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15	Hydrologic flushing rates drive nitrogen cycling and plant invasion in a freshwater coastal
16	wetland model
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ABSTRACT

Coastal wetlands intercept significant amounts of nitrogen (N) from watersheds, especially when 33 surrounding land cover is dominated by agriculture and urban development. Through plant 34 uptake, soil immobilization, and denitrification wetlands can remove excess N from flow through 35 36 water sources and mitigate eutrophication of connected aquatic ecosystems. Excess N can also change plant community composition in wetlands, including communities threatened by invasive 37 species. Understanding how variable hydrology and N loading impact wetland N removal and 38 39 community composition can help attain desired management outcomes, including optimizing N 40 removal and/or preventing invasion by non-natives. By using a dynamic, process-based ecosystem simulation model, we are able to simulate various levels of hydrology and N loading 41 42 that would otherwise be difficult to manipulate. We investigate *in silico* the effects of hydroperiod, hydrologic residence time, N loading, and the NH₄⁺:NO₃⁻ ratio on both N removal 43 44 and the invasion success of two non-native species (Typha x glauca or Phragmites australis) in temperate freshwater coastal wetlands. We found that when residence time increased, annual N 45 46 removal increased up to 10-fold while longer hydroperiods also increased N removal, but only when residence time was >10 days and N loading was >30 g N m⁻² y⁻¹. N removal efficiency also 47 48 increased with increasing residence time and hydroperiod, but was less affected by N loading. However, longer hydrologic residence time increased vulnerability of wetlands to invasion by 49 both invasive plants at low to medium N loading rates where native communities are typically 50 more resistant to invasion. This suggests a potential tradeoff between ecosystem services related 51 52 to nitrogen removal and wetland invasibility. These results help elucidate complex interactions of community composition, N loading and hydrology on N removal, helping managers to 53 prioritize N removal when N loading is high or controlling plant invasion in more vulnerable 54 55 wetlands.

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Keywords: denitrification, ecosystem services, invasive species, nitrogen cycling, nutrient
retention, *Phragmites australis*, residence time, *Typha* x *glauca*, wetland management

- 59
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- 61 Introduction
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63 Nutrient loads delivered to lakes and oceans have increased by orders of magnitude in the last half century, often due to changing land use or management practices in their watersheds, 64 such as urban development and agriculture (Howarth et al. 2002). These large nutrient loads can 65 66 lead to hypoxic dead zones (Diaz and Rosenberg 2008) and harmful algal blooms in receiving 67 waters (Michalak et al. 2013, Lapointe et al. 2015) with consequences that reverberate from aquatic communities to local economies (Hoagland et al. 2002). Wetlands can provide services 68 69 that mitigate impacts of elevated nutrient loading in some circumstances. For example, constructed wetlands are used as a tertiary treatment measure to remove large loads of nutrients 70 71 from effluent (Kadlec and Wallace 1997) while wetlands along the paths of streams and rivers may sequester nutrients from the flow-through water (Knox et al. 2008). This has led many 72 73 managers to optimize or expand nutrient removal in wetlands within their jurisdiction. However, conditions that improve nutrient removal may hinder other wetland functions and services, such 74 as maintaining plant biodiversity or resisting invasive plant species (Hansson et al. 2005). 75 Understanding the environmental conditions (e.g. water level or nutrient loads) that most 76 influence certain wetland functions can help to optimize the most desired services while 77 minimizing the sacrifice of others (Jessop et al. 2015). 78

79 Freshwater wetlands are widespread along lakeshores and in river channels and deltas, 80 and many are hydrologically managed to influence water levels, wildlife habitat, or achieve other 81 goals. In the Laurentian Great Lakes region of the Upper Midwest, USA, they are also widespread in coastal zones including river mouths and embayments. Because of their position 82 83 on the landscape, these wetlands receive nutrient loads from surrounding water inflow (both upland runoff and open water fluxes) and can provide important nutrient removal services from 84 85 these flow-through sources. Specifically, excessive nitrogen (N) loading can be ameliorated through important biotic pathways of removal, including plant uptake (Tylova-Munzarova et al. 86

2005), immobilization in litter and sediment organic matter (Vymazal 2007), and microbial 87 transformation (e.g. denitrification; Jordan et al. 2015). However, excessive N loading to 88 89 wetlands may also shift plant community structure, altering ecosystem function and potentially increasing vulnerability of plant communities to invasive species (Erwin 2009, Martina et al. 90 2016). In turn, the service of wetland N removal is likely to be affected by the interaction among 91 92 N loading, plant growth and litter production, water levels, and hydrologic residence time (Pezeshki 2001). Given this complex set of interactions, understanding and managing N removal 93 in wetlands is intrinsically challenging, especially when management goals are not 94 complementary (Jessop et al. 2015). 95

N removal in wetlands is dominated by plant N uptake, immobilization in litter and 96 sediments, and microbial denitrification, which are all controlled by various biotic and abiotic 97 98 drivers. Removal via plant uptake and immobilization in soil occurs as plants assimilate inorganic N from porewater and overlying water to meet metabolic nutrient demands (Vymazal 99 100 2007). However, as plant detritus and soil organic matter decompose, organic N is subject to mineralization and rerelease in place or downstream as detritus and organic matter is flushed out 101 102 of wetlands (Han et al. 2009). Unlike plant uptake and soil immobilization, denitrification (NO₃⁻ -N transformation to gaseous N) is a more permanent removal pathway that occurs in anaerobic 103 water and soil and is often coupled with aerobic nitrification, which converts NH4⁺-N to NO3⁻-N 104 (Reddy et al. 1989). Hydrology, through its control on anaerobic and aerobic conditions, is an 105 106 important modulator of these N removal mechanisms. For example, hydroperiod determines the phasing and periodicity of aerobic and anaerobic cycles in wetlands which in turn control the rate 107 108 of plant growth and N uptake by controlling soil anoxia (Reed and Cahoon 1992), the rate of litter decomposition, and whether aerobic nitrification or anaerobic denitrification is occurring 109 (Ishida et al. 2006). 110

111 N removal is typically greater the more time N spends in wetlands and thus, in addition to 112 hydroperiod, is also controlled by hydrologic residence time (henceforth, RT_h). RT_h modulates 113 the contact time of N with microbes and plant rhizospheres for transformation and uptake, 114 respectively (Kirk and Kronzucker 2005). The relationship of N removal and RT_h has been well 115 studied in flow-through, constructed, and tertiary-treatment wetlands (Kadlec and Wallace 1997, 116 Saunders and Kalff 2001, Ishida et al. 2006). Yet N removal in coastal wetlands is rarely studied 117 (but see Dettmann 2007), in part due to the complex hydrology and N transport dynamics of

coastal zones. For example, water levels of the Laurentian Great Lakes fluctuate on decadal time 118 scales, changing the hydrologic gradient from upland water sources to the Great Lakes, thus 119 affecting water flow and RT_h of coastal wetlands that intercept these waters (Keough et al. 120 1999). Variable hydroperiods can further complicate our understanding of N removal in these 121 wetlands. As soils alternate from aerobic to anaerobic with fluctuating water level, obligate 122 aerobic and anaerobic processes change in tandem. The coincidence of fluctuating water levels 123 with seasonal changes in temperature and plant productivity can lead to further complex 124 interactions of N removal drivers. Finally, many N removal studies only focus on abiotic drivers, 125 such as hydrology, and rarely incorporate biotic drivers or peripheral impacts to plant community 126 structure despite well-known feedbacks between biotic and abiotic drivers (Corenblit et al. 127 2011). 128

In fact, plant communities have a powerful influence on nutrient cycling and soil 129 biogeochemistry in wetlands, including the accumulation of nutrients stored in detritus (Weltzin 130 131 et al. 2005). Likewise, greater nutrient availability can shift plant competition dynamics and plant community composition. For example, increased N loading can facilitate invasion of large-132 133 stature, non-native plant species that are better competitors for nutrients and light and deposit more litter than native competitors, thus increasing soil N pools and therefore N removal 134 135 (Martina et al. 2016, Uddin and Robinson 2017). In particular, the success of *Phragmites* australis and Typha × glauca—both noxious, large-stature invaders of Great Lakes and other 136 137 North American wetlands—is largely driven by increased N loading (Martina et al. 2016). Through superior competition for N and intraspecific N transfers within clones, these invaders 138 can expand to the extent that they create near-monocultures in coastal wetlands (Zedler and 139 Kercher 2004, Rickey and Anderson 2004). In facilitating these invasive plants, N availability 140 141 likely interacts with other factors including nutrient cycling dynamics and hydrological 142 disturbances (Wilcox 2012, Bansal et al. 2019). To improve our understanding of these complex drivers we need to examine how hydroperiod and RT_h of coastal wetlands interact to affect N 143 removal and how changes in N removal will potentially alter the invasibility of wetland plant 144 communities (Fig. 1). 145

Simulation models allow us to explore a wide range of these complex processes and interactions in thousands of structured scenarios and factorial combinations that would be difficult or impossible to perform in field studies. Here we examined *in silico* how RT_h ,

hydroperiod, and N loading interact to affect N cycling and N removal rates in emergent 149 wetlands, thereby influencing the outcomes of wetland plant invasions. We examine various 150 hydroperiod frequencies with the same flooding range and total number of flooded days but with 151 different flooding duration, in addition to wetlands with constant low and high water level. We 152 also examined N loading with various nitrate (NO_3) to ammonium (NH_4) ratios as N removal 153 and transformation processes can require one or the other species and because these ratios vary 154 across the landscape (Hamlin et al. 2020; L Wan pers comm). We then assessed how these 155 conditions influence N removal in two ways: annual N removal (i.e. the total N mass removed 156 from an area in a given time) and N removal efficiency (i.e. N removed and denitrified relative to 157 N entering wetlands). 158

We simulated a range of these hydrologic and nutrient cycling variables in scenarios 159 where one of two non-native invasive graminoids (*Phragmites australis* or *Typha* \times *glauca*) was 160 introduced into an established native plant community typical of Great Lakes coastal wetlands 161 162 using Mondrian, a process-based model of wetland ecosystems that includes plant competition and dynamic community change over time. We hypothesized that longer RT_h would increase the 163 164 percent of N inflow denitrified, while N loading dominated by NH₄⁺ would limit denitrification, resulting in less overall N removal (Fig. 1, H₁). Second, we hypothesized that, assuming the total 165 166 number of flooded days is equal, simulated wetlands with longer hydroperiod would result in less annual denitrification and subsequent N removal (Fig. 1, H₂). When wetlands flood and 167 draw down often, aerobic nitrification, which transforms NH_4^+ to NO_3^- , can also occur more 168 frequently replenishing depleted stocks for denitrifying microbes compared to less frequently 169 170 flooded wetlands. Finally, in scenarios of long RT_h whereby N inflow exceeds N outflow, we hypothesized that higher levels of plant-available inorganic N would drive the success of wetland 171 172 plant invasion and subsequently increase N uptake and ecosystem N removal due to the high N demands of these large-stature invaders (Fig. 1, H₃). We demonstrate the potential for a novel 173 ecosystem tradeoff between N removal and invasion risk driven by RT_h in freshwater coastal 174 wetlands. 175

176 Materials and methods

177 Mondrian Simulation Model

We used an individual-based, spatially-explicit wetland ecosystem model, Mondrian,
which spans multiple levels of ecological organization from individual plant physiology to

population, community, and ecosystem processes. The model was previously developed to study
N cycling and plant invasion (Currie et al. 2014, Martina et al. 2016, Elgersma et al. 2017,
Goldberg et al. 2017). We give a brief overall description with some detail on processes and
functions either newly added or key to understanding the present study.

Mondrian utilizes a grid space that can be divided into ≤ 625 cells. Over this framework 184 of grid cells, a user-defined number of individual propagules (i.e. ramets) are stochastically 185 dispersed. Individual ramets have defined, species-specific traits, including relative growth rate, 186 maximum plant size and tissue nutrient requirements. Ramets within grid cells compete for 187 available N and light within the same cell (for details on light competition see Martina et al. 188 2016). Plants clonally reproduce, spreading rhizomes stochastically through the model space, and 189 share resources via translocation among rhizome chains. The modeled substrate is vertically 190 191 organized with mineral soil organic matter (MSOM) on the bottom, then muck, and aboveground litter on top. Although the thickness of the MSOM layer is fixed (30 cm), the thicknesses of the 192 muck and litter pools vary depending on relative rates of litter production and decomposition, 193 allowing accretion or subsidence of the muck surface. At the ecosystem level, the user defines 194 195 daily N inflow, daily water level and water flow rate, daily temperature, and growing season length. Several ecosystem processes emerge from these fine-scale processes, including plant 196 productivity, community composition, and C and N cycling dynamics. The model has balanced 197 C and N cycles and explicitly represents and tracks ecosystem C and N stocks, export, 198 199 transformation, and removal (defined below).

In this study, we introduce an updated version of Mondrian (version 4.3) parametrized for 200 201 wetlands of the Great Lakes region with improved realism in certain aspects of clonal plant growth and N cycling. The updated model simulates lateral and terminal branching of rhizomes 202 203 in clonal plants (see Martina et al. in prep. for full description), and now includes floodinginduced mortality for individual plants. It also explicitly partitions available NH₄⁺-N and NO₃⁻-204 N, includes inflow and export of each separately, and includes nitrification and denitrification 205 processes (described below). Finally, the modified model allows flexibility in the inflow and 206 207 hydrologic flushing rate of N, which can be constant or vary daily.

208

209 Nitrification and denitrification

210 N cycling in Mondrian has been augmented to include coupled nitrification and

- 211 denitrification, the latter providing an additional N removal pathway. In previous model
- versions, N that was not taken up by plants or immobilized in detritus was flushed out of the
- 213 wetland at a certain rate, the balance remaining as plant-available N. We calculate nitrification

and denitrification as daily fluxes (g N m⁻² day⁻¹) spatially explicit within grid cells, using

- equations (1) and (2), respectively.
- 216 Daily nitrification $(g N m^{-2} day^{-1}) = l_{amm} \cdot f_{aer}(NH_4^+) \cdot f(T_{soil}) \cdot \theta_n$ (1)

217 Daily denitrification
$$(g N m^{-2} day^{-1}) = l_{nitr} \cdot f_{ana}(NO_3^-) \cdot F_{resp} \cdot \theta_d$$
 (2)

218

where, lamm and lnitr represent grid cell NH4⁺-N and NO3⁻-N pools (g N m⁻²), respectively, and 219 $f(T_{soil})$ represents the effect of soil temperature. In Mondrian, we assume that for any soil above a 220 defined water level height, soil temperature (T_{soil}) is equal to ambient air temperature and T_{soil} of 221 any flooded soil below this water level equals the temperature of the overlying water. As 222 223 nitrification requires aerobic conditions and denitrification requires anaerobic, these processes are constrained by the terms $f_{aer}(NH_4^+)$ and $f_{ana}(NO_3^-)$, which represent the proportion of l_{amm} that 224 is aerobic and *l_{nit}* that is anaerobic, respectively. Unlike nitrification, which involves oxidizing 225 ammonia (NH₄⁺) to nitrate (NO₃⁻) and is modulated by $f(T_{soil})$, denitrification is a heterotrophic 226 process and involves the oxidation of labile soil organic C. Heterotrophic respiration, including 227 the effects of temperature and the size of detrital pools, is already included in Mondrian. 228 Therefore, F_{resp} , a unitless factor that tracks rates of soil heterotrophic respiration, conveys a 229 temperature effect and tracks substrate availability for denitrifying microbes in a similar fashion 230 as other denitrification models (Parton et al. 1996). Finally, the model was calibrated (described 231 below) to ecosystem-scale observations using scaling parameters for both nitrification (θ_n) and 232 denitrification (θ_d). 233

Nitrification and denitrification occur in the model within explicit vertical limits we refer to as the 'active zone' for each process. This allows us to calculate, based on daily water level, which proportion of the active zone is aerobic and anaerobic. The top of the vertical active zone is defined as the top of the muck layer for denitrification, and for nitrification extends up to 5 cm into the aboveground litter layer above the muck where conditions are likely to be more aerobic than in muck and MSOM, even when flooded. For this study, the lower boundary of the active zone is set to 5 cm depth in the mineral soil, below which the rates for both processes have been

observed to be negligible (Brodrick et al. 1988). Any detrital pool (or partial pool) below a 5-day 241 trailing average of water level is anaerobic in the model, but these pools become aerobic when 242 above the water level on a daily basis. Mondrian does not include nitrification or denitrification 243 in the overlying water column. At temperatures below 4°C, rates of nitrification and 244 denitrification are assumed to be negligible (Bremner and Shaw 1958). 245 To calibrate the ecosystem-level scaling parameters (θ_n and θ_d) we used 5 sentinel sites 246 from the Great Lakes region with observational data for multiyear data sets of in situ 247 denitrification. We only included studies with field measurements of denitrification (i.e. 248 measured fluxes of $N_2 + N_2O$) and omitted studies that measured only potential denitrification in 249 ideal laboratory settings or with an augmented supply of nitrate. We simulated the relevant 250

conditions reported at each sentinel site in Mondrian, including annual average temperature,

temperature range, growing season length, water level, N inputs, and plant community (Table 1).

For sites that did not report both NH_4^+ and NO_3^- inputs, we used a 1:3 ratio of $NH_4^+-N:NO_3^--N$,

typical of land use dominated by high intensity agriculture in which these sites were situated

(Hamlin et al. 2020). We then adjusted both θ_n and θ_d to achieve a best fit using a residual sum of squares (Fig. 2).

257

258 Simulated experimental design

We used 5 hydroperiods, $5 RT_h$, 6 levels of N loading, 5 N species ratios, and 2 invasion 259 260 scenarios amounting to 1380 unique combinations of these factors (Table 2). Here we describe each of these factors in turn. In Mondrian, hydroperiod is controlled by defining water level 261 262 daily. In these simulations we used 5 hydroperiods, including permanently flooded (water level +15cm in relation to the MSOM soil horizon), permanently exposed (water level -15cm), and 263 264 sinusoidal fluctuating water level (±50 cm) with weekly, monthly or semi-annual periodicity. 265 These fluctuating hydroperiods reflect weather events that occur on short (weekly) and medium (monthly) time scales and seasonal (semi-annual) fluctuations that occur on a longer time scale 266 with water level peaking in mid-June. All wetlands with variable hydroperiod in these 267 simulations (weekly, monthly, and semi-annual) experienced the same maximum flooding depth 268 269 and total number of days with overlying surface water per year with the only difference being the timing of flooding. 270

In Mondrian, the proportion of the NH₄⁺-N and NO₃⁻-N pools exported daily from the 271 wetland is controlled by a hydrologic flushing parameter, which equals the inverse of hydrologic 272 273 residence time (RT_h) . Daily values of RT_h and water level are read in from an input file, allowing 274 simulation of seasonal hydrological trends. For this study, we modeled RT_h either as a fixed rate throughout the simulation (four scenarios independent of water level) or as a function of water 275 276 level (three scenarios). For fixed rates, we chose RT_h values of 1, 10, 100 and 365 days to capture a range of wetland types found in the Great Lakes region, from a small, flow-through wetland to 277 a coastal embayment with a one-year residence time, respectively (Morrice et al. 2004). In our 278 scenario where RT_h is a function of water level we used an exponential relationship 279

$$280 RT_h = \frac{1}{ae^{bh}} (3)$$

where *a* and *b* are constants, *h* is water level (m), and where lower water level corresponds to longer RT_h . To parameterize the constants *a* and *b*, when water level was lowest we used $RT_h =$ 365 d and when water was highest we used $RT_h = 1$ d. Under constant water level scenarios of permanently flooded and permanently exposed, RT_h as a function of water level would also be constant. Therefore, these scenarios are omitted as a treatment combination, leaving only weekly, monthly, and semi-annual hydroperiods with RT_h as a function of water level.

In addition to hydroperiod and RT_h , we used 6 levels of N-loading, ranging from 287 oligotrophic, precipitation-fed wetlands (1 g N m⁻² y⁻¹) to highly eutrophic wetlands (100 g N m⁻² 288 289 y⁻¹; Krieger 2003). We then partitioned the 6 levels of N-loading into NH₄⁺-N and NO₃⁻-N proportions that included conceptual NH₄⁺-only or NO₃⁻-only N inputs as end points, together 290 with three NH₄⁺-N:NO₃⁻-N ratios that characterize wetland N loading from three dominant land 291 292 use classes in the region: urban (1:7.3), high-intensity agriculture (1:3), and rural (4:1; Hamlin et 293 al. 2020). Finally, we simulated plant communities in which either *Phragmites australis* or Typha x glauca, two common invasive species in the Great Lakes region, are introduced into 294 295 established communities comprising three native wetland species: Eleocharis smallii, Juncus balticus, and Schoenoplectus acutus. At year 15, after the native community has reached a 296 steady-state density, we introduce a cohort of 15 individual ramets of one of the two invasive 297 species and introduce another identical cohort 5 years later. A background colonization rate of 1 298 299 ramet per year per species continues for all species after initial introduction into the modeling 300 space.

Each of the 1380 combinations was run for 55 years, enough time for the simulation to 301 achieve ecosystem stability, with 3 stochastic replications. Mondrian outputs large amounts of 302 data after each model run ranging from stem density to total ecosystem C. For this study, we 303 averaged all output of the last 5 years of each simulation (years 51-55) to integrate across inter-304 annual variation. We limited the response variables we examined to annual N removal (g N m⁻² 305 y^{-1}), percent denitrification (%), N removal efficiency (%), and invader percentage of community 306 NPP (%). To account for the large disparity between denitrification rates under low and high N 307 loading, we interpreted denitrification as the percentage of annual N inflow denitrified. We 308 define annual N removal (N_{rem}) as 309

$$310 \quad N_{rem} = N_{in} - N_{out} \tag{4}$$

311 percent denitrification (N_{dntr}) as

312
$$N_{dntr} = \frac{Annual \,denitrification \,(g \,N \,m^{-2} \,y^{-1})}{N_{in} \,(g \,N \,m^{-2} \,y^{-1})}$$
(5)

313 and N removal efficiency as

314 N removal efficiency =
$$\frac{N_{rem}}{N_{in}}$$
 (6)

where N_{in} is the sum of annual N inputs, including annual surface N loading and atmospheric N deposition and N_{out} includes the annual hydrologic export of all NO₃⁻-N, NH₄⁺-N, and detritusbound organic N.

318

319 Statistical analysis

320 We used Generalized Linear Mixed Models (GLMM) to examine the effects of treatment combinations of predictor variables, including N loading, NH_4^+ -N:NO₃⁻-N ratio, RT_h , 321 322 hydroperiod, and plant invader species (Table 2) on total annual N removal, N removal efficiency, percent of annual N inflow denitrified, and invader proportion of community NPP 323 324 response variables averaged over the last 5 years of simulations (Bates et al. 2015). N loading and RT_h were analyzed as continuous numeric variables and NH₄⁺-N:NO₃⁻-N ratio, hydroperiod, 325 326 and plant invader species as factors with discrete levels. When RT_h was a function of water level, we used the average annual RT_h ($RT_h \approx 4$ days) to include this treatment within the range of other 327 continuous RT_h values (see Figs. 3-5). To develop a best-fit GLMM, we used a forward stepwise 328 algorithm in which terms are iteratively added, starting from a null model lower bound to a 329 global model (i.e. a model including all main effects and their possible interactions) upper 330

bound. This algorithm uses Akaike Information Criterion (AIC) to select the best GLMM by 331 scoring each model based on goodness-of-fit and model parsimony, only adding more terms 332 333 when such additions improve the AIC value. In addition to ranking models based on AIC and goodness-of-fit (adjusted R²), we also ranked terms within each best fit GLMM by their relative 334 variable importance (RVI) value (Burnham and Anderson 2002) to focus our analysis to only the 335 most important main effects and interactions, despite other main effects and interactions also 336 being important, albeit less so (Table 4). RVI values are calculated by summing the Akaike 337 weights, a goodness-of-fit measure of a single model weighted across an array of models, for all 338 possible GLMMs in which a given variable occurs. Because RVI values of main effects and 339 interactions are relative they cannot be directly compared to one another (e.g. RVI values of two-340 way interaction terms can only be compared to RVI values of other two-way interaction terms 341 and not with RVI values of main effects or higher order interactions), we interpret these terms 342 separately. All data were analyzed using the "lme4" (Bates et al. 2015) and "MuMIn" (Barton 343 2019) packages in the statistical computing software R version 3.6.1 (R Core Team 2019). 344

345 **Results**

346 In our simulations of Great Lakes coastal wetlands, we found that hydrologic residence time (RT_h) , hydroperiod, and N loading were all strong predictors of wetland N removal, 347 including annual N removal, N removal efficiency, and percent denitrification (Tables 3 and 4). 348 Furthermore, these drivers interacted such that N removal was greatest when RT_h and 349 350 hydroperiod were longest, yet each measure of N removal was affected differently by changes in N loading (Figs. 3-6). Drier wetlands (e.g. wetlands with constant low water) had a limited 351 352 capacity for N removal compared to flooded wetlands in our simulations. As plant litter and organic matter pools became aerobic, denitrification stopped, decomposition was accelerated, 353 354 and mineralized N was exported downstream. Alone, NH4+-N:NO3--N ratio and plant invader identity had little influence on any measure of N removal, but when interacting with N loading 355 were important predictors of annual N removal. Under semi-permanent flooding, N removal was 356 greater when N loading had a higher proportion of NO₃⁻ compared to N loading with a higher 357 proportion of NH₄⁺ (Fig. 7). Under high N loading, in communities where *Typha* was introduced 358 359 but failed to establish, slightly more N was removed annually compared to *Phragmites*-invaded communities. Finally, although invader identity was an important predictor of invasion success, 360

which, like N removal, was driven by RT_h , N loading, and less so, hydroperiod, it was less important in predicting wetland N removal.

363 Due to the similarity in outcomes of several treatment levels and in an effort to simplify the presentation of results, we dropped several treatment levels from figures, but still included 364 them in all analyses. We chose a single land use-derived NH₄⁺-N:NO₃⁻-N ratio, 1:3 (representing 365 high-intensity agriculture, the most dominant land cover in the region) because N species ratios 366 had negligible effects in most scenarios. We omitted non-flooded wetlands where N removal was 367 always very low, and combined results from wetlands with permanent and semi-annual 368 hydroperiods (hereafter referred to as semi-annual), which always had similar responses to each 369 other. We also omitted the lowest N loading scenario (1 g N m⁻² y⁻¹), and only present low (5 g N 370 m⁻² y⁻¹), medium (30 g N m⁻² y⁻¹), and high (100 g N m⁻² y⁻¹) N loading treatments. 371

372

373 Annual N removal

We assessed N removal in either absolute terms of annual N removal (g N m⁻² y⁻¹) or 374 relative terms of N removal efficiency (i.e. N removed and denitrified relative to N entering the 375 376 wetland). Annual N removal (including soil immobilization, plant uptake, and denitrification; Figs. 3 & 5), N removal efficiency (Fig. 6), and percent denitrification (i.e. % of N inflow 377 denitrified; Fig. 7) generally increased with longer RT_h , but N loading and RT_h interacted with 378 hydroperiod such that N removal was greatest with longer hydroperiod only under certain 379 380 combinations of N loading and RT_h. Permanently exposed wetlands exhibiting very low annual N removal as organic N in the soil quickly mineralized (data not shown) and microbes were unable 381 382 to denitrify under aerobic conditions. Annual N removal (Fig. 3) increased most with increasing N loading (5-100 g N m⁻² y⁻¹) and RT_h (1-365 days). However, only under high N loading (100 g 383 N m⁻² y⁻¹) and $RT_h > 10$ days did longer hydroperiod (weekly to semi-annual) result in a notable 384 increase (>10 g N m⁻² y⁻¹) in annual N removal. In wetlands with N loading of 30 and 100 g N m⁻ 385 2 y⁻¹, as *RT_h* increased from 10 to 100 days annual N removal increased nearly 10-fold while in 386 wetlands with low N loading annual N removal was relatively unaffected by RT_h . In addition to 387 RT_h , hydroperiod, and N loading and their interaction, the interactions of NH₄⁺-N:NO₃⁻-N ratios 388 389 with these main effects were also important predictors of annual N removal (Table 4). Wetlands with semi-annual hydroperiod and N loading dominated by NH₄⁺ had lower annual N removal 390 compared to wetlands with other N loading ratios because without NO_3^- or the aerobic conditions 391

needed to transform NH_4^+ to NO_3^- in these wetlands, denitrification was arrested (Fig. 4). Invader identity only affected annual N removal under high N loading (100 g N m⁻² y⁻¹), with native communities where *Typha* was introduced but failed to establish removing approximately 5 g N m⁻² y⁻¹ more N than *Phragmites*-invaded communities, a relatively small increase when compared to the differences resulting from longer hydoperiod (>10 g N m⁻² y⁻¹) and longer *RT_h* (>60 g N m⁻² y⁻¹; Fig. 3). However, at lower rates of N loading, annual N removal was similar across both communities.

The dominant mechanism of N removal in our simulations was uptake by plants and 399 subsequent deposition of plant litter into soil pools, where under anaerobic conditions it 400 accumulates, resulting in the largest N pool in the wetland (soil organic N; Fig. 5). As the major 401 contributor to annual N removal, soil organic N pools similarly increased with longer RT_h , 402 greater N loading, and longer hydroperiod. In particular, soil organic N was limited by aerobic 403 conditions from weekly flooding while semi-annually flooded conditions allowed larger soil 404 organic N pools to accumulate. Plant uptake also increased with RT_h and N loading but was not 405 constrained by hydroperiod. Plants and soil pools became somewhat N saturated under N loading 406 of 30 g N m⁻² y¹ when RT_h was ≥ 10 days and across all levels of RT_h under N loading of 100 g N 407 $m^{-2} y^{-1}$ as soil N pools and N uptake plateaued (Fig. 5). 408

N removal efficiency increased from 6% to 74% under higher N loading as RT_h increased 409 from 1 to 365 days, was slightly higher under longer hydroperiods (Fig. 6). Yet under low N 410 loading (5 g N m⁻² y⁻¹), N removal efficiency reached only 62% when RT_h was longest. Similar 411 to annual N removal, in semi-annually flooded wetlands N removal efficiency was only affected 412 by high NH₄⁺-N:NO₃⁻-N ratios in which denitrification was arrested (Appendix S1: Fig. S1). In 413 wetlands with short RT_h (1-10 days), N removal efficiency was consistently low when N loading 414 was high (100 g N m⁻² y⁻¹), unlike wetlands with N loading <100 g N m⁻² y⁻¹ where efficiency 415 steadily increased with increasing RT_h . 416

Percent denitrification only increased with high N loading (30-100 g N m⁻² y⁻¹) and longer RT_h (100-365 days; Table 3, Fig. 7). In addition, wetlands with semi-annual hydroperiod denitrified up to 10 g N m⁻² y⁻¹ more than weekly flooded wetlands and percent denitrification increased from <1% to 69% as RT_h and N loading increased (Fig. 7). The NH₄⁺-N:NO₃⁻-N ratio affected denitrification rates only in wetlands with longer, semi-annual hydroperiod where obligate-aerobic nitrification was inhibited (Appendix S1: Fig. S1). Under semi-annual 423 hydroperiod, as N loading became dominated by NH_4^+ -N, denitrification decreased by as much

424 as 89% under high N loading compared to N loading dominated by NO_3^--N (Appendix S1: Fig.

425 S1) and was negligible (<0.02 g N m⁻² y⁻¹) under low N loading

426

427 *Community invasion*

Invasion was mostly driven by N availability and was even successful under the lowest N 428 loading scenario as longer RT_h resulted in large enough pools of plant-available N to facilitate 429 the dominance of both *Phragmites* and *Typha* over native plant communities (Figs. 4-6; 430 Appendix S1: Fig. S2). Although invader identity was an important predictor of invasion success 431 (measured by invader % NPP of community NPP), with Phragmites a more successful invader 432 than Typha, it was not an important predictor of N removal (Table 4). A 3-way interaction of 433 invader identity, N loading, and RT_h was also an important predictor of invasion success (Table 434 3). As RT_h and N loading increased, native communities became increasingly invader dominated, 435 but only up to N loading of 10 g N m⁻² y⁻¹, above which *Phragmites* invasion occurred regardless 436 of RT_h and Typha invasion occurred only with shorter RT_h . 437

Under the lowest N loading regime (1 g N m⁻² y⁻¹), Phragmites successfully invaded 438 plant communities (i.e. >75% community NPP) in non-flooded, permanently exposed wetlands 439 with $RT_h > 100$ days, but failed to establish in any flooded wetlands, regardless of RT_h (Appendix 440 S1: Fig. S2). Yet with each increasing level of N loading and RT_h , *Phragmites* % of NPP also 441 increased. At N loading of 30 g N m⁻² y⁻¹, wetlands communities were nearly 100% invaded by 442 *Phragmites* at even the shortest RT_h (1 day). At N loading of 5 g N m⁻² y⁻¹, *Phragmites* invasion 443 was successful at RT_h of 10 days and at 15 g N m⁻² y⁻¹ was successful at RT_h of only 1 day 444 (Appendix S1: Fig. S2). 445

446 *Typha* invasion, however, was successful only in discrete ranges of N loading and RT_h . Typha comprised >75% of community NPP at 5-10 g N m⁻² y⁻¹ when RT_h was longest (100 and 447 365 days) and at 15 g N m⁻² y⁻¹ when RT_h was 4 to 10 days long (Appendix S1: Fig. S2). Typha 448 invasion was also successful when N loading was 30-100 g N m⁻² y⁻¹ and RT_h was shorter (1 to 449 10 days). In scenarios where plant-available N was abundant, yet in which Typha did not 450 451 successfully invade, we observed *Schoenoplectus acutus*, a large-stature native plant, would grow quickly, reaching high NPP similar to a *Typha*-dominated community (ca. 1750 g C m⁻² y⁻ 452 ¹). S. acutus would fill the model space before year 15 when invaders are introduced in our 453

model, effectively resisting invasion. This mechanism of resistance was confirmed with a set of
diagnostic model simulations (Appendix S1: Fig. S3) in which *Typha* was either introduced at
year one (rather than year 15), introduced with an equal number of propagules as native species
(65 propagules rather than 15), or both (introduced on year 1 with 65 propagules). Only in
scenarios in which *Typha* was introduced on year one with 65 propagules did it successfully
establish and dominate native communities.

460 Discussion

Our model findings suggest that while annual N removal increased with both longer RT_h 461 and increasing N loading, N removal efficiency most significantly increased with longer 462 residence time (RT_h) . Furthermore, under high N loading the increase in N removal efficiency 463 with increasing RT_h only occurred in the 100-365 day range. Under low N loading (1-15 g N m⁻² 464 y⁻¹) these same drivers of N removal also facilitated the invasion of *Phragmites australis* and 465 Typha x glauca. Specifically, we find that longer RT_h can result in an accumulation of N in 466 simulated wetlands that provides more substrate for microbial transformation, like 467 denitrification, and ample nutrients for plants to quickly grow and colonize. This introduces a 468 469 potential trade-off of ecosystem N removal services and wetland invasion control, whereby hydrologic drivers that facilitate more N removal are also more likely to decrease resistance to 470 471 invasion by *Phragmites* or *Typha*. Furthermore, these simulations help elucidate complex interactions of hydrology, N loading, and community composition on wetland N removal. As we 472 473 demonstrate a potential tradeoff between N removal and wetland invasibility, we also present practitioners with information to help prioritize management objectives in coastal wetlands that 474 475 are receiving large amounts of N or are at risk of invasion. However, these simulation results should be interpreted cautiously. 476

477 Although Mondrian incorporates many complex interactions across several levels of 478 ecological organization, it offers only a functional representation of wetland ecosystems. Mondrian does not include every meaningful mechanism and driver of N removal and invasion 479 480 in these environments and users should understand the assumptions and limitations of the model 481 before using it as a decision-making tool. For example, in Mondrian the aerobic-anaerobic 482 boundary occurs along a very discrete soil horizon at the top of the water table below the soil surface. In fact, anaerobic conditions and denitrification are known to occur in the overlying 483 water column and be heterogeneous across soil porespace regardless of water table position 484

(Piña-Ochoa and Álvarez-Cobelas 2006, Kjellin et al. 2007). Therefore, Mondrian likely
underestimates N removal via denitrification and managers should consider this in their decision
making (Table 1; Fig. 2).

Furthermore, Mondrian does not explicitly model all plant-soil and plant-hydrology 488 interactions, including (but not limited to) gas transport through plant stems, modulation of the 489 rhizosphere environment, plant transpiration, and the drag imposed by vegetation on flowing 490 water. Yet, these mechanisms can be important drivers of N removal processes which should be 491 accounted for when interpreting Mondrian output (Reddy et al. 1989, Chanton and Whiting 492 1996, Kröger et al. 2009). For example, soil oxygen levels may increase where stem density is 493 high or because of the physiology of particular species, feedbacks which Mondrian does not 494 explicitly model (but that can be accounted for when calibrating the model with empirical data), 495 potentially leading to an underestimation of the proportion of soil that is aerobic. Finally, 496 transpiration and the drag vegetation imposes on flow-through water, important plant-hydrology 497 interactions, are not included in Mondrian but are known to effect water level and RT_h , 498 respectively (Sánchez-Carrillo et al. 2004, Kröger et al. 2009). However, Mondrian does allow 499 500 for user-defined, daily changes in water level and RT_h to account for these effects. Despite these limitations, the effect size of RT_h and N loading on N removal and plant invasion is large enough 501 502 to support use of the general patterns presented in this study to inform wetland management across the region and other freshwater coastal wetlands affected by variable hydrology and N 503 504 loading.

505

506 N removal, RT_h , and denitrification

Inorganic N inputs are initially retained in wetlands through immobilization in microbial 507 508 communities or assimilation in plants. Annual N removal, which combines plant uptake, soil 509 immobilization, and denitrification, generally increased with more N loading and longer RT_h . Yet at higher N loading both annual N removal and N removal efficiency remained low at RT_h of 1-510 10 days as soil and plants became N saturated, N was flushed out faster, and there was less N 511 contact time for denitrifying microbes. Surprisingly, under long RT_h (100-365 days), N loading 512 of 100 g N m⁻² y⁻¹ was just as efficient at N removal as wetlands under lower N loading. 513 However, this also indicates that wetlands with high N loading require very long RT_h to be 514 effective at N removal. Supporting our hypothesis and similar to other model analyses (e.g., 515

516 Dettmann 2007), we found that longer RT_h also increases rates of denitrification. As RT_h 517 increases, the flushing of N out of the system slows, causing it to accumulate in the wetland 518 (Perez et al. 2011). Increases in available N pools supply more N substrate for transformation by 519 denitrifying microbes. Similarly, longer RT_h in the wetland creates more opportunity for plant 520 uptake, thus increasing N removal compared to scenarios with shorter RT_h .

Invader identity had little impact on denitrification in our simulation, despite being 521 recognized as an important driver in field studies (Findlay et al. 2003). For example, compared to 522 native plants, *Phragmites* provides more labile organic carbon to soil providing energy subsidies 523 for microbes and more oxygen to the rhizosphere which facilitates nitrification in coupled 524 nitrification-denitrification N removal (Windham and Meyerson 2003, Ehrenfeld 2003). 525 Although Mondrian does include subsidies of organic carbon, it does not explicitly model gas 526 transport in plants and this may result in underestimates of denitrification in our simulations. 527 However, the influence of *Phragmites* in particular can be highly variable (Alldred and Baines 528 529 2016), and likely driven by small scale variation at spatial resolutions outside the limits of our model. Furthermore, only a small portion of N removal in our studies was attributed to 530 531 denitrification suggesting the impacts of *Phragmites* on denitrification does not affect the overall patterns of N removal we observed. 532

533 Annual N removal was affected by hydroperiod only in extreme scenarios (e.g. nonflooded vs. permanently flooded wetlands). More frequent flooding and shorter hydroperiods did 534 535 not result in significantly higher percent denitrification as we predicted. Rather, percent denitrification was highest when hydroperiod was longest (e.g. semi-annual), although this 536 difference was marginal compared to the large effects incurred by changes in RT_h (Fig. 5). We 537 believe this is due in part to the seasonal timing of flooding in these simulations, a known driver 538 539 of denitrification and other wetland processes (Valett et al. 2005, Langhans and Tockner 2006). 540 Although wetlands with weekly hydroperiod were flooded the same total number of days in a year as wetlands with semi-annual hydroperiod, flooded conditions in semi-annual wetlands 541 were concentrated in the growing season (water level peaks during June) when soil temperature 542 is high and microbes are most active. In other words, denitrification conditions were near optimal 543 544 for all flooded days in semi-annual wetlands but only half the flooded days when hydroperiod was weekly, the other flooded days being too cold for denitrification to occur. Only when NO₃-545 was scarce (i.e. when NH4+-N:NO3--N ratios were high) did wetlands with weekly hydroperiod 546

have higher percent denitrification than wetlands with semi-annual hydroperiod (Fig. 5). In these scenarios, NO_3^- is limiting and frequent shifts to aerobic soil conditions facilitate oxygendependent nitrification, transforming NH_4^+ to NO_3^- needed for denitrification.

Indeed, others have found that under high inputs of NO₃-, wetlands with longer, less 550 variable hydroperiods removed more N and had higher rates of denitrification than wetlands with 551 more variable, shorter hydroperiods (Ishida et al. 2006). Compared to drier wetlands or wetlands 552 with shorter hydroperiod, wetlands with semi-annual hydroperiod remove and store more N as 553 anaerobic conditions slow decomposition of plant litter and mineralization of organic N (Fig. 3). 554 Decomposition and N mineralization are also slowed by low temperatures. Yet unlike 555 denitrification, N removal via burial of N is less permanent and is more sensitive to changes in 556 oxygen availability and temperature, especially as water levels draw down, or as organic matter 557 558 is flushed downstream where it may be mineralized later in more oxygen rich waters (Venterink et al. 2002). Nonetheless, organic N stocks were higher in wetlands with longer hydroperiods, 559 subsidizing overall N removal. 560

561

562 *Plant invasion*

In addition to increasing N removal, we found that longer RT_h also increases invasion 563 success of Phragmites australis and Typha x glauca. While it was previously known that there 564 was a threshold of invasion (~15 g N m⁻² y⁻¹) across a N loading gradient for these two species 565 (Martina et al. 2016), it was unknown that this threshold would be sensitive to RT_h . As RT_h 566 increases, thresholds of successful Phragmites invasion shifted towards lower N loads, with 567 invasion occurring even under the lowest N load we simulated (1 g N m⁻² y⁻¹). When RT_h is 568 longer, N is flushed out of wetlands more slowly and begins to accumulate, resulting in more 569 570 available N for plant uptake. *Phragmites* is an opportunistic invader capable of outcompeting natives for this available N, growing taller, and shading out neighboring plants (Mozdzer and 571 Zieman 2010, Holdredge and Bertness 2011). Under shorter RT_h , N is quickly flushed from 572 wetlands, reducing available N and preventing rapid *Phragmites* growth and shading of natives 573 (Borin and Tocchetto 2007). However, when N loading exceeded 15 g N m⁻² y⁻¹ even the shortest 574 RT_h we simulated (1 day) cannot prevent *Phragmites* from invading and dominating wetland 575 communities. This suggests that invasion is most sensitive to changes in RT_h in wetlands 576 receiving low inputs of N. 577

Typha invasion was similarly successful under lower N loading regimes as RT_h 578 lengthened. However, at higher levels of N loading, Typha invasion success declined for all RT_h 579 scenarios except the shortest (1 day; Appendix S1: Fig. S2). This outcome is likely due to the 580 robust productivity of natives under high N loads or increased ecosystem N as a result of longer 581 RT_h . As natives grow and reproduce quickly with abundant N in the 15 years prior to invader 582 introduction, the community is effectively able to prevent *Typha* from invading. We tested this 583 explanation by performing a small set of diagnostic simulations. By increasing Typha propagule 584 pressure (65 individuals in a cohort rather than 15) and introducing Typha with the native 585 community at year one before the natives can fill the model space, Typha was able to dominate 586 the community under high N loading and long RT_h scenarios that it failed to invade if introduced 587 in year 15 (Appendix S1: Fig. S3). This indicates that *Typha* establishment was indeed prevented 588 589 by the rapid expansion and productivity of the native community, particularly by the larger native, Schoenoplectus acutus, which can grow up to 3m tall (Gleason and Cronquist 1991). This 590 591 has been further demonstrated in arid grasslands, where diverse native communities exhibited high resistance to invasion by exotic knapweed, even with abundant available resources thought 592 593 to facilitate the invader (Maron and Marler 2007). We believe this response was unique to Typha, and not observed in Phragmites invasion scenarios, because of their differences in 594 595 physiology and morphology. Compared to Typha, Phragmites has a higher relative growth rate, maximum size, and leaf architecture that more completely shades neighboring plants, allowing it 596 597 to outcompete even the densest stand of natives (Martina et al. 2016).

598

599 Conclusions

600 Reducing nutrient loads downstream and controlling invasive species are both common 601 management objectives and we found that optimizing one may come at the cost of the other. 602 Optimizing management to mitigate negative outcomes is practical in wetlands where hydrology and RT_h can be directly controlled, like tertiary treatment wetland or waterfowl impoundments 603 (Winton et al. 2016). The simulations we present are modeled after coastal wetlands of the Great 604 Lakes, where controlling hydrology is more difficult and occurs less often (Wilcox 1993). 605 606 Process-based simulation models, like Mondrian, provide needed insight into functions governed by complex interactions of drivers, including hydrology and nutrient loading, which would be 607 difficult to infer from field studies. In Great Lakes wetlands RT_h is modulated by multi-year 608

water level fluctuations that determine the direction and rate of water flow in river mouths and 609 along coastlines. With accurate predictions of lake levels, practitioners can anticipate changes in 610 RT_h and subsequent shifts in N removal services and wetland invasibility. For example, when 611 lake levels are high, the hydrologic gradient from coastal wetlands to the lake is shallower, 612 wetland water outflow is slower, and RT_h is longer. In these scenarios management strategies 613 614 should focus on invasion threats as longer that results from high lake level will facilitate greater N removal, reducing the need for intervention. When lake levels are lower, priorities should shift 615 to reducing N loading into wetlands, when ideal conditions for N removal decline as downslope 616 hydrologic gradients increase, RT_h shortens, and invasion resistance increases, particularly 617 wetlands receiving ≤ 15 g N m⁻² y⁻¹ where changes in RT_h can be a determining factor of wetland 618 invasibility. 619

620 These results can provide timely guidance in the management of both N delivery to the Great Lakes and invasion of vulnerable coastal wetlands as Great Lakes watersheds continue to 621 deliver high amounts of N (Choquette et al. 2019) and lakes experience record-breaking water 622 levels (Gronewold and Rood 2019). By combining lake level predictions with our understanding 623 624 of invasive species propagation and land use change impacts on watershed nutrient transport we can prioritize intervention in wetlands most vulnerable to change while optimizing those with 625 626 high potential for service provisioning. Although our results are specific to Great Lakes coastal wetlands, these trends and tradeoffs are general enough to be applied to other freshwater coastal 627 628 wetlands with similar seasonal hydrology and climate. Furthermore, Mondrian's ability to simulate complex mechanisms shared among temperate herbaceous wetlands throughout time 629 and across regions gives practitioners freedom to explore scenario-specific management 630 strategies by simply defining the environmental setting (e.g. climate patterns, hydrology, and 631 632 plant communities). This control allows users to fine-tune model predictions to seasonal timing 633 of N delivery, anticipated shifts in seasonal hydrology patterns, including timing of high water, and climate change impacts on wetland biota to further enhance our understanding of the future 634 and function of important and vulnerable coastal wetlands. 635

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- 637

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- 642

643 SUPPORTING INFORMATION

- Additional supporting information may be found online at: [link to be added in production].
- 645

646 DATA AVAILABILITY

- 647 Data are available from the Deep Blue repository at the University of Michigan (Sharp 2020):
- 648 <u>https://doi.org/10.7302/thef-4p55</u>

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Table 1. List of sites, empirical field data, and Mondrian model output and input values used to determine scaling parameters and 808 calibrate denitrification in Mondrian. Mondrian was calibrated using empirical values of annual average denitrification, biomass, 809 ÷.,

810	nitrogen inputs	(NH ₄ ⁺ -N and NO ₃ ⁻ -N), water depth, and hydrologic residence time (RT_h) .

	Empirical values		Model output		Model inpu	t			
							Water		
0	Denitrification	Biomass	Denitrification	Biomass	$\mathrm{NH_{4}^{+}}\left(\mathrm{g}\ \mathrm{N}\right.$	NO3 ⁻ (g	depth	RT_h	
Site	(g N m ⁻² y ⁻¹)	(g C m ⁻²)	(g N m ⁻² y ⁻¹)	(g C m ⁻²)	m ⁻² y ⁻¹)	N m ⁻² y ⁻¹)	(cm)	(days)	Citation
Old Woman									McCarthy et
Creek, OH	10.6	No data	9.3	494	50.2	228	0±100	4.2	al. 2008
Champaign,									
	10.0	500	11.9	494	36.0	144	16±25	7.0	Xue et al. 1999
St Louis Bay									Bellinger et al.
Estuary, MN	5.7	157	0.3	267	0.0	10.8	75±0	13.0	2014
Olentangy									
River,									
Columbus,									Hernandez and
OH	2.7	779	1.2	624	24.5	98.1	-2±40	1.0	Mitsch 2007
Cheboygan									Lishawa et al.
Marsh, MI	0.7	591	0.3	281	0.0	12.9	4±6	3.2	2014

Table 2. Predictor variables and their various factor levels used in model simulations for this

- study. Each predictor variable was crossed in a semi-factorial manner with the other drivers (i.e.
- 814 $RT_h = f$ [water level] was not crossed with constant hydroperiod resulting in n=1380 unique
- treatment combinations). RT_h = hydrologic residence time (days).

N loading	NH4 ⁺ -N:NO3 ⁻ -	RT_h (days)	Hydroperiod	Plant invader
(g N m ⁻² y ⁻¹)	N mass ratio			identity
1	0:1	<i>f</i> (water level)	Constant 15cm	Phragmites australis
5	1:7.3	1	Constant -15cm	Phragmites australis
10	1:3	10	Weekly (±50cm)	Typha x glauca
15	4:1	100	Monthly (±50cm)	
³⁰ 100	1:0	365	Semi-annual (±50cm)	
π	3			
	-			

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818 Table 3. Values of the differences (Δ) in AIC (Akaike Information Criterion) between each Generalized Linear Mixed Model (GLMM) relative to the best model (in **bold**) of four response 819 variables: annual N removal, percent of N inflow denitrified, N removal efficiency, and invader 820 percent of total NPP. Model variables include annual N loading (N Load), N-species ratio (N 821 822 *ratio*), hydrologic residence time (RT_h) , hydroperiod (*Hydro*), and invader species identity (Invader). Included model terms selected base on a forward stepwise selection process. 823 Interaction terms include all lower order interactions and main effects (e.g. 3-way interaction 824 includes the 3 main effects and possible 2-way interactions). P<0.001 for all models. 825 Variable Model equation df ΔAIC Adj. R² Annual N $a = N load \times RT_h \times Hydro$ 149 355 0.95

removal

$$b = a + (N \ load \times Hydro \times N \ ratio)$$
 474 37 0.96

 $c = b + (N \ load \times RT_h \times N \ ratio)$ 624 13 0.96

$$c + (N \ load \times RT_h \times Invader)$$

$$684 \qquad 0 \qquad 0.96$$

N removal	$a = (Hydro \times RT_h) + (Hydro \times N \ load)$	54	97	0.83
efficiency				
	$b = a + (N load \times Invader)$	66	91	0.83
	$b + (N \ load \times RT_h \times Hy \ dro)$	161	0	0.84
% N denitrified	$a = N \ load \times RT_h \times Hydro$	149	39	0.83
	$b = a + (N ratio \times N load)$	179	9	0.83
	$c = b + (N ratio \times Hydro)$	209	4	0.83
C	$c + (N \ ratio \times RT_h)$	234	0	0.83
Invader % of total NPP	$a = N \ load \times RT_h \times Invader$	59	1	0.31
	$a + (RT_h \times Hydro)$	85	0	0.32

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Table 4. Relative variable importance (RVI) values of all main effects, 2-way, and 3-way interactions of predictor variables used in best fit GLMM models. The highest RVI values within each order (main effect or interactions) of each response variable are in **bold**, representing the terms we discuss in this study. Note that RVI is a relative value such that the RVI of main effects and interaction terms can only be compared to similar order terms (e.g. a main effect can be compared to another main effect, but not to any interaction term).

0	Annual N	N removal	% N	Invader %
0	removal	efficiciency	denitrified	of total NPP
Main effect RT_h	1.00	1.00	1.00	1.00
Hydro	1.00	1.00	1.00	0.99
N load	1.00	1.00	1.00	1.00
N ratio	0.08	0.21	0.29	0.02
Invader	0.51	0.54	0.66	1.00
2-way $RT_h \times Hydro$	1.00	0.99	0.99	0.65
interactions				
$RT_h \times N$ load	1.00	0.58	0.99	0.99
$RT_h \times N$ ratio	0.10	0.03	0.62	0.00

	$RT_h \times Invader$	0.36	0.34	0.27	0.99
	N load × Hydro	1.00	0.99	0.99	0.26
	$N load \times N ratio$	1.00	0.30	0.89	0.00
	N load × Invader	1.00	0.90	0.42	0.99
	Hydro × N ratio	0.00	0.00	0.08	0.00
3-way	N load × RT_h × Hydro	1.00	0.99	0.99	0.00
interactions					
	N load $\times RT_h \times N$ ratio	1.00	0.00	0.08	0.00
	<i>N</i> load × RT_h × Invader	0.99	0.00	0.51	0.72
	N load × Hydro × N ratio	1.00	0.91	0.01	0.00

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Figure 1. Conceptual model depicting the influence of various biotic and abiotic drivers on
wetland N availability and invasion success of wetland macrophytes. Blue boxes represent larger
storages or processes while orange ovals represent smaller processes that occur within the larger
blue boxes. Wetland N pool includes inorganic NO₃⁻-N and NH₄-N as well as litter and soil
organic N. Solid lines represent direct effects and dashed lines represent indirect effects. H₁, H₂,
and H₃ boxes represent hypotheses predicting effects of water residence time, hydroperiod, and

841 plant invasions on N cycling.

Figure 2. Observed and simulated values of denitrification from 5 regional sentinel sites used for

843 Mondrian calibration of ecosystem-level scaling parameters. Diagonal line represents

844 hypothetical 1:1 relationship of predicted model and observed field data.

Figure 3. Annual nitrogen (N) removal \pm S.E. as a function of water residence time (RT_h , plotted

on a log scale) in simulations of weekly (left panels) and semi-annual and permanent (labeled as

semi-annual; right panels) flooding regimes. Each row of panels corresponds to a different level

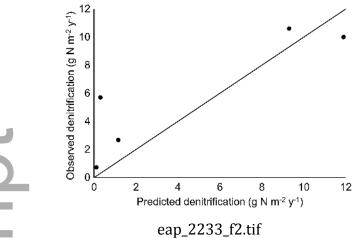
of wetland N inflow in g N m⁻² y⁻¹. Larger circles represent greater percentage (%) of invader

- NPP relative to total community NPP. Points on the x axis that fall between 1 and 10 days
- 850 represent treatments where residence time was a function of water level with an annual average
- 851 water residence time of ca. 4 days.
- Figure 4. Annual nitrogen (N) removal across a range of NH_4^+ -N:NO₃⁻-N ratios. Ratios of 1:7.3,
- 1:3, and 4:1 reflect watershed N inputs for urban, high-intensity agriculture, and rural land use

- classes, respectively. Ratios of 0:1 and 1:0 represent hypothetical ammonium-only and nitrate-
- only N loading, respectively. Bar colors represent water residence time (RT_h) .
- 856
- Figure 5. Plant available inorganic N (IN; NH_4^+ -N + NO_3^- -N), plant IN uptake, and total organic
- N (ON) in soil pools as a function of N loading in simulations of weekly (left panels) and semi-
- annual and permanent (labeled as semi-annual; right panels) flooding regimes. Bar colors
- 860 represent water residence time (RT_h) .
- Figure 6. Nitrogen (N) removal efficiency $(N_{rem}/N_{in}) \pm S.E.$ as a function of water residence time
- 862 $(RT_h, \text{ plotted on a log scale})$ in simulations of weekly (left panels) and semi-annual and
- 863 permanent (labeled as semi-annual; right panels) flooding regimes. Each row of panels
- corresponds to a different level of wetland N inflow in g N m⁻² y⁻¹. Larger circles represent
- greater percentage (%) of invader NPP relative to total community NPP. Points on the x axis that
- fall between 1 and 10 days represent treatments where residence time was a function of water
- level with an annual average water residence time of ca. 4 days.
- Figure 7. Percentage (%) \pm S.E. of available N from N_{inflow} that is denitrified on an annual basis
- as a function of water residence time $(RT_h, plotted on a \log scale)$ in simulations of weekly (left
- panels) and semi-annual and permanent (labeled as semi-annual; right panels) flooding regimes.
- 871 Each row of panels corresponds to a different level of wetland N inflow in g N m⁻² y⁻¹. Larger
- circles represent greater percentage (%) of invader NPP relative to total community NPP. Points
- on the x axis that fall between 1 and 10 days represent treatments where residence time was a
- function of water level with an annual average water residence time of ca. 4 days.

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