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The Role of Trace Gas Flux Networks in the Biogeosciences

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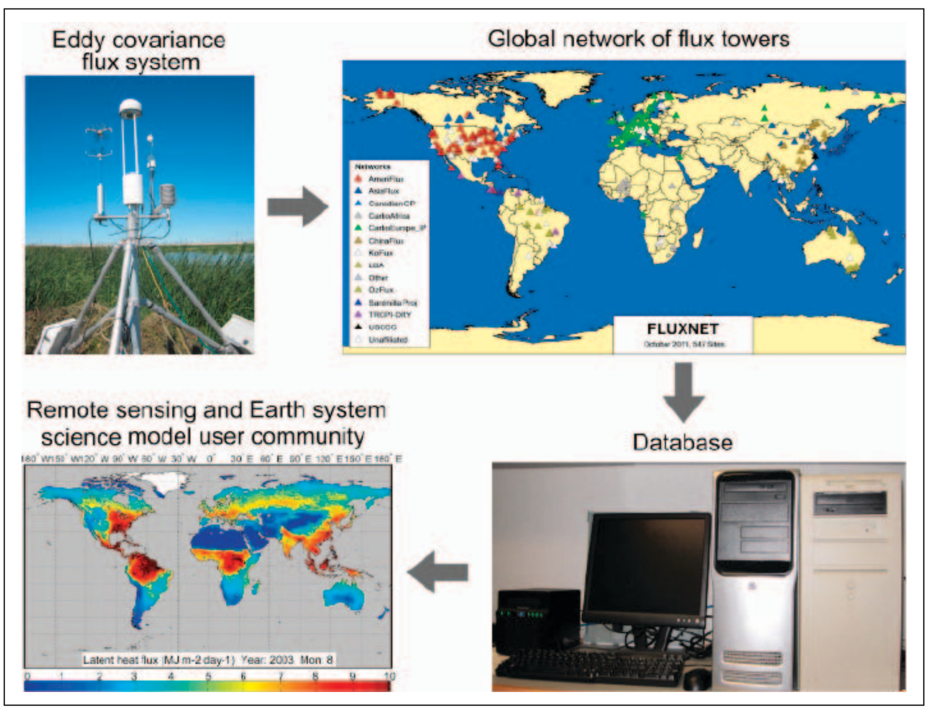
Vast networks of meteorological sensors ring the globe, providing continuous measurements of an array of atmospheric state variables such as temperature, humidity, rainfall, and the concentration of carbon dioxide [*New et al.*, 1999; *Tans et al.*, 1996]. These measurements provide input to weather and climate models and are key to detecting trends in climate, greenhouse gases, and air pollution. Yet to understand how and why these atmospheric state variables vary in time and space, biogeoscientists need to know where, when, and at what rates important gases are flowing between the land and the atmosphere. Tracking trace gas fluxes provides information on plant or microbial metabolism and climate-ecosystem interactions.

The existence of trace gas flux networks is a relatively new phenomenon, dating back to research in 1984. The first gas flux measurement networks were regional in scope and were designed to track pollutant gases such as sulfur dioxide, ozone, nitric acid, and nitrogen dioxide. Atmospheric observations and model simulations were used to infer the depositional rates of these hazardous chemicals [*Fowler et al.*, 2009; *Meyers et al.*, 1991]. In the late 1990s, two additional trace gas flux measurement networks emerged. One, the United States Trace Gas Network (TRAGNET), was a short-lived effort that measured trace gas emissions from the soil and plants with chambers distributed throughout the country [*Ojima et al.*, 2000]. The other, FLUXNET, was an international endeavor that brought many regional networks together to measure the fluxes of carbon dioxide, water vapor, and sensible heat exchange with the eddy covariance technique [*Baldocchi et al.*, 2001]. FLUXNET, which remains active today, currently includes more than 400 tower sites, dispersed across most of the world's climatic zones and biomes, with sites in North and South America, Europe, Asia, Africa, and Australia. More recently, several specialized networks have emerged, including networks dedicated to urban areas (Urban Fluxnet), nitrogen compounds in Europe (NitroEurope), and methane (MethaneNet).

Technical Aspects of Flux Networks

Eddy covariance flux measurements are the preferred method by which biogeoscientists measures trace gas exchange between ecosystems and the atmosphere [*Baldocchi*, 2003]. In the eddy covariance technique, trace gas fluxes are calculated from the instantaneous changes in the vertical wind velocity and atmospheric gas concentration. A key attribute of the eddy covariance method is its ability to measure fluxes in situ with minimal disturbance to the environment, at a spatial scale of hundreds of meters, and on time scales spanning hours, days, and years.

For the eddy covariance method to work, trace gas sensors must be able to respond to fluctuations in atmospheric gas concentrations over as little as a tenth of a second, maintain a stable calibration, possess a high signal-to-noise ratio, and, in cases where pumps are needed to move air to the sensor, have access to a power line. The current generation of carbon dioxide and water vapor sensors easily meets these criteria, and a revolution in instrument development is producing trace gas sensors capable of measuring a broad suite of compounds at high sampling rates with high sensitivity and precision. Those measuring stable isotopes of carbon, oxygen, and carbonyl sulfide can help partition fluxes between the vegetation and the soil. Those measuring methane and nitrous oxide can assess microbial activity in the soil. And measurements of hydrocarbons, ozone, and nitrogen oxides can assess



The components of a flux network: (top left) An eddy covariance flux tower, which acts as one site in (top right) a global network (FLUXNET, a component of NASA's Oak Ridge National Laboratory Distributed Active Archive Center (ORNL DAAC)) that produces data that are merged and distributed through (bottom right) an integrative database. These data, used in conjunction with models and remote sensing information, produce (bottom left) high-resolution, spatially gridded maps of trace gas fluxes between the land and the atmosphere.

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pollutant loads on the atmosphere. For gases whose sensors are too slow, such as nitric acid and mercury vapor, one can rely on the relaxed eddy accumulation method or flux gradient techniques to measure their fluxes [*Dabberdt et al.*, 1993].

While many of these sensors can be operated unattended, the best data tend to come from sites where technicians, students, and postdoctoral researchers pay frequent visits to ensure the instruments are maintained and calibrated. Nevertheless, there will likely always be gaps in the observational record due to instrument malfunction or failure caused by disturbances from rain, snow, animals, insects, and vandalism. Other data gaps result from rejecting data when air travels from a wind direction that is not representative of the ecosystem under study. To test and validate models and construct trace gas budgets, data gaps need to be filled in systematic and vetted ways to compute integrated fluxes on daily and annual time scales [*Falge et al.*, 2001; *Moffat et al.*, 2007].

To interpret trace gas fluxes, it is critical that a suite of data that characterize meteorological conditions, land use and disturbance history, and the state of the vegetation and soil be measured concurrently. Some plant and soil variables, such as leaf area index and predawn water potential, must be measured manually and regularly, while others, including the dynamics of canopy structure, can be measured remotely and continuously with digital cameras and spectral radiometers. Wireless networks of soil moisture and temperature sensors can quantify the spatial and temporal variation of soil conditions within the area surrounding a flux measurement tower.

What Information Do Networks of Flux Towers Produce?

Individual flux towers provide information on the daily, seasonal, annual, and interannual variations in trace gas fluxes for a given plant functional type in a specific climate region and biome. Such observations provide insight into how the flows of trace gases may respond to changes in biophysical drivers such as light, temperature, soil moisture, and leaf area index.

Groups of towers at the landscape, regional, continental, and global scales allow scientists to study a greater range of climate and ecosystem conditions such as the dominant plant functional type; biophysical attributes; biodiversity; time since the last disturbance from fire, logging, wind throw, flooding, or insect infestation; or the effect of management practices such as fertilization, irrigation, or cultivation. A global flux network has the potential to observe how ecosystems are affected by, and recover from, low-probability but high-intensity disturbances associated with rare weather events.

So far, flux measurement networks have revealed a number of new insights on the consequences of environmental change. They have yielded unique information on how annual sums of trace gas fluxes covary with climate, plant functional type, drought, heat spells, and nitrogen deposition [*Law et al.*, 2002; *Magnani et al.*, 2007; *Reichstein et al.*, 2007]. They have revealed how biophysical variables, including albedo and canopy height, vary with plant functional type and nutrition [*Hollinger et al.*, 2010; *Simard et al.*, 2011]. They are improving scientists' understanding of phenology, the study of how seasonal or climatic change affects the timing of plant behavior [*Richardson et al.*, 2012]. They are also monitoring the effect of pollution control efforts on deposition [*Fowler et al.*, 2009].

Networks that focus on measuring surface-atmosphere carbon dioxide exchange have produced new information on how the length of the growing season modulates annual photosynthesis; how peak photosynthesis acclimates with temperature increases; how light use efficiency increases with the fraction of diffuse, rather than direct, sunlight; how photosynthetic capacity varies with season; how rain induces large pulses in ecosystem respiration; and how the net ecosystem-atmosphere carbon exchange varies with the time since the last disturbance [*Amiro et al.*, 2010; *Baldocchi*, 2008; *Reichstein et al.*, 2007].

There is also potential to apply flux networks toward problems associated with network theory [*Newman*, 2003]. Recently, flux networks were used to produce new information on feedbacks between carbon and water fluxes and meteorological and soil conditions using transfer entropy methods [*Kumar and Ruddell*, 2010].

Attributes of Effective Networks

An effective flux network possesses a number of key attributes. Data are best when there are standards and protocols for instrument performance, data quality, and calibration; data gaps are minimized if redundant or replacement sensors are available.

Data are converted into information and knowledge when there is a shared and integrated database [*Agarwal et al.,* 2010; *Papale et al.,* 2012], with which researchers can merge flux measurements with a cohort of meteorological, ecological, and soil variables. A centralized database can harmonize data processing, produce value-added products such as daily or annual sums or averages, establish version control and sharing policies, and archive data. Databases can be queried to pull data for specific times, locations, or variables.

The success of a scientific flux network relies on creating a human network too. Data sharing depends on fostering trust among colleagues, crossing cultural and political obstacles and devising a fair use data sharing policy. Shared leadership and frequent communication through workshops, internet forums, and newsletters can also help to build trust.

Current Activities and Future Opportunities

In research done in collaboration with the remote sensing and Earth system modeling communities, scientists are finding flux networks to be a critical tool in efforts to produce information on trace gas fluxes that are occurring everywhere, all of the time. Biophysical, biogeochemical, and ecological models that diagnose and forecast the state of the land's trace gas budgets depend on data from a network of "supersites" that measure a broad suite of site characteristics to identify or quantify important biophysical processes and develop parameterizations for mechanistic algorithms.

Other types of models need a dense network of less intensive flux measurement sites that are sampling representative climate and ecological spaces. These models digest flux, remote sensing, and climate data to produce maps of trace gas fluxes at regional, continental, and global scales using neural networks, regression trees, or genetic algorithms [*Jung et al.,* 2011]. Improvements in empirical machine learning models will require additional flux measurement instruments to be installed in clusters at sites that experience different types of ecosystem disturbances or that include underrepresented climate and ecological spaces such as the tropics and tundra, where spatial gaps in current flux measurement networks remain the greatest.

At present, data generated by flux measurement networks are being used to test and improve the land-atmosphere flux algorithms used in climate models [*Bonan et al.,* 2011]. They may also be used in the next generation of data assimilation models, which use Bayesian statistics and are coupled to climate and weather models [*Williams et al.,* 2009]. In addition, flux networks have the potential to supply data that will be used to validate maps of sources and sinks that are being generated by the global network of trace gas concentration monitors and those that will be generated from inverting the next generation of satellite-based carbon dioxide observations.

Sustained operation of flux networks, through programs such as the National Ecological Observation Network or the Integrated Carbon Observation System, has the potential to detect long-term and gradual ecological changes that are occurring against the background of faster physiological variations as carbon dioxide concentrations and air temperature continue to rise. Finally, there is potential to use information emerging from flux networks to better quantify carbon sources and sinks for carbon market valuation, to inform land use policy, and to provide information on pollutant deposition for assessing the efficacy of pollution control policies.

References

Agarwal, D. A., M. Humphrey, N. F. Beekwilder, K. R. Jackson, M. M. Goode, and C. van Ingen (2010), A data-centered collaboration portal to support global carbon-flux analysis, *Concurrency Comput. Pract. Exper., 22*(17), 2323–2334, doi:10.1002/cpe.1600.

Amiro, B. D., et al. (2010), Ecosystem carbon dioxide fluxes after disturbance in forests of North America, *J. Geophys. Res., 115,* G00K02, doi:10.1029/2010JG001390. [Printed 116(G4), 2011.]

Baldocchi, D. D. (2003), Assessing the eddy covariance technique for evaluating carbon dioxide exchange rates of ecosystems: Past, present and future, *Global Change Biol., 9,* 479–492, doi:10.1046/j.1365-2486.2003.00629.x.

Baldocchi, D. D. (2008), 'Breathing' of the terrestrial biosphere: Lessons learned from a global network of carbon dioxide flux measurement systems, *Aust. J. Bot., 56*(1), 1–26. doi:10.1071/BT07151

Baldocchi, D. D., et al. (2001), FLUXNET: A new tool to study the temporal and spatial variability of ecosystem-scale carbon dioxide, water vapor, and energy flux densities, *Bull. Am. Meteorol. Soc., 82*(11), 2415–2434, doi:10.1175/1520-0477(2001)082<2415:FANTTS>2.3.CO;2.

Bonan, G. B., P. J. Lawrence, K. W. Oleson, S. Levis, M. Jung, M. Reichstein, D. M. Lawrence, and S. C. Swenson (2011), Improving canopy processes in the Community Land Model version 4 (CLM4) using global flux fields empirically inferred from FLUXNET data, *J. Geophys. Res., 116,* G02014, doi:10.1029/2010JG001593.

Dabberdt, W. F., D. H. Lenschow, T. W. Horst, P. R. Zimmerman, S. P. Oncley, and A. C. Delany (1993), Atmosphere-surface exchange measurements, *Science, 260*(5113), 1472–1481, doi:10.1126/science.260.5113.1472.

Falge, E., et al. (2001), Gap filling strategies for defensible annual sums of net ecosystem exchange, *Agric. For. Meteorol., 107,* 43–69, doi:10.1016/S0168-1923(00)00225-2.

Fowler, D., et al. (2009), Atmospheric composition change: Ecosystems-atmosphere interactions, *Atmos. Environ., 43*(33), 5193–5267, doi:10.1016/j.atmosenv.2009.07.068.

Hollinger, D. Y., et al. (2010), Albedo estimates for land surface models and support for a new paradigm based on foliage nitrogen concentration, *Global Change Biol., 16*(2), 696–710, doi:10.1111/j.1365-2486.2009.02028.x.

Jung, M., et al. (2011), Global patterns of land-atmosphere fluxes of carbon dioxide, latent heat, and sensible heat derived from eddy covariance, satellite, and meteorological observations, *J. Geophys. Res., 116,* G00J07, doi:10.1029/2010JG001566.

Kumar, P., and B. L. Ruddell (2010), Information driven ecohydrologic self-organization, *Entropy, 12*(10), 2085–2096, doi:10.3390/e12102085.

Law, B. E., et al. (2002), Environmental controls over carbon dioxide and water vapor exchange of terrestrial vegetation, *Agric. For. Meteorol., 113*(1-4), 97–120, doi:10.1016/S0168-1923(02)-00104-1.

Magnani, F., et al. (2007), The human footprint in the carbon cycle of temperate and boreal forests, *Nature, 447*(7146), 849–851, doi:10.1038/nature05847.

Meyers, T. P., B. B. Hicks, R. P. Hosker Jr., J. D. Womack, and L. C. Satterfield (1991), Dry deposition inferential measurement techniques—Part II. Seasonal and annual deposition rates of sulfur and nitrate, *Atmos. Environ. Part A, 25*(10), 2361–2370, doi:10.1016/0960-1686(91)90110-S.

Moffat, A. M., et al. (2007), Comprehensive comparison of gap-filling techniques for eddy covariance net carbon fluxes, *Agric. For. Meteorol., 147*(3-4), 209–232, doi:10.1016/j.agrformet.2007.08.011.

New, M., M. Hulme, and P. Jones (1999), Representing twentieth-century space-time climate variability. Part I: Development of a 1961–90 mean monthly terrestrial climatology, *J. Clim., 12*(3), 829–856, doi:10.1175/1520-0442(1999)012<0829:RTCSTC>2.0.CO;2.

Newman, M. E. J. (2003), The structure and function of complex networks, *SIAM Rev., 45,* 167–256, doi:10.1137/S003614450342480

Ojima, D., A. Mosier, S. Del Grosso, and W. J. Parton (2000), TRAGNET analysis and synthesis of trace gas fluxes, *Global Biogeochem. Cycles, 14*(4), 995–997, doi:10.1029/2000GB001331.

Papale, D., D. Agarwal, D. Baldocchi, R. Cook, J. B. Fisher, and C. van Ingen (2012), Database maintenance, data sharing policy, collaboration, in *Eddy Covariance: A Practical Guide to Measurement and Data Analysis,* edited by M. Aubinet, pp. 399–424, Springer, New York.

Reichstein, M., et al. (2007), Determinants of terrestrial ecosystem carbon balance inferred from European eddy covariance flux sites, *Geophys. Res. Lett., 34,* L01402, doi:10.1029/2006GL027880.

Richardson, A. D., et al. (2012), Terrestrial biosphere models need better representation of vegetation phenology: Results from the North American Carbon Program site synthesis, *Global Change Biol., 18*(2), 566–584, doi:10.1111/j.1365-2486.2011.02562.x.

Simard, M., N. Pinto, J. B. Fisher, and A. Baccini (2011), Mapping forest canopy height globally with spaceborne lidar, *J. Geophys. Res., 116,* G04021, doi:10.1029/2011JG001708.

Tans, P. P., P. S. Bakwin, and D. Guenther (1996), A feasible global carbon cycle observing system: A plan to decipher today's carbon cycle based on observations, *Global Change Biol., 2,* 309–318. doi:10.1111/j.1365-2486.1996.tb00082.x

Williams, M., et al. (2009), Improving land surface models with FLUXNET data, *Biogeosciences, 6*(7), 1341–1359, doi:10.5194/bg-6-1341-2009.

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