



Editorial

Special Issue “Remote Sensing of Greenhouse Gases and Air Pollution”

Xiaozhen Xiong ^{1,*} , Jane Liu ² , Liangfu Chen ³, Weimin Ju ⁴ and Fred Moshary ⁵¹ NASA Langley Research Center, Hampton, VA 23681, USA² Department of Geography and Planning, University of Toronto, Toronto, ON M5S 1A8, Canada; janejj.liu@utoronto.ca³ State Key Laboratory of Remote Sensing Science, Aerospace Information Research Institute, Chinese Academy of Sciences, Beijing 100029, China; chenlf@aircas.ac.cn⁴ International Earth System Science Institute, Nanjing University, Nanjing 210023, China; juweimin@nju.edu.cn⁵ Optical Remote Sensing Laboratory, Electrical Engineering, Grove School of Engineering, CUNY City College, New York, NY 10031, USA; moshary@ccny.cuny.edu

* Correspondence: xiaozhen.xiong@nasa.gov

Continuous increases in the human population and human activities have resulted in remarkable changes in the composition of the atmosphere since the industrial revolution. Climate change and air pollution are two major consequences of such changes. The scientific understanding of these two issues requires a variety of observations of the atmosphere on different platforms. Among them, satellite remote sensing has added a new dimension to these observations because of its advantages in global coverage, frequent revisit time, and consistently improved quality in recent decades. Particularly, the remote sensing of greenhouse gases has already illustrated promising applications related to climate change studies. Remote sensing data are also becoming more and more widely used in the monitoring of air pollution, which helps to identify variations of air pollutants in space and time and untangle the underlying mechanisms responsible for these variations.

This Special Issue (SI) aims to invite contributions on recent advances in remote sensing of greenhouse gases, particle matters, and polluted gases, as well as the applications of these remote sensing data for climate change and air pollution studies. With the six papers finally selected and published in this SI, four of them are associated with the satellite observations of column-averaged CO₂ dry air mole fraction (XCO₂), its validation, and the analysis of XCO₂ trend using satellite observations in conjunction with ground-based observations and model simulations [1–4]. The other two papers focus on the satellite observation of aerosol and its application on air pollution study, with one on the validation of satellite-observed aerosol optical depth (AOD) from the Visible Infrared Imaging Radiometer Suite (VIIRS) onboard S-NPP, and the other on the use of the AOD from the Advanced Himawari Imager (AHI) onboard the Himawari-8, a geostationary satellite, in order to estimate surface fine particulate matter (PM_{2.5}) concentrations and analyze its spatiotemporal variation over central East China [5,6].

The COVID-19 pandemic is projected to cause a significant decrease in annual CO₂ emissions, which was up to 8% globally in 2020 (see [1] and reference therein). Sussmann et al. [1] used the ground-based XCO₂ measurements from the Total Carbon Column Observing Network (TCCON) to explore if the decrease in CO₂ emissions can be detectable by the TCCON measurements in terms of CO₂ concentrations. A method was used to fit the XCO₂ trends in multiple sites and to derive the annual growth rates of XCO₂. It was found that the range of XCO₂ growth rates for 2012–2019 was between 2.00 and 3.27 ppm/yr, with a mean uncertainty of 0.38 ppm/yr. In fact, the TCCON measurements were historically high for XCO₂ in April 2020, suggesting some combined influences from multiple factors of XCO₂. By separating these influences, the authors concluded that TCCON



Citation: Xiong, X.; Liu, J.; Chen, L.; Ju, W.; Moshary, F. Special Issue “Remote Sensing of Greenhouse Gases and Air Pollution”. *Remote Sens.* **2021**, *13*, 2057. <https://doi.org/10.3390/rs13112057>

Received: 17 March 2021

Accepted: 18 May 2021

Published: 23 May 2021

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observations could provide a readily available basis to potentially detect COVID-19-related reduction in XCO_2 of -0.3 ppm in 2020, with a detection delay well below 1 year. For better quantifying the land and ocean sinks that dominate the interannual variability, a reduction of the forecast uncertainties is required through improved terrestrial ecosystem models and ocean observations.

Space-borne measurements of XCO_2 data from multiple satellites, ground observations, and model simulations were inter-compared over the Mount Zugspitze region of Germany in Yuan et al. [2]. The satellite data include the Scanning Imaging Absorption Spectrometer for Atmospheric Cartography sensor (SCIAMACHY) on the Environmental Satellite (ENVISAT) from 2002 to 2012, the Fourier Transform Spectrometer of the Thermal and Near-infrared Sensor for Carbon Observation Sensor (TANSO-FTS) on the Greenhouse Gases Observing Satellite (GOSAT) since 2009, and measurements from the Orbiting Carbon Observatory 2 (OCO-2) satellite since July 2014. The ground-based measurements and model simulations include the continuous in situ CO_2 measurements over the Global Atmospheric Watch (GAW) site at Zugspitze, the co-located column-averaged XCO_2 from TCCON, and the outputs from the National Oceanic and Atmospheric Administration (NOAA) Carbon Tracker model. It was found that the mean annual growth rates among the datasets agree well with a value of ~ 2.2 ppm yr⁻¹ over a 17-year period (2002–2018). However, the column-averaged measurements exhibited smaller seasonal amplitudes and clearly delayed phases based on the seasonal maximum and minimum values. This study demonstrated that, by using consistent data processing routines with proper data retrieval and gap interpolation algorithms, the trend and seasonality of XCO_2 can be well extracted from all these measurements.

A global XCO_2 dataset was constructed by He et al. [3]. To construct such a long-term spatiotemporal continuous XCO_2 dataset using different satellite observations with different temporal periods and spatial coverage, a precision-weighted spatiotemporal kriging method was applied. Using satellite data from ENVISAT/SCIAMACHY, GOSAT, and OCO-2, a globally mapped XCO_2 (GM- XCO_2) with a spatial resolution of $1^\circ \times 1^\circ$ every eight days from 2003 to 2016 was generated. The predicted GM- XCO_2 precision is improved in most grids compared with the conventional spatiotemporal kriging results, especially during the satellites overlapping period the precision is improved by 0.3–0.5 ppm. A comparison with TCCON measurements shows that the precision of GM- XCO_2 in nine of the twelve TCCON sites examined is within 1.0 ppm, with an average absolute bias of 0.92 ppm, and the standard deviation of the difference for all twelve sites is 1.05 ppm. This method has potential applications for integrating and mapping XCO_2 from multiple satellite sensors.

For a better understanding of CO_2 variation trends in Asia, Mustafa et al. [4] compared the model outputs from the NOAA CarbonTracker model with two datasets: one is the GOSAT data from September 2009 to August 2019, and the other is OCO-2 data from September 2014 to August 2019. The results show that XCO_2 from GOSAT is higher than the CarbonTracker model by 0.61 ppm, whereas the OCO-2 XCO_2 is lower than the model by 0.31 ppm over Asia. Overall, the model demonstrates a good agreement with GOSAT and OCO-2 in terms of spatial distribution, monthly averaged time series, and seasonal climatology. However, larger uncertainties exist in the southwest part of China. These results suggest that CO_2 data from either the model or the satellite observations from GOSAT and OCO-2 can help to understand the role of CO_2 in the carbon budget and its impact on climate change at regional to global scales.

As for the second topic of this SI, i.e. the use of remote sensing data in the monitoring of air pollution, there are many published research studies on the use of moderate resolution imaging spectroradiometer (MODIS) AOD products, the conversion of the AOD to estimate $PM_{2.5}$ or PM_{10} , and analysis of air pollution events based on AOD or estimated $PM_{2.5}$, especially in China in the past decade. Here, Wang et al. [5] evaluated the AOD products from VIIRS, a difference sensor onboard on S-NPP, and produced at NOAA. The ground-based measurements used were from the Campaign on Atmospheric Aerosol Research

Network of China (CARE-China). Compared with ground-based observations at six sites, Wang et al. [4] found the performance of the retrievals in five of the six sites examined was satisfactory, but the AOD retrievals with the dust model show poor consistency as compared to the retrievals obtained from the other models. The poor AOD retrieval with the dust model was also verified by a comparison with the MODIS aerosol product. Further analysis of the ground-based Ångström exponent (α) values shows that for α in the range between -0.6 to 1.0 , the dust model percentage exceeds 40%, but in VIIRS retrievals, the values of α are centered around 1.1 for the “dust” aerosol model that it used. This mismatching of the aerosol model can partly explain the low accuracy of VIIRS retrievals at one of the six sites. The use of an appropriate aerosol model in the retrieval, especially the dust model, was recommended as a key step to improve the AIRS AOD products.

While many previous studies have focused on estimating daily $PM_{2.5}$ concentrations using polar-orbiting satellite data (e.g., from MODIS), which are inadequate for understanding the daily evolution of $PM_{2.5}$ distributions in an area of interest, Liu et al. [6] used the AOD from Geostationary satellite Himawari. By developing an ensemble learning model incorporated with AOD from Himawari and meteorological variables from the ERA-Interim reanalysis, Liu et al. [6] derived the hourly $PM_{2.5}$ concentrations and analyzed its spatial agglomeration patterns over central East China. Overall, the estimated $PM_{2.5}$ concentrations agree well with ground-based data. It was found that the satellite-based $PM_{2.5}$ concentrations over central East China display a north-to-south decreasing gradient with the highest concentration in winter and the lowest concentration in summer, and concentrations are higher in the morning and lower in the afternoon. High-frequency spatiotemporal $PM_{2.5}$ variations from this study can help to improve our understanding of the formation and transportation processes of regional pollution episodes.

In summary, this Special Issue has provided an enhanced understanding of remote sensing of XCO_2 in terms of detecting the impact of COVID-19 [1], mapping XCO_2 [3], and validating XCO_2 products from SCIAMACHY, GOSAT, and the OCO-2 satellite over Asia [4] and the Zugspitze Region [2]. For the remote sensing of air quality, a new methodology is presented for the retrieval of hourly $PM_{2.5}$ from a geostationary satellite, Himawari [6], and the need to improve dust AOD retrieval in the VIIRS products is highlighted [5].

This Special Issue would not have been possible without the hard work of all authors and reviewers. We also would like to extend our sincere appreciation to the Editorial Office of *Remote Sensing* for their professional and excellent management work.

Author Contributions: X.X. wrote this Editorial with contributions from all authors. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

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