



1     **Reduction in C<sub>2</sub>H<sub>6</sub> from 2015 to 2020 over Hefei, eastern China**  
2             **points to air quality improvement in China**

3     Youwen Sun<sup>1</sup>, Hao Yin<sup>1,3,\*</sup>, Cheng Liu<sup>1,2,4,5,\*</sup>, Emmanuel Mahieu<sup>6</sup>, Justus Notholt<sup>7</sup>, Yao Té<sup>8</sup>, Xiao  
4     Lu<sup>9</sup>, Mathias Palm<sup>7</sup>, Wei Wang<sup>1</sup>, Changong Shan<sup>1</sup>, Qihou Hu<sup>1</sup>, Min Qin<sup>1</sup>, Yuan Tian<sup>10</sup>, and Bo  
5     Zheng<sup>11</sup>

6     <sup>1</sup>*Key Laboratory of Environmental Optics and Technology, Anhui Institute of Optics and Fine*  
7     *Mechanics, HFIPS, Chinese Academy of Sciences, Hefei 230031, China*

8     <sup>2</sup>*Center for Excellence in Regional Atmospheric Environment, Institute of Urban Environment,*  
9     *Chinese Academy of Sciences, Xiamen, 361021, China*

10    <sup>3</sup>*University of Science and Technology of China, Hefei, 230026, China*

11    <sup>4</sup>*Key Laboratory of Precision Scientific Instrumentation of Anhui Higher Education Institutes,*  
12    *University of Science and Technology of China, Hefei, 230026, China*

13    <sup>5</sup>*Anhui Province Key Laboratory of Polar Environment and Global Change, USTC, Hefei,*  
14    *230026, China*

15    <sup>6</sup>*Institute of Astrophysics and Geophysics, University of Liège, Belgium*

16    <sup>7</sup>*University of Bremen, Institute of Environmental Physics, P. O. Box 330440, 28334 Bremen,*  
17    *Germany*

18    <sup>8</sup>*Laboratoire d'Etudes du Rayonnement et de la Matière en Astrophysique et Atmosphères*  
19    *(LERMA-IPSL), Sorbonne Université, CNRS, Observatoire de Paris, PSL Université, 75005 Paris,*  
20    *France*

21    <sup>9</sup>*School of Engineering and Applied Sciences, Harvard University, Cambridge, MA 02138, USA*

22    <sup>10</sup>*Anhui University Institutes of Physical Science and Information Technology, Hefei 230601,*  
23    *China*

24    <sup>11</sup>*Institute of Environment and Ecology, Tsinghua Shenzhen International Graduate School,*  
25    *Tsinghua University, Shenzhen 518055, China*

26    \*Corresponding authors.

27    E-mail addresses: chliu81@ustc.edu.cn (C. Liu), yhyh95@mail.ustc.edu.cn (H. Yin)

28     **Abstract**

29             Ethane (C<sub>2</sub>H<sub>6</sub>) is an important greenhouse (GHG) gas and plays a significant role in  
30     tropospheric chemistry and climate change. This study first presents and quantifies the variability,  
31     source, and transport of C<sub>2</sub>H<sub>6</sub> over densely populated and industrialized eastern China by using  
32     ground-based high-resolution Fourier transform infrared (FTIR) remote sensing technique. We  
33     obtained a retrieval error of  $6.21 \pm 1.2$  (1 $\sigma$ )% and degrees of freedom (DOFS) of  $1.47 \pm 0.2$  (1 $\sigma$ ) in  
34     retrieval of C<sub>2</sub>H<sub>6</sub> tropospheric column-averaged dry-air mole fraction (troDMF) over Hefei, eastern  
35     China (117°E, 32°N, 30 m a.s.l.). The observed C<sub>2</sub>H<sub>6</sub> troDMF reached a minimum monthly mean  
36     value of  $(0.36 \pm 0.26)$  ppbv in July and a maximum monthly mean value of  $(1.76 \pm 0.35)$  ppbv in  
37     December, and showed a negative change rate of  $(-2.60 \pm 1.34)$  %/yr from 2015 to 2020. The  
38     dependencies of C<sub>2</sub>H<sub>6</sub> troDMF on meteorological and emission factors were analyzed by using  
39     generalized additive models (GAMs). Generally, both meteorological and emission factors have  
40     positive influences on C<sub>2</sub>H<sub>6</sub> troDMF in cold season (DJF/MAM) and negative influences on C<sub>2</sub>H<sub>6</sub>  
41     troDMF in warm season (JJA/SON). GEOS-Chem chemical model simulation captured the



1 observed C<sub>2</sub>H<sub>6</sub> troDMF variability and was thus used for source attribution. GEOS-Chem model  
2 sensitivity simulations concluded that the anthropogenic emissions (fossil fuel plus biofuel  
3 emissions) and the natural emissions (biomass burning plus biogenic emissions) accounted for 49.2%  
4 and 37.1% of C<sub>2</sub>H<sub>6</sub> troDMF abundance over Hefei, respectively. The observed C<sub>2</sub>H<sub>6</sub> troDMF  
5 abundance mainly results from the emissions within China (74.1%), where central, eastern, and  
6 northern China dominated the contribution (57.6%). Seasonal variability in C<sub>2</sub>H<sub>6</sub> transport inflow  
7 and outflow over the observation site is largely related to the mid-latitude westerlies and Asian  
8 monsoon system. Reduction in C<sub>2</sub>H<sub>6</sub> abundance from 2015 to 2020 mainly results from the decrease  
9 in local and transported C<sub>2</sub>H<sub>6</sub> emissions, which points to air quality improvement in China in recent  
10 years.

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

## 12 1. Introduction

13 Ethane (C<sub>2</sub>H<sub>6</sub>) is an important greenhouse (GHG) gas and one of the most abundant Volatile  
14 Organic Compounds (VOCs) in the atmosphere (Abad et al. 2011; Singh et al. 2001; Steinfeld 1998).  
15 Although C<sub>2</sub>H<sub>6</sub> is much less abundant than methane (CH<sub>4</sub>) and also less efficient relative to mass,  
16 it plays a significant role in tropospheric chemistry and climate change (Tzompa-Sosa et al. 2017).  
17 In the presence of nitrogen oxides (NO<sub>x</sub> = NO + NO<sub>2</sub>), the C<sub>2</sub>H<sub>6</sub> oxidation can enhance tropospheric  
18 ozone (O<sub>3</sub>) generation, which shows a positive radiative influence on climate (Sun et al. 2018a) and  
19 threatens crop yields (Sun et al. 2018a; Van Dingenen et al. 2009) and human health (Sun et al.  
20 2018a; Tzompa-Sosa et al. 2017). In addition, as a major source of acetaldehyde (CH<sub>3</sub>CHO), C<sub>2</sub>H<sub>6</sub>  
21 has a great impact on the production of peroxyacetyl nitrate (PAN) which is a key reservoir species  
22 of NO<sub>x</sub> (Fischer et al. 2014). The main sink of tropospheric C<sub>2</sub>H<sub>6</sub> is predominantly destruction via  
23 reaction with the hydroxyl radical (OH) (Xiao et al. 2008), which determines the residence time of  
24 most tropospheric species (Steinfeld 1998). As a result, tropospheric C<sub>2</sub>H<sub>6</sub> can decrease the  
25 atmospheric oxidative capacity and indirectly impact the climate by extending the CH<sub>4</sub> lifetime  
26 (Monks et al. 2018; Taylor et al. 2020). Atmospheric C<sub>2</sub>H<sub>6</sub> has a relatively long residence time of a  
27 few months (Franco et al. 2016), allowing it to undergo intercontinental transport. As a result,  
28 observations of C<sub>2</sub>H<sub>6</sub> can be assimilated into a chemical transport model to estimate nonlocal  
29 emissions and air quality, and provide valuable insights into model biases of C<sub>2</sub>H<sub>6</sub> simulations  
30 (Tzompa-Sosa et al. 2017).

31 On a global scale, the main sources of C<sub>2</sub>H<sub>6</sub> are leakage from production, processing, and  
32 transport of natural gas (62%), biofuel combustion (20%) and biomass burning emission (18%),  
33 largely occurred in the Northern Hemisphere (NH) (Franco et al. 2016; Xiao et al. 2008). Additional  
34 minor sources of C<sub>2</sub>H<sub>6</sub> are from biogenic and oceanic sources. However, on a regional scale, the  
35 proportion of each C<sub>2</sub>H<sub>6</sub> source may show large difference. Natural gas leakage contribution can  
36 reach 80% of C<sub>2</sub>H<sub>6</sub> emissions in regions with active oil and natural gas production (Gilman et al.  
37 2013), where C<sub>2</sub>H<sub>6</sub> emissions are highly correlated with CH<sub>4</sub> emissions. In such regions, C<sub>2</sub>H<sub>6</sub> can  
38 be applied as a tracer for separation of fossil fuel CH<sub>4</sub> emissions from multiple methane (CH<sub>4</sub>)  
39 sources (e.g., oil and gas, cows, wetlands, and rice yield) (McKain et al. 2015; Roscioli et al. 2015).  
40 The C<sub>2</sub>H<sub>6</sub> abundance in the Southern Hemisphere (SH) is much lower than those in the NH since  
41 the anthropogenic C<sub>2</sub>H<sub>6</sub> sources are low in the SH, and the residence time of C<sub>2</sub>H<sub>6</sub> is shorter than  
42 the interhemispheric exchange rate. Many studies concluded that C<sub>2</sub>H<sub>6</sub> in the SH is primarily emitted



1 from biomass burning, and is closely correlated with CO and HCN emissions (Notholt et al. 2000;  
2 Rinsland et al. 2002; Vigouroux et al. 2012; Zeng et al. 2012).

3 C<sub>2</sub>H<sub>6</sub> is one of the target gases of a global ground-based Fourier transform infrared  
4 spectroscopy (FTIR) network, namely the Network for Detection of Atmospheric Composition  
5 Change (NDACC) (De Mazière et al. 2018). FTIR time series of C<sub>2</sub>H<sub>6</sub> with different time periods  
6 have been reported in many stations for validation of satellite data or chemical model simulation  
7 (Abad et al. 2011; Franco et al. 2015; Franco et al. 2016; Glatthor et al. 2009), or evaluation of local  
8 air quality and air pollutants transport caused by anthropogenic emission and biomass burning  
9 (Angelbratt et al. 2011; Lutsch et al. 2016; Lutsch et al. 2019; Nagahama and Suzuki 2007; Rinsland  
10 et al. 2002; Simpson et al. 2012; Viatte et al. 2015; Viatte et al. 2014; Vigouroux et al. 2012; Zeng  
11 et al. 2012; Zhao et al. 2002). Several FTIR sites have observed the decrease in C<sub>2</sub>H<sub>6</sub> over 1990 –  
12 2010, and characterized consistent interannual trends in the –1 to –2.7% yr<sup>-1</sup> range (Franco et al.  
13 2015; Franco et al. 2016; Simpson et al. 2012; Zeng et al. 2012). This declining trend has been  
14 largely attributed to the reduction of global fugitive emissions (Franco et al. 2015; Simpson et al.  
15 2012). Recently, several studies concluded that the long-term decline in C<sub>2</sub>H<sub>6</sub> in the NH reversed  
16 from 2009 onwards (Franco et al. 2015; Franco et al. 2016). Using ground-based FTIR C<sub>2</sub>H<sub>6</sub> total  
17 columns derived at five selected NDACC sites, Franco et al. (2016) characterized the C<sub>2</sub>H<sub>6</sub>  
18 evolution from 2009 – 2015 and determined growth rates of ~3% yr<sup>-1</sup> at remote sites and of ~5%  
19 yr<sup>-1</sup> at mid-latitudes. This change is mainly attributed to the exploitation of shale gas and tight oil  
20 reservoirs in North America (Franco et al. 2016; Helmig et al. 2016).

21 The NDACC network has been operating for almost three decades around the globe (De  
22 Mazière et al. 2018; Sun et al. 2018a). However, most instruments are located in Europe and  
23 Northern America, but the number of observation sites in the rest parts of world remains sparse, and  
24 there is only one qualified observations site in China, i.e., the Hefei site (117°E, 32°N, 30 m a.s.l.)  
25 located in a densely populated and industrialized area in eastern China (Sun et al. 2018a). The Hefei  
26 site is not yet affiliated to the NDACC network but its observation routine is following the NDACC  
27 standard convention since 2015 (Sun et al. 2018a). As the consequence of a series of actions for  
28 emission control, air pollution over China in recent years has been significantly improved (Zhang  
29 et al. 2019; Zheng et al. 2018). However, the atmospheric pollution over densely populated and  
30 industrialized eastern China is still in severe situation (Zhang et al. 2019; Zheng et al. 2018). The  
31 complexity, extension, and severity of the atmospheric pollution in eastern China are still unrivaled  
32 compared to the rest of world (Lu et al. 2018; Zheng et al. 2018). FTIR observations at Hefei have  
33 been used extensively for evaluation of satellite data (Tian et al. 2018; Wang et al. 2017), chemical  
34 model simulation (Tian et al. 2018; Yin et al. 2020; Yin et al. 2019), local air quality (Shan et al.  
35 2019; Sun et al. 2018a) and the transport of air pollutants caused by anthropogenic and biomass  
36 burning emissions (Sun et al. 2018a; Sun et al. 2020a; Sun et al. 2020b).

37 In this study, we first present and quantify the variability, source, and transport of C<sub>2</sub>H<sub>6</sub> over  
38 densely populated and industrialized eastern China by using FTIR observation, GEOS-Chem model  
39 simulation, and atmospheric circulation pattern techniques. The seasonality and interannual  
40 variability of C<sub>2</sub>H<sub>6</sub> over Hefei, eastern China from 2015 – 2020 are investigated. The dependencies  
41 of C<sub>2</sub>H<sub>6</sub> on meteorological and co-emitted gases (hereafter emission factors) are analyzed by using  
42 generalized additive models (GAMs)(Wood and Simon 2004). The ground-based FTIR C<sub>2</sub>H<sub>6</sub> time  
43 series are for the first time applied to evaluate the GEOS-Chem model for the specifics of C<sub>2</sub>H<sub>6</sub>  
44 simulation over eastern China. We further run a series of GEOS-Chem sensitivity simulations to



1 quantify relative contributions of various source categories and regions to the observed  $C_2H_6$   
2 abundance. The three-dimensional (3D) transport inflow and outflow pathways of  $C_2H_6$  over the  
3 observation site are finally determined by the GEOS-Chem sensitivity simulations and atmospheric  
4 circulation pattern. This study can not only enhance the understanding of regional emission,  
5 transport, and air clean actions over eastern China, but also contribute to form new reliable remote  
6 sensing data in this sparsely-monitored regions for climate change research.

7 The next section describes the retrieval for FTIR tropospheric column-averaged dry-air mole  
8 fraction (troDMF) of  $C_2H_6$ , the configuration of GEOS-Chem model simulation, and the GAMs  
9 regression approach. Section 3 reports the variability of  $C_2H_6$  troDMF and comparison with the  
10 GEOS-Chem simulation. Section 4 reports the GAMs regression results and the interpretation.  
11 Section 5 reports the results for source attribution using GEOS-Chem sensitivity simulation and  
12 atmospheric circulation pattern. We conclude the study in Section 6.

## 13 2. Methods and data

### 14 2.1 $C_2H_6$ troDMF retrieval

15 The  $C_2H_6$  troDMF time series were calculated by using direct solar absorption spectra saved  
16 with a FTIR spectrometer in operation at Hefei, eastern China (Sun et al. 2018a; Tian et al. 2018).  
17 Site description and instrumentation can be found in (Sun et al. 2018a). Briefly, the FTIR  
18 observatory includes a high resolution FTIR spectrometer (IFS125HR, Bruker) and a solar tracker  
19 (Solar Tracker-A 547, Bruker). This FTIR observatory alternately saved near infrared (NIR) and  
20 middle infrared (MIR) solar spectra in routine observations (Tian et al. 2018). The NIR and MIR  
21 spectra are saved with different spectral resolutions but both of them can be used to retrieve total  
22 columns and volume mixing ratio (VMR) profiles of a variety of trace gases in the atmosphere. The  
23 MIR spectra used in present work are saved with a spectral resolution of  $0.005\text{cm}^{-1}$  following the  
24 requirements of NDACC standard convention (<http://www.ndacc.org/>, last accessed on 27  
25 December 2020). The FTIR instrument is equipped with a KBr beam splitter, a filter centered at  
26  $2800\text{cm}^{-1}$ , and an InSb detector for  $C_2H_6$  measurements. The number of  $C_2H_6$  measurements on  
27 each measurement day varied from 1 to 17 with an average of 6. In total, there were 743 days of  
28 qualified measurements between 2015 and 2020.

29 In this study, the VMR profile of  $C_2H_6$  was first retrieved by using the SFIT4 algorithm updated  
30 from SFIT2 (Pougetchev et al. 1995) and implementing the optimal estimation method (Rodgers  
31 2000). The  $C_2H_6$  troDMF was then calculated by taking a weighting average of the  $C_2H_6$  VMR  
32 profile and the air mass using a fixed tropospheric altitude. The  $C_2H_6$  VMR profile was retrieved in  
33 a broad window of  $2976 - 2978\text{cm}^{-1}$ . The VMR profiles of  $CH_4$  and  $H_2O$  and column of  $O_3$  were  
34 also retrieved together with the  $C_2H_6$  VMR profile for minimizing the atmospheric absorption  
35 interference. Spectroscopic absorption parameters of all gases are based on the atm16 line list from  
36 the compilation of Geoffrey Toon (Sun et al. 2020a). The *a priori* vertical profiles of temperature  
37  $H_2O$ , and pressure were interpolated from the National Centers for Environmental Protection (NCEP)  
38 reanalysis data and the *a priori* vertical profiles of other gases were from the statistical averages of  
39 the Whole-Atmosphere Community Climate Model version 6 (WACCM) simulations from 1980 to  
40 2020. The diagonal elements of the *a priori* covariance matrices  $S_a$  and the measurement noise  
41 covariance matrices  $S_e$  were set to standard deviation (SD) of the WACCM simulations and the  
42 inverse square of the signal-to-noise ratio (SNR) of each spectrum, respectively (Franco et al. 2015).



1 The non-diagonal elements of both  $S_a$  and  $S_e$  were set to zero. The instrument line shape (ILS) of  
2 the FTIR instrument deduced from optical path alignment diagnosis with a low-pressure HBr cell  
3 was adopted in the retrieval (Hase 2012; Sun et al. 2018b).

4 For each retrieval, the averaging kernels reflect the sensitivity of the retrieved profile to the  
5 real profile. The area of the averaging kernels at a specific height is calculated as the sum of the  
6 elements of the corresponding averaging kernels (Pougetchev et al. 1995). It represents the fraction  
7 of the retrieval at that height which comes from the measurement rather than from the *a priori*  
8 information (Rodgers, 2000). A value close to unity at a specific height indicates that the retrieved  
9 profile at that height is nearly independent of the *a priori* profile and is thus from the measurement.  
10 The trace of the averaging kernel matrix is defined as degrees of freedom for signal (DOFS) and it  
11 quantifies the number of independent information in the retrieved profile. Fig. 1 shows the averaging  
12 kernels as well as their area, cumulative sum of DOFS, and VMR profile of randomly selected  $C_2H_6$   
13 retrieval at Hefei. Ground-based FTIR  $C_2H_6$  observations at Hefei have a sensitivity of larger than  
14 0.7 from ground to about 10 km altitude, indicating that the retrievals are mainly sensitive to the  
15 troposphere. This also means that the retrieved profile information below 10 km comes for more  
16 than 70% from the measurement, or in other words, that the *a priori* signal impacts the retrieval by  
17 less than 30% [Fig 1(a)]. The typical DOFS obtained at Hefei over the total atmosphere for  $C_2H_6$  is  
18  $1.69 \pm 0.29$  ( $1\sigma$ ), meaning that we can roughly provide two pieces of information on the vertical  
19 profile [Fig 1(b)]. The shape of the retrieved profile is heavily weighted toward the lower  
20 troposphere. As shown in Fig.1(c), the  $C_2H_6$  concentration decreased by 72.7% with an increase in  
21 the height from surface to 2 km and kept decreasing slowly in the rest part of the atmosphere till  
22 approaching around zero in the stratosphere and above. The  $C_2H_6$  partial column below 10 km  
23 accounted for 88.6% of  $C_2H_6$  total column. This percentage is expected to show less seasonal  
24 variation since the shape of the retrieved profile is similar to the shape of the *a priori* profile due to  
25 the low DOFS [Fig. 1 (c)]. As a result, in subsequent analysis, the  $C_2H_6$  VMRs averaged between  
26 the surface and 10 km are selected as representatives of  $C_2H_6$  troDMF. The selected tropospheric  
27 layer (from surface up to 10 km) corresponds to  $1.47 \pm 0.2$  ( $1\sigma$ ) of DOFS and can be used with  
28 confidence. This selected layer is totally within the tropopause height (~ 16 km) at Hefei over four  
29 seasons (Sun et al. 2020b). The Hefei site is located in the northeastern margin of a GEOS-Chem  
30 grid cell [Fig. 2 and Table 3]. This selected layer also ensures the line of sights of all observations  
31 are totally within the same grid cell.

32 We calculated the error budget for  $C_2H_6$  retrieval at Hefei following the formalism of Rodgers  
33 (2000), and separated all error components into systematic or random errors according to whether  
34 they vary steadily or randomly over consecutive measurements. The random, systematic, and the  
35 combined error budgets for the selected tropospheric layer (from surface up to 10 km) are  
36 summarized in Table 1. The input covariance matrix of temperature is based on the differences  
37 between Sonde and an ensemble of NCEP temperature profiles near Hefei, leading to 2 to 5 K in  
38 the troposphere and 3 to 7 K in the stratosphere. For each interfering gases, the corresponding  
39 covariance matrix is obtained with the WACCM v6 climatology. The input covariance matrix of  
40 measurement error is based on the inverse square of the SNR of each spectrum. We regularly use a  
41 low-pressure HBr cell to diagnose the misalignment of the FTIR spectrometer and to realign the  
42 instrument when indicated. The FTIR spectrometer at Hefei is assumed to be not far from the ideal  
43 condition, and the input uncertainties for zero level, background curvature, field of view, optical  
44 path difference, solar zenith angle, interferogram phase, and ILS are estimated to be 1%. For the



1 C<sub>2</sub>H<sub>6</sub> spectroscopic absorption coefficients, the line list in atm16 follows HITRAN 2012 (Rothman  
2 et al., 2013), and we use 5% for line intensity, pressure-, and temperature-broadening coefficients.  
3 For the retrieval parameter and smoothing error, the input covariance matrix are prescribed from the  
4 optimal estimation retrieval outputs. To estimate the retrieval error of C<sub>2</sub>H<sub>6</sub> troDMF at Hefei, the  
5 elements of all gain matrices were set to zero for the altitudes outside the selected layer. The  
6 contributions of all error components to C<sub>2</sub>H<sub>6</sub> troDMF retrieval at Hefei are summarized in Table 1.  
7 The dominant random errors are from temperature uncertainty (1.69%) and the zero level  
8 uncertainty (1.54%), and the dominant systematic error is from the line intensity uncertainty  
9 (5.12%). Total random and systematic errors are estimated to be 2.32% and 5.48%, respectively.  
10 Total retrieval error calculated as square root sum of the squares of total random and systematic  
11 errors is estimated to be 6.21%.

12 In order to exclude the measurements that seriously affected by instable weather conditions or  
13 by the *a priori* profile due to low measurement information content in less favourable observational  
14 conditions, e.g., around noontime when the probed atmosphere is thinner, or in summer when C<sub>2</sub>H<sub>6</sub>  
15 is less abundant. The FTIR measurements saved with a solar intensity variation (SIV) of larger than  
16 10% or retrievals with total DOFS of less than 0.7 or the root-mean-square (RMS) of fitting residuals  
17 of larger than 2%, which accounted for 11.2% of total measurements, were excluded in this study.

## 18 2.2 GEOS-Chem sensitivity simulation

19 Relative contribution of various source categories and regions to the observed C<sub>2</sub>H<sub>6</sub> abundance  
20 were quantified by a series of sensitivity simulations using the GEOS-Chem chemical model version  
21 12.2.1 (Bey et al. 2001) (<http://geos-chem.org>, last access on 24 August 2020). All simulations  
22 implemented a universal tropospheric-stratospheric Chemistry (UCX) mechanism (Eastham et al.  
23 2014; Fisher et al. 2017) and were driven by the Goddard Earth Observing System-Forward  
24 Processing (GEOS-FP) meteorological fields at a degraded horizontal resolution of 2°×2.5°. The  
25 temporal resolutions are 1 hour (hr) for surface variables and boundary layer height, and 3 hr for  
26 other variables. Dry deposition was calculated by the resistance-in-series algorithm (Wesely 1989;  
27 Zhang et al. 2001) and wet deposition followed that of Liu et al. (2001). The photolysis rates were  
28 available from the FAST-JX v7.0 photolysis scheme (Bian and Prather 2002). All simulations were  
29 spun up for one year (July 2014 to July 2015) and output hourly mean C<sub>2</sub>H<sub>6</sub> VMR profiles globally  
30 ranging from the surface to 0.01 hPa at a horizontal resolution of 2°×2.5°. This study only  
31 considered the C<sub>2</sub>H<sub>6</sub> simulations from 2015 to 2020 in the grid box containing Hefei (31.52°–  
32 32.11°N by 116.53°–118.02°E).

33 In the recent past, the inventories led to significant underestimation of the C<sub>2</sub>H<sub>6</sub> simulation  
34 (e.g., HTAP2 in Franco et al. 2016). Since then, some efforts have improved the situation (e.g.,  
35 Tzompa-Sosa et al. 2017). In this study, we refer to Sun et al. (2020a) for more details on  
36 implementation of emission inventories. Briefly, global anthropogenic emissions were from the  
37 Community Emissions Data System (CEDS) inventory which overwrites Asia by the latest Multi-  
38 resolution Emission Inventory for China (MEIC) (Hoesly et al. 2018; Li et al. 2017; Lu et al. 2019;  
39 Zheng et al. 2018). Global biomass burning and biogenic emissions were from the Global Fire  
40 Emissions Database (GFED v4) inventory (Giglio et al. 2013) and the Model of Emissions of Gases  
41 and Aerosols from Nature (MEGAN version 2.1) inventory (Guenther et al. 2012), respectively.  
42 The CH<sub>4</sub> emission fields are prescribed based on NOAA measurements for 1983–2016 and are





1 extended to 2020 using the linear extrapolation of local 2011–2016 change rates (Murray, 2016; Lu  
2 et al., 2019).

3 Particular improvements have been done for the latest bottom-up MEIC emission inventory in  
4 the accuracy of vehicle emission modelling (Zheng et al. 2014), power plant emission calculation  
5 (Liu et al. 2015), and the non-methane VOCs (NMVOCs) speciation method (Li et al. 2014). Many  
6 studies have verified that the MEIC emission inventory can reasonably represents the anthropogenic  
7 emissions over Asia (Hoesly et al. 2018; Li et al. 2017; Lu et al. 2019; Sun et al. 2020a; Tian et al.  
8 2018; Yin et al. 2020; Yin et al. 2019; Zheng et al. 2018). Anthropogenic C<sub>2</sub>H<sub>6</sub> emissions in China  
9 by region and category for the 2015 and 2019 MEIC emission inventories are summarized in Table  
10 2. All subdivided geographical regions are shown in Fig. 2 and the resulting delimitations are  
11 summarised in Table 3. The delimitations of these geographical regions are based on the levels of  
12 urbanization and industrialization in China. Region ① in Fig. 2 only covers a few sparsely city  
13 clusters representing the region with least population and industrialization in China (Lu et al. 2019).  
14 Regions ②, ④, and ⑤ cover the North China Plain (NCP), Yangtze River Delta (YRD), and  
15 Pearl River Delta (PRD) city clusters, respectively, which are the three most developed city clusters  
16 facing severe air pollution in China. Region ③ covers the Sichuan Basin (SCB) and central  
17 Yangtze River (CYR) city clusters with newly emerging severe air pollution in China. Total annual  
18 Chinese anthropogenic emissions of C<sub>2</sub>H<sub>6</sub> in 2015 and 2019 are 0.883 Tg and 0.859 Tg, respectively.  
19 In both years, anthropogenic C<sub>2</sub>H<sub>6</sub> emissions in China are dominated by industry and residential  
20 emissions. The highest anthropogenic C<sub>2</sub>H<sub>6</sub> emission rates (calculated as the ratio of total C<sub>2</sub>H<sub>6</sub>  
21 emission to the coverage) are in densely populated and industrialized region clusters in eastern part  
22 of China (including northern China (NR), eastern China (ER), central China (CR), southern China  
23 (SR), and adjacent regions) with little seasonal variation [Fig.A1]. The anthropogenic emissions in  
24 WR region are typically lower than those in other parts of China because of lower population and  
25 industries in the region (Lu et al. 2019; Zheng et al. 2018).

26 In order to quantify the contributions of different source categories and regions to the observed  
27 C<sub>2</sub>H<sub>6</sub>, we first conducted a reference full chemistry simulation (BASE) with implementation of all  
28 emission inventories as described above. Then, we conducted a series of sensitivity simulations to  
29 assess the change of each sensitivity simulation relative to the BASE simulation. Model  
30 configurations in this study were similar to those in Sun et al. (2020a) but with a different emission  
31 perturbation method. When an emission inventory was shut off in Sun et al. (2020a), the emissions  
32 of all atmospheric compounds in that inventory were suppressed. In contrast, this work only  
33 suppressed C<sub>2</sub>H<sub>6</sub> in each case except for biogenic and biomass burning emission perturbations,  
34 which suppressed all atmospheric compounds since we cannot separate C<sub>2</sub>H<sub>6</sub> emission from current  
35 biogenic and biomass burning emission inventories. Model configurations in this study are  
36 summarised in Table 3 and were described as follows.

37 (i) To analyse the contributions of different emission categories, we shut off C<sub>2</sub>H<sub>6</sub> in each  
38 individual emission inventory to evaluate the change of the simulation in the presence of C<sub>2</sub>H<sub>6</sub>  
39 in other emission inventories. As a result, the relative contribution of each emission category was  
40 estimated as the relative difference between the GEOS-Chem simulation in the presence and  
41 absence of C<sub>2</sub>H<sub>6</sub> in that emission inventory. We have conducted four such sensitivity simulations by  
42 shutting off C<sub>2</sub>H<sub>6</sub> emissions in (1) fossil fuel emission inventory (including emissions from  
43 agriculture, industry, power plant, residential, and transport), (2) biogenic emission inventory, (3)  
44 biomass burning emission inventory, and (4) biofuel emission inventory (Table 3). The sum of fossil



1 fuel and biofuel C<sub>2</sub>H<sub>6</sub> emissions is defined as anthropogenic C<sub>2</sub>H<sub>6</sub> source and the sum of biogenic  
2 and biomass burning C<sub>2</sub>H<sub>6</sub> emissions is referred to as natural C<sub>2</sub>H<sub>6</sub> source.

3 (ii) To analyse the contributions of different geographical regions, we shut off all categories of  
4 C<sub>2</sub>H<sub>6</sub> emissions (i.e., the aforementioned anthropogenic plus natural C<sub>2</sub>H<sub>6</sub> sources) within each  
5 geographical region to assess the change of the simulation in the presence of C<sub>2</sub>H<sub>6</sub> emissions outside  
6 that geographical region. Thus, the relative contribution of each geographical region was estimated  
7 as the relative difference between the GEOS-Chem simulation in the presence and absence of C<sub>2</sub>H<sub>6</sub>  
8 emissions within that geographical region. We have conducted five such sensitivity simulations by  
9 shutting off C<sub>2</sub>H<sub>6</sub> emissions within five geographical regions shown in Fig. 2.

### 10 2.3 Generalized additive models (GAMs) regression

11 In this study, we investigate the dependencies of C<sub>2</sub>H<sub>6</sub> on meteorological and emission factors  
12 by using the GAMs regression (Wood and Simon 2004; Wood 2004). Regression analysis is  
13 proceeded using the thin plate smoothing spline function (Pearce et al. 2011). Smoothing parameters  
14 and confidence intervals are calculated according to the Restricted Maximum Likelihood standard  
15 (REML) and the unconditional Bayesian method, respectively (Pearce et al. 2011). The GAMs  
16 regression is better than the traditional statistical models in dealing with nonlinear fittings (Veaux  
17 and Richard 2012). For climate change applications, where there are many non-linear relationships  
18 between variables, the GAMs regression is particularly attractive (Zhang et al. 2019).

19 We introduced a variety of potential meteorological and emission factors into the GAMs  
20 regression one at a time and performed significance tests based on the Akaike's Information Criteria  
21 (AIC) values (Wood and Simon 2004). The explanatory variables which passed the significance  
22 tests with the smallest AIC values were included into the final GAMs model. Furthermore,  
23 explanatory variables in GAMs regression may interact with each other and result in unstable  
24 fittings due to the internal multicollinearity. For the explanatory variables that show a strong  
25 collinearity with each other, we only included one of them in the final GAMs model. The degree of  
26 multicollinearity can be quantified by the variance inflation factor (VIF) (Ma et al. 2020). Generally,  
27 a stronger collinearity between the explanatory variables results in a larger VIF, and the VIF of an  
28 explanatory variable could be 1.0 if it is not correlated with other explanatory variables (Ma et al.  
29 2020). In this study, we included all the meteorological and emission factors in the GAMs and  
30 calculated the VIF for all the influencing factors. The multicollinearity diagnosis concluded that the  
31 main causes of multicollinearity are between the HCN and CO, and between the tropopause height  
32 and planetary boundary layer height (PBLH). Including either of these two data pairs in the GAMs  
33 regression showed significant collinearities with the VIF values of greater than an empirical  
34 threshold of 4.0, indicating an unstable regression (Lin et al. 2018). After omitting HCN and PBLH  
35 in the final GAMs model, the adjusted VIF values of all the variables were less than 4.0 and the  
36 variables uniformly passed the significance tests. As a result, the final GAMs model in the context  
37 of the C<sub>2</sub>H<sub>6</sub> troDMF time series  $y$  can be described as (Pearce et al. 2011):

$$38 \quad \log(y) = \beta + S(ua) + S(va) + S(omega) + S(qv) + S(troph) \quad (1) \\ 39 \quad \quad \quad + S(pres) + S(temp) + S(ch_4) + S(co) + \varepsilon$$

40 where  $\beta$  and  $\varepsilon$  are the mean response constant and the fitting residual, respectively.  $S(ua)$ ,  $S(va)$ ,  
41  $S(omega)$ ,  $S(qv)$ ,  $S(troph)$ ,  $S(pres)$ ,  $S(temp)$ ,  $S(ch_4)$ , and  $S(co)$  are the smoothing functions of daily  
42 average zonal wind (with a unit of m s<sup>-1</sup>), meridional wind (m s<sup>-1</sup>), vertical wind (Pa s<sup>-1</sup>), water vapor





1 concentration (%), tropopause height (km), pressure (hPa), temperature (°C), CH<sub>4</sub> troDMF (ppbv),  
2 and CO troDMF (ppbv). Positive values of  $ua$ ,  $va$ , and  $omega$  represent northward, eastward, and  
3 upward winds, respectively. The sum of  $S(ch_4)$  and  $S(co)$  is referred to as the emission influences,  
4 and the sum of remaining smoothing functions is referred to as the meteorological influences.

5 For driving the GAMs regression, we first derived CH<sub>4</sub> and CO VMR profiles from direct solar  
6 absorption spectra similar to that of C<sub>2</sub>H<sub>6</sub>, see section 2.1. The spectra for CH<sub>4</sub> retrievals are exactly  
7 the same as those of C<sub>2</sub>H<sub>6</sub> but the spectra for CO are saved at a different filter channel. The  
8 respective VMR profiles were then converted to troDMF values following the method of C<sub>2</sub>H<sub>6</sub>. The  
9 retrieval configurations, waveband selections and the interfering gases considerations for CH<sub>4</sub> and  
10 CO can be found in Sun et al. (2018b). The DOFS of the retrievals between surface and 10 km  
11 altitude for both CH<sub>4</sub> and CO are larger than 1.5 and the corresponding retrieval errors are less than  
12 8% (Sun et al., 2018b). All meteorological factors are from the GEOS-FP meteorological fields at  
13 their native resolution of  $0.25^\circ \times 0.3125^\circ$  ranging from the surface to 0.01 hPa at a temporal  
14 resolution of 1 hr. Since the meteorological fields and C<sub>2</sub>H<sub>6</sub> concentration are not uniformly  
15 distributed along the altitude, the summing mean values of the meteorological fields cannot properly  
16 characterize the meteorological influences. In this study, we use a method similar to that of  
17 Shaiganfar et al. (2017) to increase the influence weighting toward lower troposphere. As a result,  
18 all meteorological parameters except tropopause height ( $troph$ ) are converted into the C<sub>2</sub>H<sub>6</sub> profile  
19 weighting averaged value  $\omega_{avg}$  through Eq. (2):

$$20 \quad \omega_{avg} = \frac{\sum_i \omega(z_i) \cdot c(z_i) \cdot \mathbf{Airmass}(z_i)}{\sum_i c(z_i) \cdot \mathbf{Airmass}(z_i)} \quad (2)$$

21 where  $\omega(z_i)$ ,  $c(z_i)$ , and  $\mathbf{Airmass}(z_i)$  represent the value of the meteorological factor, C<sub>2</sub>H<sub>6</sub>  
22 concentration, and the air mass at the altitude  $z_i$ .

### 23 3. Variability and comparison with GEOS-Chem model data

24 We have compared the observed daily mean time series and seasonal cycle of C<sub>2</sub>H<sub>6</sub> troDMF to  
25 the GEOS-Chem BASE simulations for investigating the chemical model performance for the  
26 specifics of polluted regions over eastern China. As the vertical resolution of GEOS-Chem is  
27 different from the FTIR observation, smoothing correction has been done for the GEOS-Chem  
28 profiles (Rodgers and Connor 2003). First, the GEOS-Chem daily mean profiles of C<sub>2</sub>H<sub>6</sub> have been  
29 interpolated to the FTIR altitude grid for ensuring a common altitude grid. In order to match the  
30 FTIR observations which only operates during daytime, the average for GEOS-Chem simulations  
31 was only performed during daytime from 9:00 to 17:00 local time (LT). The interpolated profiles  
32 were then smoothed by the concurrent seasonal mean values of the FTIR averaging kernels and  $a$   
33 *priori* profiles (Rodgers 2000; Rodgers and Connor 2003). The smoothed GEOS-Chem profiles  
34 were subsequently converted to troDMF values by using the corresponding regridded air density  
35 profiles from the model with the method described in section 2.1. Finally, the GEOS-Chem C<sub>2</sub>H<sub>6</sub>  
36 troDMF time series only for the days with available FTIR observations were averaged by month  
37 and compared with the FTIR monthly mean data.

38 Fig. 3 (a) shows the comparison of daily mean time series of C<sub>2</sub>H<sub>6</sub> troDMF between the FTIR  
39 observation and the smoothed GEOS-Chem model simulation from 2015 to 2020. Fig. 3 (b)  
40 compares the seasonal cycles derived from Fig. 3 (a) for the days with available FTIR observations  
41 only. Generally, the measured features in terms of seasonality and interannual variability can be



1 reproduced by the GEOS-Chem simulations with a correlation coefficient ( $r$ ) of 0.88. Large GEOS-  
2 Chem vs. FTIR differences tended to occur in the trough and peak of the observations. For instance,  
3 the observed monthly mean value of  $C_2H_6$  troDMF was overestimated by 35.6% in July and  
4 overestimated by 17.4 % in December by the GEOS-Chem. These discrepancies may be mainly  
5 attributed to uncertainties in the horizontal transport and vertical mixing schemes simulated by the  
6 GEOS-Chem model at a relatively coarse spatial resolution, which are difficult to match column  
7 observation over a single point. In addition, the number of  $C_2H_6$  measurements at Hefei on each  
8 measurement day varied a wide range from 1 to 17 depending on the weather condition, but GEOS-  
9 Chem simulations are available consecutively by hour for the same day. This difference in the  
10 temporal resolution of GEOS-Chem and FTIR could also cause inconsistencies due to the high  
11 variability of atmospheric  $C_2H_6$ . However, considering the concurrent data pairs only ( $\pm 30$  min),  
12 the averaged difference between GEOS-Chem and FTIR data (GEOS-Chem minus FTIR) is  $(-0.02$   
13  $\pm 0.05)$  ppbv ( $-1.6 \pm 4.2$  %), which is within the FTIR uncertainty budget. As a result, GEOS-Chem  
14 can simulate  $C_2H_6$  concentration and variability for the specifics of polluted regions over eastern  
15 China. With improved emission inventories, previous studies have also found that global chemistry  
16 transport models were able to reproduce the absolute values as well as seasonal cycles of the ground-  
17 based FTIR  $C_2H_6$  observations in the other parts of the world (Franco et al., 2015; Franco et al.,  
18 2016; Tzompa-Sosa et al. 2017).

19 As typically observed, the peak-to-peak amplitude of the modulation with respect to the  
20 monthly mean of  $C_2H_6$  troDMF spanned a large range of  $-16.0\%$  to  $72.8\%$  depending on season  
21 [Fig. 3 (b)]. The observed  $C_2H_6$  troDMF roughly decreases over time for the first half of the year  
22 and increases over time for the second half of the year [Fig. 3 (b)]. High levels of  $C_2H_6$  troDMF  
23 occur in the late autumn to early spring and low levels of  $C_2H_6$  troDMF occur in late spring to early  
24 autumn. The observed  $C_2H_6$  troDMF reached a minimum monthly mean value of  $(0.36 \pm 0.26)$  ppbv  
25 in July and a maximum monthly mean value of  $(1.76 \pm 0.35)$  ppbv in December.  $C_2H_6$  troDMFs in  
26 December were on average 4.9 times higher than those in July. Since the tropospheric OH oxidation  
27 capability in summer is higher than that in winter, the  $C_2H_6$  seasonality characterized by a winter  
28 maximum and a summer minimum was also observed in other FTIR stations (Angelbratt et al. 2011;  
29 Franco et al. 2015; Franco et al. 2016; Lutsch et al. 2019; Nagahama and Suzuki 2007; Rinsland et  
30 al. 2002; Simpson et al. 2012; Viatte et al. 2015; Viatte et al. 2014; Vigouroux et al. 2012; Zeng et  
31 al. 2012; Zhao et al. 2002). We have used the bootstrap resampling method of Gardiner et al. (2008)  
32 to evaluate the seasonality and interannual variability of  $C_2H_6$  troDMF, where a 3<sup>rd</sup> Fourier series  
33 plus a linear function was used to fit daily mean time series of  $C_2H_6$  troDMF by both FTIR  
34 observations and GEOS-Chem model simulations. We incorporated the errors arising from the  
35 autocorrelation in the residuals into the uncertainties in the change rates following the procedure of  
36 Santer et al. (2008). The observed  $C_2H_6$  troDMFs from 2015 to 2020 showed a negative change rate  
37 of  $(-2.60 \pm 1.34)\%$  yr<sup>-1</sup>, which is in reasonable agreement with the modelled change rate of  $(-2.1 \pm$   
38  $0.7)\%$  yr<sup>-1</sup> [Fig. 3 (a)].

#### 39 4. GAMs regression results and interpretation

40  $C_2H_6$  troDMF time series from 2015 to 2020 over Hefei by the FTIR and the GAMs regression  
41 model are shown in Fig. 4. The observed  $C_2H_6$  variability can be reproduced by the GAMs  
42 regression model with a good agreement, as confirmed by a correlation coefficient ( $r$ ) of 0.90 [Fig.



1 4(a)]. Meanwhile, the observed C<sub>2</sub>H<sub>6</sub> troDMF time series also show high correlations with both the  
2 accumulated meteorological factor ( $r=0.88$ ) [Fig. 4 (b)] and the accumulated emission factor ( $r =$   
3  $0.70$ ) [Fig. 4(c)], indicating both meteorological and emission influences are important factors for  
4 driving the C<sub>2</sub>H<sub>6</sub> troDMF variability. Generally, both meteorological and emission factors show  
5 positive influences on C<sub>2</sub>H<sub>6</sub> troDMFs in cold season (DJF/MAM) and negative influences on C<sub>2</sub>H<sub>6</sub>  
6 troDMFs in warm season (JJA/SON). However, the seasonal dependency of meteorological  
7 influence is stronger than that of emission influence. During the studied years, the year to year  
8 differences in meteorological influence are small, while the positive emission influence showed an  
9 overall decreasing change rate since 2016, which probably drives a decreasing change rate in C<sub>2</sub>H<sub>6</sub>  
10 troDMF in recent years.

11 The influence of each explanatory variable  $x_i$  in GAMs regression calculated as  $100\% \cdot [e^{(\beta_i x_i)} - 1]$   
12 are shown in Fig. 5, which reflects the influence of each individual variable on the relative change  
13 of C<sub>2</sub>H<sub>6</sub> troDMF. The corresponding DOFS of each smoothing function are also shown in Fig.5. If  
14 an explanatory variable is linearly correlated with the C<sub>2</sub>H<sub>6</sub> troDMF, the DOFS of the resulting  
15 smoothed variable could be equal to 1, and the larger the slope the higher the linear response.  
16 Otherwise, the larger the deviation of DOFS relative to 1, the more significant the nonlinear  
17 relationship is (Veaux and Richard 2012). During the studied years, the DOFS of zonal wind ( $ua$ ),  
18 convection wind ( $omega$ ), pressure ( $pres$ ), tropopause height ( $troph$ ), temperature ( $temp$ ), and CO  
19 troDMF ( $co$ ) were close to 1, reflecting a roughly linear relationship of these explanatory variables  
20 with the C<sub>2</sub>H<sub>6</sub> troDMF. In contrast, the DOFS of meridional wind ( $va$ ), H<sub>2</sub>O troDMF ( $qv$ ) and CH<sub>4</sub>  
21 troDMF ( $ch4$ ) were much greater than 1, reflecting a significant nonlinear relationship with the C<sub>2</sub>H<sub>6</sub>  
22 troDMF.

23 The observed C<sub>2</sub>H<sub>6</sub> troDMF was influenced by many factors. The zonal wind ( $ua$ ), meridional  
24 wind ( $va$ ), CH<sub>4</sub> troDMF ( $ch4$ ), and CO troDMF ( $co$ ) showed positive influences and the other  
25 explanatory variables showed negative influences on the observed C<sub>2</sub>H<sub>6</sub> troDMF variability. The  
26 results show that the northward, eastward, and downward convection winds facilitate the  
27 accumulation of C<sub>2</sub>H<sub>6</sub> over the observation site and result in higher C<sub>2</sub>H<sub>6</sub> troDMF. Since most  
28 anthropogenic and biomass burning sources of CO, and fossil fuel source of CH<sub>4</sub> are common  
29 sources of C<sub>2</sub>H<sub>6</sub>, C<sub>2</sub>H<sub>6</sub> troDMF gradually went up as CH<sub>4</sub> and CO troDMFs increased. In contrast,  
30 meteorological conditions as high temperature, high humidity, and low pressure are more favorable  
31 to C<sub>2</sub>H<sub>6</sub> oxidation, resulting in lower C<sub>2</sub>H<sub>6</sub> troDMF. Meanwhile, deep upward convection wind and  
32 high tropopause height facilitate the diffusion of C<sub>2</sub>H<sub>6</sub> over the observation site and result in lower  
33 C<sub>2</sub>H<sub>6</sub> troDMF.

## 34 5. Source attribution

### 35 5.1 Contributions of different source categories and regions

36 The absolute and relative seasonal contributions of fossil fuel, biogenic, biomass burning, and  
37 biofuel emissions to C<sub>2</sub>H<sub>6</sub> abundance from 2015 to 2020 over Hefei are shown in Fig. 6. The GEOS-  
38 Chem annual mean C<sub>2</sub>H<sub>6</sub> troDMF simulations were decreased by 0.53, 0.26, 0.31, and 0.20 ppbv  
39 in the absence of fossil fuel, biogenic, biomass burning, and biofuel C<sub>2</sub>H<sub>6</sub> emission inventories, which  
40 correspond to 34.5, 14.7, 22.4, and 14.7% of relative contribution to the modelled C<sub>2</sub>H<sub>6</sub> abundance,  
41 respectively. The anthropogenic emissions account for 49.2% and the natural emissions account for  
42 37.1% of the C<sub>2</sub>H<sub>6</sub> abundance. The remaining contribution calculated as the difference between the



1 BASE simulation and the sum of anthropogenic and natural contributions is 0.17 ppbv (13.7%).  
2 This missing rest can be largely attributed to nonlinear interactional effects among different sources  
3 which were not captured by the sensitivity simulations. Indeed, shutting off an emission inventory  
4 may induce significantly lower concentrations in atmospheric compounds (i.e.,  $C_2H_6$  for noFF and  
5 noBIOF or all suppressed compounds for noBVOC and noBB simulations) globally. On the one  
6 hand, some of them may react with OH, which would lead to higher OH concentrations available  
7 for the oxidation of  $C_2H_6$ , and eventually enhances the  $C_2H_6$  destruction from other emission  
8 categories. On the other hand, some of them may form OH by a series of oxidation reaction, which  
9 would lead to lower OH concentrations available for the oxidation of  $C_2H_6$ , and eventually mitigates  
10 the  $C_2H_6$  destruction from other emission categories. However, it is difficult to quantify the  
11 nonlinear impact of each individual emission category, since the concentration and spatial  
12 distribution of  $C_2H_6$  in each emission category are different. Especially when biogenic and biomass  
13 burning emissions are suppressed, the impacts become hard to assess, since all NMVOCs  
14 compounds play a key role in both OH formation and destruction. Investigating the nonlinear impact  
15 of each individual emission category would require additional work that is beyond the scope of the  
16 present work.

17 The contributions of all emission sources are seasonal dependent, and the fossil fuel  
18 contribution shows the largest seasonal difference, which consolidates the GAMs regression results  
19 that the emission influences are seasonal dependent. The fossil fuel contribution in winter and spring  
20 (DJF/MAM) are larger than those in summer and autumn (JJA/SON), with a maximum of 52.0% in  
21 DJF and a minimum of 13.0% in JJA. The JJA/SON meteorological conditions which show stronger  
22 solar radiation, higher temperature, wetter atmospheric condition, and lower pressure than those in  
23 DJF/MAM are more favorable for increasing VOCs emissions from biogenic sources (BVOCs),  
24 which consolidates the fact that  $C_2H_6$  abundance from biogenic source in JJA/SON are larger than  
25 those in DJF/MAM. The missing rest contributes to a maximum of 32% in JJA when the  $C_2H_6$   
26 oxidation reaches the seasonal maximum and is thus more sensitive to the on-off state of different  
27 sources.

28 Fig. 7 explores the absolute and relative seasonal contributions of ER, CR, NR, WR, and SR  
29 regions to the  $C_2H_6$  abundance from 2015 to 2020 over Hefei. The GEOS-Chem annual mean  $C_2H_6$   
30 troDMF simulations were decreased by 0.28, 0.22, 0.29, 0.07, and 0.12 in the absence of the  $C_2H_6$   
31 emissions in ER, CR, NR, WR, and SR regions, which correspond to 21.5%, 15.8%, 20.3%, 5.7%,  
32 and 8.9%, of relative contribution to the modelled  $C_2H_6$  abundance, respectively. The contributions  
33 of all geographical regions are also seasonal dependent. The results show that the observed  $C_2H_6$   
34 abundance was largely attributed to emissions within China (74.1%), which show a maximum in  
35 JJA/SON and a minimum in DJF/MAM. As vicinities of the observation site, the ER, CR, and NR  
36 regions dominated the contribution within China (57.6%). The remaining contribution calculated as  
37 the difference between the BASE simulation and the total contributions of above individual source  
38 regions is 0.42 ppbv (25.9%). This contribution is the sum of  $C_2H_6$  emissions outside China (ROW)  
39 and the nonlinear interactional effects among the geographical sensitivity simulations. This rest  
40 contribution in DJF/MAM are ~ 4.0 times larger than those in JJA/SON. Considering the nonlinear  
41 interactional effects mainly occur in JJA/SON but this rest contribution in the meantime shows the  
42 seasonal minimum value, this remaining contribution can be largely attributed to ROW  
43 contributions.

44 As a relatively long lifetime species (a few months),  $C_2H_6$  emissions originating from either



1 nearby or in distant areas can be transported to Hefei site under favourable weather conditions, and  
2 thus contribute to the observed  $C_2H_6$  abundance. In addition, atmospheric compounds originating  
3 either nearby or in distant areas, which affect the chemistry of  $C_2H_6$  oxidation, could also affect the  
4 observed  $C_2H_6$  abundance. For contributions within China, the lowest contribution of the WR region  
5 to the observed  $C_2H_6$  abundance is largely attributed to the lowest  $C_2H_6$  emission rates in this region  
6 (Table 2). A smaller contribution of the SR region to the observed  $C_2H_6$  abundance in DJF/MAM in  
7 comparison with the ER, CR, and NR regions is mainly attributed to less air masses that originated  
8 in south China under the dry winter monsoon conditions, see section 5.2.

## 9 5.2 Transport inflow and outflow pathways

10 The direct GEOS-Chem sensitivity simulations can clearly characterize the 3D transport inflow  
11 and outflow pathways of  $C_2H_6$  over the observation site. Fig.8 shows the spatial distribution of  
12 GEOS-Chem  $C_2H_6$  BASE simulations around China along with horizontal wind vectors at 900 hPa  
13 in different seasons. General atmospheric circulation patterns over eastern China are typically  
14 affected by mid-latitude westerlies and Asian monsoon, including the East Asian summer monsoon  
15 and South Asian summer monsoon (Chen et al. 2009; Liang et al. 2005; Liu et al. 2003). Fig. 9  
16 illustrates the latitude – height distributions of  $C_2H_6$  VMR over China from six source regions along  
17 with the 3D atmospheric circulation patterns in different seasons. The 3D transport inflow and  
18 outflow pathways of  $C_2H_6$  over the observation site are thus deduced as follows.

19 As indicated by the arrows in Figs. 8 and 9, the high pressure system over the Eurasian  
20 continent in DJF triggers the descending of strongly cold air over eastern China and results in air  
21 masses converging toward the observation site from western and northern areas, while the high  
22 pressure system over the Indian ocean and Pacific in JJA triggers the ascending of strongly heated  
23 air over eastern China and results in air masses converging toward the observation site from South  
24 Asia and East Asia (SEAS) (Liang et al. 2004; Liu et al. 2003). In DJF, the mid-latitude westerlies  
25 extend to tropics (about  $15^\circ N$ ) over middle and upper troposphere, and subtropics (about  $30^\circ N$ )  
26 near the surface, while the easterlies mainly prevail in tropics and are weak over eastern China [Figs.  
27 8 and 9]. In the summer monsoon season, the atmospheric circulation patterns over eastern China  
28 change dramatically and is dominated by surface wind regime originating from Pacific, South China  
29 Sea, or Arabian Sea [Figs.8 and 9]. Meanwhile, the mid-latitude westerlies recede to the North  
30 Temperate Zone (north of  $30^\circ N$ ) and the westerly jet center shifts to north of  $50^\circ N$  in JJA (from ~  
31  $30^\circ N$  in DJF) [Fig. 8]. In JJA, the tropical region is characterized by the strong easterlies in the  
32 upper troposphere and by the southwesterly air flow in the lower troposphere [Fig. 9]. The prevailing  
33 winds in the transition seasons in MAM and SON are still westerlies with frequent cold fronts [Figs.  
34 8 and 9]. These above seasonal circulation patterns determine the transport inflow and outflow of  
35  $C_2H_6$  around the observation site. However, the transported scales are also influenced by source  
36 location and strength, travel trajectory and travel time (Liu et al. 2003).

37 Generally,  $C_2H_6$  emissions from CR, NR, and WR regions can be transported to the observation  
38 site by the strong westerlies throughout the year [Fig. 9].  $C_2H_6$  from the SR region can be transported  
39 to the observation site by deep convection followed by northward transport into the mid-latitude  
40 westerlies in MAM or driven by the South Asian summer monsoon or westerlies in other seasons  
41 (Liu et al. 2003)[Fig. 8]. The observed  $C_2H_6$  transport inflow originating from the local ER region  
42 is mainly driven by the local circulation cell or Asian monsoon. The driver for  $C_2H_6$  transport inflow



1 originating from the northern ROW ( $> 32^{\circ}\text{N}$ ) is the same as those from the CR, NR, and WR regions.  
2 The driver for  $\text{C}_2\text{H}_6$  transport inflow originating from the southern ROW ( $< 32^{\circ}\text{N}$ ) is the same as  
3 that from the SR region. However,  $\text{C}_2\text{H}_6$  originating from ROW relative to those from China reaches  
4 a higher altitude due to longer transport distances. The ROW contributions in JJA/SON are lower  
5 than those in DJF/MAM can be partly attributed to a stronger removal along the long-range transport  
6 pathway by the abundant wet precipitation and oxidation during the summer monsoon and post  
7 monsoon season.

8 Seasonal variability in  $\text{C}_2\text{H}_6$  transport outflow over the observation site is mainly associated  
9 with the monsoon system. In DJF,  $\text{C}_2\text{H}_6$  over the observation site is capped in the lower troposphere  
10 by the subsidence over eastern China and is swept by northeasterly southwestward into southwestern  
11 areas, where they are lifted up into the free troposphere by convection and then flow away  
12 northeastward [Fig. 9]. In JJA, the observed  $\text{C}_2\text{H}_6$  is transported northeastward by the Asian  
13 monsoon and is undergone frequent lifting into the upper troposphere by deep convection [Figs. 8  
14 and 9]. Frequent cold fronts are common phenomena during meteorologically transitional periods  
15 in MAM and SON. In SON, the winter monsoon builds continental high system, and sweeps the  
16 observed  $\text{C}_2\text{H}_6$  in the lower troposphere northward to relatively high latitudes where they can be  
17 lifted up into the free troposphere by deep convection or cold fronts. In MAM, convection over  
18 lower latitudes at Asian continent starts to rise, which lifts up the observed  $\text{C}_2\text{H}_6$  into the free  
19 troposphere and then flow away southward.

### 20 **5.3 Potential factors driving interannual variability of $\text{C}_2\text{H}_6$**

21 China has implemented a series of active clean air policies since 2013 to mitigate severe air  
22 pollution problems (Sun et al. 2020b; Zhang et al. 2019; Zheng et al. 2018). Since then the emissions  
23 of major air pollutants have decreased, and the overall air quality has greatly improved (Sun et al.  
24 2020b; Zhang et al. 2019; Zheng et al. 2018). Many air pollutants, such as  $\text{NO}_2$ , sulphur dioxide  
25 ( $\text{SO}_2$ ), particulate matter 2.5 ( $\text{PM}_{2.5}$ ),  $\text{PM}_{10}$ , CO, black carbon (BC), and organic carbon (OC),  
26 showed negative trends in recent years (Lu et al., 2019; Zhang et al. 2019; Zheng et al. 2018). We  
27 follow the method of Zheng et al. (2018) to estimate the relative change rate of anthropogenic  $\text{C}_2\text{H}_6$   
28 emissions in China during 2015 – 2019 using the MEIC emission inventory. As tabulated in Table  
29 2, anthropogenic  $\text{C}_2\text{H}_6$  emissions in all geographical regions showed a decreasing change rate during  
30 2015 – 2019 except those in WR region where industrialization, urbanization, land use, and  
31 infrastructure construction have expanded rapidly in recent years, resulting in an increasing change  
32 rate of anthropogenic  $\text{C}_2\text{H}_6$  emissions in the region (Ran et al. 2014). The relative change rates of  
33 anthropogenic  $\text{C}_2\text{H}_6$  emissions in China during 2015 – 2019 are estimated as: 12.12% for WR, –  
34 5.32% for NR, –1.03% for CR, –7.66% for ER, –5.01% for SR, and –2.74% in total. The major  
35 driving forces for the decline in  $\text{C}_2\text{H}_6$  emissions over China are attributed to the reductions from  
36 residential and transport sectors, with relative change rates of –14.53% and –3.53%, respectively  
37 (Table 2).

38 The interannual change rate of anthropogenic  $\text{C}_2\text{H}_6$  emissions in China in recent years is  
39 estimated to be  $-0.69\% \text{ yr}^{-1}$  (calculated as  $-2.74\% / (2019 - 2015)$ ), which is much lower than the  
40 observed decreasing change rate in  $\text{C}_2\text{H}_6$  tropDMF ( $-2.60 \pm 1.34\% \text{ yr}^{-1}$ ), indicating additional  
41 driving forces could exist, e.g., reductions in natural  $\text{C}_2\text{H}_6$  emissions in China or reductions in long  
42 range transport of  $\text{C}_2\text{H}_6$  emissions originating either anthropogenic or natural sources outside China.





1 On the one hand, the Law of the People's Republic of China on the Prevention and Control of  
2 Atmospheric Pollution included the prohibition of crop residue burning over China in 2015 because  
3 crop residue burning emissions can result in poor air quality (<http://www.chinalaw.gov.cn>, last  
4 access on 19 June 2020). Since then the crop residue burning events over China decreased  
5 dramatically (Sun et al. 2020b). Meanwhile, biomass burning events in Africa, SEAS, and Oceania  
6 regions in 2015 were higher than those in onward years due to the El Niño Southern Oscillation  
7 (ENSO) (Sun et al. 2020b). The decreased global biomass burning emissions could probably also  
8 contribute to the observed decreasing change rate in  $C_2H_6$  troDMF over Hefei since 2015. On the  
9 other hand, large oil price fluctuations in recent years probably tightened oil and gas development  
10 around the globe which can cause a reduction in  $C_2H_6$  leakage around the globe. However,  $C_2H_6$   
11 observations around the globe and more statistical data are needed to support this deduction, which  
12 is beyond the scope of this paper and requires further study.

## 13 6. Summary and conclusion

14 Ethane ( $C_2H_6$ ) is an important greenhouse (GHG) gas and plays a significant role in  
15 tropospheric chemistry and climate change. As a relatively long residence time species (a few  
16 months), observations of  $C_2H_6$  can reflect regional and hemispheric changes in emissions and  
17 climate, and can be assimilated into a chemical transport model to assess nonlocal emissions and  
18 provide valuable insights into model biases of  $C_2H_6$  simulations.

19 This study for the first time presents and quantifies the variability, source, and transport of  
20  $C_2H_6$  over densely populated and industrialized eastern China by using ground-based high-  
21 resolution Fourier transform infrared (FTIR) observations. Seasonal and interannual variability of  
22  $C_2H_6$  over Hefei, eastern China from 2015 – 2020 have been investigated. The dependencies of  
23  $C_2H_6$  on meteorological and emission factors were analyzed by using generalized additive models  
24 (GAMs). The FTIR  $C_2H_6$  time series are for the first time applied to evaluate the standard GEOS-  
25 Chem full-chemistry model for the specifics of  $C_2H_6$  simulation over eastern China. GEOS-Chem  
26 model simulation with the state-of-the art inventory is in good agreement with the FTIR observation.  
27 The GEOS-Chem model was further run in a sensitivity mode to quantify relative contribution of  
28 various source categories and regions to the observed  $C_2H_6$  abundance. The three-dimensional (3D)  
29 transport inflow and outflow pathways of  $C_2H_6$  over the observation site were finally determined  
30 by the GEOS-Chem sensitivity simulation and atmospheric circulation pattern.

31 We obtained a retrieval error of  $6.21 \pm 1.2$  ( $1\sigma$ )% and degrees of freedom (DOFS) of  $1.47 \pm$   
32  $0.2$  ( $1\sigma$ ) in retrieval of  $C_2H_6$  tropospheric column-averaged dry-air mole fraction (troDMF). The  
33 observed  $C_2H_6$  troDMF reached a minimum monthly mean value of  $(0.36 \pm 0.26)$  ppbv in July and  
34 a maximum monthly mean value of  $(1.76 \pm 0.35)$  ppbv in December, and showed a negative change  
35 rate of  $(-2.60 \pm 1.34)$  %/yr from 2015 to 2020. Generally, both meteorological and emission factors  
36 have positive influences on  $C_2H_6$  troDMF in cold season (DJF/MAM) and negative influences in  
37 warm season (JJA/SON). GEOS-Chem model sensitivity simulations concluded that the  
38 anthropogenic emissions (fossil fuel plus biofuel) accounted for 49.2% and the natural emissions  
39 (biomass burning plus biogenic) accounted for 37.1% of  $C_2H_6$  abundance over Hefei. The observed  
40  $C_2H_6$  abundance over Hefei was mainly attributed to the emissions within China (74.1%), where  
41 central, eastern, and northern China dominated the contribution (57.6%). Seasonal variability in  
42  $C_2H_6$  transport inflow and outflow over the observation site is largely related to the mid-latitude



1 westerlies and Asian monsoon system. Reduction in C<sub>2</sub>H<sub>6</sub> from 2015 to 2020 mainly results from  
2 the decrease in local and transported C<sub>2</sub>H<sub>6</sub> emissions, which points to air quality improvement in  
3 China in recent years.

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

7 **Code and data availability.** The new ground-based Fourier transform infrared (FTIR) spectroscopic  
8 remote sensing dataset for atmospheric C<sub>2</sub>H<sub>6</sub> over Hefei, eastern China in this study can be accessed  
9 from <https://doi.org/10.6084/m9.figshare.13020545>. The MEIC emission inventories used in this  
10 study are available from <http://meicmodel.org/>.

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

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

15 **Acknowledgements.** The processing and post processing environment for SFIT4 are provided by  
16 National Center for Atmospheric Research (NCAR), Boulder, Colorado, USA. The NDACC  
17 network is acknowledged for supplying the SFIT software. The LINEFIT code is provided by Frank  
18 Hase, Karlsruhe Institute of Technology (KIT), Institute for Meteorology and Climate Research  
19 (IMK-ASF), Germany. We thank the senate of Bremen, Germany for support. We thank the FTIR  
20 group at university of Wollongong, Australia for help in setting up and operating the FTIR  
21 spectrometer at Hefei. We thank the GEOS-Chem team and Tsinghua University, China for  
22 providing the latest MEIC inventory.

23 **Financial support.** This work is jointly supported by the National Key Research and Development  
24 Program of China (No.2019YFC0214802, No.2017YFC0210002, No. 2016YFC0203302,  
25 2018YFC0213201, 2019YFC0214702, 2016YFC0200404), the National Science Foundation of  
26 China (No.41775025, No. 41575021, No. 51778596, No. 91544212, No. 41722501, No. 51778596),  
27 and the Sino-German Mobility programme (M-0036). Emmanuel Mahieu is a Senior Research  
28 Associate with the Fonds de la Recherche Scientifique -FNRS. His contribution has been primarily  
29 supported by the F.R.S.-FNRS under Grant no J.0147.18.

## 30 References

- 31 Abad, G. G., Allen, N. D. C., Bernath, P. F., Boone, C. D., McLeod, S. D., Manney, G. L., Toon, G. C.,  
32 Carouge, C., Wang, Y., Wu, S., Barkley, M. P., Palmer, P. I., Xiao, Y., and Fu, T. M.: Ethane, ethyne  
33 and carbon monoxide concentrations in the upper troposphere and lower stratosphere from ACE and  
34 GEOS-Chem: a comparison study, *Atmos. Chem. Phys.*, 11, 9927-9941, 2011.
- 35 Angelbratt, J., Mellqvist, J., Simpson, D., Jonson, J. E., Blumenstock, T., Borsdorff, T., Duchatelet, P.,



- 1 Forster, F., Hase, F., Mahieu, E., De Maziere, M., Notholt, J., Petersen, A. K., Raffalski, U., Servais,  
2 C., Sussmann, R., Warneke, T., and Vigouroux, C.: Carbon monoxide (CO) and ethane (C<sub>2</sub>H<sub>6</sub>) trends  
3 from ground-based solar FTIR measurements at six European stations, comparison and sensitivity  
4 analysis with the EMEP model, *Atmos. Chem. Phys.*, 11, 9253-9269, 2011.
- 5 Bey, I., Jacob, D. J., Yantosca, R. M., Logan, J. A., Field, B. D., Fiore, A. M., Li, Q. B., Liu, H. G. Y.,  
6 Mickley, L. J., and Schultz, M. G.: Global modeling of tropospheric chemistry with assimilated  
7 meteorology: Model description and evaluation, *J. Geophys. Res.-Atmos.*, 106, 23073-23095, 2001.
- 8 Bian, H. S., and Prather, M. J.: Fast-J2: Accurate simulation of stratospheric photolysis in global chemical  
9 models, *J. Atmos. Chem.*, 41, 281-296, 2002.
- 10 Chen, D., Wang, Y., McElroy, M. B., He, K., Yantosca, R. M., and Le Sager, P.: Regional CO pollution  
11 and export in China simulated by the high-resolution nested-grid GEOS-Chem model, *Atmos. Chem.*  
12 *Phys.*, 9, 3825-3839, 2009.
- 13 De Mazière, M., Thompson, A. M., Kurylo, M. J., Wild, J. D., Bernhard, G., Blumenstock, T., Braathen,  
14 G. O., Hannigan, J. W., Lambert, J. C., Leblanc, T., Mcgee, T. J., Nedoluha, G., Petropavlovskikh,  
15 I., Seckmeyer, G., Simon, P. C., Steinbrecht, W., and Strahan, S. E.: The Network for the Detection  
16 of Atmospheric Composition Change (NDACC): history, status and perspectives, *Atmos. Chem.*  
17 *Phys.*, 18, 4935-4964, 2018.
- 18 Eastham, S. D., Weisenstein, D. K., and Barrett, S. R. H.: Development and evaluation of the unified  
19 tropospheric-stratospheric chemistry extension (UCX) for the global chemistry-transport model  
20 GEOS-Chem, *Atmos. Environ.*, 89, 52-63, 2014.
- 21 Fischer, E. V., Jacob, D. J., Yantosca, R. M., Sulprizio, M. P., Millet, D. B., Mao, J., Paulot, F., Singh, H.  
22 B., Roiger, A., Ries, L., Talbot, R. W., Dzepina, K., and Deolal, S. P.: Atmospheric peroxyacetyl  
23 nitrate (PAN): a global budget and source attribution, *Atmos. Chem. Phys.*, 14, 2679-2698, 2014.
- 24 Fisher, J. A., Murray, L. T., Jones, D. B. A., and Deutscher, N. M.: Improved method for linear carbon  
25 monoxide simulation and source attribution in atmospheric chemistry models illustrated using  
26 GEOS-Chem v9, *Geosci. Model. Dev.*, 10, 4129-4144, 2017.
- 27 Franco, B., Bader, W., Toon, G. C., Bray, C., Perrin, A., Fischer, E. V., Sudo, K., Boone, C. D., Bovy, B.,  
28 Lejeune, B., Servais, C., and Mahieu, E.: Retrieval of ethane from ground-based FTIR solar spectra  
29 using improved spectroscopy: Recent burden increase above Jungfraujoch, *J. Quant. Spectrosc. Ra.*,  
30 160, 36-49, 2015.
- 31 Franco, B., Mahieu, E., Emmons, L. K., Tzompa-Sosa, Z. A., Fischer, E. V., Sudo, K., Bovy, B., Conway,  
32 S., Griffin, D., Hannigan, J. W., Strong, K., and Walker, K. A.: Evaluating ethane and methane  
33 emissions associated with the development of oil and natural gas extraction in North America,  
34 *Environ. Res. Lett.*, 11, 2016.
- 35 Gardiner, T., Forbes, A., de Maziere, M., Vigouroux, C., Mahieu, E., Demoulin, P., Velazco, V., Notholt,  
36 J., Blumenstock, T., Hase, F., Kramer, I., Sussmann, R., Stremme, W., Mellqvist, J., Strandberg, A.,  
37 Ellingsen, K., and Gauss, M.: Trend analysis of greenhouse gases over Europe measured by a  
38 network of ground-based remote FTIR instruments, *Atmos. Chem. Phys.*, 8, 6719-6727, 2008.
- 39 Giglio, L., Randerson, J. T., and van der Werf, G. R.: Analysis of daily, monthly, and annual burned area  
40 using the fourth-generation global fire emissions database (GFED4), *J. Geophys. Res.-Biogeo.*, 118,  
41 317-328, 10.1002/jgrg.20042, 2013.
- 42 Gilman, J. B., Lerner, B. M., Kuster, W. C., and de Gouw, J. A.: Source Signature of Volatile Organic  
43 Compounds from Oil and Natural Gas Operations in Northeastern Colorado (vol 47, pg 1297, 2013),  
44 *Environ. Sci. & Tech.*, 47, 10094-10094, 2013.



- 1 Glatthor, N., von Clarmann, T., Stiller, G. P., Funke, B., Koukouli, M. E., Fischer, H., Grabowski, U.,  
2 Hopfner, M., Kellmann, S., and Linden, A.: Large-scale upper tropospheric pollution observed by  
3 MIPAS HCN and C<sub>2</sub>H<sub>6</sub> global distributions, *Atmos. Chem. Phys.*, 9, 9619-9634, 2009.
- 4 Guenther, A. B., Jiang, X., Heald, C. L., Sakulyanontvittaya, T., Duhl, T., Emmons, L. K., and Wang, X.:  
5 The Model of Emissions of Gases and Aerosols from Nature version 2.1 (MEGAN2.1): an extended  
6 and updated framework for modeling biogenic emissions, *Geosci. Model. Dev.*, 5, 1471-1492, 2012.
- 7 Hase, F.: Improved instrumental line shape monitoring for the ground-based, high-resolution FTIR  
8 spectrometers of the Network for the Detection of Atmospheric Composition Change, *Atmos. Meas.*  
9 *Tech.*, 5, 603-610, 2012.
- 10 Helmig, D., Rossabi, S., Hueber, J., Tans, P., Montzka, S. A., Masarie, K., Thoning, K., Plass-Duelmer,  
11 C., Claude, A., Carpenter, L. J., Lewis, A. C., Punjabi, S., Reimann, S., Vollmer, M. K., Steinbrecher,  
12 R., Hannigan, J., Emmons, L. K., Mahieu, E., Franco, B., Smale, D., and Pozzer, A.: Reversal of  
13 global atmospheric ethane and propane trends largely due to US oil and natural gas production, *Nat.*  
14 *Geosci.*, 9, 490-495, 2016.
- 15 Hoesly, R. M., Smith, S. J., Feng, L. Y., Klimont, Z., Janssens-Maenhout, G., Pitkanen, T., Seibert, J. J.,  
16 Vu, L., Andres, R. J., Bolt, R. M., Bond, T. C., Dawidowski, L., Kholod, N., Kurokawa, J., Li, M.,  
17 Liu, L., Lu, Z. F., Moura, M. C. P., O'Rourke, P. R., and Zhang, Q.: Historical (1750-2014)  
18 anthropogenic emissions of reactive gases and aerosols from the Community Emissions Data  
19 System (CEDS), *Geosci. Model. Dev.*, 11, 369-408, 2018.
- 20 Li, M., Zhang, Q., Streets, D. G., He, K. B., Cheng, Y. F., Emmons, L. K., Huo, H., Kang, S. C., Lu, Z.,  
21 Shao, M., Su, H., Yu, X., and Zhang, Y.: Mapping Asian anthropogenic emissions of non-methane  
22 volatile organic compounds to multiple chemical mechanisms, *Atmos. Chem. Phys.*, 14, 5617-5638,  
23 2014.
- 24 Li, M., Zhang, Q., Kurokawa, J., Woo, J. H., He, K. B., Lu, Z. F., Ohara, T., Song, Y., Streets, D. G.,  
25 Carmichael, G. R., Cheng, Y. F., Hong, C. P., Huo, H., Jiang, X. J., Kang, S. C., Liu, F., Su, H., and  
26 Zheng, B.: MIX: a mosaic Asian anthropogenic emission inventory under the international  
27 collaboration framework of the MICS-Asia and HTAP, *Atmos. Chem. Phys.*, 17, 935-963, 2017.
- 28 Liang, Q., Jaegle, L., Jaffe, D. A., Weiss-Penzias, P., Heckman, A., and Snow, J. A.: Long-range transport  
29 of Asian pollution to the northeast Pacific: Seasonal variations and transport pathways of carbon  
30 monoxide, *J. Geophys. Res.-Atmos.*, 109, 2004.
- 31 Liang, Q., Jaegle, L., and Wallace, J. M.: Meteorological indices for Asian outflow and transpacific  
32 transport on daily to interannual timescales, *J. Geophys. Res.-Atmos.*, 110, 2005.
- 33 Lin, X., Liao, Y., and Hao, Y.: The burden associated with ambient PM<sub>2.5</sub> and meteorological factors in  
34 Guangzhou, China, 2012–2016: A generalized additive modeling of temporal years of life lost,  
35 *Chemosphere*, 212, 705-714, 2018.
- 36 Liu, F., Zhang, Q., Tong, D., Zheng, B., Li, M., Huo, H., and He, K. B.: High-resolution inventory of  
37 technologies, activities, and emissions of coal-fired power plants in China from 1990 to 2010,  
38 *Atmos. Chem. Phys.*, 15, 13299-13317, 2015.
- 39 Liu, H. Y., Jacob, D. J., Bey, I., and Yantosca, R. M.: Constraints from Pb-210 and Be-7 on wet deposition  
40 and transport in a global three-dimensional chemical tracer model driven by assimilated  
41 meteorological fields, *J. Geophys. Res.-Atmos.*, 106, 12109-12128, 2001.
- 42 Liu, H. Y., Jacob, D. J., Bey, I., Yantosca, R. M., Duncan, B. N., and Sachse, G. W.: Transport pathways  
43 for Asian pollution outflow over the Pacific: Interannual and seasonal variations, *J. Geophys. Res.-*  
44 *Atmos.*, 108, 2003.



- 1 Lu, X., Hong, J. Y., Zhang, L., Cooper, O. R., Schultz, M. G., Xu, X. B., Wang, T., Gao, M., Zhao, Y. H.,  
2 and Zhang, Y. H.: Severe Surface Ozone Pollution in China: A Global Perspective, *Environ. Sci.*  
3 *Tech. Lett.*, 5, 487-494, 2018.
- 4 Lu, X., Zhang, L., Chen, Y. F., Zhou, M., Zheng, B., Li, K., Liu, Y. M., Lin, J. T., Fu, T. M., and Zhang,  
5 Q.: Exploring 2016-2017 surface ozone pollution over China: source contributions and  
6 meteorological influences, *Atmos. Chem. Phys.*, 19, 8339-8361, 2019.
- 7 Lutsch, E., Dammers, E., Conway, S., and Strong, K.: Long-range transport of NH<sub>3</sub>, CO, HCN, and C<sub>2</sub>H<sub>6</sub>  
8 from the 2014 Canadian Wildfires, *Geophys. Res. Lett.*, 43, 8286-8297, 2016.
- 9 Lutsch, E., Strong, K., Jones, D. B. A., Blumenstock, T., Conway, S., Fisher, J. A., Hannigan, J. W., Hase,  
10 F., Kasai, Y., Mahieu, E., Makarova, M., Morino, I., Nagahama, T., Notholt, J., Ortega, I., Palm, M.,  
11 Poberovskii, A. V., Sussmann, R., and Warneke, T.: Detection and Attribution of Wildfire Pollution  
12 in the Arctic and Northern Mid-latitudes using a Network of FTIR Spectrometers and GEOS-Chem,  
13 *Atmos. Chem. Phys. Discuss.*, 2019, 1-57, 10.5194/acp-2019-881, 2019.
- 14 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  
15 and air pollution on tropospheric ozone using a generalized additive model in Western China:  
16 Lanzhou, Gansu, *Atmos. Environ.*, 224, 2020.
- 17 McKain, K., Down, A., Raciti, S. M., Budney, J., Hutyrá, L. R., Floerchinger, C., Herndon, S. C.,  
18 Nehrkorn, T., Zahniser, M. S., Jackson, R. B., Phillips, N., and Wofsy, S. C.: Methane emissions  
19 from natural gas infrastructure and use in the urban region of Boston, Massachusetts, *P. Natl. Acad.*  
20 *Sci. USA*, 112, 1941-1946, 2015.
- 21 Monks, S. A., Wilson, C., Emmons, L. K., Hannigan, J. W., Helmig, D., Blake, N. J., and Blake, D. R.:  
22 Using an Inverse Model to Reconcile Differences in Simulated and Observed Global Ethane  
23 Concentrations and Trends Between 2008 and 2014, *J. Geophys. Res.-Atmos.*, 123, 11262-11282,  
24 2018.
- 25 Nagahama, Y., and Suzuki, K.: The influence of forest fires on CO, HCN, C<sub>2</sub>H<sub>6</sub>, and C<sub>2</sub>H<sub>2</sub> over northern  
26 Japan measured by infrared solar spectroscopy, *Atmos. Environ.*, 41, 9570-9579, 2007.
- 27 Notholt, J., Toon, G. C., Rinsland, C. P., Pougatchev, N. S., Jones, N. B., Connor, B. J., Weller, R.,  
28 Gautrois, M., and Schrems, O.: Latitudinal variations of trace gas concentrations in the free  
29 troposphere measured by solar absorption spectroscopy during a ship cruise, *J. Geophys. Res.-*  
30 *Atmos.*, 105, 1337-1349, 2000.
- 31 Pearce, J. L., Beringer, J., Nicholls, N., Hyndman, R. J., and Tapper, N. J.: Quantifying the influence of  
32 local meteorology on air quality using generalized additive models, *Atmos. Environ.*, 45, 1328-  
33 1336, 2011.
- 34 Pougatchev, N. S., Connor, B. J., and Rinsland, C. P.: Infrared Measurements of the Ozone Vertical-  
35 Distribution above Kitt Peak, *J. Geophys. Res.-Atmos.*, 100, 16689-16697, 1995.
- 36 Ran, L., Lin, W. L., Deji, Y. Z., La, B., Tsering, P. M., Xu, X. B., and Wang, W.: Surface gas pollutants  
37 in Lhasa, a highland city of Tibet &ndash; current levels and pollution implications, *Atmos. Chem.*  
38 *Phys.*, 14, 10721-10730, 10.5194/acp-14-10721-2014, 2014.
- 39 Rinsland, C. P., Jones, N. B., Connor, B. J., Wood, S. W., Goldman, A., Stephen, T. M., Murcray, F. J.,  
40 Chiou, L. S., Zander, R., and Mahieu, E.: Multiyear infrared solar spectroscopic measurements of  
41 HCN, CO, C<sub>2</sub>H<sub>6</sub>, and C<sub>2</sub>H<sub>2</sub> tropospheric columns above Lauder, New Zealand (45 degrees S latitude),  
42 *J. Geophys. Res.-Atmos.*, 107, 2002.
- 43 Rodgers, C.: Inverse Methods for Atmospheric Sounding - Theory and Practice, in, 2000.
- 44 Rodgers, C. D., and Connor, B. J.: Intercomparison of remote sounding instruments, *J. Geophys. Res.-*



- 1 Atmos., 108, Artn 411610.1029/2002jd002299, 2003.
- 2 Rothman, L. S., Gordon, I. E., Babikov, Y., Barbe, A., Benner, D. C., Bernath, P. F., Birk, M.,  
3 Bizzocchi, L., Boudon, V., Brown, L. R., Campargue, A., Chance, K., Cohen, E. A., Coudert, L.  
4 H., Devi, V. M., Drouin, B. J., Fayt, A., Flaud, J.-M., Gamache, R. R., Harrison, J. J., Hartmann,  
5 J.-M., Hill, C., Hodges, J. T., Jacquemart, D., Jolly, A., Lamouroux, J., Roy, R. J. L., Li, G.,  
6 Long, D. A., Lyulin, O. M., Mackie, C. J., Massie, S. T., Mikhailenko, S., Müller, H. S. P.,  
7 Naumenko, O. V., and Nikitin, A. V.: The HITRAN2012 molecular spectroscopic database, *J.*  
8 *Quant. Spectrosc. Ra.*, 130, 4–50, <https://doi.org/10.1016/j.jqsrt.2013.07.002>, 2013.
- 9 Roscioli, J. R., Yacovitch, T. I., Floerchinger, C., Mitchell, A. L., Tkacik, D. S., Subramanian, R.,  
10 Martinez, D. M., Vaughn, T. L., Williams, L., Zimmerle, D., Robinson, A. L., Herndon, S. C., and  
11 Marchese, A. J.: Measurements of methane emissions from natural gas gathering facilities and  
12 processing plants: measurement methods, *Atmos. Meas. Tech.*, 8, 2017–2035, 2015.
- 13 Santer, B. D., Thorne, P. W., Haimberger, L., Taylor, K. E., Wigley, T. M. L., Lanzante, J. R., Solomon,  
14 S., Free, M., Gleckler, P. J., Jones, P. D., Karl, T. R., Klein, S. A., Mears, C., Nychka, D., Schmidt,  
15 G. A., Sherwood, S. C., and Wentz, F. J.: Consistency of modelled and observed temperature trends  
16 in the tropical troposphere, *Int. J. Climatol.*, 28, 1703–1722, 2008.
- 17 Shaiganfar, R., Beirle, S., van der Gon, H. D., Jonkers, S., Kuenen, J., Petetin, H., Zhang, Q., Beekmann,  
18 M., and Wagner, T.: Estimation of the Paris NO<sub>x</sub> emissions from mobile MAX-DOAS observations  
19 and CHIMERE model simulations during the MEGAPOLI campaign using the closed integral  
20 method, *Atmos. Chem. Phys.*, 17, 7853–7890, 2017.
- 21 Shan, C. G., Wang, W., Liu, C., Sun, Y. W., Hu, Q. H., Xu, X. W., Tian, Y., Zhang, H. F., Morino, I.,  
22 Griffith, D. W. T., and Velazco, V. A.: Regional CO emission estimated from ground-based remote  
23 sensing at Hefei site, China, *Atmos. Res.*, 222, 25–35, 2019.
- 24 Simpson, I. J., Andersen, M. P. S., Meinardi, S., Bruhwiler, L., Blake, N. J., Helmig, D., Rowland, F. S.,  
25 and Blake, D. R.: Long-term decline of global atmospheric ethane concentrations and implications  
26 for methane, *Nature*, 488, 490–494, 2012.
- 27 Singh, H., Chen, Y., Staudt, A., Jacob, D., Blake, D., Heikes, B., and Snow, J.: Evidence from the Pacific  
28 troposphere for large global sources of oxygenated organic compounds, *Nature*, 410, 1078–1081,  
29 2001.
- 30 Steinfeld, J. I.: Atmospheric Chemistry and Physics: From Air Pollution to Climate Change,  
31 *Environment: Science and Policy for Sustainable Development*, 40, 26–26,  
32 10.1080/00139157.1999.10544295, 1998.
- 33 Sun, Y., Yin, H., Liu, C., Zhang, L., Cheng, Y., Palm, M., Notholt, J., Lu, X., Vigouroux, C., Zheng, B.,  
34 Wang, W., Jones, N., Shan, C., Tian, Y., Hu, Q., and Liu, J.: Mapping the drivers of formaldehyde  
35 (HCHO) variability from 2015–2019 over eastern China: insights from FTIR observation and  
36 GEOS-Chem model simulation, *Atmos. Chem. Phys. Discuss.*, 2020, 1–24, 10.5194/acp-2020-544,  
37 2020a.
- 38 Sun, Y. W., Liu, C., Palm, M., Vigouroux, C., Notholt, J., Hui, Q. H., Jones, N., Wang, W., Su, W. J.,  
39 Zhang, W. Q., Shan, C. G., Tian, Y., Xu, X. W., De Maziere, M., Zhou, M. Q., and Liu, J. G.: Ozone  
40 seasonal evolution and photochemical production regime in the polluted troposphere in eastern  
41 China derived from high-resolution Fourier transform spectrometry (FTS) observations, *Atmos.*  
42 *Chem. Phys.*, 18, 14569–14583, 2018a.
- 43 Sun, Y. W., Palm, M., Liu, C., Hase, F., Griffith, D., Weinzierl, C., Petri, C., Wang, W., and Notholt, J.:  
44 The influence of instrumental line shape degradation on NDACC gas retrievals: total column and





- 1 profile, *Atmos. Meas. Tech.*, 11, 2879-2896, 2018b.
- 2 Sun, Y. W., Liu, C., Zhang, L., Palm, M., Notholt, J., Hao, Y., Vigouroux, C., Lutsch, E., Wang, W., Shan,  
3 C. G., Blumenstock, T., Nagahama, T., Morino, I., Mahieu, E., Strong, K., Langerock, B., De  
4 Maziere, M., Hu, Q. H., Zhang, H. F., Petri, C., and Liu, J. G.: Fourier transform infrared time series  
5 of tropospheric HCN in eastern China: seasonality, interannual variability, and source attribution,  
6 *Atmos. Chem. Phys.*, 20, 5437-5456, 2020b.
- 7 Taylor, T. E., Eldering, A., Merrelli, A., Kiel, M., Somkuti, P., Cheng, C., Rosenberg, R., Fisher, B., Crisp,  
8 D., Basilio, R., Bennett, M., Cervantes, D., Chang, A., Dang, L., Frankenberg, C., Haemmerle, V.  
9 R., Keller, G. R., Kurosu, T., Laughner, J. L., Lee, R., Marchetti, Y., Nelson, R. R., O'Dell, C. W.,  
10 Osterman, G., Pavlick, R., Roehl, C., Schneider, R., Spiers, G., To, C., Wells, C., Wennberg, P. O.,  
11 Yelamanchili, A., and Yu, S.: OCO-3 early mission operations and initial (vEarly) XCO<sub>2</sub> and SIF  
12 retrievals, *Remote Sens. Environ.*, 251, 112032, <https://doi.org/10.1016/j.rse.2020.112032>, 2020.
- 13 Tian, Y., Sun, Y. W., Liu, C., Wang, W., Shan, C. G., Xu, X. W., and Hu, Q. H.: Characterisation of  
14 methane variability and trends from near-infrared solar spectra over Hefei, China, *Atmos. Environ.*,  
15 173, 198-209, 2018.
- 16 Tzompa-Sosa, Z. A., Mahieu, E., Franco, B., Keller, C. A., Turner, A. J., Helmig, D., Fried, A., Richter,  
17 D., Weibring, P., Walega, J., Yacovitch, T. I., Herndon, S. C., Blake, D. R., Hase, F., Hannigan, J.  
18 W., Conway, S., Strong, K., Schneider, M., and Fischer, E. V.: Revisiting global fossil fuel and  
19 biofuel emissions of ethane, *J. Geophys. Res.-Atmos.*, 122, 2493-2512, 2017.
- 20 Van Dingenen, R., Dentener, F. J., Raes, F., Krol, M. C., Emberson, L., and Cofala, J.: The global impact  
21 of ozone on agricultural crop yields under current and future air quality legislation, *Atmos. Environ.*,  
22 43, 604-618, 2009.
- 23 Veaux, D., and Richard, D.: Generalized Additive Models, *Technometrics*, 34, 225-226, 2012.
- 24 Viatte, C., Strong, K., Walker, K. A., and Drummond, J. R.: Five years of CO, HCN, C<sub>2</sub>H<sub>6</sub>, C<sub>2</sub>H<sub>2</sub>, CH<sub>3</sub>OH,  
25 HCOOH and H<sub>2</sub>CO total columns measured in the Canadian high Arctic, *Atmos. Meas. Tech.*, 7,  
26 1547-1570, 2014.
- 27 Viatte, C., Strong, K., Hannigan, J., Nussbaumer, E., Emmons, L. K., Conway, S., Paton-Walsh, C.,  
28 Hartley, J., Benmergui, J., and Lin, J.: Identifying fire plumes in the Arctic with tropospheric FTIR  
29 measurements and transport models, *Atmos. Chem. Phys.*, 15, 2227-2246, 2015.
- 30 Vigouroux, C., Stavrakou, T., Whaley, C., Dils, B., Duflot, V., Hermans, C., Kumps, N., Metzger, J. M.,  
31 Scolas, F., Vanhaelewyn, G., Muller, J. F., Jones, D. B. A., Li, Q., and De Maziere, M.: FTIR time-  
32 series of biomass burning products (HCN, C<sub>2</sub>H<sub>6</sub>, C<sub>2</sub>H<sub>2</sub>, CH<sub>3</sub>OH, and HCOOH) at Reunion Island  
33 (21 degrees S, 55 degrees E) and comparisons with model data, *Atmos. Chem. Phys.*, 12, 10367-  
34 10385, 2012.
- 35 Wang, W., Tian, Y., Liu, C., Sun, Y. W., Liu, W. Q., Xie, P. H., Liu, J. G., Xu, J., Morino, I., Velasco, V.  
36 A., Griffith, D. T., Notholt, J., and Warneke, T.: Investigating the performance of a greenhouse gas  
37 observatory in Hefei, China, *Atmos. Meas. Tech.*, 10, 2627-2643, 2017.
- 38 Wesely, M. L.: Parameterization of Surface Resistances to Gaseous Dry Deposition in Regional-Scale  
39 Numerical-Models, *Atmos. Environ.*, 23, 1293-1304, 1989.
- 40 Wood, and Simon, N.: Stable and Efficient Multiple Smoothing Parameter Estimation for Generalized  
41 Additive Models, *Journal of the American Statistical Association*, 99, 673-686, 2004.
- 42 Wood, S. N.: Stable and efficient multiple smoothing parameter estimation for generalized additive  
43 models, *Journal of the American Statistical Association*, 99, 673-686, 2004.
- 44 Xiao, Y. P., Logan, J. A., Jacob, D. J., Hudman, R. C., Yantosca, R., and Blake, D. R.: Global budget of



- 1 ethane and regional constraints on US sources, *J. Geophys. Res.-Atmos.*, 113, 2008.
- 2 Yin, H., Sun, Y. W., Liu, C., Zhang, L., Lu, X., Wang, W., Shan, C. G., Hu, Q. H., Tian, Y., Zhang, C. X.,  
3 Su, W. J., Zhang, H. F., Palm, M. A., Notholt, J., and Liu, J. G.: FTIR time series of stratospheric  
4 NO<sub>2</sub> over Hefei, China, and comparisons with OMI and GEOS-Chem model data, *Opt. Express*,  
5 27, A1225-A1240, 2019.
- 6 Yin, H., Sun, Y. W., Liu, C., Lu, X., Smale, D., Blumenstock, T., Nagahama, T., Wang, W., Tian, Y., Hu,  
7 Q. H., Shan, C. G., Zhang, H. F., and Liu, J. G.: Ground-based FTIR observation of hydrogen  
8 chloride (HCl) over Hefei, China, and comparisons with GEOS-Chem model data and other ground-  
9 based FTIR stations data, *Opt. Express*, 28, 8041-8055, 2020.
- 10 Zeng, G., Wood, S. W., Morgenstern, O., Jones, N. B., Robinson, J., and Smale, D.: Trends and variations  
11 in CO, C<sub>2</sub>H<sub>6</sub>, and HCN in the Southern Hemisphere point to the declining anthropogenic emissions  
12 of CO and C<sub>2</sub>H<sub>6</sub>, *Atmos. Chem. Phys.*, 12, 7543-7555, 2012.
- 13 Zhang, C. X., Liu, C., Hu, Q. H., Cai, Z. N., Su, W. J., Xia, C. Z., Zhu, Y. Z., Wang, S. W., and Liu, J. G.:  
14 Satellite UV-Vis spectroscopy: implications for air quality trends and their driving forces in China  
15 during 2005-2017, *Light-Sci. Appl.*, 8, 2019.
- 16 Zhang, L. M., Gong, S. L., Padro, J., and Barrie, L.: A size-segregated particle dry deposition scheme for  
17 an atmospheric aerosol module, *Atmos. Environ.*, 35, 549-560, 2001.
- 18 Zhao, Y., Strong, K., Kondo, Y., Koike, M., Matsumi, Y., Irie, H., Rinsland, C. P., Jones, N. B., Suzuki,  
19 K., Nakajima, H., Nakane, H., and Murata, I.: Spectroscopic measurements of tropospheric CO,  
20 C<sub>2</sub>H<sub>6</sub>, C<sub>2</sub>H<sub>2</sub>, and HCN in northern Japan, *J. Geophys. Res.-Atmos.*, 107, 2002.
- 21 Zheng, B., Huo, H., Zhang, Q., Yao, Z. L., Wang, X. T., Yang, X. F., Liu, H., and He, K. B.: High-  
22 resolution mapping of vehicle emissions in China in 2008, *Atmos. Chem. Phys.*, 14, 9787-9805,  
23 2014.
- 24 Zheng, B., Tong, D., Li, M., Liu, F., Hong, C. P., Geng, G. N., Li, H. Y., Li, X., Peng, L. Q., Qi, J., Yan,  
25 L., Zhang, Y. X., Zhao, H. Y., Zheng, Y. X., He, K. B., and Zhang, Q.: Trends in China's  
26 anthropogenic emissions since 2010 as the consequence of clean air actions, *Atmos. Chem. Phys.*,  
27 18, 14095-14111, 10.5194/acp-18-14095-2018, 2018.
- 28
- 29



1 **Tables**

2 **Table 1.** Error budget and degrees of freedom (DOFS) for signal of randomly selected C<sub>2</sub>H<sub>6</sub> troDMF retrieval at  
 3 Hefei, eastern China

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

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

5 **Table 2.** Anthropogenic C<sub>2</sub>H<sub>6</sub> emissions in China by region and category for the 2015 and 2019 MEIC emission  
 6 inventories

Region		Industry (Tg yr <sup>-1</sup> )	Power plant (Tg yr <sup>-1</sup> )	Residential (Tg yr <sup>-1</sup> )	Transport (Tg yr <sup>-1</sup> )	Sum (Tg yr <sup>-1</sup> )
WR	2015	0.084	<0.01	0.011	<0.01	0.1
	2019	0.097	<0.01	0.011	<0.01	0.112
	change	15.36%	82.54%	- 6.61%	- 3.41%	12.12%
NR	2015	0.241	<0.01	0.125	0.026	0.394
	2019	0.241	<0.01	0.105	0.025	0.373
	change	0.04%	2.51%	- 15.96%	- 4.38%	- 5.32%
CR	2015	0.144	<0.01	0.041	<0.01	0.189
	2019	0.15	<0.01	0.033	<0.01	0.187
	change	4.68%	- 7.00%	-20.75%	- 1.13%	- 1.03%
ER	2015	0.07	<0.01	0.026	0.01	0.11
	2019	0.067	<0.01	0.022	0.01	0.097
	change	-4.83%	5.40%	-16.79%	- 3.70%	-7.66%
SR	2015	0.06	<0.01	0.026	0.01	0.09
	2019	0.056	<0.01	0.027	0.01	0.09
	change	- 7.94%	- 9.26%	1.52%	- 4.24%	- 5.01%
China	2015	0.60	<0.01	0.231	0.05	0.883
	2019	0.612	<0.01	0.197	0.048	0.859
	change	1.91%	4.04%	-14.53%	-3.93%	-2.74%

7  
 8



1 **Table 3.** GEOS-Chem model configurations and delimitations of all geographical regions used in sensitivity  
2 simulations.

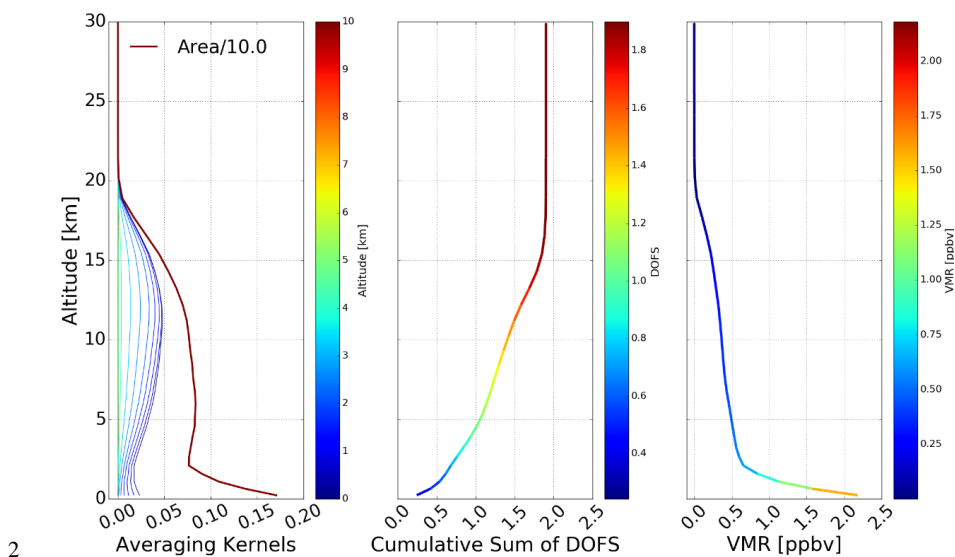
Simulation	Region	Description
BASE	Global	Standard simulation with all anthropogenic and natural C <sub>2</sub> H <sub>6</sub> emissions. The BASE simulation is taken as the reference and used for model evaluation
noFF	Global	Turn off global fossil fuel C <sub>2</sub> H <sub>6</sub> emissions in BASE simulation
noBVOC	Global	Turn off global biogenic C <sub>2</sub> H <sub>6</sub> emissions in BASE simulation
noBB	Global	Turn off global biomass burning C <sub>2</sub> H <sub>6</sub> emissions in BASE simulation
noBIOF	Global	Turn off global biofuel C <sub>2</sub> H <sub>6</sub> emissions in BASE simulation
Rest	Global	Difference between BASE and the sum of FF, BVOC, BB, and BIOF contributions
noWR	78.6° E – 103.4° E; 27.6°N - 48.8°N	Turn off fossil fuel, biogenic, biomass burning, and biofuel C <sub>2</sub> H <sub>6</sub> emissions within western China (WR), i.e., region ① in Fig. 2, in BASE simulation
noNR	103.4°E – 129.8°E; 34.6°N – 53.5°N	Turn off fossil fuel, biogenic, biomass burning, and biofuel C <sub>2</sub> H <sub>6</sub> emissions within northern China (NR), i.e., region ② in Fig. 2, in BASE simulation
noCR	103.4°E – 115.6°E; 27.6°N – 34.6°N	Turn off fossil fuel, biogenic, biomass burning, and biofuel C <sub>2</sub> H <sub>6</sub> emissions within central China (CR), i.e., region ③ in Fig. 2, in BASE simulation
noER	115.6°E – 123.6°E; 21.0°N – 34.6°N	Turn off fossil fuel, biogenic, biomass burning, and biofuel C <sub>2</sub> H <sub>6</sub> emissions within eastern China (ER), i.e., region ④ in Fig. 2, in BASE simulation
noSR	98.1°E – 115.6°E; 21.0°N – 27.6°N	Turn off fossil fuel, biogenic, biomass burning, and biofuel C <sub>2</sub> H <sub>6</sub> emissions within southern China (SR), i.e., region ⑤ in Fig. 2, in BASE simulation
ROW	Rest of world	Difference between BASE and the sum of WR, NR, CR, ER, and SR contributions

3

4

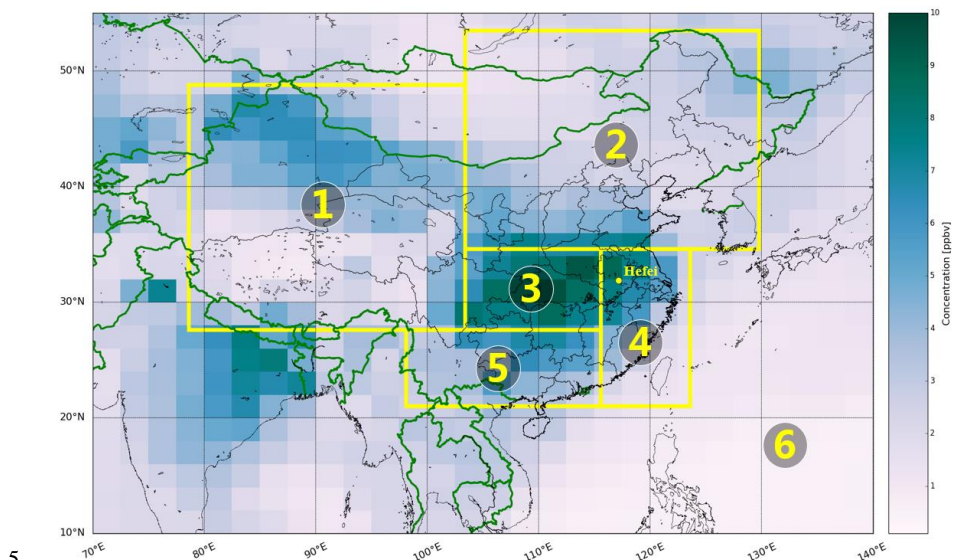


## 1 Figures



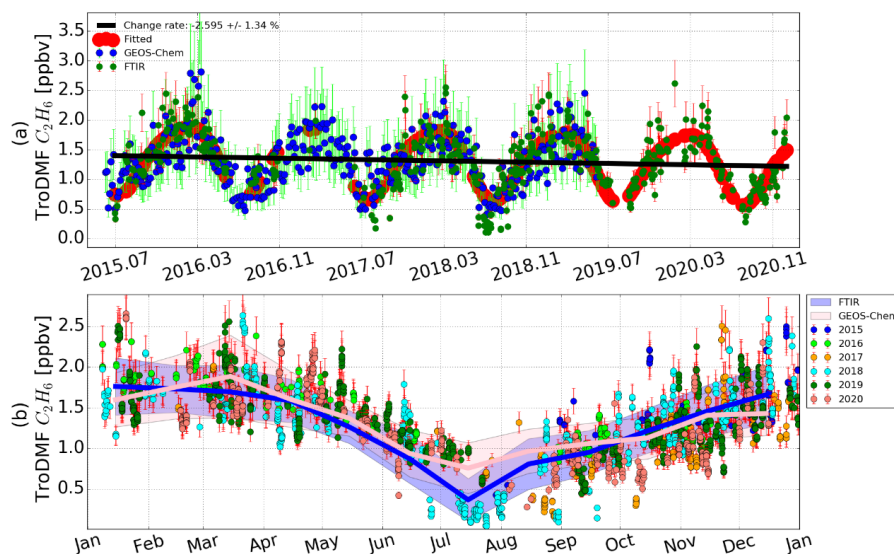
2

3 **Fig. 1.** Averaging kernels and their area scaled by a factor of 0.1, cumulative sum of degrees of freedom for signal  
4 (DOFS), and volume mixing ratio (VMR) profile of randomly selected C<sub>2</sub>H<sub>6</sub> retrieval over Hefei, eastern China.

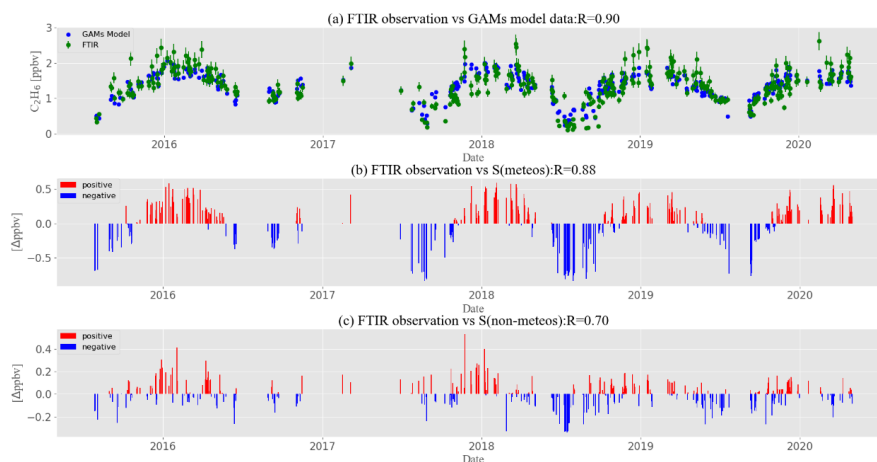


5

6 **Fig. 2.** Geographical regions used for GEOS-Chem sensitivity simulations. The numbers ①–⑥ represent western,  
7 northern, central, eastern, and southern China, and the rest of world, respectively. See Table 3 for latitude and  
8 longitude delimitations. Daily mean values of C<sub>2</sub>H<sub>6</sub> troDMF on 1 January 2017 provided by GEOS-Chem BASE  
9 simulation was selected as a representative of wintertime enhancement in eastern China.

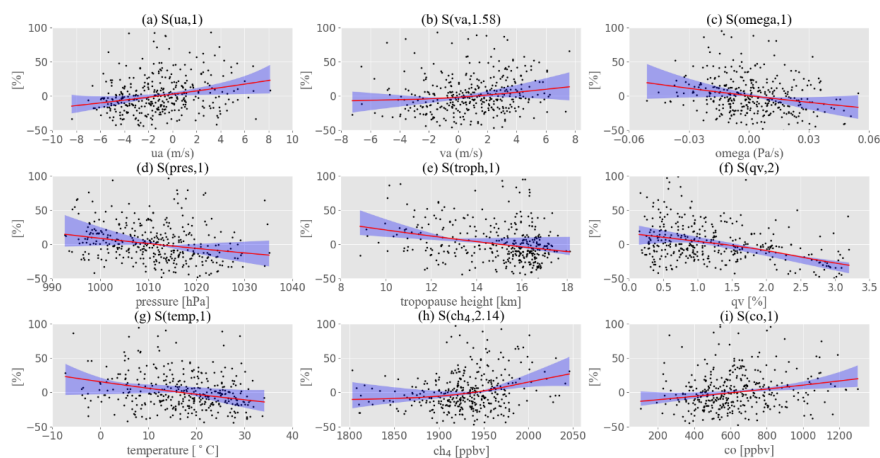


1  
 2 **Fig. 3.** (a)  $C_2H_6$  troDMF time series comparison between FTIR observation and GEOS-Chem model BASE  
 3 simulation from 2015 to 2020 over Hefei, eastern China. The seasonality and interannual variability are represented  
 4 by red dots and black line, respectively, which are fitted by using a bootstrap resampling model with a 3<sup>rd</sup> Fourier  
 5 series plus a linear function. (b) Seasonal variations of  $C_2H_6$  troDMF by FTIR and GEOS-Chem simulation. Bold  
 6 curves and the shadows are monthly mean values and the 1- $\sigma$  standard variations, respectively. Vertical error bars  
 7 for FTIR and GEOS-Chem represent retrieval uncertainties and diurnal variabilities, respectively.

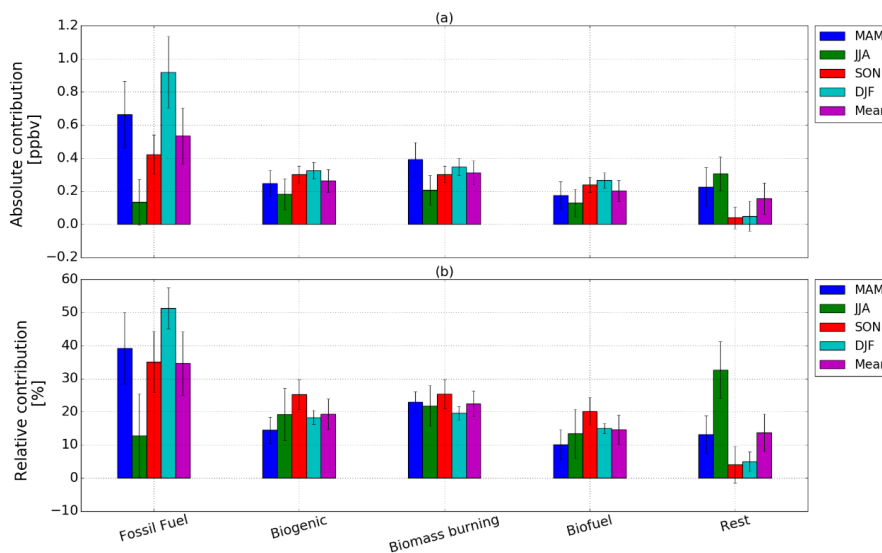


8  
 9 **Fig. 4.** (a)  $C_2H_6$  troDMF time series from 2015 to 2020 over Hefei, eastern China by FTIR and GAMS regression  
 10 model. (b) Time series of accumulated meteorological smooth functions ( $S(meteos)$ ), and (c) time series of  
 11 accumulated emission smooth functions ( $S(non-meteos)$ ). Positive and negative influences are indicated with red  
 12 and blue bars, respectively. Correlation coefficients for the total, meteorological, and emission influences are also  
 13 shown.

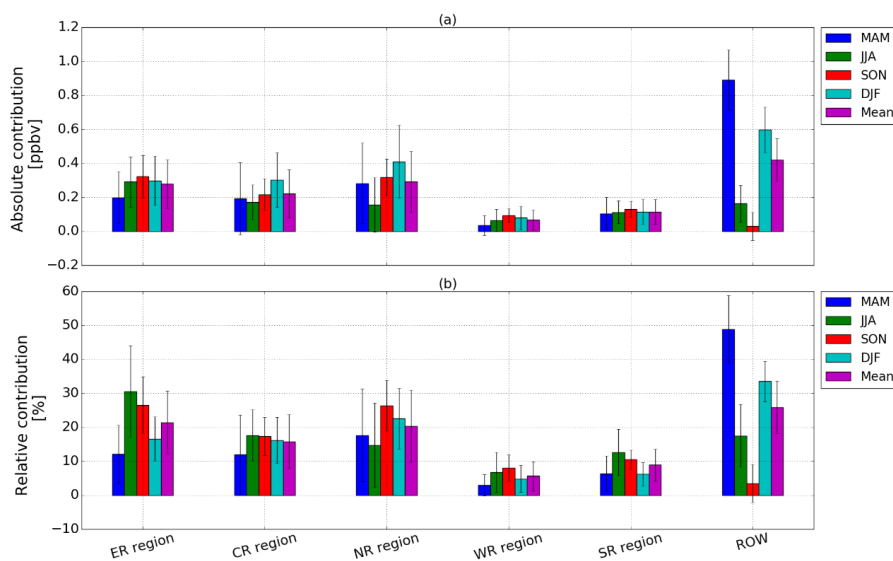




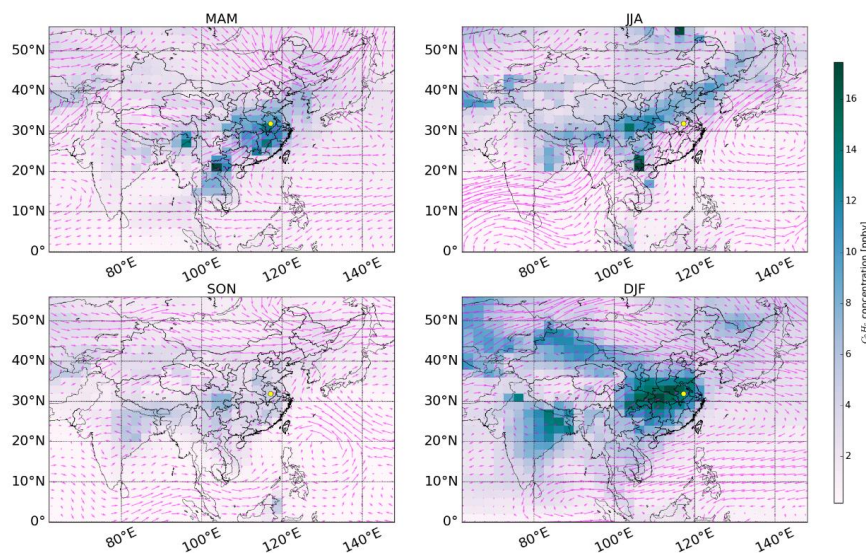
1  
 2 **Fig. 5.** Influence of each individual variable in the GAMS model on  $C_2H_6$  troDMF from 2015 to 2020 over Hefei,  
 3 eastern China. (a) to (i) are for zonal wind ( $ua$ ), meridional wind ( $va$ ), convection wind ( $omega$ ), pressure ( $pres$ ),  
 4 tropopause height ( $troph$ ),  $H_2O$  troDMF ( $qv$ ), temperature ( $temp$ ),  $CH_4$  troDMF ( $ch_4$ ), and  $CO$  troDMF ( $co$ ),  
 5 respectively. The DOFS of each smoothing function is included in the bracket in each panel. The x-axis represents  
 6 variation range of each variable and the y-axis represents relative percentage change of  $C_2H_6$  troDMF relative to its  
 7 annual mean value.



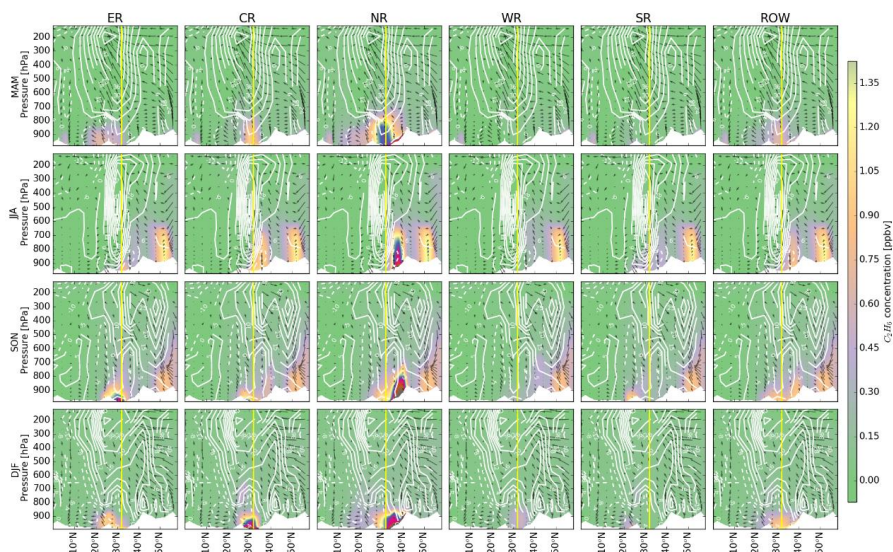
8  
 9 **Fig. 6.** Absolute (a) and relative (b) contributions of fossil fuel, biogenic, biomass burning, and biofuel emission  
 10 sources to the observed  $C_2H_6$  abundance from 2015 to 2020 over Hefei, eastern China. The remaining contribution  
 11 calculated as the difference between the BASE simulation and the sum of anthropogenic and natural contributions  
 12 is also shown. All contributions are grouped by season. Vertical error bars represent  $1-\sigma$  standard variation.



1  
2 **Fig. 7.** Absolute (a) and relative (b) contributions of ER, CR, NR, WR, SR, and ROW regions to the observed  $C_2H_6$   
3 abundance from 2015 to 2020 over Hefei, eastern China. All contributions are grouped by season. Geographical  
4 definition of each region is summarised in Table 3. Vertical error bars represent 1- $\sigma$  standard variation.

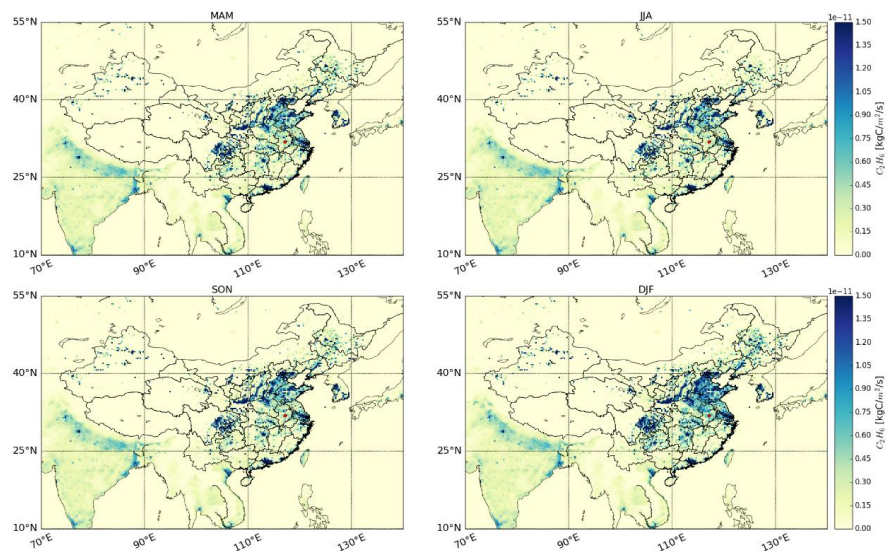


5  
6 **Fig. 8.** Spatial distribution of  $C_2H_6$  tropDMF in the GEOS-Chem BASE simulations in different seasons. The arrows  
7 indicate horizontal wind vectors at 900 hPa; the observation site is marked with a yellow dot. Meteorological fields  
8 are from the GEOS-FP 0.25° x 0.3125° dataset.



1  
 2 **Fig. 9.** The first row shows the latitude–height distributions of  $C_2H_6$  VMR averaged over  $113\text{--}121^\circ E$  in spring  
 3 (MAM), originating in different source regions (corresponding to different columns). See Table 3 for latitude and  
 4 longitude definitions. The white area indicates topography, and the white contours at intervals of  $6\text{ m s}^{-1}$  are the  
 5 easterly (dashed) and westerly (solid) mean meridional winds; the wind vectors (consisting of zonal wind in  $\text{m s}^{-1}$   
 6 and vertical velocity in units of  $\text{Pa s}^{-1}$ ) are represented by arrows; the observation site is marked with a yellow line.  
 7 The second to fourth rows are the same as the first row but for summer (JJA), autumn (SON), and winter (DJF),  
 8 respectively. Meteorological fields are from the GEOS-FP  $0.25^\circ \times 0.3125^\circ$  dataset.

9 **Appendix.**



10  
 11 **Fig. A1.**  $C_2H_6$  emission distribution in 2019 ( $0.25^\circ \times 0.25^\circ$ ) from the Multi-resolution Emission Inventory for China  
 12 (MEIC) over China and surroundings. Units are in  $\text{kgC}/\text{m}^2/\text{s}$ . The observation site is marked with a red dot.  
 13