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1 **Plant compartments and developmental stages**
2 **modulate the balance between niche-based and neutral**
3 **processes in soybean microbiome**

4

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33 **Abstract**

34 Understanding the dynamics of plant-associated microbial communities within agriculture
35 is well documented. However, the ecological processes that assemble the plant microbiome are
36 not well understood. This study elucidates the relative dominance of assembly processes across
37 plant compartments (root, stem, and leaves) and developmental stages (emergence, growth,
38 flowering, and maturation). Bacterial community composition and assembly processes were
39 assessed using 16S rRNA gene amplicon sequencing. Null models that couple phylogenetic
40 community composition and species distribution models were used to evaluate ecological
41 assembly processes of bacterial communities. All models highlighted that the balance between the
42 assembly process was modulated by compartments and developmental stages. Dispersal limitation
43 dominated amongst the epiphytic communities and at the maturation stage. Homogeneous
44 selection dominated assembly across plant compartments and developments stages. Overall, both
45 sets of models were mostly in agreement in predicting the prevailing assembly processes. Our
46 results show, for the first time, that even though niche-based processes dominate in the plant
47 environment, the relative influence of dispersal limitation in community assembly is important.

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56 **Introduction**

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58 Microbial communities that colonise plant surface from the roots to the leaves and the

59 inside of plant organs help overcome abiotic stress [1]. The colonisation, diversity, and succession

60 patterns of these microbial communities have become a research focus of interest for ecologists,

61 including efforts to identify and include microbial communities in sustainable agricultural

62 practices [2, 3]. One of the prerequisites to such efforts is to understand the ecological processes

63 that delimit microbiomes across plant compartments and growth stages, not only at the root-soil

64 interface [3, 4]. Ecological communities are assembled simultaneously by both niche-based

65 (environmental filtering) and neutral processes (dispersal limitations, ecological drift, and

66 speciation events)[5, 6]. However, the dominance of these processes across developmental stages

67 and plant compartments within a single genotype remains unknown.

68

69 Fundamentally, plant microbial communities are defined by 1) their taxonomic

70 compositions, 2) functional capacity, and 3) dominance of assembly processes. These inherent

71 community characteristics are influenced by plant genotype[7] , plant species [8] , and plant

72 nutrient status[9]. These studies have highlighted that there is an interaction between the different

73 components of the microbiomes. For instance, microbial taxa in the rhizosphere tend to influence

74 community assembly processes by modulating the expression of crucial plant functional genes [10,

75 11], and assembly processes within rhizosphere microbiome vary across crops [12].

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77 Essentially, there are two classes of models from which community assembly can be

78 inferred. Firstly, phylogenetic null models (PNM), where the integration of phylogenetic and

79 species pool data has led to a framework from which mechanisms of community assembly can be

80 inferred [13, 14]. At their core, these approaches combine a phylogenetic community structure
81 index such as beta mean nearest taxon distance (β MNTD) which estimates phylogenetic turnover
82 between assemblages[15, 16] and null models to quantify deviation from null expectations[15, 17,
83 18]. The null model randomly shuffles the taxa across tips of the phylogenetic tree and β MNTD
84 is recalculated, and this provides one null value for β MNTD[15, 19]. After several rounds of
85 iterations, the model provides a distribution of β MNTD values and deviations between the
86 observed β MNTD value and null β MNTD distributions are quantified as β -nearest taxon index
87 (β NNTI)[15, 20]. Niche-based selection imposed by the environment are then quantified as 1)
88 homogenous selection (β NNTI less than 2) implies that selective pressure exerted by the
89 environment is spatially homogenous and does not significantly change between periods, 2)
90 heterogeneous selection (β NNTI greater than 2) implies that the selective pressure changes between
91 periods [20]. Under homogenous selection, taxa that are selected at a specific period will be
92 continuously selected; whereas, under heterogeneous selection, different taxa will be selected
93 across different periods. These models have been used to quantify the relative influence of different
94 assembly processes [4] to predict niche constraints of soil microbes [21] and to elucidate microbial
95 biogeographical patterns[22, 23]. Secondly, species distribution models (SDM) use taxonomic
96 composition and niche-based or neutral assembly models to predict the prevailing assembly
97 processes. Typically, niche-based SDM models predict that changes in species abundance and
98 distribution are interconnected to changes in environmental conditions (environmental filtering)
99 [24, 25]. These models aim to describe the abundance distribution of taxa given the occupied niche
100 space. Broadly, these models predict how taxa that occupy similar niche spaces can coexist by
101 niche partitioning [26-28]. Under niche-based assembly, niche partitioning within communities
102 can be modelled with several models: 1) broken stick, pre-emption, log-normal, and Zipf-

103 Mandelbrot [25, 29]. Species distribution models use abundance and distribution of taxa to
104 quantify niche partitioning. Conversely, neutral SDM models predict that the abundance and
105 distribution of taxa is a direct consequence of dispersal limitation and species abundance [30, 31].
106 The zero-sum model (ZSM) predicts that the abundance and distribution of taxa into niche spaces
107 will be dominated by neutral processes [30, 32]. Similar to PNM models, SDM models have been
108 useful in predicting soil microbial biogeographical patterns [33], soybean rhizosphere taxonomic
109 and functional patterns [34, 35], and predict the composition of fungal leaf communities [36].

110 To date, studies that have elucidated community assembly processes within plant
111 microbiomes have used either of these approaches and have focused mainly on a single plant
112 compartment or developmental stage. Here, we were interested in using both PNMs and SDMs to
113 quantify assembly processes of soybean microbiomes across spatial (plant compartments) and
114 temporal (developmental stages) scales. We focused on elucidating assembly processes in soybean
115 plants growing in pots under controlled growth chamber experimental conditions. Using the
116 phylogenetically conserved regions of the 16S rRNA marker gene, we aimed at 1) elucidating the
117 relative dominance of neutral and niche-based processes in assembling the plant bacterial
118 community along spatial and temporal axes, and 2) comparing different complementary
119 approaches to model assembly processes.

120

121 **Methods**

122 *Plant growth conditions and microbiome sampling*

123

124 Plants were grown in a Conviron growth chamber (Winnipeg, Canada), and were

125 destructively sampled at the following developmental stages: V1 (emergence), V3 (growth), R1

126 (flowering), and R3 (maturation). The soil was collected in autumn of 2017 from an experimental

127 field that had no history of agricultural practice, passed through a 40 mm sieve, and homogenised

128 prior to potting. Soil analyses were performed in October 2017 by AgroEnviro Lab (La Pocatiere,

129 QC) and revealed an average pH of 7.2, P concentration of 193 (kg/ha), total N 0.15%, C/N of

130 13.1 and other soil properties reported in Table S1. Plants were supplemented with a modified

131 Hoagland's plant nutrient solution weekly [37]. A total of five plants were destructively sampled

132 at each developmental stage, and DNA extraction was performed right after sampling. Samples

133 were collected from rhizosphere, root, stem, and leaves. At each sampling period, the rhizosphere

134 samples were considered as all the soil that was directly attached to the root surface. The entire

135 epiphytic community (leaves, stem, and roots) was extracted using a modified protocol from [Qvit-](#)

136 [Raz, Jurkevitch and Belkin \[38\]](#). Briefly, the samples were placed in sterile 50 ml plastic Falcon

137 test tubes (Corning, Tewksbury, MA, USA) and filled with sterile phosphate-buffered saline (PBS

138 0.1M, pH 7.4). The samples were then placed in a sonication tub (Fisher FS20, Fisher Scientific,

139 Waltham, USA) for 15 min and vortexed for 10 s. The samples were then transferred into a new

140 tube containing PBS and rinsed twice. The wash was pooled and spun down in a centrifuge at

141 2,000 g for 20 min, and the resulting pellet was considered to be the epiphytic community. The

142 endophyte community was considered to be all the remaining microbes after the sonication and

143 rinse treatment. Plant tissue was then pulverised in liquid nitrogen using a sterile pestle and mortar.

144 For each sample, 0.25 g was added to the bead tubes from the Qiagen Power Soil DNA kit (Hilden,
145 Germany) and DNA was extracted following the manufacturer's instructions.

146

147 *16S rRNA gene amplification and sequencing*

148 The bacterial/archaeal V2-V3 hypervariable regions of the 16S rRNA gene were amplified
149 using 520F and 799R primer pairs, which were shown to exclude chloroplast sequences [39]. The
150 average lengths of 16S amplicon sequences were of approximately 280 bp. Briefly, extracted DNA
151 was used to construct sequencing libraries according to Illumina's "16S Metagenomic Sequencing
152 Library Preparation" guide (Part # 15044223 Rev. B), with the exception of using Qiagen HotStar
153 MasterMix for the first PCR ("amplicon PCR") and halving reagent volumes for the second PCR
154 ("index PCR"). The first PCR ("amplicon PCR") was carried out for 25 cycles with annealing
155 temperatures of 55 °C. The resulting amplicons were pooled together and sequenced at the McGill
156 University and Genome Québec Innovation Center (MUGQIC). Diluted pooled samples were
157 loaded on an Illumina MiSeq and sequenced using a 500-cycle (paired-end sequencing
158 configuration of 2x250 bp) MiSeq Reagent Kit v3. In total, 4,851,927 16S rRNA gene reads were
159 received. Reads were processed using the AmpliconTagger pipeline [40, 41]. Briefly, raw reads
160 were scanned for sequencing adapters, and PhiX spike-in sequences and remaining reads were
161 merged using their common overlapping part with FLASH [42]. Primer sequences were removed
162 from merged sequences, and remaining sequences were filtered for quality such that sequences
163 having an average quality (Phred) score lower than 27 or one or more undefined base (N) or more
164 than 10 bases lower than quality score 15 were discarded. Remaining sequences were clustered at
165 100% identity and then clustered/denoised at 99% identity (DNACLUST v3) [43]. Clusters having
166 abundances lower than 3 were discarded. Remaining clusters were scanned for chimeras with

167 VSEARCH's version of UCHIME denovo [44], UCHIME reference [45], and clustered at 97%
168 (DNACLUST) to form the final clusters/OTUs. OTUs were then assigned a taxonomic lineage
169 with the RDP classifier [46], using the AmpliconTagger 16S training sets [47], respectively. The
170 RDP classifier gives a score (0 to 1) to each taxonomic depth of each OTU. Each taxonomic depth
171 having a score ≥ 0.5 was kept to reconstruct the final lineage. Multiple sequence alignment was
172 then obtained by aligning the 16S rRNA gene OTU sequences on the SILVA R128 database [48]
173 using the PyNAST v1.2.2 aligner [49]. Alignments were filtered to keep only the hypervariable
174 region of the alignment. For cross-sample comparisons of alpha diversity, ten iterations were
175 performed on a random subsample of 1,000 reads rarefactions, and the average number of reads
176 of each OTU of each sample was then computed to obtain a consensus rarefied OTU table (Fig.S1).
177 Samples represented by less than 1,000 reads were removed from the analyses (2 samples were
178 removed). Alpha (observed species) and taxonomic summaries were then computed using the
179 QIIME v1.9.1 software suite using the consensus rarefied OTU table[50, 51].

180

181 *Statistical analyses*

182 The OTU rank distribution for each sample was fit to niche-based models (null, pre-emption,
183 log-normal, Zip f, and Mandelbrot) using the 'radfit' command in R [52], and neutral
184 model (zero-sum model- ZSM) using TeTame v.2.1 [53] using the same OTU table used to
185 construct the phylogenetic tree. The Akaike Information Criterion (AIC) was used to assess the
186 relative quality of each model, and the model that had the lowest AIC value was considered the
187 best fit model for the data [54, 55]. The AIC values for each model were calculated using the
188 equation $AIC = -2 \times \log\text{-likelihood} + 2 \times \text{npar}$, where npar is the number of parameters used in the
189 model[33, 36]. The statistical output is reported in Table 1. Dispersal rates were calculated by

190 Etienne's formula, using TeTame Software [53] (Table S3). Values of dispersal are between 0 and
191 1, where 0 means no tendency to migration and 1 means total tendency to migration in a specific
192 community.

193 A maximum-likelihood tree was built from that all the aligned sequences of representative
194 OTUs (a single representative sequence assigned to each OTU was used in subsequent analyses)
195 with FastTree v2.1.10. using the GTR substitution model [56]. For cross-sample comparisons, the
196 aligned fasta was subsampled to 1000 reads per samples, and samples with fewer than 1000s reads
197 were discarded from all downstream phylogenetic analysis (Table S4; 26 samples were removed).
198 Phylogenetic community turnover was evaluated using beta Nearest Taxon Index (β NTI) whose
199 absolute magnitude reveals the relative influences of either niche-based or neutral processes.
200 Briefly, using the mean nearest taxon index (MNTD), the standard effect size is calculated using
201 the null mode 'taxa.labels' (999 randomisations in *Picante* [57]). The SES.MNTD index measures
202 phylogenetic clustering in communities, with values >0 indicating phylogenetic overdispersion
203 (distantly related taxa tend co-occur less than expected by chance) and values <0 indicating
204 phylogenetic clustering (closely related taxa tend to co-occur more than expected by chance) [13].
205 The phylogenetic turnover across all communities was calculated as the beta MNTD (β MNTD).
206 The β NTI index is calculated as the difference between the observed β MNTD and mean of the
207 normalised (standard deviation) null distribution of β MNTD. β NTI values that are <-2 indicating
208 significantly less than expected phylogenetic turnover whilst values $>+2$ indicating significantly
209 more than expected phylogenetic turnover [16, 19, 20]. When β NTI values deviate from null
210 expectation and value is between <-2 and $>+2$ it indicates the dominance of neutral processes [17],
211 thus, observed differences in phylogenetic community compositions are the results of decreased
212 dispersal rates (dispersal limitation), high dispersal rates (homogenising dispersal), or

213 undominated by a specific process. The Bray-Curtis based Raup-Crick (RC_{bray}) was used to
214 determine the prevailing processes on pairwise comparison with βNTI values that lie between $<-$
215 2 and $>+2$ [15, 20, 58]. Briefly, the contributions dispersal limitation was calculated as the
216 percentage of pairwise comparisons with $|\beta\text{NTI}| < +2$ and $RC_{\text{bray}} > +0.95$, homogenising dispersal
217 $|\beta\text{NTI}| < +2$ and $RC_{\text{bray}} < -0.95$, and those that did not fall into those categories indicated
218 undominated selections. This randomisation holds constant the observed taxa richness, occupancy
219 and, turnover. Thus, this technique provides the expected level of βNTI given observed richness,
220 occupancy, and turnover [19]. A t-test was performed on the mean βNTI value to evaluate whether
221 it significantly deviated from zero- which is expected under neutral assembly.

222 *Sequence data deposition*

223 The raw sequencing reads have been deposited in the NCBI SRA under Bioprect
224 accession PRJNA601979: "Soybean microbiome - temporal and spatial development".

225

226 **Results and discussion**

227 To our knowledge, this is the first report that simultaneously provides evidence for the
228 current assembly processes within bacterial niches across spatial and temporal axes in a controlled
229 environment. Our aim to elucidate the overall processes within the plant microbiome highlighted
230 that homogenous selection and dispersal limitations were the prevailing assembly processes across
231 plant compartments and developmental stages. We were able to demonstrate that seemingly
232 complementing approaches to quantifying assembly do reveal the dominance of similar processes
233 across spatial and temporal axes, and these processes influence diversity patterns.

234
235 Overall, diversity patterns varied significantly across developmental stages and plant
236 compartments. For instance, alpha diversity (OTU richness: developmental stage $\chi^2=12.37^{***}$;
237 plant compartment $\chi^2=50.67^{***}$), beta diversity PERMANOVA (belowground: developmental
238 stage $R^2=0.21^{***}$, plant compartment $R^2=0.25^{***}$; aboveground: developmental
239 stage $R^2=0.08^{***}$, plant compartment $R^2=0.19^{***}$), and relative abundance of taxa at the phylum
240 and order level varied significantly (Fig.S2). Recently, we demonstrated that these observed
241 diversity patterns are modulated by interactions of spatial and temporal dynamics [59]. At a glance,
242 the mean β NTI value of the community significantly deviated from null expectations but was
243 between <-2 and $>+2$ indicating the dominance of neutral processes (Fig.1 one sample t-
244 test $p<0.05$). When disentangling the relative influence of different assembly processes,
245 homogenous selection and dispersal limitation were the prevailing assembly processes across all
246 plant compartments with heterogenous selection playing a minor role across all plant
247 compartments : Leaf (endophyte $\mu = -0.52^{***}$; epiphyte $\mu = -0.21^{***}$), Stem (endophyte $\mu = -$
248 0.64^{***} ; epiphyte $\mu = -1.01^{***}$), Root (endophyte $\mu = -0.82^{***}$; epiphyte $\mu = -0.76^{***}$), and

249 Rhizosphere ($\mu = -0.14^*$) (Fig.1; Fig.S3). Phylogenetic beta diversity indices such as beta nearest
250 taxon (BNTI) show probabilistic (the likelihood of closely related taxa to co-occur less frequently
251 than expected by chance) rather than absolute quantification of co-occurrences. This property of
252 the models makes them ideal for detection of influences of environmental filtering rather than the
253 nuanced ecological processes such as interspecific competition, for instance [60]. Equally, all
254 species distribution models (SDMs) indicated that, for the abundance and distribution of
255 communities, niche-based models were always the best model with the lowest Akaike Information
256 Criterion (AIC) (Table 1; Fig. 2).

257 When nutrients are limiting, such as at the root-soil interface under certain conditions [61],
258 there will be a more substantial influence of niche-based processes [62]. In soybean field trials,
259 when micronutrients become limiting, there are increased dispersal rates across temporal axes [34].
260 Both PNMs and SDMs elucidated the dominance of niche-based selection (homogeneous) and
261 increased dispersal at the root-soil interface (Fig.2; Fig.3; Fig.S3). This zone is a very selective
262 environment [63], with rhizodeposition leading to the assembly of a microbial community in sharp
263 contrast with bulk soil communities [10, 34, 35]. Also, it is possible that the reductionist
264 experimental setup (i.e. closed chamber) significantly influenced the distribution and abundance
265 of the bacterial community as detected by SDMs and increased dispersal rates within the epiphytic
266 communities.

267 In contrast, SDM neutral assembly model had the best explanatory power for the assembly of the
268 microbial communities of some leaf and root samples, suggesting that the plant selection
269 stringency of these environments is relatively more relaxed. Successful colonisation of new
270 bacterial niche spaces is predominantly dominated by species-sorting (niche-based) and dispersal
271 limitation (neutral) [64]. The increased surface area of leaves and roots provides increases

272 dispersal opportunities for air-borne and free-living soil microbes to occupy these niche spaces,
273 and dispersal limitation reinforces these current processes that occurred during initial colonisation
274 [65]. The stem endosphere is a relatively nutrient-poor environment, or at least unbalanced, with
275 a nitrogen content of sap directly affecting diversity and abundance of microbes [66, 67]. As such,
276 homogenous selection dominated assembly at later developmental stages whilst heterogenous
277 selection dominated at emergence (Fig.S3). We suggest that during the shorter developmental
278 stages (emergence/flowering) the selective pressure asserted by the plant produces heterogeneous
279 selection; whereas, at the longer reproductive stages (vegetative growth and maturation)
280 homogeneous selection dominates.

281
282 For the growth stages, again, the mean β NTI value of the epiphytic community
283 significantly deviated from null expectations but was between <-2 and $>+2$ indicating the
284 dominance of neutral processes: Emergence ($\mu = -0.21^{***}$), Growth ($\mu = -0.19^{***}$), Flowering (μ
285 $= -0.23^{***}$), Maturation ($\mu = -0.07^{***}$), and Overall ($\mu = -0.70$) (Fig.4). On average,
286 homogenising dispersal and selection (homogenous and heterogenous) processes accounted for
287 majority assembly processes *ca.*60% at each developmental stage (Fig.5). Similarly, SDMs
288 highlighted that neutral processes play a minor role in community assembly across other
289 developmental stages (Fig.6). Generally, niche-based processes (homogenous and heterogenous)
290 dominated at the growth and flowering stage, and dispersal dominated at the growth and
291 maturation stages. It is proposed that as the plant's metabolic demand for nutrient and carbon
292 increases at this stage, there will be a stringent selection for microbial taxa that can help in the
293 provision of those nutrients [68, 69]. In the case of soybean, secondary metabolites (e.g.
294 ethylamine and betaine) are produced during the flowering stage, and we suggest that the presence

295 of these molecules act as a robust environmental filter [68]. In fact, at the flowering stage, the
296 abundance and distribution were best predicted solely by the niche-based model despite increased
297 dispersal rates. It is then possible that within the communities, microbial taxa that were assembled
298 by neutral processes (speciation or drift) are competitively excluded due to their inability to
299 withstand strong environmental selection. These results presented here support observed
300 successional patterns of field- and laboratory-grown soybean plants, as we found the same
301 specialist taxa (Fig. S2) that characteristically dominate at different developmental stages in
302 soybean [69-71].

303 Dispersal rates varied across the plant compartment and developmental stages (Fig.3; Fig.5;
304 Fig.S3). The root and stem endophytic communities had a higher propensity for dispersal at the
305 flowering stage, whilst the leaf and stem epiphytic was during the growth stage. The leaf endophyte
306 and root epiphyte communities had increased dispersal rates at the maturation stage, whilst the
307 rhizosphere community has little to intermediate dispersal rates across all developmental stages.
308 For instance, SDMs neutral model had the best explanatory power for some communities at the
309 emergence, growth, and maturation stages, indicating that both neutral and niche-based processes
310 are essential in shaping the initial community, but also in explaining the temporal variation
311 observed in the microbial communities associated to soybean [68]and other plants [72, 73].
312 Additionally, at the maturation stage, phylogenetic null models indicated that the community was
313 neither dominated by niche-based nor by neutral processes. This shift in the community assembly
314 processes suggests changes in plant metabolic quality, i.e. decrease in metabolites supplied to
315 microbial symbiont as the plant enters senescence [74, 75]. Here, we propose that the influence of
316 niche-based processes on abundance and distribution of microbes at this stage, as shown by SDMs,

317 may be a relic of previous environmental selection perpetuated by microbe-microbe interaction,
318 as previously highlighted in the rhizosphere of desert plants [\[76\]](#).

319

320 Our study highlighted the difficulty in getting clear data on community assembly when
321 considering niche space to be the same in different plant compartments, suggesting that modelling
322 community assembly across space and time is far from trivial and would require some sort of
323 normalization for volume and population size across compartments. With that cautionary note in
324 mind, we were still able to demonstrate that seemingly complementing approaches to quantifying
325 assembly do reveal the dominance of niche-based processes across spatial and temporal axes. Both
326 classes of models indicated that the plant compartment and developmental stage modulate the
327 balance between niche-based and neutral processes. Dispersal limitations did have some influence
328 at some specific growth stages or in defined compartments. These stages and compartments might
329 be more readily amenable to inoculation or other microbiome manipulation approaches, as
330 communities under stringent niche-based assembly processes are probably challenging to displace.
331 This knowledge could orient the ongoing efforts to manipulate plant microbiomes for increased
332 beneficial services and more sustainable agriculture.

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353 **Conflict of interest**

354 The authors declare no conflict of interest.

355

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612 **Table and Figures**

613 **Fig.1 Boxplot of β NTI observations across plant compartments, where each observation is**
614 **the number of null model standard deviations the observed value is from the mean of null**
615 **distribution. The dashed blue lines indicate the significant upper and lower limits thresholds**
616 **of β NTI at +2 and -2. A t-test was performed on the mean value of the β NTI to test if it**
617 **significantly deviated from zero which is expected under neutral assembly: Leaf (Endophyte**
618 **$\mu = -0.52^{***}$; Epiphyte $\mu = -0.21^{***}$), Stem (Endophyte $\mu = -0.64^{***}$; Epiphyte $\mu = -1.01^{***}$**
619 **), Root (Endophyte $\mu = -0.82^{***}$; Epiphyte $\mu = -0.76^{***}$), and Rhizosphere ($\mu = -$**
620 **0.14^* ;)Where * indicates significance level ($* < 0.05$; $** < 0.001$, $*** < 0.0001$)**

621

622 **Fig.2 Bacterial community assembly processes (across plant organs) of fitted rank**
623 **abundance models; models with lowest Akaike Information Criterion (AIC) values were best**
624 **fit. AIC values were calculated from the equation: $AIC = -2\loglikelihood + 2 * npar$**

625

626 **Fig.3 The percentage of dispersal in community assembly and dispersal rates were calculated**
627 **using TeTame software with Etienne's formula, where m values are between 0 and 1. When**
628 **$m=1$ indicates increased tendency to migrate and $m=0$ indicates no tendency to migrate**
629 **across plant compartment.**

630

631 **Fig.4 Boxplot of β NTI observations across developmental stages, where each observation is**
632 **the number of null model standard deviations the observed value is from the mean of null**

633 **distribution. The dashed blue lines indicate significant upper and lower limits thresholds of**
634 **β NTI at +2 and -2. A t-test was performed on the mean value of the β NTI to test if it**
635 **significantly deviated from zero which is expected under neutral assembly: Emerging ($\mu = -$**
636 **0.21***), Growth ($\mu = -0.19***$), Flowering ($\mu = -0.23***$), Maturation ($\mu = -0.07***$), and**
637 **Overall ($\mu = -0.70$). Where * indicates significance level (* <0.05 ; ** <0.001 , *** <0.0001)**

638

639 **Fig. 5 The percentage of turnover in community assembly modulated by various niche-based**
640 **(homogenous and heterogeneous selection), neutral processes (dispersal limitation and**
641 **homogenising dispersal), and a fraction that was not dominated by any process across**
642 **developmental stages.**

643

644 **Fig.6 Bacterial community assembly processes (across developmental stages) of fitted rank**
645 **abundance models; models with lowest Akaike Information Criterion (AIC) values were best**
646 **fit. AIC values were calculated from the equation: $AIC = -2\loglikelihood + 2 * npar$**

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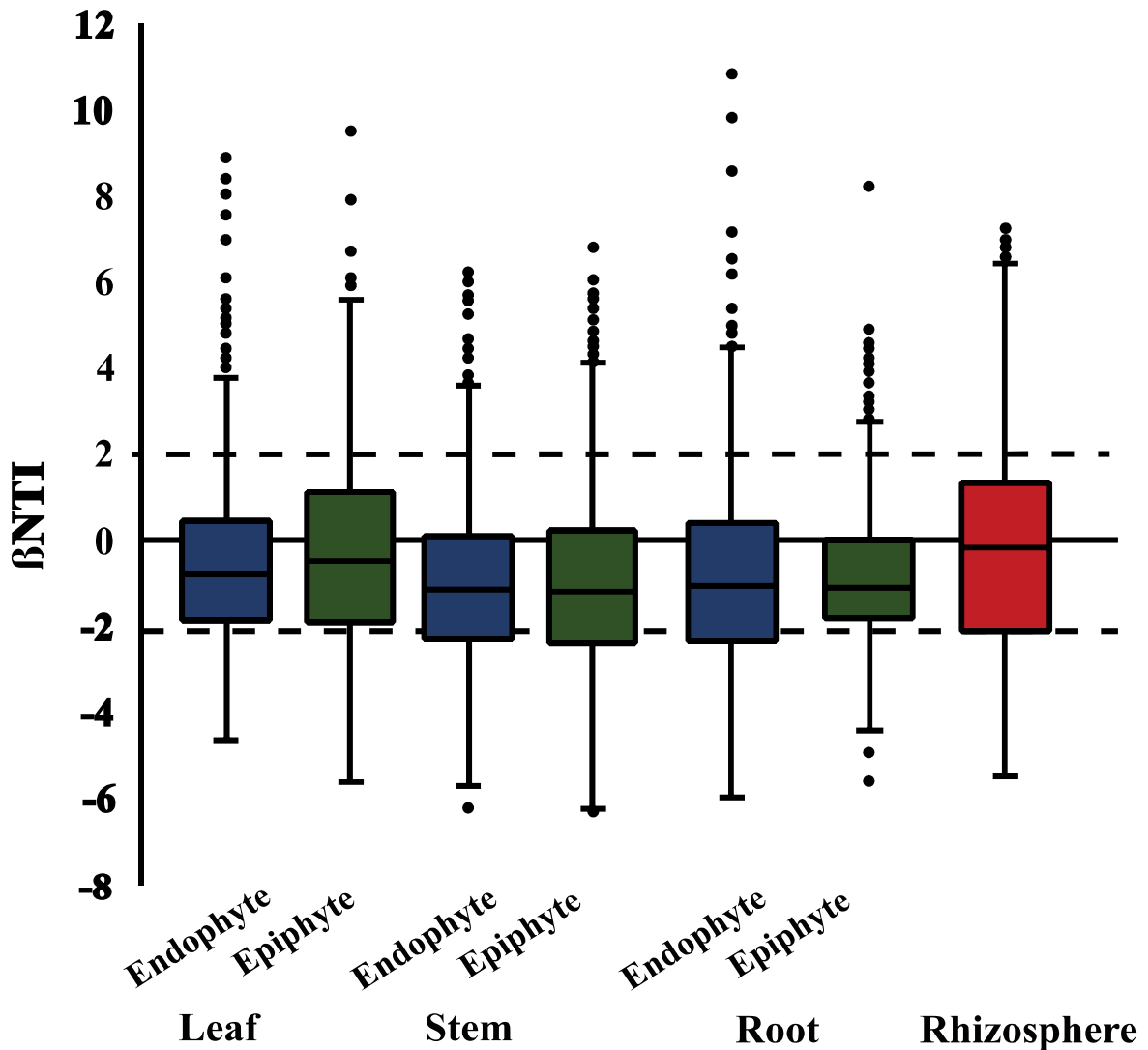


Fig.1 Boxplot of β NTI observations across plant compartments, where each observation is the number of null model standard deviations the observed value is from the mean of null distribution. The dashed blue lines indicate the significant upper and lower limits thresholds of β NTI at +2 and -2. A t-test was performed on the mean value of the β NTI to test if it significantly deviated from zero which is expected under neutral assembly: Leaf (Endophyte $\mu = -0.52^{***}$; Epiphyte $\mu = -0.21^{***}$), Stem (Endophyte $\mu = -0.64^{***}$; Epiphyte $\mu = -1.01^{***}$), Root (Endophyte $\mu = -0.82^{***}$; Epiphyte $\mu = -0.76^{***}$), and Rhizosphere ($\mu = -0.14^*$); Where * indicates significance level ($* < 0.05$; $** < 0.001$, $*** < 0.0001$)

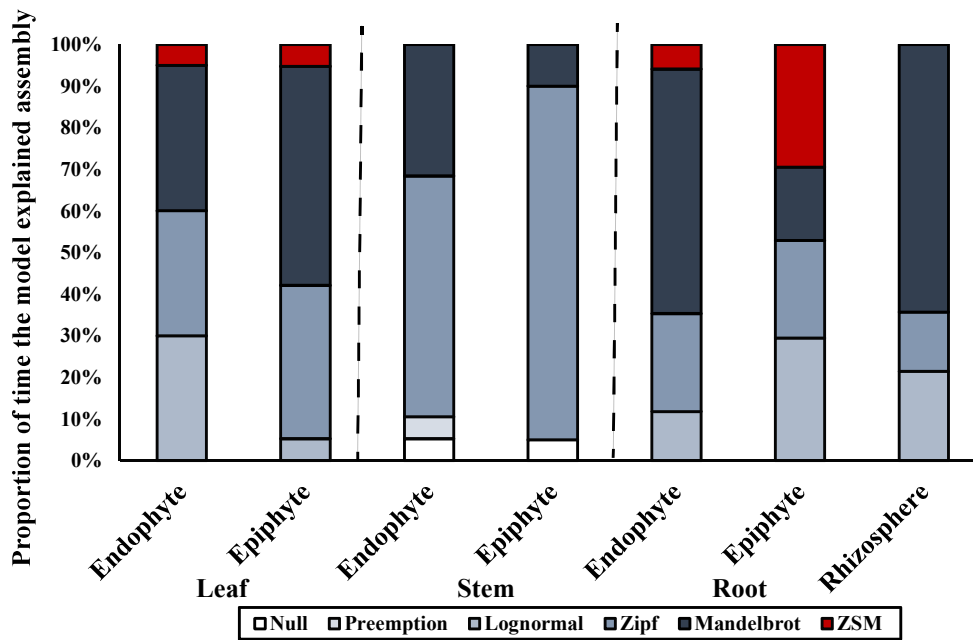


Fig.2 Bacterial community assembly processes (across plant organs) of fitted rank abundance models; models with lowest Akaike Information Criterion (AIC) values were best fit. AIC values were calculated from the equation: $AIC = -2\loglikelihood + 2 * npar$

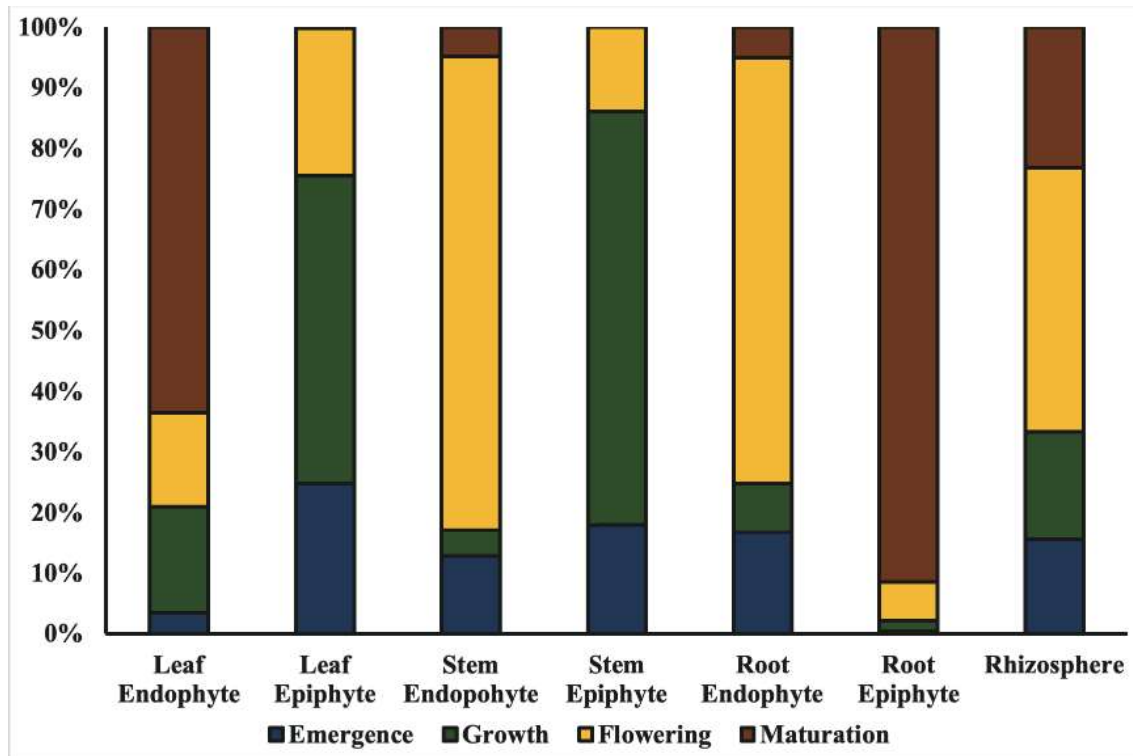


Fig.3 The percentage of dispersal in community assembly and dispersal rates were calculated using TeTame software with Etienne's formula, where m values are between 0 and 1. When $m=1$ indicates increased tendency to migrate and $m=0$ indicates no tendency to migrate across plant compartment.

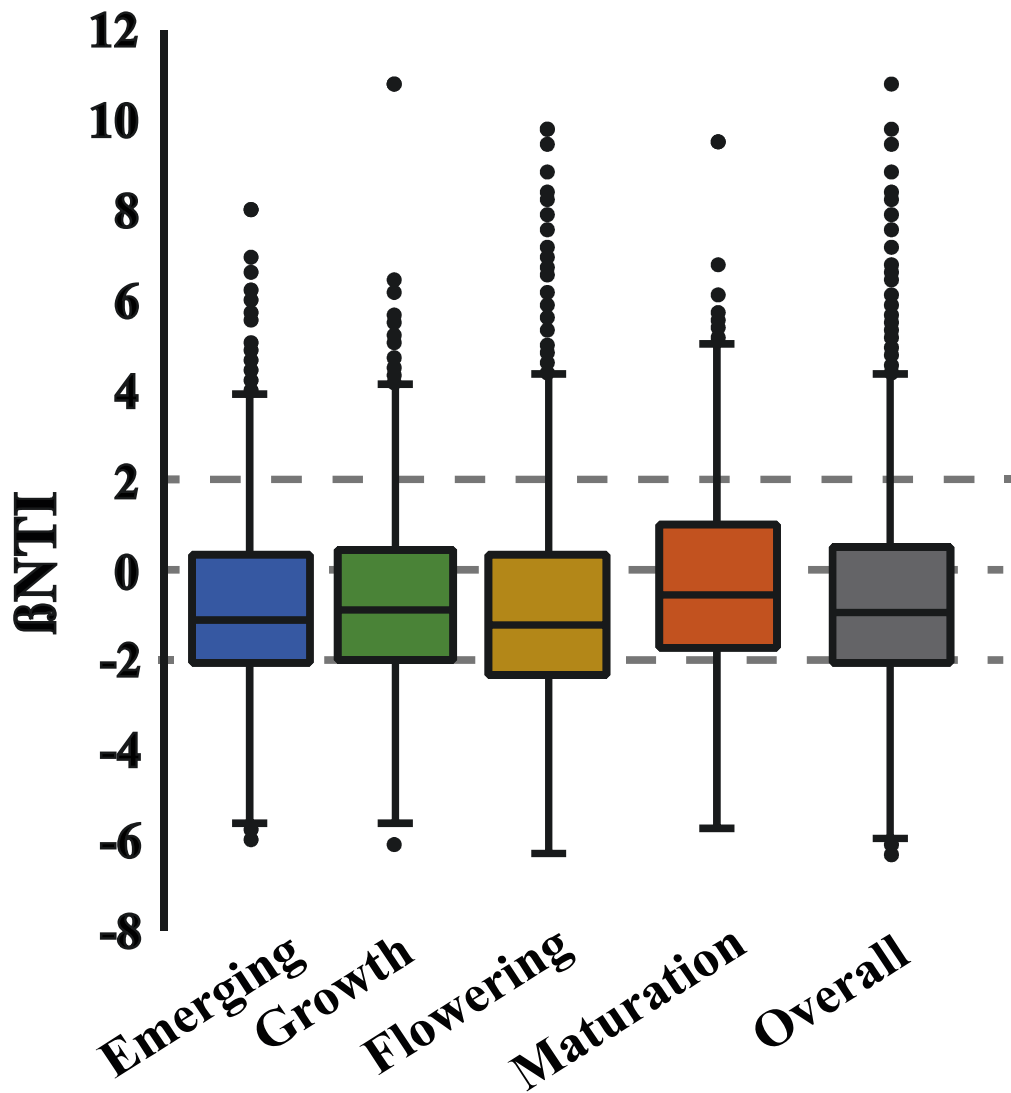


Fig.4 Boxplot of βNTI observations across developmental stages, where each observation is the number of null model standard deviations the observed value is from the mean of null distribution. The dashed blue lines indicate significant upper and lower limits thresholds of βNTI at +2 and -2. A t-test was performed on the mean value of the βNTI to test if it significantly deviated from zero which is expected under neutral assembly: Emerging ($\mu = -0.21^{***}$), Growth ($\mu = -0.19^{***}$), Flowering ($\mu = -0.23^{***}$), Maturation ($\mu = -0.07^{***}$), and Overall ($\mu = -0.70$). Where * indicates significance level ($* < 0.05$; $** < 0.001$, $*** < 0.0001$)

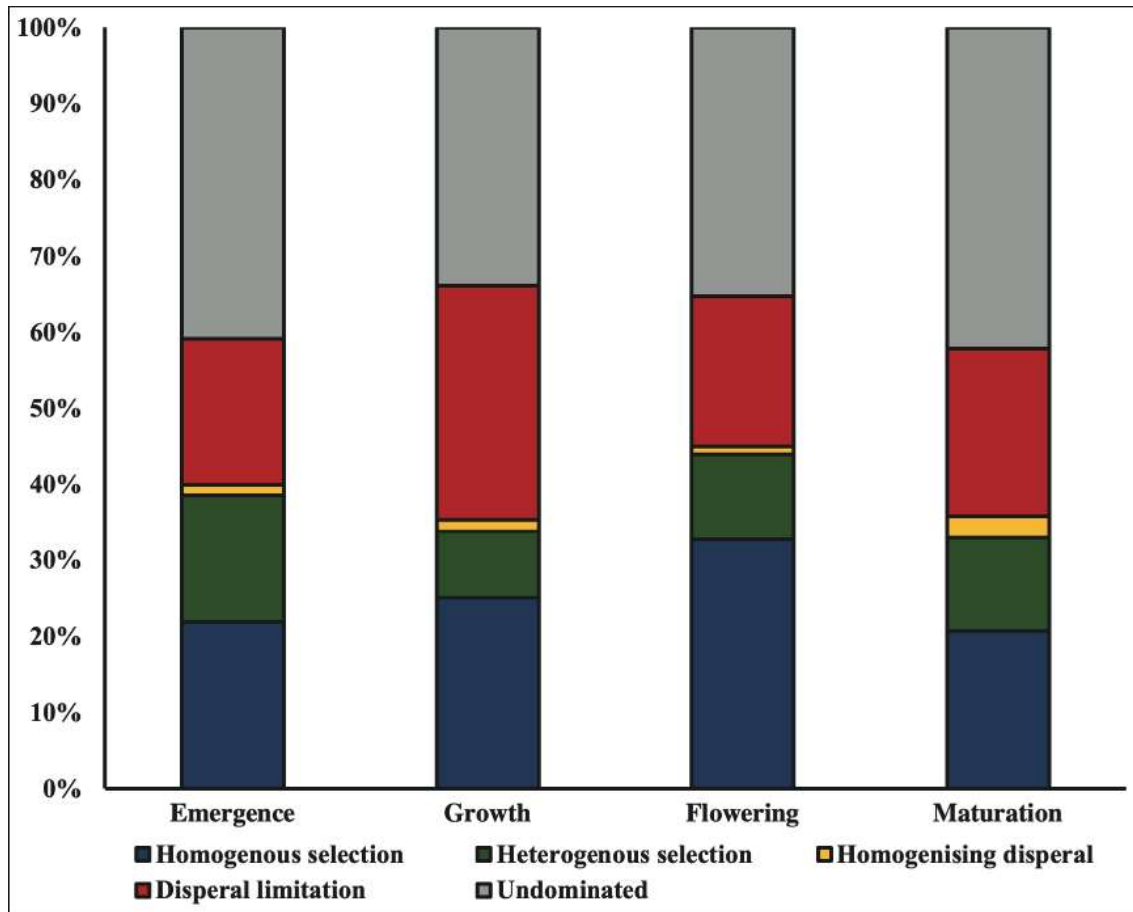


Fig. 5 The percentage of turnover in community assembly modulated by various niche-based (homogenous and heterogeneous selection), neutral processes (dispersal limitation and homogenising dispersal), and a fraction that was not dominated by any process across developmental stages.

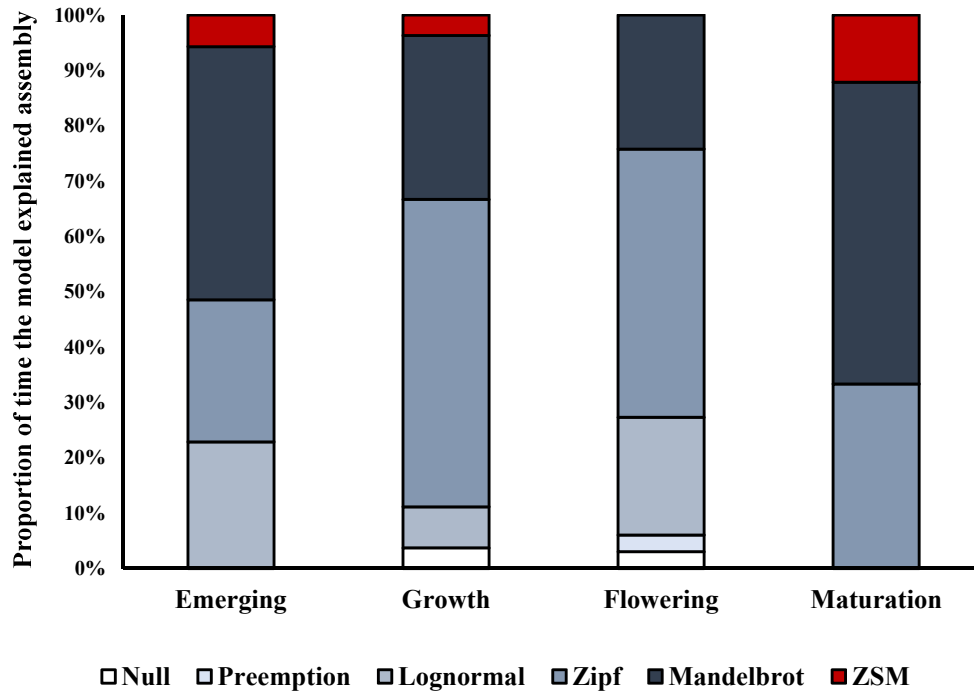


Fig.6 Bacterial community assembly processes (across developmental stages) of fitted rank abundance models; models with lowest Akaike Information Criterion (AIC) values were best fit. AIC values were calculated from the equation: $AIC = -2\loglikelihood + 2 * npar$

Table 1. Bacterial Akaike Information Criterion (AIC) values of fitted rank abundance models. models with lowest Akaike Information Criterion (AIC) values were best fit. AIC values were calculated from the equation: $AIC = -2\log\text{likelihood} + 2 * npar$

Organ	Developmental stage	ID	Akaike Information criterion (AIC)					Neutral
			Niche-based					
			Null	Preemption	Lognormal	Zipf	Mandelbrot	ZSM
Leaf Endophyte	Emerging	LE1-1	1731.30	1636.61	1063.21	2057.79	1611.09	2151.64
		LE1-2	1259.84	1504.27	1032.45	1841.66	1453.29	2727.94
		LE1-3	4927.37	4868.88	1573.91	2518.82	2106.26	3785.24
		LE1-4	1675.18	1973.17	1026.15	1696.63	1544.46	2167.11
		LE1-5	6728.90	6915.60	2123.10	2694.90	2696.90	4424.70
	Growth	LE2-1	87015.80	39446.40	5198.60	2924.10	2926.10	2257.24
		LE2-2	7966.14	6809.24	2061.90	1420.73	1422.73	1964.87
		LE2-3	4508.65	4155.71	1519.77	1049.60	1051.60	1917.98
		LE2-4	6382.61	5047.45	1635.65	1176.68	1178.68	1559.45
		LE2-5	8214.80	7027.90	2245.40	1572.40	1574.40	2018.11
	Flowering	LE3-1	7277.60	3059.96	1126.86	1301.90	767.68	2633.86
		LE3-2	1671.15	1182.84	696.00	767.64	550.13	2261.44
		LE3-3	5405.77	4206.96	1192.67	824.27	826.27	1952.84
		LE3-4	537.73	597.40	466.02	457.51	459.18	1931.33
		LE3-5	673.46	719.96	504.30	608.39	542.89	2033.88
	Maturation	LE4-1	159.64	147.87	143.62	147.56	132.80	587.88
		LE4-2	280.67	290.54	252.62	243.32	242.59	1238.01
		LE4-3	445.21	474.87	385.28	370.36	370.15	1776.41
		LE4-4	515.30	535.25	382.43	347.64	344.61	1611.13

Table 2. Dispersal rates across developmental stages and plant compartments of soybean-associated bacterial communities.

Organ	Developmental stage	Dispersal rate (<i>m</i>)
Leaf endophyte	Emerging	0.008
	Growth	0.041
	Flowering	0.036
	Maturation	0.148
Leaf epiphyte	Emerging	0.142
	Growth	0.290
	Flowering	0.139
	Maturation	0.001
Rhizosphere	Emerging	0.073
	Growth	0.084
	Flowering	0.205
	Maturation	0.109
Root endophyte	Emerging	0.033
	Growth	0.016
	Flowering	0.139
	Maturation	0.010
Root epiphyte	Emerging	0.001
	Growth	0.004
	Flowering	0.015
	Maturation	0.215
Stem endophyte	Emerging	0.087
	Growth	0.030
	Flowering	0.531
	Maturation	0.033
Stem epiphyte	Emerging	0.044
	Growth	0.166
	Flowering	0.034
	Maturation	6.17604E-07

Dispersal rates were calculated using TeTame software with Etienne's formula, where m values are between 0 and 1. When $m=1$ indicates increased tendency to migrate and $m=0$ indicates no tendency to migrate