assessing international carbon mitigation progress requires an approach linking both bottom-up and top-down estimates within an assimilation and attribution system that integrates information on both natural and anthropogenic carbon fluxes.

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