

1 Are dominant microbial sub-surface communities affected by 2 water quality and soil characteristics?

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12 Abstract

13 Subsurface microorganisms must deal with quite extreme environmental conditions.
14 The lack of light, oxygen, and potentially nutrients are the main environmental stresses
15 faced by subsurface microbial communities. Likewise, environmental disruptions
16 providing an unbalanced positive input of nutrients force microorganisms to adapt to
17 varying conditions, visible in the changes in microbial community diversity. In order to
18 test microbial community adaptation to environmental changes, we performed a study
19 in a surface Managed Aquifer Recharge facility, consisting of a settlement basin (two-
20 day residence time) and an infiltration pond. Data on groundwater hydrochemistry, soil
21 texture, and microbial characterization was compiled from surface water, groundwater,
22 and soil samples at two distinct recharge operation conditions.

23 Multivariate statistics by means of Principal Component Analysis (PCA) was the
24 technique used to map the relevant dimensionality reduced combinations of input
25 variables that properly describe the system behavior. The methodology selected allows
26 including variables of different nature and displaying very different range values. Strong
27 differences in the microbial assemblage under recharge conditions were found,
28 coupled to hydrochemistry and grain-size distribution variables. Also, some microbial
29 groups displayed correlations with either carbon or nitrogen cycles, especially showing

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abundant populations of denitrifying bacteria in groundwater. A significant correlation was found between *Methylothermobacter mobilis* and the concentrations of NO₃ and SO₄, and also between *Vogesella indigofera* and the presence of DOC in the infiltrating water. Also, microbial communities present at the bottom of the pond correlated with representative descriptors of soil grain size distribution.

1. Introduction

Groundwater systems are perceived as relatively stable environments as compared to most aquatic ecosystems (Zhou et al., 2012). Despite that, investigations have shown that soil-aquifer systems support a wide diversity of organisms (e.g., Griebler and Lueders, 2009). Actually, the unsaturated zone, and more specifically the topsoil, supports the highest microbial activity and biomass of all compartments within the subsurface environment (Lapworth et al., 2012). Likewise, microorganisms are responsible for most biological processes in aquifers (Stein et al., 2010).

Several studies evidence microbial adaptation to groundwater extreme environments (thermal or hypersaline) (e.g., Rothschild and Mancinelli, 2001) or disturbed by human activities (Meckenstock et al., 2015). Human activities have caused disruption in aquifer dynamics to some extent (Griebler and Lueders, 2009; et al., 2017), with biological implications as indigenous microorganisms can acclimate (Pett-Ridge and Firestone, 2005) or even take advantage (Rezanezhad et al., 2014) of environmental disturbances.

In fact, the water treatment industry has benefited from the adaptability and metabolic capabilities of microorganisms to maximize the improvement of water quality. Several laboratory experiments and engineering applications have tested the effectiveness of microbial engineered techniques for water reclaim purposes. The former has been conducted aiming at (1) describing degradation pathways of specific pollutants and quantifying their degradation rates (Greskowiak et al., 2017; Regnery et al., 2015;

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Rodriguez-Escales and Sanchez-Vila, 2016), (2) determining the physical and hydrochemical conditions that can govern the behavior of specific microbial groups (Alidina et al., 2014; Drewes et al., 2014; Freixa et al., 2015; Kolehmainen et al., 2008; Perujo et al., 2017), or (3) understanding the role of organic matter (dissolved organic carbon -DOC- or micropollutants), on the growth of microbial communities (Li et al., 2013, 2012). Regarding the engineered applications of microbial ecology designed to improve the quality of reclaimed water, examples are constructed wetlands (Faulwetter et al., 2009; Truu et al., 2009; Zhang et al., 2018) and sand filters (D'Alessio et al., 2015).

Natural and induced microbial attenuation have been studied and applied at the field scale concerning groundwater related environmental issues; this includes, e.g., landfill leakage affections (Röling et al., 2001; Staats et al., 2011), contaminant spills (Fahrenfeld et al., 2014; Haack et al., 2004; Martínez-Pascual et al., 2010; Nijenhuis and Kuntze, 2016), or nitrate polluted aquifers (Bellini et al., 2018, 2013).

In recent years, the number of soil aquifer treatment (SAT) facilities have increased worldwide. SAT is a particular case of the Managed Aquifer Recharge (MAR) family, that combines the replenishment of groundwater bodies with the treatment of water during infiltration, by taking advantage of the potential of the soil for the degradation of subsurface microbial communities (Bouwer, 2002). Studies testing the link between water quality and microbial communities in MAR systems depend on the system type, whether recharge wells (Ginige et al., 2013), riverbank areas (Schütz et al., 2009), or surface infiltration ponds (Barba et al., 2019; Reed et al., 2008; Regnery et al., 2016). Infiltration ponds are low-cost, low-tech, passive facilities compared to advanced water treatment methods (Drewes et al., 2003; San-Sebastián-Sauto et al., 2018); for these reasons, they are widely implemented, mostly in arid or semi-arid environments (Goren et al., 2014; Greskowiak et al., 2006; Rodríguez-Escales et al., 2018).

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82 Biodegradation processes in surface infiltration ponds include aerobic oxidation of DOC
83 (Maeng et al., 2011; Mermillod-Blondin et al., 2015), denitrification (Grau-Martínez et
84 al., 2018), and removal of some emerging organic compounds (Hamann et al., 2016;
85 Valhondo et al., 2015). Parameters modifying bioprocesses, such as DOC availability,
86 dissolved oxygen content, redox conditions, temperature, nutrient concentrations, or
87 soil moisture have been widely reported (Alidina et al., 2015; Bekele et al., 2011; Dutta
88 et al., 2015; Goren et al., 2014; Greskowiak et al., 2005; Hellauer et al., 2017; Laws et
89 al., 2011; Massmann et al., 2006; Rezanezhad et al., 2014). Apart from environmental
90 parameters, properties of the porous media, such as porosity and the distributions of
91 grain sizes and pore sizes, determine the spatial and temporal distributions of
92 microorganisms in soils (Chau et al., 2011); they also influence hydraulic conductivity,
93 and thus the access to nutrients, affecting in a distinct way the growth and activity of
94 microorganisms (Perujo et al., 2018, 2017).

95 Subsequently, determining how much and to what extent physical, geochemical,
96 biological and operational parameters influence a SAT system functioning is useful for
97 managing purposes (Dutta et al., 2015; Grau-Martínez et al., 2018; Hellauer et al.,
98 2017; Pedretti et al., 2012a; Rodríguez-Escales et al., 2017). Yet, it is difficult to find
99 multidisciplinary research dealing with integrated approaches to improve understanding
100 of infiltration problems. One such example is the Llobregat MAR surface infiltration
101 system, where a number of experiments have been performed in the last decade. The
102 system is, thus, well characterized in terms of natural and induced flow regime,
103 including numerical modelling (Valhondo et al., 2016), DOC mapping (Valhondo et al.,
104 2015) and the evaluation of nitrate attenuation (Grau-Martínez et al., 2018), and the
105 fate of several emerging compounds (Valhondo et al., 2018) along the infiltration path.
106 Finally, microbial fingerprinting was studied, and the spatial distribution of dominant
107 microbial phylotypes was linked to the overall recharge processes (Barba et al., 2019).
108 In that work, the microbial assemblage was characterized and discussed under an

109 ecological point of view. However paramount aspects, such as the effect of
110 hydrochemical composition or the grain-size distribution, in water and soil samples,
111 linked to their role in the presence of specific microbial signatures were not addressed.

112 We contend that a full analysis of processes occurring in any MAR facility should
113 involve the simultaneous study of physical, hydraulic, geochemical and microbial data;
114 therefore, it includes the joint analysis of continuous, discrete and categorical data, with
115 different ranges of values and resolution windows, calling for the use of multivariate
116 (MV) statistical techniques. Such techniques have been widely used in hydrogeology to
117 provide process understanding and to accompany groundwater models (El Alfy et al.,
118 2017; Menció et al., 2012). In the case of microbial ecology, the development of
119 molecular analyses allowed the generation of large data sets, best treated using MV
120 statistical techniques (see Paliy and Shankar, 2016 for a review).

121 Here, we aim at combining ecological, hydrochemical and hydrological approaches to
122 understand the spatial distribution of subsurface microbial communities under changing
123 recharge conditions, with significant consequences in the management of MAR
124 facilities. For this purpose, we used a physical-bio-geochemical dataset from an
125 existing infiltration facility, and then applied PCA, aiming at statistically discriminate the
126 relationships among different parameters corresponding to microbial community
127 structure, geochemical variables, soil grain size distribution, and operational conditions.

128 This work allows providing the most relevant microbial indicators present in the system
129 and to correlate them with soil and groundwater local characteristics and feeding water.
130 Furthermore, the existing data between microbial clades both in water and soil were
131 also analyzed separately to obtain further relevant inter-clade correlations.

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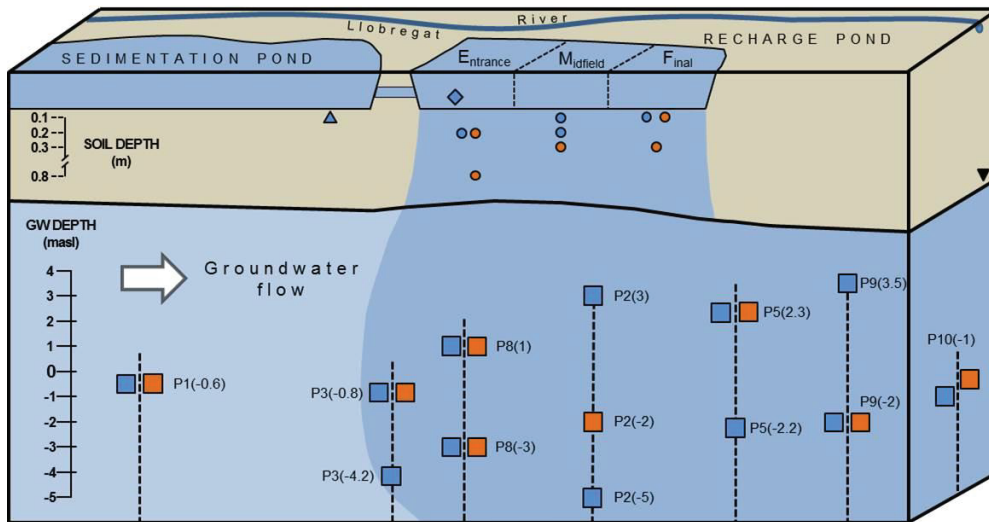
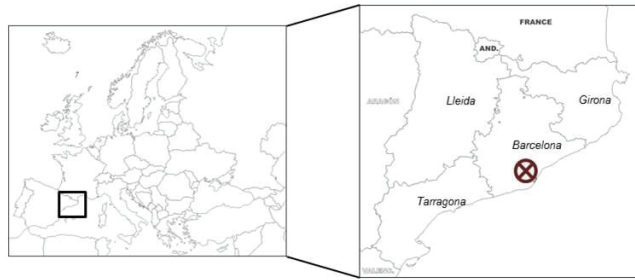
133 **2. Material and methods**

134 The present work is built on the dataset compiled and presented in Barba et al. (2019).
135 This work describes in detail the fieldwork procedures and laboratory tasks performed
136 to obtain data representative of the Llobregat MAR site regarding a large set of
137 physical, geochemical and biological variables, and from two sampling campaigns
138 involving different recharge conditions. In this section, we provide only the essential
139 information to contextualize the statistical analysis, being the core of this work.

140 **2.1. Study site**

141 The field site is located in the Llobregat River Basin (Sant Vicenç dels Horts,
142 Catalonia), 10 km SW of Barcelona. The recharge system replenishes the Lower Valley
143 Aquifer, a strategic groundwater source for the Barcelona Conurbation. It is an alluvial
144 aquifer, composed mainly by sands and gravels with small paleo-channels of clay
145 (Pedretti et al., 2012b). Hydrogeologically, it is of high transmissivity that reaches
146 $14000 \text{ m}^2 \cdot \text{d}^{-1}$ locally, with an average thickness of 15m.

147 The system is composed of two ponds. The first one (7300 m^2) is fed with river water,
148 and acts as a sedimentation pond for fine particles, with 2-3 day residence time. Then,
149 water passes through a pipe to the second pond (6500 m^2), where it infiltrates to the
150 aquifer through 4-10m of vadose zone. Being devised as a research facility, in 2011 an
151 organic layer was placed at the bottom of the infiltration pond to test its efficiency for
152 the removal of emergent pollutants by the addition of labile DOC to the inflow water.



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154 **Figure 1** Geographical situation and cross-section of the Llobregat MAR System. Triangles and circles
 155 represent the location of soil samples. Diamond and squares represent those of water and groundwater
 156 samples, respectively. Blue symbols indicate samples taken in July 2014, after six months of continuous
 157 uninterrupted recharge. Orange samples were taken after recharge was discontinued for 4 months in
 158 March 2015.

159 The system includes a network of piezometers for monitoring and groundwater
 160 sampling corresponding to different travel times after recharge (Figure 1). Detailed
 161 information about the conceptual regional flow model and the local flow and transport
 162 models can be found in Barba et al. (2019) and Valhondo et al. (2016), respectively.

163 **2.2. Input data for the multivariate statistical approach**

164 Water and soil samples were taken in two different periods, July 2014 and March 2015,
 165 representing different recharge operation conditions. In the July campaign, sampling
 166 was performed after six months of uninterrupted recharge; in the March one, recharge
 167 had been discontinued for four months prior to sampling. In total, 21 water samples (20

168 for groundwater and 1 for recharge water) and 10 soil samples were subjected to
169 molecular analyses, in duplicate (only average values are presented in this work).
170 Furthermore, water samples were hydrochemically characterized, while granulometric
171 curves were obtained for the soil samples. The sampling and analysis methodologies
172 for chemistry, granulometry, DNA extraction, PCR, DGGE, diversity indices and relative
173 abundances of the microbial clades, are reported in Barba et al. (2019).

174 The present study divides the statistical analyses according to the nature of the
175 samples, treating those from water and soil separately, as different variables are
176 included in each case. In the former, the statistical analysis accounted for (1) microbial
177 diversity indexes, (2) relative microbial abundances at the taxonomical rank level of
178 class and species, and (3) hydrochemical characterization (major, minor and trace
179 elements). Instead, statistical analyses of soil samples contained (1) microbial diversity
180 indexes, (2) relative microbial abundances at the taxonomical rank level of class and
181 species, (3) grain-size distribution representative parameters, (4) depth, and (5) an
182 operational binary variable indicating dry/wet conditions characterized by the presence
183 or absence of recharge. Finally, a general statistical analysis was performed for all soil
184 and water samples (31 in total) and the common variables (i.e., (1) and (2) from the
185 previous lists), plus a binary variable indicating the sample nature (soil or water).

186 **2.3. Rationale for the multivariate statistical approach: requirements for PCA**

187 Multivariate statistics is a useful technique to treat large datasets involving different
188 types of variables, allowing the inclusion of quantitative and categorical data together.
189 In short, PCA transforms a set of data values of variables that in principle are
190 correlated into a set of values of linearly uncorrelated variables called principal
191 components (PCs). PCs are defined such that the first one accounts for as much of the
192 variability in the data as possible, and each succeeding component, in turn, has the
193 highest variance possible under the constraint that it is orthogonal to the preceding

194 ones. Thus, a multidimensional system in terms of variables is projected into a low
195 dimensional map of components. Solutions were subjected to a varimax rotation of the
196 original system corresponding to the directions of the largest variance in the dataset.
197 Statistical analysis was done using software SPSS (IBM SPSS Statistics 24).

198 The full dataset is provided as supplementary material. It also includes plots
199 corresponding to some of the PCA analyses that are included for completeness but do
200 not provide enough additional information to merit inclusion in the body of the text.

201 **2.3.1. Selecting variables for the statistical analysis of water samples**

202 Statistical parametric methods perform best when data follows a unimodal symmetric
203 distribution (Paliy and Shankar, 2016). For this reason, some variables from the initial
204 dataset were eliminated, grouped and/or transformed in order to conform better to the
205 assumptions of PCA analysis. For example, hydrochemical variables with most values
206 below the detection limit were eliminated (this is the case of Al, B, Cd, Co, Fe, Pb, and
207 P). Also, Ba concentration values were rejected for data inconsistency. Second,
208 hydrochemical variables that displayed a positive skewness were log transformed (Cu,
209 DOC, Ni, S and V concentrations). Finally, sample depth, electrical conductivity (EC),
210 temperature, and the concentrations of HCO₃, Ca, Cl, Li, Mg, Mn, Na, NO₃, pH, Si,
211 SO₄, and Zn were added to the analysis without any data transformation.

212 With reference to variables of microbial abundances, they were all transformed into
213 new variables. For ecological data, displaying a large number of zero values, Legendre
214 and Gallagher (2001) recommend applying either the Chord or the Hellinger
215 transformations to the data values. In our case, we applied the latter one, because after
216 some preliminary analyses, the transformed variables presented higher correlation
217 coefficients (r^2) than the non-transformed ones. Hellinger transformation (x'_{ij}) of a
218 datum x_{ij} pertaining to the i -class and j -object is given as:

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$$x'_{ij} = \sqrt{\frac{x_{ij}}{\sum x_{i+}}} ; \text{ where } i+ \text{ denotes all } i\text{'s.}$$

220 Finally, in the case of microbial diversity indices, the input data for the PCA were the
221 Shannon, Richness and Evenness index values for each sample.

222 The next step was to perform bivariate correlation analyses with all variables taken two
223 by two, including hydrochemical variables (both raw and log-transformed; actually this
224 was the way of selecting whether the log-transformation was finally applied or not) and
225 Hellinger-transformed microbial variables in order to select the ones that would be used
226 in the final PCA analyses. Since the objective was to emphasize the correlations with
227 the microbial data, most redundant geochemical variables, as well as those displaying
228 very low values of the Pearson r^2 coefficient to the biological ones, were removed. This
229 was the case of As, HCO₃, Ca, Li, Mg, Mn, Si, Zn, and also depth, pH, and
230 temperature. In the case of microbial phylotypes, some of them were eliminated
231 because they did not show significant correlations with other variables; e.g., Bacilli,
232 Acidobacteria, Actinobacteria, Chlorobia, Nitrospira, Gammaproteobacteria,
233 Alphaproteobacteria, *Subgroup3 sp* (Acidobacteria), *Stenotrophomonas sp*,
234 *Chryseomicrobium sp*, *Nitrospira1 sp*, *Methylobacterium sp*, and *Nitrospira2 sp*.

235 The selected variables could not be incorporated all together in a single PCA because
236 the total variance was too high to allow proper discrimination of components. Then,
237 different PCAs (each one involving a different subset of parameters) were performed,
238 trying to maximize the amount of explained information. We performed two PCAs for
239 microbial abundances at the class level and two more at the species level. The most
240 informative set of variables were selected as the subset that maximized the measure of
241 sampling adequacy reported by Kaiser-Meyer-Olkin test (KMO); the variables included
242 in each analysis are provided in Table 1.

243 **2.3.2. Selecting variables for the statistical analysis of soil samples**

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244 Soil samples were subjected to sieve analysis, obtaining grain-size distribution curves.
245 For each sample, the uniformity coefficient (*CU*) and the coefficient of curvature (*CC*)
246 were calculated as (Terzaghi et al., 1996): $CU = \frac{D_{60}}{D_{10}}$, $CC = \frac{(D_{30})^2}{D_{60} \cdot D_{10}}$, where D_{60} , D_{30} and D_{10}
247 are the diameters so that 60%, 30% and 10% of the material (in weight) pass the
248 corresponding sieve. D_{10} has also been used as one of the variables in the statistical
249 analysis. Another variable incorporated in the analysis was the proportion (in weight) of
250 fine material (<0.074 mm) for each sample. Soil sample depth and sampling campaign
251 (operation) were also included.

252 However, here Hellinger transformation was not applied to relative abundances of
253 microbial species, because correlations were high already for the raw relative
254 abundances. Some microbial variables were removed for the final analyses, based on
255 the low bivariate r^2 coefficients obtained (this was the case of Cyanobacteria,
256 Nitrospira, Gammaproteobacteria, Alphaproteobacteria, *Stenotrophomonas sp*,
257 *Chryseomicrobium sp*, and *Nitrospira1 sp*).

258 Here, the optimization between the number of PCAs, the measurement of sampling
259 adequacy (KMO) and the number of considered variables was done following the same
260 criteria indicated in the statistical analysis of the water samples.

261 **2.3.3. PCA for microbial print in water and soil samples**

262 Taking advantage of the shared variables by water and soil samples, a third statistical
263 analysis was performed, now including all 31 samples (soil and water) together.
264 Microbial classes and species were treated separately and were Hellinger transformed.
265 In addition to microbial data, the type of sample (water or soil) was also included as a
266 binary variable. From the bivariate correlation analysis, some variables were removed
267 from the final statistical analysis: Cyanobacteria, Gammaproteobacteria,
268 Alphaproteobacteria, *Methylothera mobilis*, *Vogesella indigofera*, *Stenotrophomonas*

269 *sp*, *Chryseomicrobium sp*, *Methylobacterium sp*, and *Nitrospira2 sp*. The optimization
270 criteria were the same as indicated in the two previous sections.

271 **3. Results**

272 As a consequence of the preliminary analysis, PCAs of water samples considered 10
273 hydrochemical variables, 2 diversity indices and 10 microbial variables (5 classes and 5
274 species). PCAs of soil samples took into account 1 operational variable, depth, 4 grain-
275 size soil parameters, 3 diversity indices and 14 microbial variables (7 classes and 7
276 species). Finally, the statistical approach for the total of 31 samples (soil and water)
277 included 3 diversity indices, the type of sample and 13 microbial variables (9 classes
278 and 4 species).

279 We present firstly global results of the eleven PCAs performed (Table 1). We indicate,
280 in the same table and for each statistical analysis performed, the extracted components
281 with their variables and the proportion of variance represented for each component.
282 Also, the measure of sampling adequacy (KMO test value) is reported for each
283 analysis.

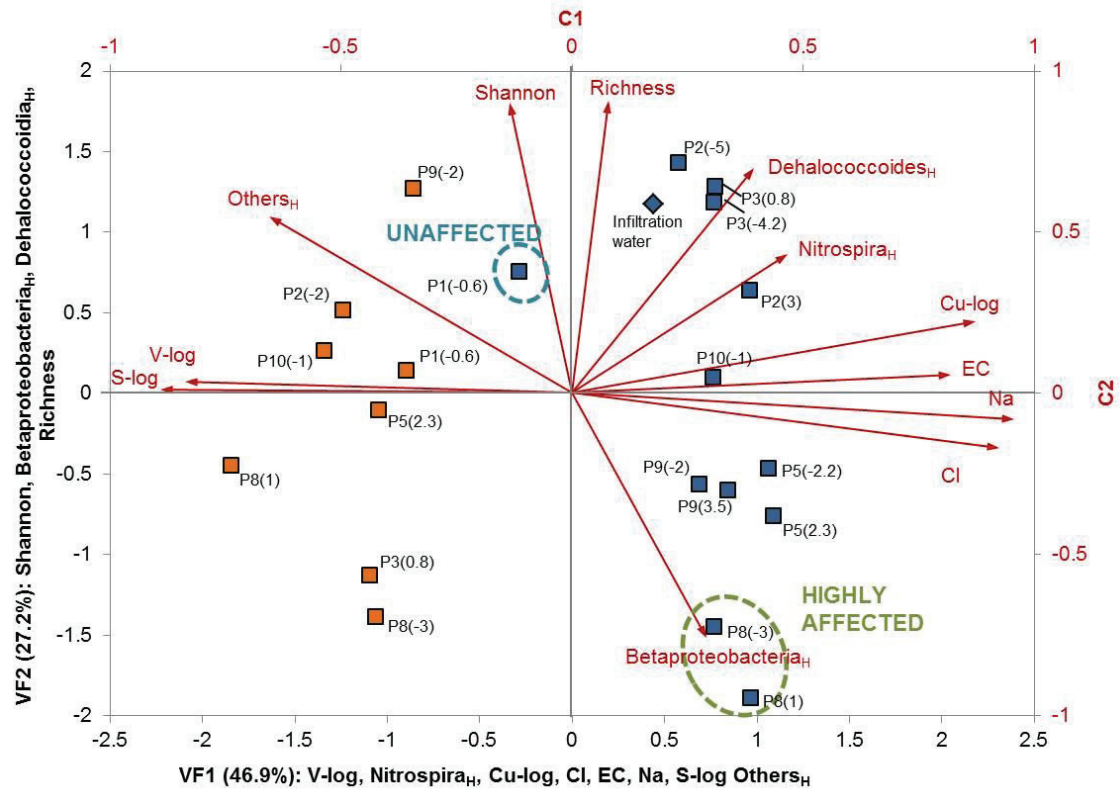
Type of sample	Microbial clade data treated	PCAs performed	PCA number	Extracted components	% of variance	KMO Test value
Water	Classes	2	PCA ₁	C1: V-log , Cu-log, Cl, EC, S-log , Na, Others_H	46.9	0.744
				C2: Shannon, Betaproteobacteria_H , Dehalococcoidia _H , Richness	27.2	
	Species	2	PCA ₃	C1: Cyanobacteria _H , EC, Cl, Cu-log, Ni-log	52.6	0.701
				C2: Cytophagia_H , Richness	24.4	
Soil	Classes	2	PCA ₄	C1: <i>Methylobacterium mobilis</i> _H , NO ₃ , SO ₄ , DOC-log	61.5	0.797
				C2: <i>Nitrospira</i> _sp2 _H , EC, Na, V-log , Cu-log, Cl	15.4	
	Species	2	PCA ₅	C1: Pontibacter _sp _H , <i>Dehalogenimonas</i> _sp _H , Richness	52.9	0.635
				C2: <i>Vogesella</i> _indigofera _H , Shannon, DOC-log	24.3	
Water and soil	Classes	2	PCA ₆	C1: Betaproteobacteria_H , Actinobacteria _H , Dryness, Depth, Cytophagia _H	62.5	0.750
				C2: CU, % Fine, Acidobacteria _H	22.1	
	Species	2	PCA ₇	C1: Richness, Dehalococcoidia _H , Chlorobia _H	75.5	0.727
				C2: Shannon, Evenness, Actinobacteria_H , Bacilli_H	12.3	
Water and soil	Classes	2	PCA ₈	C1: <i>Nitrospira</i> _2sp, Dryness, Shannon , <i>Pontibacter</i> _sp,	64.6	0.640
				C2: % Fine, <i>Subgroup3</i> _sp, CU	27.6	
	Species	2	PCA ₉	C1: CC, D10, <i>Methylobacterium mobilis</i> , <i>Methylobacterium</i> sp,	59.5	0.692
				C2: % Fine, CU, <i>Dehalogenimonas</i> _sp, <i>Vogesella indigofera</i>	23.9	
Water and soil	Classes	2	PCA ₁₀	C1: Shannon, Richness, Actinobacteria _H , Type, Evenness	53.8	0.696
				C2: Others _H , Betaproteobacteria_H	16.4	
	Species	1	PCA ₁₁	C3: Bacilli _H	12.5	0.705
				C1: Shannon, Evenness, Richness	44.0	
Water and soil	Classes	2	PCA ₁₁	C2: Dehalococcoides _H , Cytophagia_H , Acidobacteria _H	26.4	0.696
				C3: <i>Nitrospira</i> _H , Chlorobia_H	14.4	
	Species	1	PCA ₁₁	C1: Shannon, Richness, Evenness, Type, <i>Nitrospira</i> _sp1 _H	48.8	0.705
				C2: Pontibacter _sp _H , <i>Dehalogenimonas</i> _sp _H , <i>Subgroup3</i> _sp _H	25.5	

Table 1 Relation to main correlations among variables obtained by PCA analysis (inverse correlations in bold). Subscript "H" in microbial variables indicates that Hellinger transformation had been applied to the data. Suffix "-log" in geochemical variables indicates that log transformation was performed.

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285 3.1. **Key parameters influencing microbial classes in surface water and**
286 **groundwater**

287 Two PCAs were developed; the first one (PCA₁ in Table 1) included Shannon and
288 Richness indices, Cl, EC, Na, the log transformations of S, Cu, and V, as well as
289 Betaproteobacteria_H, Dehalococcoidia_H, Nitrospira_H and Others_H classes. The group
290 “Others” includes microbial classes that could not be classified. Results of this PCA
291 show that these twelve variables could be mostly explained with only two principal
292 components (combined they explained 74% of the total variance). The strength of the
293 analysis is supported by a value of 0.744 in the KMO test. Results of a 2D
294 representation of varifactors and components (Figure 2) show the significance of
295 hydrochemistry beyond microbial variables. All the chemical variables included in the
296 analysis are grouped in the first component, showing a high correlation amongst them;
297 Na, Cl, EC and Cu-log (“-log” indicates log-transformed) are positively correlated,
298 whereas V-log and S-log are situated in the opposite side of the plot (negative
299 correlation).



300

301 **Figure 2** PCA₁ analysis including diversity indices, microbial classes and hydrochemical data from
 302 groundwater samples (squares) and one infiltration water sample (diamond) during the recharge period
 303 (blue) and no-recharge period (orange). The position of samples is scaled in VF1 and VF2 axes for
 304 visualization purposes. Red arrows represent the contribution of each variable projected into the varifactor
 305 plane. Samples are labeled corresponding to the sampling point and the height (meters above sea level, or
 306 masl) indicated in brackets. The symbols assignment follows the same criteria in all PCA plots.

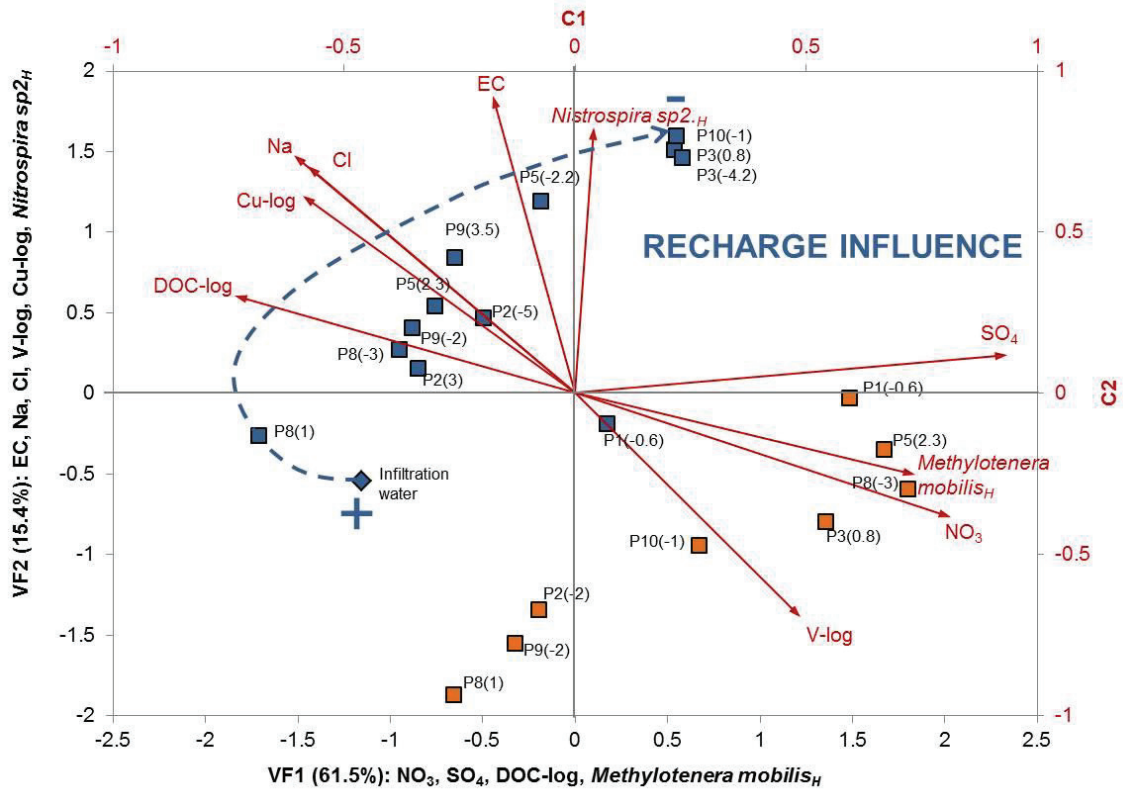
307 The second component relates inversely the presence of Betaproteobacteria_H to the
 308 Shannon and Richness indices. Furthermore, Betaproteobacteria_H is most significant in
 309 the samples most affected by recharge (piezometer P8, located directly below the
 310 infiltration pond). Finally, the projection of sample data in the plane composed of the
 311 two varifactors (VF1, VF2) clearly separate data according to the operational period
 312 (recharge/no-recharge). Moreover, the sample not affected by recharge (P1, placed
 313 upstream) is displayed between the samples corresponding to the no-recharge and
 314 recharge periods.

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315 The second PCA (Figure S1, PCA₂ in Table 1) also separates data corresponding to
316 operational periods in the VF1-VF2 plane. Furthermore, two groups of variables can be
317 distinguished. The first one relates Cyanobacteria_H, Cl, EC, Cu-log and Ni-log. Apart
318 from hydrochemical differences that force the separation of samples between
319 operational periods, Cyanobacteria are more abundant in the groundwater samples in
320 the recharge period. Component 2 shows an inverse correlation between Richness and
321 Cytophagia_H.

322 **3.2. Key parameters influencing microbial species in water samples**

323 PCA₃ analysis (Table 1) included variables EC, Na, Cl, V-log, Cu-log, NO₃, SO₄, DOC-
324 log, and two microbial species (as opposed to microbial classes, that were the
325 objective of PCA₁ and PCA₂): *Methylotenera mobilis*_H and *Nitrospira sp2*_H. From the
326 projection on the varifactor plane (Figure 3), samples corresponding to operational
327 conditions clearly display on different areas within the plot. Furthermore, samples taken
328 during active operation display a disturbance degree caused by recharge (indicated in
329 qualitative terms by the blue arrow). On the other hand, the sample representing
330 background conditions (P1) is located separated from the rest, indicating that in no
331 recharge periods the areas that were recharged kept some memory of the events, i.e.,
332 the microbial communities did not go back to the pre-recharge conditions.



333

334 **Figure 3** PCA₃ analysis including diversity indices, microbial species and hydrochemical data from
 335 groundwater samples (squares) and the infiltration water sample (diamond). The discontinuous blue arrow
 336 indicates the degree of disturbance caused by recharge.

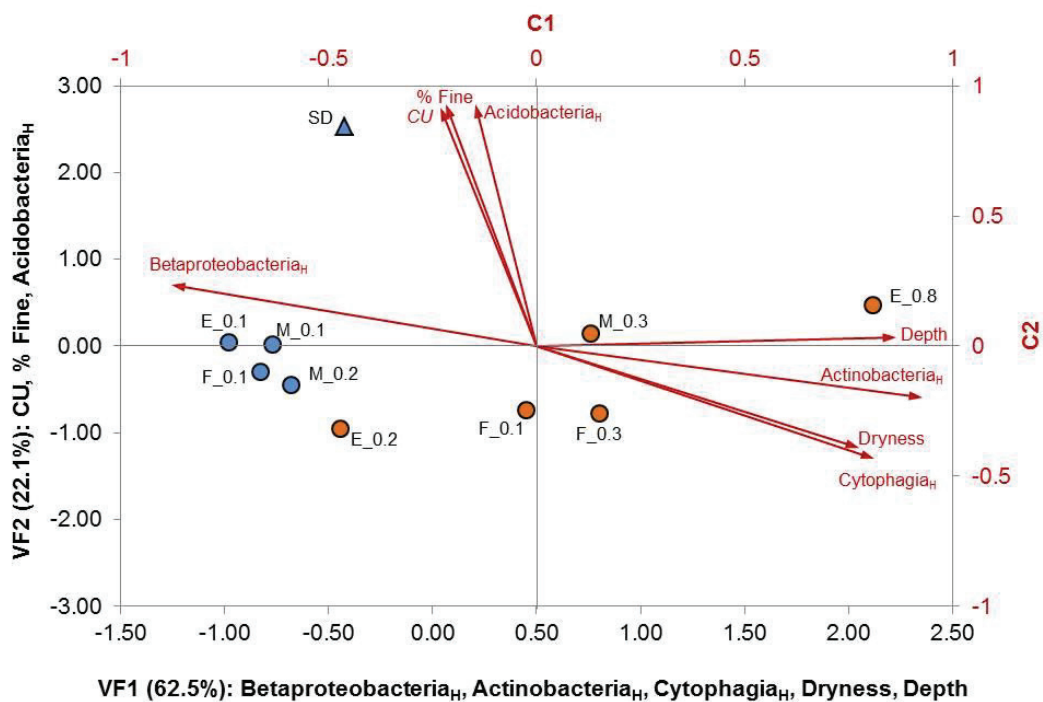
337 Figure 3 also shows the main relations amongst variables. The first component groups
 338 mainly SO₄, NO₃ and DOC-log (inversely) with *Methylothera mobilis*_H. The behavior of
 339 *Nitrospira sp*_{2H} and its high correlation with conductivity were explained by the second
 340 component.

341 PCA₄ indicated a relationship between *Dehalogenimonas sp.*_H, *Pontibacter sp.*_H and
 342 *Vogesella indigofera*_H with some hydrochemical and biological indicators (Figure S2).
 343 *Dehalogenimonas sp.*_H appears to be a key contributor to Richness and Diversity
 344 indices and in turn, is inversely correlated with *Pontibacter sp.*_H. However, *Vogesella*
 345 *indigofera*_H is correlated with DOC-log (see Figure S2), placed in the vicinity of the P8
 346 samples projection, indicating the effect of recharge on both variables.

347

348 **3.3. Key parameters influencing microbial classes in MAR soils**

349 PCA₅ to PCA₈ provide statistical analyses for samples taken from soils. Here, the
 350 parameters extracted from the grain-size distribution curves are included, together with
 351 microbial variables, depth and the operational variable. In all cases, the position of
 352 samples is scaled in VF1 and VF2 axes. Red arrows represent the contribution of each
 353 variable projected into the plane defined by the two varifactors (Figure 4).



354 **Figure 4** PCA₅ analysis including microbial classes, grain-size distribution curve parameters and depth
 355 from soil samples during the recharge period (blue) and no-recharge period (orange). Circles are related to
 356 the infiltration pond samples (E-Entrance, M-Midfield and F-Final stretch). Numbers indicate the depth the
 357 sample was taken (in m below surface). Triangle corresponds to the sedimentation pond sample. Symbols
 358 follow the same criteria in the following PCA charts.

359 PCA₅ involved microbial soil classes (Acidobacteria_H, Betaproteobacteria_H,
 360 Actinobacteria_H, Cytophagia_H), Uniformity Coefficient (*CU*), fine material content (%
 361 Fine), Dryness (operation condition dry-wet) and Depth (Table 1). From Figure 4,
 362 Betaproteobacteria_H displays oppositely to Depth, Actinobacteria_H, Cytophagia_H and
 363 Dryness, suggesting that Betaproteobacteria_H is more favorable to live in wet and
 364 shallow soils, while Actinobacteria_H and Cytophagia_H are preferably found in dry and

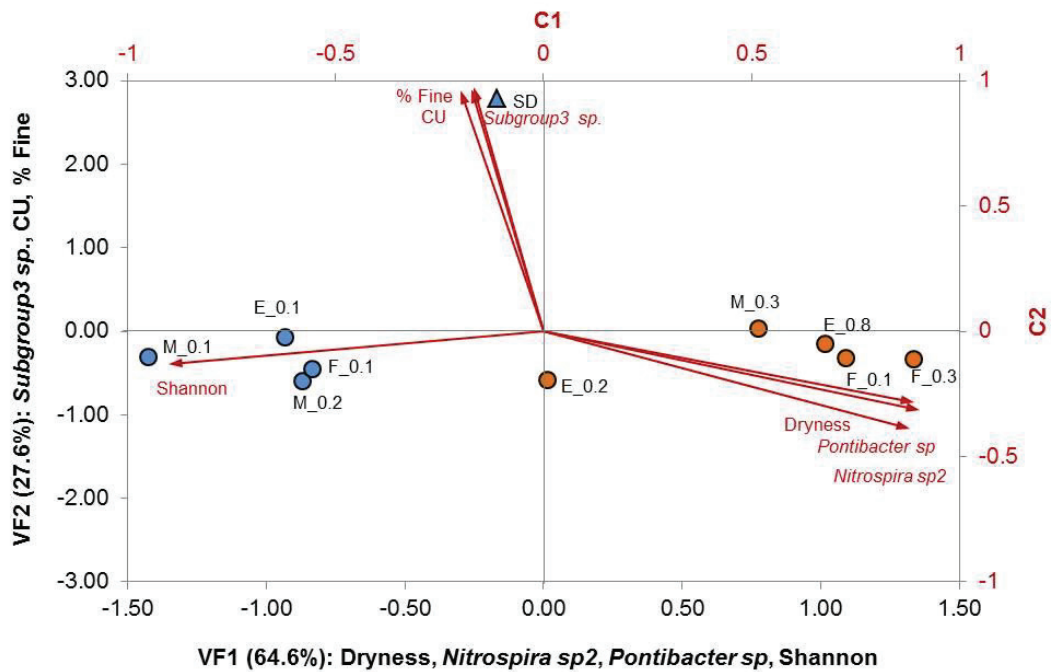
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365 deep soils. It should also be noted that when projected over the first two varifactors
366 plane, wet samples (blue circles) are clustered, whereas dry samples (orange circles)
367 are more scattered in space, indicating that they are affected by depth gradients.
368 Finally, *Acidobacteria_H* is positively correlated with *CU* and proportion of fines, well
369 represented by the sample taken in the sedimentation pond (blue triangle).
370 *PCA₆* clusters microbial classes with diversity indices (Shannon, Richness and
371 Evenness), *Actinobacteria_H*, *Dehalococcoidia_H*, *Chlorobia_H*, *Bacilli_H* and *Others_H* (Figure
372 S3). Whereas *Bacilli_H* behavior is basically explained by the second component,
373 Shannon, Evenness and *Actinobacteria_H* are partially included in both components.
374 Same as shown in a previous analysis, *Actinobacteria_H* is negatively correlated with
375 Shannon and Evenness indices. *Chlorobia_H* and *Dehalococcoidia_H* are explained by the
376 first component and contribute visibly to the microbial print of the wet soil samples.

377

378 **3.4. Key parameters influencing microbial species in MAR soils**

379 In *PCA₇* (Figure 5, Table 1), the first two components explain 92% of the total variance.
380 Projection of samples on varifactor space provides a clear separation of samples
381 according to the operational period (during recharge and no-recharge periods), while
382 the sample from the sedimentation pond remains separated. This last sample (SD in
383 Figure 5) is explained mainly by the proportion of fines, *CU* and notably, the presence
384 of Subgroup_3 *Acidobacteria*. Moreover, Shannon Index and Dryness are displayed in
385 opposite sides of the plot, while the latter is placed in the same side as *Pontibacter sp*
386 and *Nitrospira sp2*, highlighting that both species have a high affinity to dry conditions.



388

389 **Figure 5** PCA₇ analysis including microbial species, grain-size distribution curve parameters and the
 390 operational period from sediment samples during the recharge period (blue) and no-recharge period
 391 (orange). Codes and symbols are reported in Figure 4.

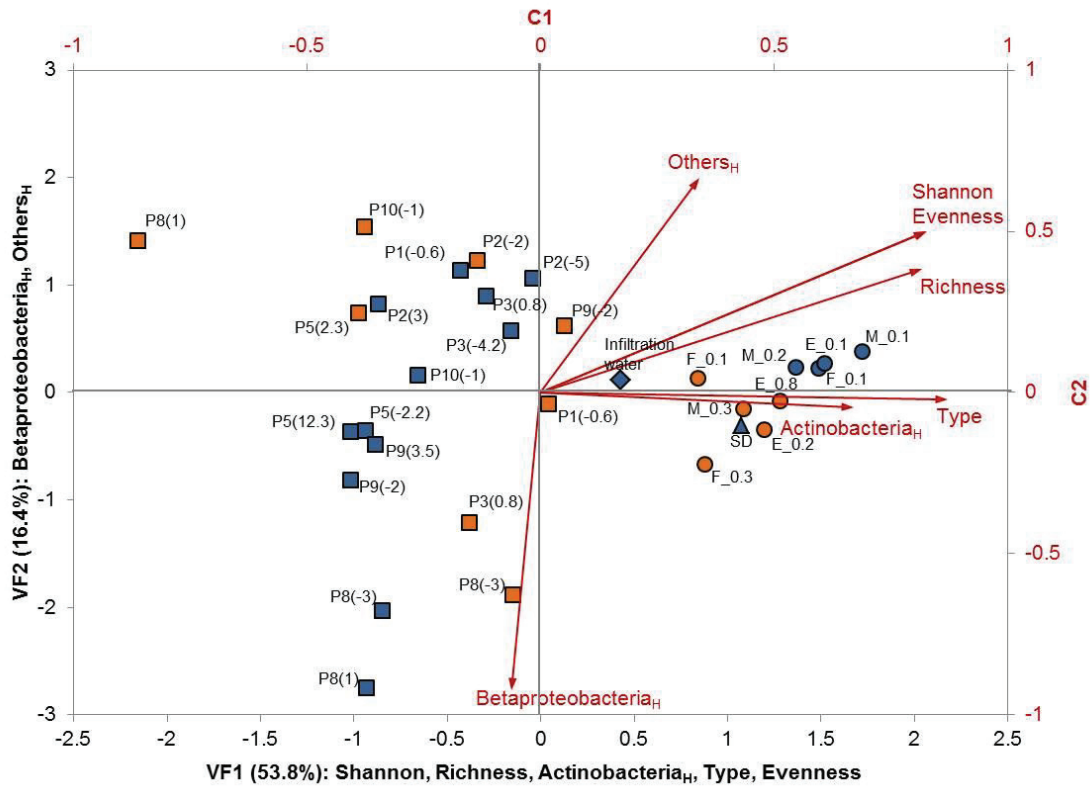
392 PCA₈ indicates the affinity of *Vogesella indigofera* to silty soils (Figure S4). Despite
 393 *Dehalogenimonas sp.* behavior is explained by the second component, this species
 394 does not show correlation with *V. indigofera* or *CU*. However, the bivariate correlations
 395 matrix (not showed) revealed the correlation of *Dehalogenimonas sp.* with fine particles
 396 proportion. On the other hand, both *Methylothera mobilis* and *Methylobacterium sp.*
 397 are correlated positively with two other soil characteristics, *CC* and *D10*.

398 3.5. Interclass and interspecies relationships

399 PCA₉ – PCA₁₁ involves the statistical analysis of all 31 samples together. In PCA₉, soil
 400 and water samples are distinctly located in the varifactor plane involving the first two
 401 components (explaining 70% of the total variance, Figure 6). From the analysis, soil
 402 samples are the most diverse, equally-distributed and rich environments sustaining
 403 microbial growth, as the location of Shannon, Evenness and Richness indices indicate

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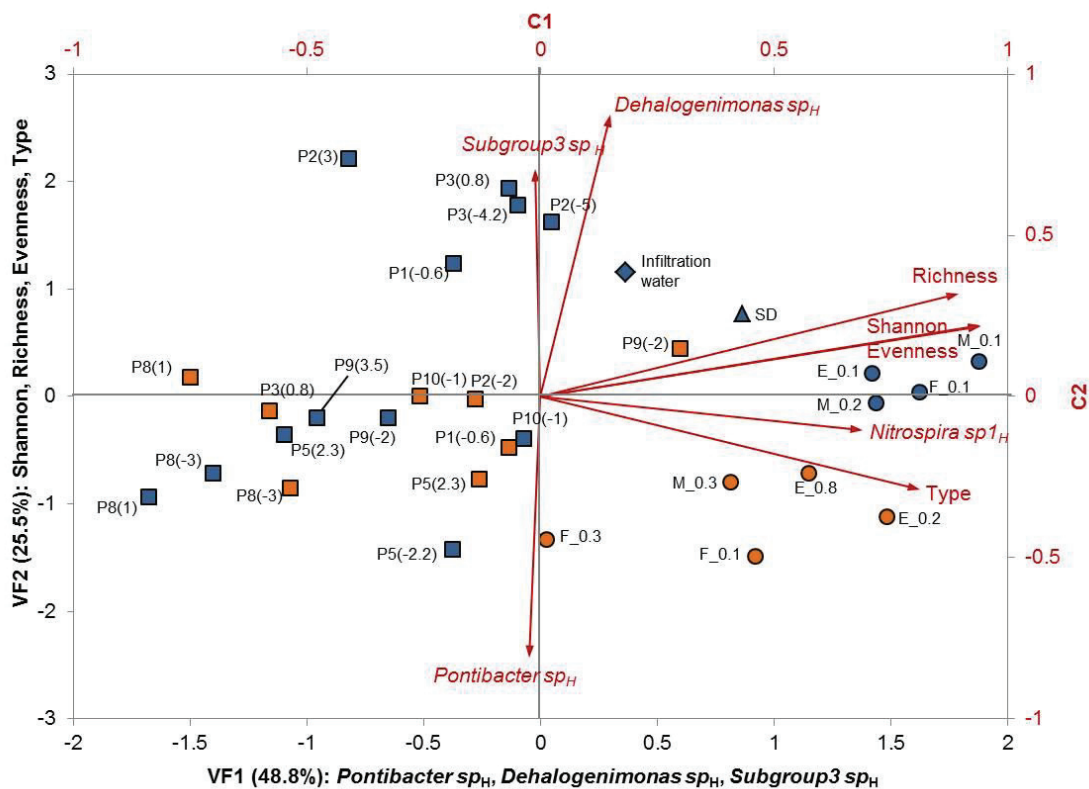
404 in the PCA. On the other hand, Betaproteobacteria_H shows higher affinity for water
405 samples. Bacilli_H becomes an independent third component explaining 13% of the total
406 variance (Table 1).



407
408 **Figure 6** PCA₉ analysis including diversity indices, microbial classes and sample type from soil (circles),
409 groundwater (squares) and surface water (diamonds and triangle) samples during the recharge period
410 (blue) and no-recharge period (orange).

411 PCA₁₀ was performed to analyze the intra-relationships among microbial classes.
412 Three components were needed to explain 85% of the total variance. The first one
413 clusters the three microbial diversity indices. The second one explains the positive
414 correlation between Dehalococcoidia_H and Acidobacteria_H and the negative one with
415 Cytophagia_H. Finally, the third component showed a negative correlation between
416 Nitrospira_H and Chlorobia_H. Samples distribution in VF axes did not show any relevant
417 association among samples (Figure S5).

418 Finally, PCA₁₁ emphasizes microbial species. Similar to PCA₁₀, the first component
 419 groups all three diversity indices, and is representative of soil samples in the varifactor
 420 plane (Figure 7). *Nitrospira sp*_H was also positively correlated with Shannon and
 421 Evenness indices. Regarding the second component, *Pontibacter sp*_H is inversely
 422 correlated with *Dehalogenimonas sp*_H and in turn, the latter correlated positively with
 423 *Subgroup3 sp*_H, pointing out that these two species seem to be more associated to
 424 water and groundwater samples during active recharge period.



425
 426 **Figure 7** PCA₁₁ analysis including diversity indices, microbial species, and type of sample from soil
 427 (circles), groundwater (squares) and surface water (diamond and triangle) during the recharge period
 428 (blue) and no-recharge period (orange).

430 **4. Discussion**

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431 The most significant result from the statistical analysis is that the projection of samples
432 on the planes defined by the principal components shows a clear influence of the
433 operational conditions, this being the parameter that is subject to optimization in a MAR
434 facility management scheme. On one hand, most of the figures show the polarization of
435 samples according to the recharge conditions (blue and orange marks); on the other
436 hand, the variable “Dryness”, indicating soil samples during non-recharge conditions,
437 remains always beside the samples obtained in dry conditions. These results together
438 redundantly imply that recharge operation drives significant changes in microbial
439 communities. Recharge results in shifts in the microbial community structure, in terms
440 of relative abundance and composition of dominant taxonomic groups.

441 Cyanobacteria, the only diazotrophs that produce oxygen as a by-product of the
442 photosynthetic process, were found most abundantly in the surface water, and the
443 measured concentrations correlated with several hydrogeochemical variables (EC, Cl,
444 Cu-log and Ni-log) (recall Figure S1). Correlations among EC and cyanobacteria
445 abundance have been already reported, for example, in a Neotropical urban lake (Frau
446 et al., 2018) or in a eutrophicated reservoir in Brazil (Chellappa and Mederios Costa,
447 2003). Cu-log is positively correlated with cyanobacteria; this follows Dwivedi et al.
448 (2006), who described the simultaneous presence of cyanobacteria and some metals
449 (including Cu) in river water samples enriched by fly-ash originated in a coal thermal
450 power station. Indeed, some cyanobacterial species have the ability to immobilize
451 metals, and this is used in some water treatment industries (de-Bashan and Bashan,
452 2010).

453 The highest relative abundance of Betaproteobacteria was found in the groundwater
454 samples most affected by recharge (e.g., conforming more than 50% of the total
455 microbial abundance in piezometer P8, located directly below the infiltration pond). This
456 microbial group correlates inversely with Richness and Shannon indices (recall Figure
457 2) suggesting that members of the Betaproteobacteria class could have an

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458 opportunistic behavior, displacing other microbial populations when recharge is active,
459 and becoming the leading microorganisms degrading organic matter.

460 We also evaluated the role of DOC, nitrate and sulfate on the abundance of
461 *Methylothera mobilis* in surface and subsurface water environments (see PCA₃). *M.*
462 *mobilis* may carry out heterotrophic denitrification by using different substrates, such as
463 methanol (Kalyuzhnaya et al., 2009; Sun et al., 2016) or methylamine (Kalyuzhnaya et
464 al., 2006) in aerobic environments. In fact, *M. mobilis* is the first methylotroph using
465 nitrate as an electron acceptor, thus being a potential explanation of the positive
466 correlation observed between *M. mobilis* abundance and nitrate concentration in water.
467 Denitrification is an anaerobic process, but in some cases occurs in the presence of
468 oxygen. In these situations, anoxic microenvironments (called microsites) may develop
469 due to the heterogeneity in flow paths that would lead to local denitrification (Knowles,
470 2005; Modin et al., 2007) even in a zone with overall aerobic conditions. One surprising
471 finding from PCA₃ is that correlation of *M. mobilis* and nitrate seems associated with
472 the non-recharge period. Therefore, denitrification conditions are not completely
473 reversed even after recharge has been discontinued for a significant amount of time.

474 On the other hand, it is not surprising that abundance of *M. mobilis* correlates with
475 *Methylobacterium sp.* presence in the soil environment (see PCA₈); since they belong
476 to different proteobacterial classes, they are both obligate methylotrophs (Kumaresan
477 et al., 2018). Indeed, correlations between both species of methylotrophs have been
478 reported by Wright et al. (2017) in a groundwater dichloromethane contaminated site in
479 the US. Unlike *M. mobilis*, *Methylobacterium sp.* is a dichloromethane degrader (Gisi et
480 al., 1998; Vuilleumier et al., 2009), capable to dechlorinate in aerobic conditions.
481 Following Wright et al. (2017), this suggests that *M. mobilis* could take advantage by
482 using the byproducts of dichloromethane degradation carried out by *Methylobacterium*
483 *sp.* However, methane has not been measured at the site, so we are not assuming its
484 presence *via* dichloromethane degradation.

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485 In any case, it is not clear whether *M. mobilis* abundance correlates with some redox
486 species; while the bivariate correlation coefficients with DOC-log and SO₄ were not
487 significant (data not shown), *M. mobilis* grouped in the same component with NO₃ and
488 SO₄. Regarding this last point, there is no evidence that SO₄ might be part of the
489 metabolic pathway of *M. mobilis*.

490 *Vogesella indigofera* positively correlates with DOC-log (PCA₅). Members of this genus
491 are important denitrifiers in groundwater systems (Bellini et al., 2018), capable of
492 oxidizing few monosaccharides in low-oxygen concentration conditions (Grimes et al.,
493 1997). Contrarily, DOC-log was negatively correlated to NO₃ concentration (PCA₃). In
494 fact, the isotopic study performed by Grau-Martínez et al. (2018) at the same facility
495 and on the same dates confirmed that recharge induced denitrification.

496 Dryness (a binary dry/wet variable) is the most significant one controlling the
497 distribution of microbial communities in soils. Similar to what was observed in water
498 samples, soil samples taken during recharge periods displayed largest diversity and
499 highest Betaproteobacteria abundance. Recharge of river water ensured the
500 continuous supply of nutrients and DOC to the system, favoring Betaproteobacteria
501 growth, as it is one of the main bacterial groups biodegrading DOC (Li et al., 2013). In
502 fact, in a work carried out in column models (Li et al., 2012), Betaproteobacteria were
503 found mainly close to the inlet, associated to the high DOC concentrations fed; they
504 also found that water content in soils (and extrapolating, recharge conditions)
505 contribute to microbial diversity in soils. Along the same line, decreasing proportions of
506 Betaproteobacteria were found in dry soils (as compared to wet ones) in an experiment
507 performed with streambed fresh sediments (Pohlon et al., 2013).

508 Distribution of microbial populations in soils is also strongly affected by granulometry
509 (PCA₈). *M. mobilis* and *Methylobacterium sp.* correlated with CC and D₁₀. There is not
510 much literature on this subject. The work performed by Madhaiyan et al. (2007)

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511 associated the variability in the distribution of pink-pigmented facultative metylootrophs,
512 such as *Methylobacterium sp*, with soil type and moisture among other environmental
513 variables. In fact, soil texture conditions is of paramount importance for nutrient
514 transference into flooded soils (Perujo et al., 2017), also influencing methane
515 consumption rates (Jäckel et al., 2001). In the same way, the presence of *Vogesella*
516 *indigofera* and *Subgroup3 sp* (Acidobacteria) in soils is linked to *CU* (an indicator of
517 grain-size heterogeneity) and proportion of fine particles, resulting in these two
518 populations being most abundant in sandy-clayey soils.

519 Members of the phylum Acidobacteria, such as *Subgroup 3 sp* are widespread
520 abundant in soils and sediments, and capable to tolerate moisture fluctuations (Ward et
521 al., 2009). This tolerance can be related to the capability to form biofilms, highly
522 hydrated structures (Kielak et al., 2016), allowing them to survive under stressful
523 dryness conditions (Ward et al., 2009); this could be the reason why they are found
524 regardless the recharge operational conditions. Moreover, it is also important to know
525 the interactions of this group with other microbial classes present in the soil. In this
526 regard, we found a significant statistical positive correlation between *Subgroup3 sp*
527 (Acidobacteria) and *Dehalogenimonas sp* (Dehalococcoidia class); we associate this
528 correlation to both groups being environmentally important, as they are involved in
529 different contaminant degradation processes (Chen et al., 2018; Song et al., 2016).

530 In the soil samples, the relative abundance of Actinobacteria was directly correlated
531 with dry conditions (PCA₅), similar to the observations of Pohlen et al. (2013). Different
532 members of this phylum have the ability to grow developing mycelia structures and
533 forming spores (Bhatti et al., 2017), providing them an advantage in the colonization of
534 soil with limited water availability. Moreover, the combined analysis of soil and water
535 samples showed the widespread presence of this phylum, especially abundant in soil
536 samples, and could be associated to their important role in the cycling of organic matter
537 due to their decomposition capabilities (Bhatti et al., 2017; Polkade et al., 2016). This

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538 behavior is consistent with results observed in our system (PCA₉), where
539 Actinobacteria is linked to microbial diversity indexes and dryness conditions. These
540 last results are not surprising, since soils probably are one of the most diverse and rich
541 environments supporting microbial life in the world (Curtis et al., 2002; Or et al., 2007;
542 Torsvik et al., 2002; Young and Crawford, 2004).

543 Characterization of microbial communities may have strong implications in MAR
544 facilities management when better understood. A particular combination of soil and
545 inflow water characteristics at the infiltration pond would result in a particular microbial
546 population signature. Such population would degrade preferably some particular
547 organic compounds. The spatial distribution of microorganisms can be used for
548 mapping the area influenced (even partially) by recharge. From another point of view,
549 such detailed mapping can be eventually used in the future for optimal design of biofilm
550 growth and composition in order to promote degradation of different target compounds.
551 Furthermore, indicator species could be included in monitoring networks in order to
552 characterize environmental conditions that take place at longer temporal scales than
553 the one represented by punctual hydrochemical data.

554 **5. Conclusions**

555 The work presented in this paper led us to draw conclusions regarding both the
556 statistical analysis proposed and the intrinsic results obtained.

557 Multivariate statistical methods allow the simultaneous treatment of interdisciplinary
558 data (physical, chemical, and biological), from different nature (categorical, binary and
559 continuous) and spanning different ranges, in a formal statistical way. This is potentially
560 very useful for many experimental studies in soil science or freshwater systems as a
561 way to integrate data in a subset of statistical components that despite being small in
562 dimensional terms, explains a large amount of the variance of the dataset.

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563 The application of this methodology in the dataset obtained in the Sant Vicenç
564 recharge facility enabled to conclude that MAR influences significantly microbial
565 communities in soil, surface and subsurface water. Therefore, they can be used to
566 assess the area of the soil and the volume of the aquifer influenced by recharge.
567 Microbial communities are directly influenced by a combination of biogeochemical
568 processes and vice versa. Aquifer recharge *via* infiltration ponds has a significant
569 impact upon carbon and nitrogen cycles in the topsoil, since most of the microbial
570 species detected in this study have a role in the aerobic degradation of organic matter
571 and in denitrification processes. Thus, a strong correlation was found between
572 hydrochemical compounds and some microbial communities, both in the soil and
573 groundwater samples; two examples are the correlation between *Vogesella indigofera*
574 with DOC and *Methylothermobacter mobilis* with NO₃.

575 The statistical analysis of both groundwater and soil samples clearly discriminate
576 operational conditions. Recharge drives distinct populations to become dominant
577 (Betaproteobacteria, Dehalococcoidia, and Nitrospira). Moreover, groundwater
578 samples can be graphically represented according to the degree of disturbance (in
579 terms of the proportion of infiltrating water versus the native one in the corresponding
580 water samples).

581 In the case of soil samples, there are two most set of significant variables affecting the
582 distribution of microbial communities: (1) grain-size distribution (affecting *Vogesella*
583 *indigofera*, *Subgroup3 sp* (Acidobacteria), *Methylothermobacter mobilis*, *Dehalogenimonas sp*
584 and *Methylobacterium sp*); and (2) operation conditions, as wet soils contain more
585 microbial diversity than dry ones. However, there are some classes (e.g.,
586 Acidobacteria) that are less affected by recharge conditions. In the future, this could
587 provide ideas for the affection of the climate change consequences in stream-flows,
588 wetlands, and other drought-vulnerable aquatic systems.

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589 Multivariate statistical analysis indicates that DOC was another determinant factor
590 shaping microbial community structure. Among them, members of Betaproteobacteria,
591 Dehalococcoidia and Acidobacteria are involved in pollutant bioremediation and can be
592 considered as potential bioindicators for recharge monitoring.

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594 **Acknowledgments**

595 This investigation was financially supported by the European Union project MARSOL
596 FP7-ENV-2013-WATER-INNO-DEMO, Generalitat de Catalunya via FI scholarship
597 program (FI-DGR 2014) and the Spanish Ministry of Economy and Competitiveness
598 and EU (project ACWAPUR PCIN-2015-239). The authors would like to acknowledge
599 Comunitat d'Usuaris d'Aigües de la Vall Baixa i del Delta del Riu Llobregat (CUADLL)
600 for their cooperation.

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602 **References**

- 603 Alidina, M., Li, D., Drewes, J.E., 2014. Investigating the role for adaptation of the
604 microbial community to transform trace organic chemicals during managed aquifer
605 recharge. *Water Res* 56, 172–180. doi:10.1016/j.watres.2014.02.046
- 606 Alidina, M., Shewchuk, J., Drewes, J.E., 2015. Effect of temperature on removal of
607 trace organic chemicals in managed aquifer recharge systems. *Chemosphere*
608 122, 23–31. doi:10.1016/j.chemosphere.2014.10.064
- 609 Barba, C., Folch, A., Gaju, N., Sanchez-Vila, X., Carrasquilla, M., Grau-Martínez, A.,
610 Martínez-Alonso, M., 2019. Microbial community changes induced by Managed
611 Aquifer Recharge activities: Linking hydrogeological and biological processes.
612 *Hydrol Earth Syst Sci.*, 23, 139-154, doi: 10.5194/hess-23-139-2019

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47
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53
54
55
56
57
58
59
60
61
62
63
64
65

613 Bekele, E., Toze, S., Patterson, B., Higginson, S., 2011. Managed aquifer recharge of
614 treated wastewater: Water quality changes resulting from infiltration through the
615 vadose zone. *Water Res* 45, 5764–5772. doi:10.1016/j.watres.2011.08.058

616 Bellini, M.I., Gutiérrez, L., Tarlera, S., Scavino, A.F., 2013. Isolation and functional
617 analysis of denitrifiers in an aquifer with high potential for denitrification. *Syst Appl*
618 *Microbiol* 36, 505–16. doi:10.1016/j.syapm.2013.07.001

619 Bellini, M.I., Kumaresan, D., Tarlera, S., Murrell, J.C., Fernández-Scavino, A., 2018.
620 Identification of active denitrifiers by DNA-stable isotope probing and amplicon
621 sequencing reveals Betaproteobacteria as responsible for attenuation of nitrate
622 contamination in a low impacted aquifer. *FEMS Microbiol Ecol* 94, fix181-fix181.

623 Bhatti, A.A., Haq, S., Bhat, R.A., 2017. Actinomycetes benefaction role in soil and plant
624 health. *Microb Pathog*. doi:10.1016/j.micpath.2017.09.036

625 Bouwer, H., 2002. Artificial recharge of groundwater: hydrogeology and engineering.
626 *Hydrogeol J* 10, 121–142. doi:10.1007/s10040-001-0182-4

627 Chau, J., Bagtzoglou, A., Willig, M., 2011. The effect of soil texture on richness and
628 diversity of bacterial communities. *Environ Forensics* 12, 333–341.
629 doi:10.1080/15275922.2011.622348

630 Chellappa, N.T., Mederios Costa, M.A., 2003. Dominant and co-existing species of
631 Cyanobacteria from a Eutrophicated reservoir of Rio Grande do Norte State,
632 Brazil, in: *Acta Oecologica*. Elsevier Masson, pp. S3–S10. doi:10.1016/S1146-
633 609X(03)00005-5

634 Chen, J., Wang, P.-F., Wang, C., Liu, J.-J., Gao, H., Wang, X., 2018. Spatial
635 distribution and diversity of organohalide-respiring bacteria and their relationships
636 with polybrominated diphenyl ether concentration in Taihu Lake sediments.
637 *Environ Pollut* 232, 200–211. doi:10.1016/J.ENVPOL.2017.08.124

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56
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58
59
60
61
62
63
64
65

638 Curtis, T.P., Sloan, W.T., Scannell, J.W., 2002. Estimating prokaryotic diversity and its
639 limits. *Proc Natl Acad Sci* 99, 10494–10499. doi:10.1073/pnas.142680199

640 D’Alessio, M., Yoneyama, B., Kirs, M., Kisand, V., Ray, C., 2015. Pharmaceutically
641 active compounds: Their removal during slow sand filtration and their impact on
642 slow sand filtration bacterial removal. *Sci Total Environ* 524–525, 124–135.
643 doi:10.1016/j.scitotenv.2015.04.014

644 de-Bashan, L.E., Bashan, Y., 2010. Immobilized microalgae for removing pollutants:
645 Review of practical aspects. *Bioresour Technol* 101, 1611–1627.
646 doi:10.1016/j.biortech.2009.09.043

647 Drewes, J.E., Li, D., Regnery, J., Alidina, M., Wing, A., Hoppe-Jones, C., 2014. Tuning
648 the performance of a natural treatment process using metagenomics for improved
649 trace organic chemical attenuation. *Water Sci Technol* 69, 628–633.
650 doi:10.2166/wst.2013.750

651 Drewes, J.E., Reinhard, M., Fox, P., 2003. Comparing microfiltration-reverse osmosis
652 and soil-aquifer treatment for indirect potable reuse of water. *Water Res* 37, 3612–
653 3621. doi:10.1016/S0043-1354(03)00230-6

654 Dutta, T., Carles-Brangarí, A., Fernández-Garcia, D., Rubol, S., Tirado-Conde, J.,
655 Sanchez-Vila, X., 2015. Vadose zone oxygen (O₂) dynamics during drying and
656 wetting cycles: An artificial recharge laboratory experiment. *J Hydrol* 527, 151–
657 159. doi:10.1016/j.jhydrol.2015.04.048

658 Dwivedi, S., Tripathi, R.D., Rai, U.N., Srivastava, S., Mishra, S., Shukla, M.K., Gupta,
659 A.K., Sinha, S., Baghel, V.S., Gupta, D.K., 2006. Dominance of algae in ganga
660 water polluted through fly-ash leaching: Metal bioaccumulation potential of
661 selected algal species. *Bull Environ Contam Toxicol* 77, 427–436.
662 doi:10.1007/s00128-006-1083-y

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65

663 El Alfy, M., Lashin, A., Abdalla, F., Al-Bassam, A., 2017. Assessing the
664 hydrogeochemical processes affecting groundwater pollution in arid areas using
665 an integration of geochemical equilibrium and multivariate statistical techniques.
666 Environ Pollut 229, 760–770. doi:10.1016/j.envpol.2017.05.052

667 Fahrenfeld, N., Cozzarelli, I.M., Bailey, Z., Pruden, A., 2014. Insights into
668 Biodegradation Through Depth-Resolved Microbial Community Functional and
669 Structural Profiling of a Crude-Oil Contaminant Plume. Microb Ecol 68, 453–462.
670 doi:10.1007/s00248-014-0421-6

671 Faulwetter, J.L., Gagnon, V., Sundberg, C., Chazarenc, F., Burr, M.D., Brisson, J.,
672 Camper, A.K., Stein, O.R., 2009. Microbial processes influencing performance of
673 treatment wetlands: A review. Ecol Eng 35, 987–1004.
674 doi:10.1016/j.ecoleng.2008.12.030

675 Frau, D., Pinto, P.D.T., Mayora, G., 2018. Are cyanobacteria total, specific and trait
676 abundance regulated by the same environmental variables? Ann Limnol 54, 3.
677 doi:10.1051/limn/2017030

678 Freixa, A., Rubol, S., Carles-Brangarí, A., Fernàndez-Garcia, D., Butturini, A.,
679 Sanchez-Vila, X., Romani, A.M., 2015. The effects of sediment depth and oxygen
680 concentration on the use of organic matter: An experimental study using an
681 infiltration sediment tank. Sci Total Environ 540, 20–31.
682 doi:10.1016/j.scitotenv.2015.04.007

683 Ginige, M.P., Kaksonen, A.H., Morris, C., Shackelton, M., Patterson, B.M., 2013.
684 Bacterial community and groundwater quality changes in an anaerobic aquifer
685 during groundwater recharge with aerobic recycled water. FEMS Microbiol Ecol
686 85, 553–567. doi:10.1111/1574-6941.12137

687 Gisi, D., Willi, L., Traber, H., Leisinger, T., Vuilleumier, S., 1998. Effects of bacterial

1
2
3
4
5
6
7
8
9
10
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17
18
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64
65

688 host and dichloromethane dehalogenase on the competitiveness of methylotrophic
689 bacteria growing with dichloromethane. *Appl Environ Microbiol* 64, 1194–1202.

690 Goren, O., Burg, A., Gavrieli, I., Negev, I., Guttman, J., Kraitzer, T., Kloppmann, W.,
691 Lazar, B., 2014. Biogeochemical processes in infiltration basins and their impact
692 on the recharging effluent, the soil aquifer treatment (SAT) system of the Shafdan
693 plant, Israel. *Appl Geochemistry* 48, 58–69.
694 doi:10.1016/j.apgeochem.2014.06.017

695 Grau-Martínez, A., Folch, A., Torrentó, C., Valhondo, C., Barba, C., Domènech, C.,
696 Soler, A., Otero, N., 2018. Monitoring induced denitrification during managed
697 aquifer recharge in an infiltration pond. *J Hydrol* 561, 123–135.
698 doi:10.1016/j.jhydrol.2018.03.044

699 Greskowiak, J., Hamann, E., Burke, V., Massmann, G., 2017. The uncertainty of
700 biodegradation rate constants of emerging organic compounds in soil and
701 groundwater – A compilation of literature values for 82 substances. *Water Res*
702 126, 122–133. doi:10.1016/j.watres.2017.09.017

703 Greskowiak, J., Prommer, H., Massmann, G., Johnston, C.D., Nützmann, G.,
704 Pekdeger, A., 2005. The impact of variably saturated conditions on
705 hydrogeochemical changes during artificial recharge of groundwater. *Appl*
706 *Geochemistry* 20, 1409–1426. doi:10.1016/j.apgeochem.2005.03.002

707 Greskowiak, J., Prommer, H., Massmann, G., Nützmann, G., 2006. Modeling Seasonal
708 Redox Dynamics and the Corresponding Fate of the Pharmaceutical Residue
709 Phenazone During Artificial Recharge of Groundwater. *Environ Sci Technol* 40,
710 6615–6621. doi:10.1021/es052506t

711 Griebler, C., Lueders, T., 2009. Microbial biodiversity in groundwater ecosystems.
712 *Freshw Biol* 54, 649–677. doi:10.1111/j.1365-2427.2008.02013.x

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55
56
57
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62
63
64
65

713 Grimes, D.J., Woese, C.R., MacDonell, M.T., Colwell, R.R., 1997. Systematic study of
714 the genus *Vogesella* gen. nov. and its type species, *Vogesella indigofera* comb.
715 nov. *Int J Syst Bacteriol* 47, 19–27. doi:10.1099/00207713-47-1-19

716 Haack, S.K., Fogarty, L.R., West, T.G., Alm, E.W., McGuire, J.T., Long, D.T.,
717 Hyndman, D.W., Forney, L.J., 2004. Spatial and temporal changes in microbial
718 community structure associated with recharge-influenced chemical gradients in a
719 contaminated aquifer. *Env Microbiol* 6, 438–448. doi:10.1111/j.1462-
720 2920.2003.00563.x

721 Hamann, E., Stuyfzand, P.J., Greskowiak, J., Timmer, H., Massmann, G., 2016. The
722 fate of organic micropollutants during long-term/long-distance river bank filtration.
723 *Sci Total Environ* 545–546, 629–640. doi:10.1016/j.scitotenv.2015.12.057

724 Hellauer, K., Karakurt, S., Sperlich, A., Burke, V., Massmann, G., Hübner, U., Drewes,
725 J.E., 2017. Establishing sequential managed aquifer recharge technology
726 (SMART) for enhanced removal of trace organic chemicals: Experiences from field
727 studies in Berlin, Germany. *J Hydrol*. doi:10.1016/j.jhydrol.2017.09.044

728 Jäckel, U., Schnell, S., Conrad, R., 2001. Effect of moisture, texture and aggregate size
729 of paddy soil on production and consumption of CH₄. *Soil Biol Biochem* 33, 965–
730 971. doi:10.1016/S0038-0717(00)00248-0

731 Kalyuzhnaya, M.G., Martens-Habbena, W., Wang, T., Hackett, M., Stolyar, S.M., Stahl,
732 D.A., Lidstrom, M.E., Chistoserdova, L., 2009. Methylophilaceae link methanol
733 oxidation to denitrification in freshwater lake sediment as suggested by stable
734 isotope probing and pure culture analysis. *Environ Microbiol Rep* 1, 385–392.
735 doi:10.1111/j.1758-2229.2009.00046.x

736 Kalyuzhnaya, M.G., Bowerman, S., Lara, J.C., Lidstrom, M.E., Chistoserdova, L., 2006.
737 *Methylotenera mobilis* gen. nov., sp. nov., an obligately methelamine-utilizing

1
2
3
4
5 738 bacterium within the family Methylophilaceae. *Int J Syst Evol Microbiol* 56, 2819–
6
7 739 2823. doi:10.1099/ijs.0.64191-0
8
9
10 740 Kielak, A.M., Barreto, C.C., Kowalchuk, G.A., van Veen, J.A., Kuramae, E.E., 2016.
11
12 741 The ecology of Acidobacteria: Moving beyond genes and genomes. *Front*
13
14 742 *Microbiol.* doi:10.3389/fmicb.2016.00744
15
16
17 743 Knowles, R., 2005. Denitrifiers associated with methanotrophs and their potential
18
19 744 impact on the nitrogen cycle. *Ecol Eng* 24, 441–446.
20
21 745 doi:10.1016/J.ECOLENG.2005.01.001
22
23
24 746 Kolehmainen, R.E., Tirola, M., Puhakka, J.A., 2008. Spatial and temporal changes in
25
26 747 Actinobacterial dominance in experimental artificial groundwater recharge. *Water*
27
28 748 *Res* 42, 4525–4537. doi:10.1016/j.watres.2008.07.039
29
30
31 749 Kumaresan, D., Stephenson, J., Doxey, A.C., Bandukwala, H., Brooks, E., Hillebrand-
32
33 750 Voiculescu, A., Whiteley, A.S., Murrell, J.C., 2018. Aerobic proteobacterial
34
35 751 methylotrophs in Movile Cave: genomic and metagenomic analyses. *Microbiome*
36
37 752 6, 1. doi:10.1186/s40168-017-0383-2
38
39
40 753 Lapworth, D.J., Baran, N., Stuart, M.E., Ward, R.S., 2012. Emerging organic
41
42 754 contaminants in groundwater: A review of sources, fate and occurrence. *Environ*
43
44 755 *Pollut.* doi:10.1016/j.envpol.2011.12.034
45
46
47 756 Laws, B. V, Dickenson, E.R. V, Johnson, T.A., Snyder, S.A., Drewes, J.E., 2011.
48
49 757 Attenuation of contaminants of emerging concern during surface-spreading aquifer
50
51 758 recharge. *Sci Total Environ* 409, 1087–1094. doi:10.1016/j.scitotenv.2010.11.021
52
53
54 759 Legendre, P., Gallagher, E.D., 2001. Ecologically meaningful transformations for
55
56 760 ordination of species data. *Oecologia* 129, 271–280. doi:10.1007/s004420100716
57
58
59 761 Li, D., Alidina, M., Ouf, M., Sharp, J.O., Saikaly, P., Drewes, J.E., 2013. Microbial
60
61 762 community evolution during simulated managed aquifer recharge in response to

1
2
3
4
5 763 different biodegradable dissolved organic carbon (BDOC) concentrations. *Water*
6
7 764 *Res* 47, 2421–2430. doi:10.1016/j.watres.2013.02.012
8
9
10 765 Li, D., Sharp, J.O., Saikaly, P.E., Ali, S., Alidina, M., Alarawi, M.S., Keller, S., Hoppe-
11 766 Jones, C., Drewes, J.E., 2012. Dissolved organic carbon influences microbial
12 767 community composition and diversity in managed aquifer recharge systems. *Appl*
13 768 *Env Microbiol* 78, 6819–6828. doi:10.1128/aem.01223-12
14
15 769 Madhaiyan, M., Poonguzhali, S., Sa, T., 2007. Influence of plant species and
16 770 environmental conditions on epiphytic and endophytic pink-pigmented facultative
17 771 methylotrophic bacterial populations associated with field-grown rice cultivars. *J*
18 772 *Microbiol Biotechnol* 17, 1645–1654.
19
20
21 773 Maeng, S.K., Sharma, S.K., Lekkerkerker-Teunissen, K., Amy, G.L., 2011. Occurrence
22 774 and fate of bulk organic matter and pharmaceutically active compounds in
23 775 managed aquifer recharge: A review. *Water Res* 45, 3015–3033. doi:
24 776 10.1016/j.watres.2011.02.017
25
26
27 777 Martínez-Pascual, E., Jiménez, N., Vidal-Gavilan, G., Vinas, M., Solanas, A.M., 2010.
28 778 Chemical and microbial community analysis during aerobic biostimulation assays
29 779 of non-sulfonated alkyl-benzene-contaminated groundwater. *Appl Microbiol*
30 780 *Biotechnol* 88, 985–995. doi:10.1007/s00253-010-2816-8
31
32
33
34 781 Massmann, G., Greskowiak, J., Dünnbier, U., Zuehlke, S., Knappe, A., Pekdeger, A.,
35 782 2006. The impact of variable temperatures on the redox conditions and the
36 783 behaviour of pharmaceutical residues during artificial recharge. *J Hydrol* 328,
37 784 141–156. doi: 10.1016/j.jhydrol.2005.12.009
38
39
40
41 785 Meckenstock, R.U., Elsner, M., Griebler, C., Lueders, T., Stumpp, C., Aamand, J.,
42 786 Agathos, S.N., Albrechtsen, H.J., Bastiaens, L., Bjerg, P.L., Boon, N., Dejonghe,
43 787 W., Huang, W.E., Schmidt, S.I., Smolders, E., Sørensen, S.R., Springael, D., Van

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49
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51
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57
58
59
60
61
62
63
64
65
- 788 Breukelen, B.M., 2015. Biodegradation: Updating the Concepts of Control for
789 Microbial Cleanup in Contaminated Aquifers. *Environ Sci Technol* 49, 7073–7081.
790 doi:10.1021/acs.est.5b00715
- 791 Menció, A., Folch, A., Mas-Pla, J., 2012. Identifying key parameters to differentiate
792 groundwater flow systems using multifactorial analysis. *J Hydrol* 472–473, 301–
793 313. doi:10.1016/j.jhydrol.2012.09.030
- 794 Mermillod-Blondin, F., Simon, L., Maazouzi, C., Foulquier, A., Delolme, C., Marmonier,
795 P., 2015. Dynamics of dissolved organic carbon (DOC) through stormwater basins
796 designed for groundwater recharge in urban area: Assessment of retention
797 efficiency. *Water Res* 81, 27–37. doi:10.1016/j.watres.2015.05.031
- 798 Modin, O., Fukushi, K., Yamamoto, K., 2007. Denitrification with methane as external
799 carbon source. *Water Res* 41, 2726–2738. doi:10.1016/j.watres.2007.02.053
- 800 Nijenhuis, I., Kuntze, K., 2016. Anaerobic microbial dehalogenation of organohalides—
801 state of the art and remediation strategies. *Curr Opin Biotechnol* 38, 33–38.
802 doi:10.1016/j.copbio.2015.11.009
- 803 Or, D., Smets, B.F., Wraith, J.M., Dechesne, A., Friedman, S.P., 2007. Physical
804 constraints affecting bacterial habitats and activity in unsaturated porous media –
805 a review. *Adv Water Resour* 30, 1505–1527. doi:
806 10.1016/j.advwatres.2006.05.025
- 807 Paliy, O., Shankar, V., 2016. Application of multivariate statistical techniques in
808 microbial ecology. *Mol Ecol*. doi:10.1111/mec.13536
- 809 Pedretti, D., Barahona-Palomo, M., Bolster, D., Fernández-García, D., Sanchez-Vila,
810 X., Tartakovsky, D.M., 2012a. Probabilistic analysis of maintenance and operation
811 of artificial recharge ponds. *Adv Water Resour* 36, 23–35. doi:
812 10.1016/j.advwatres.2011.07.008

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813 Pedretti, D., Barahona-Palomo, M., Bolster, D., Sanchez-Vila, X., Fernández-García,
814 D., 2012b. A quick and inexpensive method to quantify spatially variable infiltration
815 capacity for artificial recharge ponds using photographic images. *J Hydrol* 430–
816 431, 118–126. doi: 10.1016/j.jhydrol.2012.02.008

817 Perujo, N., Romaní, A.M., Sanchez-Vila, X., 2018. Bilayer Infiltration System Combines
818 Benefits from Both Coarse and Fine Sands Promoting Nutrient Accumulation in
819 Sediments and Increasing Removal Rates. *Environ Sci Technol* 52, 5734–5743.
820 doi:10.1021/acs.est.8b00771

821 Perujo, N., Sanchez-Vila, X., Proia, L., Romaní, A.M., 2017. Interaction between
822 Physical Heterogeneity and Microbial Processes in Subsurface Sediments: A
823 Laboratory-Scale Column Experiment. *Environ Sci Technol* 51, 6110–6119.
824 doi:10.1021/acs.est.6b06506

825 Pett-Ridge, J., Firestone, M.K., 2005. Redox fluctuation structures microbial
826 communities in a wet tropical soil. *Appl Environ Microbiol* 71, 6998–7007.
827 doi:10.1128/AEM.71.11.6998-7007.2005

828 Pohlen, E., Fandino, A.O., Marxsen, J., 2013. Bacterial community composition and
829 extracellular enzyme activity in temperate streambed sediment during drying and
830 rewetting. *PLoS One* 8, e83365. doi:10.1371/journal.pone.0083365

831 Polkade, A. V, Mantri, S.S., Patwekar, U.J., Jangid, K., 2016. Quorum sensing: An
832 under-explored phenomenon in the phylum Actinobacteria. *Front Microbiol*.
833 doi:10.3389/fmicb.2016.00131

834 Reed, D.A., Toze, S., Chang, B., 2008. Spatial and temporal changes in sulphate-
835 reducing groundwater bacterial community structure in response to Managed
836 Aquifer Recharge. *Water Sci Technol* 57, 789. doi:10.2166/wst.2008.172

837 Regnery, J., Li, D., Roberts, S., Higgins, C., Sharp, J.O., Drewes, J.E., 2016. Linking

838 Trace Organic Chemical Attenuation to Microbiome metabolic Capabilities:
839 Insights from Laboratory- and Full-scale Managed Aquifer Recharge Systems, in:
840 ACS Symposium Series. pp. 163–187. doi:10.1021/bk-2016-1241.ch011

841 Regnery, J., Wing, A.D., Alidina, M., Drewes, J.E., 2015. Biotransformation of trace
842 organic chemicals during groundwater recharge: How useful are first-order rate
843 constants? *J Contam Hydrol* 179, 65–75. doi:10.1016/j.jconhyd.2015.05.008

844 Rezanezhad, F., Couture, R.M., Kovac, R., O’Connell, D., Van Cappellen, P., 2014.
845 Water table fluctuations and soil biogeochemistry: An experimental approach
846 using an automated soil column system. *J Hydrol* 509, 245–256.
847 doi:10.1016/j.jhydrol.2013.11.036

848 Rodríguez-Escales, P., Canelles, A., Sanchez-Vila, X., Folch, A., Kurtzman, D.,
849 Rossetto, R., Fernández-Escalante, E., Lobo-Ferreira, J.-P., Sapiano, M., San-
850 Sebastián, J., Schüth, C., 2018. A risk assessment methodology to evaluate the
851 risk failure of managed aquifer recharge in the Mediterranean Basin. *Hydrol Earth
852 Syst Sci* 22, 3213–3227. doi:10.5194/hess-22-3213-2018

853 Rodríguez-Escales, P., Fernández-García, D., Drechsel, J., Folch, A., Sanchez-Vila,
854 X., 2017. Improving degradation of emerging organic compounds by applying
855 chaotic advection in Managed Aquifer Recharge in randomly heterogeneous
856 porous media. *Water Resour Res* 53, 4376–4392. doi:10.1002/2016WR020333

857 Rodríguez-Escales, P., Sanchez-Vila, X., 2016. Fate of sulfamethoxazole in
858 groundwater: Conceptualizing and modeling metabolite formation under different
859 redox conditions. *Water Res* 105, 540–550. doi:10.1016/j.watres.2016.09.034

860 Röling, W.F., van Breukelen, B.M., Braster, M., Lin, B., van Verseveld, H.W., 2001.
861 Relationships between microbial community structure and hydrochemistry in a
862 landfill leachate-polluted aquifer. *Appl Environ Microbiol* 67, 4619–29.

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
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47
48
49
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51
52
53
54
55
56
57
58
59
60
61
62
63
64
65

863 Rothschild, L.J., Mancinelli, R.L., 2001. Life in extreme environments (nature).PDF.
864 Nature 409, 1092–1101. doi:10.1038/35059215

865 San-Sebastián-Sauto, J., Fernández-Escalante, E., Calero-Gil, R., Carvalho, T.,
866 Rodríguez-Escales, P., 2018. Characterization and benchmarking of seven
867 managed aquifer recharge systems in south-western Europe. Sustain Water
868 Resour Manag 1–23. doi:10.1007/s40899-018-0232-x

869 Schütz, K., Nagel, P., Vetter, W., Kandeler, E., Ruess, L., 2009. Flooding forested
870 groundwater recharge areas modifies microbial communities from top soil to
871 groundwater table. FEMS Microbiol Ecol 67, 171–182. doi:10.1111/j.1574-
872 6941.2008.00608.x

873 Song, M., Jiang, L., Zhang, D., Luo, C., Wang, Y., Yu, Z., Yin, H., Zhang, G., 2016.
874 Bacteria capable of degrading anthracene, phenanthrene, and fluoranthene as
875 revealed by DNA based stable-isotope probing in a forest soil. J Hazard Mater
876 308, 50–57. doi:10.1016/J.JHAZMAT.2016.01.009

877 Staats, M., Braster, M., Röling, W.F.M., 2011. Molecular diversity and distribution of
878 aromatic hydrocarbon-degrading anaerobes across a landfill leachate plume.
879 Environ Microbiol 13, 1216–1227. doi:10.1111/j.1462-2920.2010.02421.x

880 Stein, H., Kellermann, C., Schmidt, S.I., Brielmann, H., Steube, C., Berkhoff, S.E.,
881 Fuchs, A., Hahn, H.J., Thulin, B., Griebler, C., 2010. The potential use of fauna
882 and bacteria as ecological indicators for the assessment of groundwater quality. J
883 Environ Monit 12, 242–254. doi:10.1039/B913484K

884 Sun, Y., Shen, D., Zhou, X., Shi, N., Tian, Y., 2016. Microbial diversity and community
885 structure of denitrifying biological filters operated with different carbon sources.
886 Springerplus 5, 1752. doi:10.1186/s40064-016-3451-3

887 Terzaghi, K., Peck, R.B., Mesri, G., 1996. Soil mechanics in engineering practice, Third

1
2
3 888 ed. ed. Wiley-Interscience.
4
5 889 Torsvik, V., Øvreås, L., Thingstad, T.F., 2002. Prokaryotic diversity - Magnitude,
6
7
8 890 dynamics, and controlling factors. *Science* (80-). doi:10.1126/science.1071698
9
10 891 Truu, M., Juhanson, J., Truu, J., 2009. Microbial biomass, activity and community
11
12 892 composition in constructed wetlands. *Sci Total Environ* 407, 3958–3971. doi:
13 893 10.1016/j.scitotenv.2008.11.036
14
15 894 Valhondo, C., Carrera, J., Ayora, C., Tubau, I., Martinez-Landa, L., Nödler, K., Licha,
16
17 895 T., 2015. Characterizing redox conditions and monitoring attenuation of selected
18
19 896 pharmaceuticals during artificial recharge through a reactive layer. *Sci Total*
20
21 897 *Environ* 512–513, 240–50. doi:10.1016/j.scitotenv.2015.01.030
22
23
24
25 898 Valhondo, C., Martinez-Landa, L., Carrera, J., Ayora, C., Nödler, K., Licha, T., 2018.
26
27 899 Evaluation of EOC removal processes during artificial recharge through a reactive
28
29 900 barrier. *Sci Total Environ* 612, 985–994. doi:10.1016/j.scitotenv.2017.08.054
30
31
32
33 901 Valhondo, C., Martínez-Landa, L., Carrera, J., Hidalgo, J.J., Tubau, I., De Pourcq, K.,
34
35 902 Grau-Martínez, A., Ayora, C., 2016. Tracer test modeling for local scale residence
36
37 903 time distribution characterization in an artificial recharge site. *Hydrol Earth Syst*
38
39 904 *Sci Discuss* 1–17. doi:10.5194/hess-2016-197
40
41
42
43 905 Vuilleumier, S., Chistoserdova, L., Lee, M.C., Bringel, F., Lajus, A., Yang, Z., Gourion,
44
45 906 B., Barbe, V., Chang, J., Cruveiller, S., Dossat, C., Gillett, W., Gruffaz, C.,
46
47 907 Haugen, E., Hourcade, E., Levy, R., Mangenot, S., Muller, E., Nadalig, T., Pagni,
48
49 908 M., Penny, C., Peyraud, R., Robinson, D.G., Roche, D., Rouy, Z., Saenempechek,
50
51 909 C., Salvignol, G., Vallenet, D., Zaining, W., Marx, C.J., Vorholt, J.A., Olson, M. V,
52
53 910 Kaul, R., Weissenbach, J., Médigue, C., Lidstrom, M.E., 2009. *Methylobacterium*
54
55 911 genome sequences: A reference blueprint to investigate microbial metabolism of
56
57 912 C1 compounds from natural and industrial sources. *PLoS One* 4.
58
59
60
61
62
63
64
65

1
2
3 913 doi:10.1371/journal.pone.0005584
4
5 914 Ward, N.L., Challacombe, J.F., Janssen, P.H., Henrissat, B., Coutinho, P.M., Wu, M.,
6
7 915 Xie, G., Haft, D.H., Sait, M., Badger, J., Barabote, R.D., Bradley, B., Brettin, T.S.,
8
9 916 Brinkac, L.M., Bruce, D., Creasy, T., Daugherty, S.C., Davidsen, T.M., DeBoy,
10
11 917 R.T., Detter, J.C., Dodson, R.J., Durkin, A.S., Ganapathy, A., Gwinn-Giglio, M.,
12
13 918 Han, C.S., Khouri, H., Kiss, H., Kothari, S.P., Madupu, R., Nelson, K.E., Nelson,
14
15 919 W.C., Paulsen, I., Penn, K., Ren, Q., Rosovitz, M.J., Selengut, J.D., Shrivastava,
16
17 920 S., Sullivan, S.A., Tapia, R., Thompson, S., Watkins, K.L., Yang, Q., Yu, C., Zafar,
18
19 921 N., Zhou, L., Kuske, C.R., 2009. Three genomes from the phylum Acidobacteria
20
21 922 provide insight into the lifestyles of these microorganisms in soils. *Appl Environ*
22
23 923 *Microbiol* 75, 2046–2056. doi:10.1128/AEM.02294-08
24
25
26 924 Wright, J., Kirchner, V., Bernard, W., Ulrich, N., McLimans, C., Campa, M.F., Hazen,
27
28 925 T., Macbeth, T., Marabello, D., McDermott, J., Mackelprang, R., Roth, K.,
29
30 926 Lamendella, R., 2017. Bacterial Community Dynamics in Dichloromethane-
31
32 927 Contaminated Groundwater Undergoing Natural Attenuation. *Front Microbiol.*
33
34
35
36 928 Young, I.M., Crawford, J.W., 2004. Interactions and self-organization in the soil-
37
38 929 microbe complex. *Science* (80-). doi:10.1126/science.1097394
39
40
41 930 Zhang, Y., Sun, R., Zhou, A., Zhang, J., Luan, Y., Jia, J., Yue, X., Zhang, J., 2018.
42
43 931 Microbial community response reveals underlying mechanism of industrial-scale
44
45 932 manganese sand biofilters used for the simultaneous removal of iron, manganese
46
47 933 and ammonia from groundwater. *AMB Express* 8, 2. doi:10.1186/s13568-017-
48
49 934 0534-7
50
51
52
53 935 Zhou, Y., Kellermann, C., Griebler, C., 2012. Spatio-temporal patterns of microbial
54
55 936 communities in a hydrologically dynamic pristine aquifer. *FEMS Microbiol Ecol* 81,
56
57 937 230–242. doi:10.1111/j.1574-6941.2012.01371.x
58
59
60
61
62
63
64
65

1
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3
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5
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51
52
53
54
55
56
57
58
59
60
61
62
63
64
65

938 Zhu, B., Wang, X., Rioual, P., 2017. Multivariate indications between environment and
939 ground water recharge in a sedimentary drainage basin in northwestern China. J
940 Hydrol 549, 92–113. doi:10.1016/j.jhydrol.2017.03.058
941

Supplementary material

1. Input data for Principal Component Analyses

Table S1 Summary of physico-chemical variables of water samples (values in bold represent concentrations under detection limit)

Table S2 Summary of diversity indices of water samples

Table S3 Summary of relative abundance (%) of microbial community classes of water samples

Table S4 Summary of relative abundance (%) of microbial community species of water samples

Table S5 Summary of diversity indices and depth of soil samples

Table S6 Summary of soil parameters from grain-size distribution curves

Table S7 Summary of relative abundance (%) of microbial community classes of soil samples

Table S8 Summary of relative abundance (%) of microbial community species of soil samples

2. Supplementary figures

Figure S1 PCA₂ analysis with microbial classes and hydrochemical data from groundwater samples and infiltration water sample

Figure S2 PCA₄ analysis with microbial species and hydrochemical data from groundwater samples and infiltration water sample

Figure S3 PCA₆ analysis with microbial classes data from soil samples

Figure S4 PCA₈ analysis with microbial species data from soil samples

Figure S5 PCA₁₀ analysis with microbial classes data from soil and water samples

1. Input data for Principal Component Analyses

Table S2 Summary of diversity indices of water samples

Operating conditions		Recharge (July 2014)														No Recharge (March 2015)									
		Infiltration water	P1(- 0.6)	P2 (3)	P2 (-5)	P3 (0.8)	P3 (- 4.2)	P5 (2.3)	P5 (- 2.2)	P8 (1)	P8 (-3)	P9(3:5)	P9(-2)	P10(-1)	P1(- 0.6)	P2 (-2)	P3 (0.8)	P5 (2.3)	P8 (1)	P8 (-3)	P9(-2)	P10(-1)			
Sample																									
Shannon	2.78	2.57	2.29	2.8	2.65	2.65	1.91	2.22	1.43	1.69	2.18	2.07	2.51	2.73	2.67	2.01	2.41	1.73	2.03	3.01	2.49				
Richness	29.00	22.00	19.00	23.00	21.00	20.00	15.00	13.00	10.00	11.00	11.00	13.00	17.00	19.00	18.00	11.00	14.00	11.00	10.00	23.00	16.00				
Evenness	0.65	0.6	0.54	0.66	0.62	0.62	0.45	0.52	0.34	0.4	0.51	0.49	0.59	0.64	0.63	0.47	0.57	0.41	0.48	0.71	0.59				

Table S3 Summary of relative abundance (%) of microbial community classes of water samples

Operating conditions	Recharge (July 2014)																No Recharge (March 2015)					
	Infiltration water	P1(-0.6)	P2(3)	P2(-5)	P3(0.8)	P3(-4.2)	P5(2.3)	P5(-2.2)	P8(1)	P8(-3)	P9(3.5)	P9(-2)	P10(-1)	P1(-0.6)	P2(-2)	P3(0.8)	P5(2.3)	P8(1)	P8(-3)	P9(-2)	P10(-1)	
Betaproteobacteria	13.81	9.48	7.29	9.09	7.24	10.49	21.88	22.88	69.94	54.76	33.71	37.80	23.50	22.69	4.83	38.52	14.29	3.02	57.02	19.60	2.69	
Cyanobacteria	12.85	11.13	6.25	2.86	13.57	13.64	9.09	7.63	5.83	8.44	8.57	6.71	21.31	8.40	4.42	5.74	7.94	1.51	0.00	3.71	8.31	
Bacilli	1.53	23.92	17.53	12.63	10.86	6.29	42.90	11.02	1.84	1.73	21.71	0.61	6.56	8.40	2.00	18.03	15.87	0.00	11.57	2.47	4.64	
Dehalococcoidia	3.74	4.54	29.86	14.98	17.19	16.43	1.42	0.00	0.00	0.00	2.86	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	9.28	0.00	
Acidobacteria	7.57	4.95	9.03	4.55	11.31	9.09	1.99	0.00	0.00	0.00	2.29	9.15	4.92	4.20	3.64	0.00	0.00	13.57	0.00	0.00	0.00	
Actinobacteria	8.53	1.24	0.52	4.21	3.17	5.24	0.00	0.00	0.92	1.08	0.00	0.00	0.00	3.36	8.14	6.15	0.00	7.44	0.00	2.20	1.81	
Cytophagia	0.19	0.00	0.00	0.00	0.00	0.00	12.22	18.64	6.75	3.90	12.00	6.71	9.29	16.81	4.91	0.00	4.76	5.53	7.02	1.51	0.00	
Chlorobia	13.52	10.52	6.77	2.53	0.00	0.00	2.84	0.00	2.76	10.61	0.00	0.00	0.00	0.00	4.09	0.00	0.00	5.03	0.00	0.00	17.18	
Nitrospira	4.03	0.00	0.00	4.38	9.50	8.39	1.14	11.02	0.00	0.00	2.86	7.32	8.20	2.52	0.00	0.00	3.17	0.00	0.00	4.27	0.00	
GAmmaproteobacteria	5.08	0.82	4.17	5.89	0.00	0.00	4.55	20.34	5.83	7.79	3.43	6.71	0.00	11.76	5.65	13.93	18.25	0.00	0.00	1.86	11.61	
Alphaproteobacteria	4.89	1.44	1.74	0.17	2.26	0.00	0.28	1.69	0.61	0.65	0.00	0.00	2.73	2.52	0.00	1.64	9.52	0.00	0.00	8.03	7.15	
Others	24.26	31.96	16.84	38.72	24.89	30.42	1.70	6.78	5.52	11.04	12.57	25.00	23.50	19.33	62.32	15.98	26.19	71.36	16.94	47.08	46.61	

Table S5 Summary of diversity indices and depth of soil samples

Operating conditions	Recharge (July 2014)						No Recharge (March 2015)					
	SD	E_0.1	M_0.1	M_0.2	F_0.1	E_0.2	E_0.8	M_0.3	F_0.1	F_0.3		
Depth (cm)	0.10	0.10	0.10	0.20	0.10	0.20	0.80	0.30	0.10	0.30		
Shannon	2.89	3.22	3.36	3.14	3.29	2.93	2.86	2.90	2.81	2.40		
Richness	25.50	35.50	37.00	30.50	34.00	25.00	24.00	21.00	19.50	16.00		
Evenness	0.68	0.76	0.79	0.74	0.77	0.69	0.67	0.68	0.66	0.57		

Table S6 Summary of soil parameters from grain-size distribution curves

Operating conditions	Recharge (July 2014)						No Recharge (March 2015)					
	SD	E_0.1	M_0.1	M_0.2	F_0.1	E_0.2	E_0.8	M_0.3	F_0.1	F_0.3		
CC	0.04	2.01	1.43	0.84	0.53	3.31	0.54	0.93	0.55	1.27		
CU	159.39	53.52	28.32	20.03	13.28	17.72	19.23	32.59	19.69	8.13		
% Fine	10.12	2.17	2.92	0.85	2.60	0.54	1.67	1.78	1.94	0.43		
D10	0.07	0.27	0.54	0.20	0.31	1.08	0.25	0.28	0.28	1.42		

Table S7 Summary of relative abundance (%) of microbial community classes of soil samples													
Operating conditions		Recharge (July 2014)						No Recharge (March 2015)					
Sample	SD	E_0.1	M_0.1	M_0.2	F_0.1	E_0.2	E_0.8	M_0.3	F_0.1	F_0.3			
Betaproteobacteria	23.01	21.37	16.97	18.29	18.89	21.32	8.06	14.28	11.31	14.01			
Cyanobacteria	8.66	5.31	8.26	6.26	3.54	11.09	8.36	3.40	4.76	2.72			
Bacilli	6.39	5.17	4.35	8.07	7.25	7.74	7.56	4.53	6.85	21.50			
Dehalococcoidia	4.40	1.77	2.10	2.97	3.37	0.00	1.93	0.00	0.00	0.00			
Acidobacteria	9.80	2.31	1.95	0.99	1.69	0.00	2.09	2.83	0.00	0.00			
Actinobacteria	3.27	2.18	4.35	3.79	2.36	4.96	15.63	9.49	7.89	16.11			
Cytophagia	0.85	2.45	0.60	3.29	4.72	4.53	13.21	10.51	13.99	11.77			
Chlorobia	0.00	2.31	2.55	2.97	4.22	0.00	0.32	0.00	0.00	0.00			
Nitrospira	5.40	1.91	7.06	6.75	4.05	14.72	10.47	5.07	5.65	4.53			
Gammaaproteobacteria	2.13	3.95	1.80	0.00	4.05	4.34	2.26	3.97	0.00	0.00			
Alphaproteobacteria	0.99	3.81	2.10	1.65	7.76	0.57	3.06	6.71	6.43	7.88			
Others	35.09	47.47	47.90	44.98	38.11	30.74	27.04	39.21	43.13	21.50			

Table S8 Summary of relative abundance (%) of microbial community species of soil samples

Operating conditions	Recharge (July 2014)						No Recharge (March 2015)					
	SD	E_0.1	M_0.1	M_0.2	F_0.1	F_0.3	E_0.2	E_0.8	M_0.3	F_0.1	F_0.3	
<i>Methylobacter mobilis</i>	0.00	0.00	0.60	0.00	0.00	0.00	2.64	0.00	0.00	0.00	0.91	
<i>Pontibacter sp</i>	0.85	2.45	0.60	3.29	4.72	13.99	4.53	13.21	10.51	13.99	11.77	
<i>Dehalogenimonas sp</i>	4.40	1.77	2.10	2.97	3.37	0.00	0.00	1.93	0.00	0.00	0.00	
Subgroup 3 sp (Acidobact.)	9.80	2.31	1.95	0.99	1.69	0.00	0.00	2.09	2.83	0.00	0.00	
<i>Vogesella indigofera</i>	8.10	7.49	4.80	4.94	4.22	4.53	2.42	2.83	3.57	0.00	0.00	
<i>Stenotrophomonas sp</i>	2.13	3.95	1.80	0.00	4.05	4.34	2.26	3.97	0.00	0.00	0.00	
<i>Chryseomicrobium sp</i>	6.39	5.17	4.35	8.07	7.25	7.74	7.56	4.53	6.85	21.50	0.00	
<i>Nitrospira sp1</i>	2.70	0.54	5.56	3.62	2.53	14.72	7.41	1.39	4.17	0.00	0.00	
<i>Methylobacterium sp</i>	0.99	3.81	2.10	1.65	7.76	0.57	3.06	6.71	6.43	7.88	4.53	
<i>Nitrospira sp2</i>	2.70	1.36	1.50	3.13	1.52	0.00	3.06	3.68	1.49	4.53	0.00	

2. **Supplementary figures**

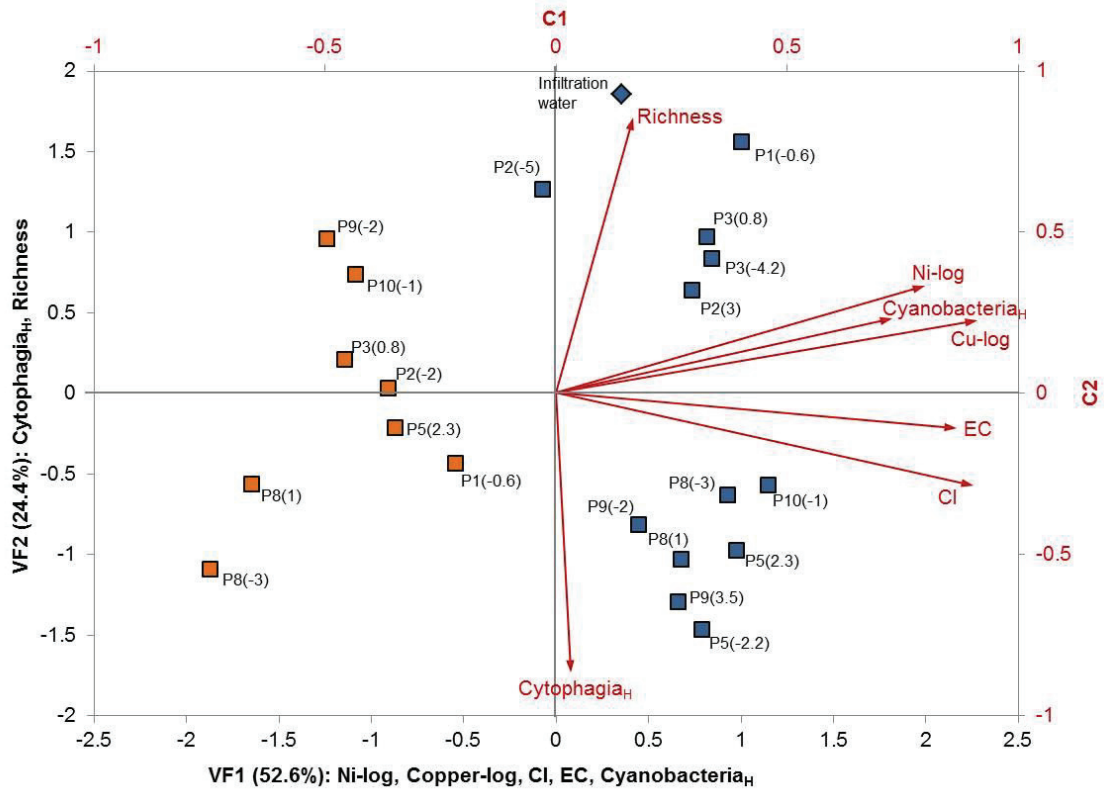


Figure S1. PCA₂ analysis with microbial classes and hydrochemical data from groundwater samples (squares) and the infiltration water sample (diamond) during the recharge period (blue) and during no-recharge period (orange). Position of samples is scaled in VF1 and VF2 axes. Red arrows represent the contribution of each variable in both Varifactors.

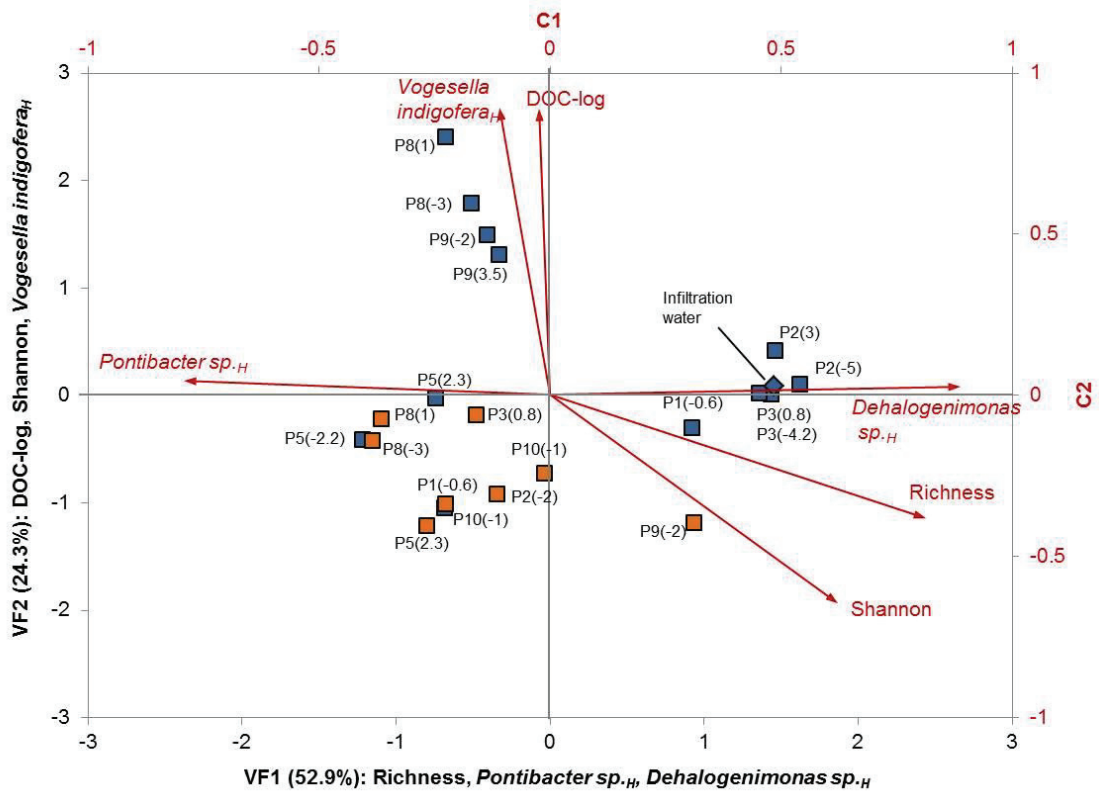


Figure S2 PCA₄ analysis with microbial species and hydrochemical data from groundwater samples (squares) and the infiltration water sample (diamond) during the recharge period (blue) and during no-recharge period (orange). Position of samples is scaled in VF1 and VF2 axes. Red arrows represent the contribution of each variable in both Varifactors.

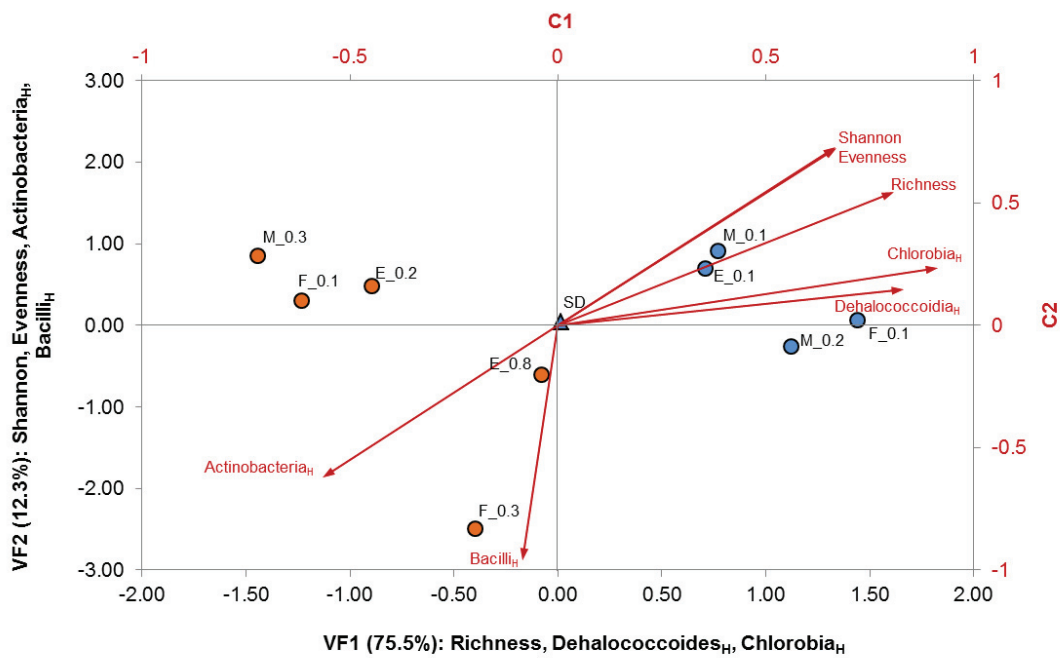


Figure S3 PCA₆ analysis with microbial classes data from soil samples during the recharge period (blue) and during no-recharge period (orange). Circles are related to the infiltration pond samples (Entrance, Midfield and Final stretch according the capital letter close to each symbol). Triangle is referred to the sedimentation pond sample. Position of samples is scaled in VF1 and VF2 axes. Red arrows represent the contribution of each variable in both Varifactors scaled by components.

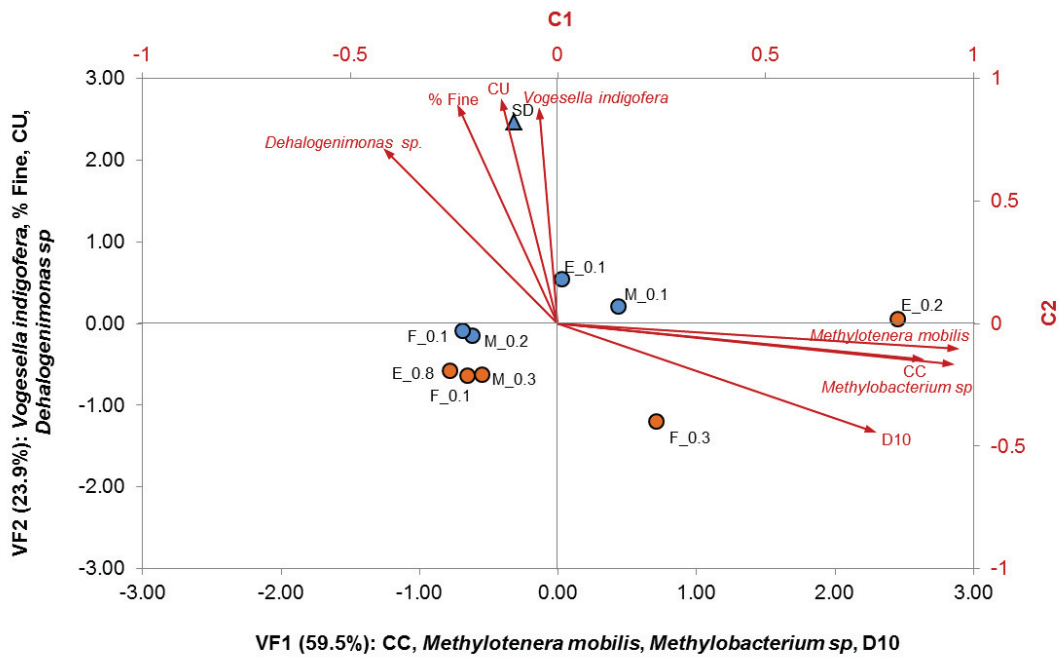


Figure S4. PCA₈ analysis with microbial species data from soil samples during the recharge period (blue) and during no-recharge period (orange). Circles are related to the infiltration pond samples (Entrance, Midfield and Final stretch according the capital letter close to each symbol). Triangle is referred to the sedimentation pond sample. Position of samples is scaled in VF1 and VF2 axes. Red arrows represent the contribution of each variable in both Varifactors scaled by components.

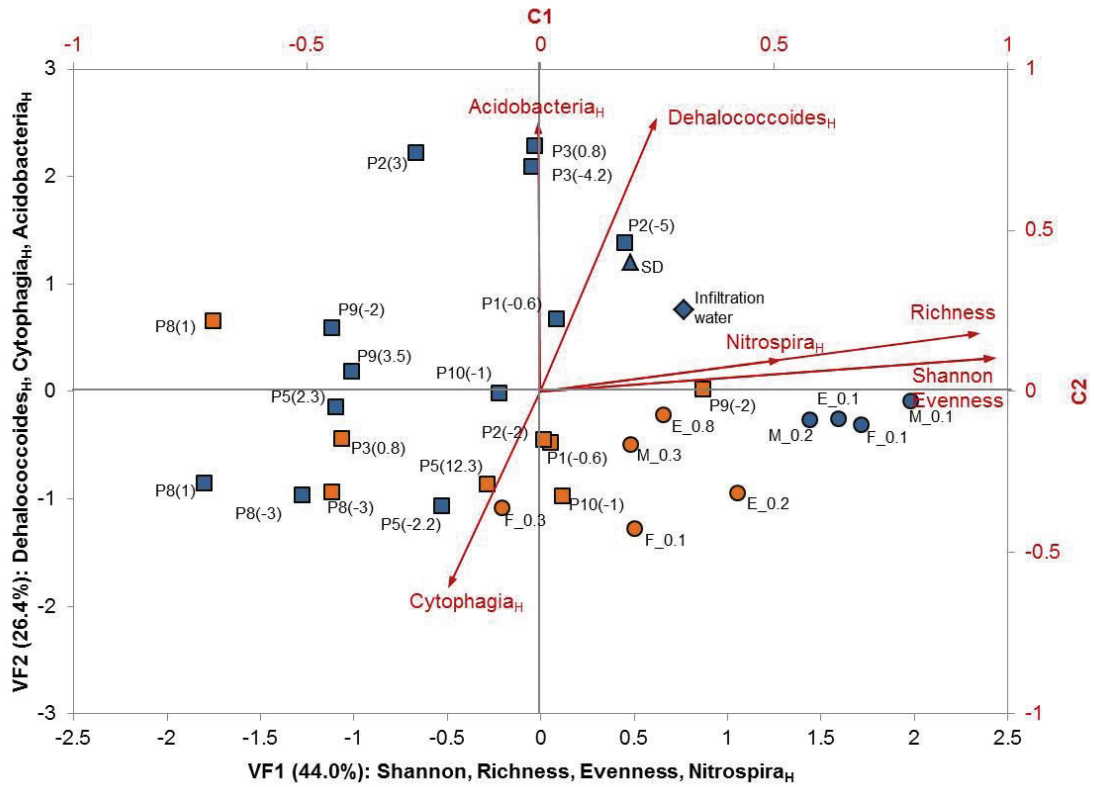


Figure S5. PCA₁₀ analysis with microbial classes data from soil and water samples during the recharge period (blue) and during no-recharge period (orange). Circles are related to soil samples (Entrance, Midfield and Final stretch according the capital letter close to each symbol). Triangle is referred to the sedimentation pond soil sample. Squares represent groundwater samples and the diamond is for infiltration water. Position of samples is scaled in VF1 and VF2 axes. Red arrows represent the contribution of each variable in both varifactors.