1	Maximum Respiration Rates in Hyporheic Zone Respiration is
2	JointlySediments are Primarily Constrained by Organic Carbon
3	Concentration and Molecular RichnessSecondarily by Organic
4	Matter Chemistry

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10 Abstract.

11 River corridors are fundamental components of the Earth system, and their biogeochemistry can be heavily influenced 12 by processes in subsurface zones immediately below the riverbed, referred to as the hyporheic zone. Within the 13 hyporheic zone, organic matter (OM) fuels microbial respiration, and OM chemistry heavily influences aerobic and 14 anaerobic biogeochemical processes. The link between OM chemistry and respiration has been hypothesized to be 15 mediated by OM molecular diversity, whereby respiration is predicted to decrease with increasing diversity. Here we 16 test the specific prediction that aerobic respiration rates will decrease with increases in the number of unique organic 17 molecules (i.e., OM molecular richness, as a measure of diversity). We use publicly available data across the United 18 States from crowdsourced samples taken by the Worldwide Hydrobiogeochemical Observation Network for Dynamic 19 River Systems (WHONDRS) consortium. Our continental-scale analyses rejected the hypothesis of a direct limitation 20 of respiration by OM molecular richness. In turn, we found that_organic carbon (OC) concentration imposes a primary 21 constraint over hyporheic zone respiration, with additional potential influences of OM richness. We specifically 22 observed respiration rates to decrease nonlinearly with the ratio of OM richness to OC concentration. This relationship 23 took the form of a constraint space with respiration rates in most systems falling below the constraint boundary. A 24 similar, but slightly weaker, constraint boundary was observed when relating respiration rate to the inverse of OC 25 concentration. These results indicate that maximum respiration rates may be governed primarily by OC concentration, 26 with secondary influences from OM richness. Our results also show that other variables often suppress respiration 27 rates below the maximum associated with the richness-to-concentration ratio. An important focus of future research 28 efforts will identify physical (e.g., sediment grain size), chemical (e.g., nutrient concentrations), and/or biological 29 (e.g., microbial biomass) factors that suppress hyporheic zone respiration below the constraint boundaries observed 30 here.

31 1 Introduction

32 River corridors are key components of the Earth system that connect terrestrial landscapes to the ocean through the 33 transport and transformation of organic matter (OM) and nutrients (Harvey and Gooseff, 2015; Schlünz and 34 Schneider, 2000; Schlesinger and Melack, 1981). In addition, river corridors have strong connections to the 35 atmosphere in terms of significant emissions of greenhouse gasses such as CO2-(Raymond et al., 2013)., 36 contributing ~3.9 Pg CO₂-C yr⁻¹ to the atmosphere (Raymond et al., 2013; Drake et al., 2018). Within river corridors 37 the hyporheic zone (Orghidan, 2010) can have a dominant influence over net metabolism and biogeochemical 38 transformations (Boulton et al., 1998; Naegeli and Uehlinger, 1997; Krause et al., 2011) to a degree that it can act as 39 the "river's liver" to remove contaminants (Fischer et al., 2005).. Here we define the hyporheic zone as shallow 40 subsurface sediments through which surface water enters, moves through and at some point returns to the main 41 channel. These zones are considered biogeochemical "hotspots" and can be responsible for 3-96% of the total stream 42 metabolism (Jones, 1995; Fuss and Smock, 1996; Naegeli and Uehlinger, 1997; Kaplan and Newbold, 2000; Battin 43 et al., 2003; Ward et al., 2018). In turn, hyporheic zones can contribute significantly to the overall CO₂ emissions 44 from inland waters (Burrows et al., 2017; Newcomer et al., 2018; Comer-Warner et al., 2019; Son et al., 2022). 45 Recent work has found that detailed properties of OM chemistry can significantly influence respiration rates in 46 hyporheic zone sediments (Stegen et al., 2018; Garayburu-Caruso et al., 2020a; Sengupta et al., 2020; Graham et al., 47 2018, 2017; Song et al., 2020a2020). These observations demonstrate a need to deepen understanding of the 48 relationships between hyporheic zone biogeochemistry (e.g., respiration rates) and OM chemistry. 49 50 A conceptual hypothesis was recently developed that may provide new insight into the connections between OM 51 chemistry and biogeochemical rates. More specifically, Lehmann et al. (2020) hypothesize that OM can be protected 52 from degradation (in part) by high levels of molecular diversity. Biogeochemical rates that depend on OM oxidation 53 (e.g., aerobic respiration) may therefore be suppressed with increases in the number of unique organic molecules 54 (referred to here as OM molecular richness). The concept is that high levels of OM molecular richness lead to low 55 returns-on-investment, relative to the energy invested in building and maintaining the molecular machinery needed 56 to metabolize any given type of organic molecule. The consequence is low respiration rates. The underlying 57 mechanism has been proposed to help protect OM in some ecosystems such as deep sea (Arrieta et al., 2015) and 58 river corridor (Stegen et al., 2018) environments. 59

60 The hypothesis of lower biogeochemical rates with higher OM molecular richness has not been evaluated in 61 hyporheic zone sediments despite the established connection between OM chemistry and hyporheic zone respiration 62 rates. We posit that higher levels of hydrologic connectivity in hyporheic zones relative to unsaturated systems (e.g., 63 soil) may diminish influences of spatial isolation such as an OM stabilization mechanism (Schmidt et al., 2011), 64 potentially leading to particularly strong relationships between respiration rates and OM chemistry. In turn, it is 65 plausible that the hyporheic zone is an ecosystem in which we may find support for the hypothesized negative 66 relationship between respiration rates and OM molecular richness. Here we test this hypothesis at the continental 67 scale using publicly available data from the Worldwide Hydrobiogeochemical Observation Network for Dynamic

River Systems (WHONDRS) consortium (Stegen and Goldman, 2018; Garayburu-Caruso et al., 2020b; Toyoda et
al., 2020; Goldman et al., 2020).

70 2 Methods

71 Sample collection and data generation

72 During the summer of 2019, the WHONDRS consortium carried out a multi-continent river corridor study to 73 evaluate interactions between metabolomes, microbial metabolism, biogeochemical function, and ecosystem 74 features. Garayburu-Caruso et al. 2020b(2020b) describe details on metadata, sample collection, analysis, and 75 processing of ultrahigh resolution mass spectrometry data. Briefly, during late July and August 2019 sediment 76 samples were collected across multiple continents, but the current study focuses on samples collected in the contiguous United States (ConUS) (Fig. 1). ShallowSampled locations spanned a broad range of environmental 77 78 conditions; for example, stream order ranged from 1st to 8th, land cover composition varied with upstream forest 79 cover ranging from 0-97 % and urban cover ranging from 0-28%, and physical settings were from relatively steep 80 headwater streams to large lowland rivers. At each site, shallow sediments (~1-53 cm depth) were collected at three 81 separate depositional zones at each site. The zones were ~ 10 m away from each other and were labeled as upstream, 82 midstream, and downstream. Samples were shipped to the Pacific Northwest National Laboratory (PNNL) campus 83 in Richland, WA (USA) on ice within 24 hours of collection. We conceptualize these sediments as part of the 84 hyporheic zone as we make the assumption that the supply and exchange of nutrients and OM from the stream 85 influences the biogeochemical processes experienced by the sediments. In turn, we assume that all samples came 86 from shallow (~1-3 cm depth) hyporheic zone sediments through which surface water enters, moves through, and at 87 some point returns to the main channel. 88 89 In the laboratory, sediments were sieved with a 2 mm sieve, and subsampled into 50 mL conical tubes (Genesee 90 Scientific OlympusTM Plastics) to separate Field and Incubation aliquots. Note that in the methods provided by 91 Garayburu-Caruso et al. (2020b) there is an error in the description of the sediment preservation prior to mass 92 spectrometry analysis. Corrected preservation methods are described immediately below. Sediments from the Field 93 aliquot were flash frozen in liquid nitrogen immediately after sieving to maintain the sediment characteristics 94 observed in the field and stored at -80°C until analysis. The Incubation aliquots were not flash frozen immediately; 95 instead they were kept in the dark inside an environmental chamber at 21°C along with other sediments to be used 96 for respiration measurements (see below) so that the two sets of sediment samples experienced the same conditions 97 leading up to the use of the sediment for respiration estimation. The next morning, Incubation aliquots were

98 retrieved from the environmental chamber, flash frozen in liquid nitrogen, and stored at -80°C until analysis. In our
 99 analyses we used the "Field" sediments to study water-extractable organic carbon concentration and OM chemistry

100 prior to the respiration incubation. We used the "Incubation" sediments as a check for changes or variation in

organic carbon concentration between Field sediments and those sediments that were actually incubated. As a
 quality assurance procedure (detailed below), we removed samples with the largest changes in organic carbon

quality assurance procedure (detailed below), we removed samples with the largest changes in organic carbonconcentration between Field and Incubation sediments.

105 Field and Incubation sediments were extracted with milli-Q water, and the resulting supernatant from sediment 106 extractions was filtered through a 0.22 µm sterivexSterivex filter (EMD Millipore). Non-purgeable organic carbon 107 (NPOC) was determined on the supernatant by a Shimadzu combustion carbon analyzer TOC-L CSH/CSN E100V 108 with ASI-L autosampler. We only included data from sites that had similar NPOC concentrations between the paired 109 Field and Incubation samples. Our rationale for this approach is based on the assumption that if NPOC is highly 110 variable across replicate sub-samples (i.e., across paired Field and Incubation samples), the associated sediments 111 used for respiration measurements may have been highly heterogeneous despite our efforts to homogenize sediments prior to analyses. In turn, we assume that high heterogeneity may lead to unreliable estimates of NPOC, respiration, 112 113 and OM molecular richness for a given site. Focusing analyses on the subset of sites that had relatively good 114 correspondence in NPOC between Field and Incubation samples is, therefore, a conservative approach aimed at 115 working with only the most reliable data. 116 117 To subset the data, we calculated the ratio between Field and Incubation NPOC concentrations within each site. H 118 the ratio was less than 1, it was inverted so that all ratios were greater than 1. Welf the ratio was less than 1, it was 119 inverted so that all ratios were greater than 1 because the important consideration was the proportional difference 120 between the Field and the Incubation NPOC concentrations. The same proportional difference could lead to ratios 121 below or above 1 depending on whether Field or Incubation NPOC was higher. For our analysis we needed to know 122 the proportional difference, not whether Field NPOC was higher or lower than Incubation NPOC. In turn, we 123 inverted the Field-to-Incubation NPOC ratio if it was below 1 so that all proportional differences were more 124 quantitatively comparable. We then regressed log-transformed Field NPOC vs. log-transformed Incubation NPOC, 125 and calculated the R² of the associated regression. Log-transformation was used due to the presence of skewed 126 NPOC distributions. Subsequently, we removed samples in order of their ratio, starting with the largest ratio (i.e., 127 the largest proportional difference between Field and Incubation NPOC). Higher R² values indicated a tighter 128 relationship between Field and Incubation NPOC, and thus more reliable data. We repeated these steps for all the 129 samples in the Field-Incubation dataset (n = 228). We then plotted the R^2 vs. the number of samples removed and 130 selected a threshold for the number of samples to remove (Fig. S1). The resulting curve showed that R² increased as 131 a function of points removed until it leveled off. This nonlinear saturating relationship was well-described by a 132 Michaelis-Menten function (Michaelis and Menten, 1913; Johnson and Goody, 2011). In this function, the half 133 saturation constant indicates the resource availability at which half of the maximum intake is reached (Mulder and 134 Hendriks, 2014). We used the half saturation constant, estimated from fitting the function to the data in Fig. S1, in a conceptually analogous way. That is, the half saturation constant indicated the number of samples that would need to 135 136 be removed to gain half of the maximum potential increase in fit between Field and Incubation NPOC. This resulted

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half way between a minimum $R^2 = 0.47$ and maximum $R^2 = 1$. This procedure was used to increase the reliability of the OM molecular richness estimates by removing samples that had the greatest variability in NPOC, which could

in removing 30 samples, leading to $R^2 = 0.74$ for the relationship between Field and Incubation NPOC, which was

140	translate into variability in OM richness as there was a weak but significant relationship between OM richness and	
141	NPOC (R ² = 0.20, p < 0.001, Fig. S2).	
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143	Subsetting the data is a data quality control challenge and there are a variety of ways in which one could approach it.	
144	In all quality control approaches there is a tradeoff between increasing confidence in data and removing so much	
145	data that statistical analyses become impossible. We aimed to increase data confidence up to an inflection point	
146	beyond which there appeared to be diminishing returns. Based on the functional form of the data, it appeared that a	
147	Michaelis-Menten function fit the data very well. This functional form also has the useful feature of estimating the	
148	half saturation constant, which we considered to be a practically useful inflection point.	
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150	Fourier Transform Ion Cyclotron Resonance Mass Spectrometry (FTICR-MS)	
151	We used ultrahigh resolution Fourier transform ion cyclotron resonance mass spectrometry (FTICR-MS) to generate	
152	mass spectra of sediment OM pools. Field sediment extracts were normalized to 1.5 mg C L ⁻¹ , acidified to pH 2 and	
153	extracted with solid phase extraction (SPE) PPL cartridges following procedures described by (Dittmar et al., 2008).	
154	Note that all samples were normalized to a consistent NPOC concentration prior to SPE and the same sample	
155	volume was extracted with the same cartridges and resin mass. Since concentrations were normalized prior SPE, we	
156	did not measure extraction efficiency post-extraction. While extraction efficiency will vary across samples, our	
157	approach assumes focuses on studying how many unique molecules were present in a sample rather than the relative	
158	concentrations of individual molecules. We assume that variation in extraction efficiency is not systematically	
159	linked to respiration rate to such a degree that the number of detected peaks becomes correlated with respiration.	
160	Although we cannot definitively determine that this assumption is upheld in this dataset, it evaluate this assumption,	
161	we do not use information on relative peak intensities, which should be influenced by SPE more than the number of	
162	peaks is influenced by SPE. It seems extremely unlikely that the number of observed peaks would become	
163	systematically and spuriously linked to respiration due to variation in extraction efficiency. In the worst case, biases	
164	would strengthen the statistical link between respiration and the number of unique peaks, but we found this	
165	relationship to be very weak (see Results and Discussion).	
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167	FTICR-MS analyses were carried out at the Environmental Molecular Science Laboratory (EMSL) in Richland, WA	
168	using a 12 Tesla (12T) Bruker SolariX FTICR mass spectrometer (Bruker, SolariX, Billerica, MA, USA) in negative	
169	mode. The method used to assign molecular formulas to FTICR-MS spectra is described in Garayburu-Caruso et al.	
170	(Garayburu-Caruso et al., 2020b). Briefly, Formularity (Tolić et al., 2017) was used to align mass lists generated	
171	using Bruker DataAnalysis V4.2. Resulting reports were processed using ftmsRanalysis (Bramer et al., 2020). It is	
172	important to note that FTICR-MS is a non-targeted approach to reliably identify molecular formulas of organic	

- 173 molecules with masses, but it is not quantitative and does not provide information about the structure of the
- 174 molecular formulas identified. Our analyses on the Field FTICR-MS data only included samples that passed through
- 175 the subsetting process described above based on Field and Incubation NPOC. We calculated OM richness as the
- 176 total number of unique peaks present in one sample.

- 177 178 179 180 Incubations and respiration rates 181 Respiration rates were determined following methods described by Garayburu-Caruso et al. (2020a). Sieved 182 sediments were subsampled into 40 mL clear glass vials (I-Chem amber VOA glass vials) with a 0.5 cm diameter 183 factory calibrated oxygen sensor dot (Fibox 3; PreSens GmbH, Regensburg, Germany). Vials with sediments and 184 unfiltered water from each site were kept in the dark inside the environmental chamber at a 21°C until next day 185 incubations. Reactors consisted of 10 mL of sieved sediments and ~30-35 mL of aerated unfiltered water with no 186 headspace, shaken at 250 rpm for 2 hours. Dissolved oxygen (DO) was measured noninvasively every 15 min for 187 the first hour and every 30 min during the second hour using an oxygen optical meter (Fibox 3; PreSens GmbH, 188 Germany) to read the oxygen sensor dots on the vials. Respiration rates were calculated as the slope of the linear 189 regression between DO concentration and incubation time for each reactor and further normalized per gram of 190 sediment in each reactor. Normalized and not-normalized rates are reported in this manuscript. 191 192 Statistical analysis 193 All statistical analyses were completed using R (version 3.6.3)(R Core Team, 2021) with p < 0.05 as the significance 194 threshold. We used ordinary least squares regressions (function "lm") to evaluate relationships between respiration 195 rates and OM richness or NPOC. While not initially expected, we observed an apparent non-linear constraint-based 196 relationship between respiration rate and the inverse of NPOC. To evaluate the statistical significance of the 197 constraint boundary, we subdivided the 1/NPOC data into 10 even bins and found the maximum respiration rate in 198 each of those bins. We then fit a negative exponential function to the relationship between maximum respiration rate 199 and 1/NPOC.rates and the 1/NPOC values associated with those maxima (i.e., we did not use the average 1/NPOC 200 of each bin). To evaluate the potential contribution of OM richness, we used the same approach to regress 201 respiration rate against the ratio of OM richness to NPOC concentration. Base functions in R and ggplot2 202 (Wickham, 2016) were used for these analyses and associated plotting. 203 204 Scripts necessary to reproduce the primary results of this manuscript are available at

 - 205 https://github.com/WHONDRS-Hub/Respiration_and_OM_Richness/.https://github.com/WHONDRS-
 - Hub/Respiration_and_OM_Richness/. Goldman et al. (2020) provides the raw, unprocessed FTICR-MS data and
 respiration rate data. FTICR-MS data used in this manuscript were processed following instructions provided in the
 - 208 Goldman et al. (2020) data package.
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- 210 3 Results and Discussion
- 211 Both respiration rates and OM molecular richness varied significantly across samples, providing a useful dataset to
- 212 study the hypothesized negative relationship between these two variables. More specifically, the distribution of
- 213 aerobic respiration rates revealed a broad range of rates that were highly skewed for rates that were either not

215 potential for biogeochemical "hot spots" (McClain et al. 2003) or "control points" (Bernhardt et al. 2017) at the 216 continental scale. The distribution for OM molecular richness (i.e., number of identified organic molecules) 217 appeared to be multimodal, but dominated by one primary peak (Fig. 2C). OM molecular richness ranged from 218 ~2000-5000 peaks, and we took advantage of this variation to evaluate the relationship between OM richness and 219 respiration rates. 220 221 We did not observe a clear negative relationship between sediment aerobic respiration rates and OM molecular richness, which rejected the hypothesis that higher OM richness will suppress respiration (Fig. 3A,C). The data in 222 223 Fig.3 suggest there may instead be a peak in maximum respiration rate near intermediate levels of OM molecular 224 richness. There may, therefore, be an optimal level of OM molecular richness that enables high respiration rates, but 225 does not guarantee elevated rates, leading to a unimodal constraint space. Regressions based on maximum 226 respiration rates across the OM richness axis were not significant, however (Fig. 3). These results further reject the 227 hypothesis of any direct relationship between respiration rate and OM richness. 228 229 While we did not observe a direct link between respiration and OM richness, extending the Lehmann et al. (2020) 230 hypothesis revealed a potential influence of OM richness, after controlling for water soluble organic carbon (OC) 231 concentration, measured as NPOC. That is, we posit that any connection between OM richness and respiration is 232 likely modified by the amount of OC. The magnitude of OM richness relative to the concentration of OC could, 233 therefore, provide a stronger constraint over respiration than OM richness alone. High ratios indicate high levels of 234 OM richness relative to the amount of OC, while low ratios indicate low levels of OM richness relative to the 235 amount of OC. In the context of the Lehmann et al. (2020) hypothesis, respiration would therefore be expected to 236 decrease with increasing richness-to-concentration ratios. 237 238 Consistent with this extended hypothesis, we find that maximum respiration rates decreased with increasing 239 richness-to-concentration ratios (Fig. 4). This suggests that at the continental scale OM molecular richness may 240 indirectly influence aerobic respiration rates. However, the influence of OM richness is likely to be relatively minor. 241 That is, maximum respiration rate was also well-explained simply to the inverse of OC concentration (Fig. 5). Note 242 thatNote that regression models applied to the whole datasets presented in Figure 4 and Figure 5, were relatively 243 weak when compared to models of the constraint boundaries ($R^2 = 0.32-0.34$ vs. $R^2 = 0.89-0.97$, Table S1). This 244 further supports our inference of respiration rates being constrained based on the richness-to-concentration ratio. 245 Additionally, the relationship between respiration rates and OC concentrations was relatively weak (Fig. S3). The 246 statistical models using the richness-to-concentration ratio are technically better models as they have higher R²

normalized (Fig. 2A) or were normalized (Fig. 2B) per gram of sediment. These skewed distributions indicate the

- values than models using only the inverse of OC concentration (cf. Figs. 4, 5). We also note that both types ofmodels are univariate, so there is no penalty for multiple explanatory variables. The bulk of variation in maximum
- 249 respiration rates (~90%) is, however, explained simply by the inverse of OC concentration.
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251 We infer that OC concentration could impose a primary constraint over maximum respiration rates, with OM 252 richness potentially contributing additional constraints. As such, any influences of OM richness over respiration 253 rates in hyporheic zone sediments are likely modulated by OC concentration. This is conceptually consistent with 254 observations in marine (Arrieta et al., 2015) and river corridor systems (Stegen et al., 2018). That is, when OM 255 molecular richness is high relative to OC concentration, the probability of a microbe repeatedly encountering the 256 same type of molecule is minimized. In that case, the costs of maintaining metabolic machinery to metabolize any 257 specific type of molecule may outweigh the energy gains (Arrieta et al., 2015). When costs outweigh gains, 258 respiration is expected to be minimized, which is consistent with the respiration constraint boundary to be lowest at 259 the highest richness-to-concentration ratios. In addition, the constraint boundary was non-linear, which is most likely 260 due to the fact that respiration rates cannot be below zero such that increasingly large richness-to-concentration 261 ratios cannot further suppress respiration. 262 263 The combined influences of OM richness and OC concentration are realized as a non-linear constraint space with the 264 vast majority of measured respiration rates falling well below the constraint boundary. This indicates that in most 265 cases, additional controls over respiration drive respiration below its potential maximum. Discerning these 266 additional controls is an important avenue of future work. For example, it would be useful to evaluate the degree to 267 which microbial community diversity, composition, biomass, and/or functional potential are related to deviations 268 from the constraint boundary. In addition, the FTICR-MS data used here provides presence-absence of organic 269 molecules, but not relative abundances of organic molecules. Accounting for among-molecule variation in 270 concentrations could provide insights into factors driving respiration below the constraint boundary. There are many 271 potential influences spanning physical (e.g., sediment texture), chemical (e.g., mineralogy), and biological (e.g., 272 fungal-to-bacterial ratios) that require investigation in context of the constraint discovered hereAny potential biases 273 introduced by solid phase extraction (see Methods) and other methodological details would, however, need to be 274 accounted for prior to including information on relative abundances. In addition, we removed data points that had 275 high measurement uncertainty (see Methods) as these could mask true relationships. This focused our analyses on 276 samples with relatively homogenous sediments. Locations with very heterogeneous sediments, even after sieving to 277 2mm, may be important to capture in future analyses. One approach to meet this challenge is analyzing a small 278 number of technical replicates (~3) for all locations, examine variation among them, and analyze numerous (>10) 279 additional technical replicates for locations with the most heterogeneous sediments. This would be an efficient way 280 to enable robust use of all sampled systems. Geography is another aspect that needs broader consideration in future 281 efforts. The current study was limited to the ConUS and within that domain there were some poorly sampled regions 282 (Fig. 1) due to logistical limitations. Improved and expanded geographic sampling may not change the constraint 283 boundary itself, but will likely help discern what drives variation below the boundary. More generally, there are 284 many potential influences spanning physical (e.g., sediment texture), chemical (e.g., mineralogy), and biological 285 (e.g., fungal-to-bacterial ratios) features that could modulate the location of any given sample or system relative to 286 the constraint boundary quantified here. Exploring system heterogeneity in context of these additional features will 287 be helpful to understand what drives samples/systems below the constraint boundary. 288

289 The outcomes of our study are useful for guiding models towards and away from features and processes that need to 290 be represented to enable predictions of river corridor biogeochemical function. For large scale models, it appears 291 there is a constraint envelope for hyporheic zone respiration rates that is related primarily to OC concentration and 292 even more strongly to OM richness relative to OC concentration. This constraint boundary emerged from sites 293 distributed across the ConUS (Fig. S4), indicating that it is transferable across a broad range of river corridor 294 systems. The richness-to-concentration ratio, therefore, offers a simple way to represent variation in maximum 295 respiration rates across river corridors. Furthermore, for sites without estimates of OM richness, our results suggest 296 that variation in maximum respiration rate could be reasonably estimated via OC concentration alone. Additionally, 297 the The constraint spaces observed here could also be included in models more mechanistically whereby they would 298 emerge from the representation of how microbial metabolism is influenced by both OM molecular richness and OC 299 concentration. The constraint spaces could, alternatively, be included more phenomenologically in models through 300 probabilistic sampling respiration rates within the constraint space. Regardless of how the constraint boundaries are 301 represented in models, they have important implications for fundamental and applied aspects of river corridors. 302 Systems that are close to the boundary will consume more oxygen within their sediments, potentially releasing more 303 CO₂ (Saccardi and Winnick, 2021) and having negative influences on fish embryos (Jensen et al., 2009), but positive 304 influences on contaminant transformations (Fischer et al., 2005; Lewandowski et al., 2019). Knowledge of what 305 environmental factors move systems closer to or further away from the constraints boundaries will, therefore, be 306 helpful in making decisions about how to manage river corridors. 307 308 There may also be additional aspects of OM molecular richness and chemical diversity more broadly (e.g., 309 thermodynamic properties, elemental ratios) that influence respiration and other biogeochemical rates in hyporheic 310 zone sediments (e.g., Garayburu-Caruso et al., 2020a; Song et al., 2020b2020). There is a need to examine such 311 possibilities at both local and global scales. There are rich opportunities for future studies to explore links between 312 respiration rates and a broad range of univariate and multivariate OM diversity measures quantified through metrics 313 such as Rao's entropy (Mentges et al., 2017) and dendrogram-based methods (Danczak et al., 2020, 2021; Hu et al., 314 2022). There is a need to examine such possibilities at both local and global scales, and to extend our river-focused 315 analyses to additional ecosystem types. The methods, data, and metadata from this study are all used/formatted 316 consistently to enable expansion of this dataset to more rivers and/or other systems such as soils and marine 317 sediments. Continuing to use the approaches and formats established here will facilitate synthesis and, in turn, 318 knowledge of what patterns and processes are or are not transferable across ecosystems. 319 320 4 Code availability: Scripts necessary to reproduce the primary results of this manuscript are available at 321 https://github.com/WHONDRS-Hub/Respiration_and_OM_Richness/. 322

5 Data availability: Data were published previously in Goldman et al. (2020): in the ESS-DIVE repository and are
 licensed for reuse under the Creative Commons Attribution 4.0 International License.

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326	6 Author contributions: JCS and VAG-C conceptualized the study, VAG-C performed analyses with feedback
327	from JCS, RED processed some of the data, AEG managed the sampling campaign, and LR, JMT, and JW
320 329	processed samples. JCS and VAG-C drafted the initial manuscript and all authors contributed to revisions.
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Figure 1. Spatial distribution of sampling locations. At each location three sediment samples were collected from locations distributed along an upstream-downstream gradient within a single stream reach. The map was generated by Sophia

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Figure 2. Density plots of aerobic respiration measured as oxygen consumption that was either not normalized relative to

sediment samples, which we refer to as OM richness.

sediment mass (A) or normalized by sediment mass (B). Panel (C) is a density plot for the number of unique peaks identified in

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 OM Richness/NPOC (mg C L⁻¹)
 OM Richness/NPOC (mg C L⁻¹)

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 Figure 4. Maximum sediment respiration rate decreased with increasing values of ratio of OM molecular richness to non

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 purgeable organic carbon concentration (NPOC). Panels A and B are for respiration that was either not normalized or normalized

 546
 by sediment mass, respectively. Maximum respiration rates (shown in the darker colors) were found by subdividing each

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 horizontal axis into 10 even bins. All other respiration rates and the corresponding richness-to-concentration ratios are shown in

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 lighter colors. Solid lines represent negative exponential models fit to the maximum respiration rates, with shaded areas

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 indicating 95% confidence intervals. Statistics for each model are provided on each panel. Statistics associated with exponential

550 regression models based on all respiration values (light purple) can be found in Table S1.

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