Reduction in C\textsubscript{2}H\textsubscript{6} from 2015 to 2020 over Hefei, eastern China points to air quality improvement in China

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Abstract

Ethane (C\textsubscript{2}H\textsubscript{6}) is an important greenhouse (GHG) gas and plays a significant role in tropospheric chemistry and climate change. This study first presents and quantifies the variability, source, and transport of C\textsubscript{2}H\textsubscript{6} over densely populated and highly industrialized eastern China by using ground-based high-resolution Fourier transform infrared (FTIR) remote sensing together with atmospheric modelling techniques. We obtained a retrieval error of 6.21 ± 1.2 (1σ)% and degrees of freedom (DOFS) of 1.47 ± 0.2 (1σ) in retrieval of C\textsubscript{2}H\textsubscript{6} tropospheric column-averaged dry-air mole fraction (troDMF) over Hefei, eastern China (117°E, 32°N, 30 m a.s.l.). The observed C\textsubscript{2}H\textsubscript{6} troDMF reached a minimum monthly mean value of 0.36 ± 0.26 ppbv in July and a maximum monthly mean value of 1.76 ± 0.35 ppbv in December, and showed a negative change rate of −2.60 ± 1.34 %/yr from 2015 to 2020. The dependencies of C\textsubscript{2}H\textsubscript{6} troDMF on meteorological and emission factors were analyzed by using generalized additive models (GAMs). Generally, both meteorological and emission factors have positive influences on C\textsubscript{2}H\textsubscript{6} troDMF in cold season (DJF/MAM) and negative influences on C\textsubscript{2}H\textsubscript{6} troDMF in warm season (JJA/SON). GEOS-Chem chemical model simulation...
captured the observed C$_2$H$_6$ troDMF variability and was thus used for source attribution. GEOS-Chem model sensitivity simulations concluded that the anthropogenic emissions (fossil fuel plus biofuel emissions) and the natural emissions (biomass burning plus biogenic emissions) accounted for 48.1% and 39.7% of C$_2$H$_6$ troDMF variability over Hefei, respectively. The observed C$_2$H$_6$ troDMF variability mainly results from the emissions within China (74.1%), where central, eastern, and northern China dominated the contribution (57.6%). Seasonal variability in C$_2$H$_6$ transport inflow and outflow over the observation site is largely related to the mid-latitude westerlies and Asian monsoon system. Reduction in C$_2$H$_6$ abundance from 2015 to 2020 mainly results from the decrease in local and transported C$_2$H$_6$ emissions, which points to air quality improvement in China in recent years.

Keywords: Remote sensing; FTIR; Ethane; Climate change; GAMs

1. Introduction

Ethane (C$_2$H$_6$) is an important greenhouse (GHG) gas and one of the most abundant Volatile Organic Compounds (VOCs) in the atmosphere (Abad et al. 2011; Singh et al. 2001; Steinfield 1998). Although C$_2$H$_6$ is much less abundant than methane (CH$_4$) and also less efficient relative to mass, it plays a significant role in tropospheric chemistry and climate change (Tzompa-Sosa et al. 2017). In the presence of nitrogen oxides (NO$_x$ = NO + NO$_2$), the C$_2$H$_6$ oxidation can enhance tropospheric ozone (O$_3$) generation, which shows a positive radiative influence on climate (Sun et al. 2018a) and threatens crop yields (Sun et al. 2018a; Van Dingenen et al. 2009) and human health (Sun et al. 2018a; Tzompa-Sosa et al. 2017). In addition, as a major source of acetaldehyde (CH$_3$CHO), C$_2$H$_6$ has a great impact on the production of peroxyacetyl nitrate (PAN) which is a key reservoir species of NO$_x$ (Fischer et al. 2014). The main sink of tropospheric C$_2$H$_6$ is predominantly destruction via reaction with the hydroxyl radical (OH)(Xiao et al. 2008), which determines the residence time of most tropospheric species (Steinfeld 1998). As a result, tropospheric C$_2$H$_6$ can decrease the atmospheric oxidative capacity and indirectly impact the climate by extending the CH$_4$ lifetime (Monks et al. 2018; Taylor et al. 2020). Atmospheric C$_2$H$_6$ has a relatively long residence time of a few months (Franco et al. 2016), allowing it to undergo intercontinental transport. As a result, observations of C$_2$H$_6$ can be assimilated into a chemical transport model to estimate nonlocal emissions and air quality, and provide valuable insights into model biases of C$_2$H$_6$ simulations (Tzompa-Sosa et al. 2017).

On a global scale, the main sources of C$_2$H$_6$ are leakage from production, processing, and transport of natural gas (62%), biofuel combustion (20%) and biomass burning emission (18%), largely occurred in the Northern Hemisphere (NH) (Franco et al. 2016; Xiao et al. 2008). Additional minor sources of C$_2$H$_6$ are from biogenic and oceanic sources. However, on a regional scale, the proportion of each C$_2$H$_6$ source may show large difference. Natural gas leakage contribution can reach 80% of C$_2$H$_6$ emissions in regions with active oil and natural gas production (Gilman et al. 2013), where C$_2$H$_6$ emissions are highly correlated with CH$_4$ emissions. In such regions, C$_2$H$_6$ can be applied as a tracer for separation of fossil fuel CH$_4$ emissions from multiple methane (CH$_4$) sources (e.g., oil and gas, cows, wetlands, and rice yield) (McKain et al. 2015; Roscioli et al. 2015).

The C$_2$H$_6$ abundance in the Southern Hemisphere (SH) is much lower than those in the NH since the anthropogenic C$_2$H$_6$ sources are low in the SH, and the residence time of C$_2$H$_6$ is shorter than the interhemispheric exchange rate. Many studies concluded that C$_2$H$_6$ in the SH is primarily emitted
from biomass burning, and is closely correlated with CO and HCN emissions (Notholt et al. 2000; Rinsland et al. 2002; Vigouroux et al. 2012; Zeng et al. 2012).

C$_2$H$_6$ is one of the target gases of a global ground-based Fourier transform infrared spectroscopy (FTIR) network, namely the infrared working group (IRWG) of the Network for Detection of Atmospheric Composition Change (NDACC) (De Mazière et al. 2018). FTIR time series of C$_2$H$_6$ with different time periods have been reported in many stations for validation of satellite data or chemical model simulation (Abad et al. 2011; Franco et al. 2015; Franco et al. 2016; Glatthor et al. 2009), or evaluation of local air quality and air pollutants transport caused by anthropogenic emission and biomass burning (Angelbratt et al. 2011; Lutsch et al. 2016; Lutsch et al. 2019; Nagahama and Suzuki 2007; Rinsland et al. 2002; Simpson et al. 2012; Viatte et al. 2015; Viatte et al. 2014; Vigouroux et al. 2012; Zeng et al. 2012; Zhao et al. 2002). Several FTIR sites have observed the decrease in C$_2$H$_6$ over 1990 – 2010, and characterized consistent interannual trends in the −1 to −2.7% yr$^{-1}$ range (Franco et al. 2015; Franco et al. 2016; Simpson et al. 2012; Zeng et al. 2012). This declining trend has been largely attributed to the reduction of global fugitive emissions (Franco et al. 2015; Simpson et al. 2012). Recently, several studies concluded that the long-term decline in C$_2$H$_6$ in the NH reversed from 2009 onwards (Franco et al. 2015; Franco et al. 2016). Using ground-based FTIR C$_2$H$_6$ total columns derived at five selected NDACC sites, Franco et al. (2016) characterized the C$_2$H$_6$ evolution from 2009 – 2015 and determined growth rates of ~3% yr$^{-1}$ at remote sites and of ~5% yr$^{-1}$ at mid-latitudes. This change is mainly attributed to the exploitation of shale gas and tight oil reservoirs in North America (Franco et al. 2016; Helmig et al. 2016).

The NDACC network has been operating for almost three decades around the globe (De Mazière et al. 2018; Sun et al. 2018a). However, most instruments are located in Europe and Northern America, but the number of observation sites in the rest parts of world remains sparse, and there is only one qualified observations site in China, i.e., the Hefei site (117°E, 32°N, 30 m a.s.l.) located in a densely populated and highly industrialized area in eastern China (Sun et al. 2018a). The Hefei site is not yet affiliated to the NDACC network but its observation routine is following the NDACC standard convention since 2015 (Sun et al. 2018a). As the consequence of a series of actions for emission control, air pollution over China in recent years has been significantly decreased (Zhang et al. 2019; Zheng et al. 2018). However, the atmospheric pollution over densely populated and highly industrialized eastern China is still in severe situation (Zhang et al. 2019; Zheng et al. 2018). The complexity, extension, and severity of the atmospheric pollution in eastern China are still unrivaled compared to the rest of world (Lu et al. 2018; Zheng et al. 2018). FTIR observations at Hefei have been used extensively for evaluation of satellite data (Tian et al. 2018; Wang et al. 2017), chemical model simulation (Tian et al. 2018; Yin et al. 2020; Yin et al. 2019), local air quality (Shan et al. 2019; Sun et al. 2018a) and the transport of air pollutants caused by anthropogenic and biomass burning emissions (Sun et al. 2018a; Sun et al. 2021; Sun et al. 2020).

In this study, we first present and quantify the variability, source, and transport of C$_2$H$_6$ over densely populated and highly industrialized eastern China by using FTIR observation, GEOS-Chem model simulation, and the analysis of the meteorological fields. The seasonality and interannual variability of C$_2$H$_6$ over Hefei, eastern China from 2015 – 2020 are investigated. The dependencies of C$_2$H$_6$ on meteorological and co-emitted gases (hereafter emission factors) are analyzed by using generalized additive models (GAMs)(Wood and Simon 2004). The ground-based FTIR C$_2$H$_6$ time series are for the first time applied to evaluate the GEOS-Chem model for the specifics of C$_2$H$_6$.
simulation over eastern China. We further run a series of GEOS-Chem sensitivity simulations to quantify relative contributions of various source categories and regions to the observed C$_2$H$_6$ variability. The three-dimensional (3D) transport inflow and outflow pathways of C$_2$H$_6$ over the observation site are finally determined by the GEOS-Chem sensitivity simulations and the analysis of the meteorological fields. This study can not only enhance the understanding of regional emission, transport, and air clean actions over eastern China, but also contribute to form new reliable remote sensing data in this sparsely-monitored regions for climate change research.

The next section describes the retrieval for FTIR tropospheric-column-averaged dry-air mole fraction (troDMF) of C$_2$H$_6$, the configuration of GEOS-Chem model simulation, and the GAMs regression approach. Section 3 reports the variability of C$_2$H$_6$ troDMF and comparison with the GEOS-Chem simulation. Section 4 reports the GAMs regression results and the interpretation. Section 5 reports the results for source attribution using GEOS-Chem sensitivity simulation and the analysis of the meteorological fields. We conclude the study in Section 6.

2. Methods and data
2.1 C$_2$H$_6$ troDMF retrieval

The C$_2$H$_6$ troDMF time series were calculated by using direct solar absorption spectra saved with a FTIR spectrometer in operation at Hefei, eastern China (Sun et al. 2018a; Tian et al. 2018). Site description and instrumentation can be found in (Sun et al. 2018a). Briefly, the FTIR observatory includes a high resolution FTIR spectrometer (IFS125HR, Bruker) and a solar tracker (Solar Tracker-A 547, Bruker). The instrument has been operating continuously since its installation; however, short data gaps of up to eight months have occurred due to a scanner problem between November 2016 and July 2017. This FTIR observatory alternately saved near infrared (NIR) and middle infrared (MIR) solar spectra in routine observations, with spectral ranges of 4,000 to 11,000 cm$^{-1}$ and 500 to 8,500 cm$^{-1}$, respectively (Tian et al. 2018). The NIR and MIR spectra are saved with different spectral resolutions but both of them can be used to retrieve total columns and volume mixing ratio (VMR) profiles of a variety of trace gases in the atmosphere. The MIR spectra used in present work are saved with a spectral resolution of 0.005 cm$^{-1}$ following the requirements of NDACC standard convention (http://www.ndacc.org/, last accessed on 27 December 2020). The FTIR instrument is equipped with a KBr beam splitter, a filter centered at 2800 cm$^{-1}$, and an InSb detector for C$_2$H$_6$ measurements. The number of C$_2$H$_6$ measurements on each measurement day varied from 1 to 17 with an average of 6. In total, there were 743 days of qualified measurements between 2015 and 2020.

In this study, the VMR profile of C$_2$H$_6$ was first retrieved by using the SFTIT4 algorithm updated from SFIT2 (Pougatchev et al. 1995) and implementing the optimal estimation method (Rodgers 2000). The C$_2$H$_6$ troDMF was then calculated by taking a weighting average of the C$_2$H$_6$ VMR profile and the air mass using a fixed tropospheric altitude. The C$_2$H$_6$ VMR profile was retrieved in a broad window of 2976 – 2978 cm$^{-1}$. The VMR profiles of CH$_4$ and H$_2$O and column of O$_3$ were also retrieved together with the C$_2$H$_6$ VMR profile for minimizing the atmospheric absorption interference. Spectroscopic absorption parameters of all gases are based on the atm16 line list from the compilation of Geoffrey Toon (Sun et al. 2021). The a priori vertical profiles of temperature H$_2$O, and pressure were interpolated from the National Centers for Environmental Protection (NCEP) reanalysis data and the a priori vertical profiles of other gases were from the statistical averages of
the Whole-Atmosphere Community Climate Model version 6 (WACCM) simulations from 1980 to 2020. The diagonal elements of the a priori covariance matrices $S_a$ and the measurement noise covariance matrices $S_e$ were set to standard deviation (SD) of the WACCM simulations and the inverse square of the signal-to-noise ratio (SNR) of each spectrum, respectively (Franco et al. 2015). The non-diagonal elements of both $S_e$ and $S_a$ were set to zero. The instrument line shape (ILS) of the FTIR instrument deduced from optical path alignment diagnosis with a low-pressure HBr cell was adopted in the retrieval (Hase 2012; Sun et al. 2018b).

For each retrieval, the averaging kernels reflect the sensitivity of the retrieved profile to the real profile. The area of the averaging kernels at a specific height is calculated as the sum of the elements of the corresponding averaging kernels (Pougatchev et al. 1995). It represents the fraction of the retrieval at that height which comes from the measurement rather than from the a priori information (Rodgers, 2000). A value close to unity at a specific height indicates that the retrieved profile at that height is nearly independent of the a priori profile and is thus from the measurement. The trace of the averaging kernel matrix is defined as degrees of freedom for signal (DOFS) and it quantifies the number of independent information in the retrieved profile. Fig. 1 shows the averaging kernels as well as their area, cumulative sum of DOFS, and VMR profile of randomly selected C$_2$H$_6$ retrieval at Hefei. Ground-based FTIR C$_2$H$_6$ observations at Hefei have a sensitivity of larger than 0.7 from ground to about 10 km altitude, indicating that the retrievals are mainly sensitive to the troposphere. This also means that the retrieved profile information below 10 km comes for more than 70% from the measurement, or in other words, that the a priori signal impacts the retrieval by less than 30% [Fig 1(a)]. The typical DOFS obtained at Hefei over the total atmosphere for C$_2$H$_6$ is 1.69 ± 0.29 (1σ), meaning that we can roughly provide two pieces of information on the vertical profile [Fig 1(b)]. The shape of the retrieved profile is heavily weighted toward the lower troposphere. As shown in Fig.1(c), the C$_2$H$_6$ concentration decreased by 72.7% with an increase in the height from surface to 2 km and kept decreasing slowly in the rest part of the atmosphere till approaching around zero in the stratosphere and above. The C$_2$H$_6$ partial column below 10 km accounted for 88.6% of C$_2$H$_6$ total column. This percentage is expected to show less seasonal variation since the shape of the retrieved profile is similar to the shape of the a priori profile due to the low DOFS [Fig. 1 (c)]. As a result, in subsequent analysis, the C$_2$H$_6$ VMRs averaged between the surface and 10 km are selected as representatives of C$_2$H$_6$ troDMF. The selected tropospheric layer (from surface up to 10 km) corresponds to 1.47 ± 0.2 (1σ) of DOFS and can be used with confidence. This selected layer is totally within the tropopause height (~ 16 km) at Hefei over four seasons (Sun et al. 2020). The Hefei site is located in the northeastern margin of a GEOS-Chem grid cell [Fig. 2]. This selected layer also ensures the line of sights of all observations are totally within the same grid cell.

We calculated the error budget for C$_2$H$_6$ retrieval at Hefei following the formalism of Rodgers (2000), and separated all error components into systematic or random errors according to whether they vary steadily or randomly over consecutive measurements. The random, systematic, and the combined error budgets for the selected tropospheric layer (from surface up to 10 km) are summarized in Table 1. The input covariance matrix of temperature is based on the differences between Sonde and an ensemble of NCEP temperature profiles near Hefei, leading to 2 to 5 K in the troposphere and 3 to 7 K in the stratosphere. For each interfering gases, the corresponding covariance matrix is obtained with the WACCM v6 climatology. The input covariance matrix of measurement error is based on the inverse square of the SNR of each spectrum. We regularly use a
low-pressure HBr cell to diagnose the misalignment of the FTIR spectrometer and to realign the instrument when indicated. The FTIR spectrometer at Hefei is assumed to be not far from the ideal condition, and the input uncertainties for zero level, background curvature, field of view, optical path difference, solar zenith angle, interferogram phase, and ILS are estimated to be 1%. For the C$_2$H$_6$ spectroscopic absorption coefficients, the line list in atm16 follows HITRAN 2012 (Rothman et al., 2013), and we use 5% for line intensity, pressure-, and temperature-broadening coefficients. For the retrieval parameter and smoothing error, the input covariance matrix are prescribed from the optimal estimation retrieval outputs. To estimate the retrieval error of C$_2$H$_6$ troDMF at Hefei, the elements of all gain matrices were set to zero for the altitudes outside the selected layer. The contributions of all error components to C$_2$H$_6$ troDMF retrieval at Hefei are summarized in Table 1. The dominant random errors are from temperature uncertainty (1.69%) and the zero level uncertainty (1.45%), and the dominant systematic error is from the line intensity uncertainty (5.12%). Total random and systematic errors are estimated to be 2.32% and 5.48%, respectively. Total retrieval error calculated as square root sum of the squares of total random and systematic errors is estimated to be 6.21%.

In order to exclude the measurements that seriously affected by instable weather conditions or by the a priori profile due to low measurement information content in less favourable observational conditions, e.g., around noontime when the probed atmosphere is thinner, or in summer when C$_2$H$_6$ is less abundant. The FTIR measurements saved with a solar intensity variation (SIV) of larger than 10% or retrievals with total DOFS of less than 0.7 or the root-mean-square (RMS) of fitting residuals of larger than 2%, which accounted for 11.2% of total measurements, were excluded in this study.

2.2 GEOS-Chem sensitivity simulation

Relative contribution of various source categories and regions to the observed C$_2$H$_6$ variability were quantified by a series of sensitivity simulations using the GEOS-Chem chemical model version 12.2.1 (Bey et al. 2001) (http://geos-chem.org, last access on 24 August 2020). All simulations implemented a universal tropospheric-stratospheric Chemistry (UCX) mechanism (Eastham et al. 2014; Fisher et al. 2017) and were driven by the Goddard Earth Observing System-Forward Processing (GEOS-FP) meteorological fields at a degraded horizontal resolution of 2°×2.5°. The temporal resolutions are 1 hour (hr) for surface meteorological variables and planetary boundary layer height (PBLH), and 3 hr for other meteorological variables. The time step used in the model is 10 minutes for transport and 20 minutes for chemistry and emissions, as recommend for the GEOS-Chem full-chemistry simulation at 2×2.5 (Philip et al., 2016). The non-local scheme for the boundary layer mixing process are described in Lin and McElroy (2010). Dry deposition was calculated by the resistance-in-series algorithm (Wesely 1989; Zhang et al. 2001) and wet deposition followed that of Liu et al. (2001). The photolysis rates were available from the FAST-JX v7.0 photolysis scheme (Bian and Prather 2002). All simulations were spun up for one year (July 2014 to July 2015) and output hourly mean C$_2$H$_6$ VMR profiles globally ranging from the surface to 0.01 hPa at a horizontal resolution of 2°×2.5°. This study only considered the C$_2$H$_6$ simulations from 2015 to 2020 in the grid box containing Hefei (31.52°–32.11°N by 116.53°–118.02°E).

In the recent past, the inventories led to significant underestimation of the C$_2$H$_6$ simulation (e.g., HTAP2 in Franco et al. 2016). Since then, some efforts have improved the situation (e.g., Tzompa-Sosa et al. 2017). In this study, we refer to Sun et al. (2020a) for more details on
implementation of emission inventories. Briefly, global anthropogenic emissions were from the Community Emissions Data System (CEDS) inventory which overwrites Asia by the latest Multi-resolution Emission Inventory for China (MEIC) (Hoesly et al. 2018; Li et al. 2017; Lu et al. 2019; Zheng et al. 2018). Global biomass burning and biogenic emissions were from the Global Fire Emissions Database (GFED v4) inventory (Giglio et al. 2013) and the Model of Emissions of Gases and Aerosols from Nature (MEGAN version 2.1) inventory (Guenther et al. 2012), respectively. The CH$_4$ emission fields are prescribed based on NOAA measurements for 1983–2016 and are extended to 2020 using the linear extrapolation of local 2011–2016 change rates (Murray, 2016; Lu et al., 2019).

Particular improvements have been done for the latest bottom-up MEIC emission inventory in the accuracy of vehicle emission modelling (Zheng et al. 2014), power plant emission calculation (Liu et al. 2015), and the non-methane VOCs (NMVOCs) speciation method (Li et al. 2014). Many studies have verified that the MEIC emission inventory can reasonably represents the anthropogenic emissions over Asia (Hoesly et al. 2018; Li et al. 2017; Lu et al. 2019; Sun et al. 2021; Tian et al. 2018; Yin et al. 2020; Yin et al. 2019; Zheng et al. 2018). Anthropogenic C$_2$H$_6$ emissions in China by region and category for the 2015 and 2019 MEIC emission inventories are summarized in Table 2. All subdivided geographical regions are shown in Fig. 2 and the resulting delimitations are summarised in Table 3. The delimitations of these geographical regions are based on the levels of urbanization and industrialization in China. Region 1 in Fig. 2 only covers a few sparsely city clusters representing the region with least population and industrialization in China (Lu et al. 2019). Regions 2, 6, and 5 cover the North China Plain (NCP), Yangtze River Delta (YRD), and Pearl River Delta (PRD) city clusters, respectively, which are the three most developed city clusters facing severe air pollution in China. Region 3 covers the Sichuan Basin (SCB) and central Yangtze River (CYR) city clusters with newly emerging severe air pollution in China. Total annual Chinese anthropogenic emissions of C$_2$H$_6$ in 2015 and 2019 are 0.883 Tg and 0.859 Tg, respectively. In both years, anthropogenic C$_2$H$_6$ emissions in China are dominated by industry and residential emissions. The highest anthropogenic C$_2$H$_6$ emission rates (calculated as the ratio of total C$_2$H$_6$ emission to the coverage) are in densely populated and industrialized region clusters in eastern part of China (including northern China (NR), eastern China (ER), central China (CR), southern China (SR), and adjacent regions) with large seasonal variation [Fig.S1]. The highest anthropogenic C$_2$H$_6$ emissions typically occur in winter [Fig.S1]. The anthropogenic emissions in WR region are typically lower than those in other parts of China because of lower population and industries in the region (Lu et al. 2019; Zheng et al. 2018).

In order to quantify the contributions of different source categories and regions to the observed C$_2$H$_6$, we first conducted a reference full chemistry simulation (BASE) with implementation of all emission inventories as described above. Then, we conducted a series of sensitivity simulations to assess the change of each sensitivity simulation relative to the BASE simulation. Model configurations in this study were similar to those in Sun et al. (2021) but with a different emission perturbation method. When an emission inventory was shut off in Sun et al. (2021), the emissions of all atmospheric compounds in that inventory were suppressed. In contrast, this work only suppressed C$_2$H$_6$ in each case except for biogenic and biomass burning emission perturbations, which suppressed all atmospheric compounds since we cannot separate C$_2$H$_6$ emission from current biogenic and biomass burning emission inventories. Model configurations in this study are summarised in Table 3 and were described as follows.
(i) To analyse the contributions of different emission categories, we shut off C$_2$H$_6$ in each individual emission inventory to evaluate the change of the simulation in the presence of C$_2$H$_6$ in other emission inventories. As a result, the relative contribution of each emission category was estimated as the relative difference between the GEOS-Chem simulation in the presence and absence of C$_2$H$_6$ in that emission inventory. We have conducted four such sensitivity simulations by shutting off C$_2$H$_6$ emissions in (1) fossil fuel emission inventory (including emissions from agriculture, industry, power plant, residential, and transport), (2) biogenic emission inventory, (3) biomass burning emission inventory, and (4) biofuel emission inventory (Table 3). The sum of fossil fuel and biofuel C$_2$H$_6$ emissions is defined as anthropogenic C$_2$H$_6$ source and the sum of biogenic and biomass burning C$_2$H$_6$ emissions is referred to as natural C$_2$H$_6$ source.

(ii) To analyse the contributions of different geographical regions, we shut off all categories of C$_2$H$_6$ emissions (i.e., the aforementioned anthropogenic plus natural C$_2$H$_6$ sources) within each geographical region to assess the change of the simulation in the presence of C$_2$H$_6$ emissions outside that geographical region. Thus, the relative contribution of each geographical region was estimated as the relative difference between the GEOS-Chem simulation in the presence and absence of C$_2$H$_6$ emissions within that geographical region. We have conducted five such sensitivity simulations by shutting off C$_2$H$_6$ emissions within five geographical regions shown in Fig. 2.

2.3 Generalized additive models (GAMs) regression

In this study, we investigate the dependencies of C$_2$H$_6$ on meteorological and emission factors by using the GAMs regression (Wood and Simon 2004; Wood 2004). Regression analysis is proceeded using the thin plate smoothing spline function (Pearce et al. 2011). Smoothing parameters and confidence intervals are calculated according to the Restricted Maximum Likelihood standard (REML) and the unconditional Bayesian method, respectively (Pearce et al. 2011). The GAMs regression is better than the traditional statistical models in dealing with nonlinear fittings (Veaux and Richard 2012). For climate change applications, where there are many non-linear relationships between variables, the GAMs regression is particularly attractive (Zhang et al. 2019).

We introduced a variety of potential meteorological and emission factors into the GAMs regression one at a time and performed significance tests based on the Akaike's Information Criteria (AIC) values (Wood and Simon 2004). The explanatory variables which passed the significance tests with the smallest AIC values were included into the final GAMs model. Furthermore, explanatory variables in GAMs regression may interact with each other and result in unstable fittings due to the internal multicollinearity. For the explanatory variables that show a strong collinearity with each other, we only included one of them in the final GAMs model. The degree of multicollinearity can be quantified by the variance inflation factor (VIF) (Ma et al. 2020). Generally, a stronger collinearity between the explanatory variables results in a larger VIF, and the VIF of an explanatory variable could be 1.0 if it is not correlated with other explanatory variables (Ma et al. 2020). In this study, we included all the meteorological and emission factors in the GAMs and calculated the VIF for all the influencing factors. The multicollinearity diagnosis concluded that the main causes of multicollinearity are between the HCN and CO, and between the tropopause height and PBLH. Including either of these two data pairs in the GAMs regression showed significant collinearities with the VIF values of greater than an empirical threshold of 4.0, indicating an unstable regression (Lin et al. 2018). After omitting HCN and PBLH in the final GAMs model, the adjusted
VIF values of all the variables were less than 4.0 and the variables uniformly passed the significance tests. As a result, the final GAMs model in the context of the C$_2$H$_6$ troDMF time series $y$ can be described as (Pearce et al. 2011):

$$\log(y) = \beta + S(u_a) + S(v_a) + S(\omega) + S(q_v) + S(troph)$$

+ $S(pres) + S(temp) + S(ch_4) + S(co) + \varepsilon$ \hspace{1cm} (1)

where $\beta$ and $\varepsilon$ are the mean response constant and the fitting residual, respectively. $S(u_a)$, $S(v_a)$, $S(\omega)$, $S(q_v)$, $S(troph)$, $S(pres)$, $S(temp)$, $S(ch_4)$, and $S(co)$ are the smoothing functions of daily average zonal wind (with a unit of m s$^{-1}$), meridional wind (m s$^{-1}$), vertical wind (Pa s$^{-1}$), water vapor concentration (%), tropopause height (km), pressure (hPa), temperature ($^\circ$C), CH$_4$ troDMF (ppbv), and CO troDMF (ppbv). Positive values of $u_a$, $v_a$, and $\omega$ represent northward, eastward, and upward winds, respectively. The sum of $S(ch_4)$ and $S(co)$ is referred to as the emission influences, and the sum of remaining smoothing functions is referred to as the meteorological influences.

For driving the GAMs regression, we first derived CH$_4$ and CO VMR profiles from direct solar absorption spectra similar to that of C$_2$H$_6$, see section 2.1. The spectra for CH$_4$ retrievals are exactly the same as those of C$_2$H$_6$ but the spectra for CO are saved at a different filter channel. The respective VMR profiles were then converted to troDMF values following the method of C$_2$H$_6$. The retrieval configurations, waveband selections and the interfering gases considerations for CH$_4$ and CO can be found in Sun et al. (2018b). The DOFS of the retrievals between surface and 10 km altitude for both CH$_4$ and CO are larger than 1.5 and the corresponding retrieval errors are less than 8% (Sun et al., 2018b). All meteorological factors are from the GEOS-FP meteorological fields at their native resolution of 0.25° × 0.3125° ranging from the surface to 0.01 hPa at a temporal resolution of 1 hr. Since the meteorological fields and C$_2$H$_6$ concentration are not uniformly distributed along the altitude, the summing mean values of the meteorological fields cannot properly characterize the meteorological influences. In this study, we use a method similar to that of Shaiganfar et al. (2017) to increase the influence weighting toward lower troposphere. As a result, all meteorological parameters except tropopause height ($troph$) are converted into the C$_2$H$_6$ profile weighting averaged value $\omega_{avg}$ through Eq. (2):

$$\omega_{avg} = \frac{\sum_i \omega(z_i) \cdot c(z_i) \cdot Airmass(z_i)}{\sum_i c(z_i) \cdot Airmass(z_i)}$$ \hspace{1cm} (2)

where $\omega(z_i)$, $c(z_i)$, and $Airmass(z_i)$ represent the value of the meteorological factor, C$_2$H$_6$ concentration, and the air mass at the altitude $z_i$.

3. Variability and comparison with GEOS-Chem model data

We have compared the observed daily mean time series, seasonal cycle and interannual variability of C$_2$H$_6$ troDMF to the GEOS-Chem BASE simulations for investigating the chemical model performance for the specifics of polluted regions over eastern China. As the vertical resolution of GEOS-Chem is different from the FTIR observation, smoothing correction has been done for the GEOS-Chem profiles (Rodgers and Connor 2003). First, the GEOS-Chem daily mean profiles of C$_2$H$_6$ have been interpolated to the FTIR altitude grid for ensuring a common altitude grid. In order to match the FTIR observations which only operates during daytime, the average for GEOS-Chem simulations was only performed during daytime from 9:00 to 17:00 local time (LT). The interpolated profiles were then smoothed by the concurrent seasonal mean values of the FTIR averaging kernels and a priori profiles (Rodgers 2000; Rodgers and Connor 2003). The smoothed
GEOS-Chem profiles were subsequently converted to troDMF values by using the corresponding regridded air density profiles from the model with the method described in section 2.1. Finally, the GEOS-Chem C$_2$H$_6$ troDMF time series only for the days with available FTIR observations were averaged by month and compared with the FTIR monthly mean data.

Fig. 3 (a) shows the comparison of daily mean time series of C$_2$H$_6$ troDMF between the FTIR observation and the smoothed GEOS-Chem model simulation from 2015 to 2020. Fig. 3 (b) compares the seasonal cycles derived from Fig. 3 (a) for the days with available FTIR observations only. Generally, the measured features in terms of seasonality and interannual variability can be reproduced by the GEOS-Chem simulations with a correlation coefficient ($r$) of 0.88 [Fig.S2]. Large GEOS-Chem vs. FTIR differences tended to occur in the trough and peak of the observations. For instance, the observed monthly mean value of C$_2$H$_6$ troDMF was overestimated by 35.6% (calculated as (GEOS-Chem – FTIR)/FTIR) in July and underestimated by 14.6% in December by the GEOS-Chem. These discrepancies may be mainly attributed to uncertainties in the horizontal transport and vertical mixing schemes simulated by the GEOS-Chem model at a relatively coarse spatial resolution, which are difficult to match column observation over a single point. In addition, the number of C$_2$H$_6$ measurements at Hefei on each measurement day varied a wide range from 1 to 17 depending on the weather condition, but GEOS-Chem simulations are available consecutively by hour for the same day. This difference in the temporal resolution of GEOS-Chem and FTIR could also cause inconsistencies due to the high variability of atmospheric C$_2$H$_6$. However, considering the concurrent data pairs only (± 30 min), the averaged difference between GEOS-Chem and FTIR data (GEOS-Chem minus FTIR) is ($-0.02 \pm 0.05$) ppbv ($-1.6 \pm 4.2$)%, which is within the FTIR uncertainty budget. As a result, GEOS-Chem can simulate C$_2$H$_6$ concentration and variability for the specifics of polluted regions over eastern China. With improved emission inventories, previous studies have also found that global chemistry transport models were able to reproduce the absolute values as well as seasonal cycles of the ground-based FTIR C$_2$H$_6$ observations in the other parts of the world (Franco et al., 2015; Franco et al., 2016; Tzompa-Sosa et al. 2017).

As typically observed, the peak-to-peak amplitude of the modulation with respect to the monthly mean of C$_2$H$_6$ troDMF spanned a large range of $-16.0\%$ to 72.8% depending on season [Fig. 3 (b)]. The observed C$_2$H$_6$ troDMF roughly decreases over time for the first half of the year and increases over time for the second half of the year [Fig. 3 (b)]. High levels of C$_2$H$_6$ troDMF occur in the late autumn to early spring and low levels of C$_2$H$_6$ troDMF occur in late spring to early autumn. The observed C$_2$H$_6$ troDMF reached a minimum monthly mean value of ($0.36 \pm 0.26$) ppbv in January and a maximum monthly mean value of ($1.76 \pm 0.35$) ppbv in December. C$_2$H$_6$ troDMFs in December were on average 4.9 times higher than those in January. Since the tropospheric OH oxidation capability in summer is higher than that in winter, the C$_2$H$_6$ seasonality characterized by a winter maximum and a summer minimum was also observed in other FTIR stations (Angelbratt et al. 2011; Franco et al. 2015; Franco et al. 2016; Lutsch et al. 2019; Nagahama and Suzuki 2007; Rinsland et al. 2002; Simpson et al. 2012; Viatte et al. 2015; Viatte et al. 2014; Vigouroux et al. 2012; Zeng et al. 2012; Zhao et al. 2002). We have used the bootstrap resampling method of Gardiner et al. (2008) to evaluate the seasonality and interannual variability of C$_2$H$_6$ troDMF, where a 3rd Fourier series plus a linear function was used to fit daily mean time series of C$_2$H$_6$ troDMF by both FTIR observations and GEOS-Chem model simulations. We incorporated the errors arising from the autocorrelation in the residuals into the uncertainties in the change rates following the procedure of Santer et al. (2008). The observed C$_2$H$_6$ troDMFs from 2015 to 2020 showed a negative change rate...
of \((-2.60 \pm 1.34)\%~\text{yr}^{-1}\), which is in reasonable agreement with the modelled change rate of \((-2.1 \pm 0.7)\%~\text{yr}^{-1}\) [Fig. 3 (a)].

4. GAMs regression results and interpretation

\(\text{C}_2\text{H}_6\) troDMF time series from 2015 to 2020 over Hefei by the FTIR and the GAMs regression model are shown in Fig. 4. The observed \(\text{C}_2\text{H}_6\) variability can be reproduced by the GAMs regression model with a good agreement, as confirmed by a correlation coefficient \((r)\) of 0.90 [Fig. 4(a); Fig. S3]. Meanwhile, the observed \(\text{C}_2\text{H}_6\) troDMF time series also show high correlations with both the accumulated meteorological factor \((r=0.88)\) [Fig. 4 (b)] and the accumulated emission factor \((r = 0.70)\) [Fig. 4(c)], indicating both meteorological and emission influences are important factors for driving the \(\text{C}_2\text{H}_6\) troDMF variability. Generally, both meteorological and emission factors show positive influences on \(\text{C}_2\text{H}_6\) troDMFs in cold season (DJF/MAM) and negative influences on \(\text{C}_2\text{H}_6\) troDMFs in warm season (JJA/SON). However, the seasonal dependency of meteorological influence is stronger than that of emission influence. During the studied years, the year to year differences in meteorological influence are small, while the positive emission influence showed an overall decreasing change rate since 2016, which probably drives a decreasing change rate in \(\text{C}_2\text{H}_6\) troDMF in recent years.

The influence of each explanatory variable \(x_i\) in GAMs regression calculated as 100\%\(\cdot\)\(\text{e}^{\beta_i}\)\(\cdot\)\(1\) are shown in Fig. 5, which reflects the influence of each individual variable on the relative change of \(\text{C}_2\text{H}_6\) troDMF. The corresponding DOFS of each smoothing function are also shown in Fig.5. If an explanatory variable is linearly correlated with the \(\text{C}_2\text{H}_6\) troDMF, the DOFS of the resulting smoothed variable could be equal to 1, and the larger the slope the higher the linear response. Otherwise, the larger the deviation of DOFS relative to 1, the more significant the nonlinear relationship is (Veaux and Richard 2012). During the studied years, the DOFS of zonal wind \((ua)\), convection wind \((omega)\), pressure \((pres)\), tropopause height \((troph)\), temperature \((temp)\), and CO troDMF \((co)\) were close to 1, reflecting a roughly linear relationship of these explanatory variables with the \(\text{C}_2\text{H}_6\) troDMF. In contrast, the DOFS of meridional wind \((va)\), \(\text{H}_2\text{O}\) troDMF \((qv)\) and \(\text{CH}_4\) troDMF \((ch_d)\) were much greater than 1, reflecting a significant nonlinear relationship with the \(\text{C}_2\text{H}_6\) troDMF.

The observed \(\text{C}_2\text{H}_6\) troDMF was influenced by many factors. The zonal wind \((ua)\), meridional wind \((va)\), \(\text{CH}_4\) troDMF \((ch_d)\), and CO troDMF \((co)\) showed positive influences and the other explanatory variables showed negative influences on the observed \(\text{C}_2\text{H}_6\) troDMF variability. The results show that the northward, eastward, and downward convection winds facilitate the accumulation of \(\text{C}_2\text{H}_6\) over the observation site and result in higher \(\text{C}_2\text{H}_6\) troDMF. Since most anthropogenic and biomass burning sources of CO, and fossil fuel source of \(\text{CH}_4\) are common sources of \(\text{C}_2\text{H}_6\), \(\text{C}_2\text{H}_6\) troDMF gradually went up as \(\text{CH}_4\) and CO troDMFs increased. In contrast, meteorological conditions as high temperature, high humidity, and low pressure are more favorable to \(\text{C}_2\text{H}_6\) oxidation, resulting in lower \(\text{C}_2\text{H}_6\) troDMF. Meanwhile, deep upward convection wind and high tropopause height facilitate removal of \(\text{C}_2\text{H}_6\) over the observation site and result in lower \(\text{C}_2\text{H}_6\) troDMF.

5. Source attribution

5.1 Contributions of different source categories and regions
The absolute and relative seasonal contributions of fossil fuel, biogenic, biomass burning, and biofuel emissions to C$_2$H$_6$ variability from 2015 to 2020 over Hefei are shown in Fig. 6. The GEOS-Chem annual mean C$_2$H$_6$ troDMF simulations were decreased by 0.51, 0.27, 0.32, and 0.20 ppbv in the absence of fossil fuel, biogenic, biomass burning, and biofuel C$_2$H$_6$ emission inventories, which correspond to 34.6, 18.4, 21.3, and 13.5% of relative contribution to the modelled C$_2$H$_6$ variability, respectively. The anthropogenic emissions account for 48.1% and the natural emissions account for 39.7% of the C$_2$H$_6$ variability. The remaining contribution calculated as the difference between the BASE simulation and the sum of anthropogenic and natural contributions is 0.17 ppbv (12.2%).

This missing rest can be largely attributed to nonlinear interactional effects among different sources which were not captured by the sensitivity simulations. Indeed, shutting off an emission inventory may induce significantly lower concentrations in atmospheric compounds (i.e., C$_2$H$_6$ for noFF and noBIOF or all suppressed compounds for noBVOC and noBB simulations) globally. On the one hand, some of them may react with OH, which would lead to higher OH concentrations available for the oxidation of C$_2$H$_6$, and eventually enhances the C$_2$H$_6$ destruction from other emission categories. On the other hand, some of them may form OH by a series of oxidation reaction, which would lead to lower OH concentrations available for the oxidation of C$_2$H$_6$, and eventually mitigates the C$_2$H$_6$ destruction from other emission categories. However, it is difficult to quantify the nonlinear impact of each individual emission category, since the concentration and spatial distribution of C$_2$H$_6$ in each emission category are different. Especially when biogenic and biomass burning emissions are suppressed, the impacts become hard to assess, since all NMVOCs compounds play a key role in both OH formation and destruction. Investigating the nonlinear impact of each individual emission category would require additional work that is beyond the scope of the present work.

The contributions of all emission sources are seasonal dependent, and the fossil fuel contribution shows the largest seasonal difference, which consolidates the GAMs regression results that the emission influences are seasonal dependent. The fossil fuel contribution in winter and spring (DJF/MAM) are larger than those in summer and autumn (JJA/SON), with a maximum of 52.0% in DJF and a minimum of 13.0% in JJA. The JJA/SON meteorological conditions which show stronger solar radiation, higher temperature, wetter atmospheric condition, and lower pressure than those in DJF/MAM are more favorable for increasing VOCs emissions from biogenic sources (BVOCs), which consolidates the fact that C$_2$H$_6$ abundance from biogenic source in JJA/SON are larger than those in DJF/MAM. The missing rest contributes to a maximum of 32% in JJA when the C$_2$H$_6$ oxidation reaches the seasonal maximum and is thus more sensitive to the on-off state of different sources.

Fig. 7 explores the absolute and relative seasonal contributions of ER, CR, NR, WR, and SR regions to the C$_2$H$_6$ variability from 2015 to 2020 over Hefei. The GEOS-Chem annual mean C$_2$H$_6$ troDMF simulations were decreased by 0.28, 0.22, 0.29, 0.07, and 0.12 in the absence of the C$_2$H$_6$ emissions in ER, CR, NR, WR, and SR regions, which correspond to 21.5%, 15.8%, 20.3%, 5.7%, and 8.9%, of relative contribution to the modelled C$_2$H$_6$ variability, respectively. The contributions of all geographical regions are also seasonal dependent. The results show that the observed C$_2$H$_6$ variability was largely attributed to emissions within China (74.1%), which show a maximum in JJA/SON and a minimum in DJF/MAM. As vicinities of the observation site, the ER, CR, and NR regions dominated the contribution within China (57.6%). The remaining contribution calculated as the difference between the BASE simulation and the total contributions of above individual source
regions is 0.42 ppbv (25.9%). This contribution is the sum of \( \text{C}_2\text{H}_6 \) emissions outside China (ROW) and the nonlinear interactional effects among the geographical sensitivity simulations. This rest contribution in DJF/MAM are \( \sim 4.0 \) times larger than those in JJA/SON. Considering the nonlinear interactional effects mainly occur in JJA/SON but this rest contribution in the meantime shows the seasonal minimum value, this remaining contribution can be largely attributed to ROW contributions.

As a relatively long lifetime species (a few months), \( \text{C}_2\text{H}_6 \) emissions originating from either nearby or in distant areas can be transported to Hefei site under favourable weather conditions, and thus contribute to the observed \( \text{C}_2\text{H}_6 \) variability. In addition, atmospheric compounds originating either nearby or in distant areas, which affect the chemistry of \( \text{C}_2\text{H}_6 \) oxidation, could also affect the observed \( \text{C}_2\text{H}_6 \) variability. For contributions within China, the lowest contribution of the WR region to the observed \( \text{C}_2\text{H}_6 \) variability is largely attributed to the lowest \( \text{C}_2\text{H}_6 \) emission rates in this region (Table 2). A smaller contribution of the SR region to the observed \( \text{C}_2\text{H}_6 \) variability in DJF/MAM in comparison with the ER, CR, and NR regions is mainly attributed to less air masses that originated in south China under the dry winter monsoon conditions, see section 5.2.

### 5.2 Transport inflow and outflow pathways

The direct GEOS-Chem sensitivity simulations can clearly characterize the 3D transport inflow and outflow pathways of \( \text{C}_2\text{H}_6 \) over the observation site. Fig.8 shows the spatial distribution of GEOS-Chem \( \text{C}_2\text{H}_6 \) BASE simulations around China along with horizontal wind vectors at 900 hPa in different seasons. General atmospheric circulation patterns over eastern China are typically affected by mid-latitude westerlies and Asian monsoon, including the East Asian summer monsoon and South Asian summer monsoon (Chen et al. 2009; Liang et al. 2005; Liu et al. 2003). Fig. 9 illustrates the latitude – height distributions of \( \text{C}_2\text{H}_6 \) VMR over China from six source regions along with the 3D atmospheric circulation patterns in different seasons. The 3D transport inflow and outflow pathways of \( \text{C}_2\text{H}_6 \) over the observation site are thus deduced as follows.

As indicated by the arrows in Figs. 8 and 9, the high pressure system over the Eurasian continent in DJF triggers the descending of strongly cold air over eastern China and results in air masses converging toward the observation site from western and northern areas, while the high pressure system over the Indian ocean and Pacific in JJA triggers the ascending of strongly heated air over eastern China and results in air masses converging toward the observation site from South Asia and East Asia (SEAS) (Liang et al. 2004; Liu et al. 2003). In DJF, the mid-latitude westerlies extend to tropics (about 15 °N) over middle and upper troposphere, and subtropics (about 30°N) near the surface, while the easterlies mainly prevail in tropics and are weak over eastern China [Figs. 8 and 9]. In the summer monsoon season, the atmospheric circulation patterns over eastern China change dramatically and is dominated by surface wind regime originating from Pacific, South China Sea, or Arabian Sea [Figs.8 and 9]. Meanwhile, the mid-latitude westerlies recede to the North Temperate Zone (north of 30°N) and the westerly jet center shifts to north of 50°N in JJA (from ~ 30°N in DJF) [Fig. 8]. In JJA, the tropical region is characterized by the strong easterlies in the upper troposphere and by the southwesterly air flow in the lower troposphere [Fig. 9]. The prevailing winds in the transition seasons in MAM and SON are still westerlies with frequent cold fronts [Figs. 8 and 9]. These above seasonal circulation patterns determine the transport inflow and outflow of \( \text{C}_2\text{H}_6 \) around the observation site. However, the transported scales are also influenced by source
location and strength, travel trajectory and travel time (Liu et al. 2003).

Generally, C\textsubscript{2}H\textsubscript{6} emissions from CR, NR, and WR regions can be transported to the observation site by the strong westerlies throughout the year [Fig. 9]. C\textsubscript{2}H\textsubscript{6} from the SR region can be transported to the observation site by deep convection followed by northward transport into the mid-latitude westerlies in MAM or driven by the South Asian summer monsoon or westerlies in other seasons (Liu et al. 2003)[Fig. 8]. The observed C\textsubscript{2}H\textsubscript{6} transport inflow originating from the local ER region is mainly driven by the local circulation cell or Asian monsoon. The driver for C\textsubscript{2}H\textsubscript{6} transport inflow originating from the northern ROW (> 32°N) is the same as those from the CR, NR, and WR regions. The driver for C\textsubscript{2}H\textsubscript{6} transport inflow originating from the southern ROW (< 32°N) is the same as that from the SR region. However, C\textsubscript{2}H\textsubscript{6} originating from ROW relative to those from China reaches a higher altitude due to longer transport distances. The ROW contributions in JJA/SON are lower than those in DJF/MAM can be partly attributed to a stronger removal along the long-range transport pathway by the abundant wet precipitation and oxidation during the summer monsoon and post monsoon season.

Seasonal variability in C\textsubscript{2}H\textsubscript{6} transport outflow over the observation site is mainly associated with the monsoon system. In DJF, C\textsubscript{2}H\textsubscript{6} over the observation site is capped in the lower troposphere by the subsidence over eastern China and is swept by northeasterly southwestward into southwestern areas, where they are lifted up into the free troposphere by convection and then flow away northeastward [Fig. 9]. In JJA, the observed C\textsubscript{2}H\textsubscript{6} is transported northeastward by the Asian monsoon and is undergone frequent lifting into the upper troposphere by deep convection [Figs. 8 and 9]. Frequent cold fronts are common phenomena during meteorologically transitional periods in MAM and SON. In SON, the winter monsoon builds continental high system, and sweeps the observed C\textsubscript{2}H\textsubscript{6} in the lower troposphere northward to relatively high latitudes where they can be lifted up into the free troposphere by deep convection or cold fronts. In MAM, convection over lower latitudes at Asian continent starts to rise, which lifts up the observed C\textsubscript{2}H\textsubscript{6} into the free troposphere and then flow away southward.

5.3 Potential factors driving interannual variability of C\textsubscript{2}H\textsubscript{6}

China has implemented a series of active clean air policies since 2013 to mitigate severe air pollution problems (Sun et al. 2020; Zhang et al. 2019; Zheng et al. 2018). Since then the emissions of major air pollutants have decreased, and the overall air quality has greatly improved (Sun et al. 2020; Zhang et al. 2019; Zheng et al. 2018). Many air pollutants, such as NO\textsubscript{2}, sulphur dioxide (SO\textsubscript{2}), particulate matter 2.5 (PM\textsubscript{2.5}), PM\textsubscript{10}, CO, black carbon (BC), and organic carbon (OC), showed negative trends in recent years (Lu et al., 2019; Zhang et al. 2019; Zheng et al. 2018). We follow the method of Zheng et al. (2018) to estimate the relative change rate of anthropogenic C\textsubscript{2}H\textsubscript{6} emissions in China during 2015 – 2019 using the MEIC emission inventory. As tabulated in Table 2, anthropogenic C\textsubscript{2}H\textsubscript{6} emissions in all geographical regions showed a decreasing change rate during 2015 – 2019 except those in WR region where industrialization, urbanization, land use, and infrastructure construction have expanded rapidly in recent years, resulting in an increasing change rate of anthropogenic C\textsubscript{2}H\textsubscript{6} emissions in the region (Ran et al. 2014). The relative change rates of anthropogenic C\textsubscript{2}H\textsubscript{6} emissions in China during 2015 – 2019 are estimated as: 12.12% for WR, –5.32% for NR, –1.03% for CR, –7.66% for ER, –5.01% for SR, and –2.74% in total. The major driving forces for the decline in C\textsubscript{2}H\textsubscript{6} emissions over China are attributed to the reductions from
residential and transport sectors, with relative change rates of −14.53% and −3.93%, respectively (Table 2).

The interannual change rate of anthropogenic \( \text{C}_2\text{H}_6 \) emissions in China in recent years is estimated to be −0.69% yr\(^{-1} \) (calculated as −2.74%/y (2019 − 2015)), which is much lower than the observed decreasing change rate in \( \text{C}_2\text{H}_6 \) tropDMF (−2.60 ± 1.34% yr\(^{-1} \)), indicating additional driving forces could exist, e.g., reductions in natural \( \text{C}_2\text{H}_6 \) emissions in China or reductions in long range transport of \( \text{C}_2\text{H}_6 \) emissions originating either anthropogenic or natural sources outside China. On the one hand, the Law of the People’s Republic of China on the Prevention and Control of Atmospheric Pollution included the prohibition of crop residue burning over China in 2015 because crop residue burning emissions can result in poor air quality (http://www.chinalaw.gov.cn, last access on 19 June 2020). Since then the crop residue burning events over China decreased dramatically (Sun et al. 2020). Meanwhile, biomass burning events in Africa, SEAS, and Oceania regions in 2015 were higher than those in onward years due to the El Niño Southern Oscillation (ENSO) (Sun et al. 2020). The decreased global biomass burning emissions could probably also contribute to the observed decreasing change rate in \( \text{C}_2\text{H}_6 \) tropDMF over Hefei since 2015. On the other hand, large oil price fluctuations in recent years probably tightened oil and gas development around the globe which can cause a reduction in \( \text{C}_2\text{H}_6 \) leakage around the globe. However, \( \text{C}_2\text{H}_6 \) observations around the globe and more statistical data are needed to support this deduction, which is beyond the scope of this paper and requires further study.

6. Conclusions

Ethane (\( \text{C}_2\text{H}_6 \)) is an important greenhouse (GHG) gas and plays a significant role in tropospheric chemistry and climate change. As a relatively long residue time species (a few months), observations of \( \text{C}_2\text{H}_6 \) can reflect regional and hemispheric changes in emissions and climate, and can be assimilated into a chemical transport model to assess nonlocal emissions and provide valuable insights into model biases of \( \text{C}_2\text{H}_6 \) simulations.

This study for the first time presents and quantifies the variability, source, and transport of \( \text{C}_2\text{H}_6 \) over densely populated and highly industrialized eastern China by using ground-based high-resolution Fourier transform infrared (FTIR) observations. Seasonal and interannual variabilities of \( \text{C}_2\text{H}_6 \) over Hefei, eastern China from 2015 – 2020 have been investigated. The dependencies of \( \text{C}_2\text{H}_6 \) on meteorological and emission factors were analyzed by using generalized additive models (GAMs). The FTIR \( \text{C}_2\text{H}_6 \) time series are for the first time applied to evaluate the standard GEOS-Chem full-chemistry model for the specifics of \( \text{C}_2\text{H}_6 \) simulation over eastern China. GEOS-Chem model simulation with the state-of-the-art inventory is in good agreement with the FTIR observation.

The GEOS-Chem model was further run in a sensitivity mode to quantify relative contribution of various source categories and regions to the observed \( \text{C}_2\text{H}_6 \) variability. The three-dimensional (3D) transport inflow and outflow pathways of \( \text{C}_2\text{H}_6 \) over the observation site were finally determined by the GEOS-Chem sensitivity simulation and the analysis of the meteorological fields.

We obtained a retrieval error of 6.21 ± 1.2 (1σ)% and degrees of freedom (DOFS) of 1.47 ± 0.2 (1σ) in retrieval of \( \text{C}_2\text{H}_6 \) tropospheric column-averaged dry-air mole fraction (troDMF). The observed \( \text{C}_2\text{H}_6 \) troDMF reached a minimum monthly mean value of (0.36 ± 0.26) ppbv in July and a maximum monthly mean value of (1.76 ± 0.35) ppbv in December, and showed a negative change rate of (−2.60 ± 1.34) %/yr from 2015 to 2020. Generally, both meteorological and emission factors
have positive influences on \( C_2H_6 \) troDMF in cold season (DJF/MAM) and negative influences in warm season (JJA/SON). GEOS-Chem model sensitivity simulations concluded that the anthropogenic emissions (fossil fuel plus biofuel) accounted for 48.1% and the natural emissions (biomass burning plus biogenic) accounted for 39.7% of \( C_2H_6 \) variability over Hefei. The observed \( C_2H_6 \) variability over Hefei was mainly attributed to the emissions within China (74.1%), where central, eastern, and northern China dominated the contribution (57.6%). Seasonal variability in \( C_2H_6 \) transport inflow and outflow over the observation site is largely related to the mid-latitude westerlies and Asian monsoon system. Reduction in \( C_2H_6 \) from 2015 to 2020 mainly results from the decrease in local and transported \( C_2H_6 \) emissions, which points to air quality improvement in China in recent years.

This study can not only enhance the insights of regional emission, transport, and air clean actions over China, but also contribute to form new reliable remote sensing dataset in this sparsely-monitored regions for climate change research.

**Code and data availability.** The new ground-based Fourier transform infrared (FTIR) spectroscopic remote sensing dataset for atmospheric \( C_2H_6 \) over Hefei, eastern China in this study can be accessed from https://doi.org/10.6084/m9.figshare.13020545. The MEIC emission inventories used in this study are available from http://meicmodel.org/.

**Author contributions.** YS designed and wrote the paper with inputs from all coauthors. HY carried out the GEOS-Chem simulations and GAMs regression. BZ provided the latest MEIC emission inventory. The rest authors contributed to this work by providing constructive comments.

**Competing interests.** The authors declare that they have no conflict of interest.

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References


Liu, F., Zhang, Q., Tong, D., Zheng, B., Li, M., Huo, H., and He, K. B.: High-resolution inventory of
technologies, activities, and emissions of coal-fired power plants in China from 1990 to 2010.
Liu, H. Y., Jacob, D. J., Bey, I., and Yantosca, R. M.: Constraints from Pb-210 and Be-7 on wet deposition
Liu, H. Y., Jacob, D. J., Bey, I., Yantosca, R. M., Duncan, B. N., and Sachse, G. W.: Transport pathways
Lu, X., Hong, J. Y., Zhang, L., Cooper, O. R., Schultz, M. G., Xu, X. B., Wang, T., Gao, M., Zhao, Y. H.,
Lutsch, E., Dammers, E., Conway, S., and Strong, K.: Long-range transport of NH₃, CO, HCN, and C₂H₆
F., Kasai, Y., Mahieu, E., Makarova, M., Morino, I., Nagahama, T., Notholt, J., Ortega, I., Palm, M.,
Poberovskii, A. V., Sussmann, R., and Warneke, T.: Detection and Attribution of Wildfire Pollution
in the Arctic and Northern Mid-latitudes using a Network of FTIR Spectrometers and GEOS-Chem,
Ma, Y. X., Ma, B. J., Jiao, H. R., Zhang, Y. F., Xin, J. Y., and Yu, Z.: An analysis of the effects of weather
and air pollution on tropospheric ozone using a generalized additive model in Western China:
McKain, K., Down, A., Raciti, S. M., Budney, J., Hutrya, L. R., Floerchinger, C., Herndon, S. C.,
from natural gas infrastructure and use in the urban region of Boston, Massachusetts, P. Natl. Acad.
Nagahama, Y., and Suzuki, K.: The influence of forest fires on CO, HCN, C₂H₆, and C₃H₇ over northern
Notholt, J., Toon, G. C., Rinsland, C. P., Pougatchev, N. S., Jones, N. B., Connor, B. J., Weller, R.,
Gautrois, M., and Schremss, O.: Latitudinal variations of trace gas concentrations in the free


Table 1. Error budget and degrees of freedom (DOFS) for signal of randomly selected $\text{C}_2\text{H}_6$ troDMF retrieval at Hefei, eastern China

<table>
<thead>
<tr>
<th>Error source</th>
<th>Input value</th>
<th>Error budget</th>
</tr>
</thead>
<tbody>
<tr>
<td>Temperature uncertainty</td>
<td>1σ of NCEP</td>
<td>1.69%</td>
</tr>
<tr>
<td>Zero level uncertainty</td>
<td>1%</td>
<td>1.45%</td>
</tr>
<tr>
<td>Retrieval parameters uncertainty</td>
<td>*</td>
<td>&lt; 0.1%</td>
</tr>
<tr>
<td>Measurement error</td>
<td>1/SNR^2</td>
<td>0.53%</td>
</tr>
<tr>
<td>Interfering species uncertainty</td>
<td>SD of WACCM</td>
<td>0.11%</td>
</tr>
<tr>
<td>Smoothing uncertainty</td>
<td>*</td>
<td>0.37%</td>
</tr>
<tr>
<td><strong>Total random error</strong></td>
<td></td>
<td>2.32%</td>
</tr>
<tr>
<td>Background curvature uncertainty</td>
<td>1%</td>
<td>0.14%</td>
</tr>
<tr>
<td>Field of view uncertainty</td>
<td>1%</td>
<td>&lt; 0.1%</td>
</tr>
<tr>
<td>Optical path difference uncertainty</td>
<td>1%</td>
<td>&lt; 0.1%</td>
</tr>
<tr>
<td>Solar zenith angle uncertainty</td>
<td>1%</td>
<td>&lt; 0.1%</td>
</tr>
<tr>
<td>Phase uncertainty</td>
<td>1%</td>
<td>&lt; 0.1%</td>
</tr>
<tr>
<td>ILS uncertainty</td>
<td>1%</td>
<td>&lt; 0.1%</td>
</tr>
<tr>
<td>Line temperature broadening uncertainty</td>
<td>5%</td>
<td>0.4%</td>
</tr>
<tr>
<td>Line intensity uncertainty</td>
<td>5%</td>
<td>5.12%</td>
</tr>
<tr>
<td>Line pressure broadening uncertainty</td>
<td>5%</td>
<td>0.93%</td>
</tr>
<tr>
<td><strong>Total systematic error</strong></td>
<td></td>
<td>5.48%</td>
</tr>
<tr>
<td><strong>Total errors</strong></td>
<td></td>
<td>6.21%</td>
</tr>
<tr>
<td><strong>DOFS (-)</strong></td>
<td></td>
<td>1.47</td>
</tr>
</tbody>
</table>

* These input values for error budget estimation are based on the retrieval output

Table 2. Anthropogenic $\text{C}_2\text{H}_6$ emissions in China by region and category for the 2015 and 2019 MEIC emission inventories

<table>
<thead>
<tr>
<th>Region</th>
<th>Industry (Tg yr$^{-1}$)</th>
<th>Power plant (Tg yr$^{-1}$)</th>
<th>Residential (Tg yr$^{-1}$)</th>
<th>Transport (Tg yr$^{-1}$)</th>
<th>Sum (Tg yr$^{-1}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>WR 2015</td>
<td>0.084</td>
<td>&lt;0.01</td>
<td>0.011</td>
<td>&lt;0.01</td>
<td>0.1</td>
</tr>
<tr>
<td>2019</td>
<td>0.097</td>
<td>&lt;0.01</td>
<td>0.011</td>
<td>&lt;0.01</td>
<td>0.112</td>
</tr>
<tr>
<td>change</td>
<td>15.36%</td>
<td>82.54%</td>
<td>-6.61%</td>
<td>-3.41%</td>
<td>12.12%</td>
</tr>
<tr>
<td>NR 2015</td>
<td>0.241</td>
<td>&lt;0.01</td>
<td>0.125</td>
<td>0.026</td>
<td>0.394</td>
</tr>
<tr>
<td>2019</td>
<td>0.241</td>
<td>&lt;0.01</td>
<td>0.105</td>
<td>0.025</td>
<td>0.373</td>
</tr>
<tr>
<td>change</td>
<td>0.04%</td>
<td>2.51%</td>
<td>-15.96%</td>
<td>-4.38%</td>
<td>-5.32%</td>
</tr>
<tr>
<td>CR 2015</td>
<td>0.144</td>
<td>&lt;0.01</td>
<td>0.041</td>
<td>&lt;0.01</td>
<td>0.189</td>
</tr>
<tr>
<td>2019</td>
<td>0.15</td>
<td>&lt;0.01</td>
<td>0.033</td>
<td>&lt;0.01</td>
<td>0.187</td>
</tr>
<tr>
<td>change</td>
<td>4.68%</td>
<td>-7.00%</td>
<td>-20.75%</td>
<td>-1.13%</td>
<td>-5.03%</td>
</tr>
<tr>
<td>ER 2015</td>
<td>0.07</td>
<td>&lt;0.01</td>
<td>0.026</td>
<td>0.01</td>
<td>0.11</td>
</tr>
<tr>
<td>2019</td>
<td>0.067</td>
<td>&lt;0.01</td>
<td>0.022</td>
<td>0.01</td>
<td>0.097</td>
</tr>
<tr>
<td>change</td>
<td>-4.83%</td>
<td>5.40%</td>
<td>-16.79%</td>
<td>-3.70%</td>
<td>-7.66%</td>
</tr>
<tr>
<td>SR 2015</td>
<td>0.06</td>
<td>&lt;0.01</td>
<td>0.026</td>
<td>0.01</td>
<td>0.09</td>
</tr>
<tr>
<td>2019</td>
<td>0.056</td>
<td>&lt;0.01</td>
<td>0.027</td>
<td>0.01</td>
<td>0.09</td>
</tr>
<tr>
<td>change</td>
<td>-7.94%</td>
<td>-9.26%</td>
<td>1.52%</td>
<td>-4.24%</td>
<td>-5.01%</td>
</tr>
<tr>
<td>China 2015</td>
<td>0.60</td>
<td>&lt;0.01</td>
<td>0.231</td>
<td>0.05</td>
<td>0.883</td>
</tr>
<tr>
<td>2019</td>
<td>0.612</td>
<td>&lt;0.01</td>
<td>0.197</td>
<td>0.048</td>
<td>0.859</td>
</tr>
<tr>
<td>change</td>
<td>1.91%</td>
<td>4.04%</td>
<td>-14.53%</td>
<td>-3.93%</td>
<td>-2.74%</td>
</tr>
</tbody>
</table>
Table 3. GEOS-Chem model configurations and delimitations of all geographical regions used in sensitivity simulations.

<table>
<thead>
<tr>
<th>Simulation</th>
<th>Region</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>BASE</td>
<td>Global</td>
<td>Standard simulation with all anthropogenic and natural C\textsubscript{2}H\textsubscript{6} emissions. The BASE simulation is taken as the reference and used for model evaluation</td>
</tr>
<tr>
<td>noFF</td>
<td>Global</td>
<td>Turn off global fossil fuel C\textsubscript{2}H\textsubscript{6} emissions in BASE simulation</td>
</tr>
<tr>
<td>noBVO</td>
<td>Global</td>
<td>Turn off global biogenic C\textsubscript{2}H\textsubscript{6} emissions in BASE simulation</td>
</tr>
<tr>
<td>noBB</td>
<td>Global</td>
<td>Turn off global biomass burning C\textsubscript{2}H\textsubscript{6} emissions in BASE simulation</td>
</tr>
<tr>
<td>noBIOF</td>
<td>Global</td>
<td>Turn off global biofuel C\textsubscript{2}H\textsubscript{6} emissions in BASE simulation</td>
</tr>
<tr>
<td>Rest</td>
<td>Global</td>
<td>Difference between BASE and the sum of FF, BVOC, BB, and BIOF contributions</td>
</tr>
<tr>
<td>noWR</td>
<td>78.6° E – 103.4° E; 27.6°N - 48.8°N</td>
<td>Turn off fossil fuel, biogenic, biomass burning, and biofuel C\textsubscript{2}H\textsubscript{6} emissions within western China (WR), i.e., region ○ in Fig. 2, in BASE simulation</td>
</tr>
<tr>
<td>noNR</td>
<td>103.4°E – 129.8°E; 34.6°N – 53.5°N</td>
<td>Turn off fossil fuel, biogenic, biomass burning, and biofuel C\textsubscript{2}H\textsubscript{6} emissions within northern China (NR), i.e., region ○ in Fig. 2, in BASE simulation</td>
</tr>
<tr>
<td>noCR</td>
<td>103.4°E – 115.6°E; 27.6°N – 34.6°N</td>
<td>Turn off fossil fuel, biogenic, biomass burning, and biofuel C\textsubscript{2}H\textsubscript{6} emissions within central China (CR), i.e., region ○ in Fig. 2, in BASE simulation</td>
</tr>
<tr>
<td>noER</td>
<td>115.6°E – 123.6°E; 21.0°N – 34.6°N</td>
<td>Turn off fossil fuel, biogenic, biomass burning, and biofuel C\textsubscript{2}H\textsubscript{6} emissions within eastern China (ER), i.e., region ○ in Fig. 2, in BASE simulation</td>
</tr>
<tr>
<td>noSR</td>
<td>98.1°E – 115.6°E; 21.0°N – 27.6°N</td>
<td>Turn off fossil fuel, biogenic, biomass burning, and biofuel C\textsubscript{2}H\textsubscript{6} emissions within southern China (SR), i.e., region ○ in Fig. 2, in BASE simulation</td>
</tr>
<tr>
<td>ROW</td>
<td>Rest of world</td>
<td>Difference between BASE and the sum of WR, NR, CR, ER, and SR contributions</td>
</tr>
</tbody>
</table>
Figures

Fig. 1. (a) Averaging kernels and their area scaled by a factor of 0.1, (b) cumulative sum of degrees of freedom for signal (DOFS), and (c) volume mixing ratio (VMR) profile of randomly selected C$_2$H$_6$ retrieval over Hefei, eastern China.

Fig. 2. Geographical regions used for GEOS-Chem sensitivity simulations. The numbers ○–○ represent western, northern, central, eastern, and southern China, and the rest of world, respectively. See Table 3 for latitude and longitude delimitations. Daily mean values of C$_2$H$_6$ troDMF on 1 January 2017 provided by GEOS-Chem BASE simulation was selected as a representative of wintertime enhancement in eastern China.
Fig. 3. (a) C$_2$H$_6$ troDMF time series comparison between FTIR observation and GEOS-Chem model BASE simulation from 2015 to 2020 over Hefei, eastern China. The seasonality and interannual variability are represented by red dots and black line, respectively, which are fitted by using a bootstrap resampling model with a 3rd Fourier series plus a linear function. (b) Seasonal variations of C$_2$H$_6$ troDMF by FTIR and GEOS-Chem simulation. Bold curves and the shadows are monthly mean values and the 1-σ standard variations, respectively. Vertical error bars for FTIR and GEOS-Chem represent retrieval uncertainties and diurnal variabilities, respectively. A retrieval error of 6.21% in Table 1 was used to estimate the absolute uncertainties of all observations. As a result, the absolute uncertainties in winter are larger than those in summer due to a higher C$_2$H$_6$ level in the season.

Fig. 4. (a) C$_2$H$_6$ troDMF time series from 2015 to 2020 over Hefei, eastern China by FTIR and GAMs regression model. (b) Time series of accumulated meteorological smooth functions (S(meteos)), and (c) time series of accumulated emission smooth functions (S(non-meteos)). Positive and negative influences are indicated with red and blue bars, respectively. Correlation coefficients for the total, meteorological, and emission influences are also shown.
Fig. 5. Influence of each individual variable in the GAMs model on C₃H₆ troDMF from 2015 to 2020 over Hefei, eastern China. (a) to (i) are for zonal wind (ua), meridional wind (va), convection wind (omega), pressure (pres), tropopause height (troph), H₂O troDMF (qv), temperature (temp), CH₄ troDMF (ch₄), and CO troDMF (co), respectively. The DOFS of each smoothing function is included in the bracket in each panel. The x-axis represents variation range of each variable and the y-axis represents relative percentage change of C₃H₆ troDMF relative to its annual mean value.

Fig. 6. Absolute (a) and relative (b) contributions of fossil fuel, biogenic, biomass burning, and biofuel emission sources to the observed C₃H₆ variability from 2015 to 2020 over Hefei, eastern China. The remaining contribution calculated as the difference between the BASE simulation and the sum of anthropogenic and natural contributions is also shown. All contributions are grouped by season. Vertical error bars represent 1-σ standard variation.
Fig. 7. Absolute (a) and relative (b) contributions of ER, CR, NR, WR, SR, and ROW regions to the observed C₂H₆ variability from 2015 to 2020 over Hefei, eastern China. All contributions are grouped by season. Geographical definition of each region is summarised in Table 3. Vertical error bars represent 1-σ standard variation.

Fig. 8. Spatial distribution of C₂H₆ troDMF in the GEOS-Chem BASE simulations in different seasons. The arrows indicate horizontal wind vectors at 900 hPa; the observation site is marked with a yellow dot. Meteorological fields are from the GEOS-FP 0.25° × 0.3125° dataset.
Fig. 9. The first row shows the latitude–height distributions of C$_2$H$_6$ VMR averaged over 113–121° E in spring (MAM), originating in different source regions (corresponding to different columns). See Table 3 for latitude and longitude definitions. The white area indicates topography, and the white contours at intervals of 6 m s$^{-1}$ are the easterly (dashed) and westerly (solid) mean meridional winds; the wind vectors (consisting of zonal wind in m s$^{-1}$ and vertical velocity in units of Pa s$^{-1}$) are represented by arrows; the observation site is marked with a yellow line. The second to fourth rows are the same as the first row but for summer (JJA), autumn (SON), and winter (DJF), respectively. Meteorological fields are from the GEOS-FP 0.25° × 0.3125° dataset.