Continuous estimation of gross primary productivity and evapotranspiration from an Unmanned Aerial System

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Introduction
Satellite-based optical imagery cannot provide information on the land surface during cloudy periods. This issue is especially relevant for high latitudes where overcast days are common. Current remote sensing-based models of gross primary productivity (GPP) or evapotranspiration (ET) are biased towards clear sky conditions, lacking important information on biophysical processes under cloudy conditions (Wang et al., 2018).

Unmanned Aerial Systems (UAS) can collect optical and thermal signals at unprecedented very high spatial resolution (≤ 1 meter) under sunny and cloudy weather conditions. This provides a great opportunity to continuously monitor vegetation carbon assimilation and water consumption under both sunny and cloudy conditions.

Objective
1. Use UAS multispectral and thermal imagery to estimate soil water content (SWC), GPP and ET from UAS observations.
2. Provide an framework to continuously estimate GPP and ET from UAS observations.

Methods and data
Methods:
The workflow of this study is shown in Figure 6. The major parts are outlined as below.

- **Snapshot estimation**
  - SWC: Temperature-vegetation dryness index (TVDI)
  - GPP and ET: A joint light use efficiency GPP and Priestley-Taylor Jet Propulsion Laboratory ET model (Wang et al., 2018)
  - Validate with eddy covariance observations

- **Continuous estimation**
  - Statistical based interpolation (Vegetation index NDVI)
  - Model based interpolation: Soil-Vegetation Energy, water and CO2 transfer model (SVEN, Figure 7)
  - Data assimilation (Ensemble Kalman filter, surface temperature Ts)

Flights campaigns and data:
- Forest flux sites: Risøe willow bioenergy plantation (11 ha)

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<th>Weather condition</th>
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- Data: UAS multispectral and thermal imagery, meteorological forcing, eddy covariance observations, field measurements (SWC)

Results
Figure 10: The spatial maps of simulated GPP (a) and LE (b) at 10:00-10:30 A.M. on May 25th 2016. The circles represent 75% footprint source for different half hours during the day time.

- **Continuous estimation of GPP and ET**

Figure 11: The simulated GPP (a, b) and LE (c, d) on May 25th 2016. LE EC corr is corrected with energy balance closure errors. Error bars stand for standard deviation.

Figure 12: The comparison between interpolated UAS NDVI (with / without one pseudo observation) and observed interpolated PAR (from PAR sensors above and below canopy). UAS NDVI is the average NDVI value of UAS observations for the willow plantation. The spline method was used for interpolation. The error bar stands for the standard deviation. Here we added one pseudo point in order to represent the true phenology change well.

Figure 13: The performance of SVEN to continuously simulate Rn, LWout, LE, GPP and SWC with interpolated UAS NDVI as inputs. The simulated daily Rn, LE, GPP and SWC (15 cm depth) were compared with daily observations. For Rn, LE, GPP and SWC, the performance is good. But for LWout, the simulation performance is not very good.

Data assimilation Ts

Figure 14: The comparison between open loop run (a), data assimilation with UAS Ts observations (b), and data assimilation with synthetic data (c) (UAS flights per day). The performance of simulation with different schemes was shown in the left table. This result indicate high frequency UAS observations are needed for improving surface temperature simulation.

Conclusion and future work
This study provides a framework on continuous estimation of GPP and ET from UAS optical and thermal imaging to fill gaps between data acquisitions. Results indicate UAS observations could accurately simulate water and CO2 flux exchange between the land surface and atmosphere. Future work will focus on assimilating spatial UAS thermal imaging into SVEN.

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