

Variability of surface energy fluxes over high latitude permafrost wetlands

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Motivations

Arctic ecosystems are undergoing a very rapid change due to global warming and their response to climate change has important implications for the global energy budget. Therefore, it is crucial to understand how energy fluxes in the Arctic will respond to any changes in climate related parameters. However, attribution of these responses is challenging because measured fluxes are the sum of multiple processes that respond differently to environmental factors. The quantification of surface energy fluxes and their variability from these regions also plays an important role in understanding the Arctic carbon cycle and changes in atmospheric methane concentrations.

Experiment setup

Direct measurements of surface energy fluxes over high latitude permafrost wetlands are sparse, very localized, inhomogeneously distributed in space, and thus difficult to use for accurate model representation of regional to global contributions from the Arctic. We aim to improve spatial coverage and spatial representativeness of fluxes by using airborne eddy covariance measurements across large areas. The research aircraft POLAR 5 was equipped with a turbulence nose boom, meteorological sensors and a fast response CH_4 analyzer (Fig. 1).

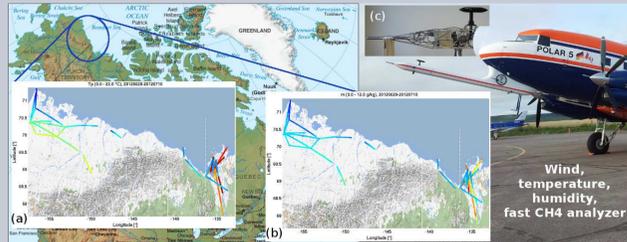


Figure 1: Flight paths, potential temperature (a) and mixing ratio (b) measurements from the AIRMETH-2012 campaign. Aircraft instrumentation for measurements of surface fluxes (c).

The AIRMETH 2012 (Airborne measurements of methane) campaign was carried out from 28 June to 10 July 2012 across the entire North Slope of Alaska and the Mackenzie Delta in Canada.

Data analysis

Following Metzger et al. (2013) we establish a functional relationship between spatially and temporally resolved flux observations and corresponding environmental drivers. The principal steps of the method are shown in Fig. 2. After thorough data pre-processing, wavelet transform is used to improve spatial discretization of flux observations and to quantify biophysically relevant land cover properties in the flux footprint. A boosted regression trees (BRT) technique is then employed to extract and quantify the functional relationships between the energy fluxes and the environmental drivers.

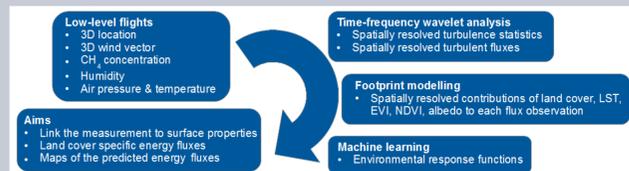


Figure 2: Flow chart showing the principal steps of the machine learning analysis.

Spatially resolved flux measurements

Computations were performed with a continuous wavelet transform enabling a spatial discretization of 100 m of the flux measurements (Fig. 3).

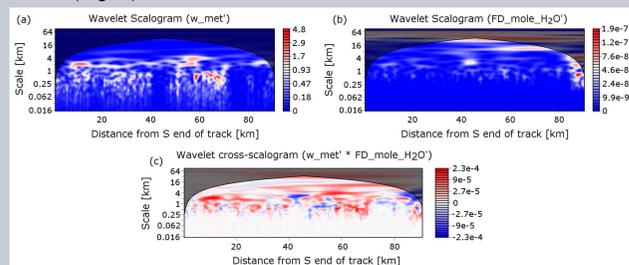


Figure 3: Wavelet scalogram for vertical wind speed (a) and water vapor concentration (b), wavelet cross-scalogram for the latent heat flux (c) along flight pattern on 30 June 2012, 01:13 - 01:35 UTC. The shaded areas identify the cone of influence.

Sensible and latent heat fluxes were calculated for overlapping sub-intervals of 1000 m length. The subintervals are centered above each cell of the land cover, land surface temperature (LST), enhanced vegetation index (EVI), and normalized difference vegetation index (NDVI) grids that was overflown by the POLAR 5. For a total of 30914 flux observations, MODIS LST, EVI, and NDVI in each flux footprint are determined (Fig. 4). In Fig. 5 latent heat flux observations along the flight line are shown together with the land cover class and LST in the respective source area.

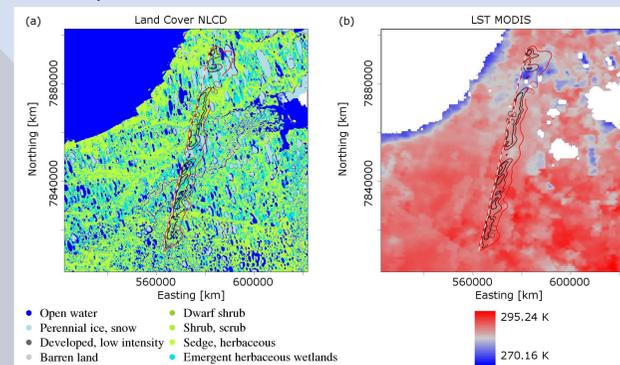


Figure 4: Flight along pattern on 30 June 2012, 01:13 - 01:35 UTC (white dashed line). The composite flux footprint along the flight line (30%, 60%, 90% contour lines) is superimposed over maps of land cover (a) and land surface temperature (b).

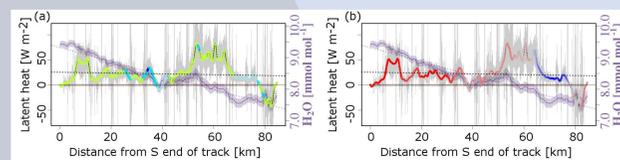


Figure 5: Latent heat flux and mixing ratio for each overflown 100m cell of the dominant land cover grid (a) and land surface temperature (b) along flight pattern on 30 June 2012, 01:13 - 01:35 UTC. Also shown is the 1σ random sampling error (gray), standard deviation (purple) for each observation, and the spatial trend (dashed line).

Boosted regression trees

Boosted regression trees are then used to infer an environmental response function (ERF) between all flux observations and biophysical (LST, EVI, NDVI), meteorological drivers (downward shortwave solar radiation S_{\downarrow} , potential temperature θ , mixing ratio MR, and ratio of measurement height to the height of the planetary boundary layer $DZM/PBLH$) and time of observation. BRTs are a non-parametric machine learning technique in which a response function is constructed according to the coherencies in the training data (Fig. 6). As a direct consequence the predictive performance of BRTs depends on how complete the combinations of state variables in the evaluation data are represented in the training data (Fig. 7).

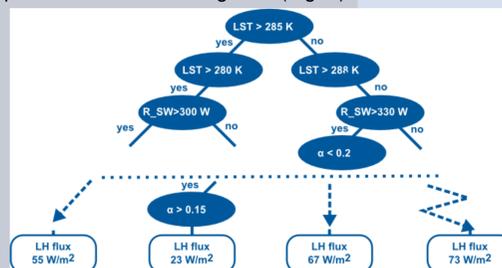


Figure 6: Machine learning and BRT approach.

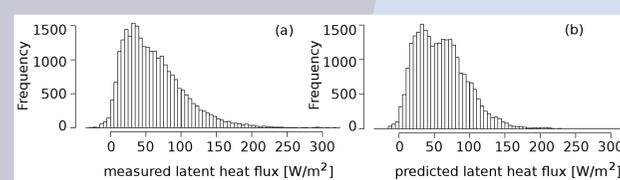


Figure 7: Histograms of measured (a) and predicted (b) latent heat fluxes.

Environmental response functions

Here, we use BRTs to extract the relationships between all flux observations, surface properties (land cover, albedo, EVI), meteorological variables (S_{\downarrow} , MR, and θ) and time of observation. While BRTs are capable of reproducing complex interactions through multilayered branching, the fitted function can be summarized, e.g. as partial dependence plots. These show the effect of each individual variable

on the response after subtraction of the offset, and accounting for the average effects of all other variables in the model. The partial dependence plots are sorted in order of the relative importance of the response variables (Fig. 8). The most important responses of latent heat flux are time of observation, linear responses of S_{\downarrow} , θ , EVI, albedo, followed by non-linear almost flat response of the MR.

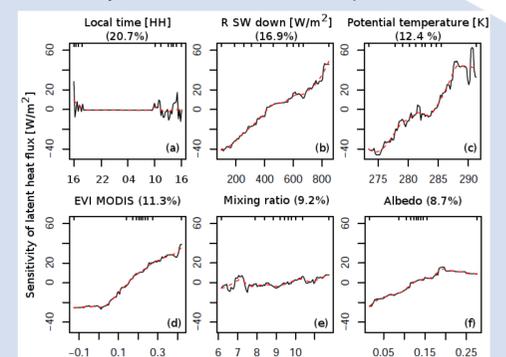


Figure 8: Environmental mean response functions. The fitted function (black) shows the variable response of the BRT over the range of one individual state variable, while the remaining state variables are held at an average, constant value. The red dashed line is a smoothed representation of the fitted function.

Fluxes over permafrost wetlands

Finally, the resulting environmental response functions are used to extrapolate the sensible heat and water vapor exchange over spatiotemporally explicit grids of the Alaskan North Slope. The supplemented simulations from the Weather Research and Forecasting (WRF) model were used to explore the dynamics of the atmospheric boundary layer and to examine results of extrapolation. In general, BRT predicted and WRF modelled latent heat fluxes correlate well with one another (Fig. 9). However, the sensible heat flux was overestimated by the WRF model.

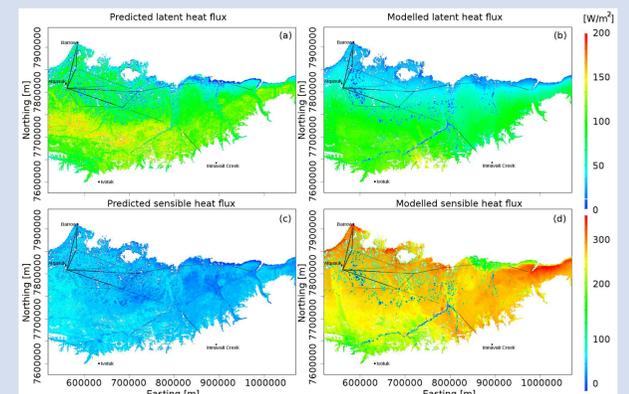


Figure 9: Maps of predicted (a,c) and WRF modeled (b,d) latent (a,b) and sensible (c,d) heat fluxes. The fluxes are averaged over flight time and representative for the period 28.06.12 - 02.07.2012 around noon.

Conclusions

The obtained results contribute to the advanced, scale dependent quantification of surface fluxes covering extensive areas of terrestrial permafrost. Wavelet decomposition yields high spatial resolution of the flux observations and significant flux contributions by large eddies (2 - 4 km) "invisible" for tower-based systems due to insufficient sampling of large-scale atmospheric motion. Strong regional differences were detected showing the non-uniform distribution of surface fluxes. This study indicates the potential of ERFs for

- extending airborne flux measurements to the regional scale,
- quantitatively linking flux observations in the atmospheric surface layer to meteorological and biophysical drivers in the flux footprints

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