CarboScale: Scaling carbon flux from towers to the northern landscape

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Summary

The northern hemisphere is a region where climate change impact is highly significant. However, detailed knowledge about carbon balance mechanisms in this region is still incomplete. Uncertainties of spatial and temporal vegetation variability prevent accurate use of carbon flux data as well as modeling of the carbon cycle and its link to the climate. The project thus aims at achieving improved understanding of ecosystem scale carbon exchange. We focus on spatial and dynamic vegetation variables for upscaling from flux towers to landscape level. Specific research aims are to: (1) Understand the influence of spatial heterogeneity of vegetation and land surface on ecosystem carbon fluxes. (2) Understand the influence of temporal vegetation variations related to phenology, snow seasonality, and wetness/drought on ecosystem carbon fluxes. (3) Based on new understanding, derive an approach to upscale carbon fluxes from towers to landscape level using spectral indices derived from remotely sensed data. The project integrates micrometeorology with novel remote sensing data from ground, unmanned aerial vehicle (UAV), and new high-resolution satellite data. Spatial and temporal modeling is used for enabling upscaling of flux data to landscape level. The 4-year project will develop a framework for upscaling flux data from infrastructures such as FLUXNET, ICOS and SITES, thereby increasing the usefulness of these data for national and global carbon assessments and modeling.

Project objective

This project addresses knowledge gaps regarding estimation of carbon flux dynamics at landscape scale at northern latitudes. The research objective is to achieve an improved understanding of processes regulating ecosystem scale carbon exchange. We focus on spatial and dynamic vegetation variables for upscaling from flux towers to landscape level, and hypothesize that better knowledge of these variables will enable more accurate upscaling. Specific aims are to:

1. Understand the influence of spatial heterogeneity of vegetation and land surface on ecosystem carbon fluxes.
2. Understand the influence of temporal vegetation variations related to phenology, snow seasonality, and wetness/drought on ecosystem carbon fluxes.
3. Based on new understanding, derive an approach to upscale carbon fluxes from towers to landscape level using spectral indices derived from remotely sensed data.

The project uses novel methodology and will develop a framework for scaling flux data from ground based infrastructures such as FLUXNET (http://fluxnet.ornl.gov), ICOS (http://www.icos-infrastructure.eu) and SITES (http://www.fieldsites.se), thereby increasing their usefulness for national and global carbon assessments.

Survey of the field

Northern land ecosystems show a major and increasing role in the global carbon cycle [1]. Although the biogeochemistry of the carbon cycle is well known, its patterns are not so clearly related to climate variables [2], particularly regarding interannual variability [3]. Important drivers affecting carbon fluxes are longer growing seasons [3-6], snow dynamics [7], water stress and water use efficiency [8-10] and vegetation heterogeneity [11, 12]. Large uncertainties in the knowledge of these patterns make regional and national estimates of carbon balances and climate impact highly uncertain [13, 14]. Reducing this uncertainty would contribute to significantly better understanding of climate change and its effect on the carbon cycle.

Flux towers provide essential data for process understanding [15]. However, vegetation heterogeneity in the immediate vicinity of a flux tower may strongly affect measured fluxes [16, 17]. Also non-forested sites may be heterogeneous, e.g. species variations in mires due to micro-topography. For accurate matching between tower fluxes and its surrounding areas, footprint models should be used. These provide the 'field-of-view' of eddy-covariance instruments [18-20]. Figure 1 (App J1) illustrates how vegetation variations near a flux tower can affect measurements.

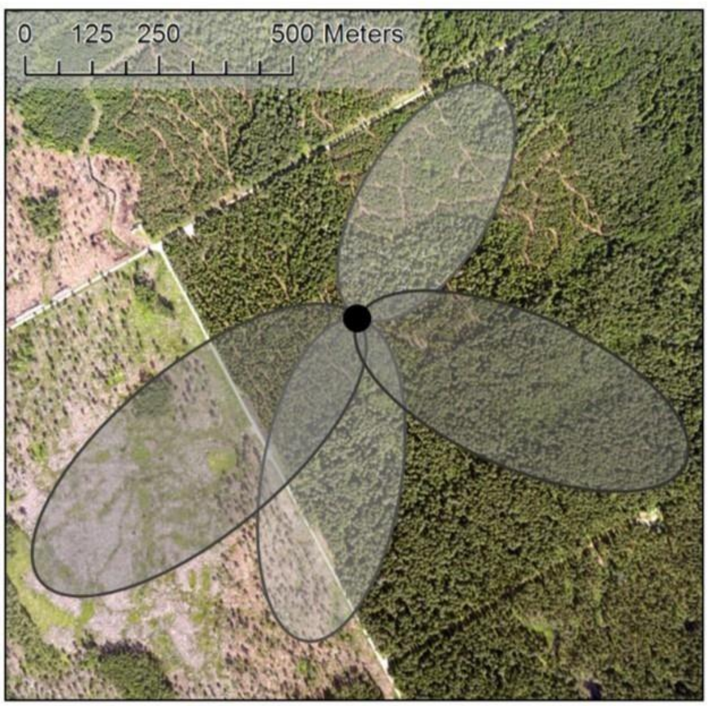

Figure 1: Example of four footprints displaying the source area of four time steps of flux measurements (30-min averages). Due to site-specific main wind directions, some land-cover / vegetation types might not 'be seen' by the flux instruments and will not contribute to the measured fluxes. The black dot denotes the flux-tower location.

Though footprint models can reduce scaling errors in GPP estimation [19] their use has not yet been fully explored [20, 21]. The models are usually driven for average conditions using static and site-averaged vegetation data. Providing data and methodology for an improved description of footprint variability is essential to improve the understanding of the impact of vegetation heterogeneity.

High-resolution dynamic data for footprint modelling can be provided by spectral data. Fixed field-installed spectral sensors can monitor biophysical vegetation parameters related to carbon fluxes [22]. These track photosynthetic activity within flux footprint areas, and can reveal influences of e.g. snowmelt, understory vegetation, and insect attacks [23]. To obtain full spatial coverage, spectral data collection from UAV (unmanned aerial vehicle) is a cost-effective novel option. Multispectral cameras and light-weight field spectrometers onboard UAVs enable detailed spatial sampling across the footprints, thereby bridging the scale gap between fixed point measurements and data from satellite sensors. This field is just emerging and the combination of fine-grained spectral data collection in time and space with footprint modeling has yet to be developed.

Consistent scaling from towers to the landscape for carbon modelling can be done with remote sensing [24-27]. However, the coarse scale and lack of precision has so far prevented accurate flux variability estimates of the towers. Today, the UAV technology as well as data from the new European Sentinel-2 satellite opens radically new possibilities to overcome these limitations. Sentinel-2 will in early 2016 generate very accurate (10-m) data at 2-5 days' time interval for mapping the vegetation in the flux footprint areas and beyond.

The fixed sensors, UAV and satellites provide data at widely different temporal and spatial scales that need to be integrated [28]. A flexible way to do this is Bayesian modelling [29, 30]. It has, for example, been successfully applied in for air pollution [31, 32], satellite wind measurements [33], sediment transport [34], and aerosol optical depth [35].

This project addresses uncertainties in spatial and temporal drivers of ecosystem functioning and carbon fluxes by employing a combination of established and novel data sampling and analysis methodologies.

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