

The Development and Application of Spatiotemporal Metrics for the Characterization and Measurement of Point Source FFCO₂ Dispersive Emissions and their Sensitivity to Physical and Environmental Parameters

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Introduction

During the mid-1800's, the time of the European Industrial Revolution, a connection between the effects of industrial emissions and the global climate was not identified. However, during this period several scientists were suggesting that certain gases found in the atmosphere were more absorptive than others. (Hulme 2009) It wasn't until 1859 that this hypothesis was recognized and strong experimental evidence supported the claim through a series of optical and vacuum chamber tests conducted upon various atmospheric gases as well as the gases emitted from the burning of coal. (Tyndall 1859; 1861) Since then, the International Panel on Climate Change (IPCC) has identified a large body of evidence to further link the effects that Greenhouse Gases (water vapor, carbon dioxide, nitrous oxide, methane, and ozone) have on the global climate. (IPCC 2013) Although all play a significant role, carbon dioxide (CO₂) accounts for 76% of all anthropogenic emissions, 65% of which comes from industrial processes and the burning of fossil fuels. This unprecedented influx of atmospheric CO₂ in relatively recent history has been accurately measured and attributed to significant changes in the Earth's biosphere. (Lüthi 2012; Keeling and Whorf 2004; LoPresti et al. 2015)

In the United States alone, 82% of Greenhouse Gas emissions are CO₂ and 51% of national emissions are generated by electricity production and industrial processes; thus, due to the potential for climatological effects, it is becoming increasingly important to monitor the sources and sinks of the global carbon cycle. In an effort to better understand CO₂ fluxes on a national and global scale, several monitoring schemes have been introduced. These approaches involve ground-based and space-based remote sensing instrumentation as well as high resolution data processing. Such methods include measurements of atmospheric CO₂ at the Mauna Loa Observatory in Hawaii, the Orbiting Carbon Observatory (OCO) and computational methods for improving space-based measurements. (Keeling and Whorf 2004; Miller et al. 2005; Zou et al. 2017) Of these techniques, space-based measurements are most useful in determining the spatial distribution of atmospheric CO₂ as these techniques can provide global, national, and regional measurements of the atmosphere whereas ground-based measurements provide a much lower spatial resolution. The results from these "top-down" measurements of atmospheric CO₂ can be used in climatological and atmospheric inverse modeling applications to determine significant carbon sources and receptors as well as the interactions between them. However, if these space-based measurements are to be validated for atmospheric modeling purposes, additional CO₂ distributions must be generated that can be used to prompt a correlative study of space-based results.

Currently, developed carbon emissions inventories can be used as a foundation for statistical atmospheric CO₂ models yet choices made during the construction of these inventories can significantly affect the results. (Hutchins et al. 2016; Shih and Tsokos 2008; Nassar et al. 2010) The Emission Database for Global Atmospheric Research (EDGAR), Open Source Data Inventory for Anthropogenic CO₂ (ODIAC), and the Vulcan project all use emissions data and locations of known large point sources (coal-fired power plants, cement production facilities, etc) as a proxy for the spatial allocation of FFCO₂ emissions.

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Three of the databases that contain relevant information on large point sources include the Emissions & Generation Resource Integrated Database (eGRID), the Greenhouse Gas Reporting Program (GHGRP), and Carbon Monitoring for Action (CarMA) all of which record the yearly emissions and geographic location of the point sources for various years. However, various reported spatial inconsistencies arise for some power plants listed in these databases. (EPA 2017; EPA 2016; CarMA 2013; Hogue et al. 2016) Additionally, measurements of geolocation, height, diameter, and exit velocity of each exhaust stack present are not included in these databases. Although these databases are widely used in both emission inventories and policy development, their exclusion of certain physical parameters make their use as components of atmospheric CO₂ models less routine.

As an argumentative means for the facilitation of more detailed emissions databases, this work presents a methodology for the characterization and comparison of two simulated CO₂ emissions scenarios: one generated strictly from the information contained in the eGRID database and another generated from the inclusion of the point source parameters listed above to demonstrate the sensitivity of the atmospheric model and the role that these parameters have in the characteristics of the dispersion. We consider three power plants from the eGRID database: The Jeffrey Energy Center located in the Emmett Township of Kansas, the John S. Cooper Power Station located near Somerset, Kentucky, and the TransAlta Centralia power plant located in Washington. Additional analyses are presented using the same methodology to understand the magnitude of impact that each of these parameters have on the model.

Methodology

To reflect diverse climatological environments, three power plants were selected based on their geographic location within the United States.

- CarMA. 2013. “Carbon Monitoring for Action.” <http://carma.org/plant>.
- EPA. 2016. “Greenhouse Gas Reporting Program (GHGRP) 2012.” U.S. Environmental Protection Agency. <https://www.epa.gov/ghgreporting>.
- . 2017. “Clean Energy: eGRID, Ninth Edition With 2012 Data.” U.S. Environmental Protection Agency. <https://www.epa.gov/energy/emissions-generation-resource-integrated-database-egrid>.
- Hogue, Susannah, Eric Marland, Robert J. Andres, Gregg Marland, and Dawn Woodard. 2016. “Uncertainty in Gridded CO₂ Emissions Estimates: UNCERTAINTY IN CO₂ EMISSIONS ESTIMATES.” *Earth’s Future* 4 (5): 225–39. doi:10.1002/2015EF000343.
- Hulme, Mike. 2009. “On the Origin of ‘the Greenhouse Effect’: John Tyndall’s 1859 Interrogation of Nature.” *Weather* 64 (5): 121–23. doi:10.1002/wea.386.
- Hutchins, Maya G., Jeffrey D. Colby, Gregg Marland, and Eric Marland. 2016. “A Comparison of Five High-Resolution Spatially-Explicit, Fossil-Fuel, Carbon Dioxide Emission Inventories for the United States.” *Mitigation and Adaptation Strategies for Global Change*, March. doi:10.1007/s11027-016-9709-9.
- IPCC. 2013. *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Book. Cambridge, United Kingdom; New York, NY, USA: Cambridge University Press. doi:10.1017/CBO9781107415324.
- Keeling, C.D., and T.P. Whorf. 2004. “Atmospheric CO₂ Concentrations Derived from Flask Air Samples at Sites in the Sio Network. in Trends: A Compendium of Data on Global Change.” Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, U.S. Department of Energy, Oak Ridge, Tennessee, U.S.A. http://cdiac.ornl.gov/trends/co2/sio-keel-flask/sio-keel-flaskmlo_c.html.
- LoPresti, Anna, Allison Charland, Dawn Woodard, James Randerson, Noah S Diffenbaugh, and Steven J Davis. 2015. “Rate and Velocity of Climate Change Caused by Cumulative Carbon Emissions.” *Environmental Research Letters* 10 (9): 095001. doi:10.1088/1748-9326/10/9/095001.
- Lüthi, D. 2012. “EPICA Dome c Ice Core 800kYr Carbon Dioxide Data. Igbp Pages/World Data Center for Paleoclimatology Data Contribution Series # 2008-055.” *800,000-Year Ice-Core Records of Atmospheric Carbon Dioxide (CO₂)*, September. World Data Center for Paleoclimatology, National Oceanic; Atmospheric Administration. http://cdiac.ornl.gov/trends/co2/ice_core_co2.html.
- Miller, Charles E., Linda R. Brown, Robert A. Toth, D. Chris Benner, and V. Malathy Devi. 2005. “Spectroscopic Challenges for High Accuracy Retrievals of Atmospheric CO₂ and the Orbiting Carbon Observatory (OCO) Experiment.” *Comptes Rendus Physique* 6 (8): 876–87. doi:10.1016/j.crhy.2005.09.005.
- Nassar, R., D. B. A. Jones, P. Suntharalingam, J. M. Chen, R. J. Andres, K. J. Wecht, R. M. Yantosca, et al. 2010. “Modeling Global Atmospheric CO₂ with Improved Emission Inventories and CO₂ Production from the Oxidation of Other Carbon Species.” *Geoscientific Model Development* 3 (2): 689–716. doi:10.5194/gmd-3-689-2010.
- Shih, Shou Hsing, and Chris P. Tsokos. 2008. “Prediction Models for Carbon Dioxide Emissions and the Atmosphere.” *Neural, Parallel & Scientific Computations* 16 (1).
- Tyndall, John. 1859. “Note on the Transmission of Radiant Heat Through Gaseous Bodies.” In *Proceedings of the Royal Society of London*, 10:37–39. <http://www.jstor.org/stable/111604>.
- . 1861. “The Bakerian Lecture: On the Absorption and Radiation of Heat by Gases and Vapours, and on the Physical Connexion of Radiation, Absorption, and Conduction.” *Philosophical Transactions of the Royal Society of London* 151: 1–36. <http://www.jstor.org/stable/108724>.
- Zou, MingMin, LiangFu Chen, ShenShen Li, Meng Fan, JinHua Tao, and Ying Zhang. 2017. “An Improved Constraint Method in Optimal Estimation of CO₂ from GOSAT SWIR Observations.” *Science China Earth Sciences* 60 (2): 286–96. doi:10.1007/s11430-015-0247-9.