East Asian CO₂ level change caused by Pacific Decadal Oscillation

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A B S T R A C T

Accurate projection of CO₂ concentration in time and space remains challenging because of complex interplay between anthropogenic emissions, biospheric responses, and climatic variabilities. While the increase of atmospheric CO₂ concentration is due primarily to fossil fuel burning, natural climate variabilities are known to introduce intermittent changes in the global CO₂ growth rates. Thus, understanding the correlation of climate and carbon cycling systems is important in assessing the anthropogenic and natural impacts. Here, we report decadal CO₂ variabilities in western Pacific based on data from several ground-based stations in the region and Atmospheric Infrared Sounder (AIRS). In addition to the well-established El Niño–Southern Oscillation (ENSO), there exists a decadal changing CO₂ trend in the datasets mentioned above. Analysis of ground-based CO₂ measurements in northern Taiwan shows a decadal signal at amplitudes of ~5 ppm. In contrast, AIRS shows a similar trend but at a reduced amplitude of ~1 ppm. We attribute the decadal signal to dynamical factors related to the Pacific Decadal Oscillation (PDO). This decadal signal, however, is not reproduced by the state-of-the-art data assimilation system, CarbonTacker, suggesting a gap in our knowledge of the modulation of carbon cycling systems and climate.

1. Introduction

Currently, fossil fuel burning emits 9.4 ± 0.5 PgC/year (averaged over 2008–2017) of CO₂ equivalent to the atmosphere. About half of this emission is absorbed by the ocean and terrestrial biosphere, leaving the other ~half in the atmosphere, which accounts for the reported global annual CO₂ increase of ~2 ppm/year (Le Quéré et al., 2018). However, the regional rates of CO₂ increase depend highly on the source/sink distributions and may vary in space and time. A major spatial inhomogeneity is the much higher CO₂ concentration in the northern hemisphere compared to the southern hemisphere, because most of the continents and anthropogenic sources are in the northern hemisphere. Another source of spatial inhomogeneity is industrial emissions from east Asia and the eastern US, and biomass burning in the tropical rainforests of Indonesia, Congo and Amazon (Chahine et al., 2008; Jiang et al., 2021; Le Quéré et al., 2018). Recent relocations of factories from east Asia to south and southeast Asia may create a new spatial pattern of CO₂ emission hotspots in the eastern hemisphere. In contrast, most of the CO₂ sinks are natural. The largest CO₂ decrease is caused by the terrestrial uptakes through photosynthesis, whose rate is the highest under direct sun during the boreal summer, creating both annual and semiannual cycles in the observed CO₂ concentration (Jiang et al., 2012; Jiang et al., 2016). Ocean variability such as the El Niño–Southern Oscillation (ENSO) also modulates atmospheric CO₂ concentration directly and indirectly on an interannual timescale (2–7 years) through the temperature dependence of CO₂ solubility in ocean water and through hydrospheric changes due to floods/droughts associated with ENSO-related climatic patterns (Jiang et al., 2013; Liu et al., 2017; Welp et al., 2011). Modulations due to natural variabilities have often led to “ramp-ups” and “ramp-downs” in the CO₂ growth rates (Chatterjee et al., 2017), which conjoin with the anthropogenic effects. Therefore, monitoring CO₂ distribution at multiple stations on regional and global scales as well as remote sensing observations is of particular importance to understanding and resolving the inter-correlation of climatic and carbon cycling systems (e.g., see Bruhwiler et al., 2021; Crisp et al., 2004).

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Current satellite observations of atmospheric CO\textsubscript{2} rely mainly on passive infrared (IR) and near-IR spectral measurements, which have the best sensitivity to middle-to-upper tropospheric CO\textsubscript{2} or the whole column CO\textsubscript{2} down at the planetary surface (Chahine et al., 2005; Crevoisier et al., 2009; Crisp et al., 2017; Kulawik et al., 2010; Schneising et al., 2011; Yokota et al., 2009). In the free troposphere, the zonal distribution of CO\textsubscript{2} is greatly influenced by large-scale dynamics that could quickly mix signatures of surface sources and sinks within ~30° longitude in a few days (Keppel-Aleks et al., 2011). As a result, the spatial variability of free-tropospheric CO\textsubscript{2} at higher altitudes is significantly smoothed out to ~1–2% of the global average value of 400 ppm. Consequently, for accurate inverse modeling of the surface sources and sinks, an accuracy of at least ~1 ppm or ~0.3% in column measurements must be achieved, and this level of precision is technologically challenging for a spaceborne instrument. Therefore, ground-based measurements of CO\textsubscript{2} constitute an important research area not only toward monitoring regional CO\textsubscript{2} emissions that cannot be probed precisely by the satellite instruments, but also toward understanding how atmospheric transport may have redistributed the signatures of the surface CO\textsubscript{2} sources and sinks before they reach the free troposphere. In addition, they provide invaluable datasets to validate satellite retrievals.

The global monitoring network managed by the National Oceanic and Atmospheric Administration (NOAA) aims to measure the background levels of CO\textsubscript{2} and other greenhouse gases. More than 20 stations have been established in remote marine environments and about two-thirds of them are in the Pacific. Stations in western Pacific, some of which have been established only recently, capture the pollutants from fast-developing regions in east and southeast Asia. Located at the downwind of those regions, Taiwan could pick up regional emissions originating from east and southeast Asia (Laskar et al., 2018). Thus, measurements in Taiwan provide a good proxy for the regional CO\textsubscript{2} level in east and southeast Asia. As a result, since 2002, Taiwan Environmental Protection Administration (EPA) has established six stations (four of them are selected for the study), monitoring CO\textsubscript{2} continuously. Furthermore, Taiwan is geographically located at the transition zone of the tropics and the subtropics, experiencing two major monsoons in east Asia: northeast (winter) and southwest (summer) (e.g., see Rangarajan et al., 2017). As a result, measurements in Taiwan are sensitive to climate variability in the Indo-Pacific region such as ENSO. In this paper, we report a new type of climatic variability controlling the CO\textsubscript{2} levels in western Pacific using data from remote sensing retrievals and ground-based measurements. We propose that the variabilities derived in this work are consequences of the dynamical changes associated with a climate fluctuation in the northern Pacific, the Pacific Decadal Oscillation (PDO; Mantua et al., 1997). We also show that this new variability can be seen in the spaceborne CO\textsubscript{2} data retrieved during recent times.

2. Materials and methods

In addition to the well-established long-term monitoring network of NOAA, we also include analyses of CO\textsubscript{2} from Taiwan EPA, two satellites (AIRS and GOSAT), and CarbonTracker model product, to assess the changing CO\textsubscript{2} levels in regional and global scales. AIRS is sensitive to CO\textsubscript{2} in the mid-troposphere, while GOSAT provides sensitivity at the surface. The datasets used in this work are summarized in Table 1.

2.1. Ground-based measurements

Fig. 1 shows the geographical locations of the ground-based stations used in this work. The surface air CO\textsubscript{2} mixing ratios are available at a monthly resolution from NOAA Earth System Research Laboratories (Dlugokencky et al., 2021) and Taiwan EPA. Non-dispersive infrared analyzers (NOAA switched to a cavity ring-down spectrometer in August 2019) are employed for NOAA flask (Conway et al., 1994; Komhyr et al., 1989) and Taiwan EPA continuous online CO\textsubscript{2} concentration measurements, both of which are traceable to the WMO X2019 CO\textsubscript{2} in air mole fraction scale. The CO\textsubscript{2} data from six NOAA and four Taiwan EPA monitoring stations are selected. NOAA sites include Bukit Kototabang, Indonesia (BKT), Mariana Islands, Guam (GMI), Mauna Loa, USA (MLO), Mt. Waliguan, China (WLG), Ta¨e-ahn Peninsula, Korea (TAP), and Ulaan Uul, Mongolia (UUM). Taiwan EPA stations are Hengchun (HC), Yilan (YL), Songshan (SS), and Mt. Yangming (YM); Ecotech EC9820 infrared analyzer is used in these latter stations.

2.2. Spaceborne measurements

The AIRS (Atmospheric Infrared Sounder) Version 5 CO\textsubscript{2} dataset between 2002 and 2017 are currently the longest spaceborne CO\textsubscript{2} observation available (Chahine et al., 2008). The mid-tropospheric CO\textsubscript{2} mixing ratios are retrieved from the wing (690–725 cm\textsuperscript{-1}) of the 15-μm CO\textsubscript{2} absorption band measured over a native 13.5-km nadir field-of-view (Chahine et al., 2008). The weighting function of the retrieved CO\textsubscript{2} can be seen in the spaceborne CO\textsubscript{2} observation available (Chahine et al., 2008). The mid-tropospheric CO\textsubscript{2} levels are sensitive to the variation of adjacent retrievals under clear-sky conditions are required to be used in the Level-3 daily average at a grid point. The CO\textsubscript{2} Level-3 product is available in grid size of 2.5° longitude × 2.0° latitude. In this study, we use the AIRS Version 5 Monthly Averaged Level-3 CO\textsubscript{2} retrieval products: denominated AIRX3C2M.005 and AIRS3C2M.005. The AIRX3C2M.005 CO\textsubscript{2} products are retrieved with the aid of the cloud

| Table 1 |

<table>
<thead>
<tr>
<th>Category</th>
<th>Provider/Mission</th>
<th>Types of measurements</th>
<th>Stations focused</th>
<th>Data length</th>
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<td>GOSAT (Version 9.3)</td>
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<td>Troposphere</td>
<td>East Asia</td>
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<tr>
<td>Model</td>
<td>CarbonTracker (CT2019B)</td>
<td></td>
<td></td>
<td>East Asia</td>
</tr>
</tbody>
</table>

Fig. 1. Geographical locations of the stations selected for the study. NOAA stations (BKT, WLG, TAP, UUM, GMI, and MLO) are shown by the circles, and Taiwan EPA stations (HC, YL, SS, and YM) are in triangles.

![Fig. 1. Geographical locations of the stations selected for the study. NOAA stations (BKT, WLG, TAP, UUM, GMI, and MLO) are shown by the circles, and Taiwan EPA stations (HC, YL, SS, and YM) are in triangles.](image-url)
information from a companion instrument, Advanced Microwave Sounding Unit (AMSU), and this product covers the period from September 2002 to February 2012; subsequent period could not be covered because of a permanent failure of AMSU in 2012. The other CO2 product, AIRS3C2M.005, are retrieved using only AIRS spectral measurements to identify cloud effects; this product covers January 2010 to February 2017. Retrieved CO2 on both ascending and descending tracks corresponding to local times 1:30 AM and 1:30 PM are included in the monthly average calculations. Validation against in situ aircraft and ground-based measurements demonstrates an accuracy of 2 ppm for monthly averaged AIRS CO2 levels between latitudes 30°S and 80°N (Chahine et al., 2008).

In addition to the 15-μm CO2 absorption band measured by AIRS, the Greenhouse Gases Observing Satellite (GOSAT) of the Japanese Aerospace Exploration Agency (JAXA) measures the CO2 absorption in the reflected solar shortwave IR at 1.56–1.72 μm and 1.92–2.08 μm over circular footprints of ~10.5 km diameter at the nadir (Yokota et al., 2009). In this study, we use the Level-2 Version 9.3 column-averaged dry-air mole fraction CO2 retrieval based on the Atmospheric CO2 Observations from Space (ACOS) project of National Aeronautics and Space Administration (NASA), which was originally developed for retrievals of the Orbiting Carbon Observatory (OCO-2) (O’Dell et al., 2012). A raw retrieval may be subject to a root-mean-square precision of as large as ~3 ppm in a clear sky. Due to the use of reflected sunlight for the retrieval, only daytime CO2 along the descending tracks at around 1 PM local times are available. We have averaged the Level-2 ACOS/GOSAT CO2 on 5° longitude × 4° latitude grids before our analysis discussed in Section 3. Because of the low sensitivity of GOSAT to the vast area of the ocean, we show the comparison of the available GOSAT retrieved CO2 over the locations of Taiwan and MLO only.

2.3. CarbonTracker model data

CarbonTracker is a modeling system developed by NOAA to estimate surface sources and sinks of CO2 globally (Peters et al., 2007). The system, driven by the transport from European Centre for Medium-Range Weather Forecasts ERA-Interim reanalysis (Dee et al., 2011), assimilates a suit of atmospheric CO2 measurements and returns exchange fluxes between the atmosphere and planetary surface and CO2 concentrations in the atmosphere. The CarbonTracker data used here is CT2019B. For comparison with NOAA ground-based measurements, we take the simulated results provided by NOAA (Jacobson et al., 2020), under the framework of ObsPack (Masarie et al., 2014), which provided the simulated CO2 at the same observation times at the stations.

2.4. Statistical trend analysis

In additional to computing 12-month running averages for the trend analysis, we also performed the empirical mode decomposition (EMD) (Huang et al., 1998; Wu and Huang, 2009). The EMD extracts the secular trend of a time series by sequentially removing short-term variabilities, such as the seasonal cycle and interannual variations (e.g., ENSO), through a sifting process, which identifies an oscillatory component if the component has at least one local maximum or minimum. The short-term variability obtained from each sift is called an intrinsic mode function (IMF). The secular trend is defined as the residual after all IMFs (extraction of such as the seasonal cycle and interannual variations (e.g., ENSO), the short-term term variability obtained from each sift is called an intrinsic mode function (IMF). The secular trend is defined as the residual after all IMFs)

\[
D(t) = \sum_k A_k(t) \exp[-i \int_0^t b_k(t) dt]
\]

where \(D(t)\) is the time series being decomposed, \(A_k(t)\) and \(b_k(t)\) are the instantaneous amplitude and phase of the \(k\)-th IMF, \(b_k(t)\) is the time derivative of \(b_k(t)\), which gives the instantaneous frequency of the \(k\)-th IMF, and the summation goes over all available IMFs. Like modern machine learning techniques, the EMD does not make any prior assumptions about the underlying signals. Thus it is effective in extracting non-linear (i.e., varying amplitudes) and non-stationary (i.e., varying frequencies) components of a climatic time series adaptively based on the time series per se. EEMD is an extension of the EMD, where mode mixing of a finite time series is minimized through Monte Carlo simulations (Wu and Huang, 2009) and is adopted for the present work.

3. Results

As mentioned before, Taiwan, located in the western Pacific region, can pick up emissions from east and southeast Asia. To explore the overall changes in this region, we compare the CO2 variabilities over 2 NOAAs in the western Pacific (BKT and TAP) and 2 Taiwan EPA (SS and YM) stations, with that over MLO (see Fig. 1 for their geographical locations). (The results for all of the stations selected in this work are provided in full in Supplementary Information.) We also compare the regional climatic variability with those obtained from simulated CO2 data and satellite observations.

We first examine the overall deviation of CO2 at the selected stations from the background site MLO (Fig. 2). Compared to the level of CO2 at MLO, YM is 4.9 ± 0.4 (mean ± standard error; \(n = 201\)) ppm more, BKT (a low latitude station in the region; 0.2°S) is 5.2 ± 0.2 (\(n = 170\)) ppm less, and TAP (a mid-latitude station at 36.7°N) is 5.2 ± 0.2 (\(n = 348\)) ppm more (statistics based on all available data); between 2006 and 2019 (the period when the YM data are less noisy), the deviations for YM, BKT, and TAP are 5.3 ± 0.4 (\(n = 168\)), −5.2 ± 0.3 (\(n = 146\)), and 6.7 ± 0.3 (\(n = 168\)) ppm, respectively. We next show the changing trend by examining the deviations between 2006 and 2011 and between 2012 and 2019. The averaged deviations at BKT and TAP between 2006 and 2011 are, respectively, −6.0 ± 0.3 ppm and 5.5 ± 0.5 ppm while the averaged deviations at BKT and TAP between 2012 and 2019 are, respectively, −4.6 ± 0.4 ppm and 7.6 ± 0.4 ppm. In contrast, the difference at YM is more pronounced; the values are 3.1 ± 0.5 ppm for 2006–2011 and 6.9 ± 0.5 ppm for 2012–2019. We hypothesize that the PDO is the cause of the change (see next section).

Fig. 3 compares the measured CO2 levels at the three selected representative sites with that from the CarbonTracker model (see Fig. S2 for other station results). The differences between the model and observational data are 4.3 ± 0.2 (\(n = 441\)), −0.9 ± 0.2 (\(n = 728\)), and 0.11 ± 0.01 (\(n = 1237\)) ppm, respectively, at BKT, TAP, and MLO. The bias from BKT is significant while the other two are less apparent, indicating that there may be unknown processes and/or incomplete knowledge of the sources and sinks that affect and control CO2 at this lower latitude site. The model imperfection is also demonstrated by the poor reproduction of the seasonal cycles of CO2 at stations other than MLO and GMI (Fig. S2).

To better extract the changing trends (or any oscillatory components with a period greater than half of the observational period, i.e., 5 years) for the signal of interest, we applied EEMD (12-month running average results are also shown for comparison), and the results at the three NOAA and two Taiwan EPA selected sites are summarized in Fig. 2 (see Fig. S1 for the results of all stations); we limit the discussion to the time period of 2006–2019 corresponding to the selected data of Taiwan EPA. If only the last (residual, non-oscillating) mode of EEMD is considered (see Fig. S3), the YM trend changes from 1.79 ± 0.03 ppm/year in year 2006 to 2.95 ± 0.03 ppm/year in year 2019; the rate of the changing trend is 0.09 ppm/year\(^2\). At TAP, the trends are 2.18 ± 0.01 ppm/year in year 2006 and 2.65 ± 0.01 ppm/year in 2019; the changing rate is 0.04 ppm/year\(^2\), a factor of ~2 less than that at YM. At BKT, the trends are roughly constant at 2.7 ± 0.1 ppm/year but the value in 2006, 0.1 ppm/ year, is systematically higher than that in 2019; the bending feature of the EEMD derived trend at BKT in 2010–2011 and 2013–2014 is due to an artifact introduced by missing data between 2011 and 2012. For comparison, the trend at MLO between 2006 and 2019 is approximately
constant at $1.830 \pm 0.002$ ppm/year, in contrast to the NOAA reported annual growth rate of 1.7 ppm/year in 2006 and 2.5 ppm/year in year 2019 (see Fig. S4 for the comparison). Further analysis shows that the previously reported changing rate at MLO is largely contributed by IMFs at periods longer than 5 years. As a result, in addition to known 2–7 years ENSO, we notice that the trend possesses an oscillating period of $\sim 10$ years, having a minimum of $1.91 \pm 0.01$ ppm/year in 2007 and maximum of $2.462 \pm 0.001$ ppm/year in 2016; the trend is $2.34 \pm 0.02$ ppm/year.

Fig. 2. Time series of monthly $\text{CO}_2$ (black symbols) at BKT, TAP, MLO, YM, and SS, along with EEMD derived (blue solid curve) and 12-month running averaged (red dashed) trends. The bending feature of the EEMD derived trend at BKT in 2010–2011 and 2013–2014 is due to missing data between 2011 and 2012. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Fig. 3. Comparison of NOAA measured (black symbols) and CarbonTracker simulated (blue solid curve) $\text{CO}_2$ at BKT, TAP, and MLO. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
ppm/year in 2019. Similar to the MLO, YM, SS, BKT, and TAP also show significant changing trends in 2006–2019 (Fig. 4). For example, including the decadal signal at YM yields a pronounced changing rate between 2006 and 2019. The value is 1.21 ± 0.05 ppm/year in 2006, increases rapidly to 3.38 ± 0.03 ppm/year in 2013, and then declines to 2.16 ± 0.06 ppm/year in 2019. Two other Taiwan stations (HC and YL), however, show distinctive changing trends from the presented at YM and SS. See Fig. S1 for the full comparison of the trends derived in this work and Table 2 for a summary of the averaged trends calculated using the EEMD results.

To see the extent of the changing trend, we analyzed AIRS and GOSAT column CO₂ data. Though the changing trend is observable, the amplitude is similar to that of MLO and both are an order of magnitude less than that of northern Taiwan (Table 2; Fig. S5). One plausible explanation is the low sensitivity of satellite retrievals to the surface CO₂ versus ground-based high precision measurements.

4. Discussion

To investigate the driving force for the changing trend, we consider two candidates: anthropogenic emission and climate variabilities in the region.

First, it was recognized that total emission has increased since ~1960 (Le Quéré et al., 2018). In east Asia, urban areas constitute the major source of CO₂ emission in recent decades going as high as 40% of the world’s total. The 2017 emission rate was 9.9 ± 0.5 PgC/year (Le Quéré et al., 2018); the value in 1990–1999 was 6.3 ± 0.3 PgC/year and increased rapidly to 9.4 ± 0.5 PgC/year in 2008–2017, contributed mainly by China, which now accounts for 27% of the total emission of the world exceeding that of USA since 2004 (Le Quéré et al., 2018). In the last decade (2008–2017), China’s emission increased steadily at 3%/year, inconsistent with the rapidly changing growth rate of CO₂ in 2010–2015 we reported above. Furthermore, from their analysis of CO₂ isotopic composition made in Taiwan, Laskar et al. (2018) showed that besides minor contributions from local emissions, this region is affected primarily by external transport in winter and spring that originated from north, west and southwest landmasses. They found an abnormal increase in the CO₂ mixing ratio (~2 ppm) in a high mountain station in central Taiwan in the spring, and biomass burning in rice growing countries of southeast Asia was the source of this CO₂ increase owing to favorable transport by the westerlies. In contrast, two studies on aerosol samples collected at Lulin Observatory (located at Mt. Lulin) involving nitrate (Guha et al., 2017) and sulfate (Chung et al., 2019) did not show any significant effect due to fossil fuel/coal burning in the east Asian countries. In case of nitrate, the signal was better interpreted by a change of reaction pathways of nitrate formation, whereas in case of sulfate, the isotopic ratios (δ³⁴S) were found to represent the regional background levels, contributed by oil refinery industry rather than coal burning. In view of these conflicting results concerning biomass-burning which yields CO₂ as a major product, we conclude that changing anthropogenic emissions in the region unlikely explain the changing trend observed in ~2010–2015 (see Figs. 2 and 4) and the decadal oscillation signals in CO₂ in the region (Fig. 5).

Second, to explore for an explanation of the changing trend, we consider dominant climate variabilities in the western Pacific. Laskar et al. (2018) have already shown that the geographical location of Taiwan such that trace gas concentrations there may be influenced by a number of interannual climate processes, such as Asian monsoons. However, the regime change over the ~10 years record described above is not due to monsoonal variability but may be caused by decadal climate variabilities. The PDO is the most dominant decadal sea-surface temperature (SST) variability in the north Pacific (Mantua et al., 1997) and is one of the three fundamental modes in the Pacific basin (Feng et al., 2020) after the linear trend and the canonical ENSO (Kao and Yu, 2009). Considering the observational period of 2006–2015, the five-year span of 2008–2012 is known to have been in a PDO negative phase, which featured a warm SST anomaly in the north Pacific and a cold SST anomaly in the tropical Pacific. In contrast, the period 2014–2018 was in a PDO positive phase, where the cold-warm anomalies in the north and tropical Pacific were reversed relative to the negative phase. The timing of the PDO phase change coincides with the rapid increase in CO₂ in 2010–2015. To get a better picture of the correspondence between PDO and CO₂, we show in Fig. 5 the retrieved decadal signals in this region. The CO₂ decadal oscillations are roughly in phase with the PDO index, and the amplitudes from the two presented sites are ~4 ppm (YM) and 7 ppm (SS); the respective correlation coefficients are 0.73 and 0.69.

Associated with changes in SST anomalies, PDO also involves changes in the circulation pattern in the Pacific basin (including the western Pacific). This is shown in Fig. 6, obtained using ERA-Interim wind fields. Fig. 6b,c are the wind anomalies (relative to the mean in 1980–2018 shown in Fig. 6a) in 2008–2011 and 2015–2018, respectively. We consider 2012–2014 as the neutral PDO years and exclude them in the calculation of anomalies in order to maximize the signal. During the negative (2008–2011) and positive (2015–2018) years, there exist secondary cyclonic and anticyclonic wind speed anomalies (shown by the wind vectors) in the Pacific basin, consistent with that reported previously (Hung et al., 2004; Matsumura and Horinouchi, 2016). The vertical velocity anomalies (shown by the contour shades) also changed from positive (i.e., downwelling motion) in 2008–2011 to negative (i.e., upwelling) in 2015–2018, which is consistent with the reduced CO₂ over Taiwan (e.g., see Fig. 4) before ~2013 because of the negative CO₂ gradient in the vertical. We note that although the anomalies in the tropical region due to the strong 2015/16 El Niño may not have been effectively canceled out by the following 2016–2018 La Niña in our 2015–2018 average, the overall changes in the circulation in the northern and western Pacific is suggestive of the dominance of the PDO influence.

As an additional evidence that the PDO may modulate the CO₂ distribution in the Pacific basin, we show in Fig. 7 the regression coefficient of AIRS CO₂ with the PDO index based on a simple regression model: \( \text{CO}_2(t) = a + b \times \text{PDO}(t) \). The PDO index is obtained using SST anomalies poleward of 20° N in the Pacific basin (Mantua et al., 1997). During 2010–2012 when the two AIRX3C2M.005 AIRS CO₂ products (AIRX3C2M.005 AIRS3C2M.005) overlap, we take the average of the two products. The spatial pattern of the regression coefficient mimics that of the PDO in SST: There is a positive correlation over the tropical Pacific and a negative correlation over the north Pacific. Note that the strongly negative coefficients above 60° N are statistically not significant.

To gain further insight into the PDO modulated CO₂ variability, we show in Fig. 8 the relative change in the mid-tropospheric CO₂ levels observed by AIRS over two major PDO regions, defined as the average

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![Fig. 4. Summary of the EEMD-derived trends (same as the solid curves in Fig. 2) at BKT, TAP, MLO, SS, and YM.](image-url)
Table 2
Summary of the linear trends (ppm/year) over the time periods indicated. The trends are calculated using the EEMD results shown in Figs. 2, S1, and S6. BKT 2012–2013 trend value is not given because of large missing data during the time period. Along with the ground-based data, the trends for the AIRS (MLO: 20°N, 157.5°W; Taiwan: 24°N, 120°E) and GOSAT (MLO: 20°N, 157.5°W; Taiwan: 24°N, 122.5°E) columns at footprints closest to the indicated stations are also shown. Over Taiwan, AIRS and GOSAT have one grid point only, covering all four EPA stations. For AIRS data, the EEMD and then the trend calculations are made to the merged data of AIRX3C2M.005 and AIRS3C2M.005 by applying simple arithmetic averaging during the time period of 2010–2012 when the two data sets overlap.

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<td>2.26 ± 0.10</td>
<td>3.91 ± 0.03</td>
<td>1.49 ± 0.08</td>
<td>2.69 ± 0.06</td>
</tr>
<tr>
<td>YM</td>
<td>1.99 ± 0.06</td>
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<td>2.76 ± 0.03</td>
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<td>Taiwan(AIRS)</td>
<td>2.16 ± 0.01</td>
<td>2.33 ± 0.01</td>
<td>1.54 ± 0.04</td>
<td>2.09 ± 0.01</td>
</tr>
<tr>
<td>Taiwan(GOSAT)</td>
<td>1.72 ± 0.02</td>
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<td>2.54 ± 0.02</td>
<td>2.24 ± 0.03</td>
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<td>Taiwan(CT2019B)</td>
<td>2.05 ± 0.01</td>
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<tr>
<td>HC</td>
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<td>2.06 ± 0.04</td>
<td>2.01 ± 0.02</td>
<td>2.03 ± 0.01</td>
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![Fig. 5. EEMD-derived decadal signals at SS and YM, along with the PDO index (12-month running average applied). The correlation coefficients of the EEMD retrieved signals with the PDO are, respectively, 0.69 and 0.73.](image-url)

CO₂ over the north Pacific (20°–50°N, 150°–220°E) subtracted from the average over the tropical Pacific (20°–5°N, 180°–270°E), which are shown as the two boxes in central Pacific in Fig. 7. This differencing procedure is adopted from Jiang et al. (2013), who successfully extracted the ENSO modulation in AIRS CO₂ by subtracting the average over western Pacific from the average over eastern Pacific. We show the calculation separately for two AIRS retrievals: the AMSU-assisted (blue line) and the AIRS-only (orange line) in order to show that the change of the cloud screening algorithm does not affect our conclusion. Note that the temporal mean difference is not centered at zero because the CO₂ level at northern mid-latitudes is higher than that in the tropics (Chahine et al., 2008); it is the temporal variation around the mean difference that relates to the PDO. From 2003 to 2010, the mid-tropospheric CO₂ over the tropical Pacific declined with time relative to the north Pacific, reaching the local minimum in 2010 when the PDO was at the center of its negative phase, as indicated by the change in the PDO index (grey solid line). After 2010, the mid-tropospheric CO₂ over the tropical Pacific rose with time, reaching the local maximum in 2016 when the PDO was at the center of its positive phase. This comparison suggests that the AIRS CO₂ retrievals have a temporal correlation with the PDO index. The amplitude of the PDO-related CO₂ difference between the two major PDO regions is ~1 ppm, similar to the ENSO-related amplitude found by Jiang et al. (2013). The signature of the ENSO in this region is also clearly seen, albeit at a reduced amplitude of ~0.5 ppm.

To consider a region more relevant to our proposition, we further calculate the difference of the mid-tropospheric CO₂ over Taiwan from that over the tropical Pacific, by replacing the average over the northern Pacific with the average over the western Pacific centering around Taiwan (20°–30°N; 110°–130°E; see Fig. 7 for the box). Fig. 9 shows that both ENSO and PDO are clearly seen in this difference, both having amplitudes of ~0.5 ppm. In addition, we also perform EEMD analysis for AIRS CO₂ at a closet location of Taiwan at 24°N and 120°E. The filtered decadal oscillation is shown by the thin red solid curve, presenting a high similarity to the PDO index. This decadal amplitude, however, is an order of magnitude smaller than the PDO-like signals obtained at ground stations of Taiwan (Fig. 5). The difference is likely due to the poorer sensitivity of the AIRS retrievals to the ground level CO₂, as mentioned above. The altitude dependence of the amplitude of the PDO-like signals (Fig. 5) is also seen in the two northern Taiwan stations where SS (~50 m above sea level) amplitude is a factor of 2 that of YM (838 m).

5. Summary
Situated next to and downwind of a rapidly developing industrial world in east and southeast Asia, Taiwan provides a good site for monitoring the continental pollution signals through their trace gas levels. In addition, Taiwan is located at the boundary between the tropics and subtropics and experiences changes in CO₂ levels affected by possible transport regime fluctuations induced by climate change. We have investigated the atmospheric CO₂ variabilities over several stations in Taiwan and compared the data with other ground stations in western Pacific regions. We found a decadal CO₂ variability in these ground-based stations, which appears clearly as a sharp increase of ~5 ppm around 2010–2015 over an otherwise constant CO₂ increase of lesser magnitude.

We reviewed the CO₂ emission database and concluded that anthropogenic factors are unlikely to be the cause of the trend change. Instead, we attributed the trend change to dynamical factors related to the Pacific Decadal Oscillations (PDO). Our proposition is supported by the presence of PDO modulation in AIRS mid-tropospheric CO₂ over Taiwan, though at a reduced amplitude (~0.5 ppm) compared to that of the ground level CO₂ in the northern Taiwan (~5 ppm). Our analysis shows for the first time an intimate connection of the regional CO₂
Fig. 6. Averaged (2008–2018) wind and wind anomalies (2008–2011 and 2015–2018) obtained from ERA-Interim. The horizontal wind and wind anomalies are shown by the vectors and the vertical wind anomalies are in the colour scale.

Fig. 7. Regression map of the PDO signal in the merged AIRS CO2 data; the two sets of AIRS data (AIRX3C2M.005 and AIRS3C2M.005) are combined using simple arithmetic averaging during the overlapping time period of 2010–2012. Simple regression against the normalized PDO index at monthly resolution is applied. See text for details. Three boxes drawn are the regions selected for subsequent ENSO and PDO analyses shown in Figs. 8 and 9. Tropical Pacific box is 20°S–20°N and 180°–270°E; northern Pacific is 20°–50°N and 150°–220°E; western Pacific is 20°–30°N and 110°–130°E. Shaded region represents 90% confidence level.
Fig. 9. Same as Fig. 8 but for the difference between the tropical and western Pacific (see Fig. 7 for the locations). The plot also shows the EEMD-retrieved decadal signal for AIRS CO₂ near Taiwan at the grid point of 24 °N and 120° E (thin red solid curve). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

concentration to the climatic oscillation induced by the PDO.

Credit author statement


Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rse.2021.112624.

References


Fig. 8. The difference of AIRS CO₂ in the tropical Pacific and northern Pacific (see Fig. 7 for the locations). Seasonal cycles are removed from the figure. Along with the EEMD trends (5-year low-pass filtered; solid curves), the EEMD results at periods >1 year are also shown (dashed curves). The 12-month running average to the difference is shown in the dotted curves. Note that the two AIRS datasets (AIRX3G2M.005 and AIRX3G2M.005) are analyzed separately. For comparison, the 12-month running averaged PDO index is also shown (grey thick solid curve).


Supplementary Information

East Asian CO₂ level change caused by Pacific Decadal Oscillation

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Supplementary figures: Figures S1–S5

Figure captions

Figure S1: Time series of the monthly CO₂ levels (symbols) for all of the stations selected in the study. The results of the EEMD derived trends and 12-month running averages are shown by the solid and dashed curves, respectively.

Figure S2: Comparison of NOAA measured (symbols) and CarbonTracker simulated (solid curve) CO₂ at DSI, UUM, WLG, and GMI.

Figure S3: Comparison of the EEMD trend from the last (residual, non-oscillating) IMF mode (dashed curves) and the EEMD trend (solid curve; sum of the IMFs at periods >5 years) calculated in this work.

Figure S4: Comparison of the growth rate derived in this work using EEMD (solid curve) and the NOAA reported annual growth rate (thin line with symbols; www.esrl.noaa.gov/gmd/ccgg/trends/gr.html).

Figure S5: The time series (symbols) of AIRS and GOSAT CO₂ columns at the locations of Taiwan (AIRS: 24 °N, 120 °E; GOSAT: 24 °N, 122.5 °E) and MLO (AIRS: 20 °N, 157.5 °W; GOSAT: 20 °N, 157.5 °W). The results of the EEMD derived trends and 12-month running averages are shown by the solid and dashed curves, respectively. We combine two sets of AIRS data (AIRX3C2M.005 and AIRS3C2M.005) by applying simple arithmetic averaging during the period 2010–2012 when the two data sets overlap, prior to subsequent EEMD analysis.
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