1 2	Nutrient dynamics and stream order influence microbial community patterns along a 2914 km transect of the Mississippi River
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40	Keywords: Mississippi River, WGCNA, microbial ecology, eutrophication

### 41 Abstract

Draining 31 states and roughly 3 million km<sup>2</sup>, the Mississippi River (MSR) and its tributaries 42 43 constitute an essential resource to millions of people for clean drinking water, transportation, agriculture, and industry. Since the turn of the 20<sup>th</sup> century, MSR water quality has continually 44 45 rated poorly due to human activity. Acting as first responders, microorganisms can mitigate, 46 exacerbate, and/or serve as predictors for water quality, yet we know little about their community 47 structure or ecology at the whole river scale for large rivers. We collected both biological (16S 48 and 18S rRNA gene amplicons) and physicochemical data from 38 MSR sites over nearly 3000 49 km from Minnesota to the Gulf of Mexico. Our results revealed a microbial community 50 composed of similar taxa to other rivers but with unique trends in the relative abundance patterns 51 among phyla, OTUs, and the core microbiome. Furthermore, we observed a separation in microbial communities that mirrored the transition from an 8<sup>th</sup> to 10<sup>th</sup> Strahler order river at the 52 53 Missouri River confluence, marking a different start to the lower MSR than the historical 54 distinction at the Ohio River confluence in Cairo, IL. Within MSR microbial assemblages we 55 identified subgroups of OTUs from the phyla Acidobacteria, Bacteroidetes, Oomycetes, and 56 Heterokonts that were associated with, and predictive of, the important eutrophication nutrients 57 nitrate and phosphate. This study offers the most comprehensive view of MSR microbiota to 58 date, provides important groundwork for higher resolution microbial studies of river 59 perturbation, and identifies potential microbial indicators of river health related to 60 eutrophication.

61

## 63 Introduction

64 By connecting terrestrial, lotic, and marine systems, rivers perform vital roles in both the 65 transport and processing of compounds in all major global biogeochemical cycles (Richey et al. 66 2002; Ensign and Doyle 2006; Withers and Jarvie 2008; Battin et al. 2009; Savio et al. 2015). 67 Within the carbon cycle alone, rivers collectively discharge organic carbon to the oceans at over 0.4 Pg C yr<sup>-1</sup> (Cauwet *et al.* 2002). Perhaps more importantly, rivers are generally net 68 69 heterotrophic (Cole *et al.* 2007), indicating that they not only transport organic matter but host 70 active metabolic processing of it as well. Conservative estimates place heterotrophic output of the world's fluvial networks (streams, rivers, and estuaries) at 0.32 Pg C vr<sup>-1</sup> (Cole and Caraco 71 72 2001; Battin et al. 2009). Although rivers contain a small minority of global fresh water at any 73 given moment, the considerable volumes that pass through these systems make them relevant to 74 models attempting to quantify global elemental transformations. However, despite the fact that 75 microbial functions likely play a vital role in ecosystem health for both rivers themselves and 76 their places of discharge, microbial functions in rivers remain understudied. 77 At 3734 km, the Mississippi River (MSR) is the fourth longest on earth, draining 31 U.S. 78 states and two Canadian provinces- a watershed consisting of 41% of the continental U.S (Turner 79 and Rabalais 2003; Dagg et al. 2004). The MSR is a major source of drinking water for many 80 U.S. cities; a critical thoroughfare for transportation, commerce, industry, agriculture, and 81 recreation; and conveys the vestiges of human activity to the Gulf of Mexico (GOM). In New Orleans, the average flow rate is over 16,990 cubic meters  $s^{-1}$  (cms) (Rabalais *et al.* 1996), but 82 83 can exceed 84,000 cms during flood stages (Singh 2012), and carries over  $150 \times 10^9$  kg of 84 suspended sediment into the northern GOM annually (Dagg et al. 2004, 2005). The MSR also 85 transports considerable amounts of carbon, nitrogen and phosphorus, with average annual fluxes

86	of 2.1 TgC yr <sup>-1</sup> , $> 1.4$ TgN year <sup>-1</sup> , and $> 0.14$ TgP yr <sup>-1</sup> , respectively (Goolsby and Battaglin 2001;
87	Cauwet et al. 2002; Aulenbach et al. 2007). Globally, the MSR represents 0.8% of the dissolved
88	organic carbon flux to the worlds oceans (Cauwet et al. 2002). When considering total nitrogen,
89	up to 62% can occur as nitrate (NO <sub>3</sub> <sup>-</sup> ) (Goolsby and Battaglin 2001). This massive discharge of
90	excess eutrophic nutrients, primarily from corn and soybean (nitrogen) and animal manure
91	(phosphorus) runoff (McIsaac et al. 2001; Turner and Rabalais 2004; Alexander et al. 2008;
92	Schilling et al. 2010; Duan et al. 2014; Staley et al. 2014a), fuels one of the largest marine zones
93	of seasonal coastal hypoxia in the world (Rabalais et al. 2002, 2007; Bianchi et al. 2010; Bristow
94	et al. 2015). Studying microbial relationships to river eutrophication will improve our
95	understanding of their contributions to either mitigating or exacerbating nutrient input.
96	Far from a homogenous jumble of organisms ferried downriver, microbial community
97	composition changes with distance from the river mouth and/or from the influence of tributaries
98	(Kolmakova et al. 2014; Read et al. 2015; Savio et al. 2015), resulting from altered nutrient
99	concentrations (Staley et al. 2014a; Van Rossum et al. 2015; Meziti et al. 2016), differing
100	dissolved organic matter (DOM) sources (Ruiz-González et al. 2013; Zeglin 2015; Blanchet et
101	al. 2016), and land use changes (Staley et al. 2014b; Van Rossum et al. 2015; Zeglin 2015). Past
102	studies of the Thames, Danube, Yenisei, and Columbia Rivers have found that planktonic river
103	microbial assemblages were dominated by the phyla Actinobacteria, Proteobacteria, and
104	Bacteriodetes; and taxa such as acl Actinobacteria, Polynucleobacter spp., GKS9 and LD28
105	Betaproteobacteria, CL500-29 Actinobacteria, LD12 SAR11 Alphaproteobacteria, and
106	Novosphingobium spp. (Crump et al. 1999; Kolmakova et al. 2014; Read et al. 2015; Savio et al.
107	2015).

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Specific to the MSR, previous 16S rRNA gene amplicon and metagenomic studies have

109 demonstrated that microbial assemblages in the Minnesota portion of the river (Lake Itasca to La 110 Crescent) correlated with organic carbon concentration, total dissolved solids, and land use 111 changes (Staley et al. 2013, 2014a; b). Species richness increased near developed land with 112 greater concentrations of nitrate and nitrite, as opposed to sites near pastureland that had greater 113 organic carbon (Staley et al. 2014a). Similar to past studies of other lotic systems (Crump et al. 114 2012; Read et al. 2015; Savio et al. 2015), Actinobacteria and Proteobacteria increased in 115 relative abundance along the upper MSR, while OTUs belonging to Bacteroidetes decreased 116 (Staley *et al.* 2013). A follow up time-series study over two summers showed a distinct seasonal 117 signal: samples from late summer of both years were more similar to each other than those from 118 early summer (Staley et al. 2015). A more recent study of another portion of the MSR (above the 119 Missouri River confluence to Natchez, La.) found bacterial communities formed distinct 120 regimes, likely due to the strong influence of their respective tributaries (Jackson *et al.* 2014; 121 Payne et al. 2017). 122 Researchers have suggested that some of these patterns supported the application of the

123 River Continuum Concept (RCC) (Vannote *et al.*, 1980) to river microbiota. The RCC postulates

124 that as a river increases in size, the influences of riparian and other inputs will decrease as the

125 river establishes a dominant core community (Vannote et al. 1980). Richness will increase with

126 stream order complexity before decreasing in higher order rivers (Vannote et al., 1980).

127 Therefore, as continuous systems with increasing volumes and residence times, river microbiota

should transition from experiencing strong influences of mass effects from terrestrial, riverbed,

and tributary sources to systems where species sorting plays a more important role (Crump *et al.* 

130 2012; Besemer et al. 2013; Savio et al. 2015; Niño-García et al. 2016).

131 Accordingly, studies examining the linkages between RCC and microbial structuring 132 mechanisms (e.g. species sorting, mass effects) have found that some of the results indeed 133 supported the RCC. Specifically, numerous lotic studies found that upstream and headwaters 134 amassed high species richness, before richness decreased further downstream (Crump et al. 135 2012; Kolmakova et al. 2014; Savio et al. 2015; Niño-García et al. 2016). This follows the 136 expected pattern outlined by the RCC where early stream and river microbial communities are 137 heavily influenced by a large input of allocthonous organisms from sediment and groundwater 138 into the river network. As the rivers progressed, such mass effects likely heeded to species 139 sorting, a process requiring an increased water residence time to allow for the selection of 140 species based on local environmental conditions (Crump et al. 2012; Savio et al. 2015; Niño-141 García et al. 2016). These types of river modulations, influenced by hydrology and 142 environmental conditions, have correlated with decreased species richness and increased core 143 community membership (the taxa found consistently throughout the entire river) in multiple 144 systems (Crump et al. 2012; Besemer et al. 2013; Savio et al. 2015; Niño-García et al. 2016). An 145 analyses of an upper portion of the MSR provided evidence for the importance of species sorting 146 (Staley et al. 2015). However, in a study of the Thames River, researchers found no association 147 between microbial assemblages and any measured variables other than residence time, leading 148 them to suggest that ecological succession was the primary driver of microbial community 149 composition (Read et al. 2015). Furthermore, a 1300 km transect of the lower MSR indicated 150 that richness actually increased instead of decreasing in particle-associated, and to a lesser 151 extent, free-living, communities, suggesting that the MSR may have fundamentally different 152 mechanisms driving microbial diversity than other rivers (Payne et al. 2017).

153	Complicating matters, particle-associated communities in rivers (frequently defined as
154	those found on filters of $> \sim 3 \mu m$ remain distinct from their free-living counterparts (Crump <i>et</i>
155	al. 1999; Riemann and Winding 2001; Jackson et al. 2014), potentially due to increased
156	production rates from access to readily obtainable carbon (Crump and Baross 1996; Crump et al.
157	1998, 1999). Typical river microorganisms associated with particles include OTUs related to the
158	Bacteroidetes clades Flavobacteria and Cytophaga, Planctomycetes, Rhizobium spp., and
159	Methylophilaceae spp. (Crump and Baross 1996; Allgaier and Grossart 2006; D'Ambrosio et al.
160	2014; Jackson et al. 2014). However, denoting consistent trends in particle community
161	composition must be tempered by recent evidence suggesting substrate availability and chemical
162	queues may trigger organisms to switch between free-living and particle-associated lifestyles
163	(Grossart 2010; D'Ambrosio et al. 2014). Rivers constitute complex and highly dynamic
164	ecosystems from a metacommunity perspective.
165	Although important insights have been gained from recent research on portions of the
166	MSR (Staley et al. 2013, 2015, 2016; Payne et al. 2017), microbiological transects at the whole-
167	river or catchment scale have yet to be completed. This study aimed to $i$ ) compare the structure
168	and abundance of size-fractionated MSR microbial community populations to those in other
169	rivers, <i>ii</i> ) examine within-river heterogeneity of microbial communities, and <i>iii</i> ) identify MSR
170	microorganisms most strongly associated with eutrophication- all at a near whole-river scale, for
171	both prokaryotes and microscopic eukaryotes. During the fall of 2014, we completed the most
172	extensive microbiological survey of the Mississippi River to date with a continual rowed transect
173	over 70 days. Rowers from the adventure education non-profit OAR Northwest collected
174	samples from Minneapolis, MN to the Gulf of Mexico (2918 km) (Fig. 1A). Our findings expand
175	the current information available on microbial assemblages in major lotic ecosystems; further

176	delineate the relationship	os between	microbial	structure and	stream order	. nutrients.	and vo	olume:
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and identify MSR taxa predictive of the eutrophication nutrients nitrate and phosphate.

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### 179 Materials and Methods

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### 181 Sampling and Cell Counts

182 We used rowboats and a simple filtration protocol (Supplementary Information) to collect 183 water from 39 sites along a continual-rowed transect of the MSR, starting in Lake Itasca and ending in the GOM, over 70 days from September 18<sup>th</sup> to November 26<sup>th</sup>, 2014. Sites were 184 185 chosen to be near major cities and above and below large tributaries. After some samples were 186 removed due to insufficient sequence data, contamination, or incomplete metadata (see below), 187 the final usable set of samples included 38 sites starting at Minneapolis (Fig. 1A, Table S1, 188 General Information). Most sampling occurred within the body of the river, although due to 189 safety issues, three samples were collected from shore (Table S1, General Information). We 190 collected duplicate samples at each site, but because separate rowboat teams frequently collected 191 these sometimes several dozen meters apart, they cannot be considered true biological replicates 192 and we have treated them as independent samples.

At each site, we filtered 120 mL of water sequentially through a 2.7  $\mu$ m GF/D filter (Whatman GE, New Jersey, USA) housed in a 25 mm polycarbonate holder (TISCH, Ohio, USA) followed by a 0.2  $\mu$ m Sterivex filter (EMD Millipore, Darmstadt, Germany) with a sterile 60 mL syringe (BD, New Jersey, USA). We refer to fractions collected on the 2.7  $\mu$ m and 0.22  $\mu$ m filters as > 2.7  $\mu$ m and 0.2-2.7  $\mu$ m, respectively. Flow-through water from the first 60 mL was collected in autoclaved acid-washed 60 mL polycarbonate bottles. Both filters were wrapped 199 in parafilm, and together with the filtrate, placed on ice in Yeti Roadie 20 coolers (Yeti, Austin, 200 TX) until shipment to LSU. Further, 9 mL of whole water for cell counts was added to sterile 15 201 mL Falcon tubes containing 1 mL of formaldehyde and placed into the cooler. The final cooler 202 containing samples from sites P-Al had substantial ice-melt. Though our filters were wrapped in 203 parafilm, we processed melted cooler water alongside our other samples to control for potential 204 contamination in these filters. Given that some of our samples were expected to contain low 205 biomass, we also included duplicate process controls for kit contamination (Salter et al. 2014; 206 Weiss *et al.* 2014) with unused sterile filters.

207 Flow-through 0.2  $\mu$ m filtered water from each collection was analyzed for SiO<sub>4</sub>, PO<sub>4</sub><sup>3-</sup>,

208  $NH_4^+$ ,  $NO_3^-$ , and  $NO_2^-$  ( $\mu$ g/L) at the University of Washington Marine Chemistry Laboratory

209 (http://www.ocean.washington.edu/story/Marine+Chemistry+Laboratory). Aboard-rowboat

210 measurements were taken for temperature and turbidity. We determined turbidity by deploying a

secchi disk (Wildco, Yulee, FL), while drifting with the current so the line hung vertically. It was

212 lowered until no longer visible, then raised until just visible, and measured for its distance below

the waterline. We then calculated secchi depth from the average of two measurements.

214 Temperature was measured with probes from US Water Systems (Indianapolis, IN), rinsed with

215 distilled water between samples. Samples for cell counts were filtered through a 2.7 µm GF/D

216 filter, stained with 1x Sybr Green (Lonza), and planktonic cells were enumerated using the

217 Guava EasyCyte (Millipore) flow cytometer as previously described (Thrash *et al.* 2015).

Throughout the transect, seven cooler exchanges occurred to ensure samples were not exposed to extended durations at *in situ* temperatures. Cooler temperatures were monitored with HOBO loggers (Onset, Bourne, MA) to ensure that samples stayed at  $\leq$  4°C. On average, a sample spent 7.6 days (median = 6 days, range=1 day minimum, 16 days maximum) at  $\leq$  4°C

222	before delivery to LSU. Though samples were not frozen immediately, previous research has
223	provided evidence that soil and water samples stored at 4°C, and for different durations ( $\geq 14$
224	days), did not show significant alterations to most community relative abundances, structure, or
225	composition (Lauber et al. 2010; Rubin et al. 2013; Tatangelo et al. 2014).
226	
227	DNA extraction and Sequencing
228	DNA was extracted from both filter fractions and controls using a MoBio PowerWater DNA kit
229	(MoBio Laboratories, Carlsbad, CA) following the manufacturer's protocol with one minor
230	modification: in a biosafety cabinet (The Baker Company, Stanford, ME), Sterivex filter
231	housings were cracked open using sterilized pliers and filters were then removed by cutting
232	along the edge of the plastic holder with a sterile razor blade before being placed into bead-
233	beating tubes. DNA was eluted with sterile MilliQ water, quantified using the Qubit2.0
234	Fluorometer (Life Technologies, Carlsbad, CA), and stored at -20° C. Bacterial and archaeal
235	sequences were amplified at the V4 region of the 16S rRNA gene using the 515f and 806r primer
236	set (Caporaso et al. 2012), and eukaryotic sequences from the V9 region of the 18S rRNA gene
237	using the 1391r and EukBR primer set (Amaral-Zettler et al. 2009). Amplicons were sequenced
238	on an Illumina MiSeq as paired-end 250 bp reads at Argonne National Laboratory. Sequencing
239	of the 16S and 18S rRNA gene amplicons resulted in 13,253,140 and 13,240,531 raw sequences,
240	respectively.
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242 Sequence Analysis

243 We analyzed amplicon data with Mothur v.1.33.3 (Schloss *et al.* 2009) using the Silva v.119

database (Pruesse et al. 2007; Quast et al. 2013). Briefly, 16S and 18S rRNA gene sequences

245	were assembled into contigs and discarded if the contig had any ambiguous base pairs, possessed
246	repeats greater than 8 bp, or were greater than 253 or 184 bp in length, respectively. Contigs
247	were aligned using the Silva rRNA v.119 database, checked for chimeras using UCHIME (Edgar
248	et al. 2011), and classified also using the Silva rRNA v.119 database. Contigs classified as
249	chloroplast, eukaryotes, mitochondria, or "unknown;" or as chloroplast, bacteria, archaea,
250	mitochondria, or "unknown;" were removed from 16S or 18S rRNA gene data, respectively. The
251	remaining contigs were clustered using the cluster.split() command into operational taxonomic
252	units (OTUs) using a 0.03 dissimilarity threshold (OTU $_{0.03}$ ). After these steps, 146,725 and
253	131,352 OTUs remained for the 16S and 18S rRNA gene communities, respectively.
254	
255	Sample quality control
256	To evaluate the potential for contamination from extraction kits, cooler water in the last set of
257	samples, or leaking/bursting of pre-filters, all samples were evaluated with hierarchical
258	clustering and NMDS analysis. Hierarchical clustering was performed in R using the hclust
259	function with methods set to "average", from the vegan package (Oksanen et al. 2015). Samples
260	were removed from our analysis if they were observed to be outliers in both the NMDS and
261	hierarchical clustering such that they grouped with our process controls. The process and cooler
262	water controls were extreme outliers in both, as was sample L2 (Fig. S1, S2). Sterivex and
263	prefilter samples generally showed strong separation with the exception of three 16S rRNA gene
264	samples- STER X2, W2, S2 (Fig. S1, S2). The only other samples that were removed were due
265	to missing chemical data (Lake Itasca1-2, A1-2) or failed sequencing (16S STER Af1; 16S PRE
266	S2, X2; 18S PRE O1). Not including process or cooler water controls, 152 samples were
267	sequenced each for prokaryotic and eukaryotic communities. After these QC measures, 144 and

268 149 samples remained in the analyses from the 16S and 18S rRNA gene amplicons, respectively. 269 Further, to control for potential contaminants, any OTU with greater 20 reads in the process or 270 cooler controls was removed from the data set. 146,725 and 131,327 OTUs remained after these 271 steps for 16S and 18S rRNA gene communities, respectively. 272 273 Alpha and Beta Diversity 274  $OTU_{0.03}$  analyses were completed with the R statistical environment v.3.2.1(R Development 275 Core Team 2015). Using the package PhyloSeq (McMurdie and Holmes 2013), alpha-diversity 276 was first calculated on the non-normalized, unfiltered OTUs using the "estimate richness" 277 command within PhyloSeq, which calculates six alpha diversity metrics (McMurdie and Holmes 278 2013). After estimating alpha diversity, potentially erroneous rare OTUs, defined here as those 279 without at least two sequences in 20% of the sites, were discarded. After this filter, the dataset 280 contained 950 and 724 16S and 18S rRNA gene OTUs, respectively. For site-specific 281 community comparisons, OTU counts were normalized using the package DESeq2 (Love et al. 282 2014) with a variance stabilizing transformation (Learman et al. 2016). Beta-diversity between 283 samples was examined using Bray-Curtis distances via ordination with non-metric 284 multidimensional scaling (NMDS). Analysis of similarity (ANOSIM) was used to test for 285 significant differences between groups of samples (e.g lower versus upper MSR) using the 286 anosim function in the vegan package (Oksanen et al. 2015). The influence of Hellinger 287 transformed environmental parameters on beta-diversity was calculated in R with the *envfit* 288 function. Relative abundances plots were made using the R package ggplot2. Linear and non-289 linear regressions were made using the command *stat\_smooth()* with the flag "level=0.95" and 290 method = "lm" or "loess" for linear and non-linear regressions, respectively.

291

# 292 Network analyses and modeling

293	To identify specific OTUs with strong relationships to environmental parameters (e.g. turbidity,
294	NO <sub>3</sub> <sup>-</sup> ), we employed weighted gene co-expression network analysis (WGCNA) (Langfelder and
295	Horvath 2008) as previously described for OTU relative abundances (Guidi et al. 2016). First, a
296	similarity matrix of nodes (OTUs) was created based on pairwise Pearson correlations across
297	samples. This was transformed into an adjacency matrix, which represents the strength at which
298	two OTUs within the matrix are connected (adjacency). To do this, the similarity matrix was
299	raised to a soft threshold power (p; p = 6 for 16S and 18S > 2.7 $\mu$ m, p = 4 for 16S 0.2-2.7 $\mu$ m, p
300	= 9 for 18S 0.2-2.7 $\mu$ m) that maximizes OTU connections with others and ensures scale-free
301	topology fit. Submodules of highly co-correlating OTUs were assigned a color (e.g. yellow,
302	green, turquoise) as defined with a topological overlap measure and hierarchical clustering,
303	which identified submodules based on an OTU's weighted correlations to other OTUs within and
304	outside the network. Each submodule, represented by an eigenvalue, was pairwise Pearson
305	correlated to individual Hellinger-transformed environmental measurements (Figs. S7-10A). To
306	explore the relationship of submodule structure to these parameters, OTUs within the submodule
307	were plotted using their individual correlation to the parameter of interest (y-axis, here nitrate or
308	phosphate) and their submodule membership (x-axis), defined as the strength of an OTU
309	(number of connections) to other OTUs within the submodule (Figs. S7-10B, D). Strong
310	correlations between submodule structure and an environmental parameter facilitate
311	identification of OTUs that are highly correlated to that parameter. To evaluate the predictive
312	relationship between a submodule and a parameter, we employed partial least square regression
313	(PLS) analysis. PLS maximizes the covariance between two parameters (e.g., OTU abundances

314	and nitrate concentration) to define the degree to which the measured value (OTU abundance)
315	can predict the response variable (nutrient concentration). The PLS model was permutated 1000
316	times and Pearson correlations were calculated between the response variable and leave-one-out
317	cross-validation (LOOCV) predicted values. Modeled values were then compared with measured
318	values to determine the explanatory power of the relationships (Figs. S7-10C, E). Relative
319	contributions of individual OTUs to the PLS regression were calculated using value of
320	importance in the projection (VIP) (Chong and Jun 2005) determination. PLS was run using the
321	R package <i>pls</i> (Mevik and Wehrens 2007), while VIP was run using additional code found here:
322	http://mevik.net/work/software/VIP.R. Though other environmental parameters had strong
323	Pearson correlations to submodules, only submodules with strong, positive correlations to
324	measures related to eutrophication were selected, in accordance with our study objectives, as
325	these were most likely to provide candidate taxa with remediation potential.
326	
327	Accession numbers
328	Community 16S and 18S rRNA gene sequence fastq files are available at the NCBI Sequence
329	Read Archive under the accession numbers: SRR3485674 - SRR3485971 and SRR3488881 -
330	SRR3489315, respectively.
331	
332	Code Availability
333	All code used for Mothur, SeqENV, PhyloSeq, WGCNA, and PLS regression analyses can be
334	found on the Thrash lab website (http://thethrashlab.com/publications) with the reference to this

335 manuscript linked to "Supplemental Information".

## 337 Results

338 Using rowboats and a simple syringe-based filtration protocol, we measured 12 biological, 339 chemical, and physical parameters (e.g. 16S and 18S rRNA gene communities,  $NH_4^+$ , river 340 speed, etc.) from 38 sites along a 2918 km transect of the MSR (Fig. 1A). River order increases 341 dramatically at the Missouri confluence [eighth to tenth Strahler order (Pierson et al. 2008)], 342 which corresponded to overall discharge (Fig. 1A) and beta diversity changes discussed below. 343 Therefore, we refer to this juncture as the separator between the upper (0 km - 1042 km, Sites A-S) and lower MSR (1075-2914 km, Sites T-Al). Within the upper MSR,  $NO_3^{-}$ ,  $PO_4^{-3}$ , and  $NO_2^{-1}$ 344 345 were variable but generally increased downriver until peak concentrations near the confluences 346 of the Illinois and Missouri Rivers. This gave way to lower and more consistent concentrations 347 along the lower MSR (Fig. 1B). Turbidity (inversely related to secchi disk visibility) increased 348 steadily downriver to a maximum near the Illinois and Missouri River confluences (1042 km, 349 Site S) (Fig. 1B, Secchi Disk), then trended downwards for the rest of the transect. Planktonic (< 2.7  $\mu$ m) cell counts varied between 1 and  $3x10^6$  cells  $\cdot$  mL<sup>-1</sup> in the upper MSR, and decreased to 350 high 10<sup>5</sup> cells · mL<sup>-1</sup> in the lower MSR (Fig. 1B, Planktonic Cell Counts). Water temperature 351 352 ranged from 19°C (133km, Site E) to 11.7°C (2552 km, Site Ag), and river speed, excluding 353 three sites sampled from shore, was between 5.5 mph at Site Y and 0.4 mph (597 km, Site L) 354 (Table S1, General Information). Spearman rank correlations of the measured environmental 355 parameters showed strong positive correlations between nitrate, phosphate, distance, and 356 increased turbidity; while nitrate and phosphate both strongly correlated negatively to water 357 temperature and river speed (Table S1, Spearman Rank). 358

359 Bacterial and archaeal communities

360	We observed a clear distinction between the 0.2-2.7 $\mu m$ and $>$ 2.7 $\mu m$ 16S rRNA gene
361	communities (ANOSIM $R = 0.65$ , $P = 0.001$ ) (Fig. S1A). Both size fractions also showed
362	significant community separation between sites above and below the Missouri River confluence
363	(ANOSIM, > 2.7 $\mu$ m: R = 0.44, P=0.001; 0.2-2.7 $\mu$ m: R = 0.48, P = 0.001) (Fig. 2A, B), that the
364	Eukaryotic fractions mirrored (below)(Fig. 2C, D). Overall richness was significantly higher in
365	the lower vs. upper rivers (Table S1, Richness comparisons). Taken separately, most
366	measurements indicated that richness increased with river distance in the upper and lower rivers,
367	and this trend was common for both the > 2.7 $\mu m$ and 0.2-2.7 $\mu m$ fractions (Fig. S3A, B).
368	Evenness measurements had less consistent trends.
369	Phosphate and turbidity had the highest correlation with the separation between the upper
370	and lower > 2.7 $\mu$ m communities (R <sup>2</sup> = 0.58, R <sup>2</sup> = 0.54, respectively), with water temperature (R <sup>2</sup>
371	= 0.52) also contributing (Table 1). At an OTU level, taxa related to the acI clade
372	(Actinobacteria) and unclassified <i>Bacillaceae</i> ( $R^2 > 0.77$ , $P = 0.001$ ) contributed most to the
373	separation between the upper and lower $> 2.7$ communities, with OTUs related to the <i>Bacillales</i> ,
374	Gemmatimonadaceae, Peptococcaceae, and Micromonosporaceae clades also a factor ( $\mathbb{R}^2$ >
375	0.70, $P = 0.001$ ) (Table 2). For the 0.2-2.7 µm fraction, nitrate were the strongest correlating
376	environmental factors with the distinction between upper and lower communities ( $R^2 = 0.443$ ),
377	although phosphate, turbidity, and water temperature ( $R^2 > 0.385$ for each) also contributed
378	(Table 1). OTUs related to Flavobacterium and an unclassified Bacterium (closest NCBI BLAST
379	hit Acidovorax sp., KM047473), most strongly contributed to the separation between the 0.2-2.7
380	$\mu$ m communities (R <sup>2</sup> > 0.503, P = 0.0001) (Table 2). Other important OTUs driving the
381	separation between upper and lower communities belonged to the clades Bacteroidetes,
382	<i>Microbacteriaceae</i> , <i>Clostridiales</i> , and <i>Holophagaceae</i> ( $R^2 > 0.49$ , $P = 0.0001$ ) (Table 2).

383	At the phylum level, Proteobacteria, Actinobacteria, and Bacteroidetes dominated
384	bacterial communities in both fractions (Figs. 3A and B) (Table S1, 16S OTU table norm.).
385	Proteobacteria abundance in the $> 2.7 \ \mu m$ fraction fluctuated over the course of the transect (Fig.
386	3A), whereas their 0.2-2.7 $\mu$ m counterparts generally increased in relative abundance downriver
387	(Fig. 3B). 0.2-2.7 $\mu$ m Bacteroidetes and Actinobacteria generally decreased in the upper river
388	and stabilized in the lower river. These phyla showed considerable abundance variation in the $>$
389	2.7 $\mu$ m fraction. Cyanobacteria in the > 2.7 $\mu$ m fraction negatively correlated with increased
390	turbidity (Spearman rank = 0.67), consistent with lower irradiance (Fig. 3A). Both > 2.7 $\mu$ m and
391	$0.2-2.7 \ \mu m$ Acidobacteria increased in abundance downriver and positively correlated with river
392	distance (Wilcoxon single ranked test, $P = < 0.01$ ) (Fig. S4A, B). Within the 0.2-2.7 µm fraction,
393	the five most abundant OTUs were classified as a LD12 (OTU11; Proteobacteria), two acI clade
394	OTUs (OTU4, OTU7; Actionbacteria), a Limnohabitans sp. (OTU2; Proteobacteria), and a LD28
395	(OTU8; Proteobacteria) (Table S1, 16S OTU table norm.). Comparatively, an unclassified
396	Methylophilaceae (OTU1; Proteobacteria), a Planktothrix sp. (OTU12; Cyanobacteria), a NS11-
397	12 marine group (OTU21; Bacteroidetes), an Candidatus Aquirestis sp. (OTU17; Bacteroidetes),
398	and an unclassified Sphingobacteriales (OTU25; Bacteroidetes) were the most abundant OTUs
399	in the $> 2.7 \mu m$ fraction (Table S1, 16S OTU table norm.). Archaea occurred at much lower
400	relative abundances: we found only eight OTUs belonging to the phyla Euryarchaeota and
401	Thaumarchaeota, collectively. These OTUs were classified as Methanobacterium sp. (OTU714,
402	1968) and soil Crenarchaeotic Group (OTU370, 389, 983, and 1253), Candidatus
403	Nitrosoarchaeum sp. (OTU1093) from the phylum Euryarcheota, and an unclassified
404	Thaumarchaeota (OTU2951) from the phylum Thaumarchaeota (Table S1, 16S OTU table
405	norm.). Overall, Thaumarchaeota increased in abundance along the transect more in the $>2.7\mu\text{m}$

406 fraction compared to the 0.2-2.7 µm fraction (Fig. S4A, B). In both fractions, we only detected 407 Euryarcheota at very low abundances. Importantly, the primers used in this study may miss some 408 archaeal taxa (Parada et al. 2015). 409 410 Microbial eukaryotic communities 411 Eukaryotic communities, observed via the 18S rRNA gene, also showed a significant separation 412 between  $> 2.7 \mu m$  and 0.2-2.7  $\mu m$  fractions (ANOSIM R = 0.689, P = 0.001) (Fig. S1B). As 413 expected due to generally larger cell sizes in microbial eukaryotes compared to prokaryotes, 414 species richness remained higher in the  $> 2.7 \,\mu\text{m}$  vs. 0.2-2.7  $\mu\text{m}$  fractions (Fig. S3C, D). Both 415 the > 2.7  $\mu$ m and 0.2-2.7 fractions also showed a significant separation between the upper and 416 lower MSR communities (ANOSIM, > 2.7  $\mu$ m: R = 0.696, P = 0.001; 0.2-2.7  $\mu$ m: R = 0.576, P = 417 (0.001) (Fig. 2C, D). Overall richness in the > 2.7 µm fraction was also higher in the lower vs. 418 upper river, but this was not true for the 0.2-2.7 µm fraction (Table S1, Richness comparisons). 419 Richness in the  $> 2.7 \,\mu m$  fraction increased along both the upper and lower river, similarly to 420 prokaryotic communities, but remained relatively stable within the 0.2-2.7 µm fraction. 421 Phosphate was the top environmental factor correlating to the distinction between eukaryotic communities in both filter fractions (> 2.7  $\mu$ m, R<sup>2</sup> = 0.49; 0.2-2.7  $\mu$ m R<sup>2</sup> = 0.56) 422 423 (Table 1). No other factors had correlations > 0.38 (Table 1). At the OTU level, taxa related to an 424 unclassified Ochrophyta (OTU63) and an unclassified Eukaryote (OTU1) separated the 0.2-2.7  $\mu$ m communities (R<sup>2</sup> > 0.645, P = 0.0001), while the same unclassified Eukaryote OTU (OTU1) 425

- 426 and a second unclassified Eukaryote (OTU222) contributed most to separating the  $>2.7\,\mu m$
- 427 communities ( $R^2 > 0.80$ , P = 0.0001) (Table 2).

428	Stramenopiles (or Heterokonts), encompassing diatoms and many other forms of algae,
429	and OTUs that could not be classified at the phylum level dominated both the $> 2.7\mu m$ and 0.2-
430	$2.7 \mu m$ communities (Fig. 3C, D). Stramenopiles accounted for over 25% of both communities,
431	with higher abundances in the upper vs. lower river. We observed a similar trend of disparate
432	abundances between the upper and lower river for $>2.7~\mu m$ Cryptomonadales and 0.2-2.7 $\mu m$
433	Nucletmycea, the latter of which include fungi (Fig. 3C; Table S1, 18S OTU table norm.).
434	Within the 0.2-2.7 $\mu$ m fraction, we identified the five most abundant OTUs as three unclassified
435	Bacillariophytina (OTU7, OTU14, OTU9), a Pythium sp. (OTU170), and an unclassified
436	Cryptomonas (OTU11) (Table S1, 18S OTU table norm.). Comparatively, two unclassified
437	Eukaryotes (OTU2 and OTU1), an unclassified Stramenopiles (OTU3), an unclassified
438	Perkinsidae (OTU13), and an unclassified Chrysophyceae (OTU6) had the highest abundance in
439	the > 2.7 $\mu$ m fraction (Table S1, 18S OTU table norm).
440	

- 441 The Mississippi River Core Microbiome
- 442 We defined the core microbiome as those OTUs detectable after normalization in greater than
- 443 90% of the sites. The 16S rRNA gene > 2.7  $\mu$ m and 0.2-2.7  $\mu$ m core microbiomes consisted of
- 444 82 and 98 OTUs, respectively, classified into eight different phyla- Proteobacteria,
- 445 Actinobacteria, Bacteroidetes, Cyanobacteria, Verrucomicrobia, Chloroflexi, Chlorobi,
- 446 Gemmatimonadetes- and composed of taxa such as freshwater SAR11 (LD12, Proteobacteria),
- 447 Limnohabitans sp. (Proteobacteria), Polynucleobacter sp. (Proteobacteria), acI clade
- 448 (Actinobacteria), LD28 clade (Proteobacteria), and *Planktothrix* sp. (Cyanobacteria) (Table S1,
- 449 16S 0.2-2.7  $\mu$ m Core Comm. and 16S > 2.7  $\mu$ m Core Comm.). Core microbome relative
- 450 abundance in both fractions decreased along the upper river but stabilized in the lower river (Fig.

451	4A). We confirmed this effect by analyzing the upper and lower core microbiomes separately.
452	Although the total OTU numbers changed (81 and 116 OTUs in the upper MSR and 160 and 144
453	OTUs in the lower MSR for the > 2.7 $\mu m$ and 0.2-2.7 $\mu m$ fractions, respectively), the trends
454	remained the same (Fig. S5).
455	Eighty OTUs comprised the > 2.7 $\mu$ m 18S rRNA gene core microbiome (Fig. 4B). We
456	classified these as Alveolata, Cryptophceae, Nucletmycea, Stramenopiles, or unclassified
457	Eurkaryota (Table S1, $18S > 2.7 \ \mu m$ Core Comm.). Again, consistent with larger organism sizes,
458	and thus fewer OTUs overall, the 0.2-2.7 $\mu$ m Eukaryotic core microbiome comprised only 21
459	OTUs (Table S1, 18S 0.2-2.7 µm Core Comm.). These OTUs consisted of Alveolata,
460	Nucletmycea, Stramenopiles, or unclassified Eurkaryota (Table S1, 18S 0.2-2.7 µm Core
461	Comm.). While the 0.2-2.7 $\mu m$ core microbiome remained relatively stable along the river, the $>$
462	$2.7 \mu m$ core decreased along the upper MSR before stabilizing in the lower river, similarly to
463	that of the prokaryotes (Fig. 4B).
464	
465	Network analyses identify taxa associated with and predictive of eutrophication
466	We applied Weighted Gene Correlation Network Analysis (WGCNA) to identify co-occurring
467	groups of OTUs (submodules) that also had significant associations with the eutrophication
468	nutrients phosphate and nitrate. Of the submodules identified through WGCNA as being most
469	strongly correlated to phosphate and nitrate, we restrict our discussion to those modeled via PLS
470	analysis to predict $> 50\%$ of the measured nutrient concentration. Our additional PLS analyses
471	for those submodules predicting < 50% of nitrate and/or phosphate concentrations are included
470	

472 in Figure S6 and Figure S7-S10.

473	Three submodules in the prokaryotic and eukaryotic fractions were strongly associated
474	with phosphate. The 0.2-2.7 $\mu m$ prokaryotic submodule most associated with phosphate was
475	composed of 51 OTUs (Table 3), and had moderate correlation between the submodule structure
476	and phosphate (Fig. S7D). Strong correlations between submodule structure and the measured
477	nutrient suggests that individual submodule OTUs that also have strong correlations to the
478	nutrient are the most important organisms associated with that nutrient (Langfelder and Horvath
479	2008). PLS modeling determined that this prokaryotic submodule predicted 80% of measured
480	phosphate concentrations (Figure S7E, Table 3). Variable importance in the projection (VIP)
481	analysis found OTUs corresponding to an unclassified Holophagaceae, an unclassified
482	Gemmatimonadaceae, and an unclassified Burkholderiaceae were the three most important in
483	the PLS model for phosphate (Fig. 5A, Table S1, 16S 0.2-2.7 $\mu m$ PO4). OTU322 (Acidobacteria
484	subgroup 6), had moderate correlation to phosphate but high node centrality ( $n = 51$ ; Fig. 5A,
485	Table S1, 16S 0.2-2.7 $\mu$ m PO4), corroborating evidence that freshwater sediment Acidobacteria
486	subgroup 6 often occur in co-culture with Alphaproteobacteria and may be metabolically
487	connected (Kielak <i>et al.</i> 2016 and refs. within). A submodule from the 0.2-2.7 $\mu$ m eukaryotic
488	fraction was also highly predictive of phosphate (Table 3, Fig. S8D). We identified the top four
489	VIP taxa as an unclassified Peronosporomycetes, an unclassified Ochrophyta, an unclassified
490	Eukaryote, and an unclassified Stramenopiles (Fig. 6A, Table S1, 18S 0.2-2.7 µm PO4). All four
491	OTUs had Pearson correlations with phosphate greater than 0.60, among which two were
492	negative (Fig. 6A, Table S1, 18S 0.2-2.7 $\mu$ m PO4). Unfortunately, the most highly
493	interconnected OTU within the submodule remained unclassified even at the Phylum level (Fig.
494	6A, Table S1, 18S 0.2-2.7 $\mu m$ PO4). A $>$ 2.7 $\mu m$ eukaryotic submodule could predict 62% of

495	measured phosphate variance (Table 3). An unclassified Eukaryote and an unclassified
496	<i>Peronosporomycetes</i> occupied top two VIP positions (Fig. 6B, Table S1, $16S > 2.7 \mu m$ PO4).
497	Only two submodules had strong associations with nitrate. The $> 2.7 \ \mu m$ prokaryotic
498	submodule most strongly correlated with nitrate contained 133 OTUs (Table 3, Fig. S9A).
499	However, despite a low structural correlation to nitrate, the submodule strongly predicted
500	measured nitrate in the PLS model (Figure S9B, Table 3). The four highest VIP scoring OTUs
501	were an Anabaena sp., a Flavobacterium sp., an unclassified bacterium, and a member of the
502	Sphingobacteriales NS11-12 marine group (Fig. 5B, Table S1, $16S > 2.7 \ \mu m NO3$ ). OTUs with
503	the highest node centrality (> 20) belonged to the Sphingomonadales (Alphaproteobacteria) and
504	Sphingobacteriales (Bacteroidetes), and each positively correlated with nitrate ( $R > 0.48$ , Fig.
505	5B, Table S1, 16S > 2.7 $\mu m$ NO3). The > 2.7 $\mu m$ eukaryotic submodule most associated with
506	nitrate predicted 57% of observed variation in nitrate concentrations (Table 3). OTUs with the
507	top VIP scores were two unclassified Chrysophyceae, an unclassified Ochrophyta, and an
508	unclassified Diatom (Fig. 6C, S10; Table S1, 18S > 2.7 $\mu$ m NO3).
509	
510	Discussion
511	Understanding microbial communities on a whole-river scale is essential for linking the complex
512	relationships between microorganisms, metabolism, and water quality. At 2914 km, this study is

513 the largest transect of the MSR to date, and the first to include both prokaryotic and eukaryotic

- 514 data by size fractions. This is also the largest river yet surveyed at this level of geographic
- 515 completion, which may account for some of its distinctive microbiological features. Although the
- 516 MSR comprised similar aquatic microbial taxa found within other rivers (Zwart *et al.* 2002;
- 517 Cottrell *et al.* 2005; Ghai *et al.* 2011; Fortunato *et al.* 2013; Jackson *et al.* 2014; Read *et al.* 2015;

518 Savio et al. 2015; Meziti et al. 2016), it hosted unique relative abundance and core microbiome 519 trends, indicating that rivers have distinguishing microbiome characteristics. Furthermore, we 520 observed two different community regimes separated at the Missouri River confluence and 521 mirrored by the measured physio-chemical properties of the MSR (Fig. 1B). This is an important 522 hydrological feature of the MSR that strongly influences its microbiology, and further 523 distinguishes it from other rivers. Our study also identified taxa associated with, and predictive 524 of, the eutrophication nutrients nitrate and phosphate that provide important targets for future 525 study and may assist in detecting and quantifying imminent changes in river water quality. 526 MSR microbial communities separated into two distinct fractions of microbial 527 assemblages, 0.2-2.7  $\mu$ m and > 2.7  $\mu$ m (ANOSIM, R = 0.65, P = 0.001), throughout the river 528 transect, a common feature of aquatic ecosystems (DeLong et al. 1993; Crump et al. 1999; 529 Allgaier and Grossart 2006; D'Ambrosio et al. 2014; Jackson et al. 2014). However, despite 530 sharing similar taxa with other rivers (Ghai et al. 2011; Fortunato et al. 2012; Crump et al. 2012; 531 Read et al. 2015; Savio et al. 2015; Meziti et al. 2016; Niño-García et al. 2016), MSR microbial 532 community abundances were distinct at a phylum level from previous work on Thames River 533 (Read et al. 2015), Danube River (Savio et al. 2015), Canadian Boral Rivers (Niño-García et al. 534 2016), Toolik catchment (Crump et al. 2012), and Yenisei River (Kolmakova et al. 2014). 535 Specifically, within the 0.2-2.7µm MSR prokaryotic fraction, Proteobacteria remained the most 536 abundant phylum throughout the river, while Bacteroidetes and Actinobacteria decreased 537 downriver (Fig. 3). In contrast, other river studies found headwaters dominated by Bacteroidetes 538 that gave way to more abundant Actinobacteria and Proteobacteria further downriver (Read et al. 539 2015; Savio et al. 2015). Similarly, the trends observed in the upper portion of the MSR (Staley 540 et al. 2013), where Bacteroidetes and Actinobacteria decreased while Proteobacteria increased,

541	diverged from the trends found in this study (Fig. 3). Further, while no clear increasing or
542	decreasing trends were observed in Payne et al. (2017), Actinobacteria occurred with the highest
543	relative abundances in the planktonic fraction, whereas in this study, Proteobacteria were the
544	most abundant phylum. This may be attributable to the difference in sampling year or possibly
545	methodology, such as an amplification step that was not undertaken in this work (Payne et al.
546	2017). Furthermore, although many of the dominant taxa found in other rivers also occupied the
547	MSR (LD12 (freshwater SAR11, Alphaproteobacteria), Limnohabitans sp.
548	(Betaproteobacteria), LD28 (Betaproteobacteria), acI clade (Actinobacteria), and Algoriphagus
549	sp. (Bacteriodetes) (Ghai et al. 2011; Fortunato et al. 2013; Kolmakova et al. 2014; Read et al.
550	2015; Savio et al. 2015; Meziti et al. 2016), we observed OTU-level abundance differences at a
551	whole-river scale. For example, OTUs belonging to the acI and LD12 freshwater clades
552	continually increased in abundance towards the river mouth in the Thames and Danube Rivers
553	(Read et al. 2015; Savio et al. 2015), whereas MSR OTUs classified as acl (OTUs 3, 4 and 7)
554	and LD12 (OTU 11) did not show any distinct change in abundance throughout the transect.
555	Specific to studies of portions of the MSR,
556	The generally greater richness (Table S1, Richness comparisons) and decreased core
557	microbial community abundances (Fig. 4) in the lower vs. upper MSR contrasted predictions by
558	the RCC (Vannote et al., 1980) and observations in previous studies from both large and small
559	rivers (Read et al. 2015; Savio et al. 2015, Niño-García et al. 2016) where these trends were
560	reversed. Importantly, we did not sample the true headwaters of the MSR (Lake Itasca to above
561	St. Cloud), and at the point of first sampling, the MSR already constituted an eighth order river.
562	Therefore, some of the trends predicted by the RCC may have been missed, although increasing

563 richness was also observed in the lower MSR during a different year (Payne *et al.* 2017).

Ultimately, the variant observations between this MSR survey and other river studies may result
from different sampling methodologies or the particular timing of sampling. Previous studies
conducted on six artic rivers (Crump *et al.* 2009), two smaller temperate rivers (Parker and
Ipswich Rivers) (Crump and Hobbie 2005), and the upper portion of the MSR (Staley *et al.*2015) showed that seasonality was important in structuring bacterial communities over three year
and two year sampling periods.

570 However, our observed differences may also stem from biological signal related to 571 unique environmental conditions, human impacts (Meziti et al. 2016; Payne et al. 2017), and 572 changes in hydrology and the level of river engineering (Ruiz-González et al. 2013, 2015; 573 Freimann et al. 2015; Niño-García et al. 2016) with distance. For instance, the most striking 574 difference between the MSR and other rivers was the distinct separation of prokaryotic and 575 eukaryotic community regimes at the Missouri River confluence. This separation matched 576 physio-chemical changes observed for the MSR such as increased Strahler river order (8 to 10) 577 and more consistent nutrient concentrations in the lower river compared to the upper (Fig. 1B) 578 (Pierson *et al.* 2008). These results are bolstered by another observation depicting a major 579 separation of communities above and below the Missouri confluence, observed during a different 580 year (2012) and roughly three months prior (late summer) to the current study (Payne *et al.*) 581 2017). This similarity to our results suggests the major influence of the Missouri River 582 confluence is not seasonally dependent. 583 Although the overall microbial community patterns in the MSR differed from other 584 rivers, we hypothesize that similar ecological processes drove the separation between the upper

resource gradient dynamics (Crump *et al.* 2012; Savio *et al.* 2015; Niño-García *et al.* 2016).

and lower MSR communities, namely changes in the importance of immigration, emigration, and

585

587 Specifically, our data suggest that mass effects play a role in structuring microbial communities 588 in the upper MSR, although instead of only in the headwaters, this process continues for almost a 589 third of the length of the river, possibly due to contributions from large tributaries and abundant 590 dams. This contrasts with the conclusion made by Staley et al. (2015) for a smaller transect in 591 the upper MSR, where they suggested species sorting was the primary influence structuring 592 upper MSR microbial communities. Increased turbidity correlated with decreased core 593 microbiome relative abundance (Spearman rank correlation,  $> 2.7 \,\mu m R = 0.53$ ; 0.2-2.7  $\mu m R =$ 594 0.63) in the upper MSR, and nutrients like phosphate and nitrate continually increased along the 595 upper river in the current study (Fig. 1B). Similarly, richness also increased along the upper river 596 (except in the 0.2-2.7 µm 18S communities) (Fig. S3). These patterns are consistent with 597 communities under the influence of strong mass effects in the upper MSR, whereby inputs from 598 allochthonous sources continually contributed nutrients, particulate matter, and additional 599 microbial taxa.

600 Conversely, nitrate, phosphate, turbidity, and core microbiome relative abundance all 601 stabilized in the lower MSR (Figs. 1B, 4), suggesting a change in the relative influence of 602 external sources for these variables. We speculate that once the MSR grew to a tenth order river, 603 its large volume and size buffered it from allochthonous inputs. Nevertheless, overall richness 604 was greater in the lower river compared to the upper (except in the  $0.2-2.7 \,\mu m$  18S communities) 605 (Table S1, Richness comparisons), and, like the upper river, richness generally increased in the 606 lower river (Fig. S3), matching a previous observation (Payne et al. 2017). However, since the 607 relative abundance of core microbiome taxa remained comparatively stable in the lower river 608 (Fig. 4), increased richness likely occurred primarily from the emergence of low abundance 609 OTUs. The extent to which a local or regional event impacts downriver populations is dependent

on the success of allochthonous taxa associated with such an event to become established within the autochthonous population (Crump *et al.* 2012; Niño-García *et al.* 2016). The larger the river, the less likely any newly immigrated taxa will establish dominance. Thus, a plausible scenario for the regime change observed at the Missouri River confluence is that the influence of mass effects was drastically reduced by the increased size of the lower river, and that allochtonous taxa immigrating there were relegated to lower abundances.

616 Alternatively, some of the increase in richness may have occurred through native 617 community differentiation within the lower river. An overall community shift from a mixture of 618 allochthonous members to a "native" population requires growth rates greater than residence 619 time over a given distance (Crump et al. 2004). Though river speed increased along the MSR, 620 the effective residence time also increased since taxa no longer experienced rapidly changing 621 environmental variables (Fig. 1B). As a result, the lower river may have provided opportunities 622 for microbial community differentiation based on microniches within the river, which is possible 623 considering average prokaryotic growth rates (Savio et al. 2015), especially among particle-624 associated (>  $2.7 \,\mu$ m) taxa (Crump *et al.* 1998). Thus, although the aggregate patterns in 625 particular phyla and the overall taxonomic richness within the MSR differ from other systems, 626 similar ecological processes may still drive these patterns, but the relative proportion of the river 627 whereby mass effects vs. species sorting dominates fosters unique community assemblages 628 (Niño-García *et al.* 2016). To resolve the relative importance of mass effects vs. species sorting 629 in the upper and lower rivers, future work will need to incorporate explicit measurements of 630 immigrating and emigrating taxa, as well as growth rates for different organisms at different 631 geographic positions.

632	Within this dynamic river system, we also sought to define the microorganisms most
633	associated with eutrophication nutrients to provide specific taxa for future study of nitrate and
634	phosphate uptake and/or metabolism, and also as plausible biological indicators of river trophic
635	state. By focusing on OTUs with the highest VIP scores in the PLS models, we identified several
636	bacterial and eukaryotic taxa that fit these criteria (Figs. 5, 6). Organisms in the
637	Sphingomonadaceae (e.g., Novosphingobium spp.) contributed strongly to the PLS models
638	predicting nitrate with both > 2.7 $\mu$ m (Fig. 5B) and 0.2-2.7 $\mu$ m (Fig. S6A) size fractions (Table
639	S1, 16S 0.2-2.7 $\mu$ m VIP NO3 and 16S > 2.7 $\mu$ m VIP NO3). <i>Novosphingobium</i> spp. isolates have
640	previously been associated with eutrophic environments (Trusova and Gladyshev 2002; Zwart <i>et</i>
641	al. 2002; Addison et al. 2007; Li et al. 2012) and some can reduce nitrate (Addison et al. 2007;
642	Li <i>et al.</i> 2012), making these specific OTUs candidates for nitrate metabolism in the river water
643	column. An <i>Anabaena</i> sp. (OTU40) from the core microbiome (Table S1, 16S > 2.7 $\mu$ m Core
644	Comm.) had the top VIP score within the > 2.7 $\mu$ m submodule that could predict 69% of nitrate
645	concentrations, and correlated negatively with nitrate (Table 3, Fig. 5B). The nitrogen-fixing
646	Anabaena spp. (Allen and Arnon 1955) typically bloom in low dissolved inorganic nitrogen
647	(DIN) conditions (Wood <i>et al.</i> 2010), making the absence of these consistent with high DIN. An
648	unclassified <i>Holophagaceae</i> OTU (OTU33) had the highest VIP score within the prokaryotic
649	$0.2-2.7 \mu\text{m}$ submodule that predicted 80% of the variance in phosphate concentrations (Table 3,
650	Fig. 5A). This same OTU was also a key driver of the beta diversity separation between upper
651	and lower river communities (Table 2), and a member of the core microbiome (Table S1, 16S
652	$0.2-2.7 \mu\text{m}$ Core Comm.). The <i>Holophagaceae</i> belong to the Acidobacteria phylum, and the
653	Ohio River contained a much higher abundance of Acidobacteria relative to other tributaries in a
654	previous study (Jackson et al. 2014). Notably, Acidobacteria increased with river distance in our

655	study as well (Fig. S4), with a peak in the 0.2-2.7 $\mu$ m fraction near the Arkansas River
656	confluence. This increase in "free-living" Acidobacteria downriver is distinct from other whole
657	river studies, making these organisms, and the Holophagaceae OTUs in particular, potentially
658	important organisms for the MSR river basin specifically.
659	Within Eukaryotes, multiple different algae, diatom, and Oomycetes OTUs occupied
660	submodules highly predictive of nitrate and phosphate (Fig. 6A-C), and specifically
661	Chrysophyceae taxa from both size fractions correlated strongly with nitrate (Fig. 6C, Fig. S6E).
662	Chrysophyceae (golden algae) commonly occupy river systems (Necchi Jr 2016) including the
663	MSR (Korajkic et al. 2015), can be autotrophic and mixotrophic (Jansson et al. 1996), and may
664	serve as predators of prokaryotes (Caron et al. 1990). Further, multiple OTUs classified as
665	Peronosporomycetes were important in predicting phosphate in both size fractions (Fig 6A, B,
666	Table S1, 18S 0.2-2.7 $\mu$ m VIP PO4 and 18S > 2.7 $\mu$ m VIP PO4). <i>Peronosporomycetes</i> are
667	fungus-like eukaryotic organisms known to be pathogenic in fish, plants, and mammals (Dick
668	2003; Islam and von Tiedemann 2011). While we also identified many other eukaryotic OTUs as
669	important predictors of nutrients, poor taxonomic resolution hindered our ability to discuss them
670	further. Improved cultivation and systematics of key microbial eukaryotes will be vital to
671	understanding river nutrient dynamics.
672	While the most geographically comprehensive analysis to date for the MSR, this study
673	only encompasses a snapshot in time. As noted previously, seasonal changes that have been
674	observed in other rivers (Crump and Hobbie 2005; Crump et al. 2009; Smith et al. 2010;

Fortunato et al. 2013; Staley et al. 2015) undoubtedly influence this dynamic system, though the

permanence of the regime change at the Missouri River confluence remains in question. Future

studies should incorporate microbial responses, at a whole-river scale, to seasonal pulse events

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678 (e.g. rain, snow melt), and how river size and volume may buffer local microbial communities 679 from allochthonous inputs (Zeglin 2015). Our current research highlights the distinctiveness of 680 MSR microbial communities and the complexities influencing their structure within the MSR 681 ecosystem. The observed association between changes in Strahler's river order, nutrient 682 dynamics, and community composition indicates the importance of hydrology on the spatial 683 dynamics structuring microbial communities (Freimann et al. 2015; Zeglin 2015; Niño-García et 684 al. 2016) and provides baseline information for future MSR studies that incorporate greater 685 temporal and spatial resolution. With river water quality of growing local and global importance 686 (Vorosmarty et al. 2010; Russell and Weller 2013), the candidate taxa predictive of eutrophic 687 nutrients determined herein also provide important targets for further research into their roles for 688 indicating, and potentially improving, river health.

689

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# 706 Conflict of Interest

707 The authors declare no competing financial interests.

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#### 996 Tables

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Variable		NMDS1	NMDS2	<b>P-value</b>	$\mathbf{R}^2$		NMDS1	NMDS2	<b>P-value</b>	$\mathbf{R}^2$	
$PO_4^{3-}$	шщ	+	+	0.001	0.404	m	+	+	0.001	0.575	
SiSO <sub>4</sub>	0.2-2.7	-	+	0.003	0.183	2.7 μ	-	-	0.015	0.115	
NO <sub>3</sub>	e <b>0.2</b>	+	+	0.001	0.443	le >	+	+	0.001	0.33	
$NH_4^+$	Gene	-	-	0.002	0.178	Gene	-	-	0.004	0.189	
NO <sub>2</sub>	rRNA (	Not significant						Not significant			
River Speed	rR)	-	-	0.001	0.261	6S rRNA	-	-	0.001	0.39	
Water Temperature	16S	-	-	0.001	0.385	16	-	-	0.001	0.524	
Turbidity		-	-	0.001	0.409		-	-	0.001	0.536	
$PO_4^{3-}$	mu	+	+	0.001	0.555	I	+	-	0.001	0.486	
SiSO <sub>4</sub>	r.	-	+	0.001	0.264	.7 µm	-	-	0.001	0.265	
NO <sub>3</sub>	0.2-2		Not signi	ficant		<b>7</b>	+	+	0.001	0.2	
$NH_4^+$	Gene (	-	+	0.019	0.106	Gene		Not signi	ficant		
NO <sub>2</sub> -		Not significant						Not significant			
River Speed	rRNA	-	-	0.001	0.282	rRNA	-	-	0.001	0.345	
Water Temperature	18S r	-	-	0.001	0.29	8S	-	-	0.001	0.372	
Turbidity	16	-	-	0.001	0.272		-	-	0.001	0.353	

**Table 1.** Summary of the correlations between environmental variables and microbial community beta diversity ordination on NMDS plots in Figure 2. +/- designates the direction of the association between the environmental variable and NMDS axis

	OTU	Classification	NMDS1	NMDS2	P-value	$\mathbf{R}^2$		OTU	Classification	NMDS1	NMDS2	P-value	$\mathbf{R}^2$
	OTU372	Unc. Bacteria	+	-	0.0001	0.604		ОТИЗ	acI clade	+	+	0.0001	0.796
	OTU135	Flavobacterium sp.	-	-	0.0001	0.522		OTU181	Unc. Bacillaceae	-	+	0.0001	0.773
Gene 0.2-2.7 μm	OTU29	<i>Fluviicola</i> sp. Unc.	-	-	0.0001	0.509	7 µm	OTU145	Desulfosporosinus sp.	-	+	0.0001	0.742
e 0.2-2	<i>OTU4</i> 8	Microbacteriaceae	-	+	0.0001	0.508	le > 2.	OTU13	Unc. Bacillales Unc.	-	+	0.0001	0.740
Gen	<i>OTU115</i>	Flavobacterium sp.	-	+	0.0001	0.503	Gene	OTU68	Micromonosporaceae	-	+	0.0001	0.726
rRNA	OTU33	Unc. Holophagaceae	+	+	0.0001	0.501	<b>r</b> RNA	<i>OTU202</i>	Unc. Bacillales Unc.	-	+	0.0001	0.725
16S	OTU161	Flavobacterium sp.	-	-	0.0001	0.501	16S	OTU60	Gemmatimonadaceae	+	+	0.0001	0.716
	<i>OTU100</i>	<i>Clostridium</i> sp. Unc.	+	+	0.0001	0.497		<i>OTU89</i>	Unc. Bacillales Unc.	-	+	0.0001	0.702
	<i>OTU</i> 85	Peptostreptococcaceae Unc.	+	+	0.0001	0.496		OTU169	Micromonosporaceae	-	+	0.0001	0.698
	OTU62	Comamonadaceae	-	+	0.0001	0.493		OTU28	Unc. Planococcaceae	-	+	0.0001	0.694
	OTU1	Unc. Eukaryota	+	+	0.0001	0.693		OTU1	Unc. Eukaryote	+	+	0.0001	0.870
a	OTU63	Unc. Ochrophyta	-	-	0.0001	0.645	_	OTU222	Unc. Ochrophyta	+	+	0.0001	0.806
7 µm	OTU241	Unc. Ochrophyta	-	+	0.0001	0.642	шщ	ОТ ИЗ	Unc. Stramenopiles	+	-	0.0001	0.796
2-2.	OTU133	Unc. Ochrophyta	-	+	0.0001	0.632	, 2.7	OTU1984	Unc. Eukaryote	+	-	0.0001	0.794
Gene 0.2-2.7	OTU219	Unc. Eukaryota	+	+	0.0001	0.630	ene >	OTU345	Unc. Ochrophyta	-	-	0.0001	0.792
A Ger	OTU113	Unc. Alveolata	+	+	0.0001	0.616	G	OTU112	Unc. Cryptomonadales	+	+	0.0001	0.779
rRNA	OTU154	Unc. Ochrophyta	-	-	0.0001	0.598	rRNA	OTU63	Unc. Eukaryote	+	+	0.0001	0.773
18S r	OTU481	Unc. Eukaryota	-	-	0.0001	0.598	<b>18S</b>	OTU154	Chrysophyceae clone P34.45	-	-	0.0001	0.773
	OTU457	Unc. Eukaryota	-	-	0.0001	0.596		OTU155	Bacillariophytina	+	+	0.0001	0.765
	OTU3	Unc. Stramenopile	+	+	0.0001	0.594		OTU1146	Unc. Eukaryote	+	+	0.0001	0.765

**Table 2**. Summary of the correlations between OTUs and microbial community beta diversity ordination on NMDS plots in Figure 2. +/- designates the direction of the association between the OTU and NMDS axis.

Fraction	Gene	Nutrient	Submodule	Eigen Correlations	Total OTUs	PLS model
0.2-2.7 μm	16S	NO3 <sup>2-</sup>	Blue	R = 0.6, P = 7e-08	77	$R^2=0.35; R = 0.65, P = 1.e-09$
$> 2.7 \mu m$	16S	NO3 <sup>2-</sup>	Brown	R = 0.56, P = 3e-07	133	$R^2 = 0.69; R = 0.83, P = < 2.2e-16$
0.2-2.7 μm	16S	PO4 <sup>3-</sup>	Turquoise	R = 0.53, P = 2e-06	51	$R^2=0.80; R = 0.89, P = < 2.3e-16$
> 2.7 µm	16S	PO4 <sup>3-</sup>	Yellow	R = 0.53, P = 1e-06	80	$R^2 = 0.48; R = 0.77, P = 4.88e-15$
0.2-2.7 µm	18S	NO3 <sup>2-</sup>	Green	R = 0.39, P = 6e-04	39	$R^2=0.38; R=0.62, P=2.97e-9$
> 2.7 µm	18S	NO3 <sup>2-</sup>	Brown	R = 0.52, P = 2e-06	59	R <sup>2</sup> =0.572; R = 0.759, P= 6.7e-15
0.2-2.7 µm	18S	PO <sub>4</sub> <sup>3-</sup>	Turquoise	R = 0.56, P = 2e-07	56	$R^2=0.80; R = 0.89, P = < 2e-16$
> 2.7 µm	18S	PO <sub>4</sub> <sup>3-</sup>	Red	R = 0.60, P = 2e-08	39	$R^2 = 0.618; R = 0.799, P = < 2e-16$

**Table 3.** Correlations between prokaryotic and eukaryotic submodules to nitrate and phosphate, as well as PLS model results

### 1005 **Figure Legends**

1006	
1007	Figure 1. Sampling map (A) with graph inserts that represent the measured discharge rate (cubic

- 1008 meter second<sup>-1</sup> [cms]) as recorded on the USGS gauges, and six environmental parameters
- 1009 measured along the transect, according to concentration or visible depth of secchi disk by
- 1010 distance (B). Throughout the figure and text, blue and red dots represent sampling
- 1011 locations above and below the Missouri River confluence, respectively, and are designated
- 1012 throughout as "upper" and "lower." Cell Counts only represent the Planktonic (< 2.7 μm)
- 1013 fraction.
- 1014 Figure 2. Non-metric multidimensional scaling (NMDS) results for whole community. The four
- 1015 plots represent > 2.7  $\mu$ m (A, C) and 0.2-2.7  $\mu$ m (B, D) fractions for the 16S (A, B) and
- 1016 18S (C, D) rRNA gene communities.
- 1017 Figure 3. Relative abundance, according to transect distance, for the top 6 and 5 phyla in the 16S
- 1018 rRNA gene > 2.7  $\mu$ m (A) and 0.2-2.7  $\mu$ m (B) communities and 18S rRNA gene > 2.7  $\mu$ m
- 1019 (C) and 0.2-2.7 μm (D) communities, respectively. Non-linear regressions with 95% CI
- 1020 (gray shading) are provided for reference.
- 1021 Figure 4. Core microbiome aggregate abundance for the 16S (A) and 18S (B) rRNA gene. In
- 1022 each, triangles and circles points represent 0.2-2.7  $\mu$ m and > 2.7  $\mu$ m fractions,
- 1023 respectively. Non-linear regressions with 95% confidence intervals (CI) (gray shading) are
- 1024 provided for reference.
- 1025 Figure 5. PLS results for the 16S rRNA gene community submodules most associated with
- 1026 phosphate (A) and nitrate (B). OTU correlation with a given nutrient is indicated on the y-
- 1027 axis according to the number of co-correlations (node centrality) on the x-axis.
- 1028 Community fractions:  $0.2-2.7 \mu m$  (A) and  $> 2.7 \mu m$  (B). Circle size is proportional to VIP

1029	scores, with top 10 VIP scoring and top node centrality OTUs labeled with their highest-
1030	resolution taxonomic classification and OTU number. Colors represent the taxonomic
1031	classification the phylum level. For all OTU taxonomic designations resulting from this
1032	analysis, see Table S1 "16S 0.2-2.7 $\mu$ m PO4" and "16S > 2.7 $\mu$ m NO3".
1033	Figure 6. PLS results for the 18S rRNA gene community submodules most associated with
1034	phosphate and nitrate. OTU correlation with a given nutrient is indicated on the y-axis
1035	according to the number of co-correlations (node centrality) on the x-axis. Community
1036	fractions: 0.2-2.7 $\mu$ m (A) and > 2.7 $\mu$ m (B, C). Circle size is proportional to VIP scores,
1037	with top 10 VIP scoring and top node centrality OTUs labeled with their highest-
1038	resolution taxonomic classification and OTU number. Colors represent the taxonomic
1039	classification the phylum level. For all OTU taxonomic designations resulting from this
1040	analysis, see Table S1 "18S 0.2-2.7 $\mu$ m NO3", "16S > 2.7 $\mu$ m PO4", and "16S >2.7 $\mu$ m
1041	NO3"
1042	
1043	Supplemental Figure Legends
1044	
1045	Figure S1. NMDS results for the 16S (A) and 18S (B) rRNA gene communities. In each, circles
1046	and triangles represent the > 2.7 $\mu m$ and 0.2-2.7 $\mu m$ fractions, respectively.
1047	Figure S2. Hclust results for the 16S (A) and 18S (B) rRNA gene communities.
1048	Figure S3. Separated upper and lower MSR Richness and Evenness indexes for the 16S > 2.7
1049	$\mu m$ (A) and 0.2-2.7 $\mu m$ (B) and 18S > 2.7 (C) and 0.2-2.7 $\mu m$ (D) communities. Linear
1050	regressions with 95% CI (gray shading) are provided for reference.
1051	Figure S4. Relative abundance, by phylum, according to transect distance, for phyla accounting

1052	for > 0.1% of the total reads for the 16S rRNA (A, B) and 18S rRNA genes (C, D) $> 2.7$
1053	$\mu m$ (A, C) and 0.2-2.7 $\mu m$ (B, D) communities. Non-linear regressions with 95% CI (gray
1054	shading) are provided for reference.
1055	Figure S5. Separated upper and lower MSR core microbiome aggregate abundance for the 16S
1056	rRNA gene communities. For the upper and lower river, the core microbiome was defined
1057	separately requiring OTUs to have greater than one read in 90% of the samples. > 2.7 $\mu$ m
1058	(A) and 0.2-2.7 $\mu$ m (B) 16S rRNA gene communities in the upper and lower MSR.
1059	Figure S6. PLS results for the 0.2-2.7 $\mu$ m and > 2.7 $\mu$ m 16S (A-D) and 18S (E-H) rRNA gene
1060	community for selected submodules with nitrate and phosphate and a VIP score $> 1$ .
1061	Correlation of submodule OTUs to nitrate and phosphate according to the number of co-
1062	correlations (node centrality) for 0.2-2.7 $\mu$ m (A, B, E, F) and > 2.7 $\mu$ m (C, D, G, H) 16S
1063	and 18S rRNA gene communities. Circle size is proportional to VIP scores, with top 10
1064	VIP scoring and top node centrality OTUs labeled with their highest-resolution taxonomic
1065	classification and OTU number. Colors represent the taxonomic classification the phylum
1066	level.
1067	Figure S7. WCGNA results for 0.2-2.7 $\mu$ m 16S rRNA gene community submodules of interest
1068	based on Pearson correlations to environmental measurements (A). Color shading depicts
1069	the strength of the Pearson correlation with individual submodule's eigenvalue. Boxes
1070	indicate the selected submodule with its Pearson correlation and P-value. Graphs of the
1071	relationship between the selected submodule OTUs and the strength of the individual
1072	OTUs to nitrate (B) and phosphate (D). PLS regression of the predicted nutrient
1073	concentrations versus measured nutrient concentrations (C, E) using the corresponding
1074	selected submodules. Linear regressions with 95% CI (gray shading) are provided for

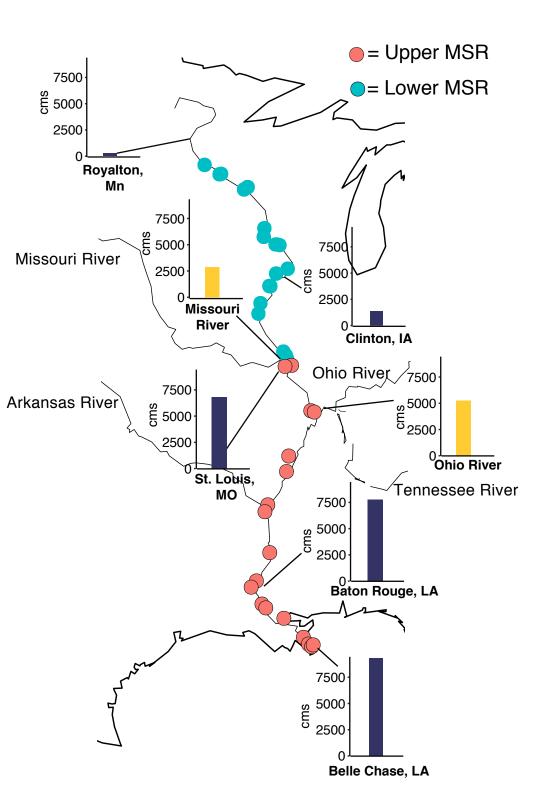
1075 reference.

1076	Figure S8. WCGNA results for 0.2-2.7 $\mu$ m 18S rRNA gene community submodules of interest
1077	based on Pearson correlations to environmental measurements (A). Color shading depicts
1078	the strength of the Pearson correlation with individual submodule's eigenvalue. Boxes
1079	indicate the selected submodule with its Pearson correlation and P-value. Graphs of the
1080	relationship between the selected submodule OTUs and the strength of the individual
1081	OTUs to nitrate (B) and phosphate (D). PLS regression of the predicted nutrient
1082	concentrations versus measured nutrient concentrations (C, E) using the corresponding
1083	selected submodules. Linear regressions with 95% CI (gray shading) are provided for
1084	reference.
1085	Figure S9. WCGNA results for > 2.7 $\mu$ m 16S rRNA gene community submodules of interest
1086	based on Pearson correlations to environmental measurements (A). Color shading depicts
1087	the strength of the Pearson correlation with individual submodule's eigenvalue. Boxes
1088	indicate the selected submodule with its Pearson correlation and P-value. Graphs of the
1089	relationship between the selected submodule OTUs and the strength of the individual
1090	OTUs to nitrate (B) and phosphate (D). PLS regression of the predicted nutrient
1091	concentrations versus measured nutrient concentrations (C, E) using the corresponding
1092	selected submodules. Linear regressions with 95% CI (gray shading) are provided for
1093	reference.
1094	Figure S10. WCGNA results for > 2.7 $\mu$ m 18S rRNA gene community submodules of interest
1095	based on Pearson correlations to environmental measurements (A). Color shading depicts
1096	the strength of the Pearson correlation with individual submodule's eigenvalue. Boxes
1097	indicate the selected submodule with its Pearson correlation and P-value. Graphs of the

1098	relationship between the selected submodule OTUs and the strength of the individual
1099	OTUs to nitrate (B) and phosphate (D). PLS regression of the predicted nutrient
1100	concentrations versus measured nutrient concentrations (C, E) using the corresponding
1101	selected submodules. Linear regressions with 95% CI (gray shading) are provided for
1102	reference.
1103	
1104	Supporting Tables
1105	Supplemental Table S1 is a spreadsheet, TableS1.xlsx. Tabs include General Information,
1106	Spearman Rank, 0.2-2.7 $\mu m$ and $>$ 2.7 $\mu m$ 16S and 18S rRNA gene Core communities, 0.2-2.7
1107	$\mu m$ and $> 2.7 \ \mu m$ 16S and 18S rRNA WGCNA, and 16S and 18S rRNA gene OTU tables
1108	(trimmed and normalized).
1109	
1110	Additional Supplemental Information, including R scripts, Table S1, and our Mothur workflow

1111 are hosted on the Thrash Lab website at: thethrashlab.com/publications.

Figure 1A



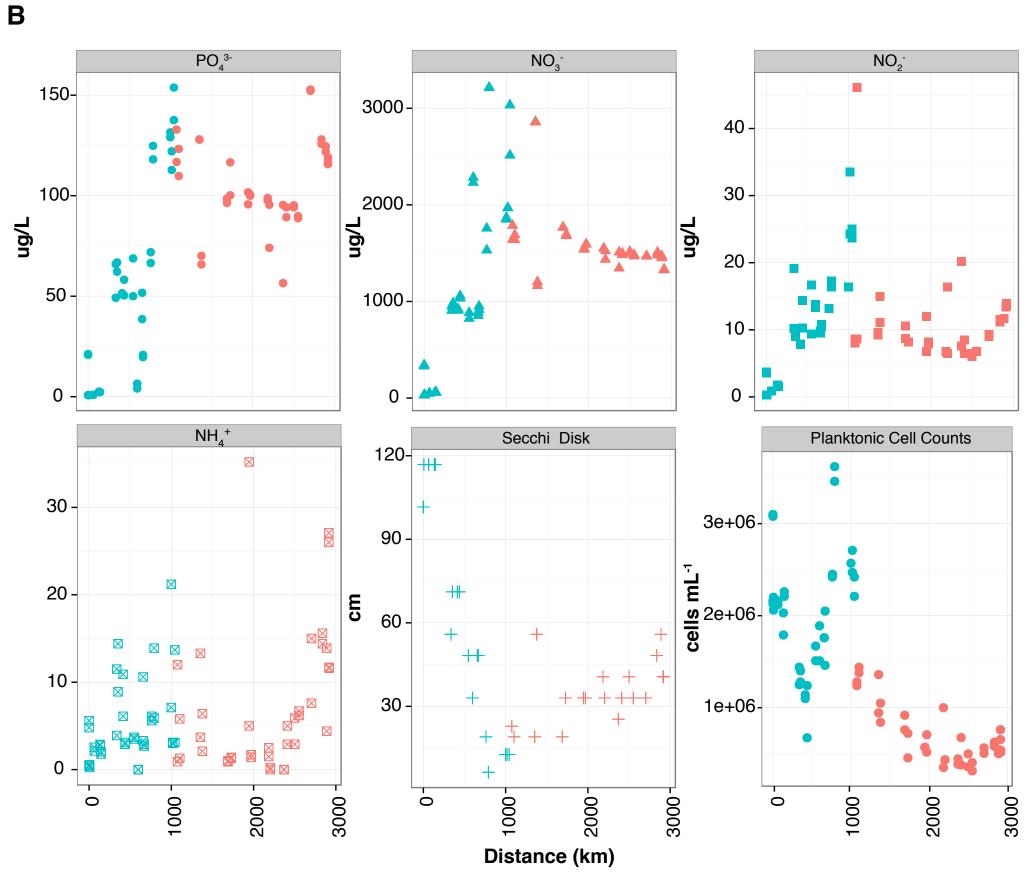
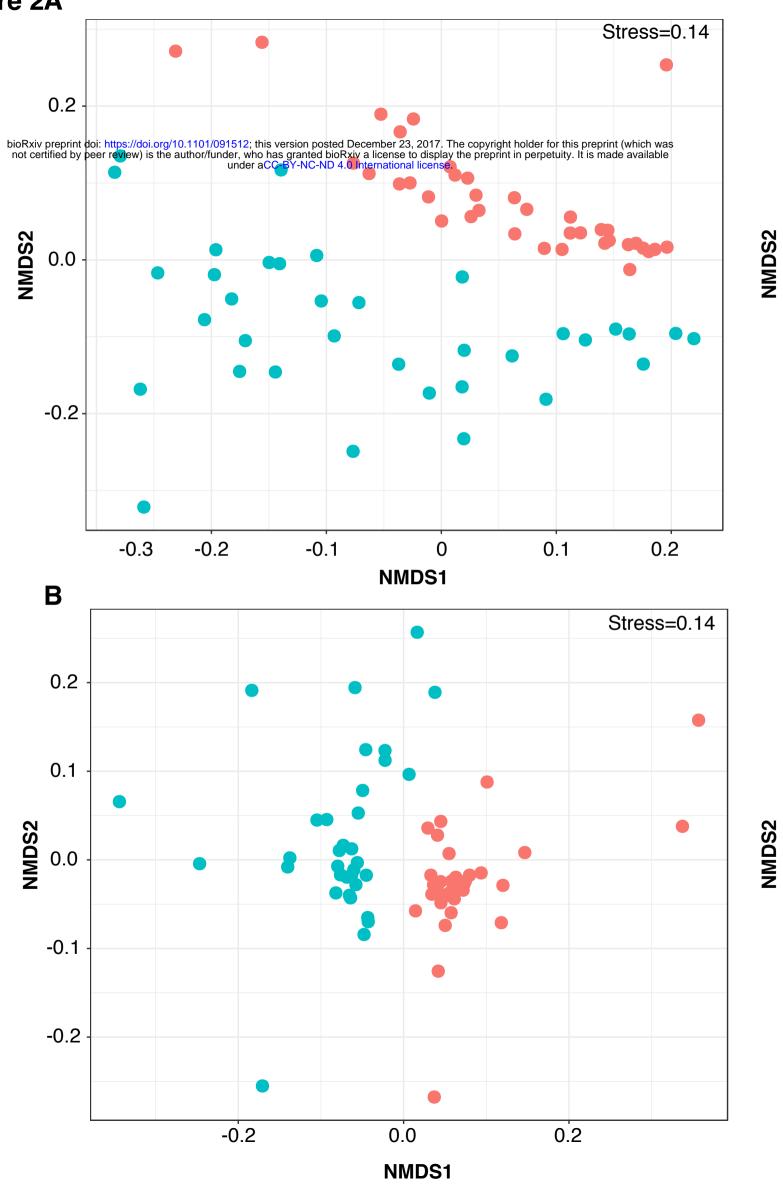
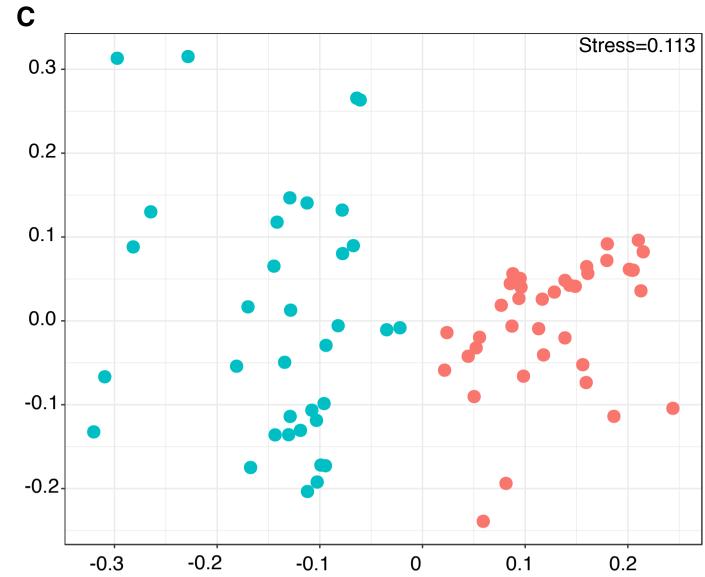
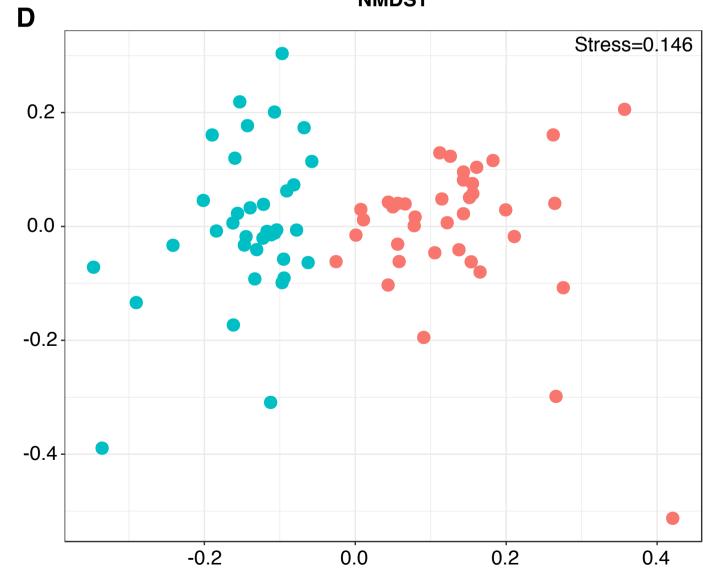


Figure 2A



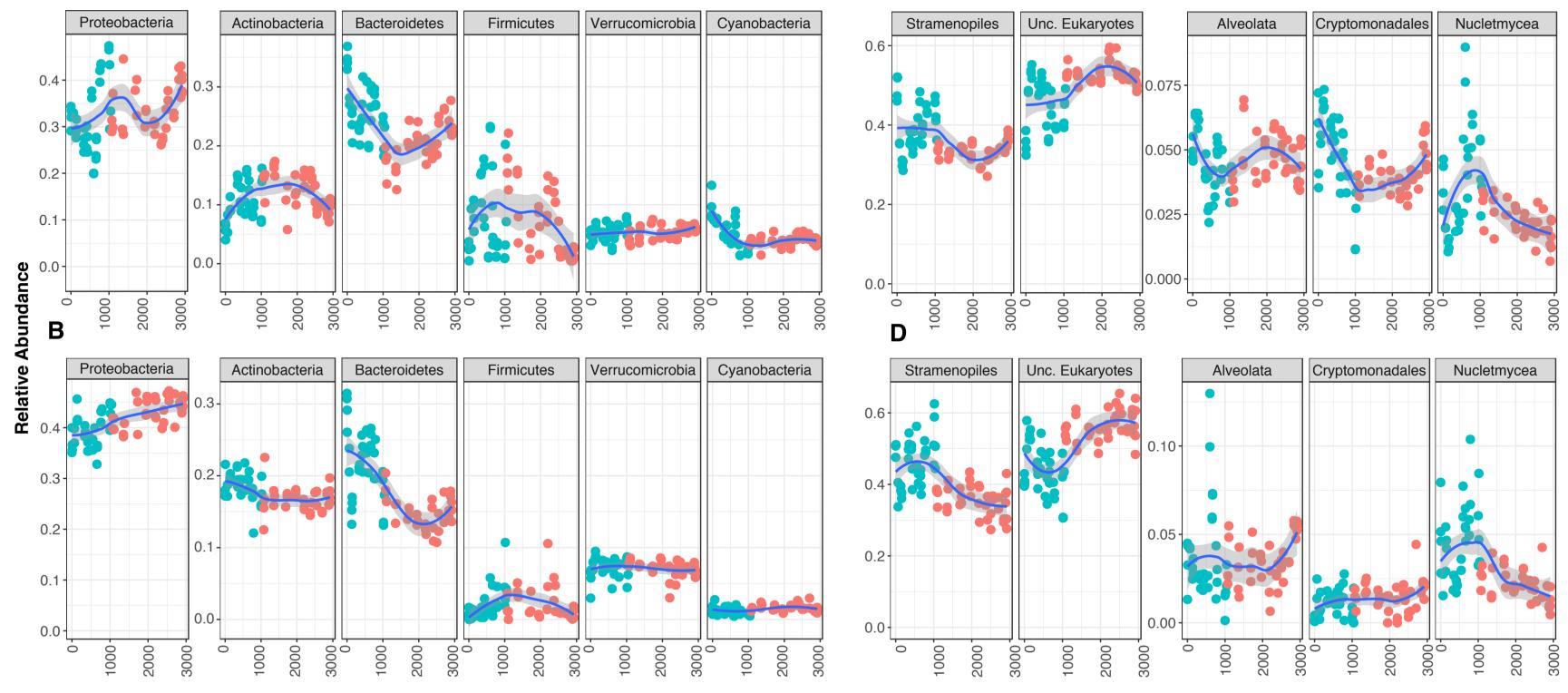






### NMDS1

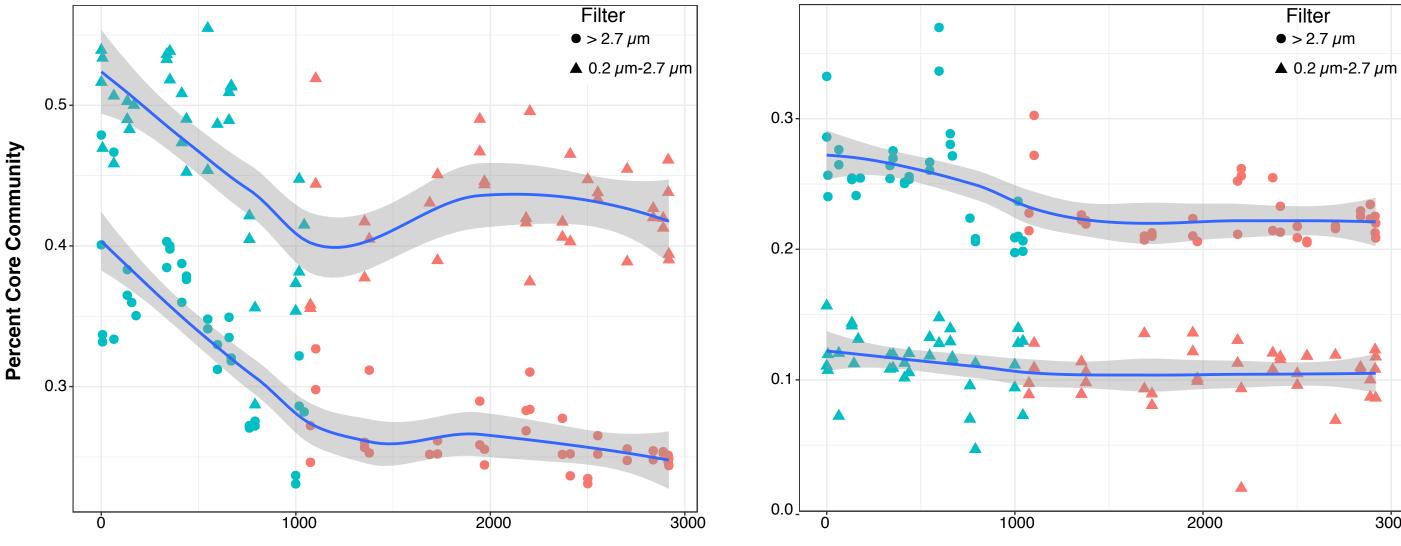
## Figure 3A



Distance (km)

С

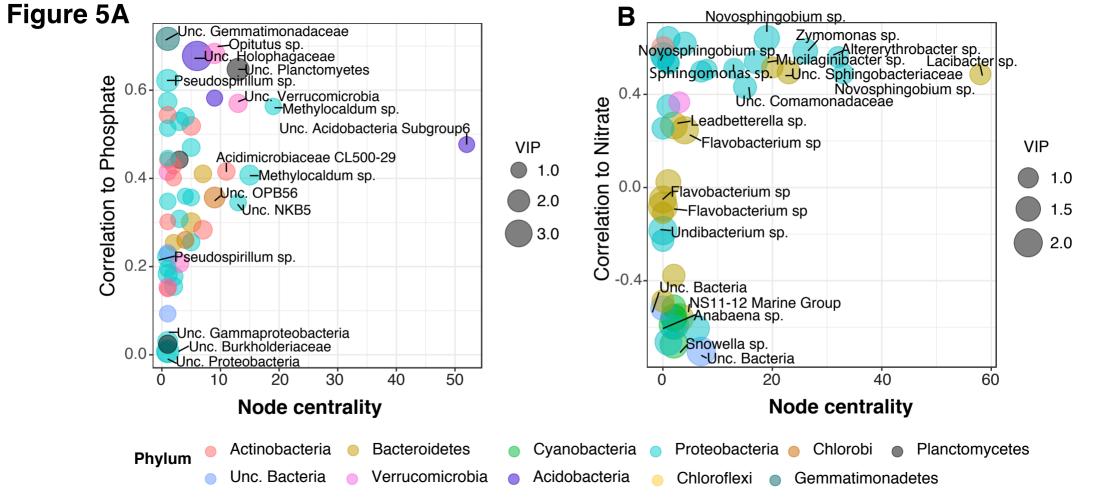
# Figure 4A



Distance (km)

Β

Filter



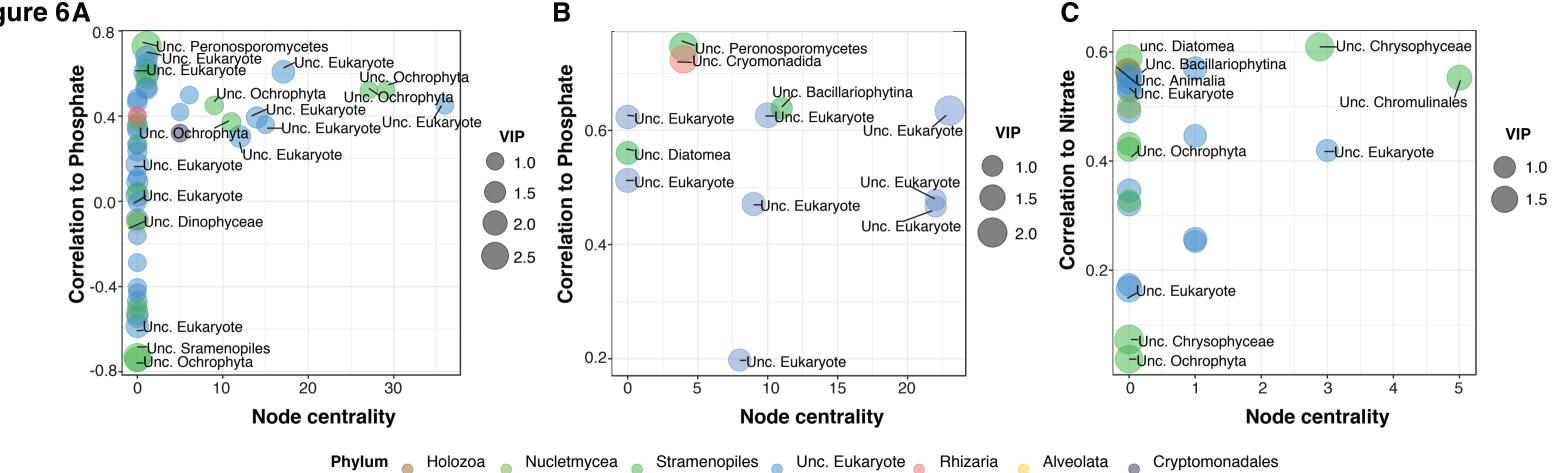


Figure 6A