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High spatial resolution monitoring land surface energy, water and CO₂ fluxes from an unmanned aerial system

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17   **Abstract:**

18   High spatial resolution maps of land surface energy, water and CO₂ fluxes, e.g. evapotranspiration (ET) and
19   gross primary productivity (GPP), are important for agricultural monitoring, ecosystem and water resources
20   management. However, it is not clear which is the optimal (e.g. coarsest possible) spatial resolution to capture
21   those fluxes accurately. Unmanned Aerial Systems (UAS) can address this by collecting very high spatial
22   resolution (<1 m, VHR) imagery. The objective of this study is to model ET and GPP dynamics using VHR
23   optical and thermal imagery and quantify the influence of the spatial heterogeneity in the flux simulations and
24   validations. The study was conducted at a deciduous willow bioenergy eddy covariance (EC) flux site in
25   Denmark. Flight campaigns were conducted during the growing seasons of 2016 and 2017 with a hexacopter
26   equipped with RGB, multispectral and thermal infrared cameras. A ‘top-down’ modeling approach consisting of
27   the Priestley–Taylor Jet Propulsion Laboratory model and a light use efficiency model sharing the same canopy
28   biophysical constraints was used to estimate ET and GPP. Model outputs were benchmarked by EC flux
29   observations with the source weighted footprint. Our results indicate that our model can well estimate the
30   instantaneous net radiation, ET, GPP, evaporative fraction, light use efficiency and water use efficiency with
31   root-mean-square deviations (RMSD) of 31.6 W·m⁻², 41.2 W·m⁻², 3.12 μmol·C·m⁻²·s⁻¹, 0.08, 0.16 g·C·MJ⁻¹ and
32   0.35 g·C·kg⁻¹, respectively. Further, it is found that using a footprint model to sample different areas of VHR
33   imagery can be a tool to provide better diurnal estimates to benchmark with EC data. Moreover, these VHR
34   maps (0.3 m) allowed us to quantify metrics of spatial heterogeneity by using semivariogram analysis and by
35   aggregating model inputs into different spatial resolutions. For instance, we find that in this site, the aggregation
36   of simulated GPP using the source weighted mean of the EC footprint was about 30% lower in RMSD than
37   using the arithmetic mean of the footprint. This demonstrates the accuracy of the modeled VHR spatial patterns.
38   Nevertheless, we also find that imagery resolution consistent with the canopy size (around 1.5 m in our study) is
39   sufficient to capture the spatial heterogeneity of the fluxes as transpiration and canopy assimilation of CO₂ are
40   processes regulated at the tree crown level. Our results highlight the importance of considering the land surface

41 heterogeneity for flux modeling and the source contribution within the EC footprint for model benchmarking at
42 appropriate spatial resolutions.

43 **Key words:** Evapotranspiration; Gross primary productivity; Eddy covariance; Optical and thermal remote
44 sensing; Instantaneous and diurnal; Spatial heterogeneity

45

46 **Highlights:**

- 47 • An operational framework to monitor land surface fluxes from a UAS is presented.
- 48 • To our knowledge, first study to map ecosystem WUE from a UAS with VHR
- 49 • Considering heterogeneity of landscapes and EC sources is crucial for model benchmark.
- 50 • Imagery resolution at the size of tree crowns is sufficient to capture fluxes.

51

52   **1. Introduction**

53   The amount of carbon assimilated by terrestrial ecosystems or gross primary productivity (GPP) is closely
54   connected to the water loss as evapotranspiration (ET), as both processes are regulated by a variety of linked
55   biotic and abiotic controls (Damm et al., 2018; Foley et al., 1996; Guan et al., 2015). This tradeoff between GPP
56   and ET requires strategies and policies for management and monitoring of water, crops and natural ecosystems
57   (Liu et al., 2015; Mo et al., 2018). Quantification of the temporal and spatial variations of ET and GPP can
58   provide valuable information for understanding the water and carbon exchanges between land surfaces and the
59   atmosphere in a changing climate (Beer et al., 2010; Ito and Inatomi, 2012). Very high spatial resolution (around
60   1m, VHR) maps are particularly important for optimizing food or bioenergy crop production. For example,
61   targeted irrigation or fertilization in precision agriculture will benefit from VHR water use efficiency (WUE)
62   maps, reflecting the amount of carbon fixed per unit of water transpired, but such information is not yet routinely
63   available (Gago et al., 2015). Further, VHR maps offer great opportunities to understand ecohydrological
64   process and to reduce the large uncertainty in estimation of land surface fluxes due to unresolved scaling issues
65   (Anderson and Gaston, 2013; Vivoni et al., 2014).

66   Numerous methods such as the eddy covariance (EC) technique, satellite and airborne remote sensing, and land
67   surface models have been developed to estimate land surface energy, water and CO₂ fluxes across leaf, canopy,
68   regional and global scales (Amthor et al., 2001; Reichstein et al., 2005; Sitch et al., 2003). Among them, the EC
69   technique is acknowledged as one of the reliable methods to estimate the exchange of tracer gases (e.g. CO₂ and
70   water vapor) between the land surface and the atmosphere at the ecosystem level (Baldocchi, 2003), often used
71   to benchmark models. However, the EC technique can only be applied in flat and homogeneous sites and the
72   footprint of the measurements usually covers areas around 100-1000 m². To estimate the spatial variation of
73   regional ET and GPP, models using satellite optical and thermal remote sensing data are a cost-effective tool.
74   However, the coarse spatial resolutions of satellite optical and thermal imagery cannot represent the spatial
75   heterogeneity in topography, soils, and vegetation accurately enough (McCabe et al., 2017). Further, the coarse

76 pixel resolution of satellite ET and GPP products, e.g. MODIS (250m-1km), Sentinel 2 missions (10m-60m) or
77 the Sentinel 3 missions (500m-1km), may not be appropriate for small-scale applications, e.g. irrigation
78 management in vineyards. Additionally, during cloudy and overcast weather conditions, satellites are not able to
79 provide optical or thermal observations of the land surface. This is an important issue especially for high latitude
80 regions, where cloudy and overcast days are common (Wang et al., 2018b) or in climates where the growing
81 season coincides with the rainy season such as monsoonal regimes (García et al., 2013).

82 With significant advances in navigation, flight control, miniaturized platforms and sensors, Unmanned Aerial
83 Systems (UAS) can provide VHR imagery (1 cm to 1 m), presenting unprecedented potential for monitoring
84 ecohydrological process at fine scales (Vivoni et al., 2014). VHR remote sensing data can facilitate our
85 understanding on the heterogeneity, scaling and uncertainties in the ecohydrological processes (Li et al., 2013).
86 Besides, UAS flight campaigns can be conducted at flexible times, locations and turnaround times. The
87 flexibility to combine various sensors and to design different flight paths is another advantage of UAS. Further,
88 UAS can collect data under both sunny and cloudy weather conditions. Additionally, the operating costs of UAS
89 campaigns are much lower than manned airborne surveys.

90 Recent studies have demonstrated that UAS remote sensing is able to produce good estimates of ET with the
91 root-mean-square-deviation (RMSD) around 10-30% of the measured fluxes over irrigated crops (Hoffmann et
92 al., 2016; Kustas et al., 2018; Ortega-Farías et al., 2016) and grasslands (Brenner et al., 2017). Most of them
93 focused on using thermal approaches based on the Two Source Energy Balance (TSEB) family of models to
94 calculate sensible heat flux and estimated ET as the residual component of the surface energy balance (Kustas
95 and Norman, 1999). However, sensible heat estimates are very dependent on the accuracy of radiometric
96 temperature, which is quite low in the case of the typically miniaturized uncooled thermal cameras on board of
97 UAS (Wang et al., 2018a). An alternative of ET estimation is vegetation-driven approaches, e.g. Priestley–
98 Taylor Jet Propulsion Laboratory model (PT-JPL, Fisher et al., (2008)), which are less sensitive to the quality of
99 radiometric temperature (García et al., 2013).

100 Compared to ET, reports on GPP and WUE estimates from UAS imagery are even scarcer and they usually do
101 not estimate GPP and WUE directly but proxies such as stomatal conductance, pigments or leaf area index (LAI).
102 For instance, Zarco-Tejada et al. (2013b) demonstrated chlorophyll fluorescence, physiological indices (e.g.
103 photochemical reflectance index, PRI), and structural indices (e.g. normalized difference vegetation index,
104 NDVI) and enhanced vegetation index derived from UAS observations correlate well with EC CO₂ fluxes.
105 Furthermore, to calculate WUE across ecosystems and compare estimates of ecosystem water and CO₂ fluxes
106 with other approaches (e.g. EC techniques), it is necessary to provide quantitative estimates of GPP and ET.

107 Models of ET and GPP for routine UAS monitoring should be operational and parsimonious with limited
108 parameterization and data inputs (ideally all data inputs from the UAS). Remote sensing satellite models for joint
109 ET and GPP estimation can be classified into ‘top-down’ and ‘bottom-up’ approaches (Houborg et al., 2009;
110 Wang et al., 2018b). ‘Top-down’ methods, e.g. CASA light use efficiency (LUE) model (Potter et al., 1993), the
111 MODIS GPP and ET algorithms (Mu et al., 2007; Running et al., 2004) or PT-JPL (Fisher et al., 2008), are
112 simpler and can be directly driven with remote sensing imagery. The ‘top-down’ models treat ecological
113 behavior of the canopy as a whole and estimate the actual status of ecosystem functioning by reduction from the
114 potential status with various environmental constraints. One example is the joint PT-JPL model and LUE model,
115 which unified the two often used ‘top-down’ ET and GPP models with the same environmental constraints and
116 has been demonstrated to successfully simulate ET and GPP dynamics in a temperate deciduous forest (Wang et
117 al., 2018b).

118 The temporal upscaling of ET from the instantaneous to the diurnal is an important issue (Gentine et al., 2007;
119 Morillas et al., 2014). Most of the studies deal with the diurnal simulation by assuming the self-preservation of
120 EF (the constant EF) in the diurnal evolution of the surface energy budget (Brutsaert and Sugita, 1992; P. D.
121 Colaizzi et al., 2006). Another approach is to average all the instantaneous estimates during the course of day.
122 Due to the particle dispersion process, areas within the footprint contribute differently to the EC measurements
123 depending on various factors, e.g. the distance between source areas and sensors, sensor height, canopy height,

124 surface roughness, wind speed and variance (Metzger, 2018). The coarse resolution satellite imagery cannot
125 assess the importance of considering the variations of the EC footprint. The VHR UAS imagery provides
126 explicitly information on the land conditions to match the variability of EC footprint during the course of the day.
127 This can facilitate our understanding on the importance of the footprint variations on the temporal upscaling
128 process.

129 Despite virtually unlimited potential of UAS to provide centimeter level VHR data, the necessity for spatial
130 detail depends on the purpose of the study and site conditions. For example, detecting plant diseases would
131 require a higher spatial resolution than mapping the spatial variability of transpiration across canopies. Further,
132 there is a tradeoff between image spatial resolution and coverage. Flying UAS at a low altitude can obtain VHR
133 images but small coverage and vice versa. Low flying height requires more images or flights to cover the target
134 area and leads to a lower efficiency of UAS campaigns. Thus, optimizing spatial resolution and flying height for
135 UAS campaigns is important. To achieve that, a first step to design the spatial resolution for observing missions
136 is to characterize the landscape spatial heterogeneity (Garrigues et al., 2006). The semivariogram, which
137 measures spatial interdependence between observations as a function of their distance, has been often adopted to
138 quantify the heterogeneity of the land surface (Curran, 1988; Kim et al., 2006).

139 Understanding the influence of landscape heterogeneity on the scaling behavior of surface fluxes with different
140 spatial resolutions is critical (McCabe and Wood, 2006; Sharma et al., 2016). Spatial scaling experiments that
141 resample model inputs to compare simulated land surface fluxes with EC observations is an efficient approach to
142 quantify the influence of spatial resolutions on the modeling performance (Ershadi et al., 2013). Besides the
143 heterogeneity of landscapes, VHR maps of land surface fluxes also enable to consider the heterogeneity of
144 source contribution within the EC footprint. Additionally, few studies have the resources to spatially validate the
145 fluxes with numerous in-situ sensors (Kustas et al., 2018). For spatial validation, some studies compare UAS
146 based stress indicator with in-situ measurements, e.g. stomatal conductance and leaf water potential, but there is
147 a potential mismatch between image at canopy scale and measurements at leaf scale (Gago et al., 2015; Zarco-

148 Tejada et al., 2013b). We hypothesize that if the spatial patterns of simulated surface fluxes from UAS imagery
149 are not accurate, model performance will not change with the different aggregation methods (arithmetic or
150 weighted means of the source contribution) within the EC footprint. This comparison with different aggregation
151 methods can provide evidence of the accuracy of the spatial patterns mapped from the UAS to some extent.

152 The overall objective of this study is to develop and validate an operational methodology for mapping land
153 surface energy, ET, GPP and WUE at an optimal spatial resolution. Specific objectives include: 1) to propose an
154 operational methodology using UAS optical and thermal imagery with minimum ground observations to map
155 land surface fluxes, 2) to quantify the accuracy of the simulated instantaneous and diurnal land surface variables
156 with EC observations and explore the importance to consider the variations of the EC footprint in the temporal
157 upscaling approaches, and 3) to evaluate the influence of heterogeneity and spatial resolution on the flux
158 simulations and identify the optimum spatial resolution to benchmark models with EC tower observations.

159 **2. Study site and in-situ data**

160 This study was conducted in an 11 hectare short rotation coppice (SRC) willow bioenergy plantation EC site.
161 This site is located at Risoe, Denmark (DK-RCW) with latitude 55°41'31.95"N, longitude 12°6'14.69"E and
162 altitude 15 m above mean seal level. This site is temperate maritime climate with mean annual temperature about
163 8.5°C and precipitation around 600 mm. The soil type is loam. The main willow species in the field are *Salix*
164 *viminialis*, *Salix schwerinii* and *Salix triandra*. In February of 2016, all willow trees were harvested and the site
165 was mainly covered by bare soil before May 2016. Then willow grew to the height of approximate 4 m during
166 growing seasons of 2016 and 2017. Rapeseed (*Brassica napus*) was grown in the nearby field (East of the SRC).
167 A grass covered access path separates the willow plantation from the rapeseed field.

168 The EC observation system has employed continuously from 2012 until now. A 12 m tall mast enables EC flux
169 measurements in the atmospheric boundary layer above the willow plantation as Figure 1. The EC system

170 consisted of an enclosed path CO₂ and H₂O sensor LI-7200 (mode 177, LI-COR, Lincoln, NE, USA) and a three
171 dimensional ultrasonic anemometer and thermometer HS-50 (Gill Instruments, Lymington, UK). Turbulent flux
172 data were recorded at 10 Hz (CR-3000 logger, Campbell, City, USA). The raw data post-processing followed the
173 same scheme as in Pilegaard et al. (2011), Ibrom et al. (2007) and Fratini et al. (2012), i.e. the standard
174 processing now adopted by ICOS. For EC data processing, the flux partitioning to separate GPP and respiration
175 was done by the look-up table approach (Reichstein et al., 2005) based on the R-package REddyProc (Wutzler et
176 al., 2018) with the half-hourly net ecosystem exchange, T_a and incoming shortwave radiation (SW_{in}) as inputs.
177 The processed EC data, ET and GPP, were used in this study for model validation.

178 In-situ EC and micrometeorological observations used for this study included water and CO₂ fluxes (ET and
179 GPP), radiation components, fraction of intercepted Photosynthetically Active Radiation (*f*_{IPAR}), air temperature
180 (T_a), air pressure (Pa), relative humidity (RH), soil moisture (SM), wind speed (WS) and direction (WD). For EC
181 data processing, the flux partitioning to separate GPP and respiration was done by the look-up table approach
182 (Reichstein et al., 2005) based on the R-package REddyProc (Wutzler et al., 2018) with the half-hourly net
183 ecosystem exchange, T_a and incoming shortwave radiation SW_{in} as inputs. A CNR4 net radiometer (Kipp &
184 Zonen, Delft, the Netherlands) installed at 10 m height of the EC tower continuously measured components of
185 the surface energy balance, which include SW_{in}, outgoing shortwave radiation SW_{out}, incoming longwave
186 radiation LW_{in} and outgoing longwave radiation LW_{out}. Photosynthetically Active Radiation (PAR)
187 measurements were obtained from ten PAR sensors (Apogee SQ-200, Apogee Instruments Inc., Logan, USA)
188 including one sensor to measure the incident PAR above the canopy (PAR_{above}), one sensor to measure canopy-
189 reflected PAR (PAR_{reflected}) and eight sensors to measure understory PAR (PAR_{below}). For in-situ SM
190 measurements, field campaigns with a mobile TDR probe (Field Scout TDR 300 portable moisture meter,
191 Spectrum Technologies Inc., Plainfield, IL, USA), were conducted to measure the spatial variability of SM on
192 18th June 2017 as shown in Figure 1. Fixed TDR probes (5TM ECH2O probes, Decagon Inc., Pullman, WA,
193 USA) were installed in the willow plantation to measure the temporal variability of SM.

194

195 **Figure 1.** Overview of Risoe EC flux site and flight pattern of campaigns. The flux tower is in the middle of the
 196 willow plantation. The red dash line shows the flying path of UAS flight campaigns. Stars are the location of the
 197 understory PAR sensors. Yellow dots show the location of SM samples conducted on 18th June 2017. FOV is the
 198 field of view of CNR4, when willow height is 0 m.

199 3. Methods and data

200 3.1 Unmanned Aerial System and campaigns

201 This UAS consisted of a vehicle and a payload, as shown in Figure 2. For the vehicle, we used an off-the-shelf
 202 DJI hexacopter Spreading Wings S900 equipped with DJI A2 flight controller. It can carry a payload with an
 203 approximate maximum weight of 2 kg. The payload included an imaging system (multispectral, thermal infrared
 204 and Red-Green-Blue RGB cameras), a Global Navigation Satellite System (GNSS) and a Single-Board
 205 Computer (SBC) Beaglebone Black for sensor communication and data storage. Details on the GNSS onboard,
 206 refer to Bandini et al. (2018). Additionally, we used a mobile real-time kinematic (RTK) GNSS (Trimble GNSS

207 R8s, Trimble Inc., CA, USA) to measure ground control points (GCPs) to improve the geometric accuracy of the
208 image mosaicking process. The imaging system included three sensors, a multispectral camera, a thermal
209 infrared camera and a RGB camera. The multispectral camera (MCA, Multispectral Camera Array, Tetracam,
210 Chatsworth, CA, USA) consists of an array of six individual channels for the visible and near infrared bands,
211 namely 470, 530, 570, 670, 710 and 800 nm with the full width at half maximum for each channel is 10nm. The
212 thermal infrared camera (FLIR Tau2 324, Wilsonville, OR, USA) has an uncooled VOx microbolometer. It
213 records longwave radiation in the wavelength range from 7.5 to 13.5 μm and is able to measure temperature
214 ranging from -25°C to 100 °C in high gain mode. The RGB camera (Sony DSC-RX100) was used to produce the
215 Digital Surface Model (DSM) to orthorectify the multispectral and thermal infrared imagery. Detailed
216 information on sensors is shown in Table 1.

217 A total of eight UAS flight campaigns were conducted at the willow site during different growing stages of
218 willow and weather conditions in 2016 and 2017 as shown in Table 2. It should be noted that during the first two
219 flights, the EC system did not work and these two flights were only used to simulate land surface energy balance
220 and SM, which were further compared with in-situ measurements. The flight patterns (Figure 1) were designed
221 using the DJI autopilot software. Before each flight campaign, the FLIR thermal camera was turned on for a
222 half-hour stabilization.

224 **Figure 2.** (a) DJI S900 vehicle platform and (b) the payload including a RGB camera, a thermal infrared camera
 225 and a multispectral camera.

226 **Table 1.** Information on optical and thermal sensors in the UAS (DSM: digital surface model; NDVI: normalized
 227 difference vegetation index; T_s : land surface temperature). *The final spatial resolution of multispectral and
 228 thermal images, which was used for modeling, was 0.03m. **The final resolution for modeling was 0.3m.

Camera	Focal length (mm)	Image dimension (pixel)	Field of View	Spectrum	Spatial resolution at ground when flying at 12 m*	Spatial resolution at ground when flying at 90 m**	Purpose
RGB	10.4	5472 × 3648	64.8°×45.9°	Red, Green, Blue broad bands	0.33 cm	2.5 cm	DSM
Multispectral	9.6	1280 × 1024	38.3°×32°	470, 530, 570, 670, 710, 800 nm	0.64 cm	4.8 cm	NDVI
Thermal	9	324 × 256	48.5° × 39.1°	0.75μm to 13.5μm	3.29 cm	24.7 cm	T_s

230 **Table 2.** Information on UAS flight campaigns (RH: relative humidity; T_a : air temperature; WS: wind speed at
 231 10 meter; Pa: air pressure; h is the tree height (m)). The measured tree height was used to calculate the on-
 232 ground field of view of the CNR4 sensors. It was also used to calculate the soil moisture and indicate the growth
 233 stages of the plantation.

Date	Time	Flying height (m)	Weather	RH (%)	T_a (°C)	WS (m s ⁻¹)	Pa (kPa)	h (m)	Growth stage
2-May-2016	14:40-14:55	12	cloudy	51.60	15.17	6.60	101.88	0.0	Early growth
12-May-2016	10:44-11:55	12	sunny	45.85	17.31	5.11	100.62	0.0	Early growth
25-May-2016	10:11-10:23	12	sunny	62.67	21.05	3.30	100.89	0.0	Early growth
7-Oct-2016	11:41-11:55	90	sunny	69.87	9.94	5.62	102.05	4.05	Dense vegetation
19-May-2017	12:07-12:19	90	sunny	79.25	19.27	2.13	100.41	4.24	Dense vegetation
22-May-2017	10:15-10:28	90	cloudy	70.82	14.72	2.91	101.66	4.34	Dense vegetation
26-May-2017	11:13-11:26	90	sunny	72.56	16.72	4.47	101.54	4.45	Dense vegetation
18-Jun-2017	12:39-12:51	90	cloudy	71.79	21.81	4.42	101.62	4.95	Dense vegetation

234

235 3.2 Image processing and validation

236 Before image processing, thorough laboratory geometric and radiometric calibrations of imaging sensors were
237 conducted. Geometric calibration of the RGB and multispectral cameras was conducted with standard
238 checkerboard calibration patterns to recover intrinsic camera geometric parameters. Radiometric calibration for
239 each channel of MCA was conducted with an integrating sphere (ISP2000, Instrument Systems, München,
240 Germany) and the in-lab calibration showed that the bias of the measured radiance was within $\pm 4.8\%$. For details,
241 refer to Wang et al. (2017). FLIR was calibrated using a Landcal P80P black body radiation source (Land
242 Instruments, Leicester, United Kingdom) with ten different target temperatures ranging from 0 to 45 °C and
243 three ambient temperatures ranging from 0 °C to 30 °C. This calibration resulted in in-lab accuracy RMSD of
244 0.50°C with same ambient and target temperatures and RMSD of 0.95°C with different ambient and target
245 temperatures (Christian Josef Köppl, 2016).

246 Images obtained from UAS flight campaigns were georeferenced using UAS GNSS data. Then these
247 georeferenced images along with pre-calibrated intrinsic camera geometric parameter values were imported into
248 Agisoft Photoscan (Agisoft LLC, St. Petersburg, Russia), which was based on the structure from motion (SfM)
249 algorithm (Westoby et al., 2012), to generate orthophotos and DSM. After that, high accuracy GCPs were added
250 to the aligned images and optimize the estimated camera positions and angles. The DSM generated from RGB
251 images was imported into both multispectral and thermal projects to orthorectify multispectral and thermal
252 images. Finally, the generated multispectral and thermal orthophotos were converted to six band reflectance and
253 surface brightness temperature (T_b), respectively.

254 The six band reflectance was calculated based on the radiance method. The incoming solar spectral radiance
255 ($L_{in,\lambda}$) measured by a handheld spectroradiometer (ASD, FieldSpec HandHeld 2^{TM}, Analytical Spectral Devices,
256 Inc., Boulder, USA) with a Spectralon panel (a nominal reflectance of 99.99%) on ground before and after each
257 flight campaign. The averaged measurements from ASD were used as $L_{in,\lambda}$. The at-sensor radiance ($L_{MCA,\lambda}$)

collected by MCA during the flight campaigns was used to represent the reflected radiance. Due to the low flight altitude and the limited influence of atmospheric attenuation, the difference between the reflected radiance at the sensor and at the surface was neglected. With the Eq. (1), the reflectance for each band was calculated. The near infrared (800 nm) and the red band (670 nm) reflectance were used to calculate NDVI $((\rho_{800} - \rho_{670})/(\rho_{800} + \rho_{670}))$ to infer the vegetation growth.

$$\rho_{\lambda} = \frac{L_{MCA,\lambda}}{L_{in,\lambda}} \quad (\text{Eq. 1})$$

Where ρ_{λ} is the reflectance from MCA. λ is the wavelength (nm). $L_{MCA,\lambda}$ is the reflected spectral radiance measured by MCA ($\text{W}\cdot\text{s}\cdot\text{m}^{-2}\cdot\text{sr}^{-1}\cdot\text{nm}^{-1}$). $L_{in,\lambda}$ is the incoming spectral radiance measured by ASD with a Spectralon panel on ground ($\text{W}\cdot\text{s}\cdot\text{m}^{-2}\cdot\text{sr}^{-1}\cdot\text{nm}^{-1}$).

To validate the accuracy of the acquired UAS data, the reflectance of tarpaulins with four different colors (green, blue, black and silver) was measured with the ASD for each flight. Tarpaulins are acknowledged to have low anisotropic effects (Korpela et al., 2011). The measured reflectance by ASD on ground was used to validate reflectance obtained from MCA. The 670 and 800 nm bands were used to calculate NDVI as model inputs. So validation of only these two bands was shown.

For thermal infrared images, the generated T_b orthophotos were compared with the brightness temperature T_{b_CNR4} converted from the outgoing longwave radiation (LW_{out_CNR4}) from CNR4 on the tower (Eq. 2). It should be noted that there may be uncertainties for this comparison, since FLIR and CNR4 have different thermal wavelength responses and sensor field of views (FOVs). FLIR measures longwave radiation ranging from 7.5 to 13.5 μm , while CNR4 has a broader response range and measures longwave emission from 4.5 to 45 μm . The FOV of FLIR is $35^{\circ} \times 27^{\circ}$ (Table 1), while the downward FOV of CNR4 is 150° . However, this comparison was necessary and can provide insights into the quality of the thermal data to some extent. Additionally, this comparison was equivalent to the comparison between LW_{out_CNR4} and the longwave radiation (LW_{out_FLIR}) estimated from FLIR T_b . This was important to understand uncertainties for calculating land

281 surface energy balance components with UAS imagery. Thus LW_{out_CNR4} was converted to brightness
 282 temperature T_{b_CNR4} by applying Stefan Boltzman's law as Eq. (2) to compare with T_b from FLIR.

$$283 \quad T_{b\_CNR4} = \left(\frac{LW_{out\_CNR4}}{\sigma} \right)^{1/4} \quad (\text{Eq. 2})$$

284 Where σ is the Stefan-Boltzmann constant ($5.67 \times 10^{-8} \text{ W} \cdot \text{m}^{-2} \cdot \text{K}^{-4}$). T_{b_CNR4} is the brightness temperature (K).
 285 LW_{out_CNR4} is the longwave radiation from CNR4 ($\text{W} \cdot \text{m}^{-2}$).

286 To obtain the corresponding pixels in the field of view (FOV) of CNR4 on the tower, the flux tower position,
 287 FOV and sensor height of CNR4, and vegetation height (Table 2) were used to calculate the radius of the FOV
 288 areas on ground according to Eq.3, as shown in Figure 1.

$$289 \quad r = (H - h) \tan\left(\frac{FOV}{2}\right) \quad (\text{Eq. 3})$$

290 Where r is the radius in m. H is the sensor height (10 m). h is the height of the willow ranging from 0 to 4.95m
 291 during the study period (Table 2). FOV is the downward FOV of CNR4, namely 150° .

292

293 3.3 Model description

294 The joint 'top-down' PT-JPL ET and LUE GPP model (Wang et al., 2018b) was used to simulate the land
 295 surface fluxes from UAS imagery. Such a 'top-down' approach is based on simple scaling rules using remote
 296 sensing estimates of the fraction of absorbed radiation by canopies and requires limited model inputs and
 297 parameters. Comparisons have shown that PT-JPL routinely outperforms more sophisticated modeling schemes
 298 using both satellite data (Ershadi et al., 2014; McCabe et al., 2017) and proximal in-situ sensors (Morillas et al.,
 299 2013), but to our knowledge the PT-JPL model has not yet been tested using UAS data. LUE models were
 300 widely applied to estimate GPP dynamics across various ecosystems at global and regional scales (Running et al.,

2004). Considering model performance, complexity and operational capabilities, this joint model (Wang et al., 2018b) was selected for this study.

The ET part of this joint model comes from the PT-JPL model (Fisher et al., 2008), which is based on the Priestley and Taylor (1972) equation for potential ET and incorporates eco-physiological variables to down-regulate the potential value to the actual one. PT-JPL is a three-source evapotranspiration model including wet surface evaporation (Ei), transpiration (Ec) and soil evaporation (Es), as described in equations (4-7).

$$\lambda ET = \lambda Ei + \lambda Ec + \lambda Es \quad (\text{Eq. 4})$$

$$\lambda Ei = f_{wet} \cdot \alpha \Delta / (\Delta + \gamma) \cdot R_{nc} \quad (\text{Eq. 5})$$

$$\lambda Ec = (1 - f_{wet}) \cdot f_g \cdot f_M \cdot f_{Ta} \cdot \alpha_c \Delta / (\Delta + \gamma) \cdot R_{nc} \quad (\text{Eq. 6})$$

$$\lambda Es = f_{SM} \cdot \alpha \Delta / (\Delta + \gamma) (R_{ns} - G) \quad (\text{Eq. 7})$$

Where λET is the latent heat flux for total evapotranspiration ($\text{W} \cdot \text{m}^{-2}$). λEi is the evaporation from the intercepted water ($\text{W} \cdot \text{m}^{-2}$). λEc is the transpiration ($\text{W} \cdot \text{m}^{-2}$). λEs is the evaporation from soil ($\text{W} \cdot \text{m}^{-2}$). f_g is the green canopy fraction reflecting the proportion of active canopy. f_M is the plant moisture constraint. f_{Ta} is the air temperature constraint indicating the limitation of temperature on photosynthesis. f_{SM} is the SM constraint. f_{wet} is the relative surface wetness to partition evapotranspiration from the intercepted water and transpiration (Fisher et al., 2008). These constraints vary from 0 to 1 to account for the relative reduction of potential λET under limiting environmental conditions. R_{nc} and R_{ns} are R_n for canopy and soil, respectively. The partitioning of PAR and R_n between canopy and soil is calculated following the Beer-Lambert law (Supplemental Table S1). G is the ground heat flux and is calculated based on a ratio to the soil net radiation (Kustas and Daughtry, 1990). Δ is the slope of saturation-to-vapor pressure curve. γ is the psychrometric constant. α is an empirical ratio of potential evapotranspiration to equilibrium potential evapotranspiration (PT coefficient) replacing the atmospheric demand and surface resistance effects in Penman-Monteith ET equation. The suggested value for

the PT-JPL model is 1.26 (Fisher et al., 2008). The supplemental Table S1 shows detailed information on the model constraints and parameters for this joint LUE GPP and PT-JPL ET model.

The GPP model shares similar features with other widely used LUE models, e.g. the MODIS algorithm (Running et al., 2004), but it also has inputs to account for the photosynthetic and transpiring proportion of the canopy (green vegetation fraction) and the plant moisture constraint based on Fisher et al. (2008).

$$\text{GPP} = \varepsilon_{\max} \cdot \text{PARc} \cdot f_g \cdot f_M \cdot f_{Ta} \cdot f_{VPD} \quad (\text{Eq. 8})$$

Where GPP is the gross primary productivity ($\mu\text{mol}\cdot\text{C}\cdot\text{m}^{-2}\cdot\text{s}^{-1}$). $\varepsilon_{\max}$ is the maximum LUE ($\mu\text{mol}\cdot\text{C}\cdot\text{m}^{-2}\cdot\text{MJ}^{-1}$). PARc is PAR intercepted by the canopy ($\text{MJ}\cdot\text{m}^{-2}\cdot\text{s}^{-1}$) based on the extinction of PAR within the canopy using the Beer-Lambert law (Supplemental Table S1). f_g , f_M and f_{Ta} are biophysical constraints and have the same meaning as in Eq. 11. f_{VPD} is the constraint indicating the stomatal response to water vapor pressure deficit (VPD). The absorbed PAR (APAR) is equal to $\text{PARc} \cdot f_g$. All constraints range from 0 and 1 and represent the reduction of maximum GPP under limiting environmental conditions. For more details, see Supplemental Table S1 and Wang et al., (2018b).

This joint model has two parameters, maximum LUE ($\varepsilon_{\max}$) and optimal temperature (T_{opt}), which need to be calibrated or extracted from look-up tables based on plant functional types. A study on long-term ET and GPP simulation based on this joint model has been applied in the nearby temperate deciduous beech forest Soroe (Wang et al., 2018b). Thus, this study used the optimized values from Soroe with $\varepsilon_{\max}$ equal to $2.97 \text{ g}\cdot\text{C}\cdot\text{m}^{-2}\cdot\text{MJ}^{-1}$ and T_{opt} equal to $16.51 \text{ }^{\circ}\text{C}$ as parameter values for this study.

Besides ET and GPP, this model can also estimate ecosystem LUE ($\text{g}\cdot\text{C}\cdot\text{MJ}^{-1}$), evaporative fraction (EF, no unit) and WUE ($\text{g}\cdot\text{C}\cdot\text{kg}^{-1}$) as shown in Eq. (9-11). These variables provide valuable information for precision agriculture and irrigation management.

$$\text{EF} = \frac{\text{ET}}{\text{R}_n - \text{G}} \quad (\text{Eq. 9})$$

$$\text{LUE} = \frac{\text{GPP}}{\text{APAR}} \quad (\text{Eq. 10})$$

$$\text{WUE} = \frac{\text{GPP}}{\text{ET}} \quad (\text{Eq. 11})$$

347

348 3.4 Model application: instantaneous and diurnal

349 The detailed workflow of the model application is shown in Figure 3. We performed two types of simulations
 350 using UAS imagery: instantaneous (at the time of flight) and diurnal (every half an hour during the daytime of
 351 the flight campaign day). The main difference between both is that in the first case the net radiation (Rn) was
 352 estimated using UAS images, while in the diurnal simulations in-situ measurements of Rn were used. For the
 353 instantaneous simulation, inputs from UAS imagery are shown in the green boxes of Figure 3. Meteorological
 354 inputs for modeling included SW_{in} , T_{a} , RH, WS and P_{a} , shown in the blue boxes of Figure 3. With these inputs,
 355 this modeling framework simulated intermediate variables such as the SM proxy, f_{IPAR} and f_{APAR} and final
 356 variables, e.g. Rn, ET, GPP.

357

Figure 3. The workflow of the instantaneous simulation. Green boxes represent inputs from UAS imagery. Blue boxes are in-situ measurements from the EC tower. Yellow boxes belong to the simulated intermediated variables. Orange boxes are the simulated final variables. Variables in green, yellow and oranges boxes were validated by in-situ measurements.

The first step for the instantaneous simulation was to estimate R_n , which is determined by SW_{in} , albedo (α), LW_{in} and LW_{out} , as shown in Eq. 12. SW_{in} in this study was obtained from the EC tower. α was calculated based on the simple ratio vegetation index (SR) as Eq. 13-14, which shows that albedo decreases as vegetation greenness increases (GAO, 1995). This method has been demonstrated to be an effective approach for various types of ecosystems (Mo et al., 2014).

$$R_n = (1 - \alpha)SW_{in} + LW_{in} + LW_{out} \quad (\text{Eq. 12})$$

$$\alpha = 0.28 - 0.14e^{(-6.08/SR^2)} \quad (\text{Eq. 13})$$

$$SR = (1 + NDVI)/(1 - NDVI) \quad (\text{Eq. 14})$$

LW_{out} was estimated from UAS FLIR T_b by applying Stefan Boltzman's law. LW_{in} for the instantaneous simulation was calculated by Stefan Boltzman's law with atmospheric emissivity ϵ_a as Patra's (1996) scheme of Eq. 15-18.

$$LW_{in} = \epsilon_a \sigma T_a^4 \quad (\text{Eq. 15})$$

$$\epsilon_a = 1 - (1 + \delta)e^{-\sqrt{(1.2+3\delta)}} \quad (\text{Eq. 16})$$

$$\delta = \frac{46.5}{T_a} e_0 \quad (\text{Eq. 17})$$

$$e_0 = RH \cdot 6.11e^{\left[\frac{L_v}{R_v} \left(\frac{1}{273.15} - \frac{1}{T_a} \right)\right]} \quad (\text{Eq. 18})$$

Where e_0 is the actual water vapor and was calculated based on the Clausius-Clapeyron equation. $L_v = 2.5 \times 10^6$ (J kg⁻¹) is the latent heat of vaporization and $R_v = 461$ (J kg⁻¹K⁻¹) is the gas constant for water vapor. T_a is the air temperature (K).

380 The second step for the modeling framework (Figure 3) was to estimate various environmental constraints from
 381 UAS NDVI and meteorological variables for the joint PT-JPL and LUE model, as shown in the Supplemental
 382 Table S1. Among them, the SM constraint was obtained from UAS thermal and optical observations. The SM
 383 proxy was calculated based on the temperature-vegetation triangle approach with theoretical dry and wet edges
 384 calculated from meteorological variables (Moran et al., 1994; Zhu et al., 2017). With this approach, the SM
 385 proxy could be used to indicate both spatial and temporal variations of SM. The details on using the temperature-
 386 vegetation triangle approach to estimate SM conditions can be found in Supplemental Section S2.

387 To obtain the actual land surface temperature (T_s) from FLIR T_b , it is necessary to conduct the atmospheric
 388 correction to remove the longwave radiation reflected by the land surface and the upwelling longwave radiation
 389 to the sensor from the atmosphere. As shown in Eq. 19, σT_b^4 indicates the at-sensor thermal radiation recorded
 390 by FLIR. $\epsilon_s \sigma T_s^4$ is the thermal radiation emitted from the surface. LW_{in} is the downwelling thermal radiation
 391 from the atmosphere to the land surface. The surface emissivity (ϵ_s) can be calculated based on the relation with
 392 NDVI as Eq. (20) (Van de Griend and M.Owe., 1993). LW_{atm} is the upwelling longwave radiation from the
 393 atmosphere to the sensor. Due to the low flight altitude and simplicity, this study neglected the influence of
 394 LW_{atm} as other UAS studies (e.g. Hoffman et al., 2016; Ortega-Farias et al., 2016; Brenner et al., 2017).

$$395 \quad \sigma T_b^4 = \epsilon_s \sigma T_s^4 + (1 - \epsilon_s) LW_{in} + LW_{atm} \quad (\text{Eq. 19})$$

$$396 \quad \epsilon_s = \begin{cases} 0.986 & (\text{NDVI} > 0.608) \\ 1.0094 + 0.047 \ln(\text{NDVI}) & (0.131 < \text{NDVI} < 0.608) \\ 0.914 & (\text{NDVI} < 0.131) \end{cases} \quad (\text{Eq. 20})$$

397 Where σ is the Stefan-Boltzmann constant ($5.67 \times 10^{-8} \text{ W} \cdot \text{m}^{-2} \cdot \text{K}^{-4}$). T_s is corrected land surface temperature (K).
 398 T_b is the brightness temperature from FLIR (K). LW_{in} is incoming thermal/longwave radiation ($\text{W} \cdot \text{m}^{-2}$). LW_{atm}
 399 is the upwelling longwave radiation ($\text{W} \cdot \text{m}^{-2}$) from the atmosphere to the sensor and is neglected in this study due
 400 to low flight altitude.

401 Finally, with the simulated Rn and environmental constraints, the instantaneous simulation used the joint LUE
402 and PT-JPL model to simulate ET, GPP, EF, LUE and WUE as shown in Figure 3.

403 Based on the instantaneous simulation, this study also conducted the diurnal simulation to simulate the land
404 surface fluxes for every half an hour during the flight campaign day. With the same constraints of vegetation and
405 SM as inputs, the diurnal simulation used the observed Rn and meteorological variables from the EC tower to
406 simulate each half an hour. There are two assumptions for the diurnal simulation. Vegetation and SM conditions
407 are constant during the course of a day. Pixels in the simulated area have the same Rn as the observations from
408 CNR4. For Rn, with relatively homogeneous underlying surface on the EC flux site, it in all pixels is almost
409 same. In general, the diurnal simulation could provide more validation on the temporal dynamics of land surface
410 fluxes for our study. It also facilitates our understanding in the temporal upscaling processes from the
411 instantaneous to the diurnal. Further, the EC footprints change positions with atmospheric conditions during the
412 day. This offers opportunities for the EC technique to sample different areas around the tower to validate the
413 obtained spatial patterns from UAS imagery.

414 In the instantaneous simulation, we further evaluated two schemes to scale up the instantaneous estimates of LE
415 to their daytime averaged values. One scheme is to use the EF obtained from the instantaneous simulation and
416 assume EF remains constant during the daytime to calculate the averaged LE of daytime. Another scheme is by
417 averaging all the instantaneous estimates of LE along the entire daytime period by considering the variations of
418 the EC footprint with the aid of VHR imagery. Finally, the EC observations were used to compare the averaged
419 daytime LE from these two schemes.

420

421 3.5 Model validation

422 This study validated both intermediate and final variables (Figure 3) in the modeling methodology. The observed
423 fraction of intercepted PAR (f_{IPAR_obs}) as Eq. 21 were used to validate the simulated f_{IPAR} in the modeling
424 methodology, as shown in Supplemental Table S1. As shown in Eq. 2, f_{IPAR_obs} was calculated based on
425 measurements of the incident PAR above the canopy (PAR_{above}), canopy-reflected PAR ($PAR_{reflected}$) and the
426 average of PAR below the canopy (PAR_{below}) from eight understory sensors in Figure 1.

$$427 \quad f_{IPAR\_obs} = \frac{PAR_{above} - PAR_{reflected} - PAR_{below}}{PAR_{above}} \quad (Eq. 21)$$

428 The simulated radiation components, e.g. SW_{net} , LW_{in} , LW_{out} (equivalent to T_b validation), and R_n were
429 validated with measured radiation components within the FOV of CNR4 (Figure 1). SM measurements from the
430 campaign on 18th June 2017 were used to validate SM proxies estimated from the temperature-vegetation
431 triangle approach. Details refer to Supplemental Section S2.

432 To validate the simulated final variables (e.g. LE, GPP, EF, LUE and WUE), the measured land surface fluxes
433 from the EC tower were used. To compare with the simulated spatial land surface fluxes from UAS imagery, a
434 footprint model, Flux Footprint Prediction (FFP), based on a scaling approach for the crosswind distribution of
435 the flux footprint (Kljun et al., 2015), was used. At given EC site conditions and measurement height, the source
436 area for a flux measurement varies with wind direction and atmospheric stability. This offers the opportunity to
437 measure fluxes from different parts of the surface and is used here to sample the spatial flux heterogeneity. The
438 spatial source density distribution function can be described with 2D flux footprint functions that are derived
439 from atmospheric flow models (Metzger, 2018). In the flux simulation validation, the estimated source area
440 density distribution was used together with a VHR resolution map of simulated fluxes to match the spatial
441 resolutions between the UAS ET and GPP simulations and the fluxes and, hence, made them comparable. A
442 threshold of 75% cumulated source contribution around the maximum of the footprint function was chosen to

443 represent the source of EC measurements. Due to the long tails of the distribution function, the EC source area
 444 size increases dramatically beyond 75% of cumulated source area contribution (Kljun et al., 2015) whilst the
 445 source area density becomes very small.

446 For the EC system, due to the energy balance closure issue, the sum of measured sensible heat (H) and latent
 447 heat (LE) is often not equal to the available energy (net radiation minus ground heat flux, $R_n - G$). To reduce the
 448 influence of the non-closure of energy balance, Energy balance Closure Ratio (ECR), as shown in Eq. 22, for
 449 each day was calculated and only measurements with EBR more than 80% were used for validation.

$$450 \quad \text{ECR} = \frac{\Sigma(H+LE)}{\Sigma(R_n-G)} \quad (\text{Eq. 22})$$

451 Further, we also compared the simulated results with three different energy balance closure correction methods,
 452 which attributed the residual of the energy balance closure based on residual correction method (only to H or LE)
 453 and Bowen Ratio energy balance correction (Knauer et al., 2018).

- 454 1. Attribute all closure errors to H and LE was kept the same (Larsen et al., 2016). LE_EC1 was used to
 455 indicate the corrected LE from this method.
- 456 2. Attribute all closure error to the latent heat flux and the sensible heat flux was kept the same. LE_EC2 was
 457 used to represent the corrected LE from this method.
- 458 3. Assuming that the ratio of sensible heat to ET (Bowen ratio) is correct, the residual of the energy balance is
 459 attributed to sensible and latent heat flux according to the Bowen ratio (Twine et al., 2000). LE_EC_BR was
 460 the corrected LE by this method.

$$461 \quad \text{LE\_EC1} = \text{LE\_EC\_raw} \quad (\text{Eq. 23})$$

$$462 \quad \text{LE\_EC2} = R_n - G - H\_EC\_raw \quad (\text{Eq. 24})$$

$$463 \quad \text{LE\_EC\_BR} = \frac{R_n - G}{H\_EC\_raw + LE\_EC\_raw} \text{LE\_EC\_raw} \quad (\text{Eq. 25})$$

464 Where LE_{EC_raw} is raw measurements of the latent heat flux ($W \cdot m^{-2}$). H_{EC_raw} is raw measurements of the
 465 sensible heat flux ($W \cdot m^{-2}$). R_n is the net radiation ($W \cdot m^{-2}$). G is the ground heat flux ($W \cdot m^{-2}$).

466 To validate the simulated land surface fluxes, statistics including root mean square deviation (RMSD),
 467 correlation coefficient (R) and relative errors (RE) were used.

$$468 \quad RMSD = \sqrt{\sum_{i=1}^N (sim_i - obs_i)^2 / N} \quad (Eq. 26)$$

$$469 \quad R = \frac{\sum_{i=1}^N (sim_i - \overline{sim})(obs_i - \overline{obs})}{\sqrt{\sum_{i=1}^N (sim_i - \overline{sim})^2} \sqrt{\sum_{i=1}^N (obs_i - \overline{obs})^2}} \quad (Eq. 27)$$

$$470 \quad RE = (\overline{sim} - \overline{obs}) / \overline{obs} \quad (Eq. 28)$$

471 Where sim is the simulation. obs is the observation. i refers to the i^{th} simulation or observation. N is the total
 472 number. $\overline{sim}$ is the average of the simulation. $\overline{obs}$ is the average of the observation.

473

474 3.6 Model error propagation analysis

475 To investigate the potential error propagation from the UAS imagery to the simulated land surface fluxes, e.g.
 476 R_n , SM , ET and GPP , an error propagation analysis was conducted. This analysis includes two cases, the early
 477 growth stage with the atmospheric forcing on 25th May 2016, and a dense vegetation growth stage with the
 478 atmospheric forcing on 7th October 2016. For the early growth stage, the pixel was assumed to be NDVI equal to
 479 0.35 with potential errors of ± 0.1 and T_b equal to 27 °C with potential errors of ± 2 °C. For the dense
 480 vegetation stage, the pixel was assumed to have NDVI equal to 0.82 with potential errors of ± 0.1 and T_b equal to
 481 10 °C with potential errors of ± 2 °C. Simulations were ran with varying levels of NDVI and T_b to simulate R_n ,
 482 SM , ET and GPP . Then, the simulated R_n , SM , ET and GPP were compared with the simulated fluxes at the
 483 reference condition ($NDVI = 0.35$, $T_b = 27$ °C and $NDVI = 0.82$, $T_b = 10$ °C) to estimate RE. This can help us to
 484 analyze the error propagation within the modeling methodology, further it can provide insights on the uncertainty
 485 of the simulated land surface fluxes respect to the uncertainties in UAS imagery.

486

487 3.7 Spatial heterogeneity analysis

488 One of the major benefits of UAS imagery is that VHR data can be used to detect spatial differences in the field,
489 for instance, to further support spatial management in precision agriculture. Further, these VHR data can also
490 help to identify the optimal spatial resolution (or the optimal UAS flying height) to capture significant
491 differences in the landscape (Garrigues et al., 2006) and model benchmarking with EC (Kim et al., 2006).
492 Semivariogram is an effective approach to assess the spatial structure of the heterogeneity (Curran, 1988).
493 Therefore, this study used this approach to analyze the spatial structure of different variables including NDVI, T_s ,
494 and surface fluxes. The optimum resolution was identified to be half of the range of the semivariogram to
495 capture differences between components in the landscape (Rahman et al., 2003). To avoid information from
496 other landscapes (e.g. the nearby farm), the semivariogram analysis was only conducted for the willow
497 plantation area, which is the source area for the EC measurements. The semivariograms of NDVI, T_b , R_n , GPP,
498 LE, EF, LUE and WUE for 25th May 2016 (early growth stage) and 07th Oct 2016 (dense vegetation stage) were
499 analyzed to quantify the change of the spatial structure of the land surface fluxes.

500 A scaling experiment was conducted to assess the effects of aggregating UAS imagery pixels on the performance
501 of the model benchmarking with EC observations. The purpose of this experiment was to establish the optimum
502 spatial resolution for model validation and to have a confirmation of the validity of the spatial patterns of surface
503 fluxes. Model inputs, NDVI and T_s , were aggregated to coarser spatial resolution and then these different spatial
504 resolution data were used to simulated GPP and LE. Since this EC flux site is homogeneous, we selected the
505 most heterogeneous UAS imagery collected on 25th May 2016 during the early growth period of vegetation for
506 this experiment. The initial NDVI and T_s with a spatial resolution of 0.03m were aggregated into 0.3, 1.5, 3, 6,
507 12, 24m. These aggregated spatial resolution data were used as inputs of flux modeling and the simulated land
508 surface fluxes were compared to EC observations.

509 To evaluate the influence of considering the heterogeneity of flux source contribution, we compared differences
510 in model validation when using the arithmetic mean or the source weighted mean for pixels within the EC
511 footprint. Calculating the arithmetic mean is equivalent to assuming that all pixels in the footprint contribute
512 equally to fluxes measured by the EC tower, while the source weighted mean reflects that different parts of the
513 footprint contribute differently to EC fluxes. Due to the particle dispersion process, contribution from each pixel
514 within the footprint is not spatially equal. This comparison provides insights into the importance of considering
515 the source weighted EC footprint. Further, as we hypothesized in the introduction, if the simulated pattern is
516 right, there should be improvement for taking the source weighted contribution into consideration. Thus, this
517 validation also provided the accuracy of the simulated spatial patterns to some extent.

518

519 **4. Results and discussion**

520 **4.1 Image validation**

521 The produced orthophotos of NDVI and T_b from UAS images were shown in Figure 4. The UAS flight
522 campaigns of this study were conducted at a low altitude (12 m in the first three flights and 90 m in last five
523 flights as shown in Table 1). UAS studies at such low flight altitude normally neglect the atmospheric correction,
524 e.g. Hoffman et al. (2016), Ortega-Farias et al. (2016) and Brenner et al. (2017). Our study only corrected the
525 thermal data with the surface emissivity and the incoming longwave radiation, neglecting the effect of the
526 atmospheric transmission from the surface to the sensor. To check the quality of these orthophotos for ET and
527 GPP modeling, reflectance and T_b were validated with in-situ measurements as shown in Figure 5.

528 Figure 5 (a) indicates that there was a good accuracy for the reflectance at 670 and 800 nm with R^2 more than
529 0.98 and RMSD about 3%. The reflectance from MCA is slightly lower than the reflectance from ASD on
530 ground (-1.11% and -1.48% for 800 nm and 670 nm, respectively). This is due to the Rayleigh scattering and the

radiance at the sensor tends lower than the reflected radiance at the surface. However, this study used vegetation indices, which can further reduce the limited uncertainties in reflectance induced by the uncorrected atmospheric effects, as model inputs. For instance, Yu et al. (2016) assessed the influence of atmospheric correction on UAS based NDVI at various flight altitudes (10, 30, 50, 100 m) and results indicate that the uncertainty in NDVI is only around 0.01. Therefore, this study did not conduct the atmospheric correction for the reflectance.

Figure 5 (b) shows the comparison between the UAS T_b and CNR4 T_b . Results show that these two brightness temperatures were very close with R^2 equal to 0.97 and RMSD about 0.93 °C. Errors of thermal data without the atmospheric correction may be significant for UAS, manned airborne and satellite platforms above 150 m (Berni et al., 2009; Hulley et al., 2012; Sabol et al., 2009). As shown in Eq. 19, the atmospheric correction of thermal data includes the correction of the reflected downwelling thermal radiation by accounting for the surface emissivity, and the correction of the atmospheric attenuation to exclude the upwelling thermal radiation from the atmosphere to the sensor. In this study, we conducted the correction of the downwelling thermal radiation with utilizing NDVI to calculate the surface emissivity. This correction approximately contributes to the improvement of the surface temperature about 1-2 °C. The MODTRAN (Berk et al., 1998) based typical atmospheric correction showed that the total errors for not correcting the atmospheric effects are around 2 °C at the 90 m flight altitude (Berni et al., 2009). It can be expected in this study without the correction of the atmospheric attenuation, the errors in the surface temperature can be around 1 °C and this also agrees with the comparison results between FLIR and CNR4. This 1 °C error can contribute to uncertainties in the longwave radiation budget to 10-15 W/m² based on the Stefan–Boltzmann law as Eq. 2. This accuracy fitted requirements for ET monitoring with an accuracy of 10% in ecosystem and crop management (Fisher et al., 2017).

Besides the atmospheric correction, this study did not consider the normalization of reflectance and thermal data between the flight trajectory due to the short flight duration time (approximately 10 minutes, Table 1). Additionally, the anisotropy effects of thermal and optical data may also contribute uncertainties. In general,

554 these issues can contribute to the uncertainties of UAS data and further to the simulated fluxes. However, the
 555 validation of our study (Figure 5) shows UAS imagery has an acceptable accuracy.

556 **Figure 4.** Orthophotos of (a-f) NDVI and (g-l) T_b . (a, g) are on 25th May 2016. (b, h) are on 7th October 2016. (c, i) are on 19th May 2017. (d, j) are on 22nd May 2017. (e, k) are on 26th May 2017. (f, l) are on 18th June 2017. The NDVI for other two flights on 2nd May 2016 and 12nd May 2016 are shown in Supplemental Figure S5.

562 **Figure 5.** Validation of UAS images. (a) Reflectance at 670 and 800 nm, (b) the comparison between FLIR T_b
563 and CNR4 T_b . The red line is the 1:1 line.

564

565 4.2 Instantaneous simulation

566 The spatial patterns of simulated final variables R_n , GPP, LE and WUE are shown in Figure 6. Compared to the
567 NDVI pattern, it can be seen that in the dense vegetation area (high NDVI), R_n was higher than the areas with
568 less dense vegetation. GPP followed the spatial pattern of NDVI. With higher NDVI, there was a higher GPP.
569 For LE, during the early growth stage (25th May 2016), it followed the pattern of the SM proxy, while during the
570 dense vegetation periods (other flights), it had the similar pattern as R_n . For WUE, the pattern was a
571 combination of GPP and LE but more similar to GPP.

572 Figure 7 (a-c) shows validation of the simulated SW_{net} , LW_{in} and R_n with considering the FOV of CNR4 (Figure
573 6 a-f). This modeling methodology can well simulate SW_{net} , LW_{in} and R_n with RMSDs of 34.46, 8.65 and 31.64
574 $W \cdot m^{-2}$, respectively. R^2 between the observed and the simulated SW_{net} , LW_{in} and R_n were 0.93, 0.94 and 0.95,
575 respectively. The relative errors (RE) for SW_{net} , LW_{in} and R_n were 0.88%, -1.88% and 0.66%, respectively. As
576 shown in Figure 7 (d), the model could simulate f_{IPAR} with RMSD equal to 0.12. The simulated spatial patterns
577 and validation results on the estimated SM proxy were shown in Supplemental Figure S2 and S3. R^2 between in-
578 situ and the estimates SM for temporal variations and spatial variations reached to 0.77 and 0.50, respectively.

579 Considering the source weighted EC footprint (the shaded area in Figure 6), the model simulated the dynamic of
580 LE, GPP, and WUE with RMSDs of 41.19 $W \cdot m^{-2}$, 3.12 $\mu mol \cdot C \cdot m^{-2} \cdot s^{-1}$, and 0.35 $g \cdot C \cdot kg^{-1}$, respectively, as shown
581 in Figure 7 (e-g). R^2 for these simulations are 0.84, 0.97, and 0.86, respectively. RE for the simulated LE, GPP,
582 and WUE are 9.31%, 9.21%, and -3.89%, respectively. Compared to other studies using UAS data to simulate
583 LE, this study has a similar or even better performance (Brenner et al., 2017; Hoffmann et al., 2016; Ortega-

584 Farías et al., 2016). This may be partially due to that this site is the radiation controlled system (Wang et al.,
585 2018b) and this methodology can give a good estimation of Rn as Figure 7 (c).

586 To normalize the estimated ET and GPP with Rn and APAR, we calculated EF and LUE as shown in Figure 7 (h
587 and i). Results shows that this model achieved a moderate simulation performance with the RMSDs of EF and
588 LUE equal to 0.08 and 0.16 g·C·MJ⁻¹, respectively. R² for these simulations are 0.44 and 0.52, respectively. RE
589 for the simulated EF and LUE are -5.79% and -8.51%, respectively. The possible approach for future
590 improvement of this modeling methodology is to introduce more spectral indices to better characterize
591 vegetation physiological status to constrain LUE and EF. For instance, the photochemical reflectance index (PRI)
592 (Gamon et al., 1992) can be utilized to indicate the light use efficiency to constrain the estimation of GPP and
593 transpiration. However, it should be noted that in the short-time scales, PRI reflects the xanthophyll de-
594 expoxidation and can indicate the change of LUE (Zarco-Tejada et al., 2013a). However, in the seasonal scales,
595 the change of PRI is more complex. The changes are related to the size of constitutive pigment pools (Zhang et
596 al., 2016) as well as affected by structural changes over the seasons. Additionally, the green or the red edge
597 based vegetation indices can also be utilized to improve the estimation of the green vegetation fraction (Gitelson
598 et al., 2003; Viña et al., 2011). In current methodology, only the soil adjusted vegetation index (SAVI) (Huete,
599 1988) with the empirical formula from the PT-JPL model (Fisher et al., 2008) was utilized to estimate the green
600 vegetation fraction.

Figure 6. Instantaneous simulation of (a-f) Rn, (g-l) GPP, (m-r) LE, and (s-x) WUE. The circles in (a-f) are the FOV of CNR4 with considering the change of vegetation height in Table 2. The shaded area in (g-x) indicates the source contribution of the EC footprint. Note the differences in the spatial resolutions and the dimensions of the displayed plots.

Figure 7. Comparison of simulated land surface fluxes from the UAS instantaneous simulation with in-situ measurements. (a) SW_{net} , (b) LW_{in} , (c) Rn , (d) f_{IPAR} , (e) GPP , (f) LE , (g) WUE , (h) EF , (i) LUE . The error bars in (d) indicate the standard deviations of the observed and estimated f_{IPAR} in the EC footprint. It should be noticed that energy relative balance closure of the measurements on 7th October 2016 was lower than 80% and this date was excluded in LE , WUE and EF analysis. The red line is the 1:1 line.

612 4.3 Diurnal simulation

613 The simulated spatial patterns from the diurnal simulation of LE for the half an hour of flight campaigns are
614 shown as the base map in Figure 8. Compared to the simulated instantaneous LE at the same time in Figure 6 (k-
615 o), the simulated spatial patterns are similar and the estimated values were close. Figure 9 shows ECR and the
616 comparison between the simulated LE and GPP with EC observations for each day. Generally, the diurnal
617 simulation captured the observed diurnal variations of LE and GPP. In most cases, the simulated LE was within
618 the LE with residual closure, as shown in Figure 9 (a-e). The model was also able to estimate GPP, as shown in
619 Figure 9 (f-j). But during the noon period, the simulation slightly overestimated GPP, while during other hours
620 the simulation underestimated GPP. The reason may be that the GPP model of this study did not consider the
621 influence of the PAR intensity to LUE. During the mid-day, the high PAR intensity can induce the saturation of
622 the canopy photosynthesis and reduce canopy LUE (Ibrom et al., 2008; Propastin et al., 2012).

623 Table 3 presents the statistics on the model validation and the simulated LE was compared with different energy
624 balance closure correction methods. Figure 10 (a) and (b) shows the scatterplot between the simulated and
625 observed GPP and LE fluxes in the diurnal simulation. Because ECR on 7th October 2016 was lower than 80%,
626 the simulation of LE on this day was excluded in the analysis. Compared to other energy balance closure
627 correction methods (LE_EC_1 and LE_EC_2), LE_EC_BR shows the best match with the simulated LE. R^2 and
628 RE for the simulated LE were $39.33 \text{ W}\cdot\text{m}^{-2}$, 0.87 and 0.52%, respectively. The diurnal simulation could well
629 capture GPP dynamics with RMSD of $5.04 \mu\text{mol}\cdot\text{C}\cdot\text{m}^{-2}\cdot\text{s}^{-1}$, R^2 of 0.83 and RE of -7.58%. As the variations of EC
630 footprints sample different source areas around the tower during the course of the day, the good performance of
631 the diurnal simulation give confidence in the performance of the simulated spatial patterns from the UAS
632 imagery. It should be also noted that the diurnal simulation of this study has assumptions that NDVI and SM are
633 constant during the course of the day. For the NDVI is a reasonable assumption. Regarding SM, the in-situ
634 measurements in our site shows that it is almost constant within one day as the Supplemental Figure S4.

635 However, in dry regions, the variations of the soil moisture during the course of a day may need to take into
 636 account.

637 Figure 10 (c) shows the comparison of these two temporal upscaling schemes, assuming the constant EF and
 638 averaging from the instantaneous during the course of the day. It can be seen that the averaged LE from the
 639 instantaneous simulations during the entire course of the day by considering the variable eddy covariance
 640 footprint has a higher R^2 and a lower RMSD than the scheme using a constant EF. This finding agrees with
 641 Morillas et al. (2014) that averaging the instantaneous estimates performs better than assuming the self-
 642 preservation of EF for the upscaling from the instantaneous to the diurnal. Moreover, this also indicates the
 643 importance to consider the variations of the footprint in model benchmarking.

644 **Figure 8.** Simulated spatial patterns of LE from diurnal simulations. The base map is the simulated the LE flux
 645 for the half an hour when UAS campaigns were conducted. EC footprints show the coverage of the footprint for
 646

each half an hour during the daytime of the UAS flight campaign day. In the validation, the source weighted footprints were used.

650 **Figure 9.** Simulated diurnal variation of (a-f) LE and (g-l) GPP. LE_EC1 was attributing all closure errors to the
651 sensible heat flux. LE_EC2 was attributing all closure errors to the latent heat flux. LE_EC_BR was attributing
652 closure errors to both latent heat flux and sensible heat flux with keeping the fixed Bowen ratio. The ECR of
653 each day is shown in each plot. Note that ECR on 7th October 2016 was less than 0.80.

654 **Table 3.** Statistics for validation of the diurnal simulation (LE was compared with different energy balance
655 closure correction methods)

	RMSD	R ²	RE (%)
LE_EC1 (W·m ⁻²)	48.65	0.84	17.89
LE_EC2 (W·m ⁻²)	44.58	0.86	-8.35
LE_EC_BR (W·m ⁻²)	39.37	0.85	0.80
GPP (μmol·C·m ⁻² ·s ⁻¹)	5.04	0.83	-7.58

656

657

658 **Figure 10.** Scatter plots between the simulated and the observed (a) GPP and (b) LE. Source weighted EC
659 footprints were used in this validation. (c) is the comparison between two upscaling schemes from the
660 instantaneous to the daytime average. The blue circle uses the averaged LE from the instantaneous simulations
661 by considering the variable eddy covariance footprint (FP) to sample different areas around the EC tower. The
662 red star represents using the fixed evaporative fraction obtained from the instantaneous simulation of each flight
663 campaign day. ECR on 7th October 2016 was less than 0.80 and LE of this day was excluded in the analysis.

664

665 4.4 Model error propagation

666 Figure 11 shows the results of error propagation from UAS imagery to the simulated R_n , SM, ET and GPP. The
667 NDVI and T_b determine the surface albedo and LW_{out} , respectively. Their uncertainties influence the estimated
668 R_n of the land surface. Thus, it can be seen that with ± 0.1 errors in NDVI and ± 2 °C errors in T_b , the simulated
669 R_n changed approximately $\pm 6\%$ in both the early growth and dense vegetation stages. For SM which was
670 estimated from the temperature-vegetation triangle approach, the possible errors of NDVI and T_b can alter the
671 relative position of the pixel respected to the dry and wet edges within the triangle and change the estimated SM.
672 As shown in Figure 11, the estimated SM has different responses to the errors in NDVI and T_b in the early
673 growth stage and dense vegetation stage. In the early growth stage, these errors of UAS imagery only
674 contributed to changes of SM within 5%. However, in the dense vegetation growth stage, the errors lead to the
675 SM changes up to 60%. This is due to that in the dense vegetation conditions (high vegetation fraction), the dry
676 and wet edges of the triangle approach have a closer distance than in the low vegetation fraction (Garcia et al.,
677 2014). Further for the estimation of ET, with $\pm 6\%$ errors from R_n and $\pm 5\%$ errors from SM, the error
678 propagation led to $\pm 12\%$ uncertainties in LE for the early growth stage. However, for the dense vegetation
679 growth stage, with the $\pm 6\%$ errors from R_n and $\pm 60\%$ errors from SM, the simulated LE has lower uncertainties
680 within 30%. This is due to that for the dense vegetation conditions, the methodology of this study is more similar
681 to the vegetation driven approach, which is the Priestley-Taylor approach to estimate ET and less relies on the
682 accuracy of surface temperature and SM (McCabe et al., 2017). Thus, it can reduce the uncertainties from the
683 estimated SM. For the bare soil conditions, more radiation is partitioned to the soil surface and this methodology
684 is more close to the Temperature-Vegetation triangle approach for the estimation of LE. Therefore, in this way
685 this methodology can achieve a good accuracy to estimate ET for both early growth and dense vegetation
686 conditions. In the error propagation of GPP, for the low vegetation conditions, GPP is more sensitive to the
687 variation of NDVI and ± 0.1 errors in NDVI can contribute to 40% changes of GPP. However, in the dense
688 vegetation conditions, NDVI gets saturation and the simulated GPP does not change so much.

Figure 11. The error propagation analysis from uncertainties of UAS imagery to the simulated fluxes. The first panel (a-d) is for the early growth stage with NDVI of 0.35 and T_b of 27 °C and the atmospheric forcing on 25th May 2016. The second panel (e-h) is for the dense vegetation growth stage with NDVI of 0.82 and T_b of 10 °C and the atmospheric forcing on 7th Oct 2016. Simulations were conducted with adding errors of NDVI equal to ± 0.1 and errors of T_b equal to ± 2 °C. (a) and (e) are the errors of simulated Rn. (b) and (f) are the errors for the simulated SM. (c) and (g) are the errors for the simulated LE. (d) and (h) are the errors for the simulated GPP.

4.5 Spatial heterogeneity

Figure 12 shows the comparison of the semivariograms on different growth stages. It can be seen that the sill values (semivariance when the semivariogram flattens out, the y-axis value) of all variables except SM during the early growth stage (25th May 2016) were larger than that during the dense vegetation period (07th Oct 2016). Furthermore, from the range (the lag distance when the sill is reached, the x-axis value), it can also be found that the range on 25th May 2016 is much smaller than 07th Oct 2016. These findings indicate the landscape was more heterogeneous on the early growth stage than the dense vegetation stage. During the early growth stage, the values of range were around 1.5-2 m. This range is approximately equal to the canopy crown size and the open-canopy structure at the early stage contributes the spatial covariance within this range. For this early growth

706 stage, to capture the variability, an optimum pixel size would be half of the range (Rahman et al., 2003) around
 707 1m. However, when the willow plantation grew to the closed canopy structure, the range values for the
 708 semivariograms were much larger. By comparing the nugget (the semivariance value when the lag is equal to 0
 709 m) and range values, it can be found that the spatial structure of GPP, LUE and WUE resembled that of NDVI,
 710 while the spatial structure of the Rn, SM, LE and EF were similar to those of T_b . These findings agrees with
 711 previous findings that in the radiation controlled Danish ecosystem, vegetation greenness controls the carbon
 712 assimilation, while the net radiation controls LE and WUE is mainly determined by GPP (Wang et al., 2018b).

713
 714 **Figure 12.** Semivariograms of (a) NDVI, (b) T_b , (c) SM, (d) Rn, (e) GPP, (f) ET, (g) WUE, (h) EF and (i) LUE
 715 on 25th May 2016 (the early growth stage, blue circles) and 07th Oct 2017 (the dense vegetation stage, orange
 716 dots). The y-axis γ is the semivariance. The left y-axis is 25th May 2016 and the right y-axis is 07th Oct 2016.

717

718 For the scaling experiment, the relationship between the accuracy of simulation outputs and degradation of the
719 spatial resolution of inputs is shown in Figure 13. We found that the model performance did not change
720 significantly when the spatial resolution was degraded from 0.03 to 1.5 m. There is slightly performance
721 degradation from 1.5 to 12 m, but there was a clear loss in model accuracy when the spatial resolution was
722 degraded from 12 to 24m. This result agrees with other scaling experiments with satellite data (Ershadi et al.,
723 2013) on that models using finer spatial resolution data performs better. It also indicates the accurate simulation
724 patterns that our UAS based methodology captured. However, this study also found no significant improvements
725 with using super high spatial resolution data (between 0.03 and 1.5 m) at this site. This indicate that comparing
726 to the observations at the EC flux tower, too high spatial resolution remote sensing data may not be necessary.

727 As the comparison between the solid and dashed lines in Figure 13, the model validation using a source
728 weighted footprint, which considered the heterogeneity of EC source contribution within the footprint, showed a
729 significantly better performance than using an arithmetic mean. In the case of GPP, R^2 were around 10% higher
730 and RMSD 30% lower when using the source weighted footprint until reaching a resolution of 12m. It was
731 noticed also a slight decrease in R^2 at the 1.5m pixel size, which corresponded with the range of the
732 semivariogram for GPP and LE. These results indicate the importance to consider the heterogeneity of the EC
733 source contribution, especially during the early growth stage of vegetation. Furthermore, these results also
734 provide confidence in the spatial pattern of fluxes, as we hypothesized that if the spatial patterns were not
735 accurate, we would not see an improvement in model performance using the weight contribution to the total flux.
736 These results also suggest that in our conditions and for model validation purposes, it is enough to have a spatial
737 resolution of around 12m (flight height of 4km) and for detecting spatial differences a spatial resolution of 1 m
738 (half of the semivariogram range) (flight height of 400m) should be enough at this site. This demonstrates an
739 approach relying on the analysis of spatial heterogeneity of high spatial resolution UAS data to determine the
740 optimum flying height (spatial resolution). The optimal resolution is the one that captures sufficient spatially
741 resolved information while maximizing the ground coverage and will change depending on each specific site

742 conditions. A targeted spatial scale analysis using the semivariogram and aggregation experiments as this study
 743 can be applied in other sites to identify such optimal spatial resolution and optimal flight height for UAS.

744
 745 **Figure 13.** The comparison of model simulation performance (a: GPP, b: LE) with the EC observations across
 746 aggregated spatial resolutions from 0.03 to 24 m and the performance using the source weighted mean (curves
 747 with circles) and arithmetic mean (curves with cross signs) of EC footprints.

748

749 5. Conclusions

750 This study designed and evaluated an operational monitoring methodology of mapping land surface energy,
 751 water and CO₂ fluxes specifically for UAS. It integrates optical and thermal imagery to map the land fluxes at an
 752 optimal spatial resolution to maximize the ground coverage while having sufficient spatial details to capture
 753 fluxes accurately. This methodology is based on a joint parsimonious evapotranspiration (ET) and gross primary
 754 productivity (GPP) model with limited data inputs and parameterization and could even be applied in data-scarce
 755 regions. It can provide very high resolution (<1 m) maps of land surface fluxes relevant for agriculture and
 756 ecosystem management such as net radiation (R_n), ET, GPP, evaporative fraction (EF), light use
 757 efficiency (LUE) and ecosystem water use efficiency (WUE).

758 This study was carried out on a flux site deciduous willow plantation where EC data are available for model
759 validation. With a footprint model, our model validation results for the instantaneous Rn, ET, GPP, evaporative
760 fraction, light use efficiency and water use efficiency showed root-mean-square deviations equal to $31.6 \text{ W}\cdot\text{m}^{-2}$,
761 $41.2 \text{ W}\cdot\text{m}^{-2}$, $3.12 \mu\text{mol}\cdot\text{C}\cdot\text{m}^{-2}\cdot\text{s}^{-1}$, 0.08, $0.16 \text{ g}\cdot\text{C}\cdot\text{MJ}^{-1}$ and $0.35 \text{ g}\cdot\text{C}\cdot\text{kg}^{-1}$, respectively. Further, in the temporal
762 upscaling from the instantaneous to the diurnal, it was found that averaging instantaneous simulations performs
763 better than the classic approach of assuming a constant evaporative fraction. Using a footprint model to sample
764 different areas of high spatial resolution UAS imagery can be a tool to upscale to diurnal estimates to benchmark
765 with EC data.

766 Moreover, we showed how spatial metrics derived from high-resolution maps can be used to identify the
767 optimum spatial resolution to capture the ET and GPP fluxes accurately. We found that a resolution consistent
768 with the canopy size (around 1.5 m in our study) is sufficient to capture the spatial heterogeneity of the fluxes.
769 Compared to the EC observations, in this willow site, the aggregation of simulated GPP using source weighted
770 mean of the footprint was about 10% higher in R^2 and the RMSD was 30% lower than using the arithmetic mean,
771 during an early growth stage. This improvement highlights the need for considering the heterogeneity of the land
772 surface and flux source contribution within the eddy covariance footprint, especially during the early growth
773 stage. Further, the improvement also indicates the accuracy of the obtained spatial patterns, since if the spatial
774 patterns would be incorrect, such an improvement would not be expected.

775 This methodology has a large potential to provide spatially resolved information on ecohydrological processes
776 valuable for agricultural and natural ecosystems applications. The unprecedentedly high spatial resolution
777 obtained is useful to examine scaling issues, benchmark models with eddy covariance fluxes and quantify spatial
778 heterogeneity within biomes.

779

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1042 LIST OF FIGURE CAPTIONS

1043 **Figure 1.** The overview of Risoe EC flux site and flight pattern of campaigns. The flux tower is in the middle of
1044 the willow plantation. The red dash line shows the flying path of UAS flight campaigns. Stars are the location of
1045 the understory PAR sensors. Yellow dots show the location of SM samples conducted on 16th June 2017. FOV is
1046 the field of view of CNR4, when willow height is 0 m.

1047 **Figure 2.** (a) The DJI S900 vehicle platform and (b) the payload including a RGB camera, a thermal infrared
1048 camera and a multispectral camera.

1049 **Figure 3.** The workflow of the instantaneous simulation. Green boxes represent inputs from UAS imagery. Blue
1050 boxes are in-situ measurements from the EC tower. Yellow boxes belong to the simulated intermediated
1051 variables. Orange boxes are the simulated final variables. Variables in green, yellow and oranges boxes were
1052 validated by in-situ measurements.

1053 **Figure 4.** Orthophotos of (a-f) NDVI and (g-l) T_b. (a, g) are on 25th May 2016. (b, h) are on 7th October 2016. (c,
1054 i) are on 19th May 2017. (d, j) are on 22nd May 2017. (e, k) are on 26th May 2017. (f, l) are on 18th June 2017.
1055 The NDVI for other two flights on 2nd May 2016 and 12nd May 2016 are shown in Supplemental Figure S5.

1056 **Figure 5.** The validation of UAS images. (a) Reflectance at 670 and 800 nm, (b) the comparison between FLIR
1057 T_b and CNR4 T_b. The red line is the 1:1 line.

1058 **Figure 6.** The instantaneous simulation of (a-f) Rn, (g-l) GPP, (m-r) LE, and (s-x) WUE. The circles in (a-f) are
1059 the FOV of CNR4 with considering the change of vegetation height in Table 2. The shaded area in (g-x)
1060 indicates the source contribution of the EC footprint. Note the differences in the spatial resolutions and the
1061 dimensions of the displayed plots.

1062 **Figure 7.** Comparison of simulated land surface fluxes from the UAS instantaneous simulation with in-situ
1063 measurements. (a) SW_{net} , (b) LW_{in} , (c) Rn, (d) f_{IPAR} , (e) GPP, (f) LE, (g) WUE, (h) LUE, (i) EF,. The error bars
1064 in (d) indicate the standard deviations of the observed and estimated f_{IPAR} in the EC footprint. It should be
1065 noticed that energy relative balance closure of the measurements on 7th October 2016 was lower than 80% and
1066 this date was excluded in LE, EF and WUE analysis. The red line is the 1:1 line.

1067 **Figure 8.** The simulated spatial patterns of LE from diurnal simulations. The base map is the simulated the LE
1068 flux at the half an hour when UAS campaigns were conducted. EC footprints show the coverage of the footprint
1069 for each half an hour during the daytime of the UAS flight campaign day. In the validation, the source weighted
1070 footprints were used.

1071 **Figure 9.** The simulated diurnal variation of (a-f) LE and (g-l) GPP. LE_EC1 was attributing all closure errors to
1072 the sensible heat flux. LE_EC2 was attributing all closure errors to the latent heat flux. LE_EC_BR was
1073 attributing closure errors to both latent heat flux and sensible heat flux with keeping the fixed Bowen ratio. The
1074 ECR of each day is shown in each plot. Note that ECR on 7th October 2016 was less than 0.80.

1075 **Figure 10.** The scatter plot between simulated and observed (a) GPP and (b) LE. Source weighted EC footprints
1076 were used. ECR on 7th October 2016 was less than 0.80 and LE of this day was excluded in the analysis.

1077 **Figure 11.** The error propagation analysis from uncertainties of UAS imagery to the simulated fluxes. The first
1078 panel (a-d) is for the early growth stage with NDVI of 0.35 and T_b of 27 °C and the atmospheric forcing on 25th
1079 May 2016. The second panel (e-h) is for the dense vegetation growth stage with NDVI of 0.82 and T_b of 10 °C

1080 and the atmospheric forcing on 7th Oct 2016. Simulations were conducted with adding errors of NDVI equal to
1081 ± 0.1 and errors of T_b equal to ± 2 °C. (a) and (e) are the errors of simulated R_n . (b) and (f) are the errors for the
1082 simulated SM. (c) and (g) are the errors for the simulated LE. (d) and (h) are the errors for the simulated GPP.

1083 **Figure 12.** Semivariograms of (a) NDVI, (b) T_b , (c) SM, (d) R_n , (e) GPP, (f) ET, (g) EF, (h) LUE and (i) WUE
1084 on 25th May 2016 (the early growth stage, blue circles) and 07th Oct 2017 (the dense vegetation stage, orange
1085 dots). The y-axis γ is the semivariance. The left y-axis is 25th May 2016 and the right y-axis is 07th Oct 2016.

1086 **Figure 13.** The comparison of model simulation performance (a: GPP, b: LE) with the EC observations across
1087 aggregated spatial resolutions from 0.03 to 24 m and the performance using the source weighted mean (curves
1088 with circles) and arithmetic mean (curves with cross signs) of EC footprints.

1089