

1 **Microbiome assembly predictably shapes diversity across a range of disturbance**
2 **frequencies**

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16 **Abstract**

17 Diversity is frequently linked to the functional stability of ecological communities. However, its
18 association with assembly mechanisms remains largely unknown, particularly under fluctuating
19 disturbances. Here, we subjected complex bacterial communities in bioreactor microcosms to
20 different frequencies of organic loading shocks, tracking temporal dynamics in their assembly,
21 structure and function. Null modelling revealed a stronger role of stochasticity at intermediate
22 disturbance frequencies, preceding the formation of a peak in α -diversity. Communities at extreme
23 ends of the disturbance range had the lowest α -diversity and highest within-treatment similarity in
24 terms of β -diversity, with stronger deterministic assembly. Stochasticity prevailed during the initial
25 successional stages, coinciding with better specialized function (nitrogen removal). In contrast,
26 general functions (carbon removal and microbial aggregate settleability) benefited from stronger
27 deterministic processes. We showed that changes in assembly processes predictably precede changes
28 in diversity under a gradient of disturbance frequencies, advancing our understanding of the
29 mechanisms behind disturbance-diversity-function relationships.

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31 **Key words:** intermediate stochasticity hypothesis, ISH, intermediate disturbance hypothesis, IDH,
32 succession, diversity, disturbance, community structure, community function, stochastic assembly,
33 deterministic assembly.

34 **Introduction**

35 Microbes exist typically as diverse, complex and dynamic communities¹, responsible for all
36 biogeochemical cycles worldwide². These microbial communities or microbiomes provide crucial
37 functions for global climate regulation, human health, biotechnology and bioremediation³. Microbial
38 diversity is often related to community function⁴ and the ability to withstand environmental
39 fluctuations that typically occur as disturbances⁵. Given the growing human population and its impact
40 on natural and engineered ecosystems⁶, management and conservation practices are faced with
41 increasing frequencies and magnitudes of various disturbances that occur on different scales. A
42 concept of ecology that can be used to explore possible outcomes is the intermediate disturbance
43 hypothesis (IDH), which predicts a diversity peak at intermediate levels of disturbance due to
44 competition-colonization trade-offs faced by organisms⁷. Although the IDH has been influential in
45 ecology⁸ and ecosystem conservation^{9,10}, it is not a coexistence mechanism as initially thought¹¹.
46 Further, many studies have not found the diversity pattern predicted by the IDH^{12,13} and its relevance
47 as a prediction tool is up for debate^{14,15}. Therefore, studies are needed to address the mechanisms
48 behind the observed disturbance-diversity relationships¹⁶.

49 Intermediate frequencies of exposure to a xenobiotic pollutant in our recent replicated sludge
50 bioreactor study demonstrated higher α -diversity and relative influence of stochastic assembly
51 compared to other exposure levels, after a short succession period of 35 days¹⁷. We hypothesized that
52 when intermediate disturbance levels result in unpredictable environments where specialized traits are
53 less advantageous to taxa, the stochastic equalization of competitive advantages would lead to a
54 higher α -diversity, a causal relationship we named the intermediate stochasticity hypothesis (ISH)¹⁷.
55 In contrast, either no disturbance or press disturbance conditions at the extreme ends of a disturbance
56 range would allow fewer adapted organisms to dominate, thus lowering the α -diversity. Unlike the
57 IDH, the ISH incorporates the role of assembly mechanisms as shapers of community structure (α -
58 and β - diversity) across a disturbance gradient. Further, it predicts patterns not only in species
59 richness but also in higher-order α -diversity indices, since variations in the underlying assembly
60 mechanisms would affect abundance distributions of taxa. The ISH also considers that the output of a

61 stochastic process is affected by some uncertainty, which means that there are several possible paths
62 for the evolution of the structure and function of a community. In this regard, stochasticity operating
63 at intermediate levels of disturbance in replicated systems could lead to similar high α -diversity
64 (local, *e.g.*, within a reactor), but not necessarily to similar β -diversity (compositional variation across
65 sites, *e.g.*, between reactors) and community function¹⁷. The idea of community assembly processes
66 underlying the observed patterns of diversity is reasonable, as such processes are believed to shape
67 community structure¹⁸, which also links them to ecosystem function. These processes, either
68 deterministic or stochastic, are known to act in combination to form community assembly¹⁹⁻²² and can
69 cause replicate communities to reach a similar or variable structure and function^{17,23}. Further, while
70 recent studies have reported positive correlations of strength of stochasticity with α -diversity in
71 bacterial²⁴ and fungal²⁵ communities, the role of assembly processes behind diversity patterns under
72 fluctuating disturbances is still unclear.

73 The objective of this work was to test the central tenet of the ISH that intermediate
74 disturbance frequencies promote stochastic assembly processes, resulting in increased α -diversity and
75 variable β -diversity¹⁷. We used an experimental system comprised of activated sludge sequencing
76 batch reactors harboring complex microbial communities collected from a full-scale wastewater
77 treatment plant. These were subjected to different frequencies of organic loading shocks, tracking
78 temporal dynamics in their overall assembly, structure and function, without focusing on any
79 particular taxa. The reactors had a working volume of 25 mL, representing a microcosm scale²⁶.
80 Replicates ($n = 5$) received double organic loading either never (L0, undisturbed), every 8, 6, 4 or 2
81 days (L1-4, intermediately-disturbed), or every day (L5, press-disturbed), for 42 days. Samples were
82 analyzed using 16S rRNA gene metabarcoding and effluent chemical characterization. Patterns of α -
83 and β -diversity were employed to assess temporal dynamics of bacterial community structure.
84 Assembly mechanisms were quantified via null model analysis of phylogenetic turnover for each
85 bioreactor.

86 **Results**

87 *Intermediate disturbance frequencies exhibit higher taxonomic and phylogenetic α -diversity*

88 Taxonomic α -diversity was evaluated using Hill diversity indices²⁷ of orders zero (0D , taxa
89 richness), one (1D) and two (2D), the latter being a robust estimate of microbial diversity¹⁷.
90 Phylogenetic α -diversity was also considered through Faith's phylogenetic distance²⁸ unweighted
91 (PD) and abundance-weighted (PD_w). There was a temporal decrease in α -diversity for all
92 disturbance frequency levels compared to the sludge inoculum for both taxonomic and phylogenetic
93 α -diversity indices (Fig. 1A, Fig. S1). This drop was more pronounced, particularly within the first 14
94 days, when variability across same-level replicates was also highest. From d14 onwards, disturbance
95 frequency had a significant effect on α -diversity (2D , Welch's ANOVA $P_{\text{adj}} = <0.001-0.015$) (Fig.
96 1A). A peak in α -diversity at intermediate frequencies of disturbance was observed for all unweighted
97 (0D , PD) and abundance-weighted (1D , 2D , PD_w) indices evaluated in this study (Fig. 1A, Fig. S2, Fig.
98 S3). Such parabolic pattern was significant from d21 onwards for 2D (Welch's ANOVA $P_{\text{adj}} \leq 0.003$),
99 from d28 onwards for 1D (Welch's ANOVA $P_{\text{adj}} = 0.002-0.01$), PD (Welch's ANOVA $P_{\text{adj}} = 0.003-$
100 0.037) and PD_w (Welch's ANOVA $P_{\text{adj}} = 0.005-0.013$), and from d35 onwards for 0D (Welch's
101 ANOVA $P_{\text{adj}} = 0.03-0.035$).

102 *Community assembly temporal dynamics precede α -diversity patterns across disturbance frequencies*

103 Assembly processes were first evaluated by modelling the phylogenetic dispersion of a given
104 community against the null expectation, through the nearest taxon index (NTI)²⁹. We observed higher
105 stochasticity at the initial stages of the experiment (d0-14), which decreased in relative intensity over
106 time across disturbance levels for both unweighted (NTI) and abundance-weighted (NTI_w) indices
107 (Fig. 1A, Fig. S2). There was a stronger role of stochastic assembly processes at intermediate
108 disturbance frequencies as shown by NTI values closer to zero (*i.e.*, lower |NTI| values); this was
109 significant from d14 onward (NTI Welch's ANOVA $P_{\text{adj}} = <0.001-0.037$) but was reduced towards
110 the end of the study becoming non-significant on d42. Games-Howell post-hoc grouping indicated
111 that the parabolic pattern of NTI across disturbance frequency levels preceded (d14-35) the formation

112 of a peak in α -diversity (d21-42) at intermediate levels of disturbance, with two to three groups
113 significantly differentiated (Fig. 1A). Stochastic assembly processes were less prevalent when
114 abundance weighing was included in the calculation of the NTI index (NTI_w), meaning that
115 phylogenetic dispersion compared to the null expectation was higher among individual organisms
116 than it was among taxa. Nonetheless, there was a significant peak in NTI_w values at intermediate
117 frequencies of disturbance on d7 and d14 (NTI_w Welch's ANOVA $P_{adj} = 0.001$). This parabolic
118 pattern of NTI_w was evident on d7, preceding that of NTI, but disappeared on d21 and reverted from
119 d28 onwards. Also, significant phylogenetic signals were observed via mantel correlogram analysis
120 (Fig. S5) mostly across relatively short phylogenetic distances, justifying the use of phylogenetic null
121 modelling to evaluate community assembly processes in this study.

122 Stochastic assembly was more important when α -diversity was higher, particularly for
123 phylogenetic diversity. This was shown by significant Kendall correlation τ values (0.24-0.46, $P_{adj} <$
124 0.001) between NTI and α -diversity indices (Figs. 1B-C, Fig. S4). Kendall correlation τ values were
125 also positive (0.20-0.26) and significant ($P_{adj} < 0.001$) between NTI_w and phylogenetic α -diversity
126 indices (PD, PD_w) and unweighted taxonomic α -diversity (0D), but not between NTI_w and
127 abundance-weighted taxonomic α -diversity (1D , 2D) (Fig. S4). The estimation of all the
128 aforementioned indices over time using rarefied ASV sequencing data yielded the same significant
129 patterns via Welch's ANOVA, with the exception of NTI_w on d21 and d42 (see supplementary file).

130 *β -diversity patterns display similarity at low and high disturbance frequencies and higher variability*
131 *at intermediate ones*

132 Community structure in terms of β -diversity showed temporal changes, which varied across
133 disturbance levels for both Unifrac phylogenetic distances (Fig. 2A) and Bray-Curtis taxonomic
134 distances (Fig. 2B). Unconstrained ordination displayed a dispersion effect in overall community
135 structure over time, particularly after 7 days, with communities in each reactor diverting from each
136 other (Fig. 2A). To disentangle the effect of disturbance from temporal dynamics, constrained
137 ordination via canonical analysis of principal coordinates (CAP) was used at each time point (Fig.

138 2B). Group-average cluster similarity (60%) was included to detect formations of clusters of
139 community structure. Differences in β -diversity across disturbance levels were statistically significant
140 at all time points evaluated (PERMANOVA $P_{\text{adj}} < 0.001$), without significant effects of
141 heteroscedasticity (PERMDISP $P_{\text{adj}} > 0.14$) (Table S1). Replicate reactors at the undisturbed (L0) and
142 press-disturbed level (L5) clustered separately from intermediate disturbance levels on all sampling
143 days (except on d7 and d21 for L0) (Fig. 2B), both levels having 0% misclassification error at all time
144 points assessed (Fig. 2C). Comparatively, reactors at intermediate disturbance frequencies (L1-4)
145 clustered together and showed higher dispersion across replicates within the same level, with CAP
146 misclassification errors above zero (Fig. 2B-C). Thus, replicate reactors were less similar to each
147 other at intermediate levels of disturbance, while replicates at low (undisturbed) and high (press-
148 disturbed) disturbance frequencies were more similar. Likewise, community assembly assessed via
149 the beta nearest taxon index (βNTI)³⁰ showed a higher relative contribution of stochasticity at
150 intermediate levels of disturbance (Fig. 2D), with βNTI values closer to zero, indicating that
151 phylogenetic turnover across within-treatment replicates was closer to the null expectation. Similarly
152 to what we observed through the NTI, the relative importance of stochasticity decreased with time in
153 the experiment (*i.e.*, higher $|\beta\text{NTI}|$ values) and when abundance weighing was included in the
154 calculation of the βNTI values (βNTI_w) (Fig. S6). The observed temporal changes in bacterial
155 community structure across disturbance frequencies were consistent with phylum-level dynamics in
156 relative abundances (Fig. S7), although the focus of this study was on overall community dynamics
157 and not on any particular group of taxa.

158 *Community function dynamics and correlations with community structure and assembly*

159 Bacterial community function was assessed over time via influent chemical oxygen demand
160 (COD) removal, sludge volume index (SVI), and influent total Kjeldahl nitrogen (TKN) removal, as
161 measure of carbon removal, sludge settleability and nitrogen removal, respectively (Fig. 3A). Carbon
162 removal and sludge settleability, which are functions associated with a broad range of taxa (*i.e.*,
163 general functions), improved over time during the experiment. High carbon removal (> 0.97) was
164 achieved at all disturbance frequency levels from d21 onwards, with no significant differences on

165 days 35 and 42, after a period of high variability for same-level replicates during the first 14 days.
166 Sludge settleability increased with disturbance frequency, with undisturbed (L0) reactors showing the
167 lowest settleability from d21 onwards and intermediately disturbed levels reaching the highest
168 settleability on d42 (SVI Welch's ANOVA $P_{\text{adj}} = 0.018$). The nitrogen removal function (TKN
169 removal), which is related to specialized bacteria (ammonia oxidizers), significantly differed across
170 disturbance frequencies (TKN removal Welch's ANOVA $P_{\text{adj}} < 0.001$) with the highest removal at
171 intermediately disturbed levels during the first 21 days. From d28 onwards, L0 to L4 reactors had
172 similarly high average nitrogen removal (> 0.9), and only the press disturbed reactors (L5) continued
173 to have lower nitrogen removal (< 0.7) than that of the initial sludge inoculum (0.8). Effluent values
174 of TKN, ammonia, nitrite and nitrate showed that TKN removal occurred via nitrification (Fig. S8).

175 Carbon removal had an overall significant negative Kendall correlation with α -diversity
176 indices ($\tau < -0.21$, $P_{\text{adj}} < 0.001$), whereas sludge settleability and nitrogen removal showed non-
177 significant correlations with α -diversity across the study (Fig. S9). Correlations between general
178 functions of carbon removal and sludge settleability and both NTI and NTI_W were negative and
179 significant across all time points and disturbance frequencies of the study (Fig. 3B-C, Fig. S9),
180 indicating improved performance of these functions under stronger deterministic assembly
181 mechanisms. Nitrogen removal had a non-significant overall correlation with NTI and NTI_W (Fig. 3D,
182 Fig. S9), which became positive and significant when only the first 21 days of the study were
183 considered (NTI $\tau_{\text{d}0-21} = 0.39$, $P_{\text{adj}} < 0.001$, Fig. 3D; NTI_W $\tau_{\text{d}0-21} = 0.46$, $P_{\text{adj}} < 0.001$, Fig. S10),
184 suggesting better performance of this function under higher stochastic assembly throughout the initial
185 weeks of the study.

186 Discussion

187 In this study we found stochastic assembly processes to be more important at intermediate
188 disturbance frequencies where the highest α -diversity was also observed, together with high β -
189 diversity dispersion across within-treatment replicates as predicted by the ISH¹⁷. Furthermore, we
190 showed that a peak in the relative contribution of stochasticity preceded a peak in α -diversity across a
191 disturbance frequency range. Also, we observed that higher stochasticity during initial successional

192 stages correlated with better nitrogen removal (specialized function) at intermediate disturbance
193 frequencies, while carbon removal and microbial aggregate settleability (general functions) improved
194 in step with more deterministic forces. These findings highlight the utility of the ISH for a
195 mechanistic understanding of disturbance-diversity-function relationships.

196 We expanded our earlier work¹⁷ by using a different type of disturbance and microbial
197 community inoculum, a relevant scenario given the multidimensional nature of disturbance³¹.
198 Employing taxonomic and phylogenetic diversity metrics, in both unweighted and abundance-
199 weighted forms, allowed us to cover a broader aspect of α -diversity. Taxonomic resolution was also
200 improved by the use of amplicon sequence variants (ASVs) compared to operational taxonomic unit
201 (OTU) clustering³² with about one to two orders of magnitude fewer spurious units³³, allowing for a
202 better estimation of unweighted α -diversity (*i.e.*, taxa richness). We further verified that the observed
203 patterns occurred independently of data rarefaction, given the lack of consensus about this practice³⁴
204 and the fact that it is known to affect (mainly unweighted) estimations of α -diversity³⁵. Assembly
205 processes were tracked over time using a phylogenetic null modelling methodology, which has been
206 tested and recommended in microbial ecology^{20,30,36}. Additionally, general and specific functions were
207 evaluated against structure and assembly. All the aforementioned enhancements allowed us to test the
208 ISH, while also gaining new insights into the role of assembly processes behind disturbance-induced
209 changes in community structure and function over time.

210 Our experimental system produced a succession scenario in which bacterial communities had to
211 adapt to change from a full-scale system to a bioreactor microcosm setup along a disturbance
212 frequency gradient, similarly to what we described in a prior study³⁷. With regards to community
213 structure, succession led to a significant hump-backed pattern of α -diversity for all composition- and
214 abundance-based indices employed in the study, which occurred after 21 days for ²D, 28 days for ¹D,
215 PD and PD_w, and 35 days for ⁰D. Thus, the observed dynamics in community structure were stronger
216 in terms of relative abundances than richness (²D, ¹D vs. ⁰D), as well as at the phylogenetic versus
217 taxonomic level (PD vs. ⁰D). The appearance of higher phylogenetic α -diversity at intermediate levels
218 of disturbance for both unweighted (PD) and abundance-weighted (PD_w) indices suggests that

219 considering evolutionary relationships among organisms³⁸ could also aid in assessing the effect of
220 varying disturbances on community structure under succession. In our study, disturbance promoted
221 the co-occurrence of phylogenetically distinct organisms, suggesting that additional niches were
222 created at intermediate disturbance frequencies that were occupied by ecologically different species,
223 thus reducing competitive exclusion. Conversely, phylogenetic clustering at undisturbed and press-
224 disturbed levels can be interpreted as communities structured by environmental filtering²⁹.
225 Additionally, temporal analysis of community structure in terms of β -diversity revealed three different
226 clusters for undisturbed, press-disturbed and intermediately disturbed reactors. Further comparison of
227 replicates within the same disturbance frequency level showed higher β -diversity variability at
228 intermediate disturbance levels, which was coherent with prior observations in freshwater ponds³⁹ and
229 sludge bioreactors¹⁷ where β -diversity increased with stochastic assembly. Our findings are relevant
230 for understanding disturbance-diversity relationships, since few studies have reported parabolic α -
231 diversity patterns using abundance-based indices⁸. Furthermore, variations in β -diversity among
232 ecological communities that are subject to large and fluctuating disturbances are believed to provide
233 insights about the mechanisms driving changes in α -diversity and function⁴⁰.

234 We observed similar trends of phylogenetic dispersion within a single community (NTI) and
235 the phylogenetic turnover between communities of the same treatment level (β NTI), compared to the
236 null expectation. Stochasticity was more important during initial successional stages of the study, with
237 initial NTI and β NTI values closer to zero (*i.e.*, closer to the null expectation of the model).
238 Relatively, the overall strength of deterministic processes increased with time, with higher |NTI| and
239 | β NTI| values. Similarly, late succession stages were shown to be governed by deterministic processes
240 in plant forest⁴¹ and microbial groundwater communities⁴². Furthermore, α -diversity-based temporal
241 assembly dynamics revealed a parabolic pattern in NTI and NTI_w, through the disturbance frequency
242 gradient, which was evident after 14 and 7 days of the study, respectively, before the appearance of
243 similar parabolic patterns across various α -diversity indices. This preceding pattern is considered here
244 as a strong indicator of assembly mechanisms operating to shape community structure. It is, therefore,
245 plausible that stochastic assembly mechanisms were first favored at intermediate disturbance

246 frequencies, prompting subsequent changes of community structure that resulted in the observed
247 higher α -diversity as the ISH proposes¹⁷. These observations are also coherent with the idea that
248 secondary succession is community assembly in action⁴³. The disturbance range in this study
249 produced different secondary succession scenarios, with communities in the sludge of each bioreactor
250 likely experiencing different re-colonization processes from their bacterial seed-bank (*i.e.*, low-
251 abundance or rare taxa), via stochastic processes such as priority effects⁴⁴ followed by historical
252 contingency⁴⁵ and legacy effects³. Importantly, external dispersal processes⁴⁶ (*i.e.*, bacterial
253 immigration) could not influence community assembly since bioreactors within this study were
254 operated as closed systems. Indeed, microbial seed-banks are thought to contribute to the maintenance
255 of microbial diversity⁴⁷ and have been described as essential for understanding temporal community
256 changes⁴⁸. Further, stochastic assembly processes were shown to be more preponderant within the rare
257 fraction of the microbial community²². Nonetheless, other processes might also be promoting
258 stochastic assembly at intermediate disturbance frequencies, like ecological drift³⁶ and feedback
259 mechanisms linked to density dependence and species interactions⁴⁹. Hence, a disturbance frequency
260 gradient can not only result in nonlinearities for growth rates that would affect the outcome of
261 competition^{14,31}, it could also alter the relative contribution of stochastic and deterministic
262 mechanisms of community assembly that underlie changes in community structure¹⁷. Furthermore,
263 our results showed that, over a range of disturbance frequencies, assessing temporal community
264 assembly patterns during succession can act as a sentinel of upcoming patterns of diversity.

265 Stochasticity was positively correlated with better nitrogen (as TKN) removal via nitrification
266 at intermediate disturbance frequencies during the initial successional stages where stochastic
267 processes were also generally prevalent. Nitrification functions are carried out by specific taxa (*i.e.*,
268 nitrifiers), which are slow growers, nutritionally inflexible, sensitive to inhibitors and less
269 phylogenetically diverse than many other key functional guilds⁵⁰. Yet, the recruitment of nitrifying
270 organisms from the microbial seed-bank was important for the recovery of nitrification, following the
271 removal of a long-term disturbance of altering food-to-biomass and carbon-to-nitrogen ratios in
272 sludge bioreactors, although resilience varied across identically treated replicates⁵¹. Also, partial
273 recovery of nitrification in sludge bioreactors was observed at intermediate frequencies of 3-

274 chloroaniline disturbance, where stochastic assembly processes and within-treatment variability were
275 also higher¹⁷. Conversely, general functions of carbon removal and settleability performed better
276 when deterministic processes were stronger (higher |NTI| values). Carbon removal was better when α -
277 diversity was lower, similarly to what was reported previously using a different xenobiotic
278 disturbance in bioreactors¹⁷. Hence, a more diverse community does not necessarily translate into
279 better ecosystem functions^{17,52}. Our data suggest that general functions thrive during stronger
280 deterministic processes, while specialized functions might be favored by stochasticity at initial
281 successional stages. Future studies assessing the effect of fluctuating disturbances on community
282 diversity and function should also consider the type of function (*e.g.*, specific or general), the stage of
283 succession after the disturbance, and the underlying assembly mechanisms.

284 The observed patterns in community assembly, structure and function were time-dependent.
285 The ISH successional pattern appears to be transient, as assembly mechanisms across disturbance
286 frequency levels were not significantly different towards the end of the study on d42, while α -
287 diversity continued to display a significant parabolic pattern. If the gradient of disturbance frequencies
288 is maintained over time, then the peak in α -diversity at intermediate levels might continue during the
289 late successional stages, but this remains to be investigated. Nonetheless, most relevant bacteria in
290 activated sludge have generation times of less than 24 h. Hence, the 42-day length of this study
291 represented around tens to hundredths of generations of many different taxa, allowing the detection of
292 significant patterns in assembly and structure. Further research in a variety of ecosystems is needed to
293 validate the broad applicability of the ISH, particularly considering that disturbance can vary in type,
294 frequency, intensity, driver and impact^{31,53}. Studies at different scales are also necessary since
295 ecological patterns can vary across spatial, temporal and phylogenetic scales³, while the effect of
296 dispersal processes could also be evaluated within open systems.

297 Although a similar study on communities of larger organisms would require considerably larger
298 scales of space and time, some modelling approaches suggest that ISH-like patterns (Fig. 4) could
299 emerge in community assembly and structure under varying disturbances. For example, forest fire
300 modelling showed that intermediate lightning strike frequency values yielded higher diversity with a

301 close balance between stochastic and deterministic forces, which were highly sensitive to probabilistic
302 events leading the system to diverse trajectories⁵⁴. Likewise, a conceptual model developed for plants
303 and animals suggested that high variation in resource abundance and location in space and time,
304 which could be caused by disturbance, would favor diversity via adaptation through novelty and
305 innovation (*i.e.*, stochasticity) generation⁵⁵. The predictions of the ISH could help to identify cases
306 when disturbance-induced stochastic assembly promotes alternative states of community structure that
307 compromise or enhance ecosystem function, so as to design mitigation or intensification strategies.
308 Furthermore, it could be used to promote community resistance and resilience to future disturbances
309 via increased α -diversity and functional-gene diversity. Alternatively, this theoretical framework
310 could help develop functionally resilient communities that do not occur naturally, through the
311 stochastic mechanisms that are initially elicited at intermediate frequencies of disturbance. Therefore,
312 we propose that the ISH has potential for a general understanding of disturbance-induced changes in
313 community structure and function during succession, by integrating the influence of the underlying
314 assembly processes over time.

315 **Materials and Methods**

316 *Experimental design and function analyses*

317 We employed 30 sequencing batch bioreactors at a microcosm scale (25-mL working volume),
318 inoculated with activated sludge from a full-scale wastewater treatment plant in Singapore and
319 operated for 42 days at 30°C in an incubator shaker. The daily complex synthetic feeding regime
320 (adapted from Santillan *et al.*⁵¹) included double organic loading at varying disturbance frequencies.
321 Six levels of disturbance were set in quintuplicate independent reactors ($n = 5$), which received double
322 organic loading either never (undisturbed), every eight, six, four, or two days (intermediately-
323 disturbed), or every day (press-disturbed). Level numbers were assigned from 0 to 5 (0 for no
324 disturbance, 1 to 5 for low to high disturbance frequency). Disturbance frequency was further
325 calculated from the rate of high organic loading at each disturbance level resulting in values of 0, $1/8$,
326 $1/6$, $1/4$, $1/2$, and 1. Ecosystem function, in the form of process performance parameters at the end of a
327 cycle, was measured weekly in accordance with Standard Methods⁵⁶ where appropriate, and targeted

328 the removal of soluble COD and TKN from the mixed liquor after feeding. Sludge settling capacity
329 was measured via the SVI (mL/g), considering 30 minutes of settling time. Concentrations in the
330 mixed liquor of the bioreactors after feeding (*i.e.*, beginning of a new cycle) were regularly 305.8
331 (± 7.4) mg COD/L and 45.6 (± 0.8) mg TKN/L, or 594.7 (± 18.6) mg COD/L and 46.1 (± 0.2) mg
332 TKN/L when double organic loading occurred. A food-to-biomass ratio (F:M) control approach was
333 used as previously described⁵¹, for which biomass was measured weekly as total suspended solids
334 (TSS) after which sludge wastage was done to target a TSS of 1,500 mg/L. The latter resulted in
335 average solids residence time (SRT) values of 30, 26, 23, 22, 19 and 15 days, for disturbance levels
336 from 0 to 5, respectively. Note that these SRT values are well above the doubling times of relevant
337 bacteria in activated sludge⁵⁷. Sludge samples of 2 mL ($m = 184$) were collected on the initial day of
338 the study (four samples, taken at random from the inoculum mix) and weekly from each reactor
339 afterwards (180 samples), for DNA extraction as previously described³⁷.

340 *16S rRNA gene metabarcoding and reads processing*

341 Bacterial 16S rRNA metabarcoding was done in two steps as described in Santillan *et al.*⁵¹. Primer set
342 341f/785r targeted the V3-V4 variable regions of the 16S rRNA gene⁵⁸. The libraries were sequenced
343 in-house at SCELSE on an Illumina MiSeq (v.3) with 20% PhiX spike-in, at 300 bp paired-end read-
344 length. Sequenced sample libraries were processed with the *dada2* (v.1.3.3) R-package³³, allowing
345 inference of ASVs³². Illumina adaptors and PCR primers were trimmed prior to quality filtering.
346 Sequences were truncated after 280 and 255 nucleotides for forward and reverse reads, respectively.
347 After truncation, reads with expected error rates higher than 3 and 5 for forward and reverse reads,
348 respectively, were removed. After filtering, error rate learning, ASV inference and denoising, reads
349 were merged with a minimum overlap of 20 bp. Chimeric sequences (0.17% on average) were
350 identified and removed. For a total of 184 samples, an average of 18,086 reads were kept per sample
351 after processing, representing 47% of the average forward input reads. Taxonomy was assigned using
352 the SILVA database (v.132)⁵⁹. Diversity and assembly analyses were carried on both unrarefied and
353 rarefied datasets. To generate the rarefied dataset, samples were rarefied to the lowest number of reads
354 (5,089) in a sample after processing (Fig. S11).

355 *Bacterial community structure analyses and statistics*

356 All reported P-values for statistical tests in this study were corrected for multiple comparisons using a
357 false discovery rate (FDR) of 5%. Hill diversity indices²⁷ were used to quantify taxonomic α -diversity
358 as described elsewhere¹⁷. Phylogenetic α -diversity was assessed through Faith's phylogenetic
359 distance²⁸ (PD) including its abundance-weighted version (PD_w). Community structure in terms of
360 taxonomic β -diversity was evaluated through: i) canonical analysis of principal coordinates (CAP)
361 ordination including ellipses of 60% group-average cluster similarity; ii) misclassification error
362 analysis for each disturbance frequency level over the six time points sampled, via the leave-one-out
363 allocation of observations to groups from CAP; and iii) multivariate tests of permutational analysis of
364 variance (PERMANOVA) and permutational analysis of dispersion (PERMDISP); all from Bray-
365 Curtis dissimilarity matrixes at each time point sampled (30 bioreactors, n = 5), constructed from
366 square-root transformed abundance data using PRIMER (v.7)⁶⁰. Phylogenetic β -diversity was
367 assessed via non-metric multidimensional (NMDS) ordination of a weighted Unifrac dissimilarity
368 matrix, constructed from Hellinger transformed abundance data of all 184 samples using the
369 *phyloseq*⁶¹ R-package (v.1.30.0) in R. The *ggplot2* package (v.3.3.2) in R⁶² was used for local
370 polynomial regression fitting via the *loess* function (including 95% confidence intervals) and box
371 plots construction (using Tukey style whiskers). The *ggdist* R-package (v.2.4.1) was used to make the
372 β NTI raincloud plot. Univariate testing through Welch's analysis of variance (ANOVA) with Games-
373 Howell post-hoc grouping was done using the *rstatix*⁶³ (v.0.6.0) R-package. Kendall correlations were
374 done using the *ggpubr*⁶⁴ package (v.0.4.0) in R. Heat maps for bacterial phyla relative abundances
375 were constructed using the *ampvis2*⁶⁵ package (v.2.6.2) in R.

376 *Bacterial community assembly analyses and statistics*

377 The effect of underlying assembly mechanisms was assessed using phylogenetic-based null modelling
378 approaches on both α - and β -diversity. First, the nearest taxon index (NTI)²⁹ was calculated for each
379 community to assess whether α -diversity was more or less structured than would be expected by
380 random chance. The model uses the mean nearest taxon distance (MNTD)²⁹, which quantifies the
381 phylogenetic distance between each ASV in one community, as a measure of the clustering of closely

382 related ASVs. Phylogenetic relatedness of ASVs was characterized by multiple-alignment of ASV
383 sequences using *decipher* (v.2.14.0) R-package⁶⁶. The phylogenetic tree was then constructed and a
384 GTR+G+I maximum likelihood tree was fitted using the *phangorn* (v.2.5.5) R-package⁶⁷. To quantify
385 the degree to which MNTD deviates from a null model expectation, ASVs and abundances were
386 shuffled across the tips of the phylogenetic tree. After shuffling, MNTD was recalculated to obtain a
387 null value, and repeating the shuffling 1,000 times provided a null distribution. Then, NTI was
388 calculated as the difference between the mean of the null distribution and the observed MNTD in
389 units of standard deviation²⁹. The closer to zero a NTI value is, the closer to the null expectation (*i.e.*,
390 higher stochasticity) is the phylogenetic dispersion of a given community. Positive NTI values
391 suggest phylogenetic clustering while negative values indicate phylogenetic overdispersion. Second,
392 β -diversity null modelling via the β -nearest taxon index (β NTI) was done to investigate if the
393 phylogenetic turnover across two samples was significantly more or less similar than would be
394 expected by just random chance³⁰. The model uses the β -mean nearest taxon distance (β MNTD),
395 which quantifies the phylogenetic distance between pairs of ASVs drawn from two distinct
396 communities. To quantify the degree to which β MNTD deviates from a null model expectation, ASVs
397 and abundances were shuffled across the tips of the phylogenetic tree. After shuffling, β MNTD was
398 recalculated to obtain a null value, and repeating the shuffling 1,000 times provided a null
399 distribution. Then, β NTI was calculated as the difference between the mean of the null distribution
400 and the observed β MNTD in units of standard deviation³⁰. The closer to zero a β NTI value is, the
401 closer to the null expectation (*i.e.*, higher stochasticity) is the phylogenetic turnover between two
402 communities. By convention, a value of $|\beta$ NTI| > 2 indicates that the observed turnover is
403 significantly deterministic, while $|\beta$ NTI| < 2 indicates dominance of stochastic assembly processes²⁰.
404 Similarly, here we consider that $|\text{NTI}| < 2$ indicates dominance of stochastic phylogenetic clustering.
405 Both unweighted and abundance-weighted NTI and β NTI values were calculated. These analyses
406 were done using the *metagMisc*⁶⁸ (v.0.0.4) and *picante*⁶⁹ (v.1.8.2) R-packages. To test for a
407 phylogenetic signal across phylogenetic distances, Mantel correlograms were constructed using the
408 *vegan*⁷⁰ (v.2.5.6) R-package, relating between-ASV niche differences to between-ASV phylogenetic

409 distances across a given phylogenetic distance, following the previously described methodology^{20,30}.
410 Environmental niches were constructed from bioreactor effluent process data (COD removal, TKN
411 removal and SVI). Phylogenetic distances were quantified for 50 phylogenetic distance bins, while the
412 significance of Pearson correlations was assessed using 1,000 permutations and FDR (5%) correction.

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420 **Author Contributions**

421 Both authors conceived the idea. ES designed and performed the experiment, as well as data
422 processing and analyses. SW obtained the funding for the study. ES wrote the manuscript draft. Both
423 authors contributed to manuscript editing.

424 **Data availability**

425 DNA sequencing data are available at NCBI BioProjects with accession number PRJNA723443. See
426 supplementary information for details about the sludge inoculum collection, synthetic feed
427 preparation, and additional figures of diversity and community assembly metrics, correlations, heat
428 maps and data rarefaction. Diversity analyses on rarefied data and all other relevant data to reproduce
429 the results of this study are available as supplementary files in the online version of this manuscript.

430 **Competing interests**

431 The authors declare no competing interests.

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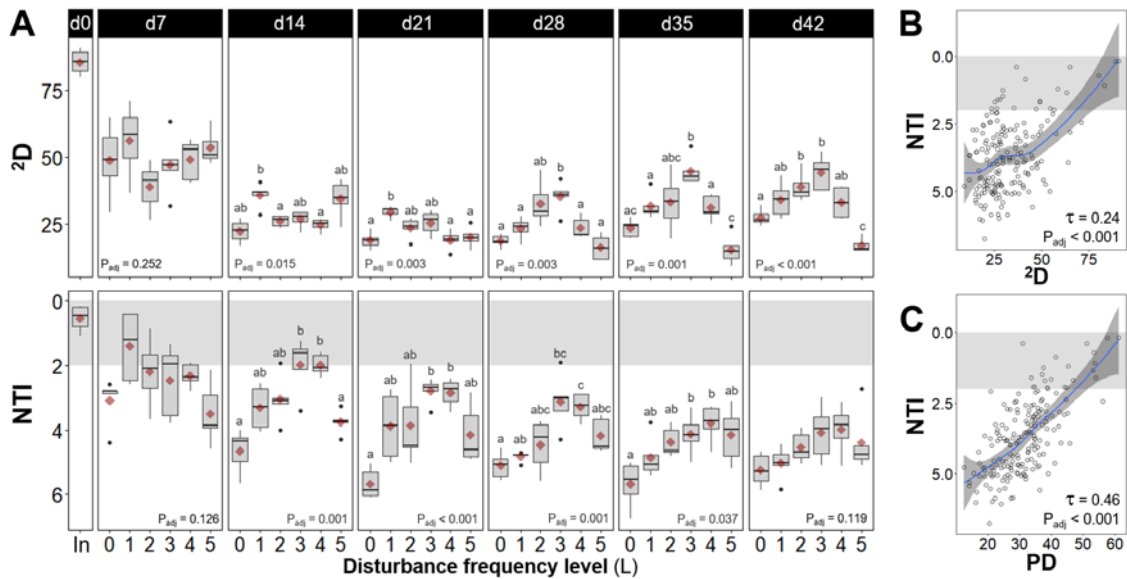
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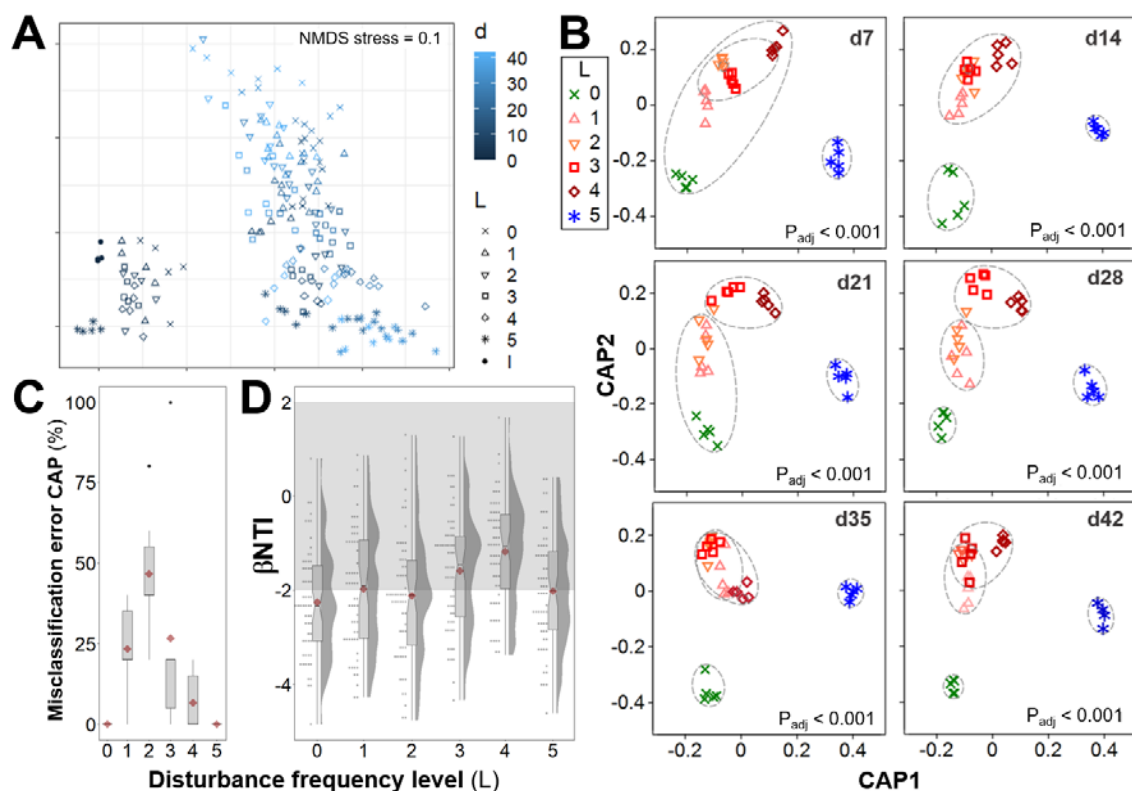
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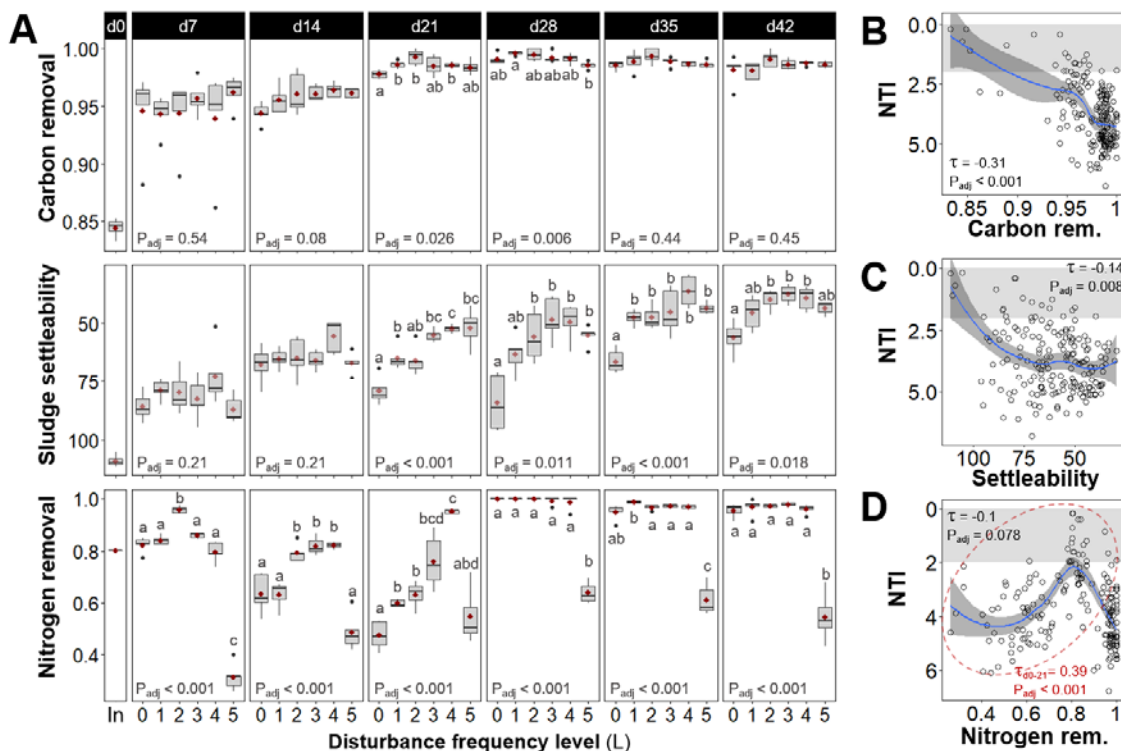
584

585 **Fig. 1** – Community dynamics in α -diversity. (A) Community structure assessed via 2nd order true α -
 586 diversity (2D , upper panels) and community assembly evaluated via the nearest taxon index (NTI,
 587 lower panels), from bacterial ASV data for different frequencies of organic loading disturbance ($n =$
 588 5). Disturbance frequency levels (L): 0 (undisturbed), 1-4 (intermediately disturbed), 5 (press-
 589 disturbed). In: sludge inoculum (day 0, $n = 4$). Each panel represents a sampling day, red diamonds
 590 display mean values. Characters above boxes display Games-Howell post-hoc grouping ($P_{adj} < 0.05$).
 591 Welch's ANOVA P -values adjusted at 5% FDR shown within panels. Correlations of (B) 2D and (C)
 592 phylogenetic diversity (PD) versus NTI from bacterial ASV data across all frequency levels and time
 593 points evaluated in this study ($m = 184$). Kendall correlation τ - and adjusted P -values are indicated
 594 within the panel. Blue line represents locally estimated scatterplot smoothing regression (loess) with
 595 confidence interval in dark-grey shading. Note the inverted y-axis for NTI, as values closer to zero
 596 indicate a higher relative contribution of stochastic assembly. Shaded in grey is the zone of significant
 597 stochastic phylogenetic dispersion, $|NTI| < 2$.



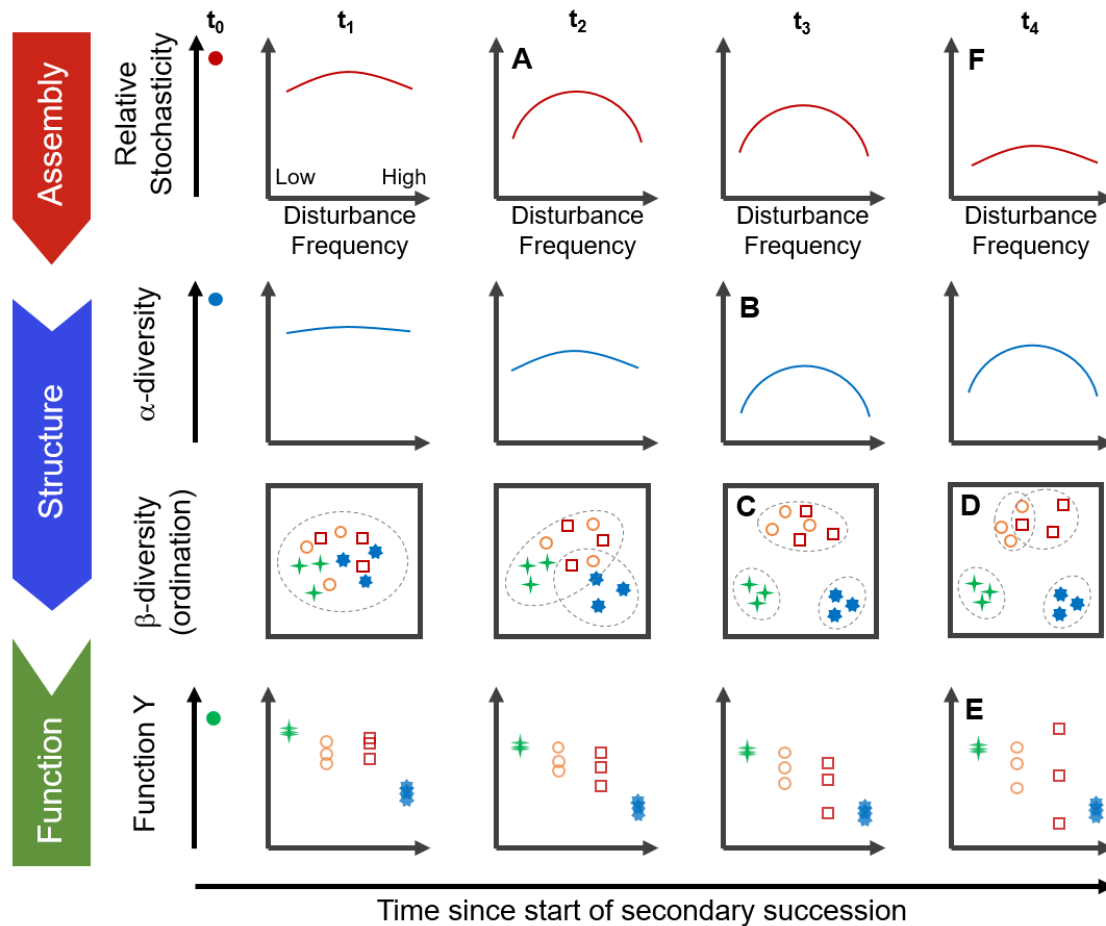
598

599 **Fig. 2** – Temporal dynamics of β -diversity community structure and assembly for bacterial ASV data
600 across different frequencies of organic loading disturbance ($n = 5$ bioreactors). **(A)** Unconstrained
601 NMDS ordination (weighed Unifrac β -diversity, Hellinger transformed data) for all 184 samples
602 collected. Disturbance frequency levels (L): 0 (undisturbed), 1-4 (intermediately disturbed), 5 (press-
603 disturbed). I: Sludge inoculum (day 0, $n = 4$). **(B)** Constrained canonical analysis of principal
604 coordinates (CAP) ordinations (Bray-Curtis β -diversity, squared root transformed data) on different
605 sampling days, including ellipses of 60% group-average cluster similarity and PERMANOVA
606 adjusted P-values. **(C)** Misclassification errors at each disturbance frequency level, via the leave-one-
607 out allocation of observations to groups from CAP at each time point after d0 ($n = 6$ sampling days).
608 Bray-Curtis β -diversity, squared root transformed data. Red diamonds display mean values. **(D)** Beta
609 nearest taxon index (β NTI) at each disturbance frequency level, from pairwise comparisons across
610 within-treatment replicates at each time point after d0 ($n = 60$ comparisons). Red diamonds display
611 mean values. Notches show the 95% confidence interval for the median. When notches do not
612 overlap, the medians can be judged to differ significantly. Shaded in grey is the zone where stochastic
613 processes significantly dominate, $|\beta$ NTI| < 2. β NTI values closer to zero indicate a higher relative
614 contribution of stochastic assembly.



615

616 **Fig. 3** – Community function assessed via influent chemical oxygen demand removal (carbon
617 removal, upper panels), sludge volume index (sludge settleability, middle panels), and influent total
618 Kjeldahl nitrogen removal (nitrogen removal, lower panels) for different frequencies of organic
619 loading disturbance ($n = 5$). Disturbance frequency levels (L): 0 (undisturbed), 1-4 (intermediately
620 disturbed), 5 (press-disturbed). In: sludge inoculum (day 0, $n = 4$). Each panel represents a sampling
621 day, red diamonds display mean values. Characters above boxes display Games-Howell post-hoc
622 grouping ($P_{adj} < 0.05$). Welch's ANOVA P-values adjusted at 5% FDR shown within panels.
623 Correlations of **(B)** carbon removal, **(C)** sludge settleability, and **(D)** nitrogen removal, versus NTI
624 from bacterial ASV data across all frequency levels and time points evaluated in this study ($m = 184$).
625 Kendall correlation τ - and adjusted P-values are indicated within the panels. Blue line represents
626 locally estimated scatterplot smoothing regression (loess) with confidence interval in dark-grey
627 shading. Shaded in grey is the zone of significant stochastic phylogenetic dispersion, $|NTI| < 2$. Red
628 ellipse and τ - and P-value in panel **(D)** indicate data at initial stages of succession (d0 to d21). Note
629 the inverted axis for sludge settleability, as it increases with decreasing SVI values, and for NTI, since
630 values closer to zero indicate a higher relative contribution of stochastic assembly.



631

632 **Fig. 4** - Conceptual representation of the intermediate stochasticity hypothesis (ISH) to describe
 633 patterns of assembly and structure along a disturbance frequency gradient, for communities in
 634 secondary succession (starting at time point t_0). (A) Initially, stochastic assembly mechanisms (*e.g.*,
 635 priority effects, historical contingency and legacy effects) are favored at intermediate disturbance
 636 frequencies, promoting re-colonization processes from the low-abundance fraction of the community
 637 or seed-bank. (B) Subsequently, these are followed by changes in the community structure that
 638 manifest as a peak of α -diversity at intermediate levels of disturbance. (C) At least three separated
 639 clusters of β -diversity ordination would form over time across the disturbance range. However,
 640 stochasticity operating at intermediate disturbance levels may lead to variable within treatment (D) β -
 641 diversity and (E) community function. (F) The overall relative contribution of stochasticity decreases
 642 with succession time. The observed patterns of diversity are stronger in terms of relative abundances
 643 than richness, as well as at the phylogenetic versus the taxonomic level.