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Paper:

Sutherland, G., Chasmer, L., Kljun, N., Devito, K. & Petrone, R. (2017). Using High Resolution LiDAR Data and a Flux Footprint Parameterization to Scale Evapotranspiration Estimates to Lower Pixel Resolutions. *Canadian Journal of Remote Sensing*, 0-0.

<http://dx.doi.org/10.1080/07038992.2017.1291338>

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2 Using high resolution LiDAR data and a flux footprint parameterization to scale evapotranspiration
3 estimates to lower pixel resolutions
4

5 **Research Paper**
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48 **Abstract**

49 Over the last several decades the hydrologically sensitive Boreal Plains ecoregion of Western
50 Canada has experienced significant warming and drying. To better predict implications of land
51 cover changes on evapotranspiration (ET) and future water resources in this region we used high
52 resolution light detection and ranging and energy balance data to spatially parameterise the
53 Penman-Monteith ET model. Within a 5 km x 5 km area of peatland ecosystems, riparian
54 boundaries, and upland mixedwood forests, the influence of land cover heterogeneity on the
55 accuracy of modelled ET is examined at pixel sizes of 1, 10, 25, 250, 500 and 1000 m,
56 representing resolutions common to popular satellite products (SPOT, Landsat and MODIS).
57 Modelled ET was compared with tower-based eddy covariance measurements using a weighted
58 flux footprint model. Errors range from 10% to 36% of measured fluxes and results indicate that
59 sensors with small pixel sizes (1 m) offer significantly better accuracy in large heterogeneous
60 flux footprints, while a wider range of pixel sizes (<25 m) can be suitably applied to smaller
61 homogeneous footprints. Mid (250 m) and coarse (>500 m) pixel sizes offered significantly less
62 accuracy, although changes in pixel size within this range offered comparable results.

63 Key words: Evapotranspiration modelling; evapotranspiration scaling; LiDAR, eddy covariance;
64 vegetation structure; Boreal.

65

66 **Introduction**

67 Climate warming is expected to have a disproportionately large impact on Canada's high latitude
68 regions and to alter precipitation (P) and evapotranspiration (ET) patterns in Boreal Canada
69 (IPCC, 2007). Western Canada's Boreal Plains ecozone covers approximately 629,527km²
70 (National Forest Inventory, 2006) and is a hydrologically sensitive region where potential ET
71 (PET) generally exceeds P on an annual basis, creating persistent water-deficit conditions that
72 are interrupted by infrequent wet years occurring on a 10-15 year cycle (Devito et al., 2005a).
73 Consequently, ET is commonly the largest component of the surface energy and water budgets
74 during the growing season in high latitude regions (Comer et al., 2000; Cleugh et al., 2007;
75 Raddatz et al., 2009). Therefore, an accurate understanding of ET and its driving processes is
76 essential for characterizing water partitioning and atmospheric losses from the water balance,
77 especially as the climate in this region continues to warm and become drier.

78 However, accurately assessing ET at the scales of interest to water managers is difficult
79 due to the heterogeneous nature of this region (Ferone and Devito, 2004; Smerdon et al., 2005),
80 the fragmented and changing land cover due to resource extraction (Lee and Boutin, 2006;
81 Turetsky and St. Louis, 2006; Graf, 2009), and accessibility issues in largely remote locations.
82 As a result, traditional point-scale or tower-based measurements of cumulative energy and water
83 flux data are sparse and difficult to spatially extrapolate (Næsset and Økland, 2002; Loheide and
84 Gorelick, 2005; Coops et al., 2007). Remote sensing offers the ability to collect information on
85 ecosystems of interest over a variety of spatial and temporal resolutions, and has provided a
86 platform from which point and tower data can be scaled to landscapes or regions of interest to
87 resource managers.

88 Modern methods linking remote sensing with energy and water balance data take the
89 form of surface energy balance methods, which rely on radiated thermal measurements to infer
90 surface temperature and available energy, from which ET can be estimated as a residual
91 (Bastiaanssen et al., 1998; Su, et al., 2002; Caparrini et al., 2003; Kustas et al., 2003; Jiang and
92 Islam, 2006). Several popular remote sensing energy balance models that have emerged include
93 SEBS (Su, 2002), S-SEBI (Roerink et al., 2000), SEBAL (Bastiaanssen, 1998; Ruhoff et al.,
94 2012) and METRIC (Allen et al., 2007). Such methods are useful as they measure physical
95 radiative properties of a surface that are directly related to ET (Overgaard et al., 2006). However,
96 errors associated with energy balance methods can originate from small inaccuracies in
97 measurement of surface temperature that propagate to larger errors in the estimation of turbulent
98 fluxes (Cleugh et al., 2007).

99 The Penman-Monteith (PM) equation (Monteith, 1965) has also been successfully used to
100 estimate ET across a variety of climates and land covers (Allen, 1998; Ventura 1999; Chen et al.,

101 2005b; Cleugh et al., 2007; Armstrong et al., 2008; Leuning et al., 2008). In the context of land
102 surface models (LSM) the PM model is often driven using energy balance and stomatal
103 resistance datasets, which provide temporal variability of surface conditions, while remote
104 sensing data products provide a platform to scale the model to land cover types based on average
105 leaf area index per land cover type or per pixel (Leuning et al., 2008; Sutherland et al., 2014).

106 Additionally, spectral vegetation index (SVI) methods indirectly estimate ET as a
107 function of vegetation distribution and reflectance parameters (Running and Nemani, 1988; Kite
108 and Spence, 1995; Chen and Cihlar, 1996; Jiang and Islam, 1999; Haboudane et al., 2004; Wang
109 et al., 2005; Pisek et al., 2011), and thus leaf area index (LAI) is the primary measure of green
110 vegetation in SVIs that estimate ET (Wang et al., 2005). However, SVIs have been shown to
111 saturate beyond certain LAI thresholds (Haboudane et al., 2004; Wang et al., 2005; Wu et al.,
112 2008). Additionally, spectral reflectance values given off by understory vegetation and soil
113 surfaces are known to introduce significant background noise in mixed pixels (Chen and Cihlar,
114 1996; Lim et al., 2003; Parker et al., 2001).

115 Both energy balance and SVI methods have been applied to many different regions and
116 have shown promising results in most cases. There are however, several drawbacks common to
117 both methods, particularly within heterogeneous environments: 1) Coarse resolutions can lead to
118 landscape heterogeneity not being resolved within mixed pixels (Moran and Jackson, 1991;
119 Hudak et al., 2002; Kustas et al., 2004; Nagler et al., 2005; McCabe and Wood, 2006; Anderson
120 et al., 2012); 2) passive remote sensors saturate at high levels of LAI (Lüdeke et al. 1991;
121 Haboudane et al., 2004; Wu et al., 2008) and therefore underestimate ET when applied to multi-
122 layer, densely foliated ecosystems; 3) while they can provide information on vegetation
123 distribution in the horizontal direction, they cannot directly sense the structure of surface

124 vegetation in the vertical direction (Hudak et al., 2002); and 4) validation of ET estimates from
125 coarse satellite data can be difficult due to the large disparity in scale between in situ ET
126 measurements and modelled ET values (Li et al., 2009; Anderson et al., 2012) resulting in the
127 inclusion of land areas not represented by the EC system for validation (Göeckede et al. 2008;
128 Chasmer et al. 2011a).

129 While spectral remote sensing data provide information on the spatial characteristics of
130 the ecosystem such as canopy cover, vegetation health, and land surface heterogeneity (Turner et
131 al., 2002; Göckede et al., 2008), air-borne light detection and ranging (LiDAR) data go a step
132 further by measuring the full three-dimensional characteristics of the land surface offering high
133 resolution data products on vegetation structure (Lim and Treitz, 2004; Hopkinson et al., 2005;
134 Morsdorf et al., 2006; Hopkinson and Chasmer, 2007; Chasmer et al., 2011b; Korhonen, et al.,
135 2011; Hansen et al., 2014; Saito et al. 2015; Schumacher et al., 2015; and many more). Of the
136 LiDAR data products available, vegetation height and LAI are the most relevant to estimating
137 ET, as these parameters influence physiological, aerodynamic, and energy components of ET
138 models.

139 To the authors' knowledge, few studies have used canopy structural information obtained
140 from LiDAR data within land surface or ecosystem models to estimate ET fluxes (Neale et al.,
141 2011; Mitchell et al., 2012), and fewer studies have integrated LiDAR data with a footprint
142 model for the direct purpose of assessing how modelled ET differs using vegetation structure
143 inputs of varying pixel sizes over heterogeneous land surface areas. Chasmer et al. (2011a)
144 introduced this topic by integrating LiDAR derivatives of canopy structure with the footprint
145 parameterization of Kljun et al. (2004) to better understand uncertainties in gross primary
146 production (GPP) within 1 km resolution MODIS pixels. Sutherland et al. (2014) built on this

147 work by using LiDAR-derived vegetation parameters to assess the accuracy of spatially explicit
148 high-resolution vs bulk average model inputs to produce estimates of ET scaled beyond the
149 tower footprint, but neither study examined a broad range of remote sensing pixel sizes.
150 Consequently, uncertainty remains surrounding the accuracy of common sensor pixel sizes that
151 may be used to characterize heterogeneous ecosystems within LSMs.

152 To examine how modelled ET varies using vegetation structure inputs at a variety of
153 pixel sizes over heterogeneous landscapes the following study uses airborne LiDAR data
154 products (LAI, canopy roughness) and a network of energy balance towers to parameterize the
155 PM ET model at a pixel size of 1 m² within the heterogeneous Boreal Plain ecozone following
156 methods of Chasmer et al. (2011b) and Sutherland et al. (2014). The primary objective of this
157 study is to assess the accuracy of variable pixel sizes (1, 10, 25, 250, 500, 1000 m) as inputs to
158 the PM ET model over homogeneous to heterogeneous land cover types in the Boreal Plains.
159 LiDAR is used to generate 3D inputs to aerodynamic roughness and LAI. The model is then run
160 on decreasing pixel sizes up to 1000 m and compared with eddy covariance data for validation.

161 The parameterization of ecosystem and land surface models using an integrated LiDAR-
162 footprint approach at different pixel sizes may improve our understanding of the influence of
163 spatial heterogeneity on model results at coarse resolutions, site representation of EC
164 measurements, and discrimination of the 3D canopy characteristics required for spatial estimates
165 of LAI and surface roughness not available using spectral remote sensing methods. This study,
166 therefore, will quantify pixel sizes that best approximate EC estimates of ET within variable
167 footprint extents and land cover types and offer insight into scaling methods in heterogeneous
168 environments.

169 **Study Site**

170 The Utikuma Region Study Area (URSA) (Figure 1) is located 370 km north of Edmonton and is
171 comprised of a network of research sites that have been the focus of numerous studies (e.g.
172 Devito et al., 2005a, b; Petrone et al., 2007; Brown et al. 2010; Chasmer et al. 2011a; Petrone et
173 al. 2011; Brown et al., 2013; Petrone et al. 2015). The URSA is characterized by a complex
174 patchwork of heterogeneous land cover types including: mixed-wood uplands comprised of
175 trembling aspen (*Populus tremuloides*), minimal balsam poplar (*Populus balsamifera*) and white
176 spruce (*Picea glauca*); sparsely treed *Sphagnum* and black spruce (*Picea mariana*) peatlands;
177 and shallow ponds with peat extension up to 40 m from the pond edge. The study area is
178 hydrologically sensitive due to the sub-humid climate and extensive anthropogenic and natural
179 disturbance (Lee and Boutin, 2006; Turetsky and St. Louis, 2006; Graf, 2009; Petrone et al.
180 2015). Mean annual temperature measured nearby at Slave Lake is 1.7 °C (1980 – 2010), while
181 average annual precipitation is 515 mm (Petrone et al. 2007).

182 Two regenerating upland mixed-wood stands are examined in this study (Figure 1b). The
183 northern stand was harvested in February of 2007, while the southern stand was harvested in
184 February of 2008. Canopy heights determined from airborne LiDAR within these regenerating
185 mixed-wood stands range from 0.5 m to 16 m and LAI ranges from 0 to 4. Both stands are
186 surrounded by a mature aspen canopy between 10-20 m in height.

187 Figure 1: a) 5 km² land cover classification; b) local land cover classification surrounding energy
188 balance and eddy covariance towers; c) 5 km² canopy height model (m); d) 5 km² digital
189 elevation model (m above sea level); and e) 5 km² leaf area index map.

190

191 **Materials and Methods**

192 ***Hydro-meteorological instrumentation used to drive modelled ET***

193 To inform and drive the PM model meteorological and hydrological data were collected from
194 June 1st to August 31st, 2008, at a 5 km x 5 km study area using a network of eleven energy
195 balance towers (Table 1) measuring ground temperature profiles (T_G , °C) (Omega copper-
196 constantin, Campbell Scientific Inc, Logan, Utah, USA) at 0.1, 0.25, 0.5 and 1 m below ground;
197 net radiation (Q^* , $W m^{-2}$) at 3 m (NRLite, Kipp and Zonen, The Netherlands); and air
198 temperature (T_a , °C) and relative humidity (RH, %) at 1 and 2 m above ground (HOBO Onset Pro
199 Temp/RH, Hoskin Scientific, Vancouver, Canada). Two energy balance towers are located each
200 in upland mature mixed-wood forests, riparian, treed wetland and open wetland land cover types
201 and are averaged for input into the PM model, while one tower is located over a pond.

202 Approximately 4000 porometry measurements of leaf stomatal conductance (g_s , $mmol m^{-2}$
203 s^{-1}) were also collected throughout the study period within regenerating mixed-wood and
204 mature aspen stands (SC-1 Decagon Devices, Inc. WA) (Giroux, 2012), coincident with EC
205 measurements. These were averaged per species type and age class (mature, regenerating) and
206 input into the PM model.

207

208 Table 1.

209

210 ***LiDAR data collection and processing***

211 Airborne scanning LiDAR data were collected prior to foliage loss in mid-September, 2008 by
212 Airborne Imaging Inc. and contracted by the Government of Alberta. The system used was a

213 small footprint discrete-return ALTM 3100EA (Optech Inc., Toronto ON), operated at a flying
214 height of 1400 m above ground level, with a pulse repetition frequency of 50 kHz and a scan
215 angle of $\pm 25^\circ$. A swath overlap of 50% ensured that all sides of trees and the ground surface
216 were sampled. Data derivatives used as input into the PM model included a high resolution (1 m)
217 digital elevation model (DEM), canopy height model (CHM), LAI, and a landcover classification
218 (Sutherland et al., 2014; Chasmer et al. 2016).

219 The land cover classification divided the land surface into groups including upland forest,
220 water, open wetland, treed wetland, and disturbance and was compared with manual delineation
221 of wetland and water areas from aerial photos (Halsey et al. 2004) and field data collection
222 (Chasmer et al. 2016). Errors of omission of wetland, upland forest and pond areas, which make
223 up the dominant land cover within the 5 km x 5 km study area were manually corrected in areas
224 where open and closed wetlands were classified as upland forest (~8% of the area).

225 While energy balance data was used to inform temporal variability in ET over the study
226 period, LiDAR data products were used to inform spatial variability in ET across the 5 km x 5
227 km study site. Leaf area index, a data product used to estimate stomatal resistance in equation
228 (1), was estimated from LiDAR-derived canopy gap fraction (number of ground returns divided
229 by all returns within a column, x, y, z), and allometric estimates of canopy clumping, needle to
230 shoot area ratio, and woody to total area ratios (Chen et al., 2006; Sutherland et al., 2014) were
231 applied per dominant species within each land cover type.

232

233 ***Description of the Penman-Monteith Model to be parameterised using energy balance and***
234 ***LiDAR data***

235 The PM model is described as:

236

$$237 \quad \lambda E = \frac{[\Delta (Q^* - Q_G)] + \rho_a C_p \frac{(e_s - e_a)}{r_a}}{\Delta + \gamma \left(1 + \frac{r_s}{r_a}\right)} \quad (1)$$

238 and requires temporally varying inputs of λ (latent heat of vaporization [MJ kg⁻¹]), Δ (slope of
239 the vapour pressure curve [kPa °C⁻¹]), Q^* (net radiation [here as MJ m⁻² h⁻¹]), Q_G (soil heat flux
240 density [MJ m⁻² h⁻¹]), ρ_a (density of the air [kg m⁻³]), c_p (specific heat of the air [KJ kg⁻¹ K⁻¹]), e_s
241 (saturation vapour pressure [kPa]), e_a (actual vapour pressure represented as [kPa]), and γ
242 (psychrometric constant [kPa °C⁻¹]) measured by energy balance towers unique to each land
243 cover type.

244 Following the methods of Sutherland et al. (2014) spatially explicit values of r_a
245 (aerodynamic resistance [s m⁻¹]) and r_s (surface resistance [s m⁻¹]) were calculated for each 1 m x
246 1 m pixel in the study area using LiDAR-derived measurements of canopy height (CHM) and
247 LAI, such that unique r_a and r_s were estimated for each pixel as:

248

$$249 \quad r_a = \frac{\ln\left[\frac{(z_m - d)}{z_{om}}\right] \ln\left[\frac{(z_h - d)}{z_{oh}}\right]}{k^2 u_z} \quad (2)$$

250 and

$$251 \quad r_s = \frac{r_l}{LAI} \quad (3)$$

252

253 where z_m is the height of wind measurements [m]; z_h is the height of humidity measurements
254 [m]), u_z is the wind speed [m s⁻¹], and k is von Karman's constant. Roughness layers dependent
255 on spatially varying vegetation structure were derived from LiDAR and include: d (zero plane

256 displacement [m]) and z_o and z_{oh} (roughness length governing momentum and heat and water
257 vapour, respectively [m]) (Oke, 1987). Bulk stomatal resistance [r_t , $s\ m^{-1}$] was determined from
258 porometry measurements and applied to land cover types. The model outputs a spatially explicit
259 high resolution (1 x 1 m) estimate of ET for each land cover type in the study area.

260

261 *Scaling the PM model to lower resolution pixels*

262 To determine the degree that landscape heterogeneity contributes to differences in modelled ET
263 across a range of pixel sizes, spatially explicit estimates of cumulative daily ET at a pixel sizes of
264 1 m x 1 m are resampled to larger sizes characteristic of commonly available satellite data (10,
265 25, 250, 500, and 1000 m). A ‘majority’ resampling methodology in ArcGIS (ESRI, CA) was
266 employed, whereby new ET values were assigned to each pixel based on the land cover type that
267 comprised the majority of each larger pixel (Turner et al., 1989). All resampling is done based on
268 original 1 m x 1 m daily ET values, as opposed to resampling from a previous aggregation (Bian
269 and Butler, 1999; Wu, 2004).

270

271 *Validating the PM model using eddy covariance measurements and a flux footprint model*

272 Two eddy covariance (EC) systems are used to measure water fluxes for validation of modelled
273 ET. One EC system, located 3 m above the northern regenerating stand, represents highly
274 localised fluxes representative of the regenerating stand. A second EC system, located 22.5 m
275 above the southern regenerating stand, represents a range of different land cover influences on
276 ET in addition to the harvested area directly in the footprint of the EC system (due to the larger
277 footprint size of the tower) (Figure 2). Within both regenerating aspen uplands vegetation was

278 sparse and remained <50 cm in height, and as a result instrument height above ground surface is
279 considered approximately equal to instrument height above the newly regenerating canopy.

280 Both sites were equipped with a three-dimensional sonic anemometer (CSAT 3,
281 Campbell Scientific, AB Canada) and an open-path infrared gas analyzer (IRGA) (LI7500, LI-
282 COR Inc., Lincoln, NE) and estimate water fluxes from ecosystems at a sampling rate of 20 Hz,
283 averaged to half-hourly periods (Brown et al., 2010; Petrone et al., 2015). EC data were filtered
284 for periods of low turbulence ($u^* < 0.23 \text{ m s}^{-1}$ based on the inflection point of u^* in relation to
285 energy balance closure) and corrected for density effects (Webb et al., 1980; Leuning and Judd,
286 1996), coordinate rotation (Kaimal and Finnigan, 1994), and sensor separation (Leuning and
287 Judd, 1996). As a final correction, energy balance closure was calculated and forced for the study
288 period to account for any differences between turbulent fluxes and available energy (Blanken et
289 al., 1997; Twine et al., 2000; Petrone et al., 2001; Barr et al., 2006). Following these quality
290 control steps, approximately 35% of data was lost and subsequently gap filled using the mean
291 over 14-day periods (Falge et al., 2001).

292 To validate ET modelled at varying pixel sizes (1, 10, 25, 250, 500, and 1000 m) with EC
293 estimates at flux towers the spatial influences on temporally-varying fluxes needs to be
294 determined. To do this, a weighted flux footprint parameterisation (Kljun et al. 2015) with a
295 pixel size of 1 m was used to model the spatial extent of the footprint (Figure 2), such that the
296 footprint area is used to map the probability of water (or CO_2 , CH_4 , etc.) flux into the atmosphere
297 as a function of atmospheric turbulence, instrument height, wind speed, and wind direction
298 measured during each half hourly period. .

299 Following Chasmer et al. (2011), weighted probability density functions (PDF) extending
300 to 80% of the total probability were calculated every 30 minutes and summed to daily footprints.

301 The result is a raster grid of the spatio-temporal footprint model where each 1 m² pixel is
302 assigned a weighting based on its probability to contribute a water flux to the eddy covariance
303 measurements (Figure 2). This unique weighting for each pixel was then used as a multiplier to
304 either increase or decrease the importance of modelled ET pixels within the footprint of the EC
305 systems. This reduces uncertainty in the validation of modelled vs. measured fluxes because,
306 instead of comparing EC estimates of ET (which is directional) with landscape-scale average
307 modelled ET, this method instead applies the same directionality to the modelled fluxes
308 (Hopkinson et al. 2016), thereby reducing comparisons with modelled values originating from
309 other parts of the ecosystem that were not measured by EC at that point in time.

310 Flux footprints were eliminated for non-ideal days (i.e. during periods of poor weather,
311 low atmospheric stability, or questionable data periods). The lower sensor height of the 3 m EC
312 system, as well as the tall aspen canopy surrounding the tower, resulted in stable atmospheric
313 conditions experienced more frequently relative to the tall 22.5 m tower measuring above the
314 aspen canopy. As a result, 72 days of footprint data were available for the 22.5 m EC tower and
315 22 days were available for the 3 m EC tower. The extraction and validation of modelled ET
316 within flux footprints is repeated for daily cumulative ET modelled at pixel sizes of 1, 10, 25,
317 250, 500, and 1000 m to determine the influence of sensor pixel size on model accuracy within
318 heterogeneous environments. When validating ET modelled at pixel sizes >1 m², larger pixels
319 were resampled to 1 m² in order to standardize and match the number of ET pixels that were
320 multiplied by PDF flux footprint pixels.

321

322 Figure 2: Cumulative weighted flux footprints from: a) 3m; and b) 22.5m EC towers for the
323 study period June 1 to Aug 31.

324

325 **Results**

326 *Footprint Climatology*

327 The dominant wind direction observed at the 3 m EC tower was between 330 - 355°, following
328 the long axis of the north regenerating aspen upland that the tower is situated in (Figure 2a).
329 Daily flux footprints extended up to 500 m upwind of the EC system, and footprint margins
330 extended out of the homogeneous regenerating aspen stand approximately 60% of the time as a
331 result of wind direction and neutral atmospheric stability. However, the probability that the point
332 of maximum flux contribution (x_{\max}) extended outside of the regenerating aspen upland remained
333 less than 10%.

334 The dominant wind direction observed at the 22.5 m EC tower was between 220 - 280°
335 (Figure 2b). In the early half of the study period unstable atmospheric conditions resulted in
336 smaller flux footprints for this site, extending up to 1 km from the EC tower and originating from
337 variable wind directions, while more stable atmospheric conditions promoted larger flux
338 footprints during the middle-to-late portion of the study period, frequently occurring from the
339 dominant wind direction (220 - 280°) and extending up to 3 km upwind of the tower into a
340 variety of heterogeneous land cover types. Consequently, while the composition of the footprint
341 surrounding the 3 m tower was relatively homogeneous, the footprint surrounding the 22.5 m
342 tower was far more heterogeneous. Within the season-average footprint surrounding the 22.5 m
343 tower 60% of the land area was mixed-wood aspen upland, 13% peatland, 10% pond, 12%
344 riparian, and 5% regenerating aspen, though the contribution of each of these land cover types
345 was highly variable from one day to the next.

346

347 *Comparing modelled ET and eddy covariance methods within footprints*

348 Cumulative measured ET in the footprint surrounding the 3 m EC tower was 54 mm over a 22-
349 day period of measured EC data (Figure 3a). During the same period, ET modelled at a pixel
350 size of 1 m within flux footprints totalled 60 mm, and showed no significant difference (Mann-
351 Whitney Rank Sum Test, $p>0.05$) from measured ET (Table 2). Increasing pixel sizes of
352 modelled ET to 10 or 25 m resulted in little change in agreement with measured ET. At pixel
353 sizes of 10 and 25 m modelled ET overestimated measured ET by 8 mm (14%) and 9 mm (15%),
354 respectively, and neither size showed a significant difference (Mann-Whitney Rank-Sum Test,
355 $p>0.05$) with measured ET. Increasing pixel size to 250 m results in a 16 mm (30%)
356 overestimation when modelled ET was compared to measured ET. A similar trend is observed
357 when pixel size was increased to 500 and 1000 m, where both of these pixel sizes overestimate
358 measured ET by 20 mm (36%) (Figure 4).

359

360

361 Figure 3: Eddy covariance measured ET and cumulative ET estimated at each pixel size and
362 extracted from flux footprints surrounding the: a) 3m EC tower; and b) 22.5m tower.

363

364

365 Cumulative measured ET at the 22.5 m EC tower was 164 mm over a 72-day period of
366 measured (Figure 3b). Over the same period cumulative ET modelled at a 1 m pixel size was 180
367 mm and overestimated measured ET by 16 mm (10%). Significant differences (Mann-Whitney
368 Rank Sum Test, $p<0.05$) were observed between ET modelled at a pixel size of 1 m and
369 measured values (Table 3). Increasing pixel size of modelled ET to 10 and 25 m resulted in
370 overestimates of 31 mm (19%) and 34 mm (20%), respectively, relative to measured ET in the

371 footprint surrounding the 22.5 m tower (Figure 4). Increasing pixel sizes further to 250, 500, and
372 1000 m yields similar results to those observed within the 3 m EC footprint, where these pixels
373 are frequently larger than the land cover types within the flux footprint, and in some cases are
374 larger than the footprint itself (Figure 4).

375

376 Table 2

377

378 Table 3

379

380 Figure 4: residual between eddy covariance ET measurements at the 3 m and 22.5 m EC towers
381 relative to ET modelled at pixel sizes of 1, 10, 25, 250, 500, and 1000 m.

382

383 *Scaling and assessing errors in ET estimates beyond the tower footprint*

384 As estimates of ET at a pixel size of 1 m proved to be closest to measured ET within the flux
385 footprints of both validation towers, these 1 m estimates were used as a basis to assess error in
386 modelled ET when scaled to the 5 km x 5 km study site (i.e. outside of EC flux footprints). At a
387 pixel size of 1 m cumulative modelled ET for the 5 km study area ranged between 151 - 239 mm
388 with an average of 162 ± 50 mm (Table 4), of which 62% was from mature aspen forests, 16%
389 was from treed peatlands, 9% was from riparian zones, 8% was from open peatlands, 5% was
390 from ponds, and 1% was from regenerating aspen stands (Table 5). Over a 90 day modelling
391 period, the greatest ET rates were observed in mature upland aspen stands (216 mm average) and
392 ponds (210 mm average) while lowest ET was observed in riparian (158 mm average) areas and
393 recently harvested regenerating aspen stands (151 mm average).

394 The greatest spatial variability in modelled ET, as indicated by the range in standard
395 deviations for ET modelled within each land cover type, was seen at land cover boundaries
396 where sharp transitions exist in canopy structure (Figure 5a). The influence of edges was
397 assessed by examining average ET (+/- standard deviation) within 10 m of edges compared to
398 ET rates in the center of large land covers such as mature aspen stands and large ponds.
399 Variability in modelled ET within 10 m of edges was, on average, 20-30% greater than ET
400 modelled at the center of large land covers. Higher than average variability in ET was also
401 evident in rough or patchy canopies which promote turbulent mixing. This was most pronounced
402 in peatlands and transitional riparian zones (Figure 5a) where a uniform canopy is not present
403 and standard deviations of ET values were twice as large as those observed in mature and
404 regenerating forested uplands.

405

406 Table 4.

407

408 Table 5.

409

410 Figure 5: ET estimates for the 5 km x 5 km study site at pixel sizes of: a) 1 m ; b) 10 m ; c) 25
411 m ; d) 250 m ; e) 500 m; and f) 1000 m.

412

413 Increasing the pixel size of modelled ET to 10 and 25 m resulted in site-scale average ET
414 increasing to ~165 mm (Table 4) with subtle (+/- 1%) changes in the contribution of each land
415 cover to total ET in the study area (Table 5), where boundaries of smaller land covers such as
416 treed peatlands and riparian zones were misclassified as adjacent open peatlands and ponds
417 (Figure 6ba,b). These changes in land cover contribution to total ET were coincident with a

418 ~17% decline in site-wide variability (standard deviation) of modelled ET at 10 and 25 m pixel
419 sizes, relative to 1 m values (Figure 5b,c).

420 Further increasing the pixel size of modelled ET to 250 m resulted in site-scale average
421 ET increasing to 167 ± 39 mm and a 21% decline in the spatial variability of ET relative to 1 m
422 values. The decline in ET heterogeneity across the study site is reflected in the contribution of
423 each land cover to total ET (Table 5), particularly in regenerating aspen stands which are
424 underestimated by 38% relative to regenerating aspen ET values modelled at a pixel size of 1 m.
425 ET modelled in ponds and treed peatlands is underestimated by 6 and 8%, respectively, and ET
426 from open peatlands is overestimated by 10% (Figure 6c) relative to 1 m values in each of these
427 land cover types. Additionally, while maximum ET (ET_{max}) rates of 450 mm were evident when
428 modelled using a pixel size of 1 m, ET_{max} was 320 mm when modelled at a pixel size of 250 m
429 due to the loss of edges.

430 Increasing the pixel size of modelled ET to 500 m results in a site-scale average ET
431 estimate of 171 ± 36 mm and a 28% decline in the spatial variability of ET relative to 1 m
432 values. At a pixel size of 500 m the contribution of each land cover to the site-average ET is
433 significantly different relative to 1 m values, where ET from ponds and open peatlands is
434 overestimated by 102 and 150%, respectively, and ET from treed peatlands, riparian zones, and
435 regenerating aspen stands are underestimated by 52, 100, and 100 %, respectively (Table 5).

436 There were similar results for 1000 m pixels, where the spatial variability in ET is
437 underestimated by 79% relative to 1 m values. Riparian zones and regenerating aspen stands are
438 eliminated (Figure 5f) from the landscape, while treed peatlands are underestimated by 75% and
439 ponds and open peatlands are overestimated by 160 and 114%, respectively, relative to values at
440 a pixel size of 1 m in each of these land cover types (Table 5).

441

442 Figure 6: Difference in cumulative ET estimates between 1m x 1m ET estimates and ET
443 estimated at pixel sizes of: a) 10 m; b) 25 m; c) 250 m; d) 500 m; and e) 1000 m. Blue pixels
444 indicate where resampled pixels overestimate 1 m ET estimates; red pixels indicate where
445 resampled pixels underestimate 1 m ET estimates.

446

447 **Discussion**

448 *Modelled ET within Eddy Covariance Footprints*

449 ET estimated at a pixel size of 1 m were most similar to measured ET at the 3 m and 22.5 m
450 towers, and were comparable to ranges of uncertainty found at other study sites using high
451 (Loheide and Gorelick, 2005) and low (Cleugh et al., 2007; Li et al., 2008) resolution ET
452 models. For a given pixel size, stronger agreement was observed between measured and
453 modelled ET in smaller footprints because the footprint was more likely to be comprised of a
454 single homogeneous land cover type. This is observed at the 3 m EC tower where x_{\max} remained
455 within the northern regenerating aspen upland for ~90% of the study period and measurements
456 from the EC system are characterized by a homogeneous land cover which is suitably resolved
457 using 1, 10, and 25 m pixel sizes. Small declines in accuracy observed with 10 and 25 m pixels
458 are due to the partial loss of edges surrounding the regenerating stand which enhance turbulence
459 and promote ET. Larger footprints, however, extend in to a variety of land covers with variable
460 ET regimes, resulting in contamination and uncertainty in observations between measured and
461 modelled ET for a given pixel size. This is observed at the 22.5 m tower, where the flux footprint
462 extends up to 3 km into a variety of land cover types and ET estimated at a pixel size of 10 m are
463 significantly different and disagree with measured ET by 19%.

464 Regardless of how homogeneous a flux footprint is, the ability to utilize remote sensing
465 platforms to accurately predict ET is largely dependent on a sensor's ability to resolve canopy
466 structural characteristics, landscape distribution, and landscape edges. Consequently, ET
467 modelled at the finest pixel size provided the closest agreement with measured ET, as 1 m pixel
468 estimates were able to suitably represent the same vegetation structural characteristics that were
469 driving ET measured at the EC system. This is particularly important in narrow land covers such
470 as riparian zones and fragmented wetlands which serve as corridors between larger forest patches
471 (O'Neill et al., 1996) and often play a crucial role in characterizing the regional water balance
472 (Kimball et al., 1999; Chen et al., 2007). As pixel size increases, pixels become larger than the
473 areal extent of land cover patches and vegetation structural characteristics are generalized,
474 resulting in a loss of landscape heterogeneity and a decline in the spatial variability of ET
475 estimates (Turner et al., 1989; O'Neill et al., 1996; Kustas and Norman, 2000; Kustas et al.,
476 2004; Nagler et al., 2005; McCabe and Wood, 2006; Li et al., 2008). Wu et al., (2004) observed
477 similar results in Boreal regions where the number of landscape patches followed a decreasing
478 trend as pixel size declined.

479 Such declines in heterogeneity result in overestimations of ET in the western Boreal
480 Plains as small land cover types are misclassified as the spatially dominant aspen uplands, which
481 are characterized by a greater LAI and higher ET rates relative to the ponds, peatlands, and
482 riparian zones which they eliminate from the landscape at larger pixel sizes. This was observed
483 in modelled results with the elimination of riparian zones and regenerating aspen uplands from
484 the landscape at pixel sizes of 500 and 1000 m. Additionally, depending on the fragmented
485 nature of a heterogeneous landscape, thresholds can be crossed beyond which variable sensor
486 resolutions yield static results, as was evident where ET estimates at pixel sizes of 500 and 1000

487 m are identical within flux footprints of both EC towers due to pixel size being larger than the
488 areal extent of the land cover patches within the flux footprint.

489 Land cover edge effects, which are an important contributor to measured ET in
490 heterogeneous landscapes due to step changes in air flow (Oke, 1987; Liu et al., 1996), also
491 become increasingly generalized as pixel size increases (Wu et al., 2004). The influence of
492 edges, which may be manifested as stand-alone shrubs within regenerating aspen stands to sharp
493 transition zones between land cover types, are observed within this study and often represent
494 ET_{max} within a land cover type. As a result, the accuracy of modelled ET sharply declines when
495 the pixel size becomes larger than individual patches of vegetation found within land cover types
496 (O’Neill et al. 1996; Kustas et al. 2004) and, although modelled ET rates were observed to
497 overestimate measured ET with increasing pixel size, ET_{max} declines from 450 to 186 mm (Table
498 4) when scaling from 1 to 1000 m resolutions as edges are generalized at landcover boundaries.
499 Although this is particularly pronounced in heterogeneous landscapes such as the western Boreal
500 Plains, McCabe and Wood (2006) noted a similar trend in decreasing variability and accuracy of
501 latent heat fluxes when scaling from 120 m to 1020 m pixels in heterogeneous agricultural
502 watersheds. Ershadi et al. (2013) also noted changes in roughness lengths around land cover
503 borders at large (>240 m) pixel sizes and found increasingly coarse pixels to underestimate latent
504 heat fluxes by up to 15% with the SEBS model. Consequently, the areal extent of the smallest
505 land cover unit of interest must be taken into consideration when choosing a suitable pixel size
506 for modelling initiatives. O’Neill et al. (1996) note that pixel size should be 2 to 5 times smaller
507 than the smallest feature of interest, and the current study confirms these findings.

508

509 *Identifying sensor resolutions appropriate for heterogeneous environments*

510 Evaluating incremental shifts in the accuracy of changing pixel sizes provides insight into
511 threshold responses of sensors within varying footprint compositions. The most pronounced shift
512 in accuracy associated with a change in sensor is observed at different pixel sizes depending on
513 the heterogeneity of the flux footprint. Within homogeneous footprints (e.g. those surrounding
514 the 3 m EC tower) the most pronounced shift in the accuracy of modelled ET was observed when
515 pixel size was changed from 25 to 250 m, suggesting that 1, 10, and 25 m pixels can suitably
516 represent the vegetation structural parameters driving ET within the homogeneous footprint.
517 Contrary to this, the most pronounced shift in the accuracy of modelled ET within heterogeneous
518 footprints (e.g. those surrounding the 22.5 m tower) was observed when pixel size was changed
519 from 1 to 10 m as well as from 25 to 250 m. Because the significantly larger and more
520 heterogeneous footprint surrounding the 22.5 m tower extends up to 3 kilometers into a variety
521 of land cover types characteristic of this region, small changes in pixel size can have pronounced
522 implications on the ability of models to appropriately characterize vegetation structural
523 characteristics and land cover edges.

524 Switching between mid (250 m) and coarse (500-1000 m) pixel sizes resulted in less
525 pronounced changes in the accuracy of modelled ET, suggesting that within this range users of
526 remote sensing data may not experience statistically significantly better results from using 250 m
527 data over 500 or 1000 m data within heterogeneous landscapes, as each of these pixel sizes are
528 unable to suitably characterize vegetation structural characteristics influencing ET. This is
529 particularly true of 500 and 1000 m data, which showed no difference in the accuracy of
530 modelled ET between pixel sizes relative to EC data. Such results indicate that ET predictions in
531 heterogeneous environments benefit from utilizing the finest pixel remote sensing data available,
532 while larger pixels can be suitably applied to homogeneous environments, although the "best"

533 pixel size is largely contextual and dependent on the spatial extent of homogeneity in the area of
534 interest (Wu et al., 2004; Zhao et al., 2015).

535

536 **Conclusions**

537 ET estimates at pixel sizes of 1 m x 1 m were scaled to increasingly coarse sizes (10, 25, 250,
538 500, 1000 m) characteristic of commonly available remote sensing data products. The objective
539 was to determine the accuracy of ET estimates derived from a variety of pixel sizes within a
540 heterogeneous environment. Comparison with measured EC data demonstrated that, within flux
541 footprints, 1 m ET estimates were the most accurate and subsequent scaling to larger pixels lead
542 to decreased accuracy due to the misrepresentation of land cover types and boundaries when
543 pixel size is larger than the fragments of land cover types within a pixel. Mixed-wood aspen
544 uplands dominate the western Boreal Plains landscape and are fragmented by relatively small
545 ponds, peatlands, and riparian zones. Consequently, increasing pixel size results in the loss of ET
546 heterogeneity as these relatively small land cover types are outweighed and misclassified as the
547 spatially-dominant mixed-wood aspen uplands, resulting in a net overestimation of ET.

548 The results of this study demonstrate the benefit of using datasets with the smallest pixel
549 size available within biogeochemical and/or land surface models applied to heterogeneous
550 environments. Often times, ecosystems are not entirely homogeneous and are becoming
551 increasingly fragmented. While two-dimensional (spectral) datasets provide some indication of
552 foliage area at a snap-shot in time, three-dimensional datasets acquired using LiDAR provide
553 additional information on canopy roughness and the impacts of ecosystem boundaries on fluxes.
554 This will no doubt become important for planning and land use monitoring in northern regions

555 where increased warming will exacerbate the sensitivity of ecosystems to drought (Michaelian et
556 al. 2011).

557

558 **Acknowledgements**

559 The authors would like to thank Mr S. Brown for his technical assistance in the field. Funding
560 for this work was provided by an NSERC Discovery Grant (Petrone), NSERC Collaborative
561 Research and Development Grant (HEAD2), NSERC Research Tools and Instrument Grant
562 (Petrone) and the Cumulative Environmental Managers Association (CEMA).

563

564 **References**

565

566 Antonarakis, A.S., J. W. Munger and P. Moorcroft. 2014. Imaging Spectroscopy- and Lidar-
567 derived Estimates of Canopy Composition and Structure Improve Predictions of Forest
568 Carbon Fluxes and Ecosystem Dynamics, *Geophysical Research Letters*. 41(7): 2535-
569 2542.

570

571 Baldocchi, D. D., R. J. Luxmoore, and J. L. Hatfield. 1991. Discerning the forest from the
572 trees: an essay on scaling canopy stomatal conductance. *Agricultural and Forest*
573 *Meteorology*. 54:197-226.

574

575 Baldocchi, D., Finnigan, J.J., Wilson, K., Paw U, K.T., Falge, E. (2000). On measuring net
576 ecosystem carbon exchange over tall vegetation on complex terrain. *Boundary-Layer*
577 *Meteorol.* 96,257–291

578

579 Barcza, Z., A. Kern, L. Haszpra, N. Kljun, 2009: Spatial Representativeness of Tall Tower Eddy
580 Covariance Measurements Using Remote Sensing and Footprint Analysis. *Agricultural*
581 *and Forest Meteorology*, 149, 795-807.

582

583 Barr A.G., Morgenstern K., Black T.A., McCaughey J.H., Nesic Z. 2006. Surface energy balance
584 closure by the eddy covariance method above three boreal forest stands and implications
585 for the measurement of CO₂ flux. *Agriculture and Forest Meteorology*, 140:322-337.

586

587 Bian, L. and R. Butler. 1999. Comparing effects of aggregation methods on statistical and
588 spatial properties of simulated spatial data. *Photogrammetric Engineering & Remote*
589 *Sensing*, 65(1), 73-84.

590

- 591 Blanken P.D., Black T.A., Yang P.C., Neumann H.H., Staebler R., Nesic Z., den Hartog G.,
592 Novak M.D., Lee X.. 1997. The energy balance and canopy conductance of a boreal
593 aspen forest: partitioning overstory and understory components. *Journal of Geophysical*
594 *Research* 102: 915–927.
- 595
- 596 Brown, S. M., R. M. Petrone, C. Mendoza and K. J. Devito. 2010. Surface vegetation
597 controls on evapotranspiration from a sub-humid Western Boreal Plain wetland.
598 *Hydrological Processes*, 24, 1072-1085.
- 599
- 600 Brown S. M., R. M. Petrone, L. Chasmer, C. Mendoza, M. S. Lazerjan, S. M. Landhäuser, U.
601 Silins, J. Leach and K. J. Devito. 2013. *Hydrological Processes* DOI: 10.1002/hyp.9879
- 602
- 603 Brümmer, C., T. A. Black, R. S. Jassal., N. J. Grant, D. L. Spittlehouse, B. Chen, Z. Nesic, B.D.
604 Amiro, M. A. Arian, A. G. Barr, C. P-A Bourque, C. Courselle, A. L. Dunn, L. B.
605 Flanagan, E. R. Humphreys, P. M. Lafleur, H. A. Margolis, J. H McCaughey, and S. C.
606 Wofsy. (2012). How climate and vegetation type influence evapotranspiration and water
607 use efficiency in Canadian forest, peatland and grassland ecosystems. *Agricultural and*
608 *Forest Meteorology*, 153, 14-30.
- 609
- 610 Chasmer, L., N. Kljun, A. Barr, A. Black, C. Hopkinson, H. McCaughey, and P. Treitz. 2008.
611 Vegetation structural and elevation influences on CO₂ uptake within a mature jack pine
612 forest in Saskatchewan, Canada, *Canadian Journal of Forest Research*, 38, 2746–2761,
613 doi:10.1139/X08-121.
- 614 Chasmer, C. Hopkinson, A. Barr, A. Black, H. McCaughey, and P. Treitz, 2009. Scaling and
615 assessment of GPP from MODIS using a combination of airborne lidar and eddy
616 covariance measurements over jack pine forests. *Remote Sensing of Environment*,
617 113:82-93.
- 618
- 619 Chasmer, L., N. Kljun, C. Hopkinson, S. Brown, T. Milne, K. Giroux, A. Barr, K. Devito, I.
620 Creed, and R. Petrone. 2011a, Characterizing vegetation structural and topographic
621 characteristics sampled by eddy covariance within two mature aspen stands using lidar
622 and a flux footprint model: Scaling to MODIS, *J. Geophys. Res.*, 116, G02026,
623 doi:10.1029/2010JG001567.
- 624
- 625 Chasmer, L., R. Petrone, S. Brown, C. Hopkinson, C. Mendoza, J. Diiwu, W. Quinton, and K.
626 Devito, 2011b, Sensitivity of modelled evapotranspiration to canopy characteristics
627 within the Western Boreal Plain, Alberta. C. Neale and R. Gerber (eds.) *IAHS Red Book*.
628 September 25, 2010. Jackson Hole, WY. 4 pgs.
- 629
- 630 Chasmer, L., J. Montgomery, C. Hopkinson. A morphological/vegetation structural wetland
631 classification for Boreal Alberta, Canada. *Canadian Journal of Remote Sensing*. Special
632 Issue on Advanced Forest Inventory. (in press).
633 <http://dx.doi.org/10.1080/07038992.2016.1196583>
- 634
- 635 Chen, J.M., Cihlar, J. 1996. Retrieving leaf area index of boreal conifer forests using Landsat
636 TM images. *Remote Sensing Environment* 55 (2), 153–162

- 637 Chen, J.M., J. Liu, J. Cihlar, M.L. Goulden. 1999. Daily canopy photosynthesis model
638 through temporal and spatial scaling for remote sensing applications. *Ecological*
639 *Modelling*, 124, pg 99-119.
640
- 641 Chen JM, Govind A, Sonnentag O, Zhang Y, BA, Amiro B. 2006. Leaf area index measurements
642 at Fluxnet-Canada forest sites. *Agricultural and Forest Meteorology* 140: 257–268.
643 doi:10.1016/j.agrformet. 2006.08.005.
644
- 645 Chen, B., J.M. Chen, G. Mo, et al. 2007. Modelling and scaling coupled energy, water, and
646 carbon fluxes based on remote sensing: An application to Canada's Landmass. *J.*
647 *Hydrometeor.* 8:123-143.
648
- 649 Cleugh, H. A., R. Leuning, Q. Mu, and S. W. Running. 2007. Regional evaporation
650 estimates from flux tower and MODIS satellite data. *Remote sensing of Environment*,
651 106, 285-304.
652
- 653 Cressie, N. A. 1993. Statistics for Spatial Data. Wiley, New York.
- 654 Devito K. J., Creed I. F., and Fraser C. J. D. 2005a. Controls on runoff from a partially
655 harvested aspen-forested headwater catchment, Boreal Plain, Canada. *Hydrological*
656 *Processes* 19, 3–25.
657
- 658 Devito, K., I. Creed, T. Gan, C. Mendoza, R. Petrone, U. Silins, and B. Smerdon. 2005b. A
659 framework for broad-scale classification of hydrologic response units on the Boreal
660 Plain: is topography the last thing to consider? *Hydrological Processes*, 19, 1705- 1714.
661
- 662 El Maayar, M., J. M. Chen, and D. T. Price, 2008. On the use of field measurements of energy
663 fluxes to evaluate land surface models. *Ecological Modelling*. 214:293-304.
664
- 665 Eriksson, H. M., L. Eklundh, A. Kuusk, and T. Nilson. 2006. Impact of understory
666 vegetation on forest canopy reflectance and remotely sensed LAI estimates. *Remote*
667 *Sensing of Environment*, 103, 408-418.
668
- 669 Ershadi, A., M.F. McCabe, J.P. Evans, J.P. Walker. 2013. Effects of spatial aggregation on
670 the multi-scale estimation of evapotranspiration. *Remote Sensing of Environment*, 131,
671 51-62.
672
- 673 Falge E, Baldocchi D, Olson R, Anthoni P, Aubinet M, Bernhofer C, Burba G, Ceulemans
674 R, Clement R, Dolman H, Granier A, Gross P, Grünwald T, Hollinger D, Jensen N-
675 O, Katul G, Keronen P, Kowalski A, Lai CT, Law BE, Meyers T, Moncrieff J, Moors
676 E, Munger JW, Pilegaard K, Rannick Ü, Rebmann C, Suyker A, Tenhunen J, Tu K,
677 Verma S, Vesala T, Ilson K, Wofsy S. 2001. Gap filling strategies for long term energy
678 flux data sets. *Agricultural and Forest Meteorology*, 107: 71–77
679
- 680 Foken, T. and Leclerc, M. Y. 2004. Methods and limitations in validation of footprint models.
681 *Agr. Forest Meteorol.*, 127: 223–234.

- 682 Gelybó, G., Z. Barcza, A. Kern, N. Kljun, 2013: Effect of Spatial Heterogeneity on the
683 Validation of Remote Sensing Based GPP Estimations, *Agricultural and Forest*
684 *Meteorology*, 174-175, 43-53.
- 685 Giroux K. 2012. Pre- and Post-Harvest Carbon Dioxide Fluxes from an Upland Boreal Aspen
686 (*Populus tremuloides*) Forest in Western Boreal Plain, Alberta, Canada. Masters Thesis.
687 Wilfrid Laurier University.
688
- 689 Göckede, M., C. Rebmann, and T. Foken. 2004. A combination of quality assessment tools
690 for eddy covariance measurements with footprint modelling for the characterisation
691 of complex sites. *Agricultural and Forest Meteorology*, 127, 175-188.
692
- 693 Göeckede, M., T. Foken, M. Aubinet, M. Aurela, J. Banza, C. Bernhofer, J.M. Bonnefond,
694 Y. Brunet, A. Carrara, R. Clement, E. Dellwik, J. Elbers, W. Eugster, J. Fuhrer, A.
695 Granier, T. Grünwald, B. Heinesch, I.A. Janssens, A. Knohl, R. Koeble, T. Laurila,
696 B. Longdoz, G. Manca, M. Marek, T. Markkanen, J. Mateus, G. Matteucci, M.
697 Mauder, M. Migliavaca, S. Minerbi, J. Moncrieff, L. Montagnani, E. Moors, J.-M.
698 Ourcival, D. Papale, J. Pereira, K. Pilegaard, G. Pita, S. Rambal, C. Rebmann, A.
699 Ridrigues, E. Rotenberg, M.J. Sanz, P. Sedlak, G. Seufert, L. Siebicke, J.F.
700 Soussana, R. Valentini, T. Vesala, H. Verbeeck, D. Yakir. 2008. Quality control of
701 CarboEurope flux data – Part 1: Coupling footprint analyses with flux data quality
702 assessment to evaluate sites in forest ecosystems. *Biogeosciences*, 5(2):433-450.
703
- 704 Graf, Martha D. 2009. Literature review on the Restoration of Alberta's Boreal Wetlands:
705 Affected by Oil, Gas and In Situ Oil Sands Development. Edmonton, AB: Ducks
706 Unlimited.
707
- 708 Haboudane, D., J. R. Miller, E. Pattey, P. J. Zarco-Tejada, I. B. Strachan. 2004. Hyperspectral
709 vegetation indices and novel algorithms for predicting green LAI of crop canopies:
710 Modeling and validation in the context of precision agriculture. *Remote Sensing of*
711 *Environment*, 90(3), pp.337-352.
712
- 713 Halsey, L.A., D. H. Vitt, D. Bellman, S. Crow, S. Meheicic, and R. Wells. 2004. Alberta
714 Wetland Inventory Classification System Version 2.2. ISBN No. 0-7785-2324-1 (On-
715 line Edition)
716
- 717 Hansen A. J., Phillips L. B., Dubayah R., Goetz S., and Hofton M. 2014. Regional-scale
718 application of lidar: Variation in forest canopy structure across the southeastern US.
719 *Forest Ecology and Management*, 329: 214-226.
- 720 Heinsch, F. A., Zhao, M., Running, S. W., Kimball, J. S., Nemani, R. R., Davis, K. J., et al.
721 2006. Evaluation of remote sensing based terrestrial productivity from MODIS using
722 regional tower eddy flux network observations. *IEEE Transactions on Geoscience and*
723 *Remote Sensing*, 44(7), 1908–1925.
724

725 Hopkinson, C. A., and L. Chasmer. (2007). Using Discrete Laser pulse return Intensity to
726 Model canopy Transmittance. *The Photogrammetric Journal of Finland*, 20(2), 16-
727 27.

728

729 Hopkinson, Chasmer, L., A. Barr, N. Kljun, T. A. Black and J. H. McCaughey. 2016. Monitoring
730 forest biomass and carbon storage by integrating airborne laser scanning and eddy
731 covariance data. *Remote Sensing of Environment*. 181:82-95.

732

733 Jin, Z., Tian, Q., Chen, J. M., and Chen, M. 2007. Spatial scaling between leaf area index maps
734 of different resolutions. *Journal of Environmental Management*, 85, 628–637.

735

736 Kaimal JC, Finnigan J. 1994. *Atmospheric Boundary Layer Flows: Their Structure and*
737 *Measurement*. Oxford Univ. Press: New York; 255–261.

738

739 Kalma, J.D., McVicar, T.R., McCabe, M.F. 2008. Estimating land surface evaporation: a review
740 of methods using remotely sensed surface temperature data. *Surv. Geophys.* 29, 421–469.

741 Kimball, J. S., S. W. Running, and S. S. Saatchi. 1999. Sensitivity of boreal forest regional water
742 flux and net primary production simulations to sub-grid-scale land cover complexity. *J.*
743 *Geophys. Res.*, 104, 27 789–27 802.

744

745 Kim, J., Q. Guo, D. D. Baldocchi, M. Y. Leclerc, L. Xu, and H. P. Schmid. 2006. Upscaling
746 fluxes from tower to landscape: Overlaying flux footprints on high-resolution
747 (IKONOS) images of vegetation cover. *Agricultural and Forest Meteorology*.
748 136:132-146.

749

750 Kljun, N., P. Calanca, M. W. Rotach, and H. P. Schmid. 2004. A simple parameterisation
751 for flux footprint predictions. *Boundary-Layer Meteorology*, 112, 503-523.

752

753 Kljun, N., P. Calanca, M. W. Rotach, and H. P. Schmid . 2015. A simple two-dimensional
754 parameterisation for Flux Footprint Prediction (FFP). *Geoscientific Model Development*,
755 8, 3695–3713, 2015

756

757 Kustas, W. P. and J.M. Norman. 2000. Evaluating the Effects of Subpixel Heterogeneity on
758 Pixel Average Fluxes. *Remote Sensing of Environment*, 74: 327-324.

759

760 Kustas, W. P., F. Li, T. J. Jackson, J. H. Prueger, J. I. MacPherson, and M. Wolde. 2004. Effects
761 of remote sensing pixel resolution on modeled energy flux variability of croplands in
762 Iowa. *Remote Sensing of Environment*, 535-547.

763

764 Kustas, W.P., M. C. Anderson, A. N. French, D. Vickers. 2006. Using a remote sensing field
765 experiment to investigate flux-footprint relations and flux sampling distributions for
766 tower and aircraft-based observations. *Advances in Water Resources*, 29:355-368.

767

- 768 Lee, P. and S. Boutin. 2006. Persistence and developmental transitions of wide seismic lines
769 in the western Boreal Plains of Canada. *Journal of Environmental Management*, 78,
770 240-250.
771
- 772 Leuning R, JuddMJ. 1996. The relative merits of open and closed path analysers for
773 measurement of eddy fluxes. *Global Change Biology* 2: 241–253.
774
- 775 Leuning, R., Y. Q. Zhang, A. Rajaud, H. Cleugh, and K. Tu. (2008). A simple surface
776 conductance model to estimate regional evaporation using MODIS leaf area index and
777 the Penman-Monteith equation. *Water Resources Research*, 44, W10419,
778 doi:10.1029/2007WR006562, 2008
779
- 780 Li, F., W.P. Kustas, M.C. Anderson, et al. 2008. Effect of remote sensing spatial resolutions
781 on interpreting tower-based flux observations. *Remote Sens. Environ.*, 112:337-349.
782
- 783 Lim, K., P. Treitz, M. Wulder, B. St-Onge and M Flood. 2003. LiDAR remote sensing of forest
784 structure. *Progress in Physical Geography*, 27(1), 88-106.
785
- 786 Lindsay, J., I. F. Creed, and F. D. Beall. 2004. Drainage basin morphometrics for depression
787 landscapes. *Water Resources Research*. 40, W09307, doi:1029/2004WR003322.
788
- 789 Liu, J., J.M. Chen, T.A. Black, and M.D Novak. 1996. E-ε modelling of turbulent air flow
790 downwind of a model forest edge. *Boundary Layer Meteorology*, 77 (1), 21-44
791
- 792 Loheide, S. P. and S. M. Gorelick. 2005. A local-scale, high-resolution evapotranspiration
793 mapping algorithm (ETMA) with hydroecological applications at riparian meadow
794 restoration sites. *Remote Sensing of Environment*, 98, 182-200.
795
- 796 Lüdeke, M., Janecek, A., & Kohlmaier, G. H. 1991. Modelling the seasonal CO₂ uptake by land
797 vegetation using the global vegetation index. *Tellus*, 43B, 188– 196.
798
- 799 Massman, W. J. and Lee, X. 2002. Eddy Covariance Flux Corrections and Uncertainties in
800 Long- Term Studies of Carbon and Energy Exchanges. *Agric. For. Meteorol.* 113,
801 121–144.
802
- 803 McCabe M.F. and E. F. Wood. 2006 Scale influences on the remote estimation of
804 evapotranspiration using multiple satellite sensors. *Remote Sensing of Environment*
805 105:271–295.
806
- 807 Michaelian, M., E. H. Hogg, R. J. Hall, and E. Arsenault, 2011. Massive mortality of aspen
808 following severe drought along the southern edge of the Canadian boreal forest. *Global*
809 *Change Biology*. 17(6):2084-2094.
810
- 811 Mitchell P. J., Lane P. N. J., and Benyon R. G. 2012. Capturing within catchment variation in
812 evapotranspiration from montane forests using LiDAR canopy profiles with measured
813 and modelled fluxes of water. *Ecohydrology*, 5: 708-720.

814
815 Monteith, J.L. 1965. Evaporation and environment. *In Symposium of the Society for*
816 *Experimental Biology, The State and Movement of Water in Living Organisms*, Fogg
817 GE (ed.) Vol. 19. Academic Press, Inc.: NY; 205–234.
818

819 Næsset, E., and Økland, T. 2002. Estimating tree height and tree crown properties using
820 airborne scanning laser in a boreal nature reserve. *Remote Sens. Environ.* 79: 105–115.
821

822 Nagler, P. J. Cleverly, E. Glenn, D. Lampkin, A. Huete, Z. Wan. 2005. Predicting riparian
823 evapotranspiration from MODIS vegetation indices and meteorological data. *Remote*
824 *Sensing of Environment*, 94, 17-30.
825

826 Neale, C. M. U., Geli H., Taghvaeian S., Masih A., Pack R. T., Simms R. D., Baker M., Milliken
827 J. A., O’Meara S., and Witherall A. J. 2011. Estimating Evapotranspiration of Riparian
828 Vegetation using High resolution Multispectral, Thermal Infrared and Lidar Data. *Remote*
829 *Sensing for Agriculture, Ecosystems, and Hydrology*, vol 81740, doi:10.1117/12.903246.
830

831 Oke TR. 1987. Boundary Layer Climates. Methuen & Co, Ltd.
832

833 O’Neill R.V., Hunsaker C.T., Timmins S.P., Timmins B.L., Jackson K.B., Jones K.B., Riitters
834 K.H. and Wickham J.D. 1996. Scale problems in reporting landscape pattern at the
835 regional scale. *Landscape Ecology* 11: 169–180.
836

837 Petrone R.M., Waddington J.M., Price J.S.. 2001. Ecosystem scale evapotranspiration and net
838 CO₂ exchange from a restored peatland. *Hydrological Processes* 15: 2839–2845.
839

840 Petrone, R. M., U. Silins, and K. J. Devito. (2007). Dynamics of evapotranspiration from a
841 riparian pond complex in the Western Boreal Forest, Alberta, Canada. *Hydrological*
842 *Processes*, 21, 1391-1401.
843

844 Petrone, R. M., Solondz D. S., Macrae M. L., Gignac D., and K. J. Devito. 2011.
845 Microtopographical and canopy cover controls on moss carbon dioxide exchange in a
846 western Boreal Plain peatland. *Ecohydrology*, 4, 115-129.
847

848 Petrone, R. M., L. Chasmer, C. Hopkinson, U. Silins, S. Landhausser, N. Kljun, K. J. Devito,
849 2015. Effects of harvesting on CO₂ and H₂O Fluxes during wet and dry years in an aspen
850 dominated Western Boreal Plain Forest. *Canadian Journal of Forest Research*. 45:87-100.

851 Pitman, A.J. 2003. The evolution of, and revolution in, land surface schemes designed for climate
852 models. *Int. J. Climatol.* 23, 479–510

853 Running S. W., Ramakrishna R. Nemani, David L. Peterson, Larry E. Band, Donald F. Potts.
854 Lars L. Pierce, Michael A. Spanner. 1989. Mapping regional forest evapotranspiration
855 and photosynthesis by coupling satellite data with ecosystem simulation. *Ecology*,
856 70 (4), 1090-1101.
857

- 858 Saito, T., Yamamoto, K., Komatsu, M., Matsuda, H., Yunohara, S., Komatsu, H., Tateishi,
859 M., Xiang, Y., Otsuki, K., and Kumagai, T. 2015. Using airborne LiDAR to determine
860 total sapwood area for estimating stand transpiration in plantations. *Hydrol.*
861 *Process.*, 29: 5071–5087. doi:[10.1002/hyp.10482](https://doi.org/10.1002/hyp.10482).
- 862 Saxton KE, Rawls WJ, Romberger JS, Papendick RI. 1986. Estimating generalized soil-water
863 characteristics from texture. *Soil Science Society of America Journal* 50(4): 1031–1036.
864
- 865 Schmid, H. P. 1994. Source areas for scalars and scalar fluxes, *Boundary Layer Meteorology*, 67,
866 293–318, doi:10.1007/BF00713146.
867
- 868 Schumacher, J. and Christiansen, J. R. Forest canopy water fluxes can be estimated using canopy
869 structure metrics derived from airborne light detection and ranging (LiDAR). 2015.
870 *Agricultural and Forest Meteorology*, 203: 131-141
- 871 Sellers, P., F.G. Hall, R.D. Kelly, et al., (1997). BOREAS in 1997: experiment overview,
872 scientific results, and future directions. *J. Geophys. Res.*, 102:28731-28769.
873
- 874 Sutherland, G., L.E. Chasmer, R.M. Petrone, N. Kljun, and K.J. Devito. 2014. Evaluating
875 the use of spatially varying versus bulk average 3D vegetation structural inputs to
876 modelled evapotranspiration within heterogeneous land covers. *Ecohydrology*, *In Press*,
877 DOI 10.1002/eco.1447
878
- 879 Treitz, P. and P. Howarth. 2000. High spatial resolution remote sensing data for forest
880 ecosystem classification: An examination of spatial scale. *Remote Sensing of*
881 *Environment*. 72:268-289.
- 882 Treitz, P. 2001. Variogram analysis of high spatial resolution remote sensing data: An
883 examination of boreal forest ecosystems. *International Journal of Remote Sensing*.
884 22(18):3895-3900.
- 885 Turetsky, M.R. and V.L. St. Louis. 2006. Disturbance in boreal peatland. R.K. Wieder and
886 D.H. Vitt, editors. *Boreal peatland ecosystems*. Springer- Verlag, Berlin, Germany.
887
- 888 Turner, M. G., R. V. O’Niell, R. H. Gardner, and B. T. Milne. 1989. Effects of changing spatial
889 scale on the analysis of landscape pattern. *Landscape Ecology*, 3, 153-162.
890
- 891 Turner, D. P., Gower, S. T., Cohen, W. B., Gregory, M., & Maersperger, T. K. 2002. Effects of
892 spatial variability in light use efficiency on satellite-based NPP monitoring. *Remote*
893 *Sensing of Environment*, 80, 397–405.
894
- 895 Turner, D. P., Ollinger, S., & Kimball, J. 2004. Integrating remote sensing and ecosystem
896 process models for landscape- to regional-scale analysis of the carbon cycle.
897 *BioScience*, 54(6), 573–584.
898
- 899 Twine T.E., Kustas W.P., Norman J.M., Cook D.R., Houser P.R., Meyers T.P., Prueger J.H.,
900 Starks P.J., Wesely M.L.. 2000. Correcting eddy-covariance flux underestimates over a
901 grassland. *Agricultural and Forest Meteorology* 103: 279–300.

902
903 Wang, Q., S. Adiku, J. Tenhunen, and A. Granier. 2005. On the relationship of NDVI with leaf
904 area index in a deciduous forest site. *Remote Sensing of Environment*, 94, 244–255.
905
906 Webb EK, Pearman G, Leuning R. 1980. Correction of flux measurements for density effects
907 due to heat and water vapour transfer. *Quarterly Journal of the Royal Meteorology*
908 *Society* 106: 85–100.
909
910 Williams, M., A.D. Richardson, M. Reichstein, et al. 2009. Improving land surface models
911 with FLUXNET data. *Biogeosci.* 6:1341-1359.
912
913 Wu, J. 2004. Effects of changing scale on landscape pattern analysis: scaling relations.
914 *Landscape Ecology*, 19, 125-138.
915
916 Xu, S., Chen, J. M., Fernandes, R., & Cihlar, J. 2004. Effects of subpixel water area fraction
917 on mapping leaf area index and net primary productivity in Canada. *Canadian*
918 *Journal for Remote Sensing*, 30, 797–804.
919
920 Zhang K., Kimball J.S., Mu Q., Jones L. A., Goetz S.J, W. Running S. W. 2009. Satellite based
921 analysis of northern ET trends and associated changes in the regional water balance from
922 1983 to 2005. *Journal of Hydrology*, 379: 92-110.

923 Zhao, G., Siebert, S., Enders, A., Rezaeil, E., Yan, C., and Ewart F. 2015. Demand for multi-
924 scale weather data for regional crop modeling. *Agricultural and Forest Meteorology* 200:
925 156-171. [doi:10.1016/j.agrformet.2014.09.026](https://doi.org/10.1016/j.agrformet.2014.09.026).

926

List of Symbols

λ = latent heat of vaporization [MJ kg^{-1}]

Δ = slope of the vapour pressure curve [$\text{kPa } ^\circ\text{C}^{-1}$]

ρ_a = density of the air [kg m^{-3}]

γ = psychrometric constant [$\text{kPa } ^\circ\text{C}^{-1}$]

Table 1: Type of tower, instrument height above ground surface, dominant vegetation, areal coverage, mean leaf area index (LAI) and standard deviation, and mean cumulative ET for each dominant land cover type in the study area. ET values are modelled using spatially explicit 1 m x 1 m vegetation structural characteristics and measured hydro-meteorologic parameters associated with each land cover (see model description in text).

Tower type	Instrument height (m)	Landcover	Number of Towers	Dominant species	Coverage (%)	LAI	Mean ET (mm)
Eddy covariance	3	Upland regeneration	1	<i>Populus balsamifera</i> <i>L. Salix</i> spp., <i>Amelanchier alnifolia</i> , <i>Rosa acicularis</i> , <i>Viburnum edule</i> , <i>Cornus Canadensis</i> ,	1	0.36 (1.23)	151.43
Eddy covariance	22.5	Upland regeneration	1	<i>Epilobium angustifolium</i> , <i>Calamagrostis canadensis</i>			
Energy balance	3	Upland regeneration	2	<i>Populus tremuloides</i> , <i>Populus balsamifera</i> <i>Rosa acicularis</i>	58	1.40 (2.08)	216.05
Energy balance	3	Riparian	2	<i>Populus balsamifera</i> , <i>Picea marianca</i> , <i>Populus tremuloides</i> , <i>Betula papyrifera</i>	11	1.20 (1.11)	157.92
Energy balance	3	Treed peatland	2	<i>Picea marianca</i> , <i>Sphagnum</i> spp.	8	2.01 (3.16)	184.08
Energy balance	3	Open Peatland	2	<i>Sphagnum</i> spp.	17	0.10 (0.60)	198.02
Energy balance	3	Pond	1	<i>See text.</i>	5	N/A	209.83

Table 2: Difference between cumulative modelled ET at each pixel size within PDF flux footprints and eddy covariance data for all days with suitable atmospheric stability to calculate PDF flux footprints at the 3 m northern tower. Statistical differences determined using the Mann-Whitney Rank-Sum Test with a 95% confidence interval.

Resolution	Modelled ET (mm)	Overestimation (mm)	Overestimation (%)	Significant Difference from EC?	
Measured	54.48	--	--	--	--
1m	60.31	5.83	10.71	No	N = 22, p = 0.484, r2 = 0.602
10m	62.09	7.61	13.97	No	N = 22, p = 0.283, r2 = 0.611
25m	62.72	8.24	15.13	No	N = 22, p = 0.170, r2 = 0.625
250m	70.86	16.38	30.07	Yes	N = 22, p = 0.002, r2 = 0.749
500m	74.00	19.52	35.83	Yes	N = 22, p < 0.001, r2 = 0.566
1000m	74.00	19.52	35.83	Yes	N = 22 p < 0.001, r2 = 0.603

Table 3: Difference between cumulative modelled ET at each pixel size within PDF flux footprints and eddy covariance data for all days with suitable atmospheric stability to calculate PDF flux footprints at the 22.5 m southern tower. Statistical differences determined using the Mann-Whitney Rank-Sum Test with a 95% confidence interval.

Resolution	Modelled ET (mm)	Overestimation (mm)	Overestimation (%)	Significant Difference from EC?	
Measured	164.61	--	--	--	--
1m	180.29	16.29	9.93	Yes	N = 72; p<0.001, r ² = 0.206
10m	195.31	31.31	19.09	Yes	N = 72; p<0.001, r ² = 0.201
25m	198.28	34.28	20.90	Yes	N = 72; p<0.001, r ² = 0.201
250m	212.17	48.17	29.37	Yes	N = 72; p<0.001, r ² = 0.213
500m	224.70	60.70	37.01	Yes	N = 72; p<0.001, r ² = 0.275
1000m	224.70	60.70	37.01	Yes	N = 72; p<0.001, r ² = 0.275

Table 4: Average ET \pm standard deviation, and maximum ET modelled at each pixel size for the 5 km x 5 km study area.

Resolution	Average ET (mm)	Standard Deviation (mm)	Maximum (mm)
1m	161.53	50.02	450
10m	165.59	41.34	352
25m	165.3	41.89	345
250m	167.43	39.49	320
500m	171.40	35.93	314
1000m	176.00	10.69	186

Table 5: Percent contribution of each land cover type to total landscape ET at each pixel size for the 5 km x 5 km study site.

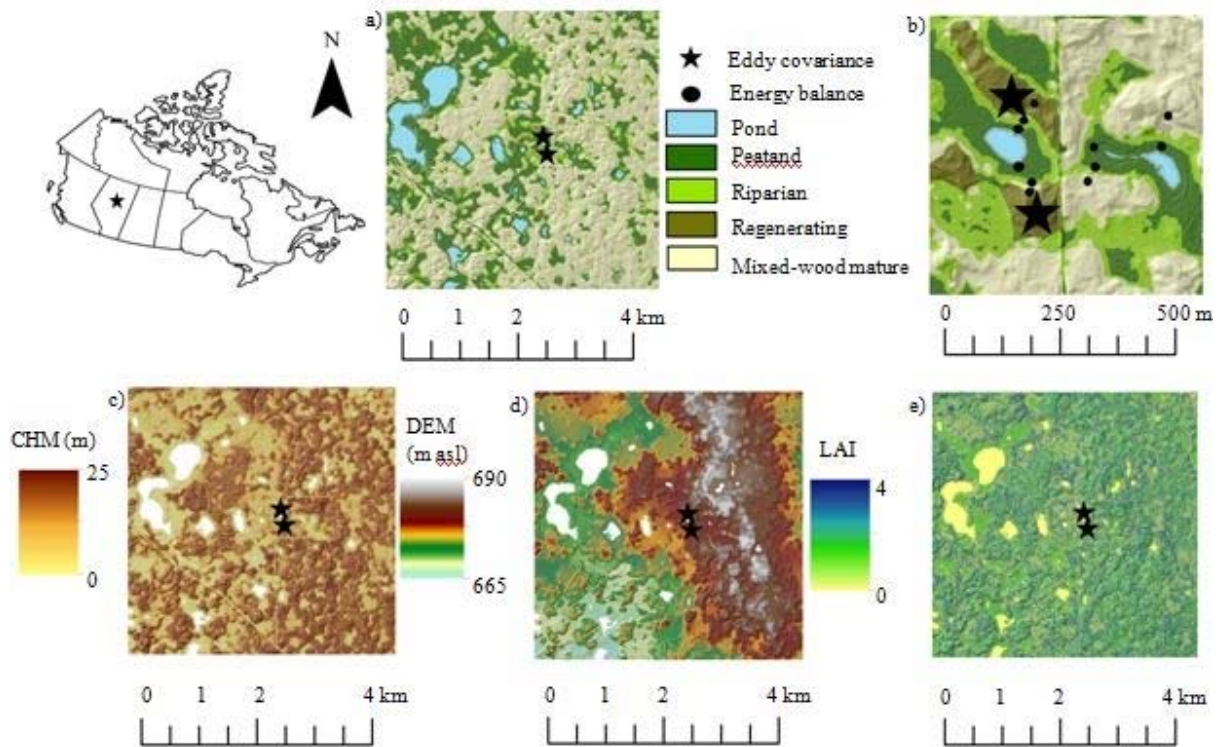
Land Cover	1m	10m	25m	250m	500m	1000m
Pond	5.23	5.26	5.25	4.94	10.57	13.60
Open Peatland	7.98	8.08	8.02	8.83	19.96	17.11
Treed Peatland	15.62	15.69	15.81	14.37	7.42	3.98
Riparian	8.69	8.67	8.63	8.61	0.00	0.00
Regenerating	0.60	0.60	0.60	0.38	0.00	0.00
Mature mixed-wood	61.87	61.74	61.69	62.88	62.05	65.32

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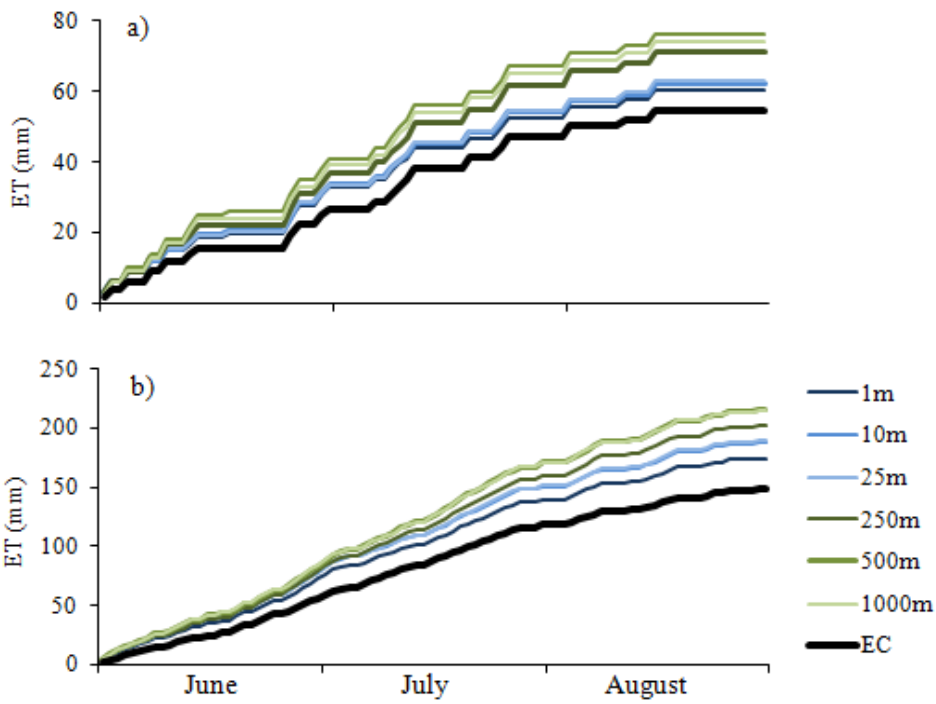
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932 Fig. 1

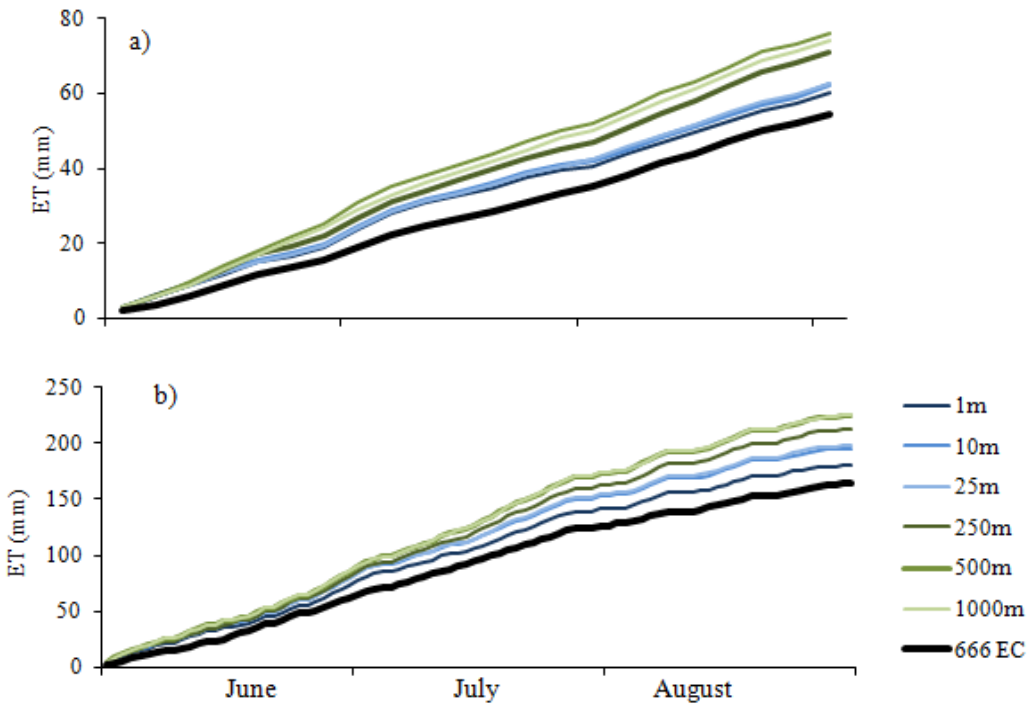
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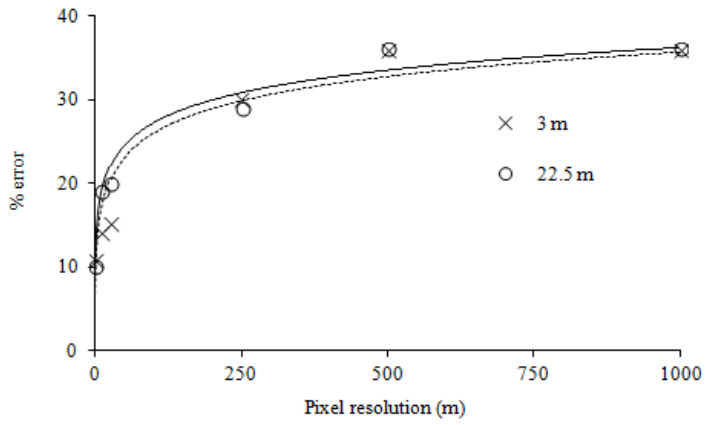
935 Fig. 2

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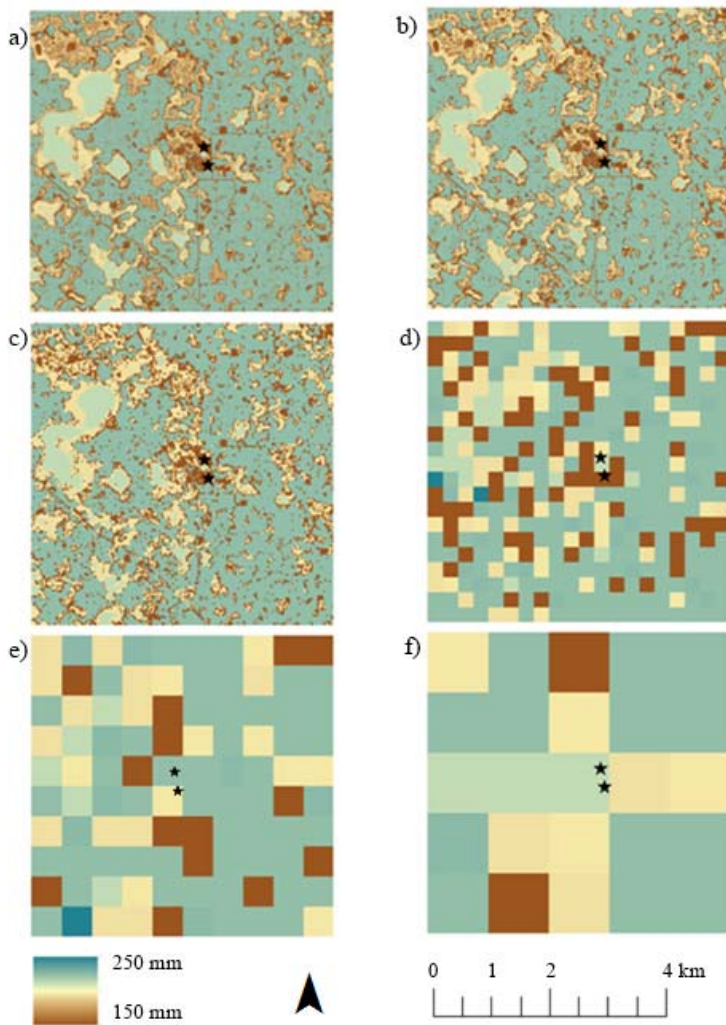
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938 Fig. 3



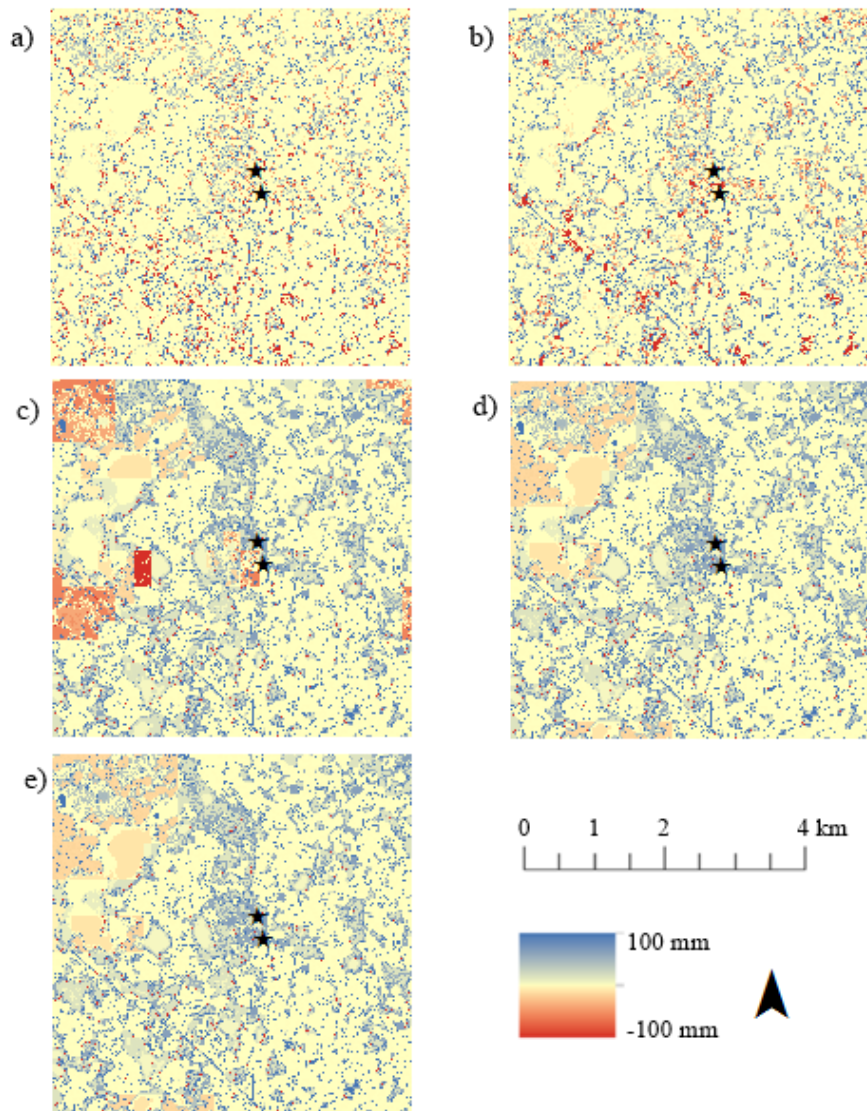
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940 Fig. 4



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942 Fig. 5



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944 Fig. 6