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Stephen M. Ogle
Colorado State University - Fort Collins

Kenneth Davis
Pennsylvania State University - University Park

Thomas Lauvaux
Pennsylvania State University - University Park

Andrew Schuh
Colorado State University - Fort Collins

Dan Cooley
Colorado State University - Fort Collins

See next page for additional authors

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LETTER

An approach for verifying biogenic greenhouse gas emissions inventories with atmospheric CO_2 concentration data

Stephen M Ogle[1], Kenneth Davis[2], Thomas Lauvaux[2], Andrew Schuh[3], Dan Cooley[4], Tristram O West[5], Linda S Heath[6], Natasha L Miles[2], Scott Richardson[2], F Jay Breidt[4], James E Smith[6], Jessica L McCarty[7], Kevin R Gurney[8], Pieter Tans[9] and A Scott Denning[10]

[1] Natural Resource Ecology Laboratory and Department of Ecosystem Science and Sustainability, Campus Delivery 1499, Colorado State University, Fort Collins, CO 80523, USA
[2] Department of Meteorology, Walker Building, The Pennsylvania State University, University Park, PA 16802, USA
[3] Cooperative Institute for Research in the Atmosphere and Natural Resource Ecology Laboratory, Campus Delivery 1375, Colorado State University, Fort Collins, CO 80523, USA
[4] Department of Statistics, Campus Delivery 1877, Colorado State University, Fort Collins, CO 80523, USA
[5] Joint Global Change Research Institute, 5825 University Research Court, Pacific Northwest National Laboratory, College Park, MD 20740, USA
[6] USDA Forest Service, Northern Research Station, Forest Sciences Laboratory, 271 Mast Road, Durham, NH 03824, USA
[7] Michigan Tech Research Institute, 3600 Green Court, Ann Arbor, MI 48105, USA
[8] School of Life Sciences, PO Box 874501, Arizona State University, Tempe, AZ 85287, USA
[9] National Oceanic & Atmospheric Administration, Earth Systems Research Laboratory, Global Monitoring Division, 325 Broadway, Boulder, CO 80305, USA
[10] Department of Atmospheric Science, Campus Delivery 1371, Colorado State University, Fort Collins, CO 80523, USA

E-mail: stephen.ogle@colostate.edu

Keywords: greenhouse gas emissions inventory, atmospheric inversion modeling, emissions verification, carbon cycle

Abstract

Verifying national greenhouse gas (GHG) emissions inventories is a critical step to ensure that reported emissions data to the United Nations Framework Convention on Climate Change (UNFCCC) are accurate and representative of a country's contribution to GHG concentrations in the atmosphere. Furthermore, verifying biogenic fluxes provides a check on estimated emissions associated with managing lands for carbon sequestration and other activities, which often have large uncertainties. We report here on the challenges and results associated with a case study using atmospheric measurements of CO_2 concentrations and inverse modeling to verify nationally-reported biogenic CO_2 emissions. The biogenic CO_2 emissions inventory was compiled for the Mid-Continent region of United States based on methods and data used by the US government for reporting to the UNFCCC, along with additional sources and sinks to produce a full carbon balance. The biogenic emissions inventory produced an estimated flux of -408 ± 136 Tg CO_2 for the entire study region, which was not statistically different from the biogenic flux of -478 ± 146 Tg CO_2 that was estimated using the atmospheric CO_2 concentration data. At sub-regional scales, the spatial density of atmospheric observations did not appear sufficient to verify emissions in general. However, a difference between the inventory and inversion results was found in one isolated area of West-central Wisconsin. This part of the region is dominated by forestlands, suggesting that further investigation may be warranted into the forest C stock or harvested wood product data from this portion of the study area. The results suggest that observations of atmospheric CO_2 concentration data and inverse modeling could be used to verify biogenic emissions, and provide more confidence in biogenic GHG emissions reporting to the UNFCCC.

Introduction

As evidence for anthropogenic impacts on climate change continue to grow (IPCC 2013), the need to reduce emissions looms as a key issue of global debate. Greenhouse gas (GHG) emission reductions continue to be at the center of negotiations about future agreements (Tollefson 2013). A key opportunity to establish a new agreement is occurring at a meeting of the United Nations Framework Convention on

Climate Change (UNFCCC) during late 2015 in Paris, France. Along with the scope and magnitude of emission reductions, methods to verify reductions has emerged as a key challenge for negotiators (NRC 2010).

Signatory countries to the UNFCCC are required to conduct an inventory and report GHG emissions to the UNFCCC. Reporting is based on GHG inventory guidelines developed by the Intergovernmental Panel on Climate Change (IPCC 2006). The guidelines include estimation of anthropogenic-driven emissions of CO_2 and other GHGs from energy use, industrial processes, waste management, agriculture, as well as biogenic carbon (C) sinks and sources from managed land, such as C stock changes in soils and biomass.

Estimating biogenic emissions is complicated because of UNFCCC reporting requirements. First, emissions are not reported for all activities, such as lateral transport of C in products that lead to CO_2 emissions elsewhere (Ciais *et al* 2007, West *et al* 2011). Consequently, inventories do not provide a full C balance for a region. Second, GHG emissions are only reported for managed land, which is a proxy to isolate emissions directly influenced by anthropogenic activity (IPCC 2010). However, emissions on managed land will also be driven by natural processes and indirect effects of anthropogenic activity, such as CO_2 fertilization or atmospheric N deposition. Third, emissions accounting may allow for exclusions, such as factoring-out of emissions due to natural disturbances (e.g., wildfires) that are not directly under the control of managers (Canadell *et al* 2007, Kurz *et al* 2013).

Biogenic emissions will likely be a part of an agreement to reduce GHG emissions, particularly if offsets are allowed through management of biogenic sources and sinks (Smith *et al* 2007a, 2007b). In addition, biogenic emissions may increase if bioenergy is used to reduce fossil fuel combustion in order to meet reduction targets (e.g., see US Energy Independence and Security Act of 2007). Bioenergy feedstock production contributes to GHG emissions, such as C stock changes in soils and biomass due to land use change (Fargione *et al* 2008). Verifying biogenic emissions will be challenging given the complexities in reporting, and due to the large uncertainties in estimation of biogenic emissions arising from the complex interactions among driving variables, including weather patterns, topographic variation, soil characteristics, disturbances and a variety of land use and management activities.

Verification of biogenic emissions could incorporate several levels of evaluation. First, inventory methods can be evaluated for consistency with UNFCCC reporting guidelines. Appropriate application of methods provides assurance that the emission estimates are credible. This type of evaluation is currently conducted by the UNFCCC on a periodic basis for developed countries through an expert review process. Second, an independent verification program could confirm adoption of land use and management practices that are reported to enhance biogenic sinks or reduce biogenic sources. Verifying practices provides confidence that managers have taken the necessary steps to reduce GHG emissions. Third, verification could incorporate further evaluation using direct measurements of C sources and sinks that are independent of the inventory compilation (IPCC 2006). For example, soil monitoring networks are in various stages of implementation in several countries that could serve as an independent check (van Wesemael *et al* 2011). Another option would be to measure fluxes using eddy-covariance flux towers that are deployed throughout a region. When combined with modeling, an independent estimate of the regional flux can be produced and compared to an inventory (Xiao *et al* 2010, Raczka *et al* 2013, Hilton *et al* 2014).

Fourth, methods have been under development for more than a decade that utilize observations of CO_2 concentrations in the atmosphere to estimate the biogenic CO_2 flux with inverse modeling (Tarantola 2004). CO_2 fluxes are estimated based on knowledge of wind speeds and directions in conjunction with CO_2 concentration changes in the atmosphere. This technique has been widely used, including applications at the global scale (Tans *et al* 1990, Bousquet *et al* 2000, Gurney *et al* 2002), continental scales (Peters *et al* 2007, Gourdji *et al* 2012), and more recently at regional scales (Göckede *et al* 2010, Lauvaux *et al* 2012a, Schuh *et al* 2013). Using these data to evaluate a biogenic emissions inventory is likely to offer a strong inference for verification by demonstrating that reported biogenic emissions are consistent with changes in atmospheric CO_2 concentrations.

Both the IPCC (2006) and US National Research Council (NRC 2010) have raised the possibility of using atmospheric measurements of GHGs to verify emission inventories. We report here on an approach evaluating how this type of verification could be accomplished for biogenic sources and sinks using national GHG emissions data. Our case study focuses on emissions reporting for 2007 in the Mid-Continent region of the United States, which is dominated by agricultural production (figure 1). Several challenges must be addressed in order to verify biogenic emissions data compiled by governments for UNFCCC reporting using this approach. First, a complete C budget is needed in order to make relevant comparisons with fluxes derived from atmospheric CO_2 concentration data (Hayes and Turner 2012). A full biogenic carbon budget is not compiled by governments for reporting to the UNFCCC, requiring estimation of additional sources and sinks. Second, inventory data from individual emission categories, such as cropland and forestland, must be combined on a common grid from a variety of data sources with different spatial and temporal resolutions. Third, an

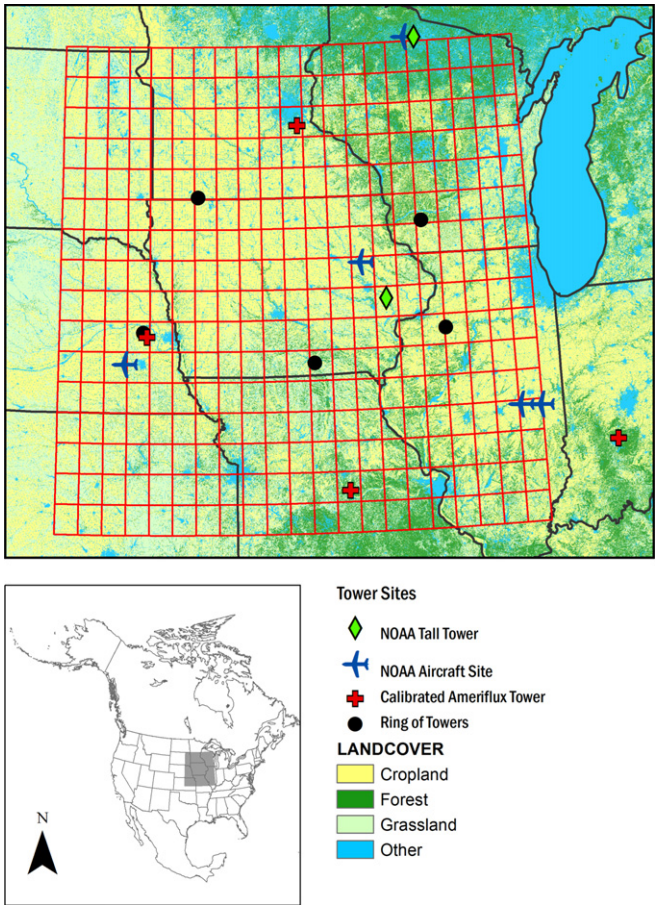

Figure 1. The Mid-Continent case study region shown in the 0.5° grid was located in an area dominated by agricultural operations in the Central United States.

approach was needed to statistically verify if CO_2 fluxes from the emissions inventory are consistent with fluxes estimated with atmospheric CO_2 concentration data based on the associated probability distributions for each set of fluxes.

Methods

Biogenic CO_2 emissions enventory

The biogenic CO_2 emissions inventory for this case study included emission categories associated with forest biomass, incorporation of C in wood products, and agricultural cropland and grassland soil C as reported in the United States GHG Inventory (US-EPA 2010, 2013) (table 1). Additional emission categories were needed to obtain the full C balance for comparison to CO_2 fluxes derived from atmospheric concentration data (Hayes and Turner 2012). Therefore, the inventory also included CO_2 emissions from decomposition of waste in landfills and agricultural residue burning (McCarty 2011), CO_2 uptake by agricultural crops and C in harvested grains, and CO_2 returned to the atmosphere from livestock and human respiration (West *et al* 2011). The emission categories can have a net positive or negative annual emission rate; net negative emissions result from CO_2 that is removed from the atmosphere and sequestered in biomass, soils or commodity products (e.g., harvested wood used in housing construction).

Agriculture dominates the study region requiring tracking C through crop and livestock production system. Cropland biomass was estimated based on county-scale crop yield data compiled in the USDA National Agricultural Statistics (USDA-NASS 2010), and crop-specific parameters for harvest indices, root: shoot ratios, moisture and C contents to convert the harvested grain data into units of C (West *et al* 2010, 2011). Grassland biomass stock changes were not estimated given the limited amount of data, and is likely a minor contributor to net C stock change in this region.

The residues remaining after harvest were burned or incorporated into soil C pools. CO_2 emissions from agricultural residue burning were estimated based on the area burned using 500 m MODIS 8-day Surface Reflectance Product (MOD09A1) and 1 km MODIS Active Fire Products (MOD14/MYD14) (McCarty *et al* 2009), fuel load (i.e., amount of crop residue biomass), combustion efficiency and CO_2 emission factors for residue burning (McCarty 2011). Soil C stock changes for agricultural cropland and grassland were

Table 1. Summary of commodity, census and remote sensing products that were used to estimate C stock changes and emissions, in addition to the spatial and temporal resolution of the original emission category data. References provide more information about the methods for deriving the estimates and uncertainties for each emission category. The asterisks (*) identifies CO_2 sources or sinks that are reported to the UNFCCC.

Biogenic emission category	Main data source	Spatial scale of data	Temporal scale of data	Inventory method references
Agricultural cropland and grassland C				
Harvested crop yield C	USDA-NASS agricultural statistics	County	Annual	West *et al* 2010
Cropland residue burning*	MODIS products (MOD09A1, MOD14/MYD14)	Sub-county (500 m)	8-day cycle	McCarty 2011
Soil C stock changes*	USDA-NRI land survey data	Sub-county (survey sample)	Daily	Ogle *et al* 2010, US-EPA 2013
Livestock respiration	USDA-NASS agricultural statistics	County	Annual	West *et al* 2011
Human respiration	United States population census	County	Annual	West *et al* 2011
Forestland C				
Biomass C stock changes*	USFS-FIA forest plot data	Sub-county (survey sample)	5 year intervals	Smith *et al* 2007a, 2007b, Heath *et al* 2011, Smith *et al* 2013, US-EPA 2010
Coarse woody debris/soil C Stock changes*	USFS-FIA forest plot data, STATSGO soil database	Sub-county (survey sample)	Annual average over 5–7 years	US-EPA 2010, Smith *et al* 2013
Harvested wood products*	US Department of Commerce statistics compiled/augmented by USFS	National, scaled to county	Annual	Skog 2008, Smith *et al* 2013, US-EPA 2010
Landfill decomposition	US-EPA landfill methane outreach program	County	Annual	This publication[a]

[a] Uncertainty in the landfill estimates was derived using a Monte Carlo approach by sampling probability distribution functions for the amount and fraction of degradable organic carbon that is decomposable, methane correction factor for aerobic decomposition, fraction of methane generated as landfill gas, and a reaction constant.

estimated by simulating the balance between C input from residues and C loss from decomposition using the land use and cropping histories from the USDA National Resources Inventory (USDA-NRCS 2009) using the DAYCENT ecosystem model (Ogle *et al* 2010, US-EPA 2013).

Harvested C from croplands is returned to the atmosphere within the region through livestock and human respiration. The remaining harvested C is transported and emitted in other regions of the United States or exported to foreign countries (West *et al* 2011). The exported C effectively represents a sink for CO_2 in the study region, but is ultimately returned to atmosphere through heterotrophic respiration in other regions. CO_2 emissions from human respiration were estimated from population data provided in the United States Population Census and total food intake by gender and age class (West *et al* 2009). CO_2 emissions from livestock respiration were derived from livestock population data compiled in the USDA National Agricultural Statistics (USDA-NASS 2010). The amount of C emitted as CO_2 was based on the difference between C intake from harvested grain and grazing pastures relative to C released as waste, milk, and methane, or incorporated into livestock growth (West *et al* 2011). C in manure was included as an input to the soil in the DAYCENT model simulations for soil C stock changes.

In addition to agricultural systems, carbon flows were monitored into forestland biomass, litter and soil C pools using the USDA Forest Service, Forest Inventory and Analysis data (FIA) (USFS 2009), and standard inventory-to-C conversion methods (Smith *et al* 2007a, 2007b, US-EPA 2010, Heath *et al* 2011, Smith *et al* 2013). Live biomass, standing and down coarse woody debris, and soil C are periodically surveyed by the FIA program. A portion of field plots are visited annually, but data were compiled across all plots for this analysis to increase precision. Average stock changes were estimated over five to seven year time blocks, which varied based on the frequency of individual plot resampling. A portion of the biomass C is harvested, removed from sites, and incorporated into wood products rather than returned to the atmosphere as CO_2 (Skog 2008, Heath *et al* 2011). Decay rates are applied to harvested wood products to estimate how much carbon remains in this pool over time.

Emissions from decomposition of waste in landfills were estimated at a county scale from information on waste disposal compiled in the US-EPA Landfill Methane Outreach Program from 2399 landfills (US-EPA 2012). CH_4 emissions were estimated according to IPCC methods (Pippatti and Svardal 2006), and were used to approximate the amount of CO_2 emissions based on guidelines developed by the US-EPA (US-EPA 2001), which assume equal amounts of CO_2 and CH_4 emissions for landfills.

Estimates and uncertainties for the biogenic emission categories were derived based on probability distribution functions for model parameters, structure and inputs as described elsewhere (see references in table 1). Some emission categories were estimated at sub-county spatial resolution or sub-annual time scales, but were aggregated to county and annual time scales for this analysis. The one exception was forest C, which was estimated on five to seven year time intervals, and were down-scaled based on annual averages. The result was a sample of 100 Monte Carlo draws of net annual emissions for all categories at a county scale. The county-scale data were interpolated to a 0.5° grid based on area weighting of the county data associated with each grid cell (figure 1). Total CO_2 emissions were estimated for each replicate draw by summing the emissions for all categories in a respective draw. The final estimate for each grid cell was the average of the 100 replicates. Uncertainty was quantified based on the standard deviation of total emissions at each location using the sample covariance matrix, capturing spatial correlation in the estimates across the entire grid. A standard shrinkage estimate was used to derive the uncertainty because the number of cells (i.e., 336) is greater than the number of Monte Carlo replicates (i.e., 100) (e.g., Schäfer and Strimmer 2005). To estimate fluxes at larger scales, we aggregated each replicate draw on the 0.5° grid to 1°, 2° and 4° grid resolutions, and the entire region.

Atmospheric measurements and inversion

The atmospheric CO_2 concentration measurement network consisted of a combination of flux towers with infrared gas analyzers (Stephens *et al* 2011), NOAA-ESRL tall radio towers with gas analyzers (Bakwin *et al* 1998), and cavity ring-down spectrometers deployed on cellular communications towers (Richardson *et al* 2012). Aircraft measurements from the NOAA-ESRL continental profiling network (Crevoisier *et al* 2010) and the Carbon Tracker global inversion system (Peters *et al* 2007) were used to provide CO_2 boundary conditions.

Inverse modeling was used to estimate the net flux of CO_2 between atmosphere and land surface based on variation in atmospheric CO_2 concentrations over space and time with knowledge of atmospheric transport (Lauvaux *et al* 2012a, 2012b, Schuh *et al* 2013). The regional inversion utilized the Weather Research and Forecast model for atmospheric transport (Skamarock *et al* 2005), Lagrangian particle dispersion model to associate surface fluxes and boundary conditions with atmospheric measurement data (Uliasz 1994), and a Bayesian style least squares solution technique to solve for the surface fluxes (Lauvaux *et al* 2012a). Prior flux estimates were obtained from the SiB-CROP model (Lokupitiya *et al* 2009). In order to focus on biogenic emissions, the atmospheric signal associated with fossil fuel emissions was subtracted

from the simulated CO_2 concentrations within the inverse modeling framework, using fine resolution fossil fuel emissions data (Gurney *et al* 2009).

Uncertainties were approximated for the *a priori* biogenic fluxes, the transport model, and the boundary conditions by performing sensitivity experiments across a range of plausible error estimates (Lauvaux *et al* 2012b). While the inversion utilized in the regional inverse modeling system provided a formal estimate of the uncertainty for the posterior fluxes, the uncertainty estimate was limited by assumptions inherent to the inverse model. To improve the estimation of uncertainty, Lauvaux *et al* (2012a) experimented with a number of the assumptions required by the regional inverse model including prior fluxes, CO_2 inflow at the domain boundaries, atmospheric CO_2 uncertainties (which encompasses transport, model-data mismatch, and observational uncertainties), and spatial coherence of corrections to prior fluxes. These experiments provided a range of posterior flux distributions and differences in the mean estimates, which were used in an ad hoc way to inflate the variance of a single inverse model simulation accounting for biases. Additional analysis of the degree of freedom in the signals showed that the inverse solution is primarily constrained by the atmospheric data rather than *a priori* information (Lauvaux *et al* 2012b). In the analysis presented here, the prior fluxes from SibCROP were not included because the annual C flux for the MCI region was imposed rather than simulated (Schuh *et al* 2013).

The inversion results and uncertainties, initially produced at a weekly time step with a 20 km resolution, were interpolated to a 0.5° grid covering the Mid-Continent study region (figure 1). This 0.5° grid did not correspond exactly to the domain on which the inversion was modeled and so the outer grid cells were removed that were only partially covered by the inversion (i.e., we did not extrapolate the results to cover the entire grid). This resulted in a slightly smaller study region and estimated CO_2 flux compared to previous publications (Lauvaux *et al* 2012a, Schuh *et al* 2013). Similar to the inventory, the data on the 0.5° grid were aggregated to the larger grid resolutions of 1°, 2° and 4°, as well as the entire region.

Verification analysis

Statistical hypothesis tests were used to formally verify the agreement between the emissions inventory and the CO_2 fluxes estimated from the atmospheric measurement network and the inverse model system. The tests are similar to two-sample t-tests for equality of means. However, a difference arises because rather than having repeated samples, this comparison is based on point estimates and covariance matrices. The information used in the hypothesis tests are the annual emissions totals on the 0.5° grid and the covariance matrices associated with the inverse modeling and inventory methods that describe both uncertainty at the location and spatial correlation between estimates on the grid. Temporal correlation was not relevant for this test because there was only one time step in the analysis.

To formalize, let $t_i^{(A)}$ denote the vector of fluxes estimated from the atmospheric CO_2 concentration data and inverse model system for each location in the study region. Likewise, let $t_i^{(E)}$ be the vector of fluxes from the emissions inventory. Let $\Sigma^{(A)}$ and $\Sigma^{(E)}$ represent the covariance matrices associated with the inversion and inventory respectively. All of the tests were performed to evaluate if $a^T t_i^{(A)}$ is significantly different from $a^T t_i^{(E)}$, where a is a vector which corresponds to the test performed. Underlying each test is the assumption that $t_i^{(A)}$ is normally distributed with mean μ and covariance matrix $\Sigma_i^{(A)}$, and likewise for $t_i^{(E)}$. Here, μ denotes the vector of true fluxes at each location in the study region. Our test statistic for each test is $a^T\left(t_i^{(A)} - t_i^{(E)}\right)$ under the assumptions that the statistic has a normal distribution with mean zero and variance $a^T\left(\Sigma_i^{(A)} + \Sigma_i^{(E)}\right)a$, and that $t_i^{(A)}$ is uncorrelated with $t_i^{(E)}$. Our tests account for the uncertainty associated with each estimate given the information comprising $\Sigma^{(A)}$ and $\Sigma^{(E)}$.

Verification of the emissions inventory using atmospheric CO_2 concentration data were evaluated at 0.5°, 1°, 2° and 4° grid resolutions, as well as the entire region. Differences were considered significant at an alpha level of 0.05. This analysis does not address multiple testing issues. However, the main purpose is to explore differences, and then further evaluate the inventory, to the extent that differences are found, and determine if an error exists. Consequently there are minimal consequences for identifying a statistically significant difference when there are no differences in reality (i.e., type I error).

Results

The Mid-Continent region was a net sink for biogenic CO_2 fluxes in 2007 according to the emissions inventory (table 2, figure 2). The flux was dominated by C uptake driven by crop production and export of grain from the region. Other emission categories contributing to the biogenic sink include forest growth, and incorporation of C into wood products, and C sequestration in agricultural soils (table 2, figure 2). Livestock respiration produced the largest net positive biogenic emissions to the atmosphere. Other biogenic emission categories such as CO_2 emissions from human respiration, crop residue burning or decomposition of waste in landfills were smaller contributors to the regional flux.

Measurements of CO_2 concentrations also indicated a strong biogenic CO_2 sink over the study region during the 2007 summer growing season, June

Table 2. CO_2 emissions (Tg CO_2 eq.) associated with individual sources of biogenic emissions in the Mid-Continent study region. Forestland C stock change includes biomass, coarse woody debris, soil and harvested wood products.

Biogenic emission categories	Estimate (Tg CO_2 eq)	95% Confidence interval
Cropland harvested yield C	−367.97	−497, −239
Forestland C stock changes	−85.08	−107.7, −62.4
Agricultural soil C stock changes	−33.56	−58.3, −8.7
Agricultural residue burning	0.79	0.78, 0.80
Landfill decomposition	2.16	1.29, 3.03
Human respiration	18.85	18.84, 18.86
Livestock respiration	56.73	30.48, 82.98
Total emissions inventory	−408.1	−544, −272
Total atmospheric inversion	−478.0	−624, −332

through August, consistent with the period of highest crop growth (Miles *et al* 2012, Lauvaux *et al* 2012a). Midday atmospheric boundary layer CO_2 concentrations had a very strong seasonal cycle over the middle of region from Southwest Minnesota to Northern Illinois (>35 ppm), which is dominated by corn and soybean production (figure 2). There was also a reduced but substantial seasonal cycle in Northern and Southern portions of the region (>25 ppm) (Corbin *et al* 2010, Miles *et al* 2012).

According to the biogenic emissions inventory, there was a net flux of −408 Tg CO_2 from the atmosphere into the study region during 2007, with a 95% confidence interval of ±136 Tg CO_2. The estimated biogenic flux was -478 ± 146 Tg CO_2 based on the atmospheric CO_2 concentration data and inversion. Consequently, the CO_2 flux according to the biogenic emissions inventory was not statistically different from the inversion. A non-significant result means that the emissions inventory is consistent and verifiable with the changes in atmospheric CO_2 concentrations, given their associated uncertainties.

Comparisons were also made between the inventory and inversion results across incrementally larger resolutions within the Mid-Continent study region, including 0.5°, 1 °, 2°, and 4° resolution grid scales (see figure 2 for 0.5° gridded data). No significant differences were found at any of the scales, except at the 0.5° scale in one isolated area of West-central Wisconsin, near the border with Minnesota. The isolated area was largely dominated by forestland, suggesting further investigation may be needed into small scale forest inventory data in this region and harvested wood product estimates.

The relative uncertainty associated with the inventory and inversion results changed with the spatial scale from the entire region to the finest resolution of a 0.5° (figure 3). However, the change in uncertainty across the scales was much greater for the inversion results. The inversion analysis was well constrained at the scale of the entire region with a coefficient of variation of 0.16, which was similar to the coefficient of variation of 0.17 for the CO_2 flux from the emissions inventory. The relative uncertainty increased dramatically in the atmospheric inversion with an average coefficient of variation of 0.91 at the 0.5° resolution, compared to a value of 0.43 for the flux estimates from the inventory.

Discussion

The results of the Mid-Continent case study show promise for using atmospheric CO_2 concentration data and inverse modeling systems to verify biogenic GHG emission inventories. North American continental scale comparisons have also been made in previous studies and demonstrated that emissions inventories are consistent with inversions of atmospheric CO_2 measurements, even though the estimates could vary by more than 1000 Tg CO_2 (Pacala *et al* 2001, Gourdji *et al* 2012, Hayes *et al* 2012, King *et al* 2012). The large differences may be caused by biases in the transport models (Baker *et al* 2006), or unrealistic constraints imposed on the inverse modeling system resulting from limited atmospheric CO_2 measurement data. The Mid-Continent study attempted to overcome limitations in CO_2 observations with a network of measurements that was denser than typically available for deriving an atmospheric-based C budget (figure 1).

Errors in the emissions inventory may have also contributed to the large differences in past comparisons with inverse modeling results due to limited, inconsistent or no data collection for certain land surface processes that influence CO_2 fluxes, such as woody encroachment in the Southwestern United States (Hayes *et al* 2012), or urban trees in regions with a large proportion of metropolitan areas (Nowak *et al* 2013). However, the Mid-Continent case study utilized extensive land-based surveys, remote sensing products, census data and commodity statistics that are collected to support trade in this important economic region for agriculture. One notable gap in the inventory, however, was the lateral transport of C from terrestrial systems into rivers and lakes (Butman and Raymond 2011). While it is less likely that limited or missing data is an issue in this region, there are still uncertainties associated with gaps that will require further study.

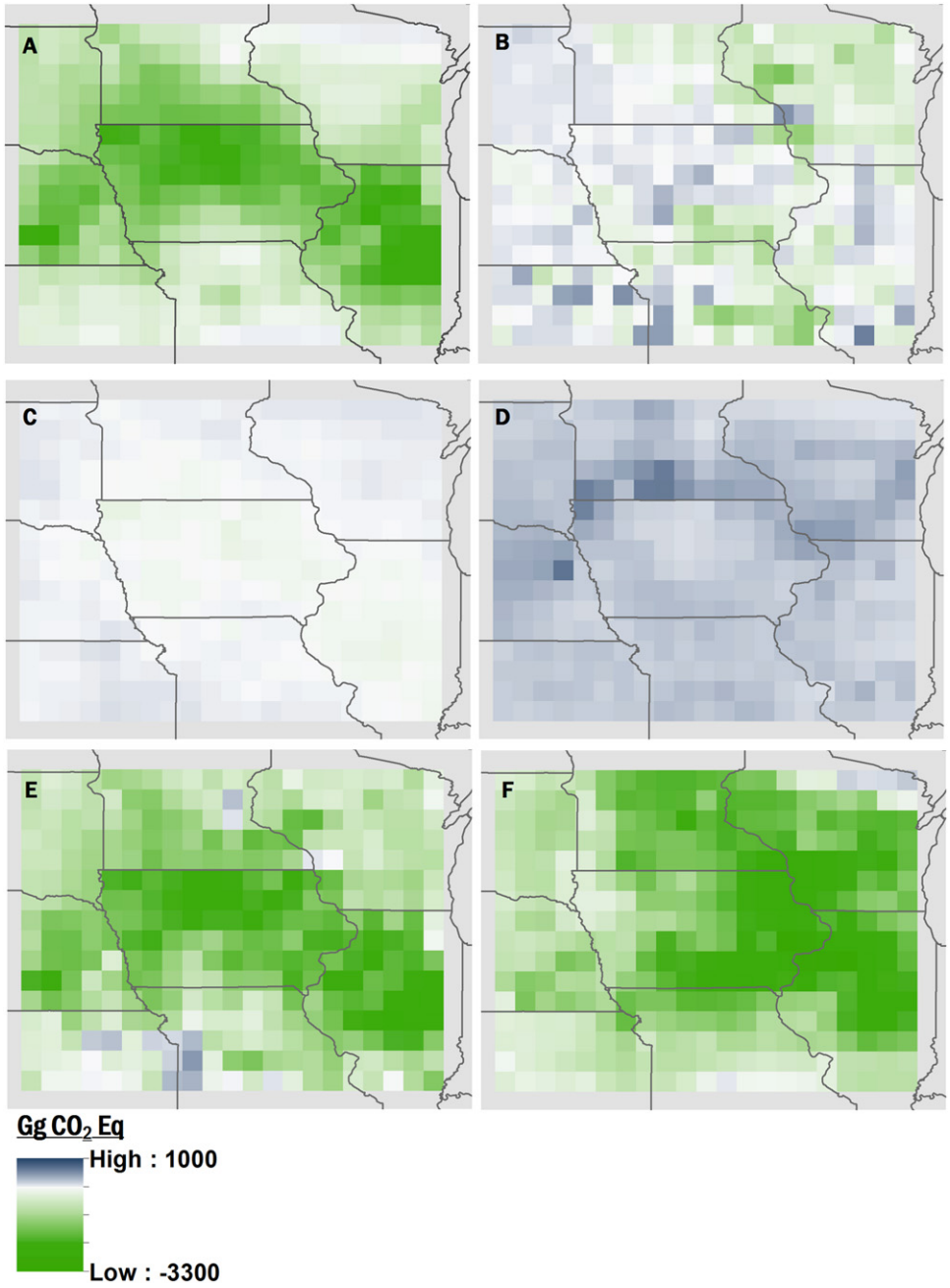

Figure 2. Net annual CO_2 emissions (Gg CO_2) in 2007 at a 0.5° spatial resolution from dominant emission categories in the Mid-Continent study region, including (A) cropland harvested crop biomass, (B) forest C stock changes and harvested wood products, (C) agricultural soil C stock changes, (D) livestock respiration emissions, (E) total biogenic emissions inventory, and (F) atmospheric CO_2 inversion. Negative emissions represent a net annual CO_2 uptake from the atmosphere to the land surface, and positive emissions represent a net annual release of CO_2 to the atmosphere from the land surface. CO_2 emissions from landfills, human respiration and agricultural residue burning have smaller net annual fluxes.

The uncertainty in the inventory and inversion results both increased from the largest scale of the entire region to the finer resolutions of 4°, 2 °, 1°, and 0.5° gridded CO_2 fluxes (figure 3). However, the uncertainty increased more with the inversion estimates than the inventory. The higher precision in the inventory estimates at smaller scales is likely due to finer resolution data that were used to estimate the emissions, such as county-scale agricultural statistics and forest plot data. In contrast, the inversion relied on the atmospheric concentration data dispersed in a ring near the boundary of the region (figure 1). To obtain more precise estimates, the atmospheric inversion would likely require more towers dispersed within the region, providing more spatially-detailed data on atmospheric CO_2 concentrations. Regardless, the relatively high precision in the inversion results for the entire region suggests that the design of the network as a ring surrounding the region can provide a reasonable constraint on the total regional flux (Lauvaux *et al* 2012a).

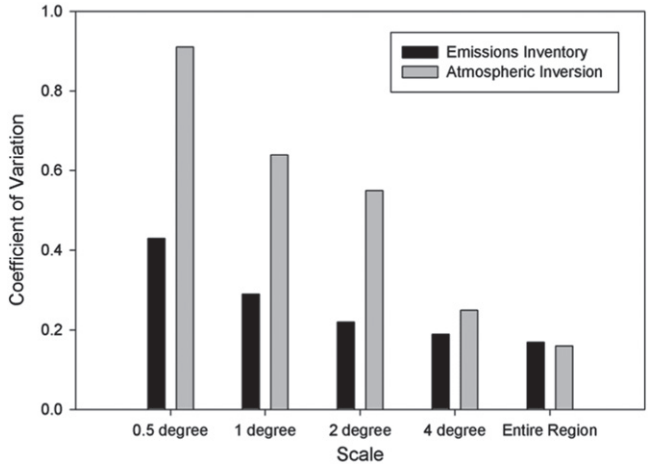

Figure 3. Coefficient of variation (i.e., standard deviation divided by the median, which is a measure of the relative uncertainty) averaged across the grid cells for biogenic CO_2 emissions inventory and atmospheric inversion at several scales, including 0.5°, 1°, 2°, and 4° grids, in addition to the entire region.

If biogenic emissions inventories are to be verified by an operational atmospheric CO_2 measurement and inverse modeling system, additional information will be needed beyond current requirements for national GHG inventory reporting to the UNFCCC. First, non-anthropogenic sources of biogenic emissions must be estimated to be comparable to CO_2 fluxes estimated from atmospheric concentration data because both anthropogenic and non-anthropogenic activities are integrated in the atmosphere. UNFCCC reporting of biogenic emissions currently only requires estimation of activity on managed land, while biogenic emissions from other areas are considered non-anthropogenic and hence, not included in an inventory (IPCC 2006, IPCC 2010).

Second, some components of the C budget that are influenced by anthropogenic activity are largely ignored in a national GHG inventory. In these cases, the impact on atmospheric CO_2 concentrations is considered transient with limited effect outside of an annual cycle. One example is the production and use of agricultural commodities that remove and return about the same amount of C to the atmosphere on annual time scales (Ciais *et al* 2007, West *et al* 2011). However, documenting the location of biogenic C uptake and release in commodities will be necessary in a national GHG inventory to make valid comparisons with fluxes estimated from atmospheric CO_2 concentration data.

The Mid-Continent region is a nearly optimal location for this case study due to the strong influence of biogenic emission categories on the CO_2 flux (e.g., agricultural crop production); relatively simple terrain and abundant meteorological data for the inverse modeling; and extensive land surveys and commodity data to support the inventory compilation (figure 1). Further testing in other regions is warranted. Moreover, new satellite-based CO_2 data are emerging that can be incorporated into inverse modeling (Crisp *et al* 2004, Houweling *et al* 2004, Kadygrov *et al* 2009), and studies are suggesting that inversion results can be further optimized by combining in situ atmospheric CO_2 concentration data from a ground-based network and aircraft campaigns, with the emerging satellite-based CO_2 data (Nassar *et al* 2011, Keppel-Aleks *et al* 2011, Basu *et al* 2013, Lauvaux and Davis 2014).

The goals of a verification system for biogenic emissions will need to be clarified before mobilizing an operational CO_2 measurement and inverse modeling system to support emissions reporting. The levels of accuracy and precision, and the spatial and temporal resolution required will dictate the investment to create a functional system. In addition, an operational system could be used to verify total biogenic emissions from a region, as we have presented here, or it could be used in combination with the inventory data to produce emission estimates. For example, Cooley *et al* (2013) found that the uncertainty in the total CO_2 flux for the Mid-Continent region is reduced by 21% if the results from the emissions inventory and inverse modeling system are combined into a single CO_2 emissions estimate.

Conclusions

Our study demonstrates how atmospheric CO_2 concentration data combined with inverse modeling technology could provide a robust check on biogenic emissions inventories using statistical methods applied in the Mid-Continent case study. This level of evaluation would complement other forms of verification, such as evaluation of inventory methods for consistency with UNFCCC reporting guidelines, confirmation that management practices have been adopted to enhance biogenic sinks, or evaluation of C stock changes and fluxes at specific locations in a

region. Over time, incorporating verification based on the atmospheric CO_2 concentration data is likely to produce more accurate and credible estimates for reporting biogenic emissions to the UNFCCC, as errors are discovered and corrected. In turn, more credible estimates will lead to less uncertainty for developing and monitoring the outcomes of climate change policies associated with biogenic sources and sinks.

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