

1 **Determining total emissions and environmental drivers of methane flux in a Lake Erie**
2 **estuarine marsh: The Old Woman Creek Wetland**

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8 **ABSTRACT**

9 Estuarine marshes can act as an important ecosystem for carbon storage and flux. We monitored
10 CH₄ and CO₂ fluxes in Old Woman Creek, an estuarine wetland of Lake Erie, Ohio. The eddy
11 covariance (EC) technique was used to measure fluxes of CH₄ and CO₂ continuously during the
12 growing seasons of 2015 and 2016. Simultaneously, monthly sampling of gas exchange was
13 conducted using accumulation chambers in four distinct land-cover types in the wetland: Open
14 water, emergent vegetation (*Typha spp.*), floating vegetation (*Nelumbo spp.*) and mud flats.
15 Chambers and EC measurements were combined to provide estimates of the continuous
16 contributions of each land cover to the total methane emissions of the wetland. In addition, water
17 and meteorological measurements were used to determine the most important environmental
18 drivers of methane flux in the wetland. We found an average rate of emission from the *Typha*
19 patch of 1.9 g CH₄ m⁻² d⁻¹, which was much higher than rates reported in similar emergent
20 vegetation types in other wetlands. Mud flats had the highest rates of CH₄ emission, followed by
21 *Nelumbo*, and *Typha* patches, and Open water. Mud flats contributed 6.8% of the total CH₄
22 emissions of the wetland despite occupying only 1.5% of the wetland area, whereas open water

23 contributed 16.1% despite occupying 47% of the wetland area. Water temperature, and wind
24 speed were the strongest environmental drivers of CH₄ flux to the atmosphere. Carbon fluxes
25 were strongly correlated to methane fluxes. Fluctuating water levels above the wetland's surface
26 had a weak effect on overall CH₄ emissions in the wetland. Providing an empirical model that
27 predicts the influence of different environmental drivers on the emissions of methane in the
28 wetland, can aid in the design of estuarine wetlands that retain nutrients and reduce coastal
29 eutrophication while minimizing greenhouse gas emissions.

30 **Keywords:** Wetland, methane, estuary, carbon, environmental drivers, marsh.

31 **Introduction**

32 Estuaries provide many beneficial ecosystem services. Estuaries process upland river water
33 before they spill into lakes or oceans (Larson et al., 2013). By processing transported nutrients,
34 they help reduce the eutrophication of coastal waters and thereby the occurrence of harmful algae
35 blooms (Horne, 2000; Michalak et al., 2013). Estuarine wetlands also serve an important role in
36 the natural carbon cycle (McLeod et al., 2011). Wetlands can sequester large amounts of carbon
37 due to their low soil oxygen contents that restricts the decomposition of biomass by aerobic
38 microbes. In wetlands, including estuarine ones, carbon in the form of carbon dioxide (CO₂) is
39 also assimilated by plant photosynthesis. In most wetlands, there is a net negative flux of CO₂,
40 which means that more carbon enters the ecosystem through gross primary production (*GPP*)
41 than carbon leaves through ecosystem respiration (*R_e*) (Bridgham et al., 2006; Mitsch et al.,
42 2013). Estuarine wetlands have the potential to become even more productive than other classes
43 of wetlands due to nutrient rich waters that increases wetland's plant growth (Horne, 2000) and
44 trapping of suspended matter and its associated organic carbon, which increases the long-term

45 carbon sequestration pool (McLeod et al., 2011). However, the same low oxygen conditions that
46 slow decomposition make wetlands sources of methane (CH₄).

47 Temperature is perhaps the most commonly cited driver of CH₄ emissions. Microbial processes
48 are directly dependent on temperature, which increases their metabolic rates (Bohn et al., 2007;
49 Kim et al., 1999; Segers, 1998). However, it's linkage to CH₄ emissions is complex due to the
50 competing interaction of anaerobic methanogenesis and aerobic methanotrophy, both of which
51 are stimulated by higher temperatures. Water level is commonly cited as a driver of CH₄,
52 typically due to its association with oxygen availability (Kettunen, 2003; White et al., 2008).
53 Oxygen is the preferred terminal electron acceptor for most methanotrophs, which can oxidize
54 60-90% of the methane produced in wetlands before it can escape to the atmosphere (Le Mer and
55 Roger, 2001). It has been shown that intermittent flooding can reduce methane emissions relative
56 to permanently flooded wetlands (Altor and Mitsch, 2006), but few studies have examined the
57 effect of short time scale variations of water level on permanently flooded, non-tidal marshes.
58 The availability of labile carbon substrate concentration in the soil also plays a crucial role in the
59 production of methane (Sha et al., 2011; Updegraff et al., 1995), typically modeled as substrate-
60 limited Monod kinetics. The pH can also have an influence on methane emissions as
61 methanogens prefer neutral to slightly alkaline conditions (Wang et al., 1993).

62 Wetlands are often composed of a mosaic of different land cover types, including open water,
63 emergent vegetation, floating vegetation, mud flats, and dry upland. The rates of CH₄ emission
64 among these land covers can be very variable and their arrangement and relative coverage can
65 strongly influence the total methane emissions from the wetland site as a whole (Matthes et al.,
66 2014; Morin et al., 2017). The presence of plants can increase the methane emission rates by a
67 factor of 3-4 in comparison to areas within the wetland with no vegetation (Hamilton et al.,

68 1994) and the type and composition of plants within a wetland also have an important effect on
69 methane emissions (Baldocchi et al., 2012; Forbrich et al., 2011; Leppala et al., 2011; Sachs et
70 al., 2010).

71 There are several methodologies to quantify CH₄ fluxes. The most common one uses non-steady-
72 state chambers, in which the rate of accumulation of a gas in the headspace of a chamber with
73 known volume provides the flux rate. Chambers are relatively simple, low-cost, and can work in
74 a wide range of applications and ecosystems. Chambers are, essentially, point measurements, and
75 thus, provide spatially detailed observations of the flux rates of particular land-cover types, but
76 over a small number of spatially replicated points. When the chamber deployment is done
77 manually and is not automated, they are limited to a very small and intermittent temporal
78 representation. The eddy covariance approach combines high-speed wind and gas concentration
79 data to determine the site level fluxes at a high temporal resolution (typically 10 – 20 Hz
80 processed to half-hourly block averages). The eddy covariance approach measures a mixture of
81 gases originating from a source footprint area that changes with wind speed, direction and
82 turbulence mixing of the atmospheric boundary layer (Detto et al., 2006; Hsieh et al., 2000;
83 Kljun et al., 2004), and often includes various land-cover types that make up the entire site.

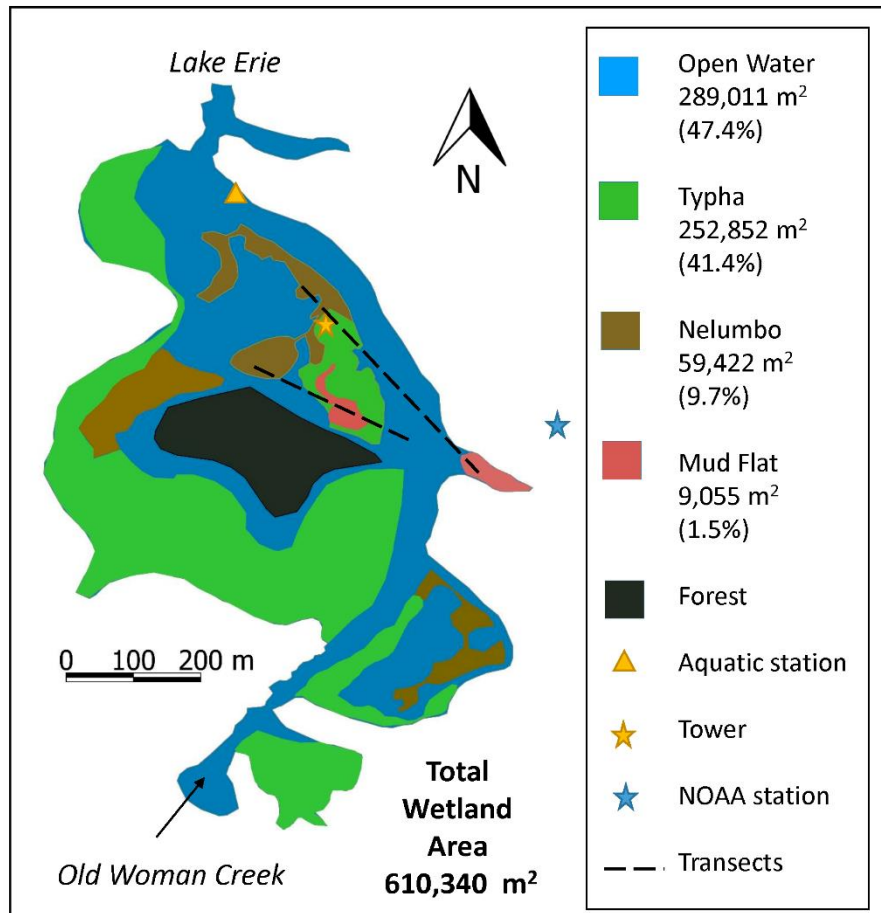
84 In this study we use the approach of Morin et al. (2017) that combines point-wise flux rate
85 estimates from each land-cover type using non-steady-state chamber campaigns, and continuous
86 site-level eddy covariance measurements. By combining these two data streams, it is possible to
87 estimate the separate contributions of different land cover types throughout the site, and provide
88 an integrated whole-site-level estimate of methane flux from the wetland. We studied the Old
89 Woman Creek National Estuarine Research Reserve wetland (OWC), a natural estuarine marsh
90 in Northern Ohio at the coast of Lake Erie (Fig. 1). The first objective of this study is to calculate

91 the total summer-time emissions of CH₄ from the OWC wetland, by integrating the contributions
92 of different land cover types. The second objective is to identify the most important
93 environmental drivers of CH₄ flux and identify environmental variables that are most strongly
94 correlated with methane flux, and thus develop an empirical model of methane emissions in the
95 wetland

96 ***2. Materials and methods.***

97 *2.1. Study site*

98 The Old Woman Creek (OWC), in Northern Ohio, is a State Nature Preserve, part of NOAA's
99 National Estuarine Research Reserve (NERR) network. OWC includes 61 Ha of natural wetland
100 area managed by NOAA and the Ohio Department of Natural Resources. There are four main
101 land-cover types in the wetland: 1) Open water, 2) mud flats, 3) Emergent vegetation: a mix of
102 emergent vegetation dominated by *Typha* spp with a small amount of *Phragmites* spp., (for
103 simplicity, we name this land-cover type – *Typha*) and 4) floating-leaf vegetation dominated by
104 *Nelumbo lutea*. Fig. 1 shows the land cover arrangement for the period of the study. Water flows
105 into the wetland from Old Woman Creek as it travels northwards into Lake Erie (Fig. 1). A
106 natural sand barrier acts as a levee that intermittently blocks the exchange of water between Lake
107 Erie and the estuary. Typically, the sand barrier limits the flow from the wetland into Lake Erie
108 (Tomaszek et al., 1997), especially during summertime low-flow periods. Periodically, during
109 storms in the lake, the sand barrier ruptures and allows a rapid flux of water between the wetland
110 and Lake Erie. With the exception of the open-water area in the main channel, most of the
111 wetland is shallow, no deeper than 0.5 m (Whyte et al., 2008).



112

113 *Figure 1. Map of the study site showing the area distribution of each of the four predominant land covers*
 114 *and the meteorological, flux and aquatic stations used in the study. The dotted lines indicate the chamber*
 115 *measurement transects. The area calculation was done by interpretation of Google Earth satellite*
 116 *imagery for the year 2015 and field corroboration.*

117 *2.2. Meteorology and flux tower*

118 An eddy-covariance tower was installed in the center of the wetland to measure both
 119 meteorological conditions and fluxes of carbon and water from June to October 2015 and from
 120 April to October 2016. The meteorological station consisted of one temperature and humidity
 121 sensor (HMP45 – Vaisala Inc., Vantaa, Finland) located at approximately 2.5 m above water
 122 level and a network of seven temperature sensors (107-L Temperature Sensors – Campbell
 123 Scientific, Inc. Logan, UT). Six of these sensors were positioned in three different land cover
 124 types (open water, *Typha* and *Nelumbo*), measuring soil temperature at 10 (ST_{10cm}) and 40 cm

125 (ST_{40cm}) below the soil surface and the final temperature sensor was positioned in the water
126 column, 30 cm above the soil surface. These data were recorded every 1 min and later
127 transformed into 30 min averages. ST_{10cm} and ST_{40cm} for the wetland were calculated as an
128 average of the three temperature sensors located at the different positions.

129 The flux tower consisted of an infrared gas analyzer (IRGA) for CO_2/H_2O and CH_4 (LI-7500, LI-
130 7700, respectively – LiCOR Bioscience, Lincoln NE), as well as a 3D ultrasonic anemometer
131 (CSAT3 – Campbell Scientific, Inc. Logan, UT). The sensors were positioned 2.7 m above the
132 mean water level of the wetland. All flux variables were recorded with a frequency of 10 Hz.
133 Meteorological and flux data were collected on a datalogger (CR3000, Campbell Scientific, Inc.
134 Logan, UT) connected wirelessly to a computer in the facilities of OWC via FM radio (RF450 –
135 Campbell Scientific, Inc. Logan, UT). After collection at 10 Hz, data were binned into half
136 hourly averages and fluxes.

137 Additional meteorological data were obtained from a NOAA-operated weather station located
138 411 m from the wetland (NOAA station, Fig. 1). From this station, we obtained photosynthetic
139 active radiation (PAR), relative humidity (RH), air temperature (T_{air}), wind speed (u), wind
140 direction (WD), and cumulative precipitation at a temporal frequency of 15 minutes. An aquatic
141 monitoring station located 303 m from the tower (Fig. 1) provided 15 min averages of water
142 temperature (WT), water level, pH, dissolved oxygen (DO) and turbidity.

143 2.3. Chamber measurements

144 We used non-steady state chambers to measure CO_2 and CH_4 fluxes at the four land cover types
145 in the wetland. The chamber sampling campaign occurred monthly, from June to October 2015
146 and from May to October 2016. We created two transects along the wetland, each comprising all

147 four land cover types (Fig. 1). *Nelumbo* was not sampled in June 2015 and the second transect
148 only included mud from June 2016 onwards. As all sites featured some standing water
149 throughout the sampling campaign, the land covers were sampled by boat when possible. Two
150 chambers were used at each point within each transect. Seven samples per chamber were
151 collected every 5 minutes, starting at time 0, for a total of 30 min of sampling. The gas extracted
152 from the chamber was injected into 10 ml evacuated vials, and later taken to the lab to be
153 analyzed on a gas chromatograph (Shimadzu GC-2014, Shimadzu Scientific Instruments, Kyoto,
154 Japan). The procedure for calculation of fluxes, calibration of the instruments and correction for
155 drifts of the gas chromatograph is fully described in Morin et al. (2017), and based on (Nahlik
156 and Mitsch, 2010; Sha et al., 2011). We incorporated selection criteria for rejecting outliers from
157 individual chamber measurements: if the r^2 value for the linear regression between the
158 accumulation rates over 30-minutes was not sufficiently high ($r^2 \geq 0.85$), we removed the point
159 with the highest residual value from the regression. This was done up to twice per chamber. If
160 three points were removed, the entire chamber observation was rejected.

161 *2.4. Flux calculations from eddy covariance*

162 We applied quality control and despiking protocols to the high frequency measurements as
163 described in Morin et al. (2014b). Wind data was subjected to a 3D rotation to force the mean
164 vertical and crosswinds components to zero (Finnigan et al., 2003). A correction was applied to
165 the temperature measurements from the sonic anemometer to account for changes in air density
166 (Kaimal and Gaynor, 1991). Following the procedure of Morin et al. (2014b), a lag correction
167 was applied to account for the separation distance between the sonic anemometers and the
168 IRGAs, and a spectral correction was applied to correct for the temperature dependence of the
169 absorption spectrum of CO₂, CH₄, and water vapor. CO₂ and CH₄ concentrations were applied

170 WPL corrections to account for the changes in air density (Webb et al., 1980). Data was
171 processed to half hourly means and filtered based on a friction velocity (u^*) threshold. We used
172 an empirical approach for defining a threshold that indicates insufficient level of turbulent
173 mixing below which data is rejected (Reichstein et al., 2005). The minimum value of u^* used in
174 this study was 0.2 m s^{-1} .

175 In the case that our observations included gaps, typically due to power supply problems, missing
176 meteorological data were replaced with data from the NOAA station, with empirical corrections
177 applied based on the linear relationship between the variables when both were available. When
178 not available, data was gap-filled using a simple bi-linear, periodic trended interpolation
179 relationship (Morin et al., 2014b) that took into account both the diurnal variation and the closest
180 available values of the variables to be gap-filled.

181 *2.5. Modelling and gap-filling of fluxes*

182 EC measurements of CO_2 flux (NEE) was partitioned into Gross Primary Productivity (GPP) and
183 ecosystem respiration (R_e). At nighttime, NEE was completely attributed to R_e as no
184 photosynthesis is expected in the wetland. An automated neural network (ANN) model (Moffat
185 et al., 2007; Morin et al., 2014a) was trained to determine an empirical model of R_e , as a function
186 of environmental variables, using a subset of available nighttime values. We then used this
187 trained ANN and environmental observations to model R_e at all periods (including daytime).
188 Subsequently, we subtracted the modeled R_e from the observed NEE to calculate GPP when
189 carbon flux observations were available. A new ANN process was then trained to model
190 daytime GPP and used to gap-fill missing GPP observations. We used ANN to gap-fill sensible
191 (H) and latent (LE) heat fluxes as well. The environmental variables that we selected to
192 contribute to the R_e model were: ST_{10cm} , H , LE , VPD , wind speed (U), U^* and T_{diff} . Whereas for

193 *GPP* the selected environmental variables included: *VPD*, *H*, *T_{diff}*, *PAR*, *LE*, Air temperature
 194 (*T_{air}*), *U*, *U** and *RH*. Variables were selected according to their pairwise linear regression with
 195 *R_e* or *GPP*. Following Morin et al. (2014a), we used a step-wise Akaike Information Criterion
 196 (AIC)-driven variable selection process to determine which of these variables have a significant
 197 and justified contribution to the model as shown in Table 1. Variables that did not reduce the
 198 AIC of the model were not included in the final model. For all ANNs, we ran 1000 iterations
 199 from which we selected the best 10% based on the *r*² of the model. The ensemble average of
 200 these top 100 iterations was used to create the final model and the subsequent gap-filling. We
 201 created these ANN-based empirical models of fluxes with the objective of: (1) understanding the
 202 relationship between environmental drivers and the fluxes; and (2) creating proxy time series to
 203 model fluxes.

204 2.6. *Scaling methodology*

205 To determine the site-level methane budget, we used an expanded version of the fixed-frame
 206 eddy-covariance (EC) scaling methodology developed by Morin et al. (2017). Briefly, this
 207 method combines EC measurements, with a footprint model, a land cover map, and land-cover
 208 specific flux measurements collected using the chamber method, to decompose the EC flux
 209 signal into its contributing parts by each land cover type. We used the (Detto et al., 2006)
 210 footprint model, which is a 2D expanded version of the Hsieh et al. (2000) formulation. We used
 211 monthly varying displacement heights and roughness lengths to account for the growth of *Typha*
 212 around the tower. Given the four land-cover types throughout the wetland, at any half hour the
 213 flux measured by the tower can be decomposed to the contributions of each land-cover type:

$$214 \quad F_{tower} = F_{op} ' e_{op} + F_{ty} ' e_{ty} + F_{ne} ' e_{ne} + F_{mu} ' e_{mu} \quad (1)$$

215 Where F' of each land cover type indicates the EC-derived flux rate of that land cover type (where
 216 subscripts: op = open water, ty = *Typha*, ne = *Nelumbo*, mu = mud flat) and e is the fraction that
 217 each patch type contributed to the total EC measurement footprint.

218 Chamber flux data determined the relative flux strengths of fluxes from each land cover type
 219 compared to open water fluxes (eq. 2, 3 and 4).

$$220 \quad m_1 = \frac{F_{ty}}{F_{op}} = \frac{F'_{ty}}{F'_{op}} \quad (2)$$

$$221 \quad m_2 = \frac{F_{ne}}{F_{op}} = \frac{F'_{ne}}{F'_{op}} \quad (3)$$

$$222 \quad m_3 = \frac{F_{mu}}{F_{op}} = \frac{F'_{mu}}{F'_{op}} \quad (4)$$

223 Where F_x is the flux measured by the chamber at each land cover type x . Because chamber
 224 measurements were taken monthly, the values of m varied monthly. Then, by substituting eqns.
 225 2-4 into eq. 1, the chamber-derived flux intensity ratios can be used to translate the total footprint
 226 flux to an equivalent open-water flux rate

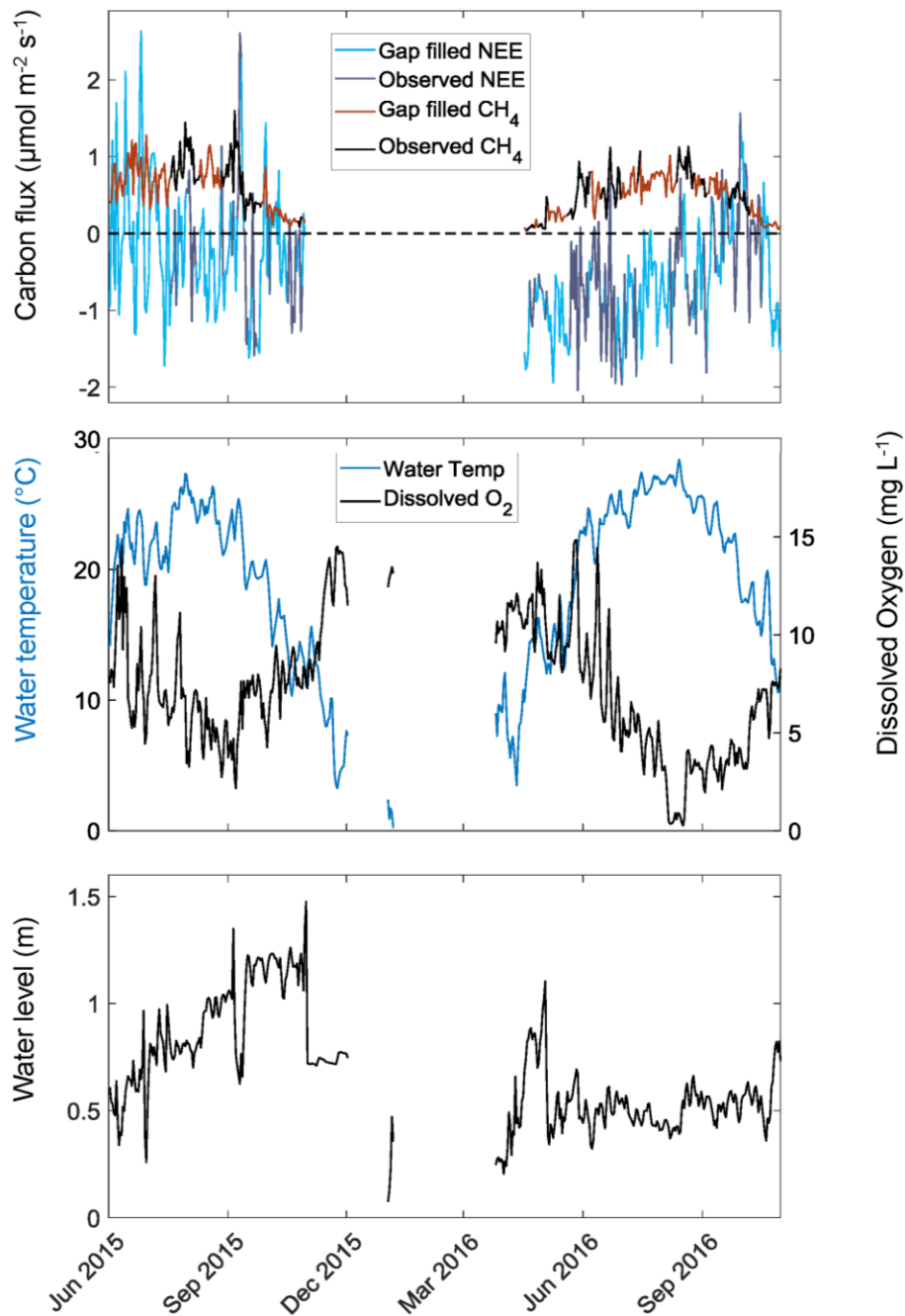
$$227 \quad F_{tower} = F'_{op} e_{op} + m_1 F'_{op} e_{ty} + m_2 F'_{op} e_{ne} + m_3 F'_{op} e_{mu} \quad (5)$$

228 Eq. 5 can be solved for F_{op} at any observed half-hour. Similarly, using eq. 1-4, a solvable system
 229 of equations can be derived for the relative flux strength of each patch type contributing to the
 230 eddy-covariance observation. Multiplying these rates by the actual area of each land-cover type
 231 within the whole wetland will yield the fixed-frame total contribution of that land-cover type to
 232 the site-level flux.

233 3. Results

234 3.1. Daily and diurnal variation of CO₂ and CH₄ fluxes

235 Our ANN simulated *H* and *LE* very efficiently. The r^2 of the relationship between the values
236 predicted by the ANN and the observed values of *H* and *LE* were 0.84 and 0.86 for 2015, and
237 0.70 and 0.82 for 2016, respectively. EC-CO₂ flux measurements indicated that *NEE* was greater
238 (more negative, therefore higher photosynthesis) in 2016 than in 2015 whereas CH₄ emissions
239 were higher in 2015 than in 2016 (Fig. 2). The daily mean *NEE* was $-0.47 \pm 0.80 \mu\text{mol m}^{-2} \text{s}^{-1}$
240 (mean \pm std), comprised of daily mean *GPP* of $-2.81 \pm 1.27 \mu\text{mol m}^{-2} \text{s}^{-1}$ and daily mean *R_e* of
241 $2.35 \pm 1.51 \mu\text{mol m}^{-2} \text{s}^{-1}$. Values of *R_e* were high when compared to other ecosystem types, likely
242 due to the soil conditions, which is rich with dissolved organic carbon, bringing the seasonal
243 total *NEE* close to zero. The correlation between observed and ANN-predicted values of *NEE*,
244 *GPP* and *R_e* achieved high coefficients of determination ($r^2 = 0.84, 0.79, 0.68$ for 2015 and $0.83,$
245 0.69 and 0.52 for 2016, respectively). Daily averages of *DO* for the period from June to October
246 were not significantly different between 2015 and 2016 (t-test, $p=0.65$), however, for the same
247 period water temperature was significantly higher in 2016 than in 2015 (t-test, $p<0.01$). Water
248 temperature had an inverse relationship with *DO*, with the lowest *DO* occurring in the warmest
249 months. Water level was highly variable and tended to increase from spring to fall in both years.



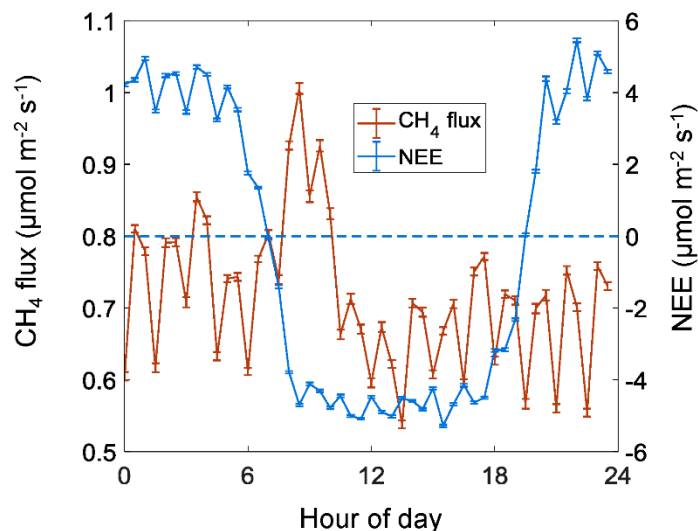
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251 *Figure 2. Temporal variation of diurnal averages of a) Net Ecosystem Exchange and methane. The gap-*
 252 *filled values represent averages for which more than 50% of the data for that day was gap-filled. b)*
 253 *Water temperature and dissolved oxygen and c) water level above the soil surface around the tower.*

254

255 The daily mean of CH_4 flux was $0.55 \pm 0.31 \mu\text{mol m}^{-2} \text{s}^{-1}$ (Fig. 2), spanning a range from 0.03 to
 256 $1.60 \mu\text{mol m}^{-2} \text{s}^{-1}$. Fig. 3 shows the observed diurnal cycles of CH_4 flux and NEE from both 2015

257 and 2016. The diurnal cycle of CH_4 flux was characterized by a sharp increase in flux around the
 258 mid-morning, approximately from 7:00 to 10:00 AM. In addition, CH_4 fluxes tended to be lower
 259 right after the mid-morning spike and during the first half of the night, whereas in the second half
 260 of the night CH_4 emissions tended to be slightly higher. The diurnal cycle of NEE had a more
 261 sinusoidal shape, as is typical, due to the competing processes of photosynthesis and respiration.
 262 During the night, NEE reached an average of 4 to 5 $\mu\text{mol m}^{-2} \text{s}^{-1}$, whereas during the day
 263 maximal NEE was close to -5 $\mu\text{mol m}^{-2} \text{s}^{-1}$.



264
 265 *Figure 3. Diurnal cycle of methane and CO₂ flux for half hour intervals as measured by the eddy*
 266 *covariance tower. The values are non-gap-filled averages for 2015 and 2016. Error bars are the standard*
 267 *error.*

268
 269 **3.2. Environmental predictors of CH_4 flux**

270 During daytime, water temperature (WT) had the highest correlation with CH_4 flux. The second
 271 most important variable was GPP , followed by u , LE and H (Table 1). Each of the subsequent
 272 variables in the model (Table 1) increased the r^2 slightly, until FP_{open} . The remaining variables,

273 including *WL* had significant, though very small, contribution to the model. Overall, r^2 of the
274 daytime CH_4 -flux model improved from 0.56 in the stepwise linear model to 0.86 using ANN.
275 During nighttime, the most important variable in the stepwise linear model of CH_4 flux was R_e
276 (Table 1). As with the daytime fluxes, *WT*, *u* and *LE* were also important in determining the CH_4
277 flux. In contrast, *DO* and *WL* had a stronger effect on CH_4 fluxes during nighttime than during
278 daytime. Other variables, such as F_{open} , atmospheric pressure (P_{atm}), u^* , half-hourly change in
279 atmospheric pressure (ΔP_{atm}) and FP_{Typha} were rejected in the ANN as their addition to the ANN
280 process did not significantly improve the model.

281 *Table 1. Results of the statistical tests to determine the most important drivers of the methane flux*
282 *models: Correlation coefficients (r) of the pairwise linear relationship indicate the strength and sign*
283 *(positive or negative) of the relationship. Stepwise linear multivariate and stepwise hierarchical Neural*
284 *Network models test the effects of each variable through their incremental improvement of the cumulative*
285 *coefficient of determination (r^2) and Akaike Information Criterion (AIC) values. A * next to an AIC value*
286 *indicates that the variable was rejected (due to a rise in AIC from the previous variable). The ANN*
287 *models included only the variables that had a significant effect on the stepwise linear model.*

		Pairwise linear	Stepwise Linear		Neural Network	
		r	Cum. r^2	Cum. AIC	Cum. r^2	Cum. AIC
Day	<i>WT</i>	0.49	0.28	22503	0.42	38557
	<i>GPP</i>	-0.33	0.27	19315	0.46	37483
	<i>U</i>	-0.32	0.32	18622	0.53	35048
	<i>LE</i>	0.41	0.39	17636	0.56	33846
	<i>H</i>	-0.33	0.43	16952	0.63	30899
	<i>VPD</i>	0.29	0.45	16547	0.71	27046
	T_{air}	0.49	0.48	15978	0.75	24234
	u^*	-0.03	0.50	15702	0.78	22180
	<i>DO</i>	0.12	0.51	15559	0.80	20825
	ST_{10cm}	-0.14	0.53	15065	0.81	19445
	FP_{open}	0.04	0.55	14959	0.82	19116
	ΔP_{atm}	-0.04	0.55	14848	0.82	18613
	P_{atm}	-0.26	0.56	14829	0.83	18373
	FP_{Typha}	0.04	0.56	14828	0.86	15160
	<i>WL</i>	-0.14	0.56	14772	0.86	14114
	<i>PAR</i>	-0.10	0.56	14776*	-	-
Night	R_e	0.54	0.31	17047	0.42	38405
	<i>W</i>	0.59	0.42	15191	0.61	31832

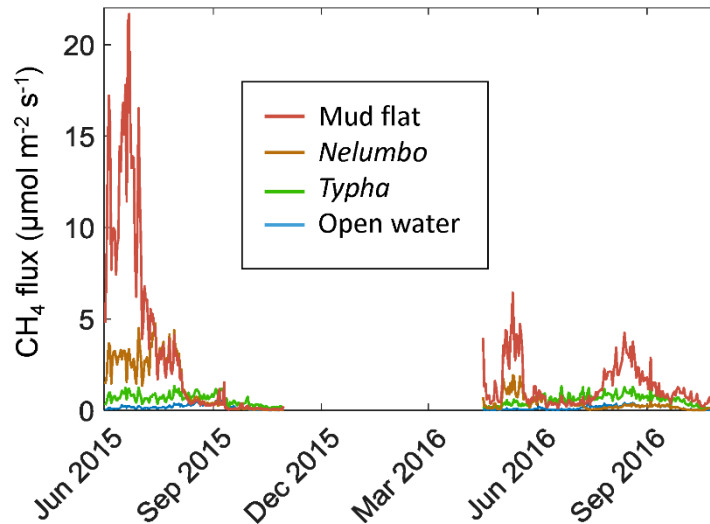
<i>U</i>	-0.31	0.45	14875	0.67	28889
<i>LE</i>	0.35	0.47	14570	0.66	29352*
<i>DO</i>	0.14	0.49	14333	0.79	21770
<i>VPD</i>	0.21	0.50	14107	0.81	19796
<i>T_{air}</i>	0.49	0.53	13666	0.82	19017
<i>H</i>	-0.39	0.55	13324	0.80	20291*
<i>WL</i>	-0.25	0.56	13163	0.83	17528
<i>FP_{open}</i>	-0.02	0.60	12840	0.80	20573*
<i>P_{atm}</i>	-0.22	0.61	12756	0.83	18175*
<i>u*</i>	-0.20	0.61	12685	0.82	18871*
<i>ST_{10cm}</i>	-0.09	0.61	12645	0.84	17344
ΔP_{atm}	-0.04	0.61	12641	0.83	18189*
<i>FP_{Typha}</i>	0.02	0.61	12636	0.80	20300*
<i>LE</i>	-	-	-	0.84	16725
<i>H</i>	-	-	-	0.84	16497
<i>FP_{open}</i>	-	-	-	0.83	18046*
<i>P_{atm}</i>	-	-	-	0.84	17210*
<i>u*</i>	-	-	-	0.84	16997*
ΔP_{atm}	-	-	-	0.84	17171*
<i>FP_{Typha}</i>	-	-	-	0.84	16920*

288

289

290 3.3. Spatial variation of CH_4 flux and its effect on the methane budget of the wetland

291 After the decomposition of the site-level eddy covariance measurements into its land-cover type
 292 components, it was clear that there was a large variation in CH_4 flux among the four land-cover
 293 types. The mud flats had the highest rate of methane emissions, reaching daily averages of up to
 294 $21 \mu\text{mol m}^{-2} \text{s}^{-1}$, while the open water areas had the lowest rates, peaking at $0.5 \mu\text{mol m}^{-2} \text{s}^{-1}$.
 295 *Nelumbo* had higher rates of CH_4 emission than *Typha* in 2015 but in 2016, *Typha* had higher
 296 rates, except for a short period early in the growing season (April and May). The mud flats had
 297 one period of high CH_4 emissions in early 2015 and 2 periods of high emissions in 2016 in May
 298 and August.

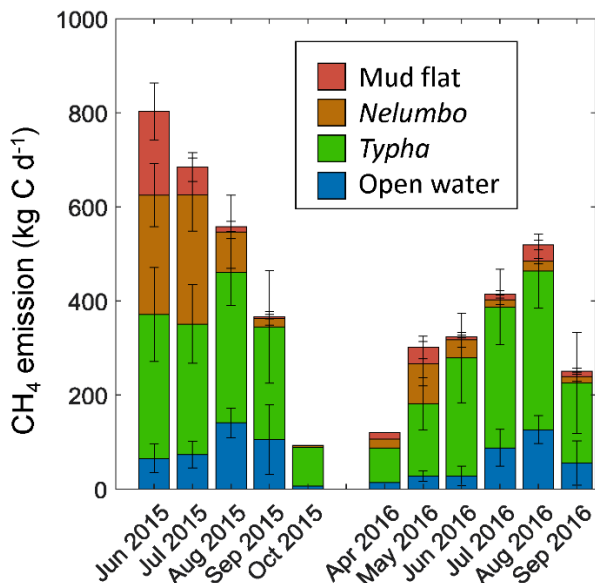


299
 300 *Figure 4. Daily averages of methane flux per land cover for the time of study. The values were calculated*
 301 *based on the chamber measurements and temporally corrected using the tower data, using the*
 302 *methodology develop by Morin et. al (2017).*

303

304 The effect of variation in CH_4 flux rates among different land cover types on the overall methane
 305 budget of the wetland is shown in Fig 5. Due to its low CH_4 emission rates, the contributions of
 306 open water to the total CH_4 emissions were relatively low (16.1 %), despite having the largest
 307 land coverage type in the site (47 % of the wetland area). In contrast, mud flats contributed
 308 significantly to the total CH_4 emissions of the wetland (6.8%), especially in June 2015 (22.2%),
 309 despite occupying only 1.5 % of the wetland area. The contributions of *Nelumbo* in 2015 were
 310 also large (15%), although it occupies a relatively small area (9.7 % of the wetland). Overall, due
 311 to its large areal coverage, *Typha* vegetation was the land-cover type from which most of the

312 CH_4 emissions originated, ranging from 34% in June 2015 to 80% in October 2015.



313

314 *Figure 5. Contributions of each land cover to the total methane emissions of the wetland. In this graph,*
315 *the fluxes from the previous graph were normalized by the area of each land cover. Note that although*
316 *the mud flats occupy only 1.5 % of the wetland area, it contributed 22.2% of the total methane emissions*
317 *in June 2015. The error bars are the standard deviation of the daily averages.*

318

319 **4. Discussion**

320 *4.1. The environmental drivers of methane flux*

321 We found that temperature is one of the main drivers of methane emissions, consistent with the
322 findings in other wetlands (Bloom et al., 2010; Bohn et al., 2007; Hatala et al., 2012b). Unlike
323 other studies, however, it was the water temperature and not the soil or air temperature that had
324 the highest correlation with methane emission rates in the OWC wetland. *WT* ranked first for the
325 daytime flux model and second for nighttime flux model (Table 1), whereas *ST_{10cm}* ranked 10th in
326 the daytime and 13th in the nighttime. The slopes of the pairwise relationship of *WT* and methane
327 flux were positive, which indicates that higher water temperatures are causing more methane
328 emissions. This result is consistent with the finding of Kim et al. (1999), whom found that the

329 diurnal cycle of water temperature and not that of the sediment temperature was correlated with
330 the diurnal cycle of methane flux. On the other hand, the slope of the relationship between the
331 temperature of the soil and methane flux was negative. This could possibly mean that higher
332 temperatures in the soil are favoring microbial methanotrophy processes at higher rate than
333 methanogenesis.

334 Wind speed was an important variable in the determination of methane fluxes, occupying the
335 third position in the rank for both daytime and nighttime models. In contrast, turbulence mixing,
336 u^* , ranked lower (8th in daytime and 12th in nighttime), opposite to previous reports (Herbst et
337 al., 2011; Morin et al., 2014a). Both variables control the rate of mixing at the top water layer
338 and the degree of gas exchange between the surface and the atmosphere. The higher effect of u
339 rather than u^* , may be a result of the overall uniform effect of wind speed, with the different
340 drag coefficients of each land-cover type making the effect of u^* highly variable among patches
341 and thus, a less consistent predictor of methane fluxes from the overall site.

342 Atmospheric pressure can also play an important role in determining methane fluxes, as it can
343 cause increases in the rates of ebullition (Tokida et al., 2007). We found that lower atmospheric
344 surface-level pressure caused a slight increase in CH₄ fluxes as noted by negative pairwise
345 correlation coefficients for both daytime and nighttime. The slope of the pairwise relationship
346 between ΔP_{atm} and methane flux suggests that a rapid decrease in atmospheric pressure caused an
347 increase in methane emissions.

348 *4.2 Other predictors of methane flux*

349 The second most important predictor of methane flux was CO₂ flux. Specifically, *GPP* during
350 the day and R_e during the night. Though a hypothetical relationship between GPP and methane

351 flux exist, as GPP provides the dissolved carbon that is rapidly consumed in the pathway that
352 leads to methanogenesis, we do not think that carbon fluxes are direct drivers of methane flux.
353 The negative correlation between *GPP* and methane fluxes indicates that higher rates of
354 photosynthesis (with a negative sign) co-occur in times and places of higher methane emissions.
355 This behavior has been identified in other studies (Bellisario et al., 1999; Hatala et al., 2012a;
356 Kim et al., 1999) and can be attributed to increased methane transport through stomata or
357 aerenchyma, or the addition of root exudates to the soil. During nighttime, the complex network
358 of environmental conditions that influence the microbial processes that control methane
359 production are similarly affecting respiration.

360 Water vapor flux, *LE*, was also an important predictor of methane flux, ranking fourth for both
361 daytime and nighttime models. The covariance between *LE* on methane fluxes has been
362 attributed to the increased vaporization of molecules at the surface of the water that allows
363 higher volatilization of methane in the turbulently mixed regime (Godwin et al., 2013). However,
364 it is also possible that the cause of the strong relationship between *LE* and CH₄ flux is also
365 related to plant transpiration, as stomatal conductance can be an important driver of CH₄ fluxes
366 (Ding and Cai, 2007; Morrissey et al., 1993).

367 *4.3. Variation in flux rates among land-cover types*

368 There was high spatial variability in methane emissions. The diurnal averages in the mud flats
369 were sometimes one order of magnitude higher than in the other land covers (Fig. 4). Such
370 variation in CH₄ emission due to heterogeneity in land covers has been found in other studies
371 (Nahlik and Mitsch, 2010; Sha et al., 2011). Sha et al. (2011) attributed this variation to
372 differences in the soil chemistry at the study sites. It is possible that part of the variation in
373 methane fluxes that our models did not explain is also related to the chemistry of the soil,

374 especially, the availability of labile carbon. It is also possible that differences in local conditions
375 and transport processes account for some of these flux-rate differences. For example, we suggest
376 that the depth of the mixed water column above the soil surface can explain the differences in
377 methane emissions between open water and *Typha*. Open water has a deeper water column,
378 which means potentially higher methanotrophy, whereas the water level above the *Typha* is
379 much lower, which could cause less oxygenation during transport through the water column.

380 The footprint variable, which quantifies the contribution of open water or *Typha* to the total flux
381 signal observed by the tower, provides a proxy for estimating the variation in flux rates among
382 land-cover types. If a certain land-cover type has a much higher flux rate than other land-cover
383 types in the site, its contribution to the footprint will be positively correlated with the total
384 observed EC flux. The percentage of the footprint coming from open water occupied in the
385 model the 11th position during the day and 10th during the night. These ranks are not at the top
386 possibly because the ANN is capturing some components of the variation in the contribution of
387 different land-cover types through other variables, mainly *GPP* and *R_e*, which ranked much
388 higher. As with methane emissions, land-cover types should similarly affect CO₂ emissions.

389 *4.4. Diurnal and seasonal variation of methane flux*

390 We found a clear peak of methane emissions occurring in the early morning around 8:30 am
391 (Fig. 3). This peak is possibly related to the opening of stomata in the morning after a nighttime
392 accumulation of methane in the plant conductive tissues. Kim et al. (1999) found similar results
393 in a temperate marsh dominated by *Phragmites* vegetation. However, the shape of the cycle and
394 the rates of CH₄ emission in our study were different. Except for the peak in the early morning,
395 we did not find large differences of methane flux between daytime and nighttime, unlike Kim et
396 al. (1999), who found a gradual increase in methane flux after sunrise that decreased in the late

397 afternoon. We also found marked seasonal variation of methane fluxes, which were lower at the
398 beginning of the growing season, reached a peak in the months of July and August and later
399 decreased in September and October (Fig. 2a). A similar pattern of seasonal methane emissions
400 was also found by Kim et al. (1999).

401 *4.5. High rates of methane emission*

402 We found very high rates of methane emission in the OWC wetland. Despite being a net sink of
403 CO₂ during the growing season (negative total NEE) the amount of carbon leaving the ecosystem
404 in the form of methane was so high that the wetland was a net carbon source to the atmosphere
405 during the growing season (Fig 2). The rate of CH₄ emission in *Typha*, the most common plant in
406 the wetland, was on average 0.58 μmol m⁻² s⁻¹, reaching maximum diurnal averages of up to 1.4
407 μmol m⁻² s⁻¹. In contrast, others reported lower methane emission of 0.47 μmol m⁻² s⁻¹ in a
408 wetland dominated by *Phragmites* (Kim et al., 1999) and 0.43 μmol m⁻² s⁻¹ in the Florida
409 everglades (Burke et al., 1988). Devol et al. (1988) found that the range of methane emission for
410 different aquatic macrophytes in the Amazon was 0.02-0.47 μmol m⁻² s⁻¹. Seasonally integrated
411 methane emissions were equal to 158.1 g CH₄ m⁻² for the 5-month period of measurements in
412 2015 and 121.8 g CH₄ m⁻² for a 6-month period of measurement in 2016. The latter estimate is
413 much higher than the estimate of 64 g CH₄ m⁻² found by Kim et al. (1999) for a similar 6-month
414 period of time (April to October) in a *Phragmites*-dominated temperate marsh. We hypothesize
415 that this high rate of methane fluxes in OWC is driven by high input rates to the wetland of
416 dissolved organic carbon and other nutrient from the upstream agriculture-dominated watershed.

417 *4.6. The importance of estuarine marshes*

418 Despite the high rates of methane emission, the OWC wetland is an important sink of phosphates
419 and nitrates (McCarthy et al., 2007). This is particularly important in the Southern coast of Lake
420 Erie in Ohio where there has been a high occurrence of harmful algae blooms due to excess of
421 phosphorus and nitrogen from agricultural runoff (Michalak et al., 2013). We have shown that
422 different land covers have different rates of emission and factoring their contributions correctly
423 is critical to calculating the true carbon budget of a wetland. This information can be useful for
424 the design of estuarine wetlands that maximize nutrient retention, reducing coastal
425 eutrophication, while minimizing greenhouse gas emissions. Although our empirical
426 model, based on physical and biological variables, provided good predictions of CH₄ flux,
427 further understanding of the chemistry and the microbiology of the sediments is needed in order
428 to improve mechanistic process-based models. Such models could predict methane emissions
429 from estuarine wetlands accurately.

430 **5. Conclusions**

431 The rates of methane emission in the OWC are higher than the rates reported in similar wetlands.
432 Water temperature and wind speed were the main environmental drivers of methane flux
433 whereas other variables, such as water level or pH, did not have a strong effect on methane
434 fluxes. Photosynthesis and respiration were highly related to methane flux, which indicated that
435 similar sediment processes and environmental drivers are affecting these fluxes. Land-cover
436 heterogeneity had a strong effect on the methane budget of the wetland. Mud flats had the
437 highest rates of methane emission, while the total contributions of the open water patches were
438 lower, despite occupying almost half of the wetland's area. Accounting for differences in
439 methane flux rates among land-cover types within a wetland and their temporal variation is
440 important to provide accurate estimates of total methane flux.

441 **Acknowledgements**

442 Data from the NOAA weather and water monitoring stations in OWC is available at
443 <http://cdmo.baruch.sc.edu/get/export.cfm>. Meteorological and flux data from OWC is available
444 through Ameriflux (<https://ameriflux.lbl.gov/data/download-data/>). We are grateful to Kristin
445 Arend, Frank Lopez, Dr. Dave, and the rest of the OWC management team for site access and
446 logistical support. We thank Austin Rechner, Dominique Haddad, Matthew Right, Sharon
447 Acosta, Golnaz Mirfenderesgi and Chante Vines for their assistance in field measurements. This
448 research was partially supported by Ohio Water Development Authority awards (#6835 and
449 6560). Data analysis was conducted at the Ohio Supercomputer Center. Graduate student support
450 was provided by the National Sciences foundation via a Doctoral Dissertation Improvement
451 Grant (to THM), by the Department of Energy Office of Science Graduate Research Program,
452 Solicitation 2 (to THM), and by the Fay Fellowship through the OSU Environmental Science
453 Graduate Program (to THM and ACRS). Flux observations and analyses were conducted with
454 partial support from U.S. Department of Energy's Office of Science, Ameriflux Management
455 project.

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